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A Study on Customer Segmentation Using MachineLearning at TVS Sai Hemanth Motors, Srikalahasthi

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Abstract: In today's competitive market, understanding customer diversity is essential for tailoring marketing strategies and improving sales. This study focuses on customer segmentation at TVS Sai Hemanth Motors, Srikalahasthi, using K-Means clustering, a machine learning technique. The aim is to classify customers based on demographic and behavioral factors and identify meaning fulpatterns in purchasing and non-purchasing behavior. Data was collected from both buyers and non-buyers, and the Elbow Method was applied to determine the optimal number of segments. The analysis resulted inclearly defined clusters that revealed specific customer characteristics and preferences. This enables the dealer to make informed decisions regarding marketing strategies and customer relationship management. The study not only enhances understanding of customer profiles but also demonstrates the practical application of data-driven segmentation in a real-world context

Keywords: K-means analysis, Elbow method, Customer segmentation, Demographic variables

I. INTRODUCTION

Customer segmentation is a critical aspect of marketing strategy in today's competitive business environment. It involves dividing a heterogeneous customer base into smaller, more homogeneousgroupsbasedonsharedcharacteristics, suchasdemographics, behavior, and preferences. The goal of customer segmentation is to enable businesses to target specific customer groups more effectively, thereby optimizing marketing efforts and improving customer satisfaction. In this context, businesses use various data analytics and machine learning techniques, such as K-Means clustering, to identify distinct customer segments and develop tailored strategies that enhance both customer acquisition and retention.

II. REVIEW OF LITERATURE

- 1) Priya and Sharma (2019) This research applied machine learning techniques for customer segmentation in the automobile industry. The study showed how clustering customers based on demographic and behavioral attributes helps improve lead conversion rates.
- 2) Naveen and Srivastava (2021) The authors examined how customer segmentation using unsupervised machine learning can help dealerships increase efficiency in customer targeting. They concluded that segmenting both buyers and non-buyers offered deeper insights.
- 3) Kavitha and Anil (2018) This paper discussed how data mining techniques, particularly clustering, can be used for strategic decision-making in automotive sales. The study highlighted that integrating behavioralvariablesenhancestheaccuracyof segments.
- 4) RajeshandMeena(2022)Thestudyutilized K-Means clustering to analyze consumer behavior in two-wheeler dealerships. It suggested that recognizing different clusters like price-sensitive, brand-conscious, and first-time buyers helps in tailoring product offerings and promotions.
- 5) Chatterjee and Das (2020) This research showed the application of clustering techniques on both demographic and behavioral data in order to differentiate between potential buyers and non-buyers in the vehicle sales industry.
- 6) Srinivas and Latha (2023) They applied Python-based machine learning algorithms, including K-Means, for customer segmentationindealershipdata. Theirworksupports the use of elbow methods
- A. Objectives of the study:



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- 1) To classify customers into different segments based on demographic factors such as age, income level, and profession
- 2) To analyze the purchasing behavior of different customer segments and identify key patterns.
- 3) Toevaluatetheimpactofdemographics, financial status, and product preferences on customer segmentation.
- 4) Toapplymachinelearningtechniques (such as K-Means clustering) for automated and data-driven segmentation

B. Need for the study:

The increasing competition in the two-wheeler market demands a deeper understanding of customer behavior to retain and attract buyers. The market needs to take necessary steps to identify distinct customer groups and address their specific needs effectively. Customers exhibit diverse preferences and behaviors, which influence their decision to buy or not buy from a shop. The growing competition for cesmuch more attention on understanding these differences to improve sales strategies. Customer segmentation helps the business by enabling targeted marketing and optimizing resource allocation for future growth. This study, based on the segmentation of buyers and non-buyers using K-means clustering, is quite essential for the TVSS aihemant hmotors to thrive in the present-day competitive market.

C. Scope of the study:

The increasing competition in the two-wheeler market demands a deeper understanding of customer behavior to retain and attract buyers. The market needs to take necessary steps to identify distinct customer groups and address their specific needs effectively. Customers exhibit diverse preferences and behaviors, which influence their decision to buy or not buy from a shop. The growing competition forces much more attention on understanding these differences to improve sales strategies. Customer segmentation helps the business by enabling targeted marketing and optimizing resource allocation for future growth. This study, based on the segmentation of buyers and non-buyers using K-means clustering, is quite essential for the TVSS aihemant hmotors to thrive in the present-day competitive market.

III. RESEARCH METHODOLOGY

A. ResearchDesign:

Exploratory Research

B. Data Collection:

Data were collected from 100 customers (50 buyers and 50 non-buyers) at TVS Sai Hemanth Motors in Srikalahasthi between March 30 andApril 12, 2025. Primary data were gathered through surveys, interviews, and feedback forms, capturing demographic details (age, gender, income, occupation, marital status) and preferences (style, speed, mileage, price, features, EMI, location, referrals, test rides). Secondary data were sourced fromthedealership'ssalesrecords, CRMsystem, and historical transaction data spanning the past 2-3 years. A convenience sampling technique was used due to the accessibility and willingness of customers to participate.

C. DataAnalysisTools:

Followingarethedifferenttoolsusedforanalyzing thedata

Dataanalyticaltoolsforclustering

- python
- Matplotliblibrary(usedforscatter plots, line graphs)
- D. Limitations of The Study:
- 1) Thestudyisbasedononly50buyersand 50 non-buyers, which may not fullyrepresentalltypesofcustomersvisiting the dealership.
- 2) The segmentation is based only on demographic data. Behavioural, transactional, or service-related data were not included, which could provide deeper insights.
- 3) Thestudyusesstaticdatacollectedatone point in time. Customer behaviour and preferences may change overtime.
- 4) The findings are specific to one TVS Sai Hemanth motors located in srikalahasthi and may not be applicable to other regions with different customer demographics



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5) The study doesn't include how buyers behave after the purchase (like service visits, satisfaction), which is crucial for long-term segmentation.

IV. DATA ANALYSIS & INTERPRETATION

A. DeterminingtheOptimalNumberofClusters-ElbowMethod

To perform effective customer segmentation using K-Means clustering, it is essential to determine the optimal number of clusters (K). The Elbow Method was used for this purpose. This technique involves plotting the Within-Cluster Sum of Squares (WCSS) against a range of K values

B. Use of Python for Efficient Clustering and visualization:

Performing K-Means clustering and related computations manually is not only

time-consumingbutalsopronetoerrors, especially when dealing with multiple variables and larger datasets. To overcome these limitations, Python programming was utilized in this project.

C. BuyersDistribution Across Clusters:

After applying K-Means clustering, the customers were segmented distinct groups based on their demographic characteristics and preferences. Out of 100 total respondents (50 buyers and 50 non-buyers), the distribution across

PYTHON CODE FOR CUSTOMER SEGMENTATION USING K-MEANS:

```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import KMeans
# Encode categorical features
df encoded = df.copy()
label encoders = {}
for col in df.columns[1:]:
    le = LabelEncoder()
    df encoded[col] = le.fit transform(df[col])
    label encoders[col] = le
# Standardize the data
scaler = StandardScaler()
X scaled = scaler.fit transform(df encoded.drop(columns=['sl no']))
# Apply KMeans
kmeans = KMeans(n clusters=3, random state=42, n init=10)
df encoded['Cluster'] = kmeans.fit predict(X scaled)
# Analyze clusters
cluster_summary = df_encoded.groupby('Cluster').mean().round(2)
print(cluster summary)
```



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Table 1. Cluster solutions for the buyer's data

Feature	Cluster0	Cluster1	Cluster2
Age	1.0(18-25	2.5(26-35)	3.8(45+)
Gender	0.6	0.55	0.65
Qualification	1.2	2.1	3
Occupation	1.5	2.3	1
MaritalStatus	0.3	0.8	4
Annual Income	1.2	2.8	0.6
Style	0.5	0.7	0.4
Speed	0.3	0.6	0.5
Mileage	0.8	0.5	0.5
Price	0.6	0.7	0.7
Features	0.4	0.6	0.3
EMI	0.9	0.6	0.6
Location	0.7	0.5	0
Referral	0.82	0.6	0.4
TestRide	0.7	0.6	0.4

Table 2.Interpretation of Final Cluster Centers

Variable	Cluster0	Cluster1	Cluster2
	18-25Age		
Age	group	Mostly26-35	mostly45+
Gender	60% aremale	Balancedgender	65%aremale
	MostlyUG students	MixofUG/PG job	Predominantly
Qualification		holders	PG/PhD
	Students, entry-level	Jobholders, self-	Business
Occupation	job holders	employed	owners, senior
			professionals
	Mostly unmarried	Mostlymarried (80%)	
MaritalStatus	(70%)		100%married
AnnualIncome	₹0–2.5L	₹2.5–10L	₹10L+
	Moderate	Highinterest (70%)	Stronginterest (83%)
Style	interest(50%)		
	Lowpriority (30%)	Highpriority (65%)	Moderate
Speed			priority(40%)
		Moderate importance	Lowpriority (50%)
Mileage	Critical(89%)	(50%)	
	Veryhigh(94% EMI	Moderate(60% EMI	Low(25%EMI
Price	users)	users)	users)





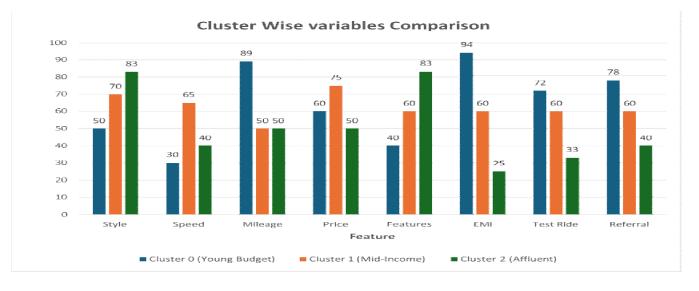
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	Someinterest in	Wantmore features	Lowpriority (30%)
Features	features		
	StrongEMI preference	EMIinterestis moderate	EMIinterestis low
EMI			
	61%Local,	60%Local,40% Non-	58%Local,
Location	39%Non-local	local	42%Non-local
	Highly influencedby		
Referral	referral	Moderate(60%)	Low(40%)
TestRide	High(72%)	Moderate(60%)	Low(33%)

- Cluster 0: Representing young price-conscious buyers (36%), shows a strong preference for mileage (89%)andEMI(94%),reflectingtheirfocusonaffordabilityandfuelefficiencyasunmarriedstudentsor entry-level job holders aged 18-25 with low income (₹0-2.5L). This cluster also values referrals (78%), indicating trust in peer recommendations, but places less emphasis on style (50%) and speed (30%)
- Cluster1:Representingthemid-incomebalancedbuyers(40%),aged26-35withmoderateincome(₹2.5-10L), demonstrates a more balanced preference profile, prioritizing price (75%), style (70%), and speed (65%), while showing moderate reliance on EMI (60%) and test rides (60%), suggesting a practical yet aspirational approach to purchasing.
- Cluster 2: Representing the affluent feature-seeking buyers (24%), aged 36-45+ with high income (₹10L+), exhibitsaclearpreferenceforstyle(83%)andfeatures(83%),withminimalrelianceonEMI(25%)ortestrides (33%), highlighting their focus on premium offerings and brand image over financing options

Table3.ClusteredDataSet

Numberofbuyersineachcluster			
CLUSTER	NOOFBUYERS	PERCENTAGE	igningbuyersof to clusters
0	18	36%	1,2,3,13,17,19,25,25,33,
			40,41,48,50
1	20	40%	4,5,7,8,9,10,11,12,14,15,
			16,20,21,22,24,26,29,32,
			35,44
2	12	24%	6,18,23,27,30,31,34,37,38
			38,42,43,47



Interpretation: The bar graph illustrating cluster-wise preferences at TVS Sai Hemanth Motors delineates distinct behavioral



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three for both buyers valuable patterns across customer segments and non-buyers, offering ₹0-2.5L, insightsfortargetedmarketing. Amongbuyers, Cluster 0, young price-conscious buyers (36%), aged 18-25 with incomes prioritizes mileage (89%) and EMI (94%), reflecting their focus on fuel efficiency and affordable financing, while also valuing referrals (78%) but showing limited interest in style (50%) and speed (30%). Cluster 1, mid-income balanced buyers (40%), aged 26-35 with incomes ₹2.5-10L, demonstrates balancedpreferencesforprice(75%),style(70%),andspeed(65%),withmoderateengagementinEMI(60%) and test rides (60%),indicating a pragmatic yet aspirational purchasing approach. Cluster 2, affluent feature- seekingbuyers(24%),aged36-45+withincomesexceeding₹10L,emphasizesstyle(83%)andfeatures(83%), with minimal relianceon EMI(25%)ortest rides (33%), highlighting apreference forpremium offerings. For non-buyers, Cluster 0, young price-conscious non-buyers (32%), aged 18-25withincomesof₹0-2.5L,mirrors its buyercounterpartby prioritizing mileage(80%),EMI,and referrals (85%),with strong interest in test rides (70%), suggesting potential for conversion with enhanced trust-building measures. Cluster 1, mid-income uncertain nonbuyers (44%), aged 26-35 with incomes of ₹2.5-6L, shows moderate interest in style (59%), speed (52%), and features (51%), but lower engagement in test rides (45%) and referrals (50%), indicating uncertainty in the buying process. Lastly, Cluster 2, affluent indifferent non-buyers (24%), aged 36-45+ with incomes of ₹6L-10L+, prioritizes style (72%) but exhibits low engagement with features (25%), test rides (20%), and referrals (30%), reflecting disinterest or unmet expectations. This graph underscores the varying engagement levels across segments, informing tailored strategies to address customer needs effectively.

D. Non-BuyersDistributionAcrossClusters:

After applying K-Means clustering, the customers were segmented distinct groups based on their demographic characteristics and preferences.Out of 100 total respondents (50 buyers and 50 non-buyers), the distribution across

Table4. Cluster solutions for the non-buyers

Feature	Cluster0	Cluster1		Cluster2
Age		0.25	1.8	2.75
Gender		0.9	0.85	1
Qualification		1.2	1.75	2.5
Occupation		0.6	2.1	3
MaritalSta		0.3	0.9	1
AnnualInc		0.45	1.6	2.8
Style		0.4	0.7	0.85
Speed		0.3	0.65	0.45
Mileage		0.8	0.5	0.4
Price		0.75	0.6	0.25
Features		0.35	55	0.2
Location		0.6	0.55	0.4
Referral		0.85	0.5	0.3
TestRide		0.7	0.45	0.25



Variable

Age

Gender

Oualification

Occupation

Mileage

Students, entry-level jobholders

Criticalfactor(80%)

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Lowpriority(40%)

Self-employed, business professionals Business owners, senior professionals

Table2.InterpretationofFinalClusterCenters

Cluster0–Budget-Conscious	Cluster1–Mid-Tier	Cluster2–Affluent
18–25Agegroup	Mostly26–35	Mostly45+
90%aremale	85%aremale	100%male
MostlyUGstudents	MixofUG/PGjobholders	PredominantlyPG/PhD

MaritalStatus	Mostlyunmarried(70%)	Mostlymarried(90%)	Allmarried
AnnualIncome	₹0–2.5L	₹2.5–6L	₹6L–10L+
Style	Lowtomoderateinterest(40%)	Moderateinterest(70%)	Highinterest(85%)
Speed	Lowpriority(30%)	Moderatepriority(65%)	Lowtomoderate(45%)

Moderateimportance(50%)

Price	Veryprice-sensitive(75%)	Moderatepriceconcern(60%)	Lowsensitivity(25%)
Features	Someinterest(35%)	Moderateinterest(55%)	Lowinterest(20%)

Locat	Mostlylocalcustomers(60%)	Local(55%)	40%arenon-local	
ion				
Referral	Highinfluenceofreferrals(85%)	Moderateinfluence(50%)	Lowinfluence(30%)	
TestRide	Highinterestintestrides(70%)	Moderateinterest(45%)	Lowinterest(25%)	
EMI	StrongEMIpreference	EMIinterestismoderate	EMIinterestislow	

- Cluster 0: Representing young price-conscious non-buyers, constitutes 32% of the non-buyer base, reflecting a significant group of younger individuals aged 18-25 with low incomes (₹0-2.5L), who prioritize affordability factors like mileage (80%) and EMI, yetremainunconverted, possibly due to trustor pricing barriers.
- Cluster 1: Representing mid-income uncertain non-buyers, emerges as the largest segment at 44%, indicating that nearly half of the non-buyer population consists of individuals aged 26-35 with moderate incomes (₹2.5-6L), who exhibit uncertainty in the buying process, as evidenced by their moderate engagement with style (59%), speed (52%), and test rides (45%).
- Cluster2: Representing affluent indifferent non-buyers, accounts for the smallest share at 24%, mirroring the proportion of affluent buyers, but these high-income individuals aged 36-45+ (₹6L-10L+) show disinterest through low engagement with features (25%) and test rides (20%), suggesting unmet expectations or lack of motivation to purchase.

Table3.ClusteredDataSet

Cluster	NonBuyerCount	•	Assigned non buyerstoclusters
0	16		1,3,6,10,13,15,16,1 7,19,24,25,28,33,39 ,41,45



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			2,4,5,7,8,9,11,12,14,
			20,21,22,23,26,29,3
1	22	44%	0,31,32,34,35,40,46
			18,27,36,37,38,42,4
2	12	24%	3,44,47,48,49,50

V. FINDINGS

The Elbow Method confirmed that K=3 is optimal for both buyers and non-buyers, enabling meaningful segmentation into three distinct customer types in each group

Buyer Segmentation:

- Cluster0: Young, low-income individuals focused on price and mileage.
- Cluster1:Mid-incomeprofessionalswho balance cost, style, and EMI options.
- Cluster 2: High-income buyers highly influencedbyfeatures, style, and testrides.

Nonbuyer Segmentation:

- Cluster0:Studentsoryoungindividuals exploring options with low intent.
- Cluster1:Moderatelyinterestedindividuals who might buy with the right offers.
- Cluster2: Uninterested group, mainly older individuals with low engagement.

Comparision:

- Buyers are more engaged with features, Emi & test rides
- Non buyers lacked motivation due to income limitations and awareness

VI. SUGGESTIONS

- 1) Offer Deals to Cluster 0 Non-Buyers: These people care about EMI and mileage. Give them low EMI and fuel-efficient options to encourage buying.
- 2) Support Cluster 1 Non-Buyers: They're unsure. Let them try test rides and explain features clearly to build confidence.
- 3) Attract Cluster 2 Non-Buyers: They have money but low interest. Show premium features or special deals to catch their attention.
- 4) UseReferrals&TestRides:Encourageword- of-mouth and offer test rides to increase customer interest.
- 5) Send Right Offers to Right Groups: Use cluster data to match offers with the right people for better results.

VII. CONCLUSION

K-Means clustering algorithm is successfully applied to segment bothbuyers and non-buyers based on demographic and behavioral variables. The analysis revealed clear patterns in customer preferences and highlighted key differencesbetween similar customer groups who did and did not make a purchase. These insights help the dealers understand their customers better and craft targeted strategies for each segment. By bridging the gap between buyers and non-buyers through focused offers and engagement, the dealership can increase conversions and optimize its marketing efforts. Overall, this study demonstrates the practical value of machine learning in solving real- world business problems

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