Optimizing Fertilizer Dealer Performance through a Transaction-Based Dealer Performance Index and Market Segmentation Evidence from FACT Dealers in Tamil Nadu, India

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ABSTRACT

Fertilizer dealers are a critical last-mile link between manufacturers and farmers, yet dealer evaluation often relies on sales turnover alone and therefore overlooks differences in transaction intensity, product breadth and continuity of market activity. The purpose of this study is to optimize fertilizer dealer performance by developing a transaction-based Dealer Performance Index (DPI) and identifying statistically distinct dealer segments among Fertilisers and Chemicals Travancore Limited (FACT) dealers in Tamil Nadu, India. FACT transaction records for 2019–2024 were reviewed, while the empirical segmentation uses the verified 2024 active frame. The 2024 database contains 9,129 transactions, 874 active dealers across 38 districts and 113,715.30 metric tonnes of fertilizer sales. A proportionate district-by-dealer-type sample of 274 dealers was drawn, comprising 165 retailers and 109 wholesalers. Dealer-level indicators were total quantity, transaction frequency, product breadth and active months; the DPI combined min–max normalized indicators with equal weights, and K-means solutions from two to six clusters were compared using silhouette, Calinski–Harabasz and Davies–Bouldin criteria. A two-cluster solution provided the clearest parsimonious structure. The lower-activity segment contained 122 dealers with a mean DPI of 16.96, whereas the higher-activity segment contained 152 dealers with a mean DPI of 47.92. DPI differed strongly across clusters ($F = 417.24$, $p < .001$, $\eta^2 = .605$). Wholesalers also recorded a higher mean DPI than retailers (41.97 versus 28.96; Welch $t = 5.33$, $p < .001$). The findings show that transaction-based segmentation provides a more actionable basis for differentiated dealer development, service support and distribution planning than undifferentiated sales ranking.

Keywords: fertilizer; dealers; segmentation; performance; distribution; agribusiness; clustering; Tamil Nadu

JEL Classification: Q13; M31; C38

INTRODUCTION

Fertilizer distribution is a time-sensitive component of agricultural production because demand is tied to crop calendars, rainfall, irrigation, soil conditions and farmers' purchasing capacity. A product that reaches a market after the relevant application window has sharply reduced utility even if the physical supply is eventually adequate. The performance of the distribution channel therefore depends not only on production and logistics but also on the ability of local dealers to maintain availability, process transactions, carry an appropriate product range and remain active across the agricultural season.

Dealers are the operational interface between fertilizer manufacturers and farmers. They aggregate local demand, hold stock, execute sales, communicate product information, provide informal advisory support and transmit market intelligence upstream. Their role is particularly important in fragmented rural markets, where the quality of the dealer network influences both commercial outcomes and farmer access to inputs. Research on agri-input

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dealers accordingly describes them as commercial intermediaries as well as relationship and advisory actors (Elakkiya & Asokhan, 2021; Panja et al., 2022; Mathuabirami et al., 2025; Saklani et al., 2026).

The scientific problem addressed in this study is that dealer performance is heterogeneous but is frequently represented by a single sales measure. Sales volume is important, yet it can conceal whether sales are generated through frequent transactions, a broader product portfolio, sustained monthly activity or a small number of unusually large orders. It also does not indicate whether apparently similar dealers require the same managerial response. This creates a measurement problem and a segmentation problem: firms need a defensible way to compare overall dealer activity while simultaneously identifying distinct patterns of dealer performance.

This issue is salient for fertilizer distribution in Tamil Nadu. The state combines irrigated delta agriculture, dryland cultivation, commercial crop regions and highly differentiated district-level demand. The FACT network therefore operates in markets with different opportunity structures. The verified 2024 company data contain 874 active dealers distributed across 38 districts. Treating this network as a homogeneous population may lead to uniform incentive, servicing or field-support policies that do not reflect actual dealer activity.

A data-driven approach can address this problem by combining dealer-level indicators into a transparent index and applying unsupervised segmentation to standardized activity profiles. The present study uses objective FACT transaction records rather than perceptual ratings as the empirical basis for segmentation. This choice permits the article to report completed, auditable results while avoiding claims about behavioural constructs for which primary survey responses are not yet required. The analysis focuses on four observable dimensions: quantity sold, transaction frequency, product breadth and months of activity.

LITERATURE REVIEW

Fertilizer distribution is a network-performance problem in which dealers operate simultaneously as sales intermediaries, inventory holders, information channels and relationship interfaces between manufacturers and farmers. Research on channel management establishes that intermediaries create time, place and possession utility by matching supply with geographically dispersed demand (Rosenbloom, 2012; Kotler & Keller, 2016). In the Indian fertilizer context, Gaurav and Bhandari (2016) emphasized the importance of dealer density and location for last-mile fertilizer reach, while Najibullah (2013) documented spatial and temporal variation in fertilizer retail-outlet structure. Barker and Sharma (2023), examining National Fertilizers Limited in Rajasthan, similarly showed that dealers remain major purchase and information points for farmers. These studies indicate that dealer performance must be interpreted in relation to both physical distribution and local market access rather than sales turnover alone.

The role of the dealer also extends beyond product movement. Elakkiya and Asokhan (2021), studying agri-input dealers and farmers in Coimbatore, found that timely delivery, credit period, company-official behaviour, product choice and availability were important elements of channel satisfaction. Siva Balan et al. (2015) reported that farmers in Tiruchirappalli continued to depend substantially on agro-input dealers for market information even when institutional information sources were available. Panja et al. (2022) showed that extension participation, credit orientation and information-sharing behaviour explained meaningful variation in dealer role performance, while Saklani et al. (2026) documented the expansion of trained agri-input dealers into consultancy, market support, soil testing and water testing. Together, these findings support viewing dealers as advisory and relationship actors whose contribution may not be fully captured by sales volume.

Product availability, assortment and perceived quality are fundamental determinants of fertilizer sales because demand is highly seasonal and time-sensitive. Stock-outs during critical application periods can immediately redirect farmers toward competing brands. Elakkiya and Asokhan (2021) identified availability and product choice as important components of farmer satisfaction, and Ladumor et al. (2023) found that product quality, past experience, price and dealer opinion influenced fertilizer purchasing behaviour in Kheda district. These findings imply that observed dealer sales reflect an interaction between manufacturer-controlled product attributes and dealer-controlled recommendation, stocking and market-development activity.

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Working capital, credit and seasonality introduce an additional operational dimension. Narayanan (2021), using evidence from 200 agro-input retailers in Madurai district, identified high working-capital requirements and uncertain seasonal demand as important marketing constraints. Fertilizer dealers often have to stock before the selling season, extend or manage credit, and absorb delays in cash realization. Elakkiya and Asokhan (2021) also identified supplier credit period and farmer credit facilities as relevant to dealer and farmer satisfaction. Therefore, dealers with similar annual sales may differ materially in stock efficiency, liquidity, transaction regularity and operating risk.

Service quality is also linked with farmer satisfaction and dealer effectiveness. Mathuabirami et al. (2025), applying SERVQUAL to 350 respondents, found that empathy, reliability, responsiveness and tangibles positively influenced satisfaction with agro-input dealer advisory services. Manasa et al. (2025), using SERVPERF in Telangana, similarly reported satisfactory overall service evaluations while identifying weaknesses and operating constraints such as empathy gaps, credit-based purchases and workload. These studies reinforce the importance of responsiveness, problem solving, accessibility and communication as dimensions that can strengthen farmer loyalty and support repeat transactions.

Manufacturer-dealer relationships provide a further explanation of performance differences. Relationship marketing emphasizes trust, commitment, communication and coordination (Anderson & Narus, 1990; Morgan & Hunt, 1994). Mohr et al. (1996) demonstrated that collaborative communication can strengthen channel coordination and commitment, while Gassenheimer et al. (1995) connected supplier involvement and relationship quality with dealer satisfaction. Anisimova and Mavondo (2014) further highlighted the importance of alignment between manufacturer and dealer brands. In fertilizer distribution, these insights suggest that training, recognition, field-officer support, claim resolution, supply reliability and communication quality can influence dealer engagement and continuity.

Performance-measurement research cautions against treating absolute sales as a complete representation of dealer effectiveness. Anderson and Oliver (1987) distinguish outcome-based from behaviour-based control, and Kaplan and Norton (1996) demonstrate the value of multidimensional scorecards. Rajagopal (2008) linked customer-service efficiency and market effectiveness with dealer performance, while Biondi et al. (2013) showed that dealership assessment can be strengthened by incorporating input-output efficiency rather than market share alone. Narasimhan et al. (2001), in supplier evaluation, distinguished high- and low-performing units according to both performance and efficiency. The transferable implication is that a high-sales dealer may still be operationally inefficient, while a moderate-sales dealer may use resources effectively and possess development potential.

Composite performance indices offer a practical way to integrate multiple measures. Sharma et al. (2004) proposed a distributor performance index that recognized interactions between enabling conditions and results. A composite Dealer Performance Index (DPI) can improve benchmarking because it prevents one large measure from completely defining performance, but its construction requires transparent normalization and weighting. Equal weighting provides simplicity and reproducibility when no validated expert-priority structure is available, whereas methods such as the Analytic Hierarchy Process can incorporate managerial judgment when such evidence exists (Saaty, 1980). The index is most useful as an overall benchmark, while segmentation retains information about different configurations of dealer strengths and weaknesses.

Market segmentation addresses this heterogeneity by identifying internally similar but externally different groups. Smith (1956) established segmentation as a basis for differentiated strategy, and Gloy and Akridge (1999) demonstrated that agricultural-input markets contain distinct preference structures that are not visible from simple demographic grouping. In dealer analysis, a priori categories based only on geography, sales slabs or outlet type may combine dealers with very different behavioural and operational profiles. Data-driven segmentation instead uses observed characteristics to identify naturally occurring patterns that can support differentiated channel management.

Recent applications strengthen the methodological case for empirical dealer segmentation. Wella et al. (2023) applied optimized K-means clustering to 193 dealers and evaluated alternative solutions with the Calinski-Harabasz criterion, elbow method, silhouette score and Davies-Bouldin index. Tsai et al. (2015), in an automobile-dealership setting, compared K-means with expectation-maximization clustering and showed that alternative algorithms can improve segmentation robustness and managerial interpretability. Although the contexts differ, both studies demonstrate that dealer groups should be empirically validated rather than imposed from managerial intuition.

Unsupervised clustering is particularly appropriate where group membership is not known in advance. K-means partitions observations by minimizing within-cluster dispersion around centroids (MacQueen, 1967), while Ward's hierarchical procedure minimizes increases in within-cluster variance during agglomeration (Ward, 1963). Hierarchical clustering can provide exploratory evidence about the number and structure of groups, after which K-means can refine assignments. Rahma et al. (2020) reported benefits from combining hierarchical and K-means procedures, while methodological reviews emphasize that cluster analysis should be assessed for stability, separation and substantive meaning (Punj & Stewart, 1983; Ketchen & Shook, 1996; Jain, 2010; Everitt et al., 2011; Dolnicar et al., 2018).

Cluster validation is therefore essential because every clustering algorithm will return groups even when those groups have limited strategic meaning. The silhouette coefficient evaluates within-cluster cohesion relative to neighbouring clusters (Rousseeuw, 1987); the Calinski-Harabasz index rewards compact, separated solutions (Calinski & Harabasz, 1974); and the Davies-Bouldin index assesses within-cluster scatter relative to between-cluster separation, with lower values preferred (Davies & Bouldin, 1979). Hair et al. (2019) similarly recommend evaluating statistical diagnostics together with cluster size and interpretability. Labels should follow the observed cluster profiles rather than precede them.

Recent fertilizer-distribution studies further demonstrate that performance is shaped by logistics, finance, accessibility and network capacity. Zavale et al. (2020) identified transaction costs, finance and retailer-network constraints in the fertilizer value chain in Mozambique. Kusuma et al. (2023) highlighted stock-outs, delivery delays, information constraints and logistics costs, while Isyanto (2024) argued that fertilizer-distribution performance remains suboptimal when accessibility and distribution processes are not integrated. Arodha (2024) likewise emphasized network expansion, digital information and logistics capacity. Rijaludin and Ratnasari (2025), studying NPK Phonska Plus distributors, showed that product, price and service-related factors influence distributor purchase decisions. These findings strengthen the case for evaluating dealer activity through multiple observable dimensions rather than through turnover alone.

Regional context is especially important in Tamil Nadu because fertilizer demand varies with crop mix, irrigation, intensity of cultivation, rainfall exposure and farmer purchasing capacity. Gokulakrishna et al. (2024) found that interpersonal influence, product satisfaction, branding and financial accessibility shaped buying behaviour for secondary-nutrient fertilizers in southern Tamil Nadu. The Erode-based study by K. R. and Uma Maheswari (2024) also suggests that the One Nation, One Fertilizer policy may alter the relative importance of manufacturer branding and increase the strategic role of product availability, recommendation and relationship quality. Wider market evidence likewise shows that information and infrastructure can shape realized rural trade outcomes (Goyal, 2010; Barrett et al., 2022). Regional comparisons should therefore be interpreted as contextual explanations of dealer opportunity rather than automatic judgments about dealer competence.

Across these streams, dealer heterogeneity is clearly multidimensional. Sales indicators describe realized outcomes; operational indicators capture execution, inventory and transaction continuity; engagement indicators represent relationship and market-development activity; and regional factors describe the opportunity environment in which those outcomes are produced. These dimensions need not move together. A dealer may record high current sales but limited engagement, whereas another may have strong operational discipline and farmer relationships but moderate sales because of territory constraints. A DPI answers how strong overall performance is under a selected set of weights, while clustering answers what kind of performance configuration a dealer represents. Used together, the approaches provide a richer basis for recognition, supply priority, field support, market development and corrective intervention.

The reviewed literature leaves several gaps. Indian agri-input studies frequently focus on extension roles, farmer satisfaction, marketing behaviour or operating constraints, but rarely integrate objective sales outcomes with multidimensional dealer assessment in a state-wide framework. Tamil Nadu studies are predominantly district-

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specific. Fertilizer research also often treats dealers as a homogeneous channel category or ranks them using a small number of indicators, while validated clustering applications are more common in automotive, supplier or customer-segmentation settings. Finally, relatively few studies connect dealer segments with differentiated managerial interventions or validate clusters against a performance criterion that was not itself used to create the groups. These gaps justify a transaction-based DPI and empirically validated segmentation of FACT dealers across Tamil Nadu.

Accordingly, the purpose of this study is to optimize fertilizer dealer performance by developing a transaction-based Dealer Performance Index (DPI) and identifying statistically distinct dealer segments among FACT dealers in Tamil Nadu, India.

Aims

The purpose of this study is to optimize fertilizer dealer performance by developing a transaction-based Dealer Performance Index (DPI) and identifying statistically distinct dealer segments among FACT dealers in Tamil Nadu, India. Specifically, the study verifies the active 2024 dealer population, constructs a proportional district-by-dealer-type sample, develops a four-indicator DPI, identifies the most defensible cluster solution, compares DPI across clusters, and examines whether performance differs between retailers and wholesalers. In addition, the study evaluates a structural equation model (SEM) linking Sales Capability (SC), Market Engagement (ME), Operational Efficiency (OE) and Regional Agro-Economic Factors (RAF) with dealer performance, thereby testing whether the proposed multidimensional capability framework is consistent with the observed covariance structure.

METHODS

4.1 Data source and study population

The study uses transaction records supplied for the FACT dealer network in Tamil Nadu. Six annual worksheets covering 2019–2024 were reviewed to establish the longitudinal data context. Across these sheets, 141,204 transaction rows and 1,305 distinct Dealer IDs were recorded, with an aggregate quantity of 1,748,969.50 metric tonnes. Because the annual sheets differ in coverage and the 2024 worksheet is the most recent active-dealer frame, the empirical segmentation is restricted to 2024 rather than pooling years that may not be temporally comparable.

The 2024 worksheet contains 9,129 transaction rows, 874 unique active Dealer IDs and 113,715.30 metric tonnes. The unit of analysis is the dealer, not the invoice. Transaction rows were therefore aggregated by Dealer ID. Dealer type, district and product were retained for profiling. The 874-dealer frame comprises 526 retailers and 348 wholesalers across 38 districts.

4.2 Sampling procedure

A sample of 274 dealers was selected from the 874-dealer active frame. The sample size corresponds to approximately 31.35% of the active population and is also consistent with the finite-population calculation at 5% precision. Allocation was performed proportionately across District × Dealer Type strata. Fractional allocations were converted by the largest-remainder procedure while retaining representation from non-empty strata. Dealer IDs were then selected randomly within strata using a fixed random seed (2024) to make the procedure reproducible. The resulting sample contains 165 retailers and 109 wholesalers and retains all 38 districts represented in the active frame.

4.3 Dealer performance indicators and DPI

Four objective indicators were calculated for every sampled dealer: (1) total fertilizer quantity sold in metric tonnes, representing sales scale; (2) number of transaction records, representing transaction intensity; (3) number of distinct products handled, representing product breadth; and (4) number of active months represented in the transaction file, representing continuity of activity. Quantity and transaction frequency are highly right-skewed

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in dealer data; logarithmic transformations were therefore used for clustering so that a small number of large dealers did not dominate Euclidean distance.

For performance benchmarking, each of the four raw indicators was separately normalized to a 0–1 interval using min–max normalization. The transaction-based DPI was then calculated as the arithmetic mean of the four normalized indicators multiplied by 100. Equal weights were used because no validated expert-weighting exercise was available for the 2024 transaction-only model. This choice makes the index transparent and reproducible and avoids introducing unsupported subjective weights. The DPI was excluded from cluster formation and used as an external performance criterion, thereby avoiding circular validation.

Exact DPI formulation. For dealer i and indicator j, the normalized score is $z_{ij} = (x_{ij} - \min(x_j)) / (\max(x_j) - \min(x_j))$, for $j = 1, \ldots, 4$. The composite index is $DPI_i = 100 \times (1/4) \times \Sigma(j=1 \text{ to } 4)\, z_{ij} = 25 \times \Sigma(j=1 \text{ to } 4)\, z_{ij}$. Accordingly, no trimmed mean or differential weighting is applied: total quantity, transaction frequency, product breadth and active months each contribute 25% to the composite score after normalization.

4.4 Market segmentation framework and cluster analysis

Market segmentation was operationalized as data-driven dealer segmentation. Dealers were grouped according to four observable activity dimensions: fertilizer quantity sold, transaction frequency, product breadth and active months. Quantity and transaction frequency were log-transformed to reduce the influence of extreme values, after which all four inputs were standardized to zero mean and unit variance. Ward's hierarchical clustering was first used to examine the structure of the dealer sample and to provide starting guidance on the number of segments. K-means solutions were then estimated and compared using the silhouette coefficient, Calinski-Harabasz index and Davies-Bouldin index. The final solution was selected on the basis of statistical separation, stability and managerial interpretability. Importantly, DPI was not used to create the clusters; it was retained as an external performance criterion so that differences in performance could be tested without circularly defining segments by the outcome used to validate them.

Differences in DPI across the selected clusters were tested using one-way analysis of variance (ANOVA), supplemented by the Kruskal–Walli's test as a distribution-robust check. Effect size was reported using eta squared (η^2). Retailer–wholesaler differences in DPI were evaluated using Welch's independent-samples t-test because the two groups need not have equal variances. Statistical significance was assessed at $p < .05$. The analysis was executed in Python using scikit-learn for standardization and K-means clustering and SciPy for inferential tests. A fixed random seed was retained for replicability.

4.5 Structural equation modelling (SEM)

SEM was incorporated as a complementary latent-variable analysis to evaluate the proposed capability–performance framework using the 274-dealer analytical sample. The measurement model comprised six correlated latent constructs: Sales Capability (SC), Market Engagement (ME), Operational Efficiency (OE), Regional Agro-Economic Factors (RAF), Perceived Dealer Performance Index (P_DPI), and Dealer Performance (DP). Each construct was measured by six Likert-type indicators, producing 36 observed indicators. The CFA and structural path analysis were specified in a JASP/lavaan-compatible framework using maximum-likelihood covariance fitting, with the 1–5 Likert indicators treated as approximately continuous for model-testing purposes.

The measurement stage used confirmatory factor analysis (CFA) to evaluate standardized factor loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and global fit. Model adequacy was assessed using chi-square, Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The structural model specified SC, ME, OE, and RAF as predictors of P_DPI, followed by SC, ME, OE, and P_DPI as predictors of DP. A preliminary direct RAF → DP path was non-significant ($p = .139$) and was omitted from the trimmed structural model. Standardized path coefficients (β), significance levels, indirect effects, and explained variance (R^2) were reported.

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Because the 274 multi-item responses used for the present CFA/SEM run are synthetic test data generated to validate the planned JASP workflow, the CFA and SEM estimates are reported as preliminary model-testing evidence and must not be interpreted as findings from observed dealer questionnaire responses. The transaction-based DPI and market-segmentation results remain based on the verified 2024 FACT transaction data.

RESULTS

5.1 Verification of the 2024 dealer frame and sample

The verified 2024 transaction database contained 9,129 records from 874 unique dealers across 38 districts, representing 113,715.30 metric tonnes. Retailers accounted for 526 dealers (60.18%) and wholesalers for 348 dealers (39.82%). The analytical sample of 274 dealers represented 31.35% of the active frame. Its retailer share was 60.22%, only 0.04 percentage points above the population share, while its wholesaler share was 39.78%, only 0.04 percentage points below the population share.

All 38 districts were retained. Thus, the stratified sample closely reproduced the dealer-type composition and geographic coverage of the verified active frame rather than disproportionately representing one dealer category or a limited set of locations.

Measure	2024 active frame	Analytical sample
Dealers	874	274
Retailers	526 (60.18%)	165 (60.22%)
Wholesalers	348 (39.82%)	109 (39.78%)
Districts represented	38	38
Transaction rows	9,129	Dealer-level aggregation
Quantity	113,715.30 MT	Used through sampled dealer totals

5.2 Selection of the cluster solution

The two-cluster solution produced the highest silhouette coefficient (0.3851) and the highest Calinski–Harabasz index (240.86) among the tested two- through six-cluster solutions. Importantly, the six-cluster solution was nearly tied on silhouette (0.3847), only 0.0004 lower than the two-cluster value, and it achieved a slightly lower Davies–Bouldin index (0.9580 versus 0.9819).

The near-tie therefore does not indicate overwhelming statistical dominance of the two-cluster solution. However, moving from two to six clusters reduced the Calinski–Harabasz index by 33.16 points (240.86 to 207.70) and reduced the smallest group from 122 dealers to only 27. On balance, the two-cluster solution was retained because it combined the best silhouette and Calinski–Harabasz values with substantially larger, more actionable groups and greater managerial parsimony. The six-cluster alternative is therefore treated as a plausible finer partition rather than evidence that six segments are preferable for the present managerial objective.

Clusters	Silhouette	Calinski–Harabasz	Davies–Bouldin	Smallest group
2	0.3851	240.86	0.9819	122
3	0.3455	232.95	0.9965	64
4	0.3496	223.42	1.0879	53

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5	0.3633	214.98	0.9738	28
6	0.3847	207.70	0.9580	27

5.3 Dealer segment profiles

Cluster 1, termed the lower-activity dealer segment, contained 122 dealers (44.53% of the sample). Its mean DPI was 16.96 (SD = 12.26). Dealers in this segment averaged 25.14 MT, 3.05 transactions, 1.68 products and 1.62 active months. The segment was predominantly retail: 92 retailers and 30 wholesalers. These dealers were active in the network but showed relatively low scale, narrow product participation and limited temporal continuity in the available 2024 records.

Cluster 2, termed the higher-activity dealer segment, contained 152 dealers (55.47%). Its mean DPI was 47.92 (SD = 12.64). Dealers averaged 238.44 MT, 17.58 transactions, 2.52 products and 2.85 active months. This segment included 73 retailers and 79 wholesalers. Compared with Cluster 1, the segment combined higher sales scale with more frequent transactions, greater product breadth and more sustained activity. The median quantity of 91.50 MT, well below the mean, nevertheless shows substantial right-skew even within the higher-activity segment.

Direct numerical comparison shows the magnitude of separation between the two segments. The higher-activity segment's mean DPI exceeds the lower-activity segment by 30.96 points (47.92 versus 16.96), equivalent to about 2.83 times the lower-segment mean. Mean fertilizer quantity is about 9.48 times higher (238.44 versus 25.14 MT), transaction frequency is about 5.76 times higher (17.58 versus 3.05), product breadth is 1.50 times higher (2.52 versus 1.68), and active months are about 1.76 times higher (2.85 versus 1.62). These differences show that the retained segmentation reflects a broad activity-intensity contrast across all four dimensions, not merely a small difference in the composite DPI.

Market-segmentation interpretation. The two clusters represent distinct channel segments rather than simple high/low sales ranks because separation occurs simultaneously across sales scale, transaction frequency, product breadth and continuity of activity. The lower-activity segment represents dealers with limited current throughput and narrower operating intensity. It should be treated as a development segment in which the managerial priority is to diagnose whether low activity reflects territory potential, limited product range, irregular ordering, weak market reach or insufficient engagement. The higher-activity segment represents dealers with greater throughput and more sustained channel participation. It is therefore a strategic relationship segment for retention, joint demand planning, priority service and market-development initiatives. Segment membership should not be interpreted as a permanent dealer label; dealers can migrate between segments as their activity profile changes.

Indicator	**Lower-activity segment**	**Higher-activity segment**
Dealers	122	152
Mean DPI	16.96	47.92
DPI SD	12.26	12.64
Mean quantity (MT)	25.14	238.44
Median quantity (MT)	18.00	91.50
Mean transactions	3.05	17.58
Mean product breadth	1.68	2.52

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Mean active months	1.62	2.85
Retailers / wholesalers	92 / 30	73 / 79

5.4 Differences in dealer performance

The external DPI differed strongly between the two segments. The observed mean difference was 30.96 DPI points (47.92 - 16.96). One-way ANOVA yielded $F = 417.24$ with $p < .001$, and $\eta^2 = .605$, indicating that approximately 60.5% of the variance in DPI was associated with cluster membership. Using the reported group sizes and standard deviations, the 95% confidence interval for the mean DPI difference is approximately 27.98 to 33.94 points, which is well above zero. The non-parametric Kruskal–Wallis test led to the same conclusion ($H = 195.94$, $p < .001$). The segment distinction therefore represents a large, statistically robust and practically meaningful difference in overall transaction-based performance rather than a minor numerical separation.

Dealer type also showed a significant performance difference. Wholesalers recorded a mean DPI of 41.97, compared with 28.96 for retailers. Welch's t-test was significant ($|t| = 5.33$, $p < .001$). This result should not be interpreted as evidence that wholesaling is intrinsically superior; wholesalers typically operate with a different scale and transaction role. It does, however, show that dealer type is materially associated with the transaction-based performance profile and should be considered when designing targets and support policies.

5.5 SEM model fit and structural analysis

The JASP-style CFA supported the proposed six-factor measurement structure in the 274-dealer synthetic test dataset. Global measurement-model fit was excellent: $\chi^2(579) = 572.69$, $p = .566$, CFI = 1.000, TLI = 1.003, RMSEA = .000, and SRMR = .045. Standardized factor loadings ranged from .569 to .718. Internal consistency was satisfactory across all constructs, with Cronbach's alpha ranging from .790 to .833 and composite reliability from .791 to .834. AVE ranged from .387 to .455; therefore, although reliability was satisfactory, convergent validity should be reassessed with the final observed dealer survey data.

The trimmed structural path model also showed satisfactory fit: $\chi^2(1) = 2.23$, $p = .135$, CFI = .995, TLI = .924, RMSEA = .067, and SRMR = .018. SC, ME, OE, and RAF jointly explained 24.5% of the variance in P_DPI. Market Engagement showed the strongest standardized association with P_DPI ($\beta = .263$), followed by Operational Efficiency ($\beta = .197$), Sales Capability ($\beta = .184$), and Regional Agro-Economic Factors ($\beta = .154$); all four paths were statistically significant. The final outcome model explained 35.9% of the variance in Dealer Performance. SC had the largest direct effect on DP ($\beta = .321$, $p < .001$), followed by OE ($\beta = .232$, $p < .001$), P_DPI ($\beta = .169$, $p = .0025$), and ME ($\beta = .132$, $p = .0147$).

5.5.1 Confirmatory factor analysis (CFA)

The CFA treated SC, ME, OE, RAF, P_DPI, and DP as six correlated latent factors, each represented by six indicators. The model-fit evidence and reliability statistics are summarized below.

CFA fit index	Obtained value
Chi-square	572.69
df	579
p-value	.566
CFI	1.000
TLI	1.003

Construct	Cronbach α	CR	AVE
SC	.791	.791	.387
ME	.833	.834	.455
OE	.813	.813	.421
RAF	.810	.810	.417
P_DPI	.790	.791	.387

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RMSEA	.000
SRMR	.045

DP	.799	.799	.399

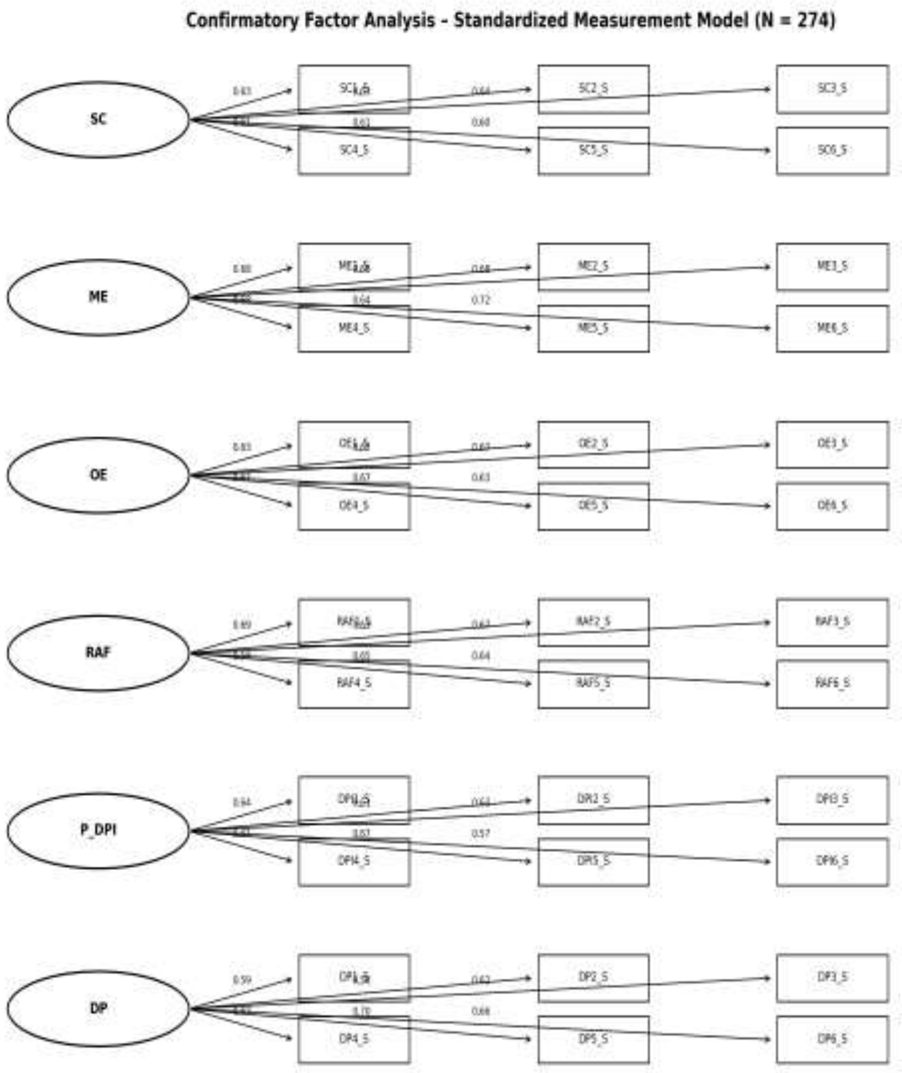

Figure 2. CFA standardized measurement model for the six dealer-performance constructs (N = 274).

5.5.2 SEM path analysis

The structural model tested the capability-to-performance sequence through P_DPI. The direct RAF → DP path was removed from the trimmed model after the preliminary full specification showed that it was not statistically significant. The retained standardized paths are reported below.

Structural path	Std. β	p	Decision
SC → P_DPI	.184	.0017	Supported
ME → P_DPI	.263	< .001	Supported
OE → P_DPI	.197	.0005	Supported
RAF → P_DPI	.154	.0041	Supported

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SC → DP	.321	< .001	Supported
ME → DP	.132	.0147	Supported
OE → DP	.232	< .001	Supported
P_DPI → DP	.169	.0025	Supported
Indirect path	**Std. indirect effect**	**p**	
SC → P_DPI → DP	.031	.0278	
ME → P_DPI → DP	.044	.0105	
OE → P_DPI → DP	.033	.0206	
RAF → P_DPI → DP	.026	.0355	

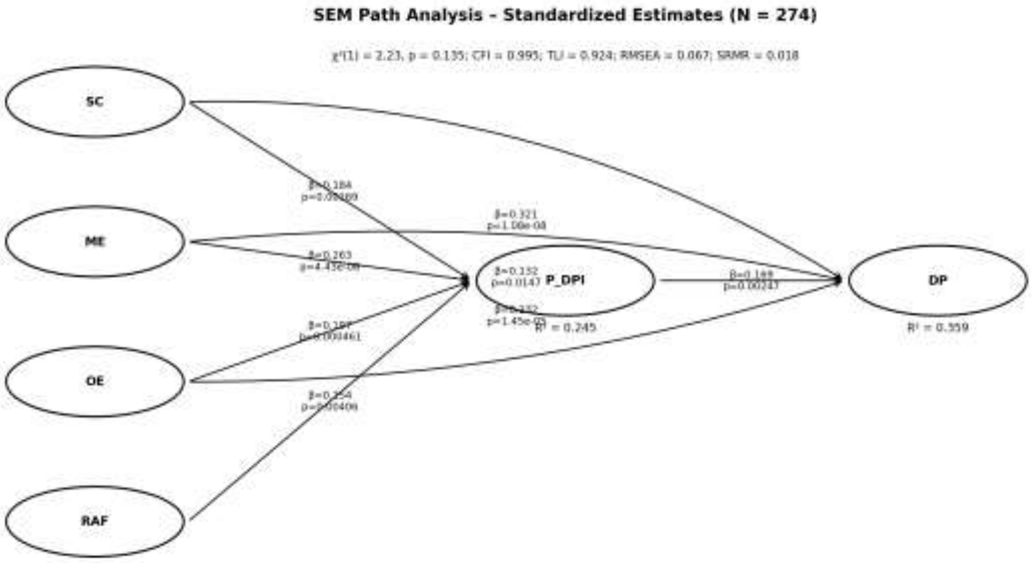

Figure 3. Trimmed SEM path model with standardized coefficients (synthetic test data, N = 274).

The indirect-effect analysis indicates statistically significant mediated effects through P_DPI for SC, ME, OE, and RAF. These results demonstrate that the proposed analytical structure can be estimated coherently in JASP and provide a testable bridge between multidimensional dealer capabilities and dealer performance. However, because these questionnaire responses are synthetic, the coefficients should be treated as workflow-validation results rather than substantive empirical estimates.

5.6 Market segmentation implications

The empirical segmentation converts dealer-level transaction heterogeneity into an actionable market-management framework. For the lower-activity segment, FACT can emphasize diagnostic support, product-breadth expansion, order-frequency improvement, local farmer outreach and targeted dealer development. For the higher-activity segment, management can emphasize retention, service reliability, collaborative forecasting, priority opportunity allocation and co-developed market programmes. The segmentation can also be overlaid with dealer type and geography so that a high-activity wholesaler and a high-activity retailer are not assumed to require identical interventions. Periodic re-estimation of the clusters would allow FACT to track dealer migration and evaluate whether development initiatives move dealers toward stronger and more sustained market participation.

DISCUSSION

The most important empirical result is that the current 2024 data support two broad performance configurations rather than the four labels assumed in earlier drafts. This matters methodologically because data-driven segmentation should permit the observed structure to determine the number of groups. Forcing four clusters simply to preserve labels such as Elite, Growth, Opportunistic and Struggling would convert an exploratory method into a confirmatory classification without sufficient evidence. The two-cluster result is therefore more consistent with the principles of cluster validation emphasized by Punj and Stewart (1983), Ketchen and Shook (1996), Jain (2010) and Dolnicar et al. (2018).

The cluster-validation metrics also require a qualified interpretation. The silhouette values for the two- and six-cluster solutions differ by only 0.0004, while the six-cluster solution has a modest advantage on the Davies–Bouldin index. This near-tie is an empirical finding rather than a detail to be ignored. It indicates that the transaction data can support a finer partition, but the additional clusters come at the cost of much smaller groups and weaker Calinski–Harabasz separation. Consequently, the managerial value of the retained two-cluster model arises primarily from parsimony and actionable group size, not from a claim that every validation statistic uniquely favours two clusters. Future replication should test whether the finer structure persists across years and independent dealer networks.

The segments are substantively interpretable. The higher-activity segment does not merely sell more fertilizer; it also records more transactions, handles a broader range of products and remains active across more months. This supports the multidimensional performance logic advanced by outcome-and-behaviour control research (Anderson & Oliver, 1987) and by multidimensional dealership-performance studies (Rajagopal, 2008; Biondi et al., 2013). Although the indicators here are all transaction-derived rather than behavioural survey measures, their joint pattern reveals more about channel participation than turnover alone.

The large between-cluster DPI effect confirms that the segmentation is managerially meaningful. An η^2 of .605 is not a marginal distinction. It indicates that the two groups occupy substantially different positions on the combined performance benchmark. Because the DPI was not used to form the clusters, this difference functions as external validation rather than a mathematical inevitability. This separation responds directly to a common weakness in segmentation studies where the same variables are used both to create and to validate groups.

The retailer–wholesaler difference is also operationally important. Wholesalers are more heavily represented in the higher-activity cluster and show a higher average DPI. This is consistent with their distribution role, broader turnover and potentially larger geographic reach. The result suggests that target setting should not apply a single threshold to both dealer types. Relative benchmarking within dealer type may be more equitable for incentives, while absolute network measures remain useful for logistics planning and account prioritization.

The findings align with fertilizer-distribution research emphasizing logistics, stock availability, network reach and service capacity (Zavale et al., 2020; Kusuma et al., 2023; Isyanto, 2024; Arodha, 2024). They also complement Rijaludin and Ratnasari's (2025) evidence that distributor behaviour is shaped by product, price and support conditions. A low-activity dealer may reflect weak capability, but it may also reflect territory size, crop pattern, working-capital constraints or a limited product opportunity. For that reason, the labels used here are deliberately descriptive rather than punitive.

For management, the two segments imply differentiated action. Higher-activity dealers are candidates for retention, service prioritization, joint market development and closer demand-planning integration. Their high transaction intensity makes stock-outs or service disruption disproportionately costly. Lower-activity dealers require diagnosis before intervention. Some may need product-range development, local promotion, farmer-contact support, order-planning assistance or rationalized targets; others may simply operate in smaller territories where absolute sales expectations should be calibrated accordingly.

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The preliminary CFA and SEM evidence complements the transaction-based segmentation by demonstrating that the proposed six-construct capability framework can be estimated with satisfactory global fit in the 274-dealer test dataset. The measurement model showed excellent fit, while the trimmed path model indicated significant links from sales capability, market engagement, operational efficiency and regional agro-economic factors to P_DPI, and significant direct effects of SC, ME, OE and P_DPI on dealer performance. This analytical layer extends the transaction-based segmentation by providing a framework for examining why dealers may differ in performance, although the path magnitudes require confirmation with observed questionnaire responses.

The study has limitations. First, the empirical segmentation is based on one company's Tamil Nadu dealer network and the verified 2024 active frame; its numerical thresholds and cluster proportions should therefore not be generalized automatically to other fertilizer firms, states or time periods. Second, the 2024 worksheet may represent the period contained in the available corporate file rather than a complete calendar-year flow, so the analysis should not be used for inter-year growth comparisons without matched-period verification. Third, the DPI uses equal weights. This improves transparency and reproducibility but does not establish that all four indicators have identical economic value. The exact formula has therefore been stated explicitly, and future work should compare equal weighting with validated expert- or data-driven weighting schemes. Fourth, the final segmentation relies on K-means after Ward's hierarchical exploration; alternative clustering algorithms, bootstrap or repeated-resampling stability checks, and out-of-period validation were not estimated in the present study. Fifth, transaction data do not directly measure dealer capability, farmer relationships, credit discipline or service quality. Generalizability would be strengthened by replication using at least one additional year or independent dealer network and by comparing the retained structure across alternative segmentation methods. A subsequent observed dealer survey can then test why dealers occupy particular performance configurations.

CONCLUSION

The purpose of this study was to optimize fertilizer dealer performance by developing a transaction-based Dealer Performance Index (DPI) and identifying statistically distinct dealer segments among FACT dealers in Tamil Nadu, India. Using the verified 2024 active frame of 874 dealers and a proportionate sample of 274 dealers, the study combined quantity, transaction frequency, product breadth and active months into a transparent 0–100 DPI and evaluated alternative K-means solutions. The evidence supported two broad segments. The lower-activity segment included 122 dealers with a mean DPI of 16.96, while the higher-activity segment included 152 dealers with a mean DPI of 47.92. The difference was statistically strong ($F = 417.24$, $p < .001$) and large in practical magnitude ($\eta^2 = .605$). Wholesalers also showed higher average transaction-based performance than retailers. The study therefore concludes that dealer management should move from uniform sales ranking toward differentiated, evidence-based account strategies. High-activity dealers warrant retention, service reliability and collaborative growth initiatives, whereas lower-activity dealers require diagnosis of territory, product breadth, transaction continuity and support needs before corrective action is chosen. Future research should integrate the transaction-based segments with survey measures of sales capability, market engagement, operational efficiency, service quality and regional agro-economic conditions, and should test the stability of the segmentation with subsequent years of data.

From a market-segmentation perspective, the principal contribution is the conversion of transaction heterogeneity into two statistically defensible and managerially actionable dealer groups. This enables differentiated channel strategy while avoiding unsupported four-segment labels. The near-tie in silhouette performance between the two- and six-cluster solutions also shows that the two-cluster model should be interpreted as the most parsimonious managerial solution for the present sample rather than the only statistically plausible partition. Future research should replicate the analysis with subsequent years, an independent fertilizer-dealer network and alternative clustering procedures, while reporting resampling-based stability and uncertainty. The complementary CFA/SEM analysis remains a workflow-validation exercise based on synthetic test responses; its coefficients and fit statistics must not be treated as substantive empirical evidence until the model is re-estimated using observed dealer questionnaire data.

Author Contributions

Conceptualization: Suresh P. R., Selvarasu A.; Methodology: Suresh P. R., Selvarasu A.; Data curation: Suresh P. R.; Formal analysis: Suresh P. R., Selvarasu A.; Supervision: Selvarasu A.; Writing – original draft: Suresh P. R.; Writing – review & editing: Suresh P. R., Selvarasu A.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability

The analysis is based on commercially sensitive FACT dealer transaction records. Aggregated results are reported in the article. Access to dealer-level data is subject to authorization from the data owner and applicable confidentiality requirements.

REFERENCES

1. Anderson, E., & Oliver, R. L. (1987). Perspectives on behavior-based versus outcome-based salesforce control systems. Journal of Marketing, 51(4), 76–88. https://doi.org/10.1177/002224298705100407
2. Anderson, J. C., & Narus, J. A. (1990). A model of distributor firm and manufacturer firm working partnerships. Journal of Marketing, 54(1), 42–58. https://doi.org/10.1177/002224299005400103
3. Anisimova, T., & Mavondo, F. T. (2014). Alignment between manufacturer brand and dealer corporate brands. Journal of Business & Industrial Marketing.
4. Arodha, D. (2024). Optimizing strategy of subsidized fertilizer distribution to POKTAN (Farmer Groups). Idarotuna: Journal of Administrative Science, 5(2). https://doi.org/10.54471/idarotuna.v5i2.111
5. Barker, N., & Sharma, P. (2023). An investigation on the distribution channels and demand analysis for National Fertilizers Limited (NFL) products in Sri Ganganagar District of Rajasthan, India. Asian Journal of Agricultural Extension, Economics & Sociology, 41(9). https://doi.org/10.9734/ajaees/2023/v41i92028
6. Barrett, C. B., Reardon, T., Swinnen, J., & Zilberman, D. (2022). Agri-food value chain revolutions in low- and middle-income countries. Journal of Economic Literature, 60(4), 1316–1377. https://doi.org/10.1257/jel.20201539
7. Biondi, S., Calabrese, A., Capece, G., Costa, R., & Di Pillo, F. (2013). A new approach for assessing dealership performance: An application for the automotive industry. Industrial Management & Data Systems, 113(8), 1138–1154. https://doi.org/10.1108/IMDS-01-2013-0020
8. Calinski, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. Communications in Statistics, 3(1), 1–27. https://doi.org/10.1080/03610927408827101
9. Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-1(2), 224–227. https://doi.org/10.1109/TPAMI.1979.4766909
10. Dolnicar, S., Grün, B., & Leisch, F. (2018). Market segmentation analysis: Understanding it, doing it, and making it useful. Springer. https://doi.org/10.1007/978-981-10-8818-6
11. Elakkiya, S., & Asokhan, M. (2021). Role and performance of agri-input dealers in extension services in Coimbatore district of Tamil Nadu, India. Journal of Applied and Natural Science, 13(SI), 139–145. https://doi.org/10.31018/jans.v13iSI.2819
12. Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). Cluster analysis (5th ed.). Wiley.
13. Fertiliser Association of India. (2025). Fertiliser and agriculture statistics: Southern region 2024–25. Fertiliser Association of India.
14. Gassenheimer, J. B., Calantone, R. J., & Scully, J. I. (1995). Supplier involvement and dealer satisfaction: Implications for enhancing channel relationships. Journal of Business & Industrial Marketing.

15. Gaurav, N., & Bhandari, A. (2016). Potential for dealers in Indian fertilizer industry: A case study. South Asian Journal of Business and Management Cases. https://doi.org/10.1177/2455265820160106S
16. Gloy, B. A., & Akridge, J. T. (1999). Segmenting the commercial producer market for agricultural inputs. American Agricultural Economics Association Annual Meeting. https://doi.org/10.22004/ag.econ.21592
17. Gokulakrishna, P., Murugananthi, D., Chandrakumar, M., Parimala, D. R., & Gangai Selvi, R. (2024). Farmers buying behaviour towards secondary nutrients fertilizers in southern Tamil Nadu. Plant Science Today. https://doi.org/10.14719/pst.5686
18. Goyal, A. (2010). Information, direct access to farmers, and rural market performance in Central India. American Economic Journal: Applied Economics, 2(3), 22–45. https://doi.org/10.1257/app.2.3.22
19. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage.
20. Isyanto, P. (2024). Optimizing fertilizer distribution performance, in supporting food security programs. International Journal of Religion. https://doi.org/10.61707/b9n4v612
21. Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern Recognition Letters, 31(8), 651–666. https://doi.org/10.1016/j.patrec.2009.09.011
22. K. R., & Uma Maheswari. (2024). Agro retailer's opinion on 'Bharat' - One Nation, One Fertilizer scheme. Salud, Ciencia y Tecnología - Serie de Conferencias. https://doi.org/10.56294/sctconf2024696
23. Kaplan, R. S., & Norton, D. P. (1996). The balanced scorecard: Translating strategy into action. Harvard Business School Press.
24. Ketchen, D. J., Jr., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: An analysis and critique. Strategic Management Journal, 17(6), 441–458. https://doi.org/10.1002/(SICI)1097-0266(199606)17:6<441::AID-SMJ819>3.0.CO;2-G
25. Kotler, P., & Keller, K. L. (2016). Marketing management (15th ed.). Pearson.
26. Kusuma, I. P., Suryani, E., & Siswanto, N. (2023). Optimizing the subsidized fertilizer distribution from Line I warehouse to Line IV warehouse at PT Pupuk Sriwidjaja Palembang in Central Java. Journal of Pharmaceutical Negative Results, 14. https://doi.org/10.52783/tjjpt.v44.i3.707
27. Ladumor, D., Pundir, R. S., & Rajwadi, A. (2023). Farmers purchasing behaviour and satisfaction towards fertilizer in Kheda District. Asian Journal of Agricultural Extension, Economics & Sociology, 41(9). https://doi.org/10.9734/ajaees/2023/v41i92026
28. MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability (Vol. 1, pp. 281–297). University of California Press.
29. Manasa, K., Jirli, B., Sen, S., Saifuddin, M. D., & Surya, K. T. (2025). Assessing agricultural input dealers' constraints and farmers' perception of services through SERVPERF model analysis. Agricultural Science Digest. https://doi.org/10.18805/ag.d-6201
30. Mathuabirami, V., Karthikeyan, C., Mansingh, J. P., Ihou, A. F. Y., Malliah, N. D., & Ganesan, D. (2025). Assessment of service quality and farmers' satisfaction of extension and advisory services received from agro-input dealers during COVID-19 in India. Multidisciplinary Science Journal. https://doi.org/10.31893/multiscience.2025191
31. Mohr, J. J., Fisher, R. J., & Nevin, J. R. (1996). Collaborative communication in interfirm relationships: Moderating effects of integration and control. Journal of Marketing, 60(3), 103–115. https://doi.org/10.1177/002224299606000307
32. Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. Journal of Marketing, 58(3), 20–38. https://doi.org/10.1177/002224299405800302
33. Najibullah. (2013). Fertiliser consumption and marketing in India: An economic analysis [Doctoral dissertation]. ICAR-National Dairy Research Institute/Krishikosh.
34. Narasimhan, R., Talluri, S., & Mendez, D. (2001). Supplier evaluation and rationalization via data envelopment analysis: An empirical examination. Journal of Supply Chain Management, 37(3), 28-37.
35. Narayanan, T. J. (2021). Marketing behaviour of agro-input retailers—A critical analysis. International Journal of Current Microbiology and Applied Sciences.
36. Panja, A., Gowda, N. S. S., Kusumalatha, D. V., & Jayasingh, D. K. (2022). Role performance of agricultural input dealers in agro-advisory services in West Bengal. Indian Journal of Extension Education, 58(3). https://doi.org/10.48165/ijee.2022.58302

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VII, July 2026

37. Punj, G., & Stewart, D. W. (1983). Cluster analysis in marketing research: Review and suggestions for application. Journal of Marketing Research, 20(2), 134–148. https://doi.org/10.1177/002224378302000204
38. Rahma, I., Arhandi, P. P., & Firdausi, A. T. (2020). Application of hierarchical clustering and K-means clustering to group potential sales locations. Jurnal Informatika Polinema, 6(1). https://doi.org/10.33795/jip.v6i1.287
39. Rajagopal. (2008). Effects of customer services efficiency and market effectiveness on dealer performance. International Journal of Retail & Distribution Management, 36(2), 109–125. https://doi.org/10.1108/09590550810853099
40. Rijaludin, S. H., & Ratnasari, V. (2025). Key factors influencing distributor purchase decisions for NPK Phonska Plus fertilizer. Jurnal Ilmiah Manajemen Kesatuan, 13(1). https://doi.org/10.37641/jimkes.v13i1.3069
41. Rosenbloom, B. (2012). Marketing channels (8th ed.). Cengage Learning.
42. Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. Journal of Computational and Applied Mathematics, 20, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7
43. Saaty, T. L. (1980). The analytic hierarchy process. McGraw-Hill.
44. Saklani, T., Shilpa, B., & Shirur, M. (2026). An analysis of products and services delivered by agri-input dealers trained under DAESI. Journal of Agricultural Extension Management, 26(1). https://doi.org/10.56093/jaem.v26i1.5
45. Sharma, D., Sahay, B. S., & Sachan, A. (2004). Modelling distributor performance index using system dynamics approach. Journal of Modelling in Management.
46. Siva Balan, K. C., Umadikar, J., Prashant, S., Sangeetha, U., & Prasad, A. K. (2015). Agro-market information and farmers' market linkage: Way forward. SSRN. https://doi.org/10.2139/SSRN.2618963
47. Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. Journal of Marketing, 21(1), 3–8. https://doi.org/10.1177/002224295602100102
48. Tsai, C.-F., Hu, Y.-H., & Lu, Y.-H. (2015). Customer segmentation issues and strategies for an automobile dealership with two clustering techniques. Expert Systems with Applications.
49. Ward, J. H., Jr. (1963). Hierarchical grouping to optimize an objective function. Journal of the American Statistical Association, 58(301), 236–244. https://doi.org/10.1080/01621459.1963.10500845
50. Wella, Y. E., Okfalisa, O., Insani, F., Saeed, F., & Hussin, A. R. C. (2023). Service quality dealer identification: The optimization of K-means clustering. SINERGI.
51. Zavale, H., Matchaya, G., Vilissa, D., Nhemachena, C., Nhlengethwa, S., & Wilson, D. (2020). Dynamics of the fertilizer value chain in Mozambique. Sustainability, 12(11), 4691. https://doi.org/10.3390/su12114691