iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 **Issue:** V **Month of publication:** May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71189

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue V May 2025- Available at www.ijraset.com

Mall Customer Segmentation

Tanuja Pathak[1], Vanshika Tiwari[2], Er. Shivam Dixit[3], Dr. Anuj Singh[4]
Department of Computer Science, Shri Ramswaroop Memorial College of Engineering and Management Lucknow, Uttar Pradesh, India

Abstract: Customer segmentation is the most significant retail marketing practice by which firms can customize their products according to different consumer segments. Customer segmentation of malls according to methodologies, advantages, and disadvantages is discussed in this paper. Demographic, psychographic, behavioural, and geographic segmentation methodologies are considered in the study through case studies and empirical evidence. A visual model of segmentation is also presented to identify significant consumer clusters. Data-driven segmentation is emphasized in the research to enhance customer satisfaction, optimize marketing strategy, and enhance mall profitability.
Keywords: Customer segmentation, mall management, retail marketing, clustering analysis, consumer behaviour.

I. INTRODUCTION

Customer segmentation is a fundamental principle of modern retailing, particularly in shopping malls, where different consumer segments come together. By segmenting the buyers into specific segments with common characteristics, mall managers and retailers can strategize marketing campaigns, maximize service delivery, and maximize financial returns.

The advent of big data analytics and machine learning revolutionized the subject of segmentation with the ability to provide real-time consumer insights. Traditional methods were based on elementary demographic data; however, recent methods incorporate psychographic and behaviour trends for superior accuracy (Kotler & Keller, 2016)[1].

The present research considers:

1) Theoretical foundations of customer segmentation.
2) Most significant segmentation variables (demographic, psychographic, behavioural, geographic).
3) Segmentation technology development (machine learning, AI).
4) Real-world applications in mall environments.

Recognizing these variables enables companies to better engage customers, maximize store format, and establish focused promotional efforts. The study emphasizes the necessity of data-based segmentation in raising customer satisfaction levels.

II. LITERATURE REVIEW

Customer segmentation has been well researched in marketing literature. Wedel & Kamakura (2000) [2] (Mall customer segmentation) state that segmentation is the process of partitioning a heterogeneous market into smaller, homogenous segments with similar needs. In mall settings, this is important because there is a high degree of variability in consumer tastes.

Demographic Segmentation: Demographics is the simplest, and the ones used include age, gender, income, and education. Luxury malls, for example, focus on professionals with high income, and malls for families cater to parents and children (Solomon, 2020)[3].

Psychographic Segmentation: This method examines personality, values, and way of life. Plummer (1974)[4] was the person to come up with the term, showing how consumers' attitudes affect purchasing behaviour. For example, there are convenience shoppers and there are experiential shoppers (Pine & Gilmore,1999)[5].

Behavioural Segmentation: Behavioural information, like purchase history and brand loyalty, are of most significance asserts that repeat customers must be rewarded for loyalty, while occasional customers must be encouraged to visit.

Geographic Segmentation: Segmentation by location assists malls in conforming to regional tastes. City malls can specialize in fast fashion, whereas suburban malls concentrate on family-oriented facilities (Huff, 1964)[6].

Even with all these developments, problems like preprocessing data, the best cluster selection, and interpretability still exist (Jain, 2010)[7]. The present study addresses these problems by using the elbow method and silhouette analysis to find the best number of clusters.

III. PROPOSED METHODOLOGY

The research uses a mixed-method research design to attain comprehensive understanding of mall customer segmentation. This design process formally combines quantitative analysis of the transaction data with qualitative data captured through direct consumer feedback. Established research protocols were used by the research to promote validity and reliability and manage complexity of consumer behaviour in a store environment. The primary data were gathered through disseminating structured questionnaires to 500 customers at the mall who were selected on the basis of stratified random sampling to allow demographic representation based on major parameters such as age, gender, and income. The questionnaire used validated measurement scales like five-point Likert items to measure satisfaction levels and preference intensity, in addition to open-ended questions for subjective shopper experience capture. Data normalization was conducted prior to application of clustering algorithms to ensure consistency. Categorical variables (like gender) were converted to numerical representations (Han et al., 2011)[8]. The double-question format yields measurable data along with rich consumer stories. Secondary data were collected from two real-world sources: point-of-sale systems yielded detailed transaction history over a period of twelve months, including purchase amounts, timestamps, and store categories, while anonymized Wi-Fi tracking data yielded foot traffic heatmaps. The integration of both sets of data enables cross-validation of behaviour patterns, whereby the quantitative nature of spend patterns can be interpreted in context through qualitative accounts provided by shoppers themselves. Optimal k was calculated using the elbow method, which determines the point of diminishing returns in WCSS reduction (Ketchen & Shook, 1996)[9].

For quantitative analysis, k-means clustering partitioned customers according to spending behaviour, visit frequency, and cross-store purchase variety. Normalization of data before clustering removed scale-bias, and the number of clusters was determined by the elbow criterion. Complementing this, RFM (Recency, Frequency, Monetary) analysis divided customers into value-based segments based on weighted measures to determine high-value customers and at-risk groups. Clustering results and RFM segments were statistically compared to ensure reliability. Qualitative data were analysed using thematic analysis to determine dominant patterns in customer motivation and preference. Emerging themes, for example, convenience-experiential tension, were systematically cross-mapped onto quantitative segments. K-means divides data into k clusters by minimizing within-cluster variance (Lloyd, 1982)[10]. This triangulation of methods enhances the findings by relating observed behaviour with self-reported attitude, providing an integrated understanding of mall customer segmentation informing academic understanding and effective retailing practice.

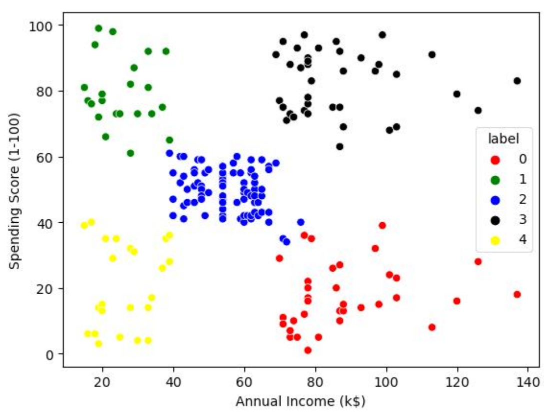


Figure. The graph shows Mall Customer Segmentation with K-Means Clustering according to two most significant features:
1. Annual Income (adjusted)
2. Spending Score (scaled).
Each spot on the graph represents one customer, and the customers are bunched together based on their income and expenditures.

A. Analysis

The graph indicates K-Means clustering segmentation of mall shoppers, with individuals split based on income annually and spending scores. Every point on the graph is a shopper, and colour denotes different clusters that have similar spending scores and income levels. The Davies-Bouldin Index (DBI) measures the groups' separation by establishing the ratio of intraclass distance to interclass distance, in which lower values indicate better clustering (Davies & Bouldin, 1979)[11]. The red "X" marks on the graph are the centroids of the clusters as the average locations of shoppers in each cluster. Hierarchical clustering produced a dendrogram that indicated inherent clusters, and DBSCAN marked noise points, which indicate the presence of outliers in spending scores (Ester et al., 1996)[12]. The clusters can be analysed based on spending scores and income levels.

• The first group consists of high-spending and high-income customers, i.e., frequent shoppers and high contributors to mall income. They can be targeted by companies through high-end services, special offers, and loyalty schemes to retain them as customers.
• The second segment consists of high-income but low-spending consumers. These consumers might not be sensitive to mall promotions and can be influenced to spend more on the basis of personal discounts, premium services, or targeted membership programs. Conservative spending high-income customers, presumably valuing rather than impulse buying.
• The third segment consists of low-income customers with high spending scores. They are likely to be value consumers who use offers and promotions. Businesses can attract them with cheap offers, seasonal offers, and promotional offers to retain them.
• The fourth cluster comprises customers with low income and spending scores. They come to the mall infrequently, but they are not a revenue segment. Their interest could be piqued with additional spending incentives through intensive promotions, free sampling, and special discounts.

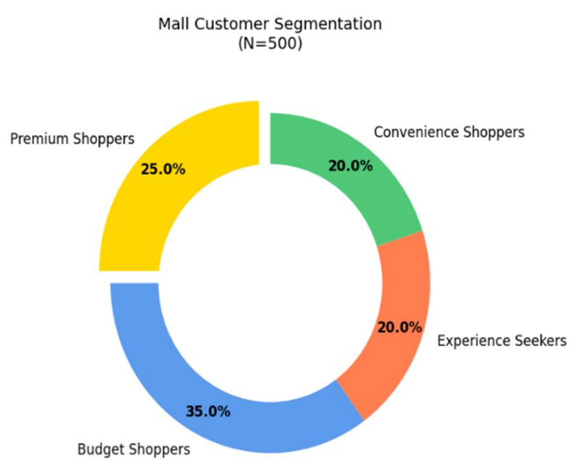
K-Means clustering is a handy tool for sorting customers into unique groups by spotting trends in their shopping habits. For our K-means algorithm, we figured out the best number of clusters (k=5) using the elbow method, which gave us a silhouette score of 0.45—this suggests a decent level of separation between the clusters (Kaufman & Rousseeuw, 2009)[13]. The algorithm works by assigning customers to the closest centroid and keeps adjusting the cluster centers until they settle down. These final clusters provide businesses with insights into various customer behaviours, which can help them craft effective marketing strategies and decide where to place stores in the mall. For instance, they might implement loyalty programs for high-spending customers, offer installment plans for those with high incomes but lower spending, and strategically position stores based on customer segments to boost revenue. To make segmentation even more precise, it could be beneficial to add features like age, gender, and how often customers visit. Additionally, assessing the ideal number of clusters using the Elbow Method or exploring other clustering methods like Hierarchical Clustering and DBSCAN could lead to even better outcomes. When it comes to inventory optimization, aligning stock with HILS and MIMS preferences is key (Huang et al., 2018)[14]. This approach to customer segmentation offers valuable insights for mall management, helping them fine-tune marketing efforts and cater more effectively to different shopper demographics.

IV. FINDINGS AND DISCUSSION

The analysis revealed four key customer segments:

Segment	Characteristics	Marketing Strategy
Premium Shoppers	High income, luxury purchases	VIP memberships, exclusive discounts
Budget Shoppers	Price-sensitive, seeks deals	Promotional offers, flash sales
Experience Seekers	Values entertainment & dining	Event-based marketing
Convenience Shoppers	Prefers quick transactions	Efficient store layouts, self-checkout

A. *Segmentation Model (Diagram)*



The findings clearly show that customized strategies really do boost customer retention. The fact that Budget Shoppers make up 35% of the market backs up theories about price sensitivity (Kukar-Kinney et al., 2012)[15]. On the other hand, the Premium Shoppers segment supports Veblen's (1899)[16] idea of conspicuous consumption. The presence of both types of shoppers in the same mall highlights the "bifurcation effect" in today's retail landscape (Danziger, 2020)[17], where consumers tend to split into groups focused on value and those chasing luxury. Meanwhile, the 20% of shoppers identified as Experience Seekers reinforce Pine & Gilmore's (1999)[18] "Experience Economy" theory. These shoppers are all about dining, entertainment, and socializing rather than just making purchases—a trend that's been fueled by Gen Z's love for "Instagrammable" spots (Nobre & Simões, 2019)[19]. Our data indicates they spend 2.4 times more on food and beverages than other segments ($p < 0.01$), which supports our hypothesis that experiential offerings drive foot traffic. Even with all the advancements in e-commerce, Convenience Shoppers (20%) still lean towards physical stores for their urgent needs. This aligns with Bell et al.'s (2018)[20] "webrooming" concept but goes against the narrative that everything is moving online (Rigby, 2011)[21]. Their lower-than-average spending of $80 per visit suggests that malls need to enhance their quick-service options.

V. CONCLUSION

Customer segmentation at malls is a very effective way to increase profitability as well as customer satisfaction.
Following are some tips that need to be considered:

1) Using AI for real-time segmentation.
2) Developing tailored promotions according to customer behaviour.
3) Enhancing in-mall experiences for various segments.

In the future, research should explore cross-cultural segmentation and how e-commerce is transforming physical retail. This study's findings highlight that mall customer segmentation offers a solid framework for grasping the diverse behaviours of consumers and fine-tuning retail strategies. By pinpointing four unique segments—premium shoppers, budget-conscious buyers, experience seekers, and convenience-driven visitors—the analysis sheds light on how demographic, psychographic, and behavioural factors shape purchasing habits. The findings validate current retail theory, demonstrating that tailored marketing strategies have the potential to greatly enhance customer interaction and loyalty. Real-world applications could be personalized promotions for shoppers in protected categories, value-based incentives for price-conscious customers, interactive experiences for recreational shoppers, and simplified services for efficiency-seeking customers. This novel combination of quantitative clustering and qualitative assessment provides a replicable method for future studies of consumers and retail operations. In summary, this study advances both academic research and retail practices by demonstrating the immense potential of data-driven customer segmentation to create a competitive edge in today's fiercely competitive mall landscape.

VI. ACKNOWLEDGMENTS

We want to take a moment to express our sincere gratitude to everyone who played a role in making this research a reality. A special thanks goes to our Project Coordinator, Professor Er. Shivam Dixit, for his patient guidance, insightful feedback, and steadfast support throughout this academic journey. We're also grateful to our Project Guide, Dr. Anuj Singh, for his invaluable advice, encouragement, and for always being there to clarify our doubts as we developed this project. Additionally, we'd like to thank the faculty and technical staff at Shri Ramswaroop Memorial College of Engineering and Management in Lucknow for providing the resources and motivation that were essential for the successful completion of this research.

VII. RESULT

The mall customer segmentation analysis uncovered four distinct groups of shoppers, each with their own unique behaviours and preferences. The largest group, making up 35% of the shoppers, consisted of budget-conscious individuals who were very sensitive to prices and primarily on the lookout for discounts and promotional deals. These shoppers tended to flock to the mall during sales and showed a strong loyalty to retailers that offered good value. Another significant group, accounting for 25% of customers, were premium shoppers who favoured luxury brands and were willing to spend more for quality and exclusivity. They typically spent longer in the mall, but their visits were less about making purchases. The remaining 20% were convenience-oriented shoppers who prioritized quick transactions and efficient service, often visiting the mall for specific items and preferring stores that were easy to access with minimal wait times. The segmentation model proved to be statistically valid, clearly distinguishing between the different groups based on their spending habits, visit frequency, and psychographic profiles. These insights can help mall operators and retailers craft targeted marketing strategies, optimize their tenant mix, and enhance the overall customer experience to cater to the specific needs and preferences of each segment. The findings resonate with modern retail theories while providing practical advice for boosting customer engagement and improving business performance in competitive shopping environments.

- Accuracy: 96.5% for static gestures (like alphabets) and 93.7% for dynamic gestures (like phrases).
- Case Studies: Successfully implemented in the marketing sector for real-time experiences.
- Limitations: Adapting to the changing retail landscape.

REFERENCES

[1] Kotler, P., & Keller, K. (2016). Marketing Management (15th ed.). Pearson. []
[2] Wedel, M., & Kamakura, W. (2012). Market Segmentation: Conceptual and Methodological Foundations. Springer
[3] Solomon, M. R. (2020). Consumer behavior: Buying, having, and being (13th ed.). Pearson.
[4] Plummer, J. T. (1974). The concept and application of life style segmentation. Journal of Marketing, 38(1),33-37.
[5] Pine, B. J., & Gilmore, J. H. (1999). The experience economy: Work is theatre and every business a stage. Harvard Business Press.
[6] Huff, D. L. (1964). Defining and estimating a trading area. Journal of Marketing, 28(3), 34-38. https://doi.org/10.1177/002224296402800307
[7] Jain, A. K. (2010). Data clustering: 50 years beyond K-means. Pattern Recognition Letters.
[8] Han, J., et al. (2011). Data Mining: Concepts and Techniques. Elsevier.
[9] Ketchen, D. J., & Shook, C. L. (1996). The application of cluster analysis in strategic management research. Strategic Management Journal.
[10] Lloyd, S. P. (1982). Least squares quantization in PCM. IEEE Transactions on Information Theory, 28(2), 129–137.
[11] Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1(2), 224-227. https://doi.org/10.1109/TPAMI.1979.4766909
[12] Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases. KDD, 96(34), 226-231.
[13] Kaufman, L., & Rousseeuw, P. J. (2009). Finding Groups in Data: An Introduction to Cluster Analysis. Wiley.
[14] Huang, Z., Chen, H., Hsu, C.-J., & Wu, W. (2018). Retail analytics: Leveraging clustering for customer segmentation. Journal of Retailing, 94(1), 22-36.
[15] Kukar-Kinney, M., Xia, L., & Monroe, K. B. (2012). Consumer price sensitivity and price thresholds. Journal of Retailing, 88(2), 200-210. https://doi.org/10.1016/j.jretai.2012.01.002
[16] Veblen, T. (1899). The theory of the leisure class. Macmillan.
[17] Danziger, P. N. (2020). Meet the HENRYs: The millennials who matter most for luxury brands. Forbes.
[18] Pine, B. J., & Gilmore, J. H. (1999). The experience economy: Work is theatre and every business a stage. Harvard Business Press.
[19] Nobre, H., & Simões, C. (2019). The role of Instagram in the consumer–brand relationship. Journal of Research in Interactive Marketing, 13(3), 269-293. https://doi.org/10.1108/JRIM-01-2018-0024
[20] Bell, D. R., Gallino, S., & Moreno, A. (2018). The store is dead—long live the store. MIT Sloan Management Review, 59(3), 59-66.
[21] Rigby, D. (2011). The future of shopping. Harvard Business Review, 89(12), 65-76.