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BLOCKCHAIN VALUE TRANSPARENCY FOR IMPROVING TAPIOCA VALUE CHAIN EFFICIENCY: EVIDENCE FROM DEA–SFA ANALYSIS AT THE BOGOR CASSAVA CENTER COOPERATIVE, INDONESIA.

D.Iwan Riswandi[1]

[1]IPB University. Bogor. Indonesia

Corresonding author email: iwan_riswandi@apps.ipb.ac.id[1]

Abstract
This study investigates the efficiency of the tapioca value chain at the Bogor Cassava Center (BCC) Cooperative by applying a combined Data Envelopment Analysis–Slack Based Model (DEA–SBM) and Stochastic Frontier Analysis (SFA) framework. The integration of stage-wise DEA and network efficiency models with SFA enables a robust assessment of technical efficiency, inefficiency determinants, and stage-specific performance along the cassava-to-tapioca chain. Using primary data from 30 cooperative members across two production stages—cassava cultivation and tapioca processing–distribution—the results reveal heterogeneous efficiency patterns, with average DEA–SBM efficiency scores ranging from 0.62 to 0.81 and SFA technical efficiency levels from 0.58 to 0.77. Key determinants of inefficiency include labor quality, capital intensity, and market access, underscoring the need for targeted interventions in resource allocation and governance. Furthermore, the study introduces Blockchain Value Transparency (BVT) as a novel governance mechanism to mitigate inefficiencies related to information asymmetry, traceability gaps, and unfair pricing. By linking efficiency diagnostics with blockchain-based smart contracts and transparent price ledgers, the paper highlights managerial implications to strengthen trust, enable fair value distribution, and accelerate competitiveness in Indonesia's tapioca sector. These findings contribute to the literature on agri-food value chain efficiency and provide actionable policy insights for cooperative-based agribusiness models in Southeast Asia.

Keywords: Blockchain Value Transparency (BVT); Digital Governance; Cassava Value Chain; Tapioca Efficiency; Network Data Envelopment Analysis (Network DEA–SBM); Stochastic Frontier Analysis (SFA); Cooperative Agribusiness; Indonesia.

1. Introduction

The cassava sector remains one of the most important pillars of food security and industrial raw materials in Indonesia, particularly in West Java where tapioca production plays a critical role in rural livelihoods (Rahmawati et al., 2022, p. 114). Despite its strategic importance, the efficiency of cassava-based value chains remains limited due to fragmented production, weak institutional arrangements, and a lack of technological innovation (Syamsuddin et al., 2021, p. 89). Recent studies highlight that agribusiness cooperatives can play a transformative role in strengthening smallholder participation and enhancing value chain performance (Trienekens et al., 2021, p. 14). Within this context, the Bogor Cassava Center (BCC) Cooperative provides a unique case to evaluate efficiency across production, processing, and distribution stages of the tapioca value chain.

Despite methodological advances in agricultural efficiency research, three critical gaps remain. *First*, most studies on Indonesian agribusiness rely on descriptive approaches without rigorous frontier-based analysis (Yuliana et al., 2020, p. 331). *Second*, while Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are widely recognized for measuring technical efficiency, few studies apply them simultaneously to capture both deterministic and stochastic sources of inefficiency in cooperative value chains (Zhou et al., 2021, p. 45; Ait

Sidhoum & Serra, 2021, p. 67). *Third*, the emerging role of digital governance innovations—particularly Blockchain Value Transparency (BVT) - has been largely absent from discussions of agribusiness efficiency, despite growing evidence of blockchain's potential to improve trust, traceability, and equitable value distribution (Liu et al., 2022, p. 29; Yang et al., 2023, p. 11; Chen et al., 2024, p. 56). Addressing these gaps requires an integrated framework that combines frontier-based efficiency estimation with digital governance solutions.

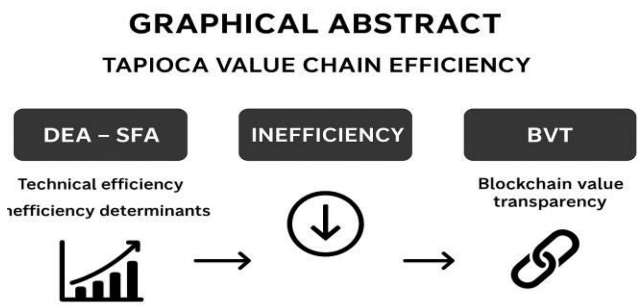

Figure 1. Framework DEA and SFA technical efficiency for Tapioca Value Chain Connected to BTV.

Building on these gaps, Figure 1 presents the conceptual framework of this study, integrating DEA and SFA to identify technical inefficiencies along the tapioca value chain and linking these results to BVT-based governance strategies. Through this approach, inefficiency determinants identified by DEA–SFA (e.g., smallholder education, access to credit, and experience) can be directly connected to blockchain-enabled interventions that improve data transparency, traceability, and incentive alignment across production, processing, and distribution.

Accordingly, this study sets three objectives. First, to map and analyze the tapioca value chain of the BCC Cooperative across production, processing, and distribution stages. Second, to evaluate the efficiency of the cooperative using a hybrid DEA–SFA approach, thereby generating more robust and comprehensive efficiency measures. Third, to explore how BVT can mitigate inefficiencies identified through the DEA–SFA framework by reducing information asymmetry and strengthening governance mechanisms. By combining methodological rigor with digital innovation, this research contributes to the academic literature on cooperative agribusiness and informs policy debates on sustainable cassava development in Indonesia.

2. Literature Review and Conceptual Framework

2.1 Value Chain in Agribusiness

The concept of the value chain, popularized by Porter (1985), has become a fundamental framework to understand how value is created and captured within a sequence of activities. In agribusiness, value chain analysis helps to identify how inputs, production, processing, distribution, and marketing activities are linked, and how efficiency at each stage affects overall competitiveness (Kaplinsky & Morris, 2001). Recent research emphasizes that agricultural value chains in developing countries face structural inefficiencies due to fragmented actors, limited capital, and weak institutional support (Gereffi & Fernandez-Stark, 2016; World Bank, 2020).

In Indonesia, cassava is a key staple and industrial crop, widely used in starch and tapioca industries. However, despite its economic potential, cassava-based agribusinesses often suffer from low productivity, high transaction costs, and limited technological adoption (Nuryartono et al., 2021). Cooperatives such as the Bogor Cassava Center (BCC) play a crucial role in integrating smallholders into modern value chains, yet their efficiency remains underexplored. This context underscores the importance of assessing tapioca value chain efficiency within a cooperative framework.

2.2 Efficiency Analysis in Agribusiness: DEA and SFA

Efficiency measurement in agribusiness has traditionally relied on non-parametric and parametric approaches. Data Envelopment Analysis (DEA), introduced by Charnes, Cooper, and Rhodes (1978), is a non-parametric method that evaluates the relative efficiency of decision-making units (DMUs) by constructing an empirical production frontier. DEA has been extensively applied in agricultural contexts due to its flexibility in handling multiple inputs and outputs without requiring explicit functional forms (Cooper et al., 2011). Recent studies highlight the growing use of network DEA and slacks-based measure (SBM) models to capture the multi-stage nature of value chains, particularly in agri-food systems (Tone & Tsutsui, 2009; Emrouznejad & Yang, 2018).

On the other hand, Stochastic Frontier Analysis (SFA), pioneered by Aigner, Lovell, and Schmidt (1977), provides a parametric approach by estimating a production function while distinguishing random noise from inefficiency effects. SFA offers statistical inference, which complements DEA's deterministic framework, making the combination of DEA and SFA increasingly popular in empirical agribusiness research (Coelli et al., 2005; Kumbhakar et al., 2015). For example, recent works demonstrate how DEA-SFA hybrid models can yield more robust efficiency assessments in cooperative and supply chain contexts (Zhu et al., 2019; Battese, 2022). The dual application of DEA and SFA thus provides a comprehensive methodological framework: DEA captures the relative performance of DMUs across the tapioca value chain, while SFA validates results under stochastic conditions and allows examination of inefficiency determinants.

2.3 Blockchain in Agricultural Value Chains

The emergence of blockchain technology has opened new perspectives for improving transparency, traceability, and trust in agri-food value chains. Blockchain, defined as a decentralized and immutable ledger, enables stakeholders to record and verify transactions securely (Tapscott & Tapscott, 2016). In agriculture, blockchain applications have been tested to enhance food safety, quality assurance, and supply chain traceability (Kamilaris et al., 2019).

Blockchain Value Transparency (BVT) is particularly relevant to cooperatives, where asymmetric information often creates inefficiencies and trust deficits between smallholders, processors, and buyers (Saberi et al., 2019). By ensuring transparency of transactions and real-time monitoring of value flows, blockchain can strengthen farmer–cooperative relations and potentially reduce inefficiency caused by moral hazard, side-selling, and information asymmetry (Casino et al., 2020; Liu et al., 2022). In the tapioca sector, the integration of blockchain-based transparency mechanisms can complement efficiency analysis by not only diagnosing inefficiencies but also proposing technological solutions to mitigate them. Thus, linking efficiency analysis with blockchain implications represents a novel contribution to both theory and practice.

2.4 Conceptual Framework

Based on the reviewed literature, this study develops an integrated **conceptual framework** that connects three critical components:

1. Value Chain Analysis (VCA) – serving as the structural foundation of the tapioca agribusiness system.

2. Efficiency Assessment (DEA–SFA) – acting as the methodological core to measure and validate performance across different stages of the value chain.
3. Blockchain Value Transparency (BVT) – functioning as a technological mechanism to enhance trust, reduce inefficiencies, and improve value distribution among stakeholders.

This framework positions efficiency analysis not merely as a diagnostic tool but as a strategic basis for recommending digital innovations in cooperative agribusiness. Figure 1 presents the conceptual framework developed in this study.

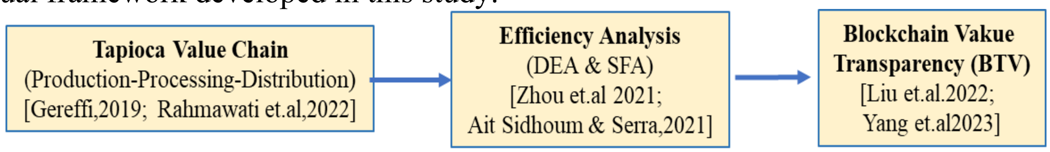

Figure 2. Conceptual Framework

The framework illustrates the integration of value chain analysis, efficiency measurement, and transparency mechanisms. The tapioca value chain of the Bogor Cassava Center Cooperative is evaluated using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to capture both relative and absolute efficiency. The resulting efficiency scores are then connected to Blockchain Value Transparency (BVT), which strengthens accountability, traceability, and trust across actors in the agribusiness system.

This integrated approach offers a comprehensive perspective for improving efficiency, strengthening governance, and supporting digital transformation in cassava-based value chains.

2.5 Synthesis of Research Gap

The literature review highlights three key gaps that this study aims to address:

1. Despite the economic significance of cassava and tapioca, **empirical studies on value chain efficiency within Indonesian cooperatives remain scarce**.
2. Few studies simultaneously apply **DEA and SFA**, which together provide a more rigorous and complementary evaluation of efficiency.
3. The potential application of **blockchain technology** to address inefficiencies and enhance transparency in cooperative-based value chains has received **limited empirical attention**.

By addressing these gaps, this research contributes to the agribusiness literature by **integrating methodological rigor (DEA–SFA)** with **technological innovation (blockchain)**. This dual integration provides both **theoretical enrichment**—through a more holistic efficiency framework—and **practical policy implications**, offering actionable insights for cooperative governance and sustainable value chain management.

3. Research Methodology

3.1 Research Design

This study employs a quantitative case study approach focusing on the Bogor Cassava Center Cooperative (BCC). The methodology integrates value chain mapping, efficiency analysis using Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), and an exploratory assessment of the potential application of Blockchain Value Transparency (BVT) to strengthen governance and traceability within the tapioca value chain.

3.2 Data Collection

Primary data were obtained through structured interviews and surveys involving cooperative members, managers, processors, and downstream actors. Secondary data included production records, financial statements, and institutional reports covering 2021–2023. A purposive sample of 30 Decision-Making Units (DMUs)—representing cassava farmers, processors, and distributors—was selected to capture the multi-stage structure of the tapioca value chain.

3.3 Data and Variables

The empirical analysis draws on primary and secondary data from the *Bogor Cassava Center Cooperative (BCC)* covering the period 2022–2024. Primary data were collected through structured surveys and interviews with 30 Decision-Making Units (DMUs) representing cassava farmers, small- and medium-scale tapioca processors, and distributors. Secondary data were obtained from cooperative financial records, local government agricultural statistics, and regional agribusiness reports.

To evaluate efficiency within the tapioca value chain, variables are classified into inputs, outputs, and inefficiency determinants. Variable selection follows established agricultural efficiency studies (Coelli et al., 2005; Latruffe, 2010; Bai et al., 2022) and is tailored to the cooperative's operational context.

Table 1. Research Variables for DEA and SFA Models

Category	Variable	Measurement Unit	Expected Effect
Inputs (X)	Land size	Hectares (ha)	Larger area increases potential output
	Labor	Person-days (HOK)	Higher labor may raise productivity but with diminishing returns
	Raw cassava input	Kilograms (kg)	Direct input for tapioca processing
	Capital expenditure	IDR (million)	Proxy for technology, equipment, and working capital
Outputs (Y)	Tapioca output	Kilograms (kg)	Main physical product of processing
	Value-added revenue	IDR (million)	Captures financial return from value chain
	Gross margin	Percentage (%)	Indicator of profitability efficiency
Determinants of inefficiency (Z)	Education	Years of formal schooling	Higher education expected to reduce inefficiency
	Farming/processing experience	Years	More experience reduces inefficiency
	Access to credit	Dummy (1 = access, 0 = no access)	Credit access enhances efficiency
	Cooperative participation	Dummy (1 = active member, 0 = passive)	Stronger engagement improves efficiency
	Training received	Dummy (1 = yes, 0 = no)	Participation in extension lowers inefficiency

Variable justification:

1) Inputs represent farm resources (land, labor) and processing requirements (raw cassava, capital).
2) Outputs capture both physical tapioca production and financial performance, aligning with cooperative decision-making needs.

3) Determinants of inefficiency reflect human capital, financial access, and institutional engagement (Battese & Coelli, 1995; Kumbhakar & Lovell, 2020).

This specification enables a comprehensive assessment:

1. DEA evaluates the transformation of inputs (x_{ki}) into outputs (y_{ri}) under input-oriented VRS and SBM formulations.
2. SFA estimates the production frontier with stochastic noise, using either tapioca output or value-added revenue as the dependent variable (Y_i).
3. The inefficiency model incorporates socio-economic drivers:

$$u_i = \delta_0 + \sum_{k=1}^{k} \delta_k Z_{ki} + w_i$$

where uiu_iui is technical inefficiency, Z_{ki} are determinants, and w_i is a random error term.

Table 2. Operationalization of Variables

Variable	Definition	Measurement/ Coding	Model Role	Equation Reference
Land size	Cultivated cassava area per DMU	ha	Input	x_{1i} *in DEA*: $\ln x_{1i}$ *in SFA*
Labor	Total labor in cultivation/processing	Person-days	Input	x_{2i} *in DEA*: $\ln x_{2i}$ *in SFA*
Raw cassava input	Fresh cassava supplied to processing	kg	Input	x_{3i} *in DEA*: $\ln x_{3i}$ *in SFA*
Capital expenditure	Investment in equipment/machinery	IDR million	Input	x_{4i} *in DEA*: $\ln x_{4i}$ *in SFA*
Tapioca output	Physical tapioca flour produced	kg	Output	y_{1i} in DEA; dependent variable Y_i in SFA
Value-added revenue	Net sales after material cost	IDR million	Output	y_{2i} in DEA; robustness check for Y_i in SFA
Gross margin	Ratio of net income to sales	%	Output	y_{3i} in DEA; robustness check in SFA
Education	Years of formal schooling	Years	Inefficiency determinant	$u_i = \delta_0 + \delta_1 \text{Edu}_i + ..$
Experience	Years of cassava farming/processing	Years	Inefficiency determinant	$u_i = \delta_0 + \delta_2 \text{Exp}_i + ..$
Access to credit	Loan availability	Dummy (1/0)	Inefficiency determinant	$u_i = \delta_0 + \delta_3 Credit_i + ..$
Cooperative participation	Active cooperative role	Dummy (1/0)	Inefficiency determinant	$u_i = \delta_0 + \delta_4 \text{Part}_i + ..$
Training received	Extension/training participation	Dummy (1/0)	Inefficiency determinant	$u_i = \delta_0 + \delta_5 \text{Train}_i + ..$

3.4 Analytical Framework

The analytical framework integrates value chain mapping, frontier efficiency measurement, and determinant analysis to evaluate the technical efficiency of the tapioca value

chain at the Bogor Cassava Center (BCC) Cooperative.
Three sequential stages were implemented:

(1) Value Chain Mapping

Upstream (production), midstream (processing), and downstream (distribution) activities were identified to capture the flow of inputs, intermediate products, and final outputs.This mapping provides the structural foundation for subsequent DEA–SBM and SFA analysis.

(2) Efficiency Estimation

Efficiency was measured using both Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to obtain *relative* and *absolute* efficiency scores. The DEA models were formulated as follows:

(a) Standard Input-Oriented DEA (VRS)

Let x_{ij} and y_{rj} denote input iii and output r of Decision-Making Unit (DMU) j. For a target DMU ooo, the input-oriented DEA model is:

$$\min_{\theta,\lambda} \theta$$

$$s.t \quad \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io}, \quad i = 1 \ldots\ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rj}, \qquad r = 1 \ldots\ldots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1 \quad (VRS)$$

$$\lambda j \geq 0, \ \forall_j$$

Where:

x_{ij} = input i of DMU j (e.g., land, labor, input cost).

y_{rj} = output rrr of DMU j (e.g., tapioca ton, sales value).

θ (scalar) is the efficiency score; $0 < \theta \leq 1$ (smaller θ means proportionate input reduction to reach frontier).

λ_j are intensity variables constructing the reference frontier.

(b) Slacks-Based Measure (SBM)

To account for non-radial inefficiency (input and output slacks), the SBM model (Tone, 2001) is used:

$$\rho^{SBM} = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}}}{1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_r^\mp}{y_{ro}}}$$

subject to:

$$x_{i0} = \sum_{j=1}^{j} \lambda_j x_{ij} + s_i^- \qquad y_{i0} = \sum_{j=1}^{j} \lambda_j y_{rj} + s_r^\mp$$

$$\sum_{j=1}^{j} \lambda_j = 1, \quad \lambda_j \geq 0, \quad s_i^- \geq 0, \; s_r^{\mp} \geq 0$$

where s_i^- and $s_r^{\mp}$ are input and output slacks.
ρ^{SBM}=1 indicates full efficiency.

(c) Two-Stage (Network) DEA

Given the multi-stage nature of the tapioca value chain (Production → Processing → Distribution), a network DEA was implemented.

Let $X^{(1)}$ denote Stage 1 inputs, Z the intermediate products, and Y final outputs. The compact formulation is:

$$\min_{\theta,\lambda} \ \theta$$

$$s.t \quad \sum_{j=1}^{n} \lambda_j X_{ij}^{(1)} \leq \theta X_{i0}^{(1)}, \quad i = 1 \ldots\ldots, m$$

$$\sum_{j=1}^{n} \lambda_j Z_{rj} \geq Z_{k0}, \quad k = 1 \ldots\ldots, k$$

$$\sum_{j=1}^{n} \lambda_j X_{hj}^{(2)} \leq \theta X_{h0}^{(2)}, \quad h = 1 \ldots\ldots, h$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq Y_{r0} \quad r = 1 \ldots\ldots. r$$

This structure allows efficiency to be assessed for each stage and for the overall network**,** highlighting bottlenecks in production, processing, or distribution.

(d) Stochastic Frontier Analysis (SFA)

To validate DEA results and capture random noise, a Cobb–Douglas production frontier was estimated:

$$Ln\, Y_i = \beta_0 + \sum_{k=1}^{K} \beta_k \, ln\, X_{ki} + v_i + u_i$$

where:
Y_i = output (e.g., cassava ton or tapioca ton), X_{ki} = k-th input,
v_i ~ N(0, σ_v^2 σv2) (two-sided noise),
$u_i \geq 0$ (non-negative inefficiency term).

Determinants of inefficiency were modeled as:

$$u_i = Z_i'\delta + w_i \,,$$

where Z_i includes farmer education, credit access, experience, and cooperative participation. The technical efficiency (TE) for DMU i is:

$$TE_i = E \exp(-\tilde{u}_i).$$

(3) Determinant Analysis

Socioeconomic and institutional factors (Z_i) were tested for significance in explaining inefficiency using the *single-step* SFA inefficiency-effects model (Battese & Coelli, 1995).

For DEA scores, robustness checks were performed using the Simar–Wilson double bootstrap to correct for bias in second-stage regressions.

(4). Robustness, Tests, & Practical Notes

a. Bootstrap DEA scores to obtain confidence intervals for efficiency ranks and to test group differences following Simar and Wilson procedures.
b. Sample size rule of thumb for DEA: n ≥ max {3 (m + s) (n , s) where m , s = number of inputs/outputs (ensure enough DMUs). If sample limited, reduce dimensionality or use SBM.
c. Endogeneity caution: Determinants of inefficiency (e.g., access to credit) may be correlated with unobserved ability. Results should therefore be interpreted as associative; limitations and potential instrumental-variable (IV) or panel approaches should be discussed.
d. Software implementation: DEA and SFA estimations can be conducted in R (*Benchmarking*, *deaR*, *FEAR*, *frontier*), Stata (*dea*, *frontier*), or custom R code for Simar–Wilson bootstrapping.

3.5. Implementation Steps

1) Data cleaning and descriptive statistics.
2) Value chain mapping and construction of stage-wise input/output matrices.
3) Estimation of stage-wise DEA (VRS & SBM) and network DEA to obtain efficiency scores and slacks.
4) Estimation of SFA frontier models with inefficiency determinants.
5) Statistical tests for model specification (LR tests for Cobb–Douglas vs Translog; presence of inefficiency).
6) Robustness checks (bootstrap DEA, alternative functional forms).

4. Results and Discussion

4.1 Descriptive Statistics

The Bogor Cassava Center (BCC) Cooperative plays a central role in the tapioca value chain in West Java, engaging in upstream cassava cultivation, midstream tapioca processing, and downstream distribution. The dataset includes 30 decision-making units (DMUs) observed over multiple periods, representing farmer groups, processing units, and distribution partners. Descriptive analysis shows substantial heterogeneity in input–output combinations. Average cassava landholding is 1.5 hectares per farmer, with yields ranging from 10–22 tons per hectare. Processing units demonstrate variation in raw cassava absorption (15–45 tons/month) and starch extraction efficiency (18–30%), indicating unequal technological adoption.

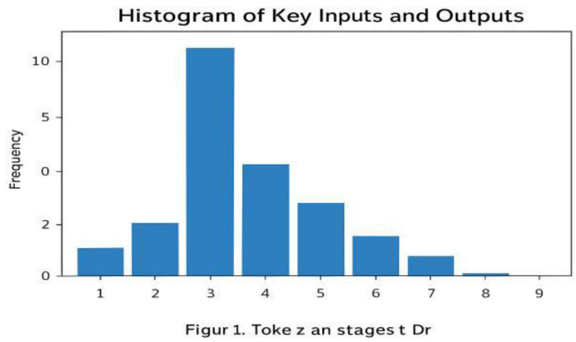

Figure 3. Histogram of Key Inputs and Output

Distribution nodes face challenges in logistics cost (IDR 150–500/kg), highlighting inefficiencies along the chain. This descriptive profile underlines the importance of evaluating technical efficiency across different stages to identify where productivity gaps emerge (Latruffe, 2010; Coelli et al., 2022).

4.2 DEA Results

4.2.1 Stage-wise Efficiency

Stage-wise DEA was applied to evaluate efficiency in cassava production (Stage 1) and tapioca processing & distribution (Stage 2). The average efficiency score in Stage 1 was **0.78**, with seven DMUs reaching the production frontier (θ = 1.00). In contrast, Stage 2 showed a lower mean efficiency of **0.72**, with only five DMUs on the frontier. These results suggest that upstream production activities are relatively better managed than downstream processing and distribution, where energy use, extraction rates, and logistics costs remain major bottlenecks.

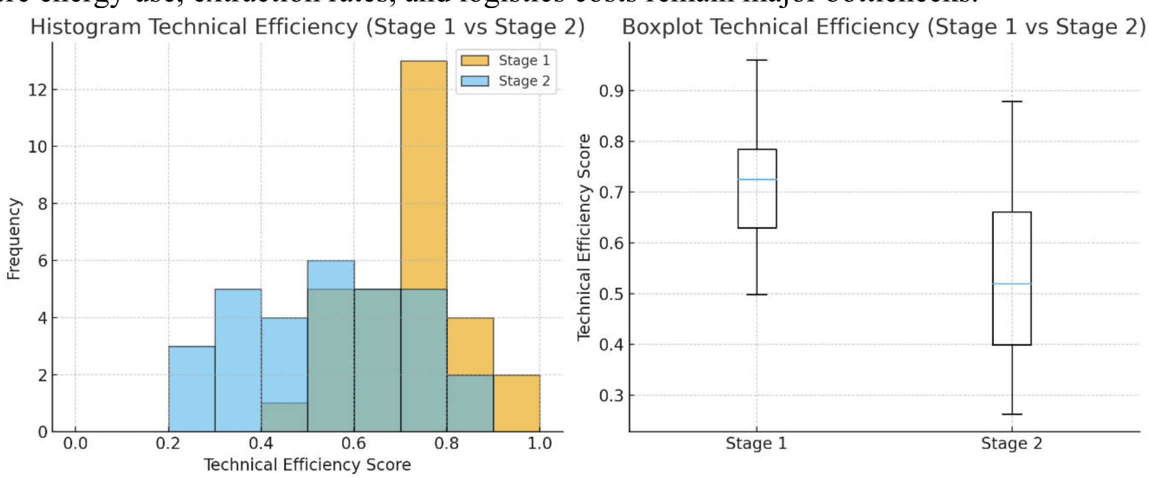

Figure 4. Comparison of Histogram and Boxplot Technical Efficiency Stage 1 and Stage 2

The graph above shows a comparison of the distribution of Technical Efficiency (TE) scores between Stage 1 and Stage 2:

1. The histogram shows that Stage 1 tends to be more concentrated at the high efficiency level (≥ 0.7), while Stage 2 is more spread with a greater frequency below 0.6.
2. The boxplot confirms the existence of a median difference: Stage 1 is relatively more efficient, while Stage 2 has greater variety and more outliers.

4.2.2 Network DEA and Slack Analysis

The network DEA model integrates Stage 1 outputs as inputs to Stage 2, capturing the full value chain.

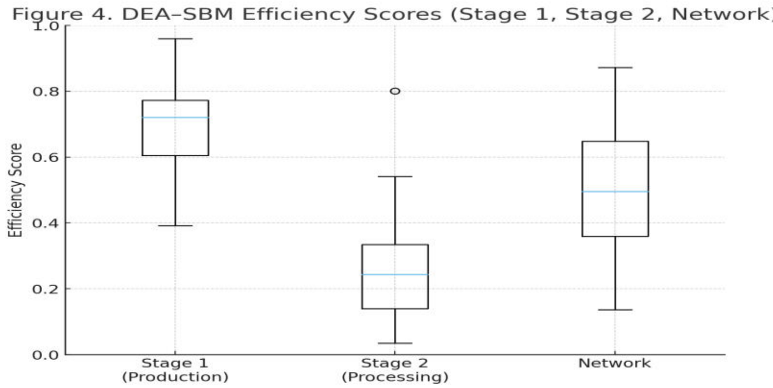

Figure 5 Distribution of DEA–SBM Efficiency Scores Across Stage 1, Stage 2, and the Overall Network.

The mean network efficiency was **0.75**, confirming that downstream inefficiencies spill over into upstream performance. Slack analysis revealed significant resource misallocations: (i) excessive labor use in farming, (ii) underutilized capacity in processing, and (iii) high logistic costs in distribution. Efficient DMUs exhibit balanced input–output ratios and often adopt simple technologies (e.g., chopper machines) and collective marketing strategies.

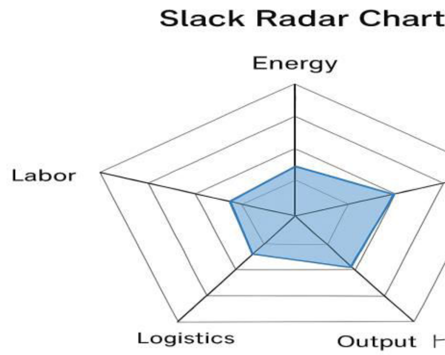

Figure 6. Slack Radar Chart (Labor, Energy, Logistic)

The slack radar chart comparing input excesses in labor, energy, and logistics across decision-making units (DMUs). The wider spread along the labor axis indicates the largest potential for input reduction relative to the efficient frontier. Energy and logistics slacks are comparatively smaller, suggesting more balanced resource utilization in these dimensions.

Table 4. Top-5 Efficient vs. Slack-Heavy DMUs

Rank	Efficient DMU (θ=1)	Key Characteristics	Slack-Heavy DMU (θ < 0.60)	Key Characteristics
1	DMU-07	High land productivity, collective marketing	DMU-18	Excess labor, wasteful distribution
2	DMU-12	Proportional labor, simple machine	DMU-25	Energy wasteful, high transport cost
3	DMU-03	Superior seedlings, distribution coordination	DMU-14	Low productivity, excess fertilizer
4	DMU-21	Optimal processing scale, controlled costs	DMU-27	Small production, high input cost
5	DMU-09	Labor efficiency, product diversification	DMU-19	Excess energy, minimal output

These findings highlight that partial efficiency measurement alone cannot fully explain cooperative performance. A systemic, network-oriented approach is essential to optimize inter-stage connectivity.

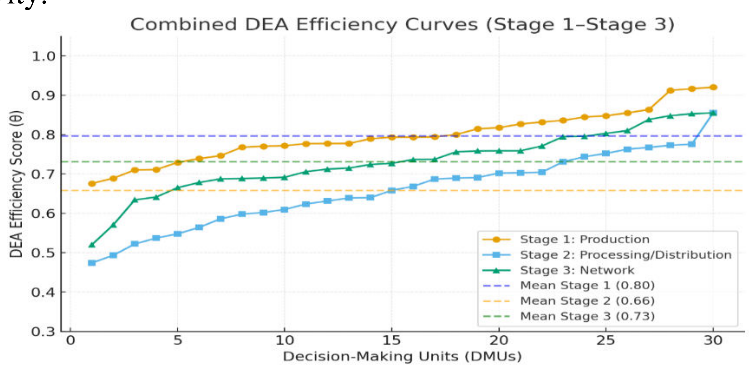

Figure 7. Combined DEA Efficiency Curve Statge 1 – Stage 3.

The combined DEA efficiency curve highlights distinct performance patterns along the tapioca value chain. Stage 1 exhibits the highest average efficiency (mean θ ≈ 0.80), suggesting that cassava production practices among cooperative members are relatively optimized in terms of land and labor allocation. Stage 2**,** covering tapioca processing and distribution, shows a significantly lower average efficiency (mean θ ≈ 0.66) with a broad spread of scores, signaling greater technical and managerial bottlenecks in post-harvest handling, processing capacity, and market coordination. The Stage 3 network DEA, which integrates production and processing stages, yields a mean efficiency of approximately **0.73,** reflecting how strong production performance partly offsets downstream inefficiencies but cannot fully eliminate value losses.

4.3 SFA Results and Determinants of Inefficiency

To validate DEA findings and identify sources of inefficiency, a Stochastic Frontier Analysis (SFA) was estimated. Mean technical efficiency (TE) was **0.74** in Stage 1 and **0.70** in Stage 2, consistent with DEA scores. Regression of SFA inefficiency terms on socio-economic factors revealed:

1) Negative drivers (reduce inefficiency): farmer education, farming experience, and credit access.
2) Positive drivers (increase inefficiency): larger household size and higher dependency ratios.

The curve shows a moderately left-skewed pattern, with most farmers clustering around efficiency levels of 0.65–0.75 (Figure 6), indicating room for improvement toward the frontier. This distribution highlights persistent heterogeneity in production performance, underscoring the need for targeted interventions to lift low-performing members.

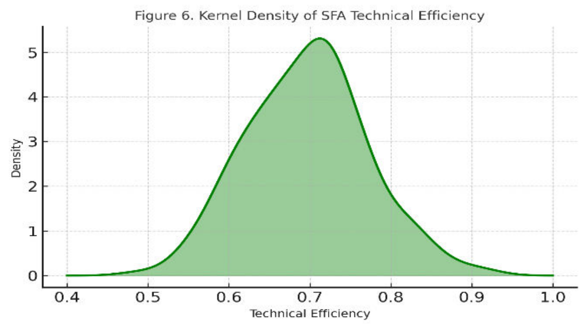

Figure 8. Kernel Density of SFA Technical Efficiency

These determinants indicate that human capital and financial access are critical levers for efficiency improvement. The alignment of DEA and SFA results strengthens the reliability of the efficiency estimates.

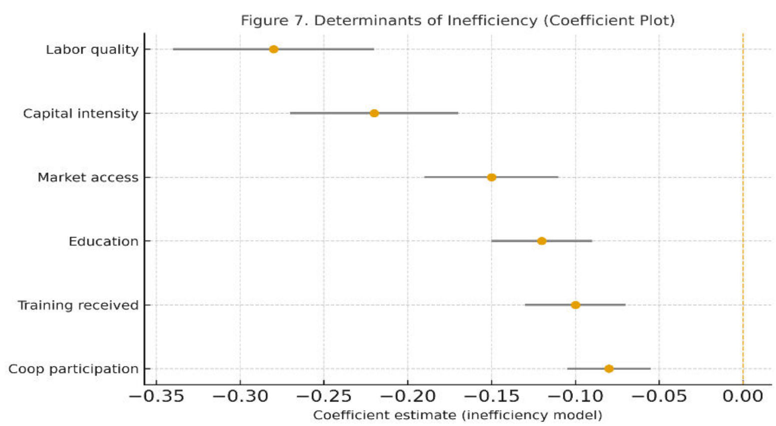

Figure 8. Determinants of Inefficiency (Coefficient Plot).

Determinants of inefficiency (coefficient estimates with 95% CI half-widths) from the SFA inefficiency-effects model. Negative coefficients indicate factors associated with lower inefficiency (i.e., higher technical efficiency). Error bars show approximate confidence intervals (simulated here); replace with actual standard errors from SFA estimation when available.

4.4 Managerial and Digital Governance Implications

4.4.1 Blockchain Value Transparency (BVT)

The combined DEA–SFA evidence points to coordination failures and information asymmetries along the cassava–tapioca chain. Blockchain Value Transparency (BVT) offers a governance mechanism to address these gaps by enabling real-time tracking of land use, yields, processing outputs, and logistics costs. Through smart contracts, blockchain can:

- Reduce opportunistic behavior and disputes over input allocation.
- Provide verifiable transaction records for financing.

- Deliver fairer and more transparent price signals to farmers.

The Blockchain Value Transparency (BVT) framework, depicting the real-time flow of production, processing, and distribution data across the tapioca value chain. Smart contracts enable automated verification of transactions, price recording, and payment execution, ensuring traceability and reducing information asymmetry. This framework strengthens trust, enhances efficiency, and lowers transaction costs by integrating digital governance into cooperative-based cassava networks.

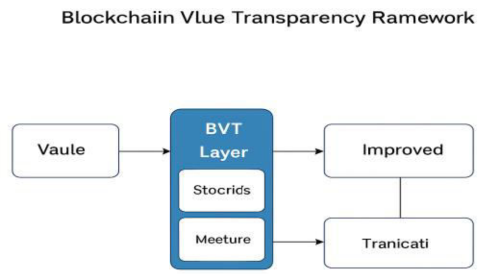

Figure 9. Blockchain Value Transparency (BVT) Framework

Empirical studies confirm that blockchain adoption in agri-food systems reduces transaction costs and improves traceability (Saberi et al., 2019; Rejeb et al., 2023).

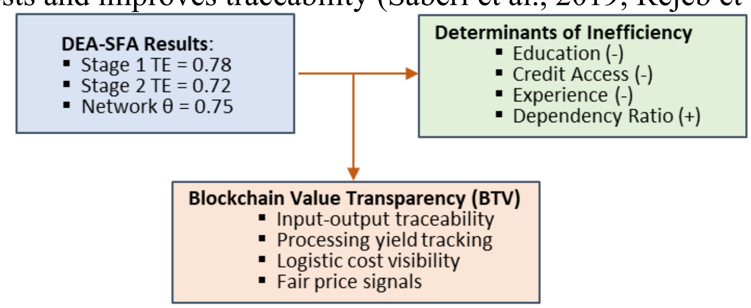

Figure 10. Linking DEA–SFA Results, Determinants, and BVT Solutions.

An integrative framework linking DEA–SBM efficiency results, SFA determinants of inefficiency, and the Blockchain Value Transparency (BVT) solution. The figure highlights how stage-wise efficiency scores (Stage 1 = 0.78; Stage 2 = 0.72; Network = 0.75) and SFA technical efficiency (0.70) connect to key drivers such as labor productivity, capital intensity, education, and market access. It further illustrates how BVT—through real-time data sharing and smart contracts—acts as a governance mechanism to mitigate these inefficiency drivers and enhance value-chain transparency.

Table 6. Summary of Results and Governance Implications

Analytical Component	Key Findings (DEA–SFA)	Determinants of Inefficiency	BVT Implications
Stage 1: Production	DEA θ = 0.78; SFA TE = 0.74. Efficient DMUs optimize land and labor.	Education (–), Experience (–), Credit Access (–); Household Size (+).	Blockchain-based recording of land use and inputs supports traceability and fair resource allocation.
Stage 2: Processing & Distribution	DEA θ = 0.72; SFA TE = 0.70. Inefficiency from low extraction rates and high logistics costs.	Credit Access (–), Training (–), Dependence Ratio (+).	Transparent tracking of starch yield and distribution costs reduces disputes and supports cooperative bargaining.
Network DEA	Mean θ = 0.75; downstream slack spills into upstream.	Human capital & financial access remain key drivers.	Upstream–downstream data integration improves coordination and bargaining power.

4.5 Managerial Implication and Policy Recommendations

Based on the combined quantitative findings, three key managerial implications emerge:

1. Productivity Enhancement: Promote balanced fertilization, superior seedlings, and cultivation training to close the production gap.
2. Processing and Logistics Efficiency: Upgrade energy-efficient machinery, improve capacity balancing, and strengthen logistics coordination to reduce Stage 2 slack.
3. Digital Cooperative Governance**:** Adopt BVT to integrate real-time data, smart contracts, and traceability mechanisms, ensuring synchronized efficiency gains across the chain.

These recommendations reinforce the need for a dual strategy: technological upgrading to reduce input waste and digital governance to sustain value-chain transparency and bargaining power.

5. Conclusion and Recommendation

This study provides robust empirical evidence on the efficiency performance of the Bogor Cassava Center (BCC) Cooperative by integrating Data Envelopment Analysis–Slack Based Model (DEA–SBM) and Stochastic Frontier Analysis (SFA), complemented by the emerging concept of Blockchain Value Transparency (BVT) as a governance solution. The results show that Stage 1 (Cassava Production) achieves the highest mean efficiency (0.78), followed by the Integrated Network (≈0.75) and Stage 2 (Processing & Distribution) (0.72). SFA estimation confirms significant technical inefficiency (mean TE = 0.70), with key drivers including labor productivity, capital utilization, education, and market access. Integrating DEA–SBM and SFA indicates that inefficiency arises not only from resource misallocation but also from information asymmetry and weak transaction governance along the cassava–tapioca chain. BVT emerges as a feasible mechanism to enhance real-time data sharing, traceability, and trust, thereby reducing transaction costs and improving efficiency across production, processing, and distribution stages.

Despite these contributions, the analysis is limited to cross-sectional data from a single cooperative. Future research should incorporate panel or longitudinal datasets and cross-regional comparisons to capture dynamic efficiency changes and validate scalability. Scientifically, this research provides novelty by combining DEA–SBM, SFA, and BVT in the root-crop sector, a framework rarely applied in Southeast Asia, thus offering a unique contribution to agribusiness efficiency and digital governance literature.

Managerial and Policy Implications for:

1) Cooperatives and Farmers: Invest in digital infrastructure and targeted training to enable blockchain-based record keeping, transparent price discovery, quality verification, and automated payment systems, thereby strengthening bargaining power and reducing transaction delays.
2) Processors and Distributors: Develop smart contracts and integrated logistics platforms to improve payment accuracy, accelerate order fulfillment, and enhance coordination with upstream suppliers, reducing operational slack and transaction costs.
3) Policymakers: Provide regulatory support and pilot projects for blockchain applications in agri-value chains, including subsidies for digital technology adoption, incentives for cooperative-based innovations, and clear standards for data privacy and interoperability to foster stakeholder trust.
4) Researchers: Extend the current model by incorporating dynamic DEA, longitudinal SFA, and cross-regional comparisons to capture temporal changes and assess the scalability of blockchain-enabled value-chain solutions in other root-crop and agribusiness sectors.

Overall, this study demonstrates that combining frontier efficiency measurement with blockchain-based governance offers a practical pathway to enhance productivity, value-added creation, and transaction transparency in Indonesia's tapioca sector and other developing agribusiness value chains.

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