International Journal of Emerging Research in Science, Engineering, and Management
Special Issue SI-1 (2026), pp. 151–157
Proceedings of Selected Papers from the
National Conference on Emerging Trends in Commerce and Management
(NCETCM-2K26, 30-31 March 2026)
Organized by Andhra Loyola College, Vijayawada, India
www.ijersem.com eISSN- 3107-9075

Consumer Segmentation in Household Appliances Market Using K-Means Clustering

[1]Krishna Babu Sambaru, [2]P. Guru Prasad, [3]Sangeetha Dhanala

[1]Dean of Management, Department of Management Studies, Aditya Degree Colleges, Andhra Pradesh, India.
[2,3]Assistant Professor, Department of MBA Business Analytics, P. B. Siddhartha college of arts and science, Vijayawada, Andhra Pradesh, India.
[1]kbsambaru@gmail.com, [2]guruprasadmbahr@gmail.com, [3]sangeethadhanala17102002@gmail.com

Abstract: In the dynamic and highly competitive household appliances market, understanding diverse consumer needs is critical for effective segmentation and targeted marketing strategies. This study aims to segment consumers based on demographic, behavioural, and psychographic variables using the K-means clustering technique. Primary data were collected from 370 respondents using a structured questionnaire. Variables such as purchase frequency, brand preference, price sensitivity, product usage, and technological awareness were considered. Exploratory Factor Analysis (EFA) was conducted to identify underlying constructs, followed by Confirmatory Factor Analysis (CFA) to validate the measurement model. Structural Equation Modeling (SEM) was applied to examine relationships among variables influencing segmentation. K-means clustering was then used to classify consumers into distinct groups. The results revealed three meaningful segments: price-sensitive buyers, quality-conscious consumers, and tech-savvy premium users. The study highlights the importance of data-driven segmentation in enhancing marketing efficiency and customer satisfaction.

Keywords: Consumer Segmentation, Household Appliances, K-Means Clustering, Machine Learning, EFA.

1 Introduction

The household appliances market has experienced significant expansion in recent years, driven by rapid urbanization, increasing disposable incomes, and continuous technological advancements. Consumers are increasingly adopting modern appliances that enhance convenience, efficiency, and quality of life. However, the diversity in consumer preferences—shaped by economic conditions, lifestyle patterns, and technological awareness—has made the market highly heterogeneous and complex. Traditional segmentation approaches based solely on demographic or geographic variables are often insufficient to capture this multidimensional consumer behavior.

Recent studies emphasize the importance of advanced analytical techniques in understanding consumption patterns. For instance, clustering and classification approaches have been effectively used to analyze residential energy consumption behavior in India, highlighting the relevance of data-driven segmentation in consumer studies [1]. Similarly, segmentation in rural electricity markets demonstrates that consumer groups differ significantly in terms of access, usage, and behavioral characteristics, necessitating more refined analytical frameworks [2]. In the context of household appliances, consumer decisions are increasingly influenced by energy efficiency and sustainability considerations, as evidenced by studies analyzing online consumer reviews and purchasing behavior [3][4].

Furthermore, technological advancements and digital transformation have reshaped consumer expectations, making segmentation based on technology acceptance and innovation adoption crucial. Research indicates that consumer acceptance of in-store and smart technologies varies across segments, reinforcing the need for targeted marketing strategies [5]. Green market segmentation studies also reveal that consumers can be grouped based on environmental consciousness and purchasing behavior, with clustering techniques providing meaningful insights into emerging markets [6]. Additionally, improving energy efficiency in household appliances has become a key global concern, influencing both consumer preferences and policy decisions [7].

Consumer purchasing behavior is also strongly influenced by product-specific attributes such as energy-saving features and functional benefits. Studies focusing on kitchen appliances demonstrate that consumers increasingly rely on online information and reviews when making purchasing decisions [8]. Moreover, segmentation based on sustainability awareness and labeling indicates that consumers differ significantly in their attitudes and usage patterns, further highlighting the need for multidimensional segmentation models [9]. In emerging markets, the growing middle-class population presents new opportunities, but also introduces variability in purchasing power and preferences, making urban-based segmentation strategies particularly relevant [10].

International Journal of Emerging Research in Science, Engineering, and Management
Special Issue SI-1 (2026), pp. 151–157
Proceedings of Selected Papers from the
National Conference on Emerging Trends in Commerce and Management
(NCETCM-2K26, 30-31 March 2026)
Organized by Andhra Loyola College, Vijayawada, India
www.ijersem.com eISSN- 3107-9075

Recent advancements in segmentation methodologies have integrated statistical and machine learning approaches to enhance analytical accuracy. Techniques such as finite mixture partial least squares (FIMIX-PLS) have been used to identify latent consumer segments in emerging product categories [11]. Similarly, robust frameworks combining preference learning with segmentation models have demonstrated improved effectiveness in capturing complex consumer behavior [12]. Among machine learning techniques, K-means clustering has emerged as a widely used method due to its simplicity, scalability, and effectiveness in handling large multidimensional datasets.

In this context, the present study adopts a hybrid analytical framework that integrates traditional statistical techniques—Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM)—with machine learning-based K-means clustering to segment consumers in the household appliances market. By combining these approaches, the study aims to identify meaningful consumer segments and provide actionable insights for marketers to design targeted strategies. This integrated methodology enhances the robustness, reliability, and practical relevance of market segmentation in a rapidly evolving consumer landscape [13][14].

2 Literature Review

Consumer segmentation has long been recognized as a fundamental tool in marketing strategy formulation, enabling firms to identify homogeneous groups within heterogeneous markets and design targeted strategies accordingly. Early studies have emphasized the growing importance of data-driven segmentation techniques in understanding consumer behavior. For instance, clustering and classification methods have been effectively applied to categorize residential electricity consumption patterns, demonstrating the ability of analytical models to uncover distinct consumer groups based on usage behavior [1]. Similarly, segmentation in rural electricity markets highlights the heterogeneity among consumers in terms of access, affordability, and consumption patterns, reinforcing the need for advanced segmentation frameworks [2].

In the domain of household appliances, consumer preferences are increasingly shaped by energy efficiency, sustainability concerns, and product performance. Empirical evidence based on e-commerce reviews indicates that consumers actively consider energy-saving features when purchasing appliances, reflecting a shift toward environmentally conscious decision-making [3][4]. This evolving behavior necessitates segmentation approaches that incorporate both behavioral and attitudinal variables. With the advancement of retail technologies, segmentation based on technology acceptance has gained importance. Studies show that consumer adoption of in-store and smart technologies varies significantly across segments, highlighting the role of innovation and technological readiness in shaping purchasing behavior [5].

Additionally, green market segmentation research demonstrates that consumers can be effectively grouped based on environmental awareness and sustainability-oriented preferences, with clustering techniques providing meaningful insights into emerging markets [6]. From a broader perspective, improving energy efficiency in household appliances has become a global priority, influencing both consumer choices and policy interventions [7]. Further research has examined the role of product-specific attributes and information sources in shaping consumer decisions. For example, studies on kitchen appliances reveal that online reviews and digital information significantly influence purchase behavior, indicating the growing importance of digital platforms in consumer decision-making [8].

Moreover, segmentation based on sustainability labels and awareness levels suggests that consumers differ widely in their attitudes and usage patterns, further supporting the need for multidimensional segmentation models [9]. In emerging markets, the expansion of the middle-class population has introduced new consumption patterns, making urban-based segmentation strategies critical for capturing market potential [10]. Recent advancements in segmentation methodologies have focused on integrating traditional statistical approaches with machine learning techniques. Methods such as finite mixture partial least squares (FIMIX-PLS) have been successfully applied to identify latent consumer segments in emerging product categories [11].

Additionally, robust frameworks that combine preference learning with segmentation models have demonstrated improved capability in capturing complex consumer behavior [12]. These approaches highlight the increasing relevance of hybrid analytical frameworks in segmentation research. Overall, the literature indicates a clear shift from traditional segmentation methods toward more sophisticated, data-driven approaches that integrate statistical and machine learning techniques. The combination of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM), and clustering methods such as K-means provides a comprehensive and reliable framework for analyzing consumer behavior. This integrated approach forms the foundation for the present study, which aims to develop a robust segmentation model for the household appliances market.

International Journal of Emerging Research in Science, Engineering, and Management
Special Issue SI-1 (2026), pp. 151–157
Proceedings of Selected Papers from the
National Conference on Emerging Trends in Commerce and Management
(NCETCM-2K26, 30-31 March 2026)
Organized by Andhra Loyola College, Vijayawada, India
www.ijersem.com eISSN- 3107-9075

3 Research Methodology

This study adopts a descriptive and analytical research design to examine consumer segmentation in the household appliances market. The descriptive approach facilitates a systematic understanding of consumer characteristics, while the analytical component enables the identification of relationships among variables and the classification of consumers into meaningful segments. A quantitative research framework was employed, as it allows for statistical validation and generalization of findings.

3.1. Data Collection and Sampling Design

Primary data were collected through a structured questionnaire administered to 370 respondents. The sample size was considered adequate for multivariate statistical analysis, including factor analysis and clustering techniques. A convenience sampling method was adopted due to accessibility and time constraints; however, efforts were made to ensure diversity in terms of demographic characteristics such as age, income, education, and occupation. The questionnaire was designed based on established scales from prior studies and consisted of three major sections: (i) demographic profile, (ii) consumer behaviour variables, and (iii) psychographic and preference-related attributes. A five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) was used to measure respondents' perceptions. The instrument was pre-tested to ensure clarity, reliability, and content validity.

3.2. Measurement of Variables

The study incorporates multiple constructs to capture consumer behaviour comprehensively. Key variables include price sensitivity, brand preference, and technological awareness, which are widely recognized determinants in consumer decision-making for durable goods. These constructs were operationalized using multiple observed indicators to enhance measurement accuracy. Reliability and validity of the constructs were assessed using Cronbach's alpha, Average Variance Extracted (AVE), and Composite Reliability (CR) during later stages of analysis.

3.3. Data Analysis Framework

The data analysis was conducted in a systematic multi-stage process integrating both traditional statistical techniques and machine learning approaches to ensure robustness and depth of insights. In the first stage, Exploratory Factor Analysis (EFA) was performed using Principal Component Analysis (PCA) with Varimax rotation to identify the underlying factor structure of the observed variables. The suitability of the data for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. Factors with eigenvalues greater than one were retained.

In the second stage, Confirmatory Factor Analysis (CFA) was employed to validate the measurement model derived from EFA. Model fit was evaluated using standard indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Convergent and discriminant validity were also assessed. In the third stage, Structural Equation Modeling (SEM) was utilized to examine the causal relationships among latent constructs. SEM provides a comprehensive framework that combines factor analysis and regression, allowing for simultaneous estimation of multiple relationships and testing of theoretical hypotheses.

In the final stage, K-means clustering, a widely used unsupervised machine learning algorithm, was applied to segment consumers into homogeneous groups based on their behavioral and psychographic characteristics. The optimal number of clusters was determined using interpretability and within-cluster variance criteria. This clustering approach enables the identification of distinct consumer segments with similar preferences and purchasing patterns.

3.4. Research Questions

The study is guided by the following research questions:

1. What are the key factors influencing consumer behaviour in the household appliances market?
2. Can consumers be effectively segmented using K-means clustering?
3. How do different consumer segments vary in terms of preferences and purchasing behaviour?

International Journal of Emerging Research in Science, Engineering, and Management
Special Issue SI-1 (2026), pp. 151–157
Proceedings of Selected Papers from the
National Conference on Emerging Trends in Commerce and Management
(NCETCM-2K26, 30-31 March 2026)
Organized by Andhra Loyola College, Vijayawada, India
www.ijersem.com eISSN- 3107-9075

3.5. Research Objectives

The primary objectives of the study are:

1. To identify the key factors influencing consumer purchase behaviour in the household appliances market.
2. To segment consumers using K-means clustering based on behavioral and psychographic variables.
3. To analyze the differences among identified consumer segments.
4. To provide strategic recommendations for marketers based on segmentation insights.

3.6. Hypotheses Development

Based on the literature and conceptual framework, the following hypotheses are formulated:
H1: Consumer behaviour factors significantly influence market segmentation.
H2: Price sensitivity has a significant impact on purchase decisions.
H3: Brand preference significantly influences consumer segmentation.
H4: Technological awareness positively influences the formation of premium consumer segments.

4 Data Analysis

This section presents the empirical results obtained through a multi-stage analytical framework comprising Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Structural Equation Modeling (SEM), and K-means clustering. The objective is to identify latent constructs, validate the measurement model, examine structural relationships, and classify consumers into meaningful segments.

4.1. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis was conducted using Principal Component Analysis (PCA) with Varimax rotation to uncover the underlying factor structure of consumer segmentation variables. The adequacy of the dataset for factor analysis was first assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity.

Table 1. KMO and Bartlett's Test

Measure	Value
Kaiser-Meyer-Olkin (KMO)	0.821
Bartlett's Test of Sphericity (Chi-square)	1256.34
Degrees of Freedom	36
Significance (p-value)	0.000

As shown in Table 1, the KMO value of 0.821 indicates meritorious sampling adequacy, while the significant Bartlett's test ($p < 0.001$) confirms that the correlation matrix is suitable for factor analysis. The communalities of the variables were examined to determine the proportion of variance explained by the extracted factors.

Table 2. Communalities

Item	Initial	Extraction
PS1	1.000	0.642
PS2	1.000	0.701
PS3	1.000	0.668
BP1	1.000	0.724
BP2	1.000	0.758
BP3	1.000	0.735
TA1	1.000	0.689
TA2	1.000	0.812
TA3	1.000	0.774

From Table 2, all communalities exceed the threshold of 0.60, indicating that the extracted factors explain a substantial portion of variance in each observed variable. The total variance explained by the extracted components is presented in Table 3.

Table 3. Total Variance Explained

Component	Eigenvalue	% of Variance	Cumulative %
Factor 1 (Price Sensitivity)	2.45	27.22	27.22
Factor 2 (Brand Preference)	2.18	24.18	51.40
Factor 3 (Technology Awareness)	1.96	21.78	73.18

As indicated in Table 3, three factors with eigenvalues greater than one were retained, collectively explaining 73.18% of the total variance, which exceeds the acceptable threshold of 60% and indicates a strong factor structure. The rotated component matrix provides insight into the factor loadings of each variable.

Table 4. Rotated Component Matrix (Varimax Rotation)

Items	Price Sensitivity	Brand Preference	Technology Awareness
PS1	0.801		
PS2	0.824		
PS3	0.765		
BP1		0.842	
BP2		0.861	
BP3		0.835	
TA1			0.821
TA2			0.884
TA3			0.857

As shown in Table 4, all factor loadings exceed 0.70 on their respective constructs, with no significant cross-loadings, confirming strong convergent and discriminant validity. To further assess internal consistency, reliability analysis was conducted using Cronbach's alpha.

Table 5. Reliability Analysis (Cronbach's Alpha)

Factor	No. of Items	Cronbach's Alpha
Price Sensitivity	3	0.78
Brand Preference	3	0.81
Technology Awareness	3	0.84

As presented in Table 5, all constructs exhibit Cronbach's alpha values above 0.70, indicating satisfactory internal consistency and reliability. Overall, the EFA results confirm a robust three-factor structure comprising Price Sensitivity, Brand Preference, and Technology Awareness. The measurement model is deemed suitable for further validation using CFA and SEM.

4.2. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis was conducted to validate the measurement model derived from EFA. Model fit indices were evaluated against recommended thresholds.

Table 6. Confirmatory Factor Analysis (CFA) Results

Fit Index	Value	Recommended
CFI	0.94	> 0.90
TLI	0.92	> 0.90
RMSEA	0.048	< 0.08
AVE	0.52	> 0.50
CR	0.80	> 0.70

As shown in Table 6, all fit indices satisfy the recommended thresholds, confirming that the measurement model demonstrates good fit, convergent validity, and construct reliability.

International Journal of Emerging Research in Science, Engineering, and Management
Special Issue SI-1 (2026), pp. 151–157
Proceedings of Selected Papers from the
National Conference on Emerging Trends in Commerce and Management
(NCETCM-2K26, 30-31 March 2026)
Organized by Andhra Loyola College, Vijayawada, India
www.ijersem.com eISSN- 3107-9075

4.3. Structural Equation Modeling (SEM)

Structural Equation Modeling was employed to examine the causal relationships among the identified constructs.

Table 7. Structural Equation Modeling (SEM) Results

Path	Estimate	p-value	Result
Price Sensitivity → Purchase	0.42	< 0.001	Supported
Brand Preference → Purchase	0.35	< 0.01	Supported
Technology Awareness → Purchase	0.47	< 0.001	Supported

As indicated in Table 7, all hypothesized relationships are statistically significant. Technology awareness exhibits the strongest influence on purchase decisions, followed by price sensitivity and brand preference.

4.4. K-Means Clustering Analysis

To identify distinct consumer segments, K-means clustering was applied using the extracted factor scores.

Table 8. K-Means Clustering Results

Cluster	Description	Characteristics
Cluster 1	Price Sensitive	Low income, high price concern
Cluster 2	Quality Conscious	Moderate income, brand-focused
Cluster 3	Tech-Savvy	High income, innovation-driven

As presented in Table 8, three distinct consumer segments were identified. The segmentation reveals clear differences in purchasing behavior, where price-sensitive consumers prioritize affordability, quality-conscious consumers emphasize brand reliability, and tech-savvy consumers focus on innovation and advanced feature.

5 Discussion And Conclusion

The study identified three distinct consumer segments in the household appliances market using K-means clustering, namely price-sensitive, quality-conscious, and tech-savvy consumers. The integration of Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modeling (SEM) ensured robustness in identifying key constructs and validating their relationships. Price-sensitive consumers prioritize affordability and discounts, while quality-conscious consumers focus on brand reliability and product durability. In contrast, tech-savvy consumers emphasize innovation, advanced features, and smart technologies. The findings highlight the need for differentiated marketing strategies tailored to each segment. Budget-oriented pricing and promotional offers are effective for price-sensitive consumers, whereas brand positioning and quality assurance appeal to quality-conscious buyers. Premium branding and technology-driven innovations are more suitable for tech-savvy consumers. Overall, the study contributes to both theoretical and practical domains by demonstrating the effectiveness of integrating machine learning techniques with traditional statistical methods for enhanced consumer segmentation and strategic decision-making.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

REFERENCES

[1] S. Palaniappan, S. Karuppannan, and D. Velusamy, "Categorization of Indian residential consumers electrical energy consumption pattern using clustering and classification techniques," *Energy*, vol. 289, p. 129992, Dec. 2023, doi: 10.1016/j.energy.2023.129992.

[2] D. R. Thomas, S. Agrawal, S. P. Harish, A. Mahajan, and J. Urpelainen, "Understanding segmentation in rural electricity markets: Evidence from India," *Energy Economics*, vol. 87, p. 104697, Feb. 2020, doi: 10.1016/j.eneco.2020.104697.

[3] C. Guan and B. Lin, "Do consumers concern about energy saving in purchasing energy-efficient home appliances? Evidence from online e-commerce review," *Energy Policy*, vol. 193, p. 114277, Aug. 2024, doi: 10.1016/j.enpol.2024.114277.

[4] C. Guan and B. Lin, "Do consumers concern about energy saving in purchasing energy-efficient home appliances? Evidence from online e-commerce review," *Energy Policy*, vol. 193, p. 114277, Aug. 2024, doi: 10.1016/j.enpol.2024.114277.

[5] A. Namin, R. P. Jindal, D. K. Gauri, B. T. Ratchford, and S. C. Ketron, "Consumers' acceptance of in-store technologies through the lens of segmentation," *Journal of Business Research*, vol. 207, p. 116010, Jan. 2026, doi: 10.1016/j.jbusres.2026.116010.

[6] D. Jaiswal, V. Kaushal, P. K. Singh, and A. Biswas, "Green market segmentation and consumer profiling: a cluster approach to an emerging consumer market," *Benchmarking an International Journal*, vol. 28, no. 3, pp. 792–812, Nov. 2020, doi: 10.1108/bij-05-2020-0247.

[7] A. Hughes and R. Larmour, "Assessment of the potential to improve the energy efficiency of household appliances in South Africa," *Energy Strategy Reviews*, vol. 56, p. 101595, Nov. 2024, doi: 10.1016/j.esr.2024.101595.

[8] C. Guan and B. Lin, "Why do consumers purchase energy-efficient kitchen appliance? An analysis based on online review comments," *Journal of Environmental Management*, vol. 373, p. 123791, Dec. 2024, doi: 10.1016/j.jenvman.2024.123791.

[9] J.-L. Vázquez, A. Lanero, J. A. García, and X. Moraño, "Segmentation of consumers based on awareness, attitudes and use of sustainability labels in the purchase of commonly used products," *Sustainable Production and Consumption*, vol. 38, pp. 115–129, Apr. 2023, doi: 10.1016/j.spc.2023.03.025.

[10] I. Kardes, "Reaching middle class consumers in emerging markets: Unlocking market potential through urban-based analysis," *International Business Review*, vol. 25, no. 3, pp. 703–710, Mar. 2016, doi: 10.1016/j.ibusrev.2016.03.005.

[11] P. Guru Prasad, Naziya Sultana and S N Sai Mohan, "Uncovering Customer Archetypes in Direct-to-Consumer Apparel: A K-Means Clustering Analysis of DMart Sales Data," *International Journal of Emerging Research in Science Engineering and Management*, vol. 2, no. si1, pp. 144–150, May. 2026, doi: 10.66710/ijersem.v2si1.19.

[12] S. Amirnequiee, J. Naoum-Sawaya, and H. Pun, "Robust framework for the joint learning of consumer preferences and market segmentation," *Omega*, vol. 138, p. 103410, Aug. 2025, doi: 10.1016/j.omega.2025.103410.

[13] B. R. Kumar, A. Madhuri, M. Shireesha, S. Melchior Reddy, "Exploring the Impact of Social Media Influencers on Consumer Behavior and Brand Loyalty in the Digital Age," *Community Practitioner*, vol. 21, no. 06, pp. 2656–2676, 2024. doi:10.5281/zenodo.12592520.

[14] Thakrar Pooja Tulshibhai, N. D. Zala, "An Analysis of the Variables Influencing Consumers' Purchasing Decisions for Organic Food Items in Rajkot," *International Journal of Emerging Research in Engineering, Science, and Management*, vol. 4, no. 1, pp. 31-36, 2025. doi: 10.58482/ijeresm.v4i1.4.