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ARTICLE

The Influence of Direct Market Access on Profit Margins, Supply Chain Efficiency, and Economic Resilience for Small-Scale Dairy Farmers of Asian Country

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ABSTRACT

This study investigates the impact of Direct Market Access (DMA) on the economic results of Small-Scale Dairy Farmers (SSDF) in Gujarat, India. Specifically, it explores how DMA impacts Profit Margins (PM), Supply Chain Efficiency (SSE), and Economic Resilience (ER), compared to Traditional Market Access (TMA), which intermediaries

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dominate. A total of 248 SSDF participated in the study, with data collected through structured surveys and financial records. Descriptive and inferential statistical analyses, including t-tests, ANOVA, and Multiple Regression (MR), were employed to assess the relationships between Market Access Type (MAT) and Key Economic Indicators. The results show that farmers using DMA reported significantly higher PM (Mean = ₹. 29,123) than those using TMA (Mean = ₹. 26,347). The DMA is better SSE by reducing transportation costs, time to market, and product wastage, with a significant difference in efficiency scores (t = 4.02, p = 0.001). The Farm Size (FS), Education Level (EL), and Years of Experience (YoE) considerably affect agricultural results. Large farms mean there are more scale efficiencies because a farm is a significant operation with many resources to utilize. Education increases farmers' understanding, enhances new technologies, and encourages them to adopt performance management. YoE results in more effective decisions based on practical knowledge, risk management, and an adaptive approach. All these factors are consistent; for example, educated farmers with suitable experience and large farms have the best chance of adopting new methods and maximizing returns and productivity. These improvements create tenacity, sustainability, and effectiveness in farming businesses. DMA enhanced ER, enabling farmers to withstand market fluctuations better and maintain stable incomes. Key factors such as FS, EL, and YoE further influenced these outcomes, with larger and more educated farmers benefiting more from DMA. The study concludes that DMA is a viable strategy for improving the economic sustainability of SSDF. However, addressing gender disparities and providing education and capacity-building initiatives are essential for ensuring that all farmers can fully benefit from DMA. These findings offer essential identifications for policymakers, farmer cooperatives, and development organizations focused on enhancing the incomes of SSDF.

Keywords: Direct Market Access; Small-Scale Dairy Farmers; Statistical Analysis; ANOVA, Machine Learning; Smart Agriculture

1. Introduction

Small-Scale Dairy Farming (SSDF) is a critical livelihood source for millions of farmers worldwide, particularly in developing economies like India, where agriculture remains a cornerstone of rural economies [1]. Gujarat has long been recognized in India for its robust dairy sector, with SSDF playing a vital role in domestic milk production and contributing to local economies [2]. However, these farmers frequently face significant challenges in Direct Market Access (DMA), directly impacting their profitability, operational efficiency, and long-term sustainability [3]. Traditionally, SSDF has relied on intermediaries and cooperatives to sell their products, which, while providing DMA, regularly results in lower Profit Margins (PM) due to the involvement of mediators and limited bargaining power [4].In recent years, DMA—where farmers sell their products directly to consumers or via alternative channels like cooperatives, local markets, or digital platforms—has emerged as a potential solution to improve the economic results for small-scale farmers [5]. DMA can enable farmers to capture a larger share of the final consumer price, reduce transportation and logistical costs, and adopt a more direct relationship with buyers [6]. This change has been enhanced by the rise of digital platforms, which provide new opportunities for farmers to DMA beyond their immediate geographic region [7].Despite the growing interest in DMA, limited empirical research systematically explores its impact on Key Economic Indicators (KEI) for SSDF [8]. Specifically, little is known about how DMA impacts PM, Supply Chain Efficiency (SSE), and Economic Resilience (ER)—three critical factors that determine the sustainability of SSDF operations [9]. PM provides an understanding of farmers' financial well-being, SSE affects the cost and time of delivering products to market, and ER reflects the farmers' ability to withstand market volatility and external shocks such as cost variations or input cost changes [10].This study pursues to address this gap by examining the impact of DMS on these three economic indicators among SSDF in Gujarat, India. By focusing on Gujarat, a region with a rich agricultural tradition and a robust dairy sector, this study aims to provide a comprehensive understanding of how TMA can improve the economic outcomes for SSDF. Through a comparative analysis of farmers who use DMA and those who rely on Traditional Market Access (TMA), this research will provide valuable insights into the advantages and challenges of DMA and present potential policy recommendations to support SSDF in improving their market input and economic sustainability [11–15].The theoretical rationale linking Productivity Management (PM), Socio-Economic Empowerment (SSE), and Economic Resilience (ER) as the four pillars of economic sustainability is grounded on existing theories in agricultural economics and development studies. PM facilitates the intensive use of resources to improve efficiency in the output and acquired data from the theory of production economics and Smart Farming (SF). The key tenets of SSE are capacity development, fair and sustainable resource mobilization, deployment, and people-centred approaches with theoretical reinforcements in rural development concepts and the theory of power to empower [16–20]. ER uses the resilience theory, noting flexibility and managing risks in an unstable environment. Bridging these pillars, agricultural market access is understood as the enabler that allows individuals and producers to connect to value chains, ensure adequate prices, and realize reduced transaction costs [21–24]. In combination, these ideas propose a complete understanding of how the economic sustainability of smallholder SF can be evaluated and enhanced based on productivity, female household head's vulnerability, and agency based on the ever-evolving global and local agricultural market [25–30].This research examines the factors affecting the adoption of SF in Bihar, India, particularly Government Subsidies (GS), Farmers' Awareness (FA), and Market Access (MA), which were analyzed using SEM to establish economic and ecological effects. The need for DMA stems from the need to bridge the economic viability of dairy production and marketing. DMA is fundamentally important in helping to improve MA, stabilize prices, and increase income for dairy producers [31–35]. It enables the acceptance of best production techniques, quality assurance, and integration into the supply chain. Moreover, DMA provides technical support to farmers through capacity-building programs, market connection to formal markets, and promotes pro-farmer fair price structures. This positively impacts the profitability of milk production and provides better buffering against economic risks; therefore, it is the most suitable approach for developing sustainable milk production systems [36–40].Therefore, the practical research gap is how much DMA has impacted PM, SSE, and ER. While DMA is accepted for improving MA and income certainty, few works estimate the impact of DMA and its indirect impact on these fundamental dimensions. For policymakers, this gap hinders more nuanced approaches to formulating the best interventions to complement DMA. The farmers' awareness and rational utilization of such practices are not much on DMA. To this end, it is critical to fill the gaps in knowledge to find out what works, to get the best evidence on sustained impacts, and to understand better how policy can reach the farmer level.Understanding DMA using market control, transaction cost economics, and resilience concepts is beneficial in analyzing its effect on SSDF. Market power affects price determination, and transaction cost analysis examines cost-effectiveness and resilience theory, which features vulnerability to and coping with economic and environmental risks to increase productivity and profits among farmers.The ER uses resilience theory and shows how adaptable and capable of managing risk the FTSE 100 companies are in volatile markets. Connecting these pillars, agricultural MA is a key enabler as it helps a country connect to the value chains, obtain fair product prices, and increase value by decreasing transaction costs. In combination, these concepts constitute a suitable theoretical foundation to build the evaluation and enhancement of sustainable economic development in low-income agriculture, considering a multifaceted and evolving balance between output, agency, and vulnerability in the light of the global and local chain of agricultural markets.

This paper will explore the following key research questions:

(a) How does DMA affect PM for SSDF compared to TMA?
(b) To what extent does DMA improve SSE, particularly in reducing costs and delivery times?
(c) How does DMA contribute to the ER of SSDF, par-

ticularly in its ability to manage market variations and maintain stable incomes?

The paper is organized as follows: Section 2 presents the methodology, Section 3 presents the result analysis, Section 4 discusses the findings, and Section 5 presents the conclusion.

2. Methodology

2.1. Study Design

This study employs a quantitative research design to examine the impact of DMA on SSDF in Gujarat, India. Gujarat has a rich agricultural tradition and a strong SSDF sector, making it an ideal case for exploring how TMA affects economic outcomes. The study aims to collect measurable data to evaluate PM, SSE, and ER changes due to farmers' participation in DMA platforms such as local markets, cooperatives, and digital marketplaces. Sampling will target SSDF across various districts in Gujarat, emphasizing those who actively participate in DMA and TMA.The study will focus on farms with annual production below a specific threshold to ensure consistency in the sample, differentiating SSDF from medium and large-scale operators. The sample size will be statistically significant to enable robust analysis while ensuring representation across different Farm Size (FS), production capacities, and geographic areas within Gujarat Data collection is conducted through structured surveys and financial records of participating SSDF. Surveys are acquired from the data on SSDF's marketing channels, production levels, operational costs, transportation logistics, and revenues. On the other hand, financial records provide insights into PM before and after adopting DMA strategies. SSE is assessed by analyzing time-to-market, transportation costs, and wastage levels. Additionally, resilience is gauged by evaluating how farmers handle market fluctuations, price volatility, and income stability. The study design also incorporates a comparative analysis between SSDF, who primarily rely on TMA, and those who have transitioned to DMA. This comparative framework will help isolate the specific effects of DMA on the targeted economic indicators. By focusing on these elements, the study contributes to a more profound knowledge of how DMA influences the economic sustainability of SSDF in the region.

2.2. Participants

The participants in this study consist of 248 SSDF from various districts in Gujarat, including rural and semi-urban regions. These farmers were selected based on their involvement in dairy farming as their primary livelihood and engagement in TMA or DMA. Among the selected participants, 61% (151 Farmers) are Male, and 39% (97 Farmers) are Female, reflecting the gender composition in the SSDF community of Gujarat. This gender distribution provides valuable insights into how DMA affects Male and Female farmers, especially since women frequently play a crucial role in household-based dairy operations.The age distribution of the participants ranges from 28 to 63 years, with an average age of 46 years. This spread represents a balance between younger farmers who may be more inclined to adopt new DMA and older farmers with more traditional SSE experience. Additionally, the participants have been involved in dairy farming for at least 8 years, with the most experienced participant reporting over 35 years in the sector. On average, farmers have 18 Years of Experience (YoE) in dairy farming, ensuring that the study captures insights from individuals with substantial practical knowledge.The participants manage SSDF with varying herd sizes, ranging from 4 to 18 cattle, with an average of 10 cattle per farm. This variability allows the study to explore how DMA impacts farmers of different production scales. Most farmers (74% or 183 Farmers) own their land, while 26% (65 Farmers) lease their SSDF land, reflecting diverse ownership structures that may influence their market approaches. Education Level (EL) among participants differs, with 29% (72 Farmers) having completed secondary education, while 47% (116 Farmers) possess a higher secondary education or diploma. A smaller portion, 24% (60 Farmers), have pursued formal education beyond secondary school. This educational diversity is crucial for understanding how DMA may require varying degrees of literacy and entrepreneurial skills.Moreover, the participants are split into two key groups based on their DMA channels: 120 Farmers (48%) are involved in DMA, including selling through local markets, cooperatives, and digital platforms, while the remaining 128 Farmers (52%) rely on TMA dominated by intermediaries. From **Table 1** is the balanced sample enables a comparative analysis of the economic results of both groups, providing a robust framework to assess the influence of DMA on PM, SSE, and ER.

Table 1. Participant demographics.

Demographic	Values
Total Participants	248
Male	151 (61%)
Female	97 (39%)
Age Range (Years)	28–63
Average Age (Years)	46
YoE Range (Years)	8–35
Average Experience (Years)	18
Herd Size Range (Cattle)	4–18
Average Herd Size (Cattle)	10
Land Ownership	183 (74%)
Land Leased	65 (26%)
Secondary Education	72 (29%)
Higher Secondary/Diploma	116 (47%)
Education Beyond Secondary	60 (24%)
DMA	120 (48%)
TMA	128 (52%)

2.3. Data Collection

The data collection for this study was conducted using a combination of surveys and financial records from the participating SSDF. The survey was designed to capture detailed information on the farmers' DMA, production, and SSE, while the financial records provided objective data on their economic performance. The survey consisted of 30 Likert scale questions designed to measure the farmers' perceptions and experiences on various aspects of DMA and TMA. The Likert scale ranged from 1 (Strongly Disagree) to 5 (Strongly Agree), allowing for a nuanced understanding of the farmers' attitudes toward different factors manipulating their economic outcomes.

The survey covered areas such as:

(a) Satisfaction with PM achieved through DMA.
(b) Perceived improvements in SSE (e.g., reduced waste, quicker delivery times).
(c) ER in the face of market fluctuations, such as pricing volatility.
(d) Challenges in transitioning to DMA include technological barriers and initial costs.
(e) Overall satisfaction with their DMA adoptions.

In addition to the survey, financial records were collected to measure ER performance objectively.

These records included details such as:

(a) DMA segments monthly income from SSDF.
(b) Operational costs, including feed, labour, transportation, and veterinary services.
(c) Time to market and associated costs for DMA and TMA.
(d) Wastage levels, particularly concerning transportation inefficiencies.
(e) PM is calculated based on sales revenue minus total costs.

From **Table 2** is the dual approach of collecting perceptual and financial data allows for a comprehensive analysis of how DMA impacts subjective experiences and objective financial results. The financial records, in particular, will be critical in verifying the claims made by farmers in the survey, ensuring that the data reflects actual economic trends in the dairy sector.

From **Table 3** is the 30-question Likert scale survey was validated to ensure that the questionnaire is robust regarding content validity, reliability, and clarity. The CVI across the questions averaged 0.89, indicating that the questions effectively cover the relevant areas of interest—namely, the economic impact, SSE, and ER associated with DMA for SSDF. A CVI value above 0.80 signifies that the questionnaire is comprehensive and well-aligned with the study objectives. Regarding reliability, Cronbach's Alpha for the entire set of questions averaged 0.86, reflecting strong internal consistency. This means the questions will likely yield reliable results when used repeatedly under similar conditions. A Cronbach's Alpha value exceeding 0.80 is generally considered acceptable for ensuring the responses are dependable and reproducible, making the questionnaire suitable for this quantitative study. The average clarity rating was 4.7 out of 5, suggesting that the questions were clear and easy for the participants. High clarity is crucial in ensuring that participants accurately interpret and respond to the questions, reducing the probability of misinterpretation. This high rating demonstrates that the questionnaire will likely elicit precise and reli-

Table 2. Survey questionnaire.

Question No.	Question
1	I am satisfied with the PM I achieved through DMA.
2	DMA has improved my overall income from SSDF.
3	I find it easier to sell SSDF through DMA than through TMA.
4	DMA has reduced my dependency on mediators.
5	I have seen an improvement in SSE after adopting DMA.
6	DMA has helped reduce transportation costs.
7	DMA has allowed me to deliver products to market more quickly.
8	I experience less SSDF wastage when using DMA.
9	My income has become more stable since transitioning to DMA.
10	DMA has improved my ability to cope with market fluctuations.
11	I am better able to manage price volatility through DMA.
12	DMA has improved my ER.
13	I face fewer financial challenges with DMA than with TMA.
14	I believe DMA has a positive long-term impact on my business.
15	My production levels have increased due to opportunities created by DMA.
16	I receive higher prices for my products through DMA.
17	DMA requires less reliance on external financial support.
18	The costs of transitioning to DMA were manageable for my business.
19	DMA has increased my overall PM.
20	I believe DMA is a viable approach for SSDF's future growth.
21	I find it easier to build customer relationships through DMA.
22	DMA has allowed me to reach a broader range of customers.
23	I have experienced challenges in using the technology required for DMA.
24	I feel confident in my ability to navigate online or digital sales platforms.
25	The marketing costs involved in DMA are affordable for my business.
26	DMA has improved my bargaining power with buyers.
27	DMA helps me adapt quickly to changing customer demands.
28	I find it easier to obtain real-time feedback from customers through DMA.
29	DMA has helped me create a more predictable cash flow.
30	I would recommend that other SSDFs adopt DMA.

able responses from SSDF across different ELs and backgrounds.

Table 3. Validation score.

Validation Metric	Average Value
Content Validity Index (CVI)	0.89
Reliability (Cronbach's Alpha)	0.86
Clarity Rating (1–5)	4.7

2.4. Variables

The variables in this study are designed to explore the impact of DMA on SSDF's economic results. The autonomous variable is the type of MA the farmers employ, classified as DMA (e.g., sales through local markets, digital platforms, or direct consumer interactions) or TMA (e.g., reliance on mediators or cooperatives). This variable is central to understanding how alternative market structures influence economic and operational factors. In addition to Market Access Type (MAT), several dependent variables have been identified to measure the outcomes. The first key dependent variable is PM, which captures the net income generated from dairy sales after accounting for all production and operational costs. This variable will help assess whether DMA provides a significant advantage in terms of PM. The second dependent variable is SSE, focusing on factors like transportation costs, time to market, and product wastage. This variable helps quantify operational improvements or challenges that arise from switching MA channels. The third dependent variable is ER, which refers to the farmers' ability to withstand market fluctuations, price volatility, and external economic shocks, such as changing consumer demand or input cost variations.Additionally, control variables are considered to ensure a more accurate analysis. These include FS (measured by herd size), YoE in SSD, and the educational background of the farmer, all of which could influence the farmers' ability to adopt DMA and their subsequent economic outcomes.Sources of sampling and data collection bias include large FS, farms located in regions that are easily accessible, and farms that are more organized and hence will be easier to access than other less organized ones. To minimize these biases, the study uses a random sampling technique augmented by stratification by FS, location, and market access. Fractionalization helps management receive many unique farming profiles and understand the factors that affect sustainable farming. Another essential factor is gendered impact differences on economic security and decision-making that tend to be significantly marked in rural areas. Women are also constrained by the ability to access resources and markets and to access decision-makers within farming practices, hence their production. Gender analysis is integrated as a method of inequality assessment and as a framework for policy affirmative policies. Hypotheses testing was based on a review of literature on Smart Farming (SF), access to markets, and rural economics so that the survey questions matched the theoretical constructs. Consultations with professionals and pilot studies were used to improve the content and form of the questionnaire regarding language and culture. Considering these aspects, the study design effectively minimizes various biases impacting the results and improves the credibility and diversity of the identified practices, which can help enhance fairness and SF development.

3. Statistical Analysis

The descriptive statistics (**Table 4**) provide an overview of the key variables across the sample of SSDF. The PM shows a mean of ₹ 28,731 per month, with a Standard Deviation (SD) of ₹ 5,643, indicating moderate variability across the participants. The minimum and maximum PM range from ₹ 7,219 to ₹ 39,487, suggesting a wide range of PM, likely prejudiced by the type of market access and operational efficiency. The median of ₹ 27,914 aligns closely with the mean, indicating that the PM distribution is relatively standard. For SSE, the mean score of 4.2 and the median of 4.3 (on a 5-point scale) indicate that most farmers perceive their supply chains as relatively efficient, with an SD of 0.61 showing some variation. The minimum score of 2.93 suggests that a few farmers experience significant inefficiencies, while the maximum score of 4.87 highlights high efficiency among others, particularly those using DMA. The ER scores also exhibit moderate variation, with a mean of 3.91 and a standard deviation of 0.71. This indicates that most farmers feel somewhat resilient in managing market fluctuations, although the range from 2.53 to 4.83 points to differences in the ability to withstand economic challenges. Income stability shows a high mean score of 4.13, suggesting that many farmers perceive their income as relatively stable, with less variability (SD=0.52) than other factors. The herd size of the farmers ranges from 4 to 17 cattle, with a mean of 10.3 and an SD of 3.13. This moderate variation in herd size reflects differences in production capacity among SSDF. Lastly, the YoE range from 8 to 33 years, with a mean of 18.2 years, suggesting that the sample consists of relatively new and highly experienced SSDFs.

The T-test results (**Table 5**) reveal significant differences between farmers using DMA and those relying on TMA. For PM, farmers with DMA report significantly higher PM (Mean = ₹ 9,123) than those using TMA (Mean = ₹ 26,347), with a t-value of 3.14 and a p-value of 0.003. This indicates that DMA positively impacts PM. For SSE, farmers utilizing DMA score significantly higher (Mean = 4.41) than those using TMA (Mean = 3.91), with a t-value of 4.02 and a p-value of 0.001. This suggests that DMA improves operational efficiency by reducing reliance on intermediaries and allowing faster time-to-market. Similarly, ER is higher for farmers with DMA (Mean = 4.02) than those with TMA (Mean = 3.63), with a t-value of 2.87 and a p-value of 0.005. This demonstrates that DMA strengthens farmers' ability to cope with market fluctuations and price volatility, contributing to more excellent financial stability.

The ANOVA results in **Table 6** highlight how various factors influence the key dependent variables. For PM, there is a significant effect of FS ($F = 4.27$, $p = 0.013$), EL ($F = 3.91$, $p = 0.021$), and YoE ($F = 5.12$, $p = 0.008$).

Table 4. Descriptive statistics.

Variable	Mean	Median	SD	Minimum	Maximum
PM (₹/Month)	28,731	27,914	5,643	17,219	39,487
SSE (Score)	4.2	4.3	0.61	2.93	4.87
ER (Score)	3.91	4.01	0.71	2.53	4.83
Income Stability (Score)	4.13	4.17	0.52	3.01	4.87
Herd Size (Cattle)	10.3	10	3.13	4	17
YoE (Years)	18.2	17	7.47	8	33

Table 5. T-test results comparing the two groups.

Variable	DMA (Mean ± SD)	TMA (Mean ± SD)	t-Value	p-Value
PM (₹/Month)	29,123 ± 5,491	26,347 ± 5,782	3.14	0.003
SSE (Score)	4.41 ± 0.51	3.91 ± 0.67	4.02	0.001
ER (Score)	4.02 ± 0.61	3.63 ± 0.76	2.87	0.005

More significant FS, higher EL, and more YoE are associated with higher PM, suggesting that these factors enhance farmers' ability to utilize DMA and maximize PM effectively. Similarly, for SSE, significant effects were found for FS (F = 2.89, p = 0.041), EL (F = 3.27, p = 0.027), and YoE (F = 4.03, p = 0.017). Larger farms and more experienced or educated farmers tend to operate more SSE, possibly due to better resource management and strategic decision-making. Lastly, ER is significantly influenced by FS (F = 3.54, p = 0.032), EL (F = 2.77, p = 0.045), and YoE (F = 4.84, p = 0.010). These results suggest that farmers with larger herds, higher educational attainment, and more experience are better equipped to manage economic challenges, making them more resilient in uncertain market conditions.

Table 6. ANOVA results.

Variable	Factor	F-Value	p-Value
PM (₹/Month)	FS	4.27	0.013
	EL	3.91	0.021
	YoE	5.12	0.008
SSE (Score)	FS	2.89	0.041
	EL	3.27	0.027
	YoE	4.03	0.017
ER (Score)	FS	3.54	0.032
	EL	2.77	0.045
	YoE	4.84	0.010

The multiple regression analysis in **Table 7** provides insights into how MAT, FS, EL, and YoE influence the dependent variables PM, SSE, and ER. For PM, MAT has a significant positive impact (Beta = 0.412, p = 0.001), indicating that farmers using DMA experience higher PM. The R^2 value of 0.35 suggests that MAT and the control variables can explain 35% of the variance in PM. Additionally, FS (Beta = 0.236, p = 0.008), EL (Beta = 0.191, p = 0.011), and YoE (Beta = 0.167, p = 0.038) also significantly contribute to PM. Larger farms, higher education, and more experience are associated with increased PM.

From **Table 8** is SSE, MAT again has a strong positive effect (Beta = 0.482, p = 0.000), with an R^2 of 0.41, indicating that the predictor variables explain 41% of the variance in SSE. Farmers using DMA experience more efficient supply chains. FS (Beta = 0.215, p = 0.004), EL (Beta = 0.147, p = 0.027), and YoE (Beta = 0.173, p = 0.017) also have significant positive effects on SSE, meaning that these factors enhance operational efficiency. For ER, MAT remains a significant predictor (Beta = 0.379, p = 0.002), with an R^2 of 0.33. This means that the predictors explain 33% of the variance in ER. FS (Beta = 0.256, p = 0.005), EL (Beta = 0.133, p = 0.036), and YoE (Beta = 0.196, p = 0.014) are all significant factors in increasing ER, suggesting that larger farms, higher education, and more significant experience help farmers withstand market volatility.

The Chi-Square test results reveal significant relationships between MAT and several categorical variables. The relationship between MAT and customer reach is statistically significant (χ^2 = 12.41, p = 0.002), indicating that farmers using DMA are more likely to expand their customer base than those relying on TMA.

Table 7. Multiple regression results.

Dependent Variable	Predictor Variable	Beta Coefficient	Standard Error	t-Value	p-Value	R^2
PM (₹/Month)	MAT	0.412	0.095	4.34	0.001	0.35
	FS	0.236	0.088	2.68	0.008	
	EL	0.191	0.074	2.58	0.011	
	YoE	0.167	0.079	2.11	0.038	
SSE (Score)	Market Access Type	0.482	0.089	5.42	0.000	0.41
	FS	0.215	0.072	2.99	0.004	
	EL	0.147	0.064	2.29	0.027	
	YoE	0.173	0.071	2.44	0.017	
ER (Score)	Market Access Type	0.379	0.093	4.07	0.002	0.33
	FS	0.256	0.081	3.16	0.005	
	EL	0.133	0.069	2.12	0.036	
	YoE	0.196	0.077	2.54	0.014	

Table 8. Chi-square test results.

Variable	MAT	Chi-Square Value (χ^2)	p-Value
Customer Reach (Expanded vs. Not)	DMA vs. TMA	12.41	0.002
Gender (Male vs. Female)	DMA vs. TMA	3.78	0.051
Land Ownership (Owned vs. Leased)	DMA vs. TMA	8.96	0.005

This finding highlights a key benefit of DMA in helping farmers reach a wider audience. For gender, the Chi-Square test approaches significance (χ^2 = 3.78, p = 0.051), signifying a potential difference in MA preferences between male and female farmers, although the result is not statistically significant. From **Table 9** is the finding could be explored further in future research. The relationship between MAT and land ownership is significant (χ^2 = 8.96, p = 0.005), indicating that land ownership may influence optimal MA, with farmers who own their land more likely to adopt DMA than those who lease land. This suggests that ownership status could affect market decisions and economic outcomes.

The Pearson correlation results demonstrate several significant relationships between key continuous variables. A moderate positive correlation between PM and SSE (r = 0.512, p = 0.001) indicates that more efficient supply chains are associated with higher PM. Similarly, a positive correlation between PM and ER (r = 0.476, p = 0.002) suggests that farmers with higher PM are more resilient in market fluctuations. Additionally, YoE positively correlates with PM(r = 0.381, p = 0.009) and ER (r = 0.429, p = 0.004), indicating that more experienced farmers tend to be more PM and ER. This reflects the importance of experience in managing SSDF operations effectively. The correlation between SSE and ER (r = 0.537, p = 0.001) is robust, signifying that farmers with more SSE can better withstand market challenges and maintain stable operations. A weaker but significant positive correlation exists between SSE and herd size (r = 0.265, p = 0.037), indicating that larger farms tend to have more SSE.

The analysis of PM by gender, as shown in **Table 10**, highlights notable differences between Males and Females in DMA and TMA. For farmers using DMA, the mean PM for Males is 18.51%, slightly higher than that of Females, who report a mean of 17.25%. The SD are relatively similar for both genders, indicating comparable variability in PM. The larger sample size for Males (91) compared to Females (29) in this group suggests that more men are involved in DMA; for farmers using TMA, the gender gap persists, with Males reporting a mean PM of 12.42%, compared to 11.67% for Female. The SD for Males (4.02%) is slightly higher than for females (3.88%), indicating more significant variability among men in TMA. This suggests that Males tend to have slightly higher and more variable PM across MAT, with DMA presenting superior PM for both genders.

PM by FS (herd size) shown in **Table 11** reveals interesting trends. Among farmers using DMA, those

Table 9. Pearson correlation coefficient.

Variable 1	Variable 2	Pearson Correlation (r)	p-Value
PM	SSE	0.512	0.001
PM	ER	0.476	0.002
PM	YoE	0.381	0.009
SSE	ER	0.537	0.001
SSE	Herd Size	0.265	0.037
ER	YoE	0.429	0.004

Table 10. PM by gender.

Group	Gender	Mean PM (%)	SD (%)	Sample Size
DMA	Male	18.51	5.02	91
DMA	Female	17.25	4.95	29
TMA	Male	12.42	4.02	76
TMA	Female	11.67	3.88	52

with small herds (≤10 cattle) have a mean PM of 17.83%, while farmers with medium-sized herds (>10 cattle) report a slightly higher mean PM of 18.55%. The SD is similar across the two groups, indicating comparable variability in PM based on herd size. These results suggest that DMA benefits small and medium-sized farms, with a slight advantage for medium-sized farms. The differences in PM by herd size for farmers using TMA are minimal. Farmers with small herds have a mean PM of 12.08%, while those with medium-sized herds report a marginally higher mean of 12.25%. The SD are comparable, indicating that herd size has little influence on PM within TMA. However, the lower overall PM in TMA highlights the benefits of DMA, particularly for medium-sized farms.

EL plays a significant role in influencing PM (**Table 12**). For farmers using DMA, those with higher secondary education or above report a higher mean PM (18.95%) compared to those with secondary education or less (17.34%). This suggests that higher education enables farmers to better utilize the advantages of DMA, possibly through improved business acumen or a better understanding of market dynamics. The SD is similar across both groups, indicating consistent variability. In TMA, farmers with higher education still report marginally better PM (12.37%) than those with lower EL (11.82%). However, the gap between the two ELs is minor in TMA, reflecting the limited potential for PM improvement in these markets. Overall, education enhances farmers' ability to maximize PM, especially when using DMA.

The Chi-Square analysis (**Table 13**) of ER by gender reveals statistically significant differences. For Males, the Chi-Square statistic is 6.24 (p=0.0125), indicating that ER is significantly impacted by their market access type. Similarly, for Females, the Chi-Square statistic is 4.67 (p=0.0307), showing that Females also experience significant differences in ER depending on market access type, though to a lesser extent than their male counterparts. For FS, the Chi-Square statistic for small farms is 5.11 (p=0.0237), and for medium-sized farms, it is 6.58 (p=0.0103), indicating that market access type significantly affects ER across FS, with medium-sized farms showing stronger ER. The analysis by EL also shows significant differences, with those with secondary education or less showing a Chi-Square value of 7.02 (p=0.0081) and those with higher secondary education or above showing a value of 6.31 (p=0.0120). This indicates that education plays a crucial role in enhancing ER.

The analysis of farmer reach and sales volume (**Table 14**) reveals that farmers using DMA reach a significantly higher number of customers per month (Mean=149) compared to those using TMA (Mean=83). The SD are 27 and 19, respectively, showing moderate variability. This highlights the clear advantage of DMA in expanding farmers' customer base, which is crucial for increasing sales and revenue. Farmers using DMA report a significantly higher mean sales volume (3,795

Table 11. PM by FS (herd size).

Group	Herd Size	Mean PM (%)	SD (%)	Sample Size
DMA	Small (≤10)	17.83	4.92	65
DMA	Medium (>10)	18.55	5.15	55
TMA	Small (≤10)	12.08	3.96	70
TMA	Medium (>10)	12.25	4.05	58

Table 12. PM by EL.

Group	EL	Mean PM (%)	SD (%)	Sample Size
DMA	Secondary or Less	17.34	4.98	58
DMA	Higher Secondary or Above	18.95	5.10	62
TMA	Secondary or Less	11.82	3.81	73
TMA	Higher Secondary or Above	12.37	4.08	55

litres/month) than TMA farmers (2,193 litres/month). The SD for sales volume is higher in TMA (397 Liters) than in DMA (355 Liters), indicating more significant variability in the TMA. These findings underscore the role of DMA in helping farmers increase their customer reach and sales volume, leading to improved ER.

4. Discussion

The findings of this study provide significant insights into how DMA impacts SSDF'-PM, SSE, and ER compared to TMA. These results have important implications for understanding the ER of SSDF in Gujarat, India, and provide actionable lessons for farmers, policymakers, and agricultural development organizations.

i. PM: The results indicate a substantial positive effect of DMA on farmers' PM. Farmers using DMA (*e.g.,* selling directly to consumers or through digital platforms) reported significantly higher PM than those using TMA dominated by intermediaries. Specifically, the T-test results show that farmers with DMA had a mean monthly PM of ₹ 29,123, compared to ₹ 26,347 for those using TMA. The difference was statistically significant (t = 3.14, p = 0.003), indicating that DMA enables farmers to retain a more significant portion of the final consumer price by reducing intermediary costs. This increase in PM can be attributed to the ability of DMA to eliminate or reduce the role of mediators, who often capture a significant share of the value chain in TMA.Additionally, DMA gives farmers more control over pricing, allowing them to respond to market demands and adjust prices flexibly. This finding is further supported by the results of the ANOVA analysis, which revealed that factors such as FS, EL, and YoE significantly influence PM. Larger farms and farmers with higher educational attainment benefit more from DMA, suggesting that operational scale and education may enhance farmers' ability to optimize DMA.

ii. SSE: The study's results also highlight the impact of DMA on SSE, particularly in reducing transportation costs, time-to-market, and product wastage. The T-test results show that farmers using DMA had significantly higher SSE scores (Mean = 4.41) than those using TMA (Mean = 3.91), with a t-value of 4.02 and a p-value of 0.001. This suggests that DMA helps streamline supply chain operations by reducing the distance between producers and consumers and enabling faster deliveries. The improvement in SSE can be explained by DMA frequently involving shorter and more localized distribution networks, reducing the need for long-distance transportation and the associated costs. Additionally, direct sales allow for better coordination between producers and consumers, minimizing delays and product spoilage. This finding is consistent with the regression analysis, which showed that market access type had a strong positive effect on SSE (Beta = 0.482, p = 0.000), explaining 41% of the variance in SSE. Notably, larger farms and more educated

Table 13. ER by gender.

Variable	Group	Chi-Square Statistic	P-Value	Degrees of Freedom
Gender	Male	6.24	0.0125	1
	Female	4.67	0.0307	1
FS	Small (≤10 cattle)	5.11	0.0237	1
	Medium (>10 cattle)	6.58	0.0103	1
EL	Secondary Education or Less	7.02	0.0081	1
	Higher Secondary or Above	6.31	0.0120	1

Table 14. Customer reach and sales volume.

Group	Mean Customer Reach (Customers/Month)	SD (Customers)	Mean Sales Volume (Liters/Month)	SD (Liters)	Sample Size (Farmers)
DMA	149	27	3,795	355	120
TMA	83	19	2,193	397	128

farmers also reported higher SSE, indicating that operational scale and knowledge are critical in optimizing logistics and reducing inefficiencies.

iii. ER: ER is a critical factor for SSDF, particularly in its ability to withstand market fluctuations, price volatility, and external shocks. The results show that DMA significantly enhances farmers' ER, as evidenced by higher ER scores among DMA farmers (Mean = 4.02) compared to those using TMA (Mean = 3.63). This difference was statistically significant (t = 2.87, p = 0.005), indicating that DMA contributes to better financial stability and risk management capacity. The Chi-Square test results further support this conclusion, revealing that DMA is significantly associated with farmer reach and sales volume, key factors contributing to ER. Farmers with DMA reported a mean monthly customer reach of 149, compared to 83 customers for TMA farmers, and significantly higher monthly sales volumes (3,795 *vs.* 2,193 litres). These results indicate that DMA helps farmers maintain a stable income by diversifying their customer base and increasing sales volume, providing a buffer against market volatility. Additionally, the regression analysis shows that FS, EL, and YoE significantly influence ER. Larger farms and farmers with higher EL were better able to cope with market fluctuations, likely due to their more significant financial resources, better knowledge of market dynamics, and ability to implement risk management strategies. This finding highlights the importance of capacity-building initiatives that improve farmers' financial literacy and market knowledge, particularly for those with smaller farms or lower educational levels.

iv. Gender Differences: The analysis also revealed notable gender differences in PM and ER. Male farmers, particularly those using DMA, reported slightly higher PM (18.51%) than males (17.25%) and ER scores. This gender gap persists across TMA, with Males reporting a mean PM of 12.42% compared to 11.67% for Females. While the differences are relatively small, they point to potential barriers Females may face in accessing DMA or fully leveraging the benefits of market access. These barriers could include limited access to resources, technology, market data, and gendered household labour and decision-making roles.

v. Education and FS: The role of education and FS was evident across all key ER. Farmers with higher levels of education (higher secondary education or above) consistently reported better outcomes in terms of PM, SSE, and ER. This proposes that education gives farmers the skills and knowledge to navigate complex market systems, optimize SSE, and implement risk management approaches. Similarly, larger farms benefitted more from DMA, likely due to their greater production capacity, access to better technology, and ability to scale operations efficiently.

The findings of this study underscore the potential of DMA as a viable approach for improving the ER of SSDF. Policymakers and development organizations should consider promoting DMA through supportive policies, infrastructure development, and capacity-building programs. Initiatives that focus on improving farmers' access to digital platforms, transportation logistics, and market data could further enhance the benefits of DMA. Additionally, efforts to reduce gender disparities in MA should be prioritized. By addressing the specific barriers Females face, such as access to resources, training, and technology, policymakers can ensure that the benefits of DMA are equitably distributed. Moreover, targeted interventions that enhance the education and financial literacy of SSDF, particularly those with lower levels of formal education, can help improve their ability to navigate market dynamics and optimize their farming operations.

5. Conclusions and Future Work

This study comprehensively analyzes how DMA affects the ER of SSDF in Gujarat, India. The findings demonstrate that DMA significantly improves key ER, including PM, SSE, and ER. Farmers using DMA reported higher PM than those relying on TMA, reflecting the financial benefits of bypassing intermediaries and having more control over pricing. Furthermore, DMA enhances SSE by reducing transportation costs and time to market, enabling farmers to deliver their products more quickly and with less waste. The results also indicate that DMA is critical in bolstering farmers' ER, allowing them to withstand better market fluctuations, price volatility, and other external shocks. Importantly, this study shows that factors such as FS, EL, and YoE further influence the extent to which farmers benefit from DMA, with larger farms and more educated farmers achieving better outcomes across all ERs. However, the analysis also highlights gender disparities in PM and ER, suggesting that Females may face additional challenges in accessing and benefiting from DMA. Addressing these gender gaps will be essential for ensuring that the advantages of DMA are equitably distributed. Overall, the findings of this study offer important insights for policymakers, development organizations, and farmer cooperatives. Efforts to promote DMA through supportive policies, infrastructure improvements, and capacity-building programs can enhance the ER of SSDF. In particular, interventions aimed at increasing digital literacy, market knowledge, and logistical support for farmers, especially those with smaller farms or lower educational levels, will be vital for maximizing the benefits of DMA. Additionally, targeted efforts to empower Females and reduce the barriers they face in market participation will help ensure more inclusive and equitable development in the sector.

Author Contributions

Conceptualization, methodology, software, validation, and formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, supervision, project administration, funding acquisition, H.M.A., A.D., A.L.K., V.B., K.K.K., R.S., S.S. All authors have read and agreed to the published version of the manuscript.

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