Community Social Capital and Farmer Development: Key Drivers of Welfare and Business Productivity in Farmer Groups

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Abstract. Community Social Capital and farmer characteristic development are seen as important factors that can influence farmer welfare and farming productivity in farmer groups. This study aims to analyze the influence of Community Social Capital and farmer characteristic development on farmer group welfare and business productivity. This study uses a quantitative method with a survey approach, with 35 respondents who are members of farmer groups in Dayun District, Riau Province. Data were collected using a questionnaire that includes the variables Community Social Capital, farmer welfare, farmer characteristic development, and farming productivity. Data analysis was carried out using path analysis through Structural Equation Modeling-Partial Least Square (SEM-PLS). The results showed that Community Social Capital and farmer characteristic development have a significant positive influence on farmer welfare and farming productivity in farmer groups. This indicates that increasing community social capital and developing farmer characteristics, such as knowledge, skills, and innovation, can contribute to improving welfare and agricultural production. This study highlights the importance of the role of Community Social Capital and the development of farmer characteristics in improving welfare and productivity of farming businesses.
Keywords: Community social capital, farmer development, welfare, business productivity

1 Introduction

Agriculture remains a key driver of economic development and food security, particularly in rural regions [1]. In Indonesia, where a large portion of the population depends on agriculture for their livelihood, the welfare of farmers and the productivity of farming businesses have become critical concerns for both policymakers and local communities [2,3]. Farmer groups, as collective organizations, play an essential role in promoting knowledge exchange, shared resources, and joint problem-solving, thus contributing to

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improved agricultural outcomes [1,4]. However, the success of farmer groups in enhancing welfare and productivity depends on several factors, among which Community Social Capital and farmer characteristic development are particularly notable.

Community Social Capital refers to the collective resources, trust, and networks embedded within a community that enable cooperation for mutual benefit. It plays a pivotal role in facilitating collective action [5,6,7], providing access to shared resources, and enhancing the overall capacity of farmers to engage in productive agricultural activities. Social capital, in this context, fosters collaboration and knowledge-sharing among group members, which can lead to better decision-making, more efficient use of resources, and improved access to markets. Previous studies have underscored the importance of social capital in driving agricultural innovation, market participation, and resilience among farming communities [8,9]. However, there remains a need to further examine how social capital specifically influences welfare and productivity within farmer groups, particularly in rural districts such as Dayun in Riau Province.

In addition to social capital, the development of farmer characteristics is another critical factor influencing agricultural success [10]. Farmer characteristics, such as knowledge, skills, experience, and the ability to innovate, directly impact their capacity to adopt new technologies and practices, manage risks, and improve yields [11]. Farmers with higher levels of knowledge and experience are generally better equipped to navigate the complexities of modern agriculture, leading to more sustainable farming practices and increased productivity [12]. The ability to innovate has become increasingly important as farmers face challenges related to climate change, market fluctuations, and limited access to resources. This study argues that enhancing these characteristics through targeted development programs can significantly improve both the welfare and business productivity of farmers.

The district of Dayun in Riau Province presents a valuable case for studying the relationship between Community Social Capital, farmer characteristic development, and agricultural outcomes. This region, like many rural areas in Indonesia, faces several challenges, including limited access to agricultural inputs, fragmented markets, and inadequate infrastructure. At the same time, farmer groups in Dayun serve as critical platforms for addressing these challenges collectively. According to Maulana [12], the ability of oil palm farmers to cultivate land effectively and efficiently, with the support of strong social capital, will increase farming productivity [12, 13, 14, 15]. In line with Futemma et al. [16], the lack of education and training for farmers to adopt better and more efficient farming practices can limit the potential for increased productivity. According to Amankwah [17], high agricultural productivity will have a positive impact on farmer welfare. More abundant harvests and better product quality can increase farmers' incomes, allowing them to reinvest, expand land, and adopt new technologies. In addition, according to Aune et al. [18] and Sampe [19] increased productivity can also create additional jobs in rural areas, contributing to poverty reduction and improving overall community welfare [20].

From a productivity perspective, many farmer groups face obstacles in increasing the efficiency of farming businesses, both in terms of product quality, resource management, and market access [19, 20]. Lack of skills in business management, limited knowledge of modern agricultural practices, and limited access to technology and innovation result in far from optimal farming productivity. Therefore, the main problem faced by farmers in Dayun is how community social capital and farmer characteristic development can be effectively improved to improve their welfare and farming productivity. This study aims to answer these problems by analyzing the extent to which community social capital and farmer characteristic development affect farmer welfare and farming productivity in farmer groups in Dayun, Riau.

2 Method

This study uses a quantitative method that can explain the causal relationship between the variables studied with data obtained from disaster-prone communities on Bengkalis and Rupat Islands, Bengkalis Regency, Riau Province. This study was conducted on the Independent Farmer Group domiciled in Dayun District, Siak Regency. The objects of research studied were Community Social Capital (X1), Farmer Characteristics (X2), Farmer Welfare (Z), Business Productivity (Y). The population used was the number of independent oil palm farmers in Dayun District, Siak Regency, with a total oil palm land area of +/- 300 hectares, which is 659 Farmers. In this study, the selection of respondents used probability sampling with the random sampling method with the consideration that each member of the population has an equal opportunity to be involved in the research sample. The sample size was determined using Slovin's formula as described follows.

$$n = \frac{N}{1 + Nd^2} = \frac{659}{1 + (659)(0{,}10)^2} = 86{,}82$$

Where *n* represents the sample size, *N* denotes the population, and *e* signifies the margin of error due to sampling inaccuracies. Based on Slovin's calculation, the sample size is 86,82, but following the decimal discretization principle, the sample size was rounded up to 100 samples. However, after the questionnaire was distributed, the response rate obtained was 40,3% so that the number of samples analyzed was 35 samples.

Causal analysis is used to see the relationship of influence and hypothesis testing using the Structural Equation Model (SEM). Data processing in this study uses the Partial Least Square (PLS) method, because all variables are latent variables and are measured by indicators, even if there is multicollinearity between these variables [21]. Partial Least Square is used to confirm the theory. Data analysis is carried out in two steps. First, descriptive analysis and then causal analysis. In the descriptive analysis, this study uses an outer model, inner model and hypothesis testing or a structural model using SmartPLS. Second, the results of the descriptive analysis are interpreted based on theory and empirical phenomena. The research model is reflective of the indicators. We consider that SmartPLS is developed based on a more accurate modeling and bootstrapping pathway to predict the research hypothesis model, and is recommended by Tenenhaus et al. [22].

Using SEM-PLS is particularly suitable in this study because it accommodates small sample sizes and is effective in testing theoretical models. Since the research involves a relatively small number of samples, due to the low response rate, SEM-PLS is an ideal choice as it does not require large sample sizes for stable results. Moreover, SEM-PLS is beneficial for theory confirmation when dealing with complex models involving latent variables measured by multiple indicators. This approach allows for a more flexible analysis path, making it possible to assess relationships between variables even in cases of multicollinearity, providing robust insights into the theoretical model being tested [23, 24].

3 Results and Discussion

In the first stage, we descriptively analyzed the PLS output results with outer model analysis, inner model and structural model. In the outer model analysis according to [25] the reliability test of the construct is measured by composite reliability and Cronbach's alpha. The construct will be declared reliable if it has a composite reliability value above 0.70 and Cronbach's alpha above 0.60. The adequacy value of Average Variance Extracted (AVE) to measure its validity is 0.5 [24]. The following table is the result of the outer model analysis. Based on the criteria in Table 1, the data output shows that all outer model criteria can be met so that it can be stated that the research data has good validity and reliability, therefore it can be continued to the inner model analysis.

Table 1. Cronbach Alpha, Composite Reliability and Average Variance Extracted

Constructs	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Area of Land Used	0,671	0,816	0,599
Basic Needs	0,935	0,958	0,884
Bonding	0,896	0,928	0,764
Bridging	0,660	0,813	0,594
Business Productivity (Y)	0,864	0,896	0,445
Characteristics of Farmers (X2)	0,832	0,871	0,401
Community Social Capital (X1)	0,853	0,889	0,483
Education Level	0,764	0,862	0,680
Experience	0,821	0,882	0,654
Farmers Walfare (Z)	0,879	0,900	0,405
Financial Aspects	0,426	0,490	0,420
Flexibility	0,712	0,839	0,636
Health	0,878	0,919	0,792
Income	0,805	0,874	0,699
Knowledge	0,807	0,868	0,624
Linking	0,467	0,784	0,647
Product Quality	0,895	0,935	0,826
Security	0,733	0,848	0,651
Social Interaction	0,693	0,837	0,649
Social Responsibility	0,750	0,858	0,670

Inner model analysis aims to ensure that the model built is robust and accurate. According to Hair et al. [24] inner model analysis can be seen from several factors, namely the coefficient of determination (R^2), predictive relevance (Q^2), goodness of fit index (GoF). $R^{2,}$ or R squared is the proportion of variables in a data that is calculated in a statistical model. This evaluation is important to determine the explanatory power of the model and its ability to predict dependent variables accurately. According to Chin [25], The R^2 value is 0.67 (Strong), 0.32 (moderate) and below 0.19 (weak). Based on the R^2 analysis of this study, the SEM-PLS model received a strong category because the average R^2 value was 0.657.

Table 2. R Square (R^2) Value

Criteria	R Square	R Square Adjusted
Farmers Walfare (Z)	0,707	0,689
Business Productivity (Y)	0,607	0,595

Predictive relevance (Q^2) is carried out to determine the predictive ability with the blindfolding procedure. According to Chin [25], if a value of 0.02 is obtained, the model has a small predictive ability. If a value of 0.15 is obtained, the model has a moderate predictive ability. And if the value received is 0.35, then the model has a strong predictive ability. The calculation of the Q^2 value is 0.684, then the model has a very strong predictive ability. To analyze Predictive Relevance (Q^2), we use the following formula:

Q2 = 1-(1-R12) × (1-R22) × …… (1-Rn2)

Q2 = 1-(1-(0,707×0,707)) × (1-(0,607×0,607))
Q2 = 0,684

Then to analyze the structural model, it is obtained from the GoF value which will be calculated mathematically [22] with the following formula:

$$GoF = \sqrt{AVE^2 \times R^2}$$

The Goodness of Fit index is obtained by squared the AVE value and multiplied by R^2.

$$AVE = \frac{\sum \lambda_i^2}{\lambda_i^2 + \sum_i var(\varepsilon_i)} = 0.434$$

Where λ_i is the loading component to the indicator and $var\ (\varepsilon_i) = 1 - \lambda_i^2$ with AVE is 0.434 and the average R^2 is 0.657. so that GoF is calculated with the following formula:

$$GoF = \sqrt{AVE^2 \times R^2}$$
$$GoF = \sqrt{0{,}434^2 \times\ 0{,}657} = 0{,}352$$

According to Tenenhaus et al. [22] , the GoF value is considered small if the value is 0.10, the GoF is considered moderate if the value is 0.25, and the GoF will be considered strong if the value is 0.38. Based on the GoF calculation of 0,352, the structural model has a strong and robust GoF value.

Table 3. Path coefficients (Mean, STDEV, T-Statistics, P-Values)

Constructs	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P-Values
Characteristics of Farmers (X2) -> Farmers Walfare (Z)	0,837	0,833	0,163	5,128	0,000
Community Social Capital (X1) -> Farmers Walfare (Z)	0,005	0,009	0,179	0,025	0,980
Farmers Walfare (Z) -> Business Productivity (Y)	0,779	0,785	0,053	14,636	0,000

After analyzing the outer and inner models, we proceeded to test the hypotheses using bootstrapping analysis. Bootstrapping is a nonparametric procedure that allows for the statistical significance testing of various PLS-SEM results, such as path coefficients, Cronbach's alpha, T-statistics, and R². In bootstrapping analysis, subsamples are randomly drawn from the original dataset (with replacement). These subsamples are then used to estimate the PLS path model. This process is repeated until many random subsamples (e.g., 5,000) have been generated. The estimates from the bootstrap subsamples are used to derive standard errors for the PLS-SEM results. Based on these, t-values, p-values, and confidence intervals are calculated to assess the significance of the PLS-SEM outcomes. Hair et al. [24] provides a more detailed explanation of bootstrapping. If the t-statistic value is greater than the critical t-value from the t-table at a 95% confidence level (> 1.96), the influence is considered significant. Furthermore, to determine the extent of the influence between variables, the loading factor from the original sample (O) output is analyzed. This can be observed in the path coefficients table from the SmartPLS output.

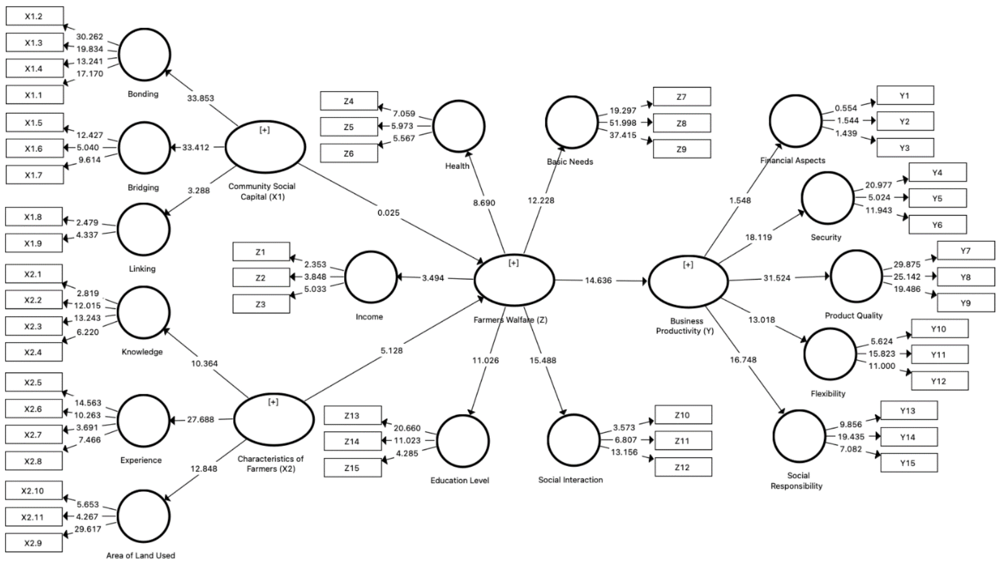

Fig.1. Bootstrapping SEM-PLS Output

Based on the results of the SEM-PLS bootstrap in Figure 1, the results of the path coefficients (Table 3) between the exogenous constructs, namely Characteristics of Farmers and Community Social Capital with the endogenous constructs, namely Farmers Welfare and Business Productivity, and of the three hypotheses, only two have a significant positive effect and are above the threshold of 1.962, but only one with an insignificant value, namely the effect of Community Social Capital on Farmers Welfare, with a factor loading value below 0.5, and a P Value above 0.05 [4].

This shows that community social capital does not have a significant effect on farmer welfare in this study. Most likely, limitations in social networks, low levels of trust, or lack of access to wider resources are factors that inhibit the positive impact of community social capital on farmer welfare [26, 27]. Conversely, the development of farmer characteristics, such as knowledge, experience, and skills, has been shown to have a significant and positive effect on farmer welfare and farming productivity. These results underline the importance of improving farmers' capacity as a key factor in supporting the growth of farming businesses and improving their welfare [16,20,28].

These findings are in line with several previous studies stating that improving farmers' knowledge and skills can strengthen their ability to manage risks, adopt new technologies, and increase yields, which ultimately have an impact on improving their economic welfare [29, 30]. On the other hand, although social capital is often considered as an important element in encouraging cooperation and solidarity among farmers, the results of this study indicate that in certain contexts, especially in farmer groups in Dayun, social capital is not strong enough to directly improve farmers' welfare.

The results of the bootstrapping analysis in the SEM-PLS model reveal several key insights into the relationships between the constructs in this study, specifically between Characteristics of Farmers, Community Social Capital, Farmers Welfare, and Business Productivity. The first relationship, between Characteristics of Farmers and Farmers Welfare, shows a strong positive and significant influence, as indicated by a high path coefficient (0,837), a T-statistic of 5,128, and a P-value of 0,000. These results suggest that farmers' characteristics, such as their knowledge, experience, and skills, play a crucial role in enhancing their welfare. This highlights the importance of focusing on improving farmers' capabilities through training and education to improve their livelihoods [31, 32].

On the other hand, the path between Community Social Capital and Farmers Welfare shows no significant relationship. The path coefficient is only 0,005, with a T-statistic of 0,025 and a P-value of 0,980, indicating no statistical significance. This suggests that, in this context, community social capital, which includes elements like trust, networks, and cooperation within the farming community, does not have a meaningful impact on the welfare of farmers. This finding may be due to a lack of strong social networks or insufficient utilization of social capital within the farming groups in the study area [10, 33, 34, 35]. Despite the theoretical importance of social capital, these results indicate that it is not a key driver of welfare improvement in this case [32,36].

The relationship between Farmers Welfare and Business Productivity, however, shows a strong and significant positive effect, with a path coefficient of 0,779, a T-statistic of 14,636, and a P-value of 0,000. This indicates that when farmers' welfare improves, whether through better income, health, or social conditions, it directly contributes to higher business productivity. This finding reinforces the idea that improving the quality of life for farmers can lead to increased productivity in their agricultural enterprises. It suggests that welfare enhancements, such as access to better healthcare, income support, or social services, can lead to tangible economic benefits in farming [11]. The analysis highlights that the development of farmer characteristics is a critical factor in improving both welfare and productivity, while community social capital, in this case, does not have a significant impact. The strong relationship between farmers' welfare and business productivity further underscores the importance of improving welfare conditions to enhance agricultural productivity. This suggests that policies and programs aimed at improving farmer education and welfare could be more effective in boosting productivity than those focusing solely on building social capital.

The relationships among the variables in this study reveal a complex interplay between individual characteristics, social capital, welfare, and productivity. The results indicate that while farmers' characteristics—such as knowledge, experience, and skills—have a direct and positive impact on both their welfare and productivity [16,20,28], community social capital does not significantly influence welfare. This suggests that, within the context of farmer groups in Dayun, the development of individual capacities plays a more crucial role than social networks in achieving positive outcomes [27,28]. However, the strong relationship between improved welfare and increased productivity underscores the interconnected nature of well-being and economic performance [11,29,30]. It suggests that efforts aimed at enhancing farmers' skills and improving their welfare can create a positive cycle, where better living conditions enable more effective farming practices, ultimately leading to higher productivity. Therefore, while both individual and collective support are important, a greater emphasis on strengthening individual capacities may be more effective in improving welfare and productivity than focusing solely on social capital [32, 36].

This analysis highlights the need for targeted policy interventions that prioritize training and education for farmers to build their capabilities, as these have proven to be critical drivers of both welfare and productivity. Programs that provide access to knowledge and skills development can help farmers better manage risks, adopt new technologies, and improve their yields, leading to enhanced economic stability and growth in agricultural communities [32, 34]. At the same time, while social capital remains a valuable component of community resilience, its role may need to be complemented by initiatives that directly address gaps in individual capabilities to maximize overall benefits [10,33].

4 Conclusion

The paper concluded that both community social capital and farmer characteristic development are critical drivers of farmer welfare and business productivity within farmer groups. Specifically, farmer characteristics such as knowledge, experience, and skills are essential for enhancing well-being and agricultural productivity. In contrast, community social capital, which encompasses elements like trust and social networks, did not significantly impact farmer well-being in this context. These findings suggest that targeted efforts to enhance farmer well-being through income growth, improved health, and social support can directly lead to increased business productivity. Consequently, strategies that focus on developing farmer characteristics, such as implementing training programs, facilitating technology transfer, and strengthening business management skills may prove to be more effective than relying solely on enhancing social capital.

Key recommendations highlight the importance of capacity-building initiatives aimed at equipping farmers with essential skills in both farming and business management. Expanding access to social services such as healthcare and financial assistance can also have a positive influence on farmers' overall well-being and productivity. While community social capital did not show a significant impact in this study, fostering trust and cooperation among farmer groups may still provide long-term advantages. Tailored interventions that address the specific needs of farmers are crucial for enhancing their skills and improving their livelihood.

Overall, this paper emphasizes the vital role that both community social capital and the development of farmer characteristics play in enhancing welfare and productivity in agricultural enterprises. By focusing on capacity building and improving access to essential services, stakeholders including government, NGOs, and the private sector can work together to create a more supportive environment for farmers. Ultimately, investing in both community social capital and farmer characteristic development will contribute to more sustainable agricultural practices and better economic outcomes for farming communities.

References

1. Merino, M. V., Gajjar, S. P., Subedi, A., Polgar, A., & Van Den Hoof, C. (2021). Resilient Governance Regimes That Support Urban Agriculture in Sub-Saharan Cities: Learning From Local Challenges. *Frontiers in Sustainable Food Systems*, *5*.
2. Khanif, A., & Yunita, F. T. (2024). Food and Land Policies Amid the Agricultural Land Conversion in Indonesia. *Law, Environment and Development Journal*, *20*(1), 58–77.
3. Moeis, F. R., Dartanto, T., Moeis, J. P., & Ikhsan, M. (2020). A longitudinal study of agriculture households in Indonesia: The effect of land and labor mobility on welfare and poverty dynamics. *World Development Perspectives*, *20*, 100261.
4. Karami, E., & Keshavarz, M. (2010). Sociology of sustainable agriculture. *Sociology, Organic Farming, Climate Change and Soil Science*, 19–40.
5. Angelstam, P., Fedoriak, M., Cruz, F., Muñoz-Rojas, J., Yamelynets, T., Manton, M., Washbourne, C.-L., Dobrynin, D., Izakovičova, Z., Jansson, N., Jaroszewicz, B., Kanka, R., Kavtarishvili, M., Kopperoinen, L., Lazdinis, M., Metzger, M. J., Özüt, D., Pavloska Gjorgjieska, D., Sijtsma, F. J., … Zhuk, A. (2021). Meeting places and social capital supporting rural landscape stewardship: A pan-european horizon scanning. *Ecology and Society*, *26*(1).

6. Hawkins, R. L., & Maurer, K. (2010). Bonding, bridging and linking: How social capital operated in New Orleans following Hurricane Katrina. *British Journal of Social Work*, *40*(6).
7. Muntasib, E. K. S. H., Sunkar, A., & Meilani, R. (2017). Community Social Capital in the Ecotourism Development of Gunung Padang Site, Cianjur, West Java. In *Balancing Development and Sustainability in Tourism Destinations*.
8. Duncan, R. (2016). Ways of knowing - out-of-sync or incompatible? Framing water quality and farmers' encounters with science in the regulation of non-point source pollution in the Canterbury region of New Zealand. *Environmental Science and Policy*, *55*, 151–157.
9. Sturiale, L., & Scuderi, A. (2018). The evaluation of green investments in urban areas: A proposal of an eco-social-green model of the city. *Sustainability (Switzerland)*, *10*(12).
10. Febrian, A. F., Maulina, E., & Purnomo, M. (2018). The influence of social capital and financial capability on sustainable competitive advantage through entrepreneurial orientation: Empirical evidence from Small and Medium Industries in Indonesia using PLS-SEM. *Advances in Social Sciences Research Journal*, *5*(12).
11. Bakce, R. (2021). Analysis of the influence of farmer characteristics on independent oil palm production in Singingi Hilir District. *Jurnal Inovasi Penelitian*, *2*(1), 7–16.
12. Maulana, A. R. (2011). The Role of Farmer Groups in Improving Farmer Welfare in Temmabarang Village, Penrang District, Wajo Regency. *Makassar: Muhammadiyah University*.
13. Kehinde, A. D., Adeyemo, R., & Ogundeji, A. A. (2021). Does social capital improve farm productivity and food security? Evidence from cocoa-based farming households in Southwestern Nigeria. *Heliyon*, *7*(3).
14. Prayitno, G., Hayat, A., Efendi, A., Tarno, H., Fikriyah, & Fauziah, S. H. (2022). Structural model of social capital and quality of life of farmers in supporting sustainable agriculture (Evidence: Sedayulawas Village, Lamongan Regency-Indonesia). *Sustainability*, *14*(19), 12487.
15. Zain, M. M., Ibrahim, H., & Musdalifah, M. (2022). Knowledge sharing behavior among farmers in Indonesia: Does social capital matter? *African Journal of Food, Agriculture, Nutrition and Development*, *22*(10), 21972–21989.
16. Futemma, C., De Castro, F., & Brondizio, E. S. (2020). Farmers and Social Innovations in Rural Development: Collaborative Arrangements in Eastern Brazilian Amazon. *Land Use Policy*, *99*.
17. Amankwah, A. (2024). Welfare Effects of Agricultural Productivity Growth–A Micro Panel Evidence from Rural Tanzania.
18. Aune, J. B., Coulibaly, A., & Giller, K. E. (2017). Precision farming for increased land and labour productivity in semi-arid West Africa. A review. *Agronomy for Sustainable Development*, *37*, 1–10.
19. Sampe, J. F. (2022). Micro, Small And Medium Enterprises Performance Indicators–Possible Application In The 5.0 Society. *JManagER*, *1*(2), 1–11.
20. Paresys, L., Saito, K., Dogliotti, S., Malézieux, E., Huat, J., Kropff, M. J., & Rossing, W. A. H. (2018). Feeding the world while reducing farmer poverty? Analysis of rice relative yield and labour productivity gaps in two Beninese villages. *European Journal of Agronomy*, *93*, 95–112.

21. WOLD, H. (1973). Nonlinear Iterative Partial Least Squares (NIPALS) Modelling: Some Current Developments. In *Multivariate Analysis–III*.
22. Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis*, *48*(1), 159–205.
23. Akter, S., Fosso Wamba, S., & Dewan, S. (2017). Why PLS-SEM is suitable for complex modelling? An empirical illustration in big data analytics quality. *Production Planning & Control*, *28*(11–12), 1011–1021.
24. Hair, J. J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)-Third Edition. In *SAGE Publications, Inc.*
25. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295–336.
26. Jääskeläinen, T., Kauppinen, T., Vesala, K. M., & Valros, A. (2014). Relationships between pig welfare, productivity and farmer disposition. *Animal Welfare*, *23*(4), 435–443
27. Kovanen, S. (2021). Social entrepreneurship as a collaborative practice: literature review and research agenda. *Journal of Entrepreneurship, Management and Innovation*, *17*(1), 97–128.
28. Barghusen, R., Sattler, C., Deijl, L., Weebers, C., & Matzdorf, B. (2021). Motivations of farmers to participate in collective agri-environmental schemes: the case of Dutch agricultural collectives. *Ecosystems and People*, *17*(1), 539–555.
29. Whitfield, S. (2014). Weighing up the risks: The challenge of studying “Risk” in empirical research. *IDS Bulletin*, *45*(2–3), 7–17.
30. Xiang, C., & Tan, M. (2019). Innovation mode and effective ways of realizing rural public management under accurate poverty alleviation. *Revista de Cercetare Si Interventie Sociala*, *65*, 306–324.
31. Girard, M. (2015). Participatory Mapping for the Preparation of Spatial Planning for Agricultural Land in Dayun Village. *Repository Unri*.
32. Jamaan, A., Yuliani, F., Adianto, A., & Sadad, A. (2019). Counseling on forest and land fire prevention in the peat area of Dayun District, Siak Sri Indrapura Regency. *Unri Conference Series: Community Engagement*, *1*, 470–476.
33. Uphoff, E. P., Pickett, K. E., Cabieses, B., Small, N., & Wright, J. (2013). A systematic review of the relationships between social capital and socioeconomic inequalities in health: A contribution to understanding the psychosocial pathway of health inequalities. In *International Journal for Equity in Health* (Vol. 12, Issue 1).
34. Williams, J. R. (2019). The use of online social networking sites to nurture and cultivate bonding social capital: A systematic review of the literature from 1997 to 2018. In *New Media and Society* (Vol. 21, Issues 11–12).
35. Yusuf, Y., Heriyanto, M., Waluyo, T. J., Fadli, M., & Febrian, A. F. (2021). Social Capital: A Literature Review In Resources Management. *International Journal of Educational Research and Social Sciences (IJERSC)*, *2*(5), 1164–1172.
36. Astuti, D., & Arnanda, R. (2021). Analysis of the Level of Public Knowledge of Zakat on Palm Oil Plantations in Teluk Merbau Village, Dayun District, Siak Regency. *Jurnal Tabarru’: Islamic Banking and Finance*, *4*(1), 84–98.