USING TRANSACTION-BASED CUSTOMER SEGMENTATION TO FORMULATE SALES STRATEGIES: EVIDENCE FROM A MOTORCYCLE DEALER IN INDONESIA

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Abstract

This study examines the problem of inconsistent sales target achievement faced by a motorcycle dealer in Indonesia, where sales targets were achieved in only a limited number of months. One of the main causes identified is the absence of clear customer segmentation, which leads to undifferentiated sales strategies and inefficient allocation of sales resources. This study aims to identify distinct customer segments based on transaction-based purchasing behavior and to demonstrate how these segments can be utilized to formulate more targeted sales strategies. A quantitative case study approach was employed using the CRISP-DM framework and transaction data from 4,289 motorcycle sales recorded between January 2022 and October 2025. Customer segmentation was conducted using the K-Modes clustering algorithm based on categorical transaction attributes, resulting in three distinct customer segments with different purchasing characteristics. The findings show that each segment exhibits unique behavioral and economic profiles, requiring differentiated sales approaches rather than a uniform strategy. Based on the segmentation results, this study proposes segment-specific sales strategies that support more focused resource allocation and improved sales effectiveness. The results highlight the importance of transaction-based customer segmentation as a practical decision-support tool for enhancing sales performance in motorcycle retail.

Keywords: Customer Segmentation, Transaction-Based Data, K-Modes Clustering, Sales Strategy, Motorcycle Retail

INTRODUCTION

The automotive industry plays a crucial role in supporting national economies, particularly in Southeast Asia where motorcycles serve as the primary mode of transportation for a large proportion of households (Statista, 2023). In Indonesia, motorcycles dominate both urban and rural mobility due to their affordability, fuel efficiency, and accessibility, especially in regions with limited public transportation infrastructure (Lubowiecki-Vikuk & Michalska-Dudek, 2025).

The Indonesian motorcycle market demonstrates strong long-term potential, with the scooter segment contributing the largest share of industry revenue (Statista, 2024). Although national motorcycle sales experienced a significant decline during the COVID-19 pandemic, the market has gradually recovered since 2021, confirming the resilience of consumer demand and the dominant position of leading brands such as Honda (PT Astra International Tbk, 2023). However, favorable industry-level trends do not always translate into consistent performance at the dealer level.

In practice, many motorcycle dealers continue to face fluctuating sales achievement and difficulties in meeting monthly targets. Performance gaps among dealers operating within similar regional and economic conditions suggest that internal strategic factors, rather than market conditions alone, play a critical role in determining sales outcomes. Previous studies indicate that ineffective targeting and the absence of customer segmentation often result in undifferentiated sales strategies, inefficient resource allocation, and suboptimal sales performance (Kotler & Keller, 2016).

Customer segmentation has been widely recognized as an essential analytical approach for understanding heterogeneous purchasing behavior and improving marketing effectiveness (Wedel & Kamakura, 2000). Advances in data analytics have enabled firms to utilize historical transaction data to identify distinct customer segments and design more targeted sales strategies (Hair et al., 2019). Nevertheless, many small and medium-sized motorcycle dealers still rely heavily on intuition-based decision-making and underutilize transaction data as a strategic resource.

Therefore, this study aims to apply transaction-based customer segmentation as a practical tool to support sales strategy formulation at the motorcycle dealer level. Specifically, this research seeks to identify distinct customer segments based on purchasing behavior captured in transaction data and to demonstrate how these segments can be translated into differentiated sales strategies. By linking data-driven segmentation results with actionable managerial implications, this study is expected to provide practical insights for motorcycle dealers in improving sales effectiveness and achieving more sustainable sales performance.

REVIEW OF LITERATURE

Sales performance has increasingly been understood as a strategic outcome shaped by managerial decisions, customer targeting, and the ability of firms to build sustainable customer relationships, rather than being driven solely by sales volume or short-term revenue figures. Recent studies suggest that firms achieve better sales outcomes when they utilize customer data to understand purchasing behavior and design strategies that align with the characteristics of different customer groups (Kasem et al., 2024). This perspective highlights the importance of identifying who the customers are and how they transact as a foundation for effective sales strategy formulation.

Market segmentation theory is based on the premise that markets are inherently heterogeneous, requiring firms to classify customers into relatively homogeneous groups to improve marketing effectiveness. Classical studies by Beane and Ennis (1987), as well as more recent work by Kotler and Keller (2016), emphasize that segmentation enables firms to develop differentiated strategies that better match customer needs, preferences, and purchasing behavior. In practice, segmentation helps firms avoid undifferentiated approaches that often result in inefficient use of marketing and sales resources.

With the increasing availability of transactional data, segmentation research has shifted from intuition-driven classification toward data-driven approaches that rely on empirical analysis of actual customer behavior. Transaction-based segmentation focuses on observed purchasing patterns, such as product choices, payment methods, and buying frequency, which provide more reliable insights than attitudinal or self-reported data (Yoseph et al., 2020; Bilgic et al., 2021). Behavioral segmentation is therefore considered particularly actionable, as it reflects real purchase decisions that can be directly linked to sales activities.

Clustering techniques are widely used in data-driven customer segmentation because they allow patterns to emerge directly from transaction data without predefined assumptions. As an unsupervised learning approach, clustering groups customers based on similarities in purchasing behavior, enabling firms to identify meaningful segments that may not be visible through traditional analysis (Alves Gomes & Meisen, 2023). Empirical studies across retail and service contexts demonstrate that clustering-based segmentation supports the development of differentiated sales and marketing strategies, contributing to improved sales effectiveness and customer management (Tabianan et al., 2022).

Among clustering algorithms, K-Modes is particularly suitable for segmenting customers using categorical transaction data. Unlike K-Means, which relies on numerical distance measures, K-Modes applies similarity measures designed for nominal variables, making it appropriate for datasets dominated by categorical attributes such as product type, payment method, and purchase channel (Huang, 1998). Previous studies confirm that K-Modes effectively identifies customer segments based on purchasing patterns while preserving the behavioral meaning of categorical transaction variables (Tabianan et al., 2022).

Beyond identifying customer segments, the literature emphasizes the importance of translating analytical insights into actionable managerial decisions. Data-driven frameworks such as CRISP-DM provide structured guidance for aligning analytical processes with business objectives and ensuring that analytical results can be applied in operational contexts (Schröer et al., 2021). However, several studies note that many firms, particularly at the small and medium enterprise level, still struggle to convert segmentation results into concrete sales strategies due to limited analytical capabilities and reliance on intuition-based decision-making (Plotnikova et al., 2022).

Overall, existing studies highlight the strategic value of transaction-based customer segmentation for improving sales performance. Nevertheless, empirical research that explicitly demonstrates how segmentation results can be translated into practical sales strategies at the motorcycle dealer level remains limited. This study addresses this gap by applying transaction-based customer segmentation to support sales strategy formulation in a motorcycle dealership context, thereby contributing practical insights into the use of data analytics for sales decision-making.

RESEARCH METHOD

This study adopts a quantitative, data-driven case study design conducted at ABC, a Honda motorcycle dealer, with the objective of supporting sales strategy formulation through customer segmentation. The analytical process follows the CRISP-DM framework to ensure a systematic progression from business understanding and data preparation to modeling, evaluation, and strategy interpretation. Transactional data are used to capture revealed purchasing behavior rather than stated customer preferences, allowing the analysis to reflect actual sales patterns.

The dataset consists of 4,289 customer transaction records extracted from the dealer's transactional system, covering the period from January 2022 to October 2025. The data include categorical attributes describing purchase characteristics, such as motorcycle type and payment method, as well as contextual information related to customer purchasing history. All data were anonymized and did not contain personally identifiable information.

Prior to analysis, data cleaning was performed to address missing and inconsistent records. Transactions with incomplete information on key segmentation variables were excluded to ensure data quality. Exploratory data analysis was then conducted to summarize category distributions and identify preliminary patterns that informed the segmentation process. To support variable adequacy and reduce redundancy among categorical attributes, association analysis using Cramér's V and Chi-Square tests was applied to assess relationships between variables and ensure that selected attributes contributed meaningful information for clustering.

Customer segmentation was carried out using the K-Modes clustering algorithm, which is appropriate for categorical transaction data due to its use of mode-based cluster representation and categorical dissimilarity measures. The optimal number of clusters was determined using a combination of internal validation criteria, including the Elbow method, Silhouette coefficient, and Davies–Bouldin Index. Based on these criteria, the final clustering model was estimated, and each customer was assigned to a segment.

Following the clustering process, customer segments were profiled to support managerial interpretation and sales strategy formulation. Segment profiles were developed based on dominant purchasing characteristics observed within each cluster, including preferred motorcycle models, payment methods, and purchasing patterns. In addition, descriptive economic indicators such as segment size, sales contribution, and average transaction value were used to provide further insights into the relative characteristics of each segment.

All data processing and clustering analysis were conducted using Python, with Microsoft Excel used for data extraction and preliminary checks. Descriptive summaries and visualizations were generated to support the interpretation of the segmentation results. This study adheres to research ethics principles by analyzing anonymized data in aggregate form and reporting findings at the segment level to protect organizational and customer confidentiality.

RESULTS AND DISCUSSION

Customer Segmentation Based on Transaction Characteristics

Customer purchasing patterns were analyzed using transaction-based customer segmentation to address the first research question. K-Modes clustering was applied to 4,289 transaction records collected between January 2022 and October 2025 using six categorical variables representing purchasing behavior, including motorcycle model preference and payment method. These variables were selected to capture revealed customer behavior derived directly from transaction records rather than stated preferences.

The optimal number of clusters was determined through a triangulation of internal validation criteria, namely the Elbow method, Silhouette coefficient, and Davies–Bouldin Index. All three criteria consistently supported a three-cluster solution (K = 3), indicating that this configuration provides an appropriate balance between statistical validity and managerial interpretability. A higher number of clusters did not yield meaningful additional differentiation, while fewer clusters masked important behavioral differences relevant to sales strategy formulation.

Table 1. Cluster Profiling and Characterization

	Cluster 0	Cluster 1	Cluster 2
Total customer	62.3% of total customers	21.9% of total customers	14.8% of total customers
Product	Scoopy dominant (48.3%)	Scooopy dominant (37.7%)	Exclusively BeAT Street
Payment	100% cash	100% credit (majority via FIF)	Cash
Profile	Established self-employed trader, geographically concentrated in Barabai, high school education, mid-range spending.	More diverse occupations (including formal workers), wider educational and spending distribution, high concentration in Barabai	Self-employed traders, wider geographic distribution, high school education, mid-range spending
Characteristic	Largest segment with the financial ability to buy in cash, loyal to Scoopy, entrepreneur profile	Similar products preferences to Cluster 0 but using financing, including customers with higher incomes use credit for cash flow management.	Highly homogeneous niche segment with exclusive preference for BeAT Street, cash-based financial capability, wider geographic distribution.

The clustering results reveal three distinct customer segments with uneven distribution sizes. Cluster 0 is the largest segment, accounting for 63.3% of total customers. This segment is dominated by Scoopy purchases conducted entirely through cash payments. The size and homogeneity of this segment indicate a mainstream customer group with strong purchasing power, high familiarity with the Scoopy product line, and a clear preference for immediate ownership without financing. This segment has historically formed the backbone of dealership sales volume.

Cluster 1 represents 21.9% of customers and is also dominated by Scoopy purchases; however, it differs fundamentally in transaction behavior due to its reliance on credit-based payment schemes. Customers in this segment use financing facilities to complete purchases, even when income levels suggest that cash purchases may be feasible. This behavior indicates different financial management preferences and higher sensitivity to installment structures, financing terms, and credit availability compared to Cluster 0.

Cluster 2 is the smallest segment, comprising 14.8% of total customers, and is characterized by exclusive purchases of the BeAT Street model using cash payments. This segment is highly homogeneous in product preference, reflecting a strong product identity and a distinct purchasing logic. Customers in this segment are more geographically dispersed than those in the dominant Scoopy segments, suggesting demand beyond the dealer's core market area and potential opportunities for geographic expansion.

Taken together, the segmentation results demonstrate that while the dealership's customer base appears homogeneous at an aggregate level, it becomes structurally heterogeneous when examined through transaction behavior. Product preference (Scoopy versus BeAT Street) and payment method (cash versus credit) emerge as the primary dimensions of differentiation, confirming that behavioral segmentation provides a more actionable basis for sales strategy formulation than demographic characteristics alone.

Segment Performance and Strategic Interpretation

An evaluation of segment performance reveals substantial differences in economic contribution and strategic roles across the three customer groups. Cluster 0 functions as the dealership's primary profit engine, contributing 69.3% of total profit and recording the highest average profit per customer at approximately IDR 629,000. Combined with its dominant customer share of 63.3%, this segment is critical for short-term financial stability and cash flow continuity.

Cluster 1 also demonstrates strong economic relevance, contributing 22.4% of total profit with an average profit per customer of approximately IDR 596,000. Although its scale is smaller than Cluster 0, this segment plays a strategically important role by enabling market access through financing mechanisms. Credit-based purchasing allows the dealership to capture demand from customers who prioritize payment flexibility, thereby supporting overall sales volume and reducing reliance on a single purchasing pattern.

In contrast, Cluster 2 exhibits the lowest current profitability, with an average profit per customer of approximately IDR 367,000 and a total profit contribution of 9.3%. Under a profit-only evaluation logic, this segment would be considered low priority. However, longitudinal analysis of transaction data reveals a fundamentally different strategic interpretation. Cluster 2 demonstrates the strongest growth trajectory, with a compound annual growth rate of approximately 31.4%. By comparison, Cluster 0 shows a slight decline in growth (approximately −1.4%), while Cluster 1 exhibits modest but volatile growth of around 3.8%.

Table 2. Profitability Summary per Cluster

Metrics	Cluster 0	Cluster 1	Cluster 2
Customer count	2,715	940	634

Total profit	IDR 1,708,987,000	IDR 560,241,000	IDR 232,678,000
Avg profit per customer	IDR 629,461	IDR 596,000	IDR 367,000
Market share	63.30%	21.92%	14.78%
Profit contribution	69.31%	22.39%	9.30%

These contrasting performance patterns highlight a clear strategic trade-off between short-term profitability and long-term growth potential. While Cluster 0 currently dominates sales performance, its declining growth trend suggests market maturity and saturation. Conversely, Cluster 2, despite its smaller size and lower margins, represents an emerging growth segment with significant expansion potential. Evaluating customer segments solely on current profit contribution therefore risks reinforcing dependence on mature segments while underinvesting in future growth opportunities.

Translating Segmentation Results into Sales Strategy

The segmentation findings provide a strong rationale for abandoning a uniform, one-size-fits-all sales strategy in favor of a differentiated, segment-driven approach. The dealership's existing strategy applies similar sales tactics across all customers, despite clear differences in purchasing behavior, payment preferences, and growth dynamics. This misalignment helps explain the observed inconsistency in sales target achievement.

For Cluster 0, which consists of Scoopy cash buyers, a defend-and-optimize strategy is most appropriate. Given its large scale and high profitability, sales efforts should prioritize customer retention, service quality, and value maximization rather than aggressive volume expansion. Strategic focus on after-sales service, repeat purchases, and selective upselling can help preserve margins and slow the decline associated with market saturation.

Cluster 1, composed of Scoopy credit buyers, should be managed through a maintain-and-support strategy. This segment's strategic value lies in its ability to expand market access through financing. Sales initiatives should emphasize financing flexibility, close coordination with leasing partners, and efficiency in credit processing. Improving the customer experience in credit transactions is likely to have a greater impact on this segment than price-based promotions or aggressive expansion efforts.

Cluster 2, consisting of BeAT Street cash buyers, requires a fundamentally different strategic orientation. Despite its lower current profitability, its strong growth momentum indicates unmet demand and a high degree of product–market fit. An invest-and-grow strategy is therefore recommended, focusing on targeted promotion, geographic outreach, and product-focused communication that reinforces the distinctive identity of the BeAT Street model. Early investment in this segment can allow the dealership to capture scale advantages before competitive pressures intensify.

Discussion

The findings of this study demonstrate that dealership sales performance is influenced not only by external market conditions, but also by the internal alignment between customer structure and sales strategy. Although aggregate sales data may suggest a relatively homogeneous customer base, transaction-based segmentation reveals substantial behavioral differences that have important strategic implications for sales planning and resource allocation.

The identification of three distinct customer segments confirms that purchasing behavior in motorcycle retail is shaped primarily by product preference and payment method rather than by demographic characteristics alone. This supports existing marketing theory that emphasizes behavioral segmentation as the most actionable basis for managerial decision-making, as it directly reflects how customers interact with products and sales systems in practice.

The dominance of the Scoopy cash buyer segment illustrates how mature segments can sustain short-term financial stability through scale and profitability. However, the observed stagnation in growth within this segment suggests that reliance on historically dominant customer groups may limit future sales expansion. This finding highlights the risk of strategic inertia when dealerships focus excessively on segments that have performed well in the past without reassessing their long-term potential.

In contrast, the BeAT Street cash buyer segment demonstrates that smaller segments with lower current profitability can represent significant growth opportunities. The strong growth trajectory observed in this segment indicates a high degree of product–market fit that has not yet been fully exploited by existing sales strategies. This reinforces the argument that growth potential should be considered alongside profitability when evaluating the strategic importance of customer segments.

The results also reveal the strategic role of credit-based Scoopy buyers in supporting sales volume and market accessibility. While this segment does not dominate in terms of scale or growth, it enables the dealership to serve customers who prioritize payment flexibility. This suggests that sales performance is not driven by a single “best” segment, but by the complementary roles played by different customer groups within the overall sales portfolio.

Taken together, these findings expose the limitations of profit-only logic in sales strategy formulation. Exclusive reliance on short-term financial indicators may lead to overinvestment in mature segments while emerging opportunities remain underdeveloped. A more balanced approach that integrates current profitability, customer scale, and growth momentum is therefore necessary to support sustainable sales performance.

From a managerial perspective, the study demonstrates the value of transaction-based customer segmentation as a practical decision-support tool. By grounding strategic decisions in observed purchasing behavior, managers can reduce reliance on intuition and improve the alignment between sales initiatives and customer needs. This is particularly important in small and medium-sized dealership contexts, where resource constraints magnify the consequences of strategic misallocation.

Overall, the study confirms that effective sales strategy formulation requires treating customer segments as a strategic portfolio rather than as a homogeneous market. By aligning sales efforts with segment-specific behavioral patterns and growth dynamics, motorcycle dealerships can enhance sales effectiveness, reduce strategic inefficiencies, and strengthen long-term performance sustainability.

CONCLUSION

This study demonstrates that transaction-based customer segmentation provides a valuable foundation for improving sales strategy formulation at the motorcycle dealer level. By analyzing 4,289 transaction records using K-Modes clustering, the study successfully identifies three distinct customer segments characterized by different product preferences and payment behaviors. These findings confirm that customer heterogeneity, which is not visible in aggregate sales data, plays a critical role in shaping sales performance.

The results show that Scoopy cash buyers represent the largest and most profitable segment, functioning as the dealership's primary source of short-term revenue and financial stability. Scoopy credit buyers, while smaller in scale, play an important strategic role by expanding market access through financing mechanisms and supporting sales volume continuity. In contrast, BeAT Street cash buyers, despite lower current profitability, exhibit strong growth momentum, indicating significant potential for future sales expansion.

Importantly, the study highlights the limitations of relying solely on profit-based evaluation in sales strategy formulation. Focusing exclusively on mature and dominant segments may lead to strategic stagnation and underinvestment in emerging opportunities. A more balanced, segment-driven approach that considers both current economic contribution and growth dynamics is therefore essential for achieving sustainable sales performance.

From a managerial perspective, the findings emphasize the need to move away from uniform, one-size-fits-all sales strategies. By aligning sales initiatives with the behavioral characteristics of each customer segment, dealerships can allocate resources more effectively, reduce strategic inefficiencies, and improve consistency in sales target achievement. Transaction-based customer segmentation thus serves as a practical decision-support tool that bridges analytical insights and actionable sales strategies.

This study contributes to the applied marketing and sales management literature by providing empirical evidence on how behavioral segmentation can be translated into differentiated sales strategies in a motorcycle retail context. While the analysis is based on a single dealer case, the methodological approach and strategic insights are relevant for similar dealerships facing challenges related to inconsistent sales performance and limited use of transaction data.

Future research may extend this study by incorporating multiple dealers, additional performance indicators, or longitudinal strategic evaluation to assess the long-term impact of segment-driven sales strategies. Nevertheless, the findings of this study underline the strategic importance of transaction-based customer segmentation in supporting data-driven sales decision-making and enhancing long-term performance sustainability in motorcycle retail.

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