EFFICIENCY OF PINEAPPLE FARMERS AND MARKETING CHANNELS IN DARJEELING, UTTAR DINAJPUR, AND JALPAIGURI DISTRICTS OF NORTH BENGAL

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ABSTRACT

This study uncovers the untapped potential of pineapple cultivation in West Bengal, India's largest pineapple-producing state, while exposing critical inefficiencies that hinder growth. Despite its status, farmers remain trapped by outdated practices, financial constraints, and a marketing system dominated by intermediaries, severely limiting their share of profits. By analyzing both cultivation and marketing practices, this research highlights the stark contrasts in efficiency across different regions, with farmers in Uttar Dinajpur & Jalpaiguri (UD & JPG) outperforming those in Darjeeling (DRJ). The study further reveals the inefficiencies of major marketing channels, where intermediaries capture the majority of profits, leaving farmers with minimal returns. Moreover, it identifies key factors like access to credit, training, and infrastructure as crucial to enhancing productivity. With actionable insights into overcoming these barriers, this paper makes a compelling case for transforming West Bengal's pineapple sector into a globally competitive force. It offers a roadmap for improving both farmer livelihoods and the region's economic potential, making it an essential read for stakeholders in agricultural development.

Keywords: Pineapple Cultivation, West Bengal, Inefficiencies, Marketing channels, Infrastructure

I. INTRODUCTION

Pineapple cultivation in West Bengal presents a paradox—vast stretches of land producing abundant fruit and contributing significantly to the state's agricultural output, yet farmers often find themselves earning far less than their hard work would seem to deserve. West Bengal is the largest pineapple-producing state in India and enjoys favourable agro-climatic conditions that could allow it to become a major force in global markets (Bhowmick et al., 2022). The fruit's strong domestic demand

and considerable export potential suggest a story of prosperity. However, the ground reality paints a more complex picture, where persistent challenges reduce farm incomes and hinder the growth of this sector.

These challenges are not confined to the farm gate. Outdated cultivation techniques, insufficient mechanization, limited access to affordable credit, and fragmented landholdings continue to affect productivity. On top of that, the marketing system is often controlled by layers of intermediaries, which results in farmers receiving only a small share of the final consumer price (Ansari & Jamaluddeen, 2023; Paul et al., 2017). Similar patterns have been observed in other high-value horticultural crops in India, where the absence of efficient supply chains has limited farmer benefits despite strong production (Mudda & Giddi, 2017). This creates a persistent imbalance where, even with bumper harvests, the economic rewards remain out of reach for many growers.

At the heart of this issue are two interconnected dimensions—production efficiency and marketing efficiency. On the production side, efficiency is not simply about how much is produced but about how well resources are managed. Technical Efficiency (TE) measures how effectively inputs such as land, labour, and technology are converted into the maximum possible output. Cost Efficiency (CE) reflects the ability to minimize production expenses while maintaining yield levels. Allocative Efficiency (AE) assesses whether scarce resources are being used in the most economically rewarding combination (Ogundari & Brümmer, 2011; Shephard, 2015; Simar & Wilson, 2020). Previous studies have shown that improving these efficiencies can lead to substantial gains in profitability, particularly for smallholder farmers (Coelli et al., 2005).

However, production-side improvements alone cannot secure better farmer incomes if marketing systems remain inefficient. The marketing efficiency of a channel determines how much of the value created in the supply chain ultimately reaches the primary producer. In many cases, weak bargaining power, limited access to direct markets, and dependence on commission agents erode potential gains for farmers. Efficient marketing channels are therefore as crucial as efficient cultivation practices in ensuring the sustainability and competitiveness of pineapple production in West Bengal.

Against this background, the present study undertakes a comprehensive examination of efficiency in pineapple cultivation, covering Technical, Cost, and Allocative Efficiency, as well as the efficiency of prevailing marketing channels. The objective is to identify the key inefficiencies that limit farmers' earnings, understand how production and marketing challenges interact, and propose targeted strategies that can enable West Bengal's pineapple growers to secure a fairer share of the value their produce generates and strengthen their position in both domestic and international markets.

II. METHODOLOGY

DATA AND SAMPLE

This was a mixed-methods research design, descriptive and analytical approach that used quantitative and qualitative data integration. The research followed a multistage purposive sampling technique where the initial selection included relevant areas and respondents. To begin with, the districts selected (Darjeeling, Uttar Dinajpur, and Jalpaiguri) are highly relevant to pineapple cultivation because they account for approximately 80% of West Bengal's total pineapple production (Ansari & Jamaluddeen, 2023). Blocks from the districts were then identified by the production level, and then GPs covering the highest cultivation areas. We collected data from a sample of 406 pineapple growers, out which 400 were used for this study. From the respondents, 200 were from Darjeeling (DRJ) and 200 from Uttar Dinajpur and Jalpaiguri (UD & JPG) combined. Additionally, data was collected from a separate sample of 30 intermediaries consisting of retailers, wholesalers, middlemen and agents. The time frame of the study period was two production cycles, in 2022 and 2023.

ANALYTICAL METHODS

Efficiency in Pineapple Cultivation

The efficiency scores for farms or producers, known as Decision-Making Units (DMUs), can be determined through parametric and non-parametric methods. One widely used non-parametric technique is Data Envelopment Analysis (DEA). DEA creates a benchmark of efficiency, where units on the frontier score a perfect 1, indicating maximum efficiency, while those below the frontier receive scores less than 1, denoting inefficiency (Kuang et al., 2020). In this context, the pineapple growers are treated as DMUs.

DEA is preferred over alternative methods due to its flexibility in input-output selection and its lack of assumptions about efficiency distribution (Chaluvadi et al., 2018). This is widely applicable across industries, including agriculture, where it identifies benchmark DMUs for inefficient units (Mardani et al., 2018; Tamatam et al., 2019).

Introduced by Charnes et al. (1978), DEA measures relative efficiency using observed inputs and outputs without assuming a specific functional form (Picazo-Tadeo et al., 2011). The method constructs a frontier from empirical data, representing the best performance, and calculates each DMU's distance from this frontier (Cook & Seiford, 2009; Thanassoulis et al., 2008).

DEA models can be designed to focus either on inputs or outputs. An input-oriented model aims to minimize the use of inputs while keeping the level of output steady. Conversely, an output-oriented model strives to maximize the output produced from a given set of inputs (Nowak et al., 2015). Efficiency is determined by dividing the total weighted output by the total weighted input, providing a measure of the DMU's performance in comparison to its peers (Kremantzis et al., 2022; Mardani et al., 2018).

DEA is widely used in agricultural efficiency studies, evaluating production, land use, irrigation, and more (Kuang et al., 2020; Toma et al., 2015). Its effectiveness depends on selecting the right inputs, as achieving similar output with fewer inputs suggests sustainable practices (Toma et al., 2015).

Technical Efficiency (TE)

To compute the technical efficiency of pineapple growers (DMUs) with output bundle y^0 from the input bundle x^0, the output-oriented variable returns to scale (VRS) DEA model is specified as:

$$\tau_y(x^0, y^0) = \frac{1}{\varphi^*}$$

Where φ^* is the optimal solution to the following maximization problem:

$$\varphi^* = \max \varphi$$

subject to

$$\sum_{j=1}^{N} \lambda_j y^j \geq \varphi y^0;$$
$$\sum_{j=1}^{N} \lambda_j x^j \leq x^0;$$

Where $\sum_{j=1}^{N} \lambda_j = 1$, and $\lambda_j \geq 0$ $(non-negative), (j = 1, 2, \ldots\ldots\ldots\ldots, N)$,

In the above model, our objective is to maximize φ, which represents the proportional expansion of the observed output bundle y^0, while keeping the inputs x^0 unchanged.

The constraints ensure that the weighted sum of outputs across all decision-making units (DMUs) is at least. φy^0, While the weighted sum of inputs remains within the observed input bundle x^0.

The convexity condition $\sum_{j=1}^{N} \lambda_j = 1$ ensures the VRS assumption.

If $\tau_y(x^0, y^0) = 1$, the DMU is technically efficient meaning no further proportional output increase is possible. If $\tau_y(x^0, y^0) < 1$, the DMU is inefficient, implying that output could be increased without increasing inputs.

Cost Efficiency (CE)

For the computation of all the cost efficiency (C*), the variable return to scale (VRS) DEA model is specified as the minimum cost under the assumption that variable returns to scale (VRS) is –

$$C^* = \min W^{0\prime}X : X \in V(y^0)$$

Here, W^0 represents the vector of input prices, X is the vector of input quantities, and $V(y^0)$ is the production possibility set for output y^0.

The Minimum cost obtained by solving the DEA Linear programming problem:

$$\min \sum_{i=0}^{n} w_i^0 \, x_i$$

Subject to,

$$\sum_{i=1}^{n} \lambda_j x_{ij} \leq x_i \ (i = 1 \ldots\ldots\ldots\ldots n)$$

$$\sum_{i=1}^{n} \lambda_j y_{rj} \geq y_{r0} \ (r = 1 \ldots\ldots\ldots\ldots n)$$

$Where, \sum_{i=1}^{n} \lambda_j = 1$, $x_{ij}$is the input quantity of the i^{th} input for the j^{th} Decision Making unit (DMU),y_{rj} is the output quantity of the r^{th} output for the j^{th} DMU, and $\lambda_j \geq 0, (j = 1 \ldots\ldots\ldots\ldots N)$, $X_i$is the input quantities utilized by i^{th}, W_i is the unit price of the firm's inputs under observation, λ is the weights, and y is the output produced by the i^{th} grower.

Allocative Efficiency (AE)

Allocative efficiency is achieved when a firm selects the most cost-effective combination of inputs based on their relative prices. The remaining allocative efficiency is determined through the relationship between cost efficiency (CE) and technical efficiency (TE) as shown in the following calculation:

$$Allocative\ Efficiency = \frac{Cost\ Efficiency}{Technical\ Efficiency}$$

Tobit Regression

The Tobit model is used to analyze the factors that influence the efficiency of pineapple growers. In some regressions, the dependent variable's data may be incomplete or censored, making the least squares (LS) method unsuitable (Jackson & Fethi, 2000; Kutlar et al., 2013). This occurs when data is truncated or censored, which can be addressed by latent variable models like the Tobit model, developed by Tobin (1958).

Heteroscedasticity, a violation of OLS assumptions, leads to inefficient estimates, as error variance is inconsistent (Kibaara, 2005). OLS yields biased results for efficiency scores constrained between 0 and 1 (Krasachat, 2003; You & Zhang, 2016). The Tobit model, suited for limited dependent variables, has been used in studies of environmental and technological efficiency, health production, railway companies, agricultural efficiency, and government spending (Kutlar et al., 2013; Long, 1997; Long et al., 2013). Therefore, the Tobit model can be applied to identify factors limiting the efficiency of pineapple cultivators. Hence, the model can be expressed as:

$$y_i^* = \alpha + \beta_1 Gen_i + \beta_2 Age_i + \beta_3 Lsize_i + \beta_4 Edu_i + \beta_5 Exp_i + \beta_6 FM_i + \beta_7 PLP_i + \beta_8 CT_i + \beta_9 SSL_i + \beta_{10} Trng_i + \beta_{11} CI_i + \beta_{12} Lown_i + u_i$$

Y = Efficiency Scores (Cost and Technical)

$Y_i = y^*$ *if* $0 < y^* < 1$

$Y_i = 0$ *if* $y^* \leq 0$

$Y_i = 1$ *if* $y^* \geq 1$

u_i= *independently distributed error term as* $N(0, \sigma^2)$

Where: Gen= Gender of the farmer, Age = Age of the Grower, LSize= Land Area (Bigha), Edu= Grower's education level, Exp= Farming experience (Years), FM= Number of family members, PLP= portion of land dedicated for pineapple, CT= Credit type (1 = External, 0 = Own Fund), SSL= No. of seasons on the same land, Trng= training (1 = Taken, 0 = otherwise), CI= Problems Index of the pineapple growers, Lown= Land owned or rented (1 = if owned, 0 = otherwise).

Marketing Channel Efficiency

The efficiency of marketing channels can be computed using several methodologies used by researchers. In this study, we have used the three most frequently used approaches, i.e., the Conventional approach (Jeyanthi, 2018; Muradi & Rahmani, 2020), Acharya and Agarwal's approach (1999), and Shepherd's Approach (1965) (Magh & Ramchandra, 2023; Muradi & Rahmani, 2020). Their mathematical expressions are as follows:

Conventional Approach:

$$\text{Marketing Efficiency (ME)} = \frac{Value\ added}{Mc}$$

Value added = (C_p – P_p), C_p = consumer's price, P_p = producer's Price, M_c = Marketing cost including a fair margin of the middleman (costs, cess, and taxes involved in the movement of products from the producers to the end consumers. It can be expressed as:

$$TMC = C_f + C_{m1} + C_{m2} + \ldots + C_{mn}$$

Where TMC = Total marketing cost of the product, C_f = the expenses incurred by the farmer from the point when the produce leaves their hands until it is sold, C_m = Marketing cost of the middlemen.

Shepherd Approach (1965)

$$:\text{Marketing Efficiency (ME)} = \frac{Cp}{Mc+M}$$

Where C_p = Consumer Price, M_c = Marketing cost, M_m = Marketing Margin

M_m = Sale price – Purchase price of i^{th} middleman.

The Shepherd measure eliminates the problem of measuring value-added by the marketing system, does not consider the net price received by the producer, and assumes that the Marketing cost (M_c) itself includes some fair margin of intermediaries, but the actual margin retained by the intermediaries is excessive.

Acharya and Agarwal's approach (1999): According to Acharya, an ideal measure of marketing efficiency should take into account the following: 1) Total marketing cost, 2) Net marketing margins, 3) Net price received by the farmers, and 4) price paid by the consumers. Acharya gives priority to the net price received by the producer. Thus,

$$\text{Marketing Efficiency (ME)} = \frac{Np}{Mc + Mm}$$

Where Np = net price received by the farmers (sale price of farmer – farmer's marketing costs), M_c = the total marketing costs, M_m = the total marketing margins.

Garret Ranking Technique: This technique has been employed to analyze the constraints faced by pineapple growers and the Intermediaries of West Bengal. The technique uses the responses of the respondents to rank different constraints based on their impact, which was then converted into a score value and ranked using the following formula:

$$\text{Percent Position} = \frac{100*(Rij - 0.5)}{Nj}$$

Here, Rij = Rank for the i^{th} item by the j^{th} respondent.
Nj = No. of items ranked by the j^{th} respondent.
The computed percent position is converted into scores using Garrett's Table (Garret & Woodworth, 1969). Then, for each factor, each respondent's scores are added, and the total and average values of scores are calculated. The factor with the highest average value is considered the most important.

III. RESULTS, FINDINGS, AND DISCUSSION

TABLE 1 provides the descriptive statistics of efficiency scores for Darjeeling (DRJ) and Uttar Dinajpur & Jalpaiguri (UD & JPG), revealing significant differences in cost, technical, and allocative efficiencies.

DESCRIPTIVE STATISTICS

In terms of cost efficiency (CE), UD & JPG exhibit slightly better performance with an average score of 0.7602 compared to DRJ's 0.7241. This implies potential cost savings of 23.98% for UD & JPG and 27.59% for DRJ. Both regions have high standard deviations in cost efficiency (0.1167 for UD & JPG and 0.1194 for DRJ), indicating variability in DRJ and more uniform cost management in UD & JPG. Direct interventions are needed in DRJ to reduce this variability.

Technical efficiency (TE), which refers to the quantity of inputs employed for labor and land usage, is close between the two regions, with UD & JPG at 0.8283 and DRJ at 0.8205. DRJ loses about 17.95% and UD & JPG lose 17.17% of their potential productivity due to inefficiency. Both regions show negative skewness (0.3292 for UD & JPG and 0.291 for DRJ), indicating that most farmers operate near full capacity but with some average lag. DRJ's slimmer skewness suggests that more farmers are at the low end of technical efficiency, indicating a need for performance upgrades.

TABLE 1: DESCRIPTIVE STATISTICS (DARJEELING AND UTTAR DINAJPUR & JALPAIGURI)

	DRJ			UD & JPG		
Particulars	**CE**	**TE**	**AE**	**CE**	**TE**	**AE**
Mean	0.724098	0.82053	0.887643	0.760188	0.828332	0.921175
Std. Error	0.008445	0.009993	0.005274	0.008251	0.009259	0.004434
Median	0.720149	0.815483	0.890198	0.762504	0.819728	0.931967
Mode	1	1	1	1	1	1

Std. Dev	0.119432	0.141325	0.074588	0.116691	0.130936	0.062701
Sample Var	0.014264	0.019973	0.005563	0.013617	0.017144	0.003931
Kurtosis	-0.0959	-0.97097	0.19406	-0.21206	-0.64507	0.911017
Skewness	0.302653	-0.29096	-0.59156	0.105754	-0.32922	-1.05989
Minimum	0.473194	0.513891	0.652911	0.478517	0.483978	0.726877
Maximum	1	1	1	1	1	1
Count	200	200	200	200	200	200

Source: Computed by the authors using MS Excel

Allocative efficiency (AE), which reflects how resources are allocated to maximize profitability, shows UD & JPG significantly outperforming DRJ. The average score for UD & JPG is 0.9212, meaning only 7.88% of resource allocation can be enhanced, compared to DRJ's score of 0.8876, indicating 11.24% inefficiency. Furthermore, UD & JPG demonstrate more consistency in allocative efficiency with a lower standard deviation of 0.0627 compared to DRJ's 0.0746. This suggests more homogeneous resource allocation practices in UD & JPG, whereas DRJ exhibits greater variability. Interventions aimed at improving resource allocation in DRJ could have a significant impact on profitability.

DISTRIBUTION OF EFFICIENCY SCORES: COMPARATIVE ANALYSIS

The efficiency scores in DRJ and UD & JPG have been compared here (TABLE 2 & TABLE 3). There is an apparent variation in terms of cost, technical, and allocative efficiency. Hence, it can be deciphered that the resource utilization and management strategies of the two regions are distinct.

As far as CE is concerned, the average distribution for UD & JPG is more uniform and higher here. In this region, around 44% of farmers fall in the 76% - 90% efficiency range, and 11% fall above 90%. When compared with DRJ, it possesses a wide range as 38% of farmers fall in the 66%-75% range, and only 9.5% fall under over 90% efficiency. This may be taken as an indication that, though cost management practices in UD & JPG are more consistent and effective, the performance of DRJ farmers is widely distributed in cost control.

In terms of TE, UD & JPG also lead the way in DRJ. For UD & JPG, as many as 44.5% lie in the 76% - 90%range, and 30.5% are above 90%, which means better input use and technical practices. For DRJ, only 32.5% have achieved higher than 90% efficiency; as many as 34.5% lie in the 76%-90% range. It also shows that at best, technical efficiency in DRJ is low-middle run, while a large number of farmers are not using their inputs as efficiently as their counterparts in UD & JPG.

TABLE 2: EFFICIENCY SCORES –DARJEELING (DRJ)

Efficiency Level	CE DEA		TE DEA		AE DEA	
	Freq.	%	Freq.	%	Freq.	%
30% - 50%	7	3.5	0	0	0	0
51% - 65%	41	20.5	21	10.5	1	0.5
66% - 75%	76	38.0	43	21.5	10	5.0
76% - 90%	57	28.5	69	34.5	108	54
Greater than 90%	19	9.5	65	32.5	81	40.5
Total	200	100	200	100	200	100

Source: Computed by the authors using MS Excel

This is the most pronounced point at which there is a divergence between the two regions in terms of allocative efficiency. Of the UD & JPG farmers, 66% are above the 90% AE level, indicating highly effective use of resources. Compared to them, only 40.5% of the farmers in DRJ reach the level, and 54% lie in the 76%-90% level. From this fact, it may be said that the farmers of DRJ are relatively good for resource allocation, but the major workers in UD & JPG are even more capable of maximizing profit generation through efficient resource use.

TABLE 3: EFFICIENCY SCORES-UTTAR DINAJPUR & JALPAIGURI (UD& JPG)

Efficiency Level	CE		TE		AE	
	Freq.	%	Freq.	%	Freq.	%
30% - 50%	7	3.5	7	3.5	0	0
51% - 65%	26	13.0	20	10.0	0	0
66% - 75%	57	28.5	23	11.5	4	2.0
76% - 90%	88	44.0	89	44.5	64	32.0
Greater than 90%	22	11.0	61	30.5	132	66.0
Total	200	100	200	100	200	100

Source: Computed by the authors using MS Excel

Hence, it can be inferred that all three efficiency measures indicate that the farmers of UD & JPG are more efficient than the farmers in DRJ. The distribution of scores indicates that the farmers have higher and more uniform levels of efficiency, but DRJ displays more variability and disparities, particularly regarding the management of cost and technical practices. Interventions that target can help fill the gap in efficiency for farmers of DRJ.

YIELD VARIATION DUE TO TECHNICAL INEFFICIENCY

The analysis of pineapple yield variations in West Bengal, specifically in the regions of Darjeeling (DRJ) and Uttar Dinajpur & Jalpaiguri (UD & JPG), offers valuable insights into the impact of TE on agricultural productivity. This examination underscores the crucial role of efficient resource utilization in maximizing crop yields, which is particularly significant in regions where agriculture is a key economic activity.

TABLE 4 presents data that shows a noticeable difference between the actual and potential yields of pineapples. These numbers highlight a significant underutilization of available resources, which could be attributed to many factors such as outdated farming techniques, inadequate access to modern agricultural inputs, or insufficient knowledge of best practices.

TABLE 4: MEAN PINEAPPLE YIELD GAP DUE TO TECHNICAL EFFICIENCY (TE) IN WEST BENGAL

Variables	DRJ	UD & JPG
Actual Yield (KGs)	21146	23482
Potential Yield (KGs)	26044	28531
Yield Gap (KGs)	4898	5049
Average Land Holding (Bigha)	4.099	4.34
Average Yield Per Bigha (KGs)	5159	5410

Source: Computed by the authors using MS Excel

The gap between actual and potential yields indicates significant potential for enhancing farming practices in these regions. Economically, the yield gap has significant implications. By improving technical efficiency and closing the yield gap, farmers in these regions could significantly increase their output, leading to higher incomes and better economic stability. In conclusion, both Darjeeling and Uttar Dinajpur & Jalpaiguri have considerable potential to increase pineapple yields by addressing technical inefficiencies. Implementing better farming practices and technologies could reduce the yield gap, resulting in more productive and profitable farming operations in these regions.

FACTORS INFLUENCING COST EFFICIENCY (CE) OF DARJEELING (DRJ) AND UTTAR DINAJPUR & JALPAIGURI (UD & JPG) (TABLE 5)

In the case of pineapple farmers in DRJ, there are several variables affecting the CE. While age is negatively correlated with efficiency, that means older farmers are likely to be less cost-efficient. It is perhaps due to resistance to new information and technology introduced, or the lower strength of the farmer. Education is positively correlated with CE, implying that educated farmers manage resources better. It further specifies the importance of the experience of the farmers regarding the farm, enhancing efficiency.

However, family size adversely impacts CE, suggesting that having large families may lead to inefficiencies in the allocation of labor. Access to external credit significantly boosts CE, as it allows farmers to invest in better inputs and technologies. Access to credit also has the highest coefficient on CE with a magnitude of 0.133. The number of seasons on the same land negatively impacts CE, likely due to soil depletion from continuous cultivation. There is a positive effect with the training/extension programs, improving efficiency through the application of better farming techniques. An enormous reduction of the CE Problems Index demonstrates the effectiveness of a higher level of challenges, thereby negatively affecting cost management.

In UD & JPG, the trends are the same but with some differences. Age negatively affects CE, while education has a positive but smaller effect. Farming experience continues to positively influence CE. Family size positively contributes to UD & JPG, presumably due to better labor division as compared with DRJ. Access to credit still remains an important positive factor, while seasons on the same land continue to negatively affect CE. Training/extension programs make a better impact than DRJ, which further highlights the necessity of skill development. Lastly, the Problems Index negativizes CE, but not as severely as in DRJ.

TABLE 5: FACTORS IMPACTING COST EFFICIENCY (CE)

	DRJ		UD & JPG	
Variable	**Coeff.**	**Probability**	**Coeff.**	**Probability**
Gen	0.046465	0.1487	-0.011073	0.6839
Age	-0.004656	0.0000***	-0.003266	0.0000***
Lsize	0.001418	0.7745	-0.003122	0.4452
Edu	0.025748	0.0000***	0.015638	0.0146**
Exp	0.024818	0.0000***	0.013230	0.0015***
FM	-0.009609	0.0125**	0.021804	0.0000***

PLP	-0.025486	0.2922	0.026371	0.3787
CT	0.038559	0.0005***	0.050351	0.0001***
SSL	-0.034713	0.0000***	-0.029664	0.0000***
Trng	0.032483	0.0035***	0.049460	0.0002***
CI	-0.279272	0.0000***	-0.063069	0.0929*
Lown	-0.001746	0.8695	-0.007107	0.6409
C	1.113073	0.0000	0.844458	0.0000
Mean dep. var		0.724098	Mean dep. var	0.760188
S.E. of regression		0.070966	S.E. of regression	0.076798
Sum sq. resid		0.936726	Sum sq. resid	1.097005
Log-likelihood		252.6413	Log-likelihood	236.6303
Avg. log-likelihood		1.263206	Avg. log-likelihood	1.183151
S.D. dep. var		0.119432	S.D. dep. var	0.116691

Note: (, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively)*

Source: Computed by authors in EViews 12SV

The two regions also have main factors, which comprise age, education, experience, and access to credit. CE is influenced by challenges and land management practices, which essentially affect efficiency in the two regions.

FACTORS IMPACTING TECHNICAL EFFICIENCY (TE) IN DARJEELING (DRJ) AND UTTAR DINAJPUR & JALPAIGURI (UD & JPG) (TABLE 6)

In DRJ, several factors have a significant impact on the TE of pineapple growers. Age has a significant negative impact, implying that younger farmers are generally more efficient, likely due to their adaptability and physical dexterity. Education is positively related to the TE, indicating that the more educated farmers make more efficient use of available resources. Farming experience also adds positively, showing how experience can help maximize the utilization of resources.

TABLE 6: FACTORS IMPACTING TECHNICAL EFFICIENCY (TE)

	DRJ		UD & JPG	
Variable	**Coeff.**	**Probability**	**Coeff.**	**Probability**
Gen	0.045523	0.2106	0.010057	0.7252
Age	-0.004818	0.0001***	-0.003775	0.0000***
Lsize	0.006219	0.1116	-0.003599	0.3885
Edu	0.025810	0.0000***	0.007421	0.3099
Exp	0.018669	0.0041***	0.022021	0.0000***
FM	-0.018269	0.0001***	0.023604	0.0001***
PLP	-0.006155	0.8451	0.028325	0.4599

CT	0.043591	0.0049***	0.055034	0.0007**
SSL	-0.030950	0.0001***	-0.022471	0.0001**
Trng	0.080177	0.0000***	0.054368	0.0009**
CI	-0.362694	0.0000***	-0.126164	0.1104
Lown	0.011334	0.4035	-0.003835	0.8413
C	1.271141	0.0000	0.898059	0.0000
Mean dep. var		0.820530	Mean dep. var	0.828332
S.E. of regression		0.091370	S.E. of regression	0.094188
Sum sq. resid		1.552803	Sum sq. resid	1.650076
Log-likelihood		201.5499	Log-likelihood	195.1419
Avg. log-likelihood		1.007749	Avg. log-likelihood	0.975710
S.D. dep. var		0.141325	S.D. dep. var	0.130936

Note: (, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively)*

Source: Computed by authors in EViews 12SV

Interestingly, family members are negatively correlated with TE. It implies that more family members might dilute the resources and hence, make farming less productive. CT is positively correlated with TE, indicating external credit has a prominent role in efficiency improvement. Continued land use is negative to TE, and it may be assigned due to soil degradation. Training is positively correlated with high value, and, therefore, technical training is important. Constraint index adversely affects TE implying that the severity of the farming-related problems significantly hamper efficiency.

Similar trends are observed in UD & JPG. Age once more proves to have a negative impact on TE, while experience in farming builds positively upon TE. Surprisingly, while family size helps positively enhance TE, it negatively impacts DRJ growers' TE. External credit positively influences TE, while continuous land use negatively affects TE. The positive influence of Training continues to reinforce the importance of constant education to keep abreast of emerging issues in farming practices.

Key drivers that affect CE and TE among the pineapple farmers of DRJ and UD & JPG are profiled. The age factor is important, where older farmers are less efficient, probably because they resist new technological change or declining physical capabilities. Encouragement to the young farming population or special support to the older farmers is required. Better education raises both CE and TE since better education enhances the competencies of farmers about better resource management and informed decisions. This brings forth the need for education programs within farming communities. Experience also positively affects efficiency, as more experienced farmers would have a better chance to optimize resources and highly contribute to both CE and TE.

The size of the family varies within regions and causes opposite effects. In DRJ, large family size often leads to the problem of labor distribution, thereby lowering CE. In UD & JPG, larger families enhance both CE & TE mainly because of better labor availability and shared responsibilities. There is the availability of external credit is one of the main reasons behind efficiency improvement, in which the investment in improved inputs and technologies will be possible for farmers. So, it calls for an improvement in credit facilities for farmers. Also, CE and TE deteriorate significantly when the land on which it occupies does not undergo rotation consistently. That means there is a high imperative need for sustainable soil management practices.

Training and extension programs further enhance efficiency, as the training and extension also highlight that the continued development of new skills and updating themselves on agricultural development are important. The problems reflected in the Problems Index negatively impact CE and TE; the worse the problems faced by farmers, the harder it becomes for them to be efficient. This speaks directly to the need to redress these issues while developing sustainable farming practices.

CHANNEL IDENTIFICATION AND EFFICIENCY OF PINEAPPLE MARKETING IN WEST BENGAL

In our study area, pineapple distribution follows six main marketing channels from growers to consumers. Of these, two channels extend beyond state borders and even internationally. For these channels, marketing efficiency was evaluated using the purchase price paid by the final middleman. For the remaining channels, efficiency was measured based on the price paid by consumers. The identified channels are as follows:

Channel I: Producer → Retailer → Consumer
Channel II: Producer → Wholesaler → Retailer → Consumer
Channel III: Producer → Trade agent → Wholesaler → Retailer → Consumer
Channel IV: Producer → Trade agent → Wholesaler → Factory (Processing)
Channel V: Producer → Trade agent → Wholesaler → Outside market→** Consumer
Channel VI: Producer → Wholesaler → Middle agent → Outside market→** Consumer

*Source: Field Survey; Note: ** represents incomplete channels*

The incomplete channels are being expanded to markets in other states, including Bihar, Jharkhand, Uttar Pradesh, Delhi, Gujarat, Punjab, and Haryana, etc. as well as to neighboring countries like Nepal, Bhutan, and Bangladesh. Within West Bengal, Kolkata, Bidhannagar, and Siliguri serve as significant markets. Among the various marketing channels identified, Channel VI, i.e., Producer → Wholesaler → Middle Agent → Outside Market → Consumer, is the most prominent. Following this is Channel II, viz. Producer → Wholesaler → Retailer → Consumer, which represents the shortest route that is prominent. In this channel, fruits are transported directly to the wholesaler's warehouse at the producer's expense. Here, fruits are categorized into ripened and non-ripened since the ripened fruits cannot be transported to far places due to their perishability. The fruits are then graded by visual inspection into three categories based on size, maturity, and colour: Grade-I (<1.0 kg), Grade-II (1.0-1.5 kg), and Grade-III (>1.5 kg), before being shipped to outside markets in truckloads. Local retail cart shop owners either sell raw fruits or juice to the direct end consumers.

TABLE 7: PINEAPPLE MARKETING CHANNEL EFFICIENCY UNDER DIFFERENT METHODS

Channel	Conventional		Shepherd's		Acharya and Agarwal's	
	DRJ	UD & JPG	DRJ	UD & JPG	DRJ	UD & JPG
Channel - I	3.17	2.62	2.08	1.79	1.32	1.14
Channel - II	2.67	2.56	1.69	1.75	0.96	1.03
Channel – III	2.8	2.54	1.47	1.43	0.84	0.82
Channel – IV	2.6	2.45	1.67	1.58	0.94	0.87
Channel –V	2.58	2.28	1.56	1.46	0.83	0.76
Channel - VI	2.58	2.38	1.53	1.5	0.81	0.75

Source: Computed by the authors

TABLE 7 demonstrates that Channel I is the most efficient of all the methods, but it lacks scale, thus not being as useful for large-scale pineapple farms. In the Conventional Approach, Channel I scored 3.17 in DRJ and 2.62 in UD & JPG, whereas Channels II and VI recorded moderate scores at 2.67 and 2.58 in DRJ, and 2.56 and 2.38 in UD & JPG, respectively. However, Channels II and VI are better suited for handling the bulk production of the region. In analyzing the pineapple marketing channels during our field study, we have found that Channels II and VI play a vital role. Nearly 75% of pineapple distribution is done using these two channels.

Shepherd's Approach shows that in all the channels, there is a great decline in efficiency. Channel II drops down to 1.69 in DRJ and to 1.75 in UD & JPG. Channel VI drops down to 1.53 and 1.50. This reflects that it is the predominant role of the marketing expense, especially due to the usurpation by intermediaries of up to 60% of profit, raising costs for the farmers.

Acharya and Agarwal's Method: Here, it paints the lowest efficiency scores by focusing on marketing cost distribution and value-added services. Channel II has fallen to 0.96 in DRJ and 1.03 in UD & JPG, while Channel VI has dipped to 0.81 and 0.75. This method only outlines the inefficiency of these channels despite the heavy involvement of intermediaries and high marketing costs.

Overall, even though Channel I is more efficient to has a higher share of the producer efficiency 63.46% (supplementary file), its low capacity will bring more feasibility to Channels II and VI for mass distribution, since they have low efficiency. Once efficiencies are removed, particularly by lowering intermediaries and streamlining logistics, profitability for these farmers relying on such channels.

IV. CONCLUSION

West Bengal holds immense promise in pineapple cultivation, yet persistent inefficiencies in both production and marketing prevent this potential from being fully realised. The comparative analysis reveals that the districts of Uttar Dinajpur and Jalpaiguri (UD & JPG) outperform Darjeeling (DRJ) in both technical and allocative efficiency. However, inefficiencies in input management and resource utilisation are evident across all districts, underscoring the need for systemic improvements. The study shows that bridging these gaps—through efficient irrigation practices, adoption of precision agriculture, and integration of advanced farming techniques—can significantly raise yields and enhance profitability.

On the marketing front, inefficiencies continue to erode farmers' earnings. Channel I, which directly links producers, retailers, and consumers, emerges as the most efficient structure in terms of farmer share, yet its capacity for large-scale distribution remains limited. In contrast, Channels II and VI, while more capable of handling larger volumes, are less efficient due to the disproportionate influence of wholesalers who capture the bulk of marketing margins. Streamlining these channels by reducing intermediary layers could markedly improve farmers' returns.

For West Bengal's pineapple belt to transition from a story of untapped potential to one of shared prosperity, the solution extends beyond increasing output—it lies in enhancing efficiency, ensuring equity, and empowering producers.

Addressing yield gaps, minimising marketing leakages, and investing in farmers' knowledge and managerial skills are essential steps. Particularly in regions like Darjeeling, the transformation requires not only better tools but also better systems—systems that integrate modern production practices with fair and transparent marketing mechanisms. With targeted interventions and coordinated policy support, West Bengal can convert its abundant harvest into sustainable economic gains, ensuring that the sweetness of its pineapples is matched by the prosperity of those who cultivate them.

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