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Analysis of the Impact of Tractor Technology Use on Time Efficiency, Rice Production Costs, and Farmers' Welfare in Cangkring Village, Plered District, Cirebon Regency

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Tractor technology; time efficiency; production cost; farmer welfare; SEM-PLS

ABSTRACT

Mechanized two-wheel tractors have become increasingly important for improving smallholder rice farming efficiency in Indonesia. This research analyzes the impact of introducing tractor-based tillage on labor time, production costs, and farmer welfare in Cangkring Village, Plered, Cirebon. A quantitative survey of 60 rice farmers was conducted, measuring farm budgets and using SEM-PLS modeling to link tractor adoption to efficiency and income outcomes. Results show average paddy yields of 7,000 kg/ha at IDR 6,500/kg, giving gross revenue ~IDR 45.5 million/ha. Total production cost averaged about IDR 20.635 million/ha (≈Rp17.97M fixed and Rp2.67M variable), yielding a net profit of IDR 24.865 million/ha (R/C≈2.2). The cost of mechanized operations (hand tractor plowing plus power-threshing) was relatively low (~IDR 1.39 million/ha). SEM-PLS analysis confirms that tractor use significantly improved field efficiency (path $\beta \approx 0.36$, $p=0.001$) and reduced unit production costs ($\beta \approx 0.58$, $p<0.001$). Both greater time efficiency ($\beta \approx 0.45$, $p<0.001$) and lower costs ($\beta \approx 0.22$, $p=0.034$) had significant positive effects on farmer welfare, and tractor use also had a significant direct positive effect on welfare ($p=0.025$). Mediation tests revealed strong indirect effects of mechanization on welfare via efficiency and cost savings (indirect $\beta \approx 0.806$ and 0.804, $p<0.001$ each). These findings indicate that small-scale tractor mechanization substantially boosts productivity and profitability for Indonesian rice farmers. In conclusion, adopting tractor-based mechanization greatly enhances labor productivity and income among rural smallholders, suggesting that targeted support (training, subsidies) for such technology can significantly improve farmer welfare and agricultural efficiency in Indonesia..

INTRODUCTION

Agriculture plays a central role in Indonesia's economy, with rice cultivation being a dominant activity among rural communities (Bajuri, 2022; Fadillah, 2022; Gilligan et al., 2018; Hartoyo et al., 2019; Jouzi et al., 2017). Despite its importance, the sector faces significant challenges, including low labor efficiency and increasing production costs. In response, the adoption of agricultural mechanization—particularly tractors—has emerged as a promising solution to improve productivity and reduce the burden of manual labor (Paltasingh & Goyari, 2018; Paltasingh & Goyari, 2018; Salamah, 2021; Sofia et al., 2022; Van Loon et al., 2020).

This study focuses on *Cangkring Village* in *Plered Subdistrict*, *Cirebon Regency*, where farmers have begun to utilize hand tractors for land preparation. The transition from traditional methods to mechanized farming reflects a broader trend in rural innovation. Tractors enable faster and more consistent land processing, reduce dependency on seasonal labor, and facilitate more timely planting and harvesting (Kahan et al., 2018; Kumar et al., 2021; Mgbenka et al., 2016; Mottaleb et al., 2016; Nuryartono et al., 2020).

Research by (Ade Fadillah, 2022; Bajuri, 2022) supports that tractor use leads to higher productivity and reduced operational costs. Farmers using tractors reported improved planting precision, reduced production time, and better crop yields, ultimately increasing their income. Tractor usage also allows for multiple planting cycles per year, thus improving land use efficiency. However, adoption remains limited among smallholder farmers due to financial constraints, lack of technical knowledge, and limited institutional support. According to (Hartoyo et al., 2019), barriers include insufficient training, high maintenance costs, and limited availability of machinery. (Sofia et al., 2022) highlight the importance of extension services and farmer education in promoting effective technology use. Nevertheless, there is still a research gap. Few studies have systematically measured the impact of agricultural mechanization at the village level while considering specific socioeconomic variables such as education, land ownership, and access to institutional support. This gap highlights the importance of localized studies that connect mechanization outcomes to farmer welfare and rural development policies.

The study employs a quantitative approach, collecting primary data from rice farmers in *Cangkring Village*. Variables analyzed include land size, land preparation methods, education level, farming experience, and access to tractor services. The findings suggest that mechanization positively correlates with increased rice productivity and improved farmer welfare, especially where institutional support and training are available.

This research is distinct because it specifically focuses on *Cangkring Village*, a rural area that represents the dynamics of smallholder farming in Indonesia. Unlike broader regional studies, this research measures detailed socioeconomic variables—such as education level, land ownership, and access to tractor services—providing a nuanced understanding of how mechanization influences both productivity and welfare. Furthermore, the study links its empirical findings directly to local policy recommendations, offering practical input for government programs, agricultural extension services, and village-level development strategies. This local focus and policy orientation highlight the novelty of the research and its contribution to both academic literature and practical decision-making.

Furthermore, tractor adoption aligns with national goals for agricultural modernization. As stated by (Salamah, 2021), promoting access to agricultural technology is critical to achieving food self-sufficiency and sustainable rural development.

Ultimately, this study underscores the need for integrated policy support, including subsidized machinery programs, technical training, and rural infrastructure improvements. The primary purpose of this research is to analyze the impact of tractor technology on efficiency, production costs, and farmer welfare at the village level, while also providing insights that can guide agricultural policy and rural development initiatives. From a theoretical perspective, this research contributes to the literature on agricultural mechanization by offering empirical evidence on how tractors influence not only productivity but also socioeconomic variables such as education, land size, and access to services. It enriches the discourse by focusing on a micro-level case study that has been relatively underexplored in existing studies. From a practical perspective, the findings provide valuable input for local governments and agricultural extension workers in designing more effective support programs. Recommendations include developing training modules tailored to smallholder farmers, implementing subsidized access to tractor services, and strengthening institutional support at the village level. Such initiatives are expected to enhance productivity, reduce poverty, and promote sustainable welfare improvement in rural farming communities.

RESEARCH METHODOLOGY

This research employed a quantitative descriptive approach to examine the impact of tractor usage on time efficiency, production costs, and farmer welfare in *Cangkring Village*, *Plered District*, *Cirebon Regency*. The location was purposively selected due to its status as a rice production center that has adopted mechanization technologies, especially hand tractors. Data collection was conducted over a six-month period through surveys, direct observation, structured interviews, and questionnaires distributed to 60 rice farmers who use tractors in their farming operations.

The variables investigated included:

1. X (Independent Variable): Use of tractor technology
2. Z_1 (Intervening Variable): Time efficiency
3. Z_2 (Intervening Variable): Rice production costs
4. Y_1 (Dependent Variable): Farmer welfare

To assess the economic and practical impact of tractor use, several key analytical tools and formulas were applied. These include:

Total Production Cost (TC)

The total farming cost is calculated as the sum of fixed and variable costs:

$$TC = TFC + TVC$$

Where:
TC = Total Cost
TFC = Total Fixed Cost (e.g., land rent, depreciation, irrigation fees)
TVC = Total Variable Cost (e.g., seeds, fertilizer, labor, fuel)

Total Revenue (TR)

Revenue is calculated based on the price and quantity of rice harvested:

$$TR = P \times Q$$

Where:
P = Price per unit (kg)
Q = Quantity of harvest (kg)

Net Income (I)

$$I = TR - TC$$

This measures the profitability per farming cycle and reflects the financial gains of the farmer after deducting production costs.

Return-to-Cost Ratio (R/C Ratio)

This ratio is used to determine the feasibility of the farming business:

$$R/C\ Ratio = \frac{TR}{TC}$$

Interpretation:
R/C > 1 → Profitable
R/C = 1 → Break-even
R/C < 1 → Not feasible

SEM-PLS Structural Model

SEM-PLS is a statistical analysis method used to measure and analyze the relationship between latent variables (not directly measurable) with the help of indicator variables (directly measurable). SEM-PLS is used to evaluate structural models (inner models) and measurement models (outer models). This method is predictive, flexible regarding data distribution, and well-suited to small samples, non-normal data, or complex models.

All data were processed using SPSS, Excel, and WarpPLS to support statistical interpretation and hypothesis testing. Indicators for time efficiency include the duration of land preparation and the number of crop cycles per year. Cost variables include labor, inputs, and machinery operation. Farmer welfare was measured by income level, access to resources, and quality of life.

This methodology provides a comprehensive framework for analyzing how tractor usage affects agricultural performance and socio-economic outcomes in rural Indonesia. The approach integrates economic feasibility with behavioral and structural modeling to provide policy-relevant insights.

RESULT AND DISCUSSION

Cost Analysis

The total production cost (TC) per hectare per season was calculated as the sum of fixed costs (FC) and variable costs (VC). Specifically,

$$TC = FC + VC = 17{,}970{,}000 + 2{,}665{,}000 = 20{,}635{,}000\ Rp/ha/season$$

Table 1. Average production costs of mechanized rice farming (per hectare per season). Fixed costs (e.g. land rent, depreciation) account for most of the total.

Cost Category	Item	Cost (Rp)	% of Category
Fixed Cost	Land rent	15,000,000	83.47%
	Equipment depreciation	2,000,000	11.13%
	Tractor rental	800,000	4.45%
	Irrigation fee	120,000	0.67%
	Other (land tax)	50,000	0.28%
Total Fixed	–	**17,970,000**	**100%**
Variable Cost	Seed	100,000	3.75%
	Fertilizer	227,000	8.52%
	Fuel (10 L)	68,000	2.55%
	Labor (daily)	100,000	3.75%
	Operator wage	170,000	6.38%
	Maintenance	2,000,000	75.06%
Total Variable	–	**2,665,000**	**100%**
Total Cost	–	**20,635,000**	**100%**

Source: Primary data processed, 2023

As shown in Table 1. Table 1 presents the breakdown of costs under mechanization. Land rent is the largest fixed cost (Rp 15,000,000, 83.47% of fixed costs), yielding a total fixed cost of Rp 17,970,000. Variable costs total Rp 2,665,000 (12.93% of total cost) and are dominated by machinery maintenance (Rp 2,000,000, 75.06% of variable costs).

Revenue and Income

Total revenue (TR) per hectare was calculated as yield times price. With an average yield of 7,000 kg/ha and farm-gate price of Rp 6,500/kg,

$$TR = 7{,}000 \times 6{,}500 = 45{,}500{,}000\ Rp/ha,$$

Table 2. Average production and revenue of mechanized rice farming (per hectare per season).

Parameter	Value
Production (kg/ha)	7,000
Price (Rp/kg)	6,500
Revenue (Rp)	**45,500,000**

Table 3. Revenue, cost, and net income of mechanized rice farming (per hectare per season).

Item	Amount (Rp)
Gross revenue	45,500,000
Total cost	20,635,000
Net income	**24,865,000**

Source: Primary data processed, 2023

As shown in Table 2. Net farm income (I) was then computed as $I = TR - TC = 45{,}500{,}000 - 20{,}635{,}000 = 24{,}865{,}000$ Rp/ha. Table 2 and Table 3 summarize the average production, revenue, and income.

These results indicate that, on average, farmers earn Rp 24,865,000 per hectare per season after covering costs. This net income reflects the profitability of mechanized rice production under the given conditions.

R/C Ratio

The return-to-cost (R/C) ratio was calculated as $R/C = TR/TC = 45{,}500{,}000/20{,}635{,}000 \approx 2.20$.Table 4 presents this calculation. An R/C ratio of 2.20 means that each rupiah of cost yields Rp 2.20 in revenue, implying a viable enterprise. Since R/C > 1, the farming operation is profitable.

Table 4. Return-to-Cost (R/C) ratio for mechanized rice farming (per hectare per season).

Gross revenue (Rp)	Total cost (Rp)	R/C ratio
45,500,000	20,635,000	2.20

Source: Primary data processed, 2023

The high R/C ratio indicates that mechanized paddy farming in the study area is economically feasible, confirming that mechanization (e.g., hand tractors) can improve profitability by increasing output relative to input costs.

SEM-PLS Results

Loading Factors

The measurement model's outer loadings are all high, indicating good indicator reliability. Table 5 below shows that every indicator has a loading well above 0.40 (most exceed 0.70) and all loadings are statistically significant ($p < 0.001$). In particular, the tractor-use indicators (PTR1–

PTR3) load 0.801–0.852 on their construct, the time-efficiency indicators (EW1–EW4) load 0.770–0.868, the production-cost indicators (BPP1–BPP4) load 0.809–0.924, and the welfare indicators (KP1–KP4) load 0.718–0.843. Thus all items meet the conventional convergent validity criterion (loading >0.70). Because all p-values are <0.001, each loading is highly significant. We therefore conclude that the measurement items reliably represent their intended constructs.

Table 5. Outer loadings for each indicator (all p < 0.001).

Indicator	Outer Loading	P-value	Convergent Validity
PTR1	0.852	<0.001	Yes
PTR2	0.824	<0.001	Yes
PTR3	0.801	<0.001	Yes
EW1	0.806	<0.001	Yes
EW2	0.770	<0.001	Yes
EW3	0.868	<0.001	Yes
EW4	0.843	<0.001	Yes
BPP1	0.924	<0.001	Yes
BPP2	0.809	<0.001	Yes
BPP3	0.812	<0.001	Yes
BPP4	0.901	<0.001	Yes
KP1	0.718	<0.001	Yes
KP2	0.729	<0.001	Yes
KP3	0.843	<0.001	Yes
KP4	0.830	<0.001	Yes

Source: SEM-PLS output processed from primary data, 2023

These results confirm that convergent validity is achieved: every item's loading exceeds the threshold, and all loadings are highly significant. In short, the indicators reliably measure their respective constructs, as required for a valid measurement model.

Average Variance Extracted (AVE)

The Average Variance Extracted (AVE) assesses convergent validity at the construct level. Each latent variable's AVE exceeds 0.50, the standard threshold. Table 6 presents the AVE for each construct, showing values from 0.782 to 0.863. In particular, the AVE is 0.826 for Tractor Technology Use, 0.823 for Time Efficiency, 0.863 for Production Cost, and 0.782 for Farmer Welfare. All of these are above the 0.50 benchmark, so convergent validity is supported for all constructs.

Table 6. AVE values for each latent construct (all > 0.50).

Construct	AVE	>0.50 Criterion	Convergent Validity
Tractor Technology Use	0.826	Yes	Yes
Time Efficiency	0.823	Yes	Yes
Production Cost (Rice)	0.863	Yes	Yes
Farmer Welfare	0.782	Yes	Yes

Source: SEM-PLS output processed from primary data, 2023

Since all AVE values are well above 0.50, each construct shows strong convergent validity. The constructs capture more than half of the variance of their indicators, confirming the adequacy of the measurement model.

Composite Reliability

Composite Reliability assesses internal consistency of each construct's indicators. As shown in Table 7, every construct's composite reliability (CR) exceeds the standard 0.70 threshold. Specifically, CR = 0.866 for Tractor Use, 0.893 for Time Efficiency, 0.921 for Production Cost, and 0.862 for Welfare. All are >0.70, indicating that the item sets reliably measure their constructs.

Table 7. Composite reliability for each construct.

Construct	Composite Reliability	>0.70 Criterion	Status
Tractor Technology Use	0.866	Yes	Reliable
Time Efficiency	0.893	Yes	Reliable
Production Cost (Rice)	0.921	Yes	Reliable
Farmer Welfare	0.862	Yes	Reliable

Source: SEM-PLS output processed from primary data, 2023

Because all CR values are well above 0.7, the constructs exhibit high reliability. This means the indicators for each latent variable are consistent with one another and contribute significantly to measuring that construct.

Cronbach's Alpha

Cronbach's alpha provides another reliability check. Table 8 shows the Cronbach's alpha for each construct, all of which exceed 0.70. The values are 0.767 for Tractor Use, 0.840 for Time Efficiency, 0.884 for Production Cost, and 0.786 for Welfare. All of these meet or exceed the 0.70 threshold, confirming internal consistency.

Table 8. Cronbach's alpha for each construct.

Construct	Cronbach's Alpha	>0.70 Criterion	Status
Tractor Technology Use	0.767	Yes	Reliable
Time Efficiency	0.840	Yes	Reliable
Production Cost (Rice)	0.884	Yes	Reliable
Farmer Welfare	0.786	Yes	Reliable

Source: SEM-PLS output processed from primary data, 2023

Since all $\alpha > 0.70$, each scale has acceptable reliability. In combination with the composite reliability results, this confirms that the measurement instruments are internally consistent.

Structural Model (Path Coefficients)

The structural model results are summarized in Table 9. All hypothesized paths are positive and significant at the 5% level ($p<0.05$). The direct path coefficients are:

Table 9. Path coefficients in the structural model.

Path	Coefficient (β)	P-value
Tractor use → Time efficiency	0.357	0.001
Tractor use → Production cost	0.583	<0.001
Tractor use → Farmer welfare	0.238	0.025
Time efficiency → Farmer welfare	0.449	<0.001
Production cost → Farmer welfare	0.221	0.034

Source: SEM-PLS output processed from primary data, 2023

These results indicate that higher tractor usage significantly improves time efficiency ($\beta=0.357$) and significantly increases production costs (negative cost impact) ($\beta=0.583$). Tractor use also has a direct positive effect on farmer welfare ($\beta=0.238$, $p=0.025$). Furthermore, both mediating paths are significant: greater time efficiency (β=0.449) and higher production cost savings (β=0.221) both lead to higher farmer welfare. In summary, all hypothesized direct effects are supported at p<0.05.

Direct and Indirect Effects (Mediation Analysis)

Finally, we examine mediation. The direct effect of tractor use on farmer welfare (path c) is 0.511 (p<0.001). The indirect (mediation) effects through the two mediators are both large and significant. Table 10 presents these effects:

Table 10. Indirect effects of tractor use on welfare (via mediators).

Path (Mediation)	Indirect Coefficient	P-value	Significant
Tractor use → Time efficiency → Farmer welfare	0.806	<0.001	Yes
Tractor use → Production cost → Farmer welfare	0.804	0.001	Yes

Source: SEM-PLS output processed from primary data, 2023

Both indirect paths are highly significant (p<0.001 and p=0.001). Thus, time efficiency and production cost both serve as significant mediators: tractor use strongly affects welfare indirectly through each of these channels. Because the direct effect (0.511) remains significant alongside these indirect effects, the mediation is partial. In other words, the positive impact of tractor technology on farmer welfare is partly explained by improvements in time efficiency and reductions in production cost, though tractor use also has a significant direct effect on welfare.

Overall, the SEM-PLS results show a well-fitting model: all measurement criteria are met (loadings, AVE, reliability) and all hypothesized relationships (direct and mediated) are supported. These findings align with the research model and confirm that tractor adoption enhances efficiency and welfare as theorized.

CONCLUSION

This study concludes that the adoption of tractor technology in rice farming significantly improves agricultural efficiency and enhances farmer welfare. The analysis of 60 respondents in *Cangkring Village*, *Plered Subdistrict*, revealed that mechanized land cultivation using two-wheel tractors reduces production time, lowers variable costs, and increases profitability. The financial analysis showed an average net income of Rp 24,865,000 per hectare per season, with a strong R/C Ratio of 2.20, indicating that every Rp 1 invested yields Rp 2.20 in return. The SEM-PLS model confirmed that tractor usage directly and indirectly affects farmer welfare through two key mediating variables: time efficiency and production cost. All path coefficients in the structural model were statistically significant ($p < 0.05$), with indirect effects from tractor use to welfare via time efficiency and production cost each exceeding 0.80. These findings demonstrate that increased mechanization enhances labor productivity, improves production timeliness, and reduces input dependency. In conclusion, the integration of tractor-based mechanization offers a strategic solution for addressing labor inefficiency and high operational costs in smallholder rice farming. Its positive impact on both technical and financial performance confirms that mechanization is not only a productivity tool but also a driver of rural economic development. Therefore, policies that support access to tractor technology—such as training programs, machinery subsidies, and farmer institutional support—are essential for promoting sustainable agricultural transformation in Indonesia.

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