

EXPLORING THE IMPACT OF PARTICIPATION IN AGRICULTURAL SOCIAL MEDIA GROUPS ON TECHNICAL EFFICIENCY: A CASE STUDY FROM ORGANIC RICE FARMERS IN INDONESIA

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Abstract: This study examines the critical role of improving farming technical efficiency in agricultural development and investigates the impact of social media group participation on this efficiency. Using data from a survey of 249 organic rice farmers in Indonesia, this research employed a stochastic production frontier to estimate technical efficiency. Additionally, a two-stage predictor substitution approach was used to assess the influence of social media group participation on technical efficiency. The findings indicate that the technical efficiency of organic rice farming in the sample was approximately 64.8%, a relatively low level. The study also found a significant positive impact of social media group participation on technical efficiency. Farmers who participated in these groups demonstrated higher technical efficiency compared with those who did not. These results suggest that social media platforms have the potential to enhance agricultural practices and efficiency. The findings imply that social media groups contribute positively to farmers' technical capabilities through information exchange, knowledge sharing, and networking.

Keywords: Agricultural social media groups, technical efficiency, productivity, stochastic production frontier, 2SPS.

Introduction

Organic farming is widely recognised for its significant role in promoting agricultural sustainability (Urta *et al.*, 2019; Gamage *et al.*, 2023) as it helps maintain soil health, biodiversity, and overall environmental well-being (Manna *et al.*, 2021). However, its productivity is lower compared with conventional methods (Boone *et al.*, 2019), with reduced yield per unit area (van der Werf *et al.*, 2020; Parizad & Bera, 2023). This productivity gap suggests that organic farming practices exhibit low technical efficiency, which can be attributed to the reliance on traditional techniques and knowledge passed down through generations (Apraku *et al.*, 2021). While this dependence on traditional practices may support the preservation of cultural farming methods, it also contributes to technical inefficiency, resulting in lower productivity and efficiency compared with modern methods (Ikerd, 2006).

Achieving technical efficiency in organic farming is especially challenging during the initial adoption phases. Farmer's transition to organic methods often encounter a steep learning curve as they adapt to new cultivation techniques and pest management strategies (Lotter, 2003). This transition period is crucial, as the success of organic farming depends heavily on farmers' ability to adopt and sustain efficient organic practices. The steep learning curve and lack of technical knowledge impede the improvement of technical efficiency in organic farming. For example, the information asymmetry among organic farmers limits their access to up-to-date information on the latest sustainable farming practices or advancements in organic technology (Isham & Kähkönen, 2002; Baptista *et al.*, 2021). This information gap may lead to poor decisions and missed opportunities for adopting efficient

organic farming methods. However, as digital technologies become increasingly prevalent, the transfer of information through the Internet can bridge the gap.

Digital platforms and social media groups have the potential to connect organic farmers and facilitate knowledge exchange (Bhattacharjee & Raj, 2016). Through these platforms, farmers can share experiences, discuss challenges, and disseminate information about successful organic farming practices (Skaalsveen *et al.*, 2020). These online platforms help farmers overcome traditional barriers to information flow in organic farming, enable them to stay updated on the latest developments, and improve their technical efficiency.

Presently, international research has extensively examined the impact of digitalisation such as Internet use, information and communication technology (ICT) adoption, and mobile and smartphone utilisation on various aspects of farmers' economic outcomes. It includes technical efficiency, well-being, innovation adoption, and chemical input usage (Ma *et al.*, 2020a; 2020b; Ma & Wang, 2020; Zheng *et al.*, 2021; Zheng & Ma, 2022; Rahman *et al.*, 2023b). For example, Zheng *et al.* (2021) explored the relationship between Internet use and technical efficiency among banana farmers, finding that those with Internet access were more technically efficient than their counterparts without access. Similarly, Rahman *et al.* (2023b) observed a significant enhancement in the well-being of farmers in Indonesia following the introduction of Internet access. Ma *et al.* (2020b) found similar findings in China. Additionally, Ma and Wang (2020) identified ICT adoption as a catalyst for sustainable agricultural practices and improved agricultural productivity while Zheng and Ma (2022) demonstrated that the ICT adoption reduced production costs. Overall, the existing literature highlighted the multifaceted impact of digitalisation on farmers' economic outcomes, particularly in improving technical efficiency, well-being, and cost-effectiveness.

Collectively, these studies underscored the potential of digital technologies to transform agricultural practices globally.

This research makes significant contributions to the existing literature in three key aspects. First, it explores the connection between participation in social media groups and farming technical efficiency, an area not previously examined. While earlier studies have investigated the link between digitalisation and economic outcomes (Ma *et al.*, 2020b; Rahman *et al.*, 2023b), none have specifically analysed the impact of social media group participation on technical efficiency. Addressing this gap provides valuable insights into the role of online communities in improving the efficiency of farming techniques.

Second, the study employs a distinctive dataset derived from organic rice farming in Indonesia, contrasting with prior research that has primarily focused on conventional farming methods (Zheng & Ma, 2021). This choice is motivated by the growing trend towards sustainable and organic practices in agriculture. By focusing on organic farming in Indonesia, the research broadens the scope of agricultural studies and addresses the specific challenges and opportunities associated with organic farming in this geographic context.

Lastly, the research addresses the issue of endogeneity by adopting a two-stage predictor substitution in its estimation strategy (Nugroho *et al.*, 2022; Rahman *et al.*, 2022). This methodological innovation is crucial for mitigating biases arising from endogenous factors that may confound the results, thereby enhancing the robustness and reliability of the findings by incorporating insights from previous studies.

The subsequent sections of the paper are structured as follows: Section 2 outlines the research methodology, Section 3 presents the results and discussion, and Section 4 concludes the study and offers potential policy implications.

Research Methodology

Research Data

The research was conducted in East Java province using a multi-stage sampling method to identify specific locations. Initially, three regencies were selected based on data from East Java's agriculture office regarding areas with high populations of organic rice farmers and active farmer organisations. Two locations were identified: Malang and Banyuwangi regencies. From each regency, one sub-district was chosen based on information from the respective regency's agriculture office. Subsequently, two villages were selected from each sub-district, resulting in a total of four villages. Respondents were randomly selected, with the aim of including 35 to 40 farmers per village, with an expected total of 249 respondents. The questionnaire was developed following an indepth literature review to ensure alignment with the research topic, issues, and objectives. The questionnaire design was also informed by interviews with key informants, including agricultural extension workers and officials from the agriculture department. The insights from these interviews supported the findings from the literature review. Local university students were recruited and trained as enumerators for data collection.

Estimation Strategy

Technical Efficiency

This study employs the stochastic frontier analysis (SFA) approach, first introduced by Aigner, Meeusen, and Van den Broeck in 1977 (Aigner, 2023). This model captures the influence of inputs on agricultural output. Mathematically, the SFA model is expressed as follows:

$$TE_i = f(X_i, M_i) + e_i = v_i - u_i \quad (1)$$

In the model, TE_i represents the technical efficiency for the i^{th} case, with X_i being a vector of variables explaining agricultural inputs such as fertilisers and seeds. The dummy variable M indicates the adaptation status of farmers

to climate change (1 for adaptation, 0 for non-adaptation), and e_i is the error term. While the estimation of the production function typically assumes equal access to technology among all farmers, this study deviates from that assumption by considering farmers' decisions to adapt to climate change based on observed characteristics. The technical efficiency values predicted by this model will be used in the next stage of analysis.

Two-stage Predictor Substitution

This research employs a methodology based on random utility theory, which posits that farmers will participate in social media groups if the perceived utility from participation exceeds that of non-participation. The participation decision is influenced by individual characteristics and can be expressed as follows:

$$SM_i^* = cX_i + e_i, \text{ and } SM_i \text{ is a dummy} \quad (2)$$

In this model, SM represents a farmer's decision to participate in social media groups while X denotes the socio-economic conditions of the farmer, including age, educational level, farming experience, and family size. The parameter c is the variable to be measured and e_i represents the error term.

To analyse the impact of participation on technical efficiency, several approaches can be employed, including propensity score matching (PSM), inverse probability weighted regression adjusted (IPWRA), and two-stage predictor substitution (2SPS) (Rahman *et al.*, 2021; 2023a; Rahman *et al.*, 2022). Among these methods, 2SPS provides more accurate estimation results as it addresses endogeneity issues arising from both observed factors (e.g., farmer characteristics) and unobserved factors (e.g., skills and motivation) (Rahman *et al.*, 2023). Therefore, this study employs the 2SPS approach to achieve robust estimation results. The 2SPS procedure involves two stages. In the first stage, the model for participation in social media groups is tested with the following equation. Unlike Equation 2, this model requires at least one instrumental variable as expressed in Equation 3:

$$SM_i^* = cX_i + sIV + e_i, \quad (3)$$

where SM_i^* represents the participation decision, X denotes the previously defined variables, IV is the instrumental variable, c and s are parameters to be measured, and e_i is the error term. Equation 3 can be executed through probit regression analysis due to the dichotomous nature of the dependent variable. Subsequently, following the estimation in Equation 3, predictions are made to form a new variable denoted as SM_i^{Pred} . This variable is used to replace the SM variable in Equation 3. More specifically, the new equation derived from Equation 1 is as follows:

$$TE_i^{\square} = aSM_i^{Pred} + \beta X_i + e_i, \text{ and } O_i \quad (4)$$

Results and Discussion

Descriptive Statistics

Table 1 presents the descriptive statistics for key variables related to agricultural production and farmers' characteristics. These variables provide insights into the sample population's characteristics and farming practices. The first variable: Production measures rice production in kilogrammes per hectare per session, with an average of approximately 11,981.730 kg per hectare. The labour variable represents the number of labour hours per session, with an average of 149.623 hours. The organic pesticide and organic fertiliser variables indicate the usage of organic inputs per hectare, with averages of 21.638 and 353.226, respectively. The seed variable measures the amount of seed used in kilogrammes per hectare, with an average of 20.732 kg per hectare. The social media group variable is a dummy variable, with a value of 1 if the farmer participates in a social media group for organic farming and 0 otherwise. On average, approximately 49.4% of the sampled farmers participated in such a group. Social media groups in Indonesia dedicated to agriculture typically share insights on farming practices, market trends, and technological innovations in the field. The age variable represents the average age of the farmers in years, with an average of 54.125 years. The education variable signifies the

education level of the farmers in years, with an average of 7.763 years. The experience variable indicates the years of farming experience, with an average of 25.428 years. The family member variable represents the average number of family members in the household, with an average of 3.179 persons. The off-farm variable is another dummy variable, assigned a value of 1 if the farmer has off-farm work and 0 otherwise. On average, about 30.4% of the farmers had off-farm employment. The training variable represents the number of training sessions that farmers attended during the season, with an average of 3.580 sessions. Income measures household income in Indonesian Rupiah per month, with an average income of 2,701,719 Rupiah per month. The cultivated area variable signifies the total cultivated area in hectares, with an average of 86.989 hectares. The relative variable is a dummy variable, assigned a value of 1 if a relative or friend participates in the social media group for organic farming and 0 otherwise. On average, approximately 67.7% of the farmers had a participating relative or friend. The perception of the Internet variable reflects the perception of its importance, with values ranging from 1 (very unimportant) to 5 (very important). On average, farmers perceived the Internet as moderately important, with a score of 2.638. Finally, the technical efficiency variable represents the farmers' technical efficiency scores, with an average of 0.648. Table 1 summarises the variables related to rice production, farmers' characteristics, and their engagement in social media groups and technology within the context of organic farming. These statistics describe the characteristics and practices of the study's sample population.

Stochastic Production Frontier Estimation for Organic Rice Farming

Table 2 presents the results of a stochastic production frontier estimation for organic rice farming. This analysis aims to understand the relationship between various input factors and rice production. The coefficients indicate the estimated impact of each input factor on rice

Table 1: Descriptive statistics of selected variables

| Variable | Measurement | Mean | Std. Dev. |
|------------------------|--|--------------|--------------|
| Production | Rice production kg per ha per session | 11981.730 | 16826.040 |
| Labour | Labour hour per session | 149.623 | 139.284 |
| Organic pesticide | Organic pesticide per ha | 21.638 | 31.130 |
| Organic fertiliser | Organic fertiliser per ha | 353.226 | 951.483 |
| Seed | Seed kg per ha | 20.732 | 22.419 |
| Social media group | Dummy, 1 if the farmers participated on the social media of organic farming group; 0 otherwise | 0.494 | 0.501 |
| Age | Age of farmer in the year | 54.125 | 11.681 |
| Education | Education of farmers in the year | 7.763 | 3.645 |
| Experience | Farming experience in the year | 25.428 | 14.793 |
| Family member | Number of family members in person | 3.179 | 1.185 |
| Off-farm work | Dummy, 1 if the farmers have an off-farm work; 0 otherwise | 0.304 | 0.461 |
| Training | Number of training sessions during the season | 3.580 | 0.614 |
| Income | Household income Rupiah per month | 2,701,719.00 | 5,769,758.00 |
| Cultivated area | The total cultivated area in ha | 86.989 | 625.530 |
| Relative | Dummy, 1 if the relative/friend participates in a social media group; 0 otherwise | 0.677 | 0.469 |
| Perception on Internet | Perception on the Internet; 1 (very unimportant) and 5 (very important) | 2.638 | 0.938 |
| Technical efficiency | Technical efficiency score | 0.648 | 0.110 |

production. The coefficient for labour is 0.690 and is statistically significant at the 1% level, indicating that increased labour input has a positive and significant effect on organic rice production. The coefficient for organic pesticides is -0.009, but it is not statistically significant, suggesting that the use of organic pesticides does not significantly impact rice production in this context. The coefficient for organic fertiliser is 0.065 and statistically significant at the 1% level, demonstrating that organic positively influences rice production. The coefficient for seed is 0.138 and highly statistically significant at the 1% level, indicating that a greater quantity or better quality of seeds positively influences organic rice production. Lastly, the coefficient for area is 0.749 and highly statistically significant

at the 1% level, implying that an increase in the cultivated area has a strong positive effect on organic rice production.

Determinants of Farmers' Decisions to Participate in Social Media Groups

Table 3 presents the determinant of farmers' participation in social media groups. The results indicate that education, family members, and perception of the Internet positively and significantly influence farmers' participation decisions. Education is a significant predictor of farmers' social media participation. The positive coefficient suggests that as education levels increase, so does the likelihood of farmers joining social media groups. Farmers

Table 2: Stochastic production frontier estimation for organic rice farming

| Production | Coef. | Std. | Z | p-value |
|--------------------|----------|---------|---------|----------|
| Labour | 0.690 | 0.037 | 18.430 | 0.000*** |
| Organic pesticide | -0.009 | 0.025 | -0.350 | 0.729 |
| Organic fertiliser | 0.065 | 0.023 | 2.900 | 0.004*** |
| Seed | 0.138 | 0.031 | 4.410 | 0.000*** |
| Area | 0.749 | 0.042 | 17.720 | 0.000*** |
| _cons | 2.738 | 0.492 | 5.560 | 0.000*** |
| /lnsig2v | -1.614 | 0.091 | -17.830 | 0.000*** |
| /lnsig2u | -10.104 | 168.721 | -0.060 | 0.952 |
| sigma_v | 0.446 | 0.020 | | |
| sigma_u | 0.006 | 0.540 | | |
| sigma2 | 0.199 | 0.018 | | |
| lambda | 0.014 | 0.543 | | |
| Log-likelihood | -152.379 | | | |
| Wald chi2(5) | 886.61 | | | |
| Prob > chi2 | 0 | | | |
| Obs. | 249 | | | |

Note: *, **, and *** denote significance on 10%, 5%, and 1%, respectively

with higher educational attainment use social media platforms more intensively for agricultural information sharing, networking, or collaboration. These findings underscore the value of educational interventions and digital literacy programmes in rural farming communities, as they can enhance the adoption of technology-driven agricultural practices and promote knowledge exchange through online platforms. The number of family members involved in farming also significantly influences farmers' participation decisions. The positive coefficient indicates that the greater the number of family members involved in farming, the more likely farmers are to engage in social media groups. Farmers who participate in social media groups tend to have higher social capital, which can improve their social networks. This may reduce information asymmetries among farmers (Guo *et al.*, 2022; Kos *et al.*, 2023). The involvement of family members

in farming plays a crucial role in influencing farmers' decisions to participate. This finding underscores the significance of social networks on a family level in agricultural communities. If more family members are engaged in farming, the interest and motivation for farmers to join online groups will also increase. This inclination may be driven by shared interests, knowledge exchange, and a collective approach to adopt new agricultural practices. Recognising the impact of family dynamics on farmers' engagement on social media underscores the interconnectedness of social factors in agricultural decision-making processes. The perception of the Internet has a significance level of 0.082, slightly above the conventional threshold of 0.05, indicating some influence on farmers' participation. The positive coefficient implies that a more favourable perception of the Internet increases the likelihood of a farmer joining social media groups.

Table 3: The determinant of farmers' decision to participate in social media group

| Social Media Group | Coef. | Err. | z | p-value |
|------------------------|------------|-------|--------|----------|
| Age | -0.007 | 0.011 | -0.670 | 0.503 |
| Education | 0.122 | 0.031 | 3.920 | 0.000*** |
| Experience | -0.005 | 0.008 | -0.630 | 0.527 |
| Family member | 0.357 | 0.087 | 4.100 | 0.000*** |
| Off-farm work | 0.133 | 0.204 | 0.650 | 0.514 |
| Internet intensity | 0.056 | 0.144 | 0.390 | 0.698 |
| Income | 0.134 | 0.112 | 1.190 | 0.233 |
| Cultivated area | 0.000 | 0.000 | 0.340 | 0.733 |
| Relative participation | 0.192 | 0.216 | 0.890 | 0.374 |
| Perception of Internet | 0.179 | 0.103 | 1.740 | 0.082* |
| _cons | -4.318 | 1.678 | -2.570 | 0.010** |
| Log-likelihood | -135.59514 | | | |
| LR chi2(10) | 85.050 | | | |
| Prob > chi2 | 0.000 | | | |
| Pseudo R2 | 0.238 | | | |
| Obs. | 249 | | | |

Note: *, **, and *** denote significance on 10%, 5%, and 1%, respectively

The Impact of Participation in Social Media Groups on Farming Technical Efficiency

Table 4 presents the impact of participation in social media groups on technical efficiency. The coefficient for social media groups is 0.083, with a significance level of 0.006. This suggests that participation in social media groups positively impacts farming technical efficiency. The positive coefficient indicates that as participation increases, farming technical efficiency tends to increase as well. The positive impact of participation on farming technical efficiency suggests that modern communication platforms can play a beneficial role in agriculture. Farmers who engage in social media groups gain access to valuable information, best practices, and innovative techniques from peers and experts. Such knowledge exchange can improve farming methods, boost productivity, and support informed decision-making. Additionally, the digital connectivity offered by social media

platforms allow farmers to stay informed about market trends such as weather forecasts and emerging technologies, helping them adapt and optimise their operations. Embracing social media, thus fosters a more efficient and informed farming community.

Table 4 also presents the influence of control variables on farming technical efficiency. Experience has a positive and significant effect on farming technical efficiency, with a significant and positive impact on agricultural practices. Years of hands-on experience provide farmers with invaluable knowledge and skills that inform their decision-making (Skaalsveen *et al.*, 2020). This accumulated wisdom enables farmers to adapt various challenges such as weather patterns and crop cycles, resulting in higher yields and reduced resource wastage. Seasoned farmers have a deep understanding of soil health, pest management, and optimal planting times, which allows them to optimise resource

Table 4: The impact of participation in social media groups on farming technical efficiency

| TE | Coef. | Std. Err. | t | p-value |
|--------------------|----------|-----------|--------|----------|
| Social media group | 0.083 | 0.030 | 2.770 | 0.006*** |
| Age | -0.001 | 0.001 | -1.180 | 0.241 |
| Education | -0.007 | 0.004 | -1.480 | 0.139 |
| Experience | 0.002 | 0.001 | 3.060 | 0.003*** |
| Family member | -0.030 | 0.012 | -2.510 | 0.013** |
| Off-farm work | -0.068 | 0.015 | -4.640 | 0.000*** |
| Training | 0.000 | 0.010 | -0.040 | 0.966 |
| Income | -0.024 | 0.009 | -2.760 | 0.006*** |
| Cultivated area | 0.000 | 0.000 | 0.790 | 0.432 |
| _cons | 1.171 | 0.155 | 7.560 | 0.000*** |
| var(e.te) | 0.010 | 0.001 | 0.008 | 0.012 |
| Log-likelihood | 224.4813 | | | |
| LR chi2(9) | 54.910 | | | |
| Prob > chi2 | 0.000 | | | |
| Pseudo R2 | 0.1394 | | | |
| Obs. | 249 | | | |

Note: *, **, and *** denote significance on 10%, 5%, and 1%, respectively

allocation and maximise productivity (Bonfiglio et al., 2020). Experience serves as a foundation for sustainable and efficient farming practices, contributing to food security (Syafrial, 2021). The family member variable has a negative and significant effect on farming technical efficiency, indicating that the number of family members can have a detrimental impact on farming technical efficiency. Family dynamics often introduce personal and emotional factors that may interfere with optimal decision-making and resource allocation, leading to inefficiency in farm management and productivity (Bonfiglio et al., 2020). This underscores the importance of adopting professional and objective approaches in agricultural operations.

Meanwhile, off-farm work negatively and significantly affects farming technical efficiency. As farmers allocate their time and energy to off-farm employment, their ability to manage agricultural operations effectively

diminishes (Andaregie & Astatkie, 2020). This shift in focus results in decreased productivity, reduced innovation, and lower overall efficiency. Household income also has a negative and significant effect on farming technical efficiency. Decreases in household income led to reduce investment in modern farming practices, advanced technologies, and skilled labour, which in turn result in lower overall efficiency in agricultural production. This highlights the crucial role of income support and poverty alleviation in enhancing agricultural productivity and ensuring sustainability.

Conclusions and Policy Implications

This study evaluates the relationship between technical efficiency in organic farming and farmers' participation in social media groups. Using stochastic frontier analysis and two-stage predictor substitution, the study reveals several key findings. First, labour input, the use of

organic fertiliser, seed quality, and the cultivated area all significantly positively influence rice production, underscoring their importance in enhancing organic farming productivity. Second, participation in social media groups dedicated to organic farming has a significant positive impact on farming technical efficiency. Farmers who engage in online communities tend to be more technically efficient, potentially due to the exchange of knowledge and innovative practices facilitated by such groups. Furthermore, experience remains a key driver of technical efficiency, highlighting the invaluable role of accumulated knowledge and expertise in sustainable agriculture.

Conversely, the number of family members, off-farm employment, and lower household incomes negatively impact technical efficiency, underscoring the need for strategies to address these challenges. Therefore, this study recommends enhancing digital literacy and education levels to enable farmers to participate in and benefit from social media groups and modern agricultural practices. Investment in digital literacy programmes can empower rural communities to leverage online resources effectively. Furthermore, the government and agricultural organisations should actively support and facilitate the formation of social media groups and online communities focusing on agriculture. These platforms can serve as valuable hubs for knowledge sharing, dissemination of best practices, and peer-to-peer learning.

This study suggests several practical implications for enhancing organic farming technical efficiency. First, promoting digital literacy and education among farmers is essential for effective participation in social media groups focused on organic farming. Governments and agricultural organisations should support the formation of these online communities for knowledge sharing and peer learning. Second, recognising the role of experience in efficiency highlights the need for continuous learning. Addressing socioeconomic challenges such as family size and household income through

targeted support can also contribute to improved efficiency. Finally, integrating sustainable practices, including the use of organic fertilisers and high-quality seeds is vital for boosting productivity and technical efficiency in organic farming.

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Conflict of Interest Statement

The authors declare that they have no conflicts of interest.

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