AI-DRIVEN CUSTOMER SEGMENTATION: A SYSTEMATIC LITERATURE REVIEW

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Abstract

In the age of data-driven marketing, Artificial Intelligence (AI) is at the center of customer segmentation, helping businesses understand the behavior and preferences of customers better. Customer segmentation is a fundamental strategy that businesses use to customize their marketing strategies, improve customer satisfaction, and maximize resource allocation. With the introduction of artificial intelligence (AI), the conventional methods of segmentation are no longer the same as it allows more accurate and dynamic segmentation of customers. This systematic literature review discusses the application of AI-based methods in customer segmentation and the recent developments, methodology, and applications. The review discusses the use of machine learning, deep learning, and natural language processing in the analysis of customer data to discover trends and predict behaviors. The research further classifies the methods of segmentation on the basis of demographic, behavioral, psychographic, and sentiment analysis. This study is based on secondary data to analyze and interpret the data. The research will prove to be of immense use to the researchers and practitioners to improve the strategies of targeting customers and managing the relationship with the customers.

Keyword: *Artificial Intelligence, Customer insights, CRM, Systematic Review, Segmenting, Targeting, Positioning.*

INTRODUCTION

In today's highly competitive business environment, understanding customer behavior is crucial for developing effective marketing strategies, improving customer experience, and driving business growth. Customer segmentation is a fundamental marketing strategy that allows businesses to identify and group consumers based on shared characteristics, preferences, and behaviors. Traditional segmentation methods rely on demographic, geographic, psychographic, and behavior information; however, with advancements in artificial intelligence (AI), more recent and dynamic segmentation frameworks have been established (Islam, 2024). AI customer segmentation employs machine learning algorithms, deep learning mechanisms, and predictive analytics to manage large datasets and identify complex patterns that may avoid traditional approaches (Rosario, 2025). The uses of AI customer segmentation cut across multiple industries, from retail, finance, healthcare, and e-commerce. In retail, AI segmentation helps companies predict buying habits, optimize inventories, and make personalized recommendations (Bhardwaj, 2025). Banks and financial institutions use AI to segment customers based on spending habits, credit risk assessment, and fraud detection, thus risk management is optimized (Bulut, 2024). E- commerce giants Amazon and Netflix rely on AI customer analytics to provide personalized product recommendations and enhance user experience, immensely enhancing customer satisfaction and loyalty (Mirza, 2025).

Customer segmentation has evolved with industrial progress, from basic grouping in Industry 1.0 to AI-driven analysis in Industry 4.0**.** During Industry 1.0**,** businesses used simple segmentation based on location and income due to limited data. Industry 2.0 introduced mass production**,** leading to demographic segmentation based on age, gender, and income, supported by print and radio marketing. With the rise of Industry 3.0**,** computers and the internet enabled behavioral segmentation, where businesses analyzed customer purchase history and online activity. Today, Industry 4.0 leverages AI, machine learning, and big data for real-time, personalized segmentation**,** helping industries like retail, banking, and healthcare predict customer needs and optimize marketing strategies. AI – Enabled Customer Relationship Management (CRM) revolutionizes how industry interact with their customers, offering innovative solutions to improve customer engagement, streamline processes and drive business growth.

REVIEW OF LITERATURE

Theoretical Foundations of AI-Driven Marketing

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Market segmentation theory, introduced by (Smith, 1956) posits that businesses must divide heterogeneous markets into smaller, homogeneous groups to effectively target consumers. Traditional segmentation relies on demographic, geographic, psychographic, and behavioral criteria. AI-driven segmentation expands upon this theory by employing machine learning (ML) algorithms to uncover hidden consumer patterns that traditional methods may overlook (Islam, 2024). CRM theory focuses on managing customer interactions to enhance loyalty and satisfaction. AI-driven CRM builds upon this by integrating predictive analytics, recommendation engines, and sentiment analysis to segment customers based on engagement levels and preferences (Choudhary, 2024).

Evolution from Traditional to AI-Driven Customer Segmentation

Early segmentation models were based primarily on rule-based methods using static data points of income, gender, and age (Kotler, 2020). While effective, the methods were rigid and were not capable of dealing with dynamic customer behavior changes (Dolnicar, 2018). Big data analysis and AI-driven algorithms delivered companies from static segmentation, offering dynamic and real-time customer clustering based on behavior (Ngai, 2009). AI-driven segmentation is more accurate and personalized, leading to higher engagement and conversion rates (Wang, 2022).

AI's Role in B2B Marketing and CRM Systems

While AI has been widely used in Business-to-Consumer (B2C) marketing, its potential in Business-to-Business (B2B) marketing is still being explored. However (Saura, 2021) suggests that AI-powered Customer Relationship Management (CRM) systems can revolutionize B2B marketing by automating tasks, improving sales forecasting, and enhancing customer service. AI-driven systems enable businesses to analyze customer data more effectively, make data-driven decisions, and improve customer satisfaction and retention. (Babina, 2024) Additionally, AI is being adopted in B2B marketing to streamline processes like account-based marketing and targeted outreach, allowing businesses to identify high-value leads and tailor marketing campaigns to specific accounts with relevant content. (Ahmed, 2024)

AI Techniques in Customer Segmentation

Machine Learning Algorithms helps supervised and unsupervised learning models, such as k-means clustering, decision trees, and neural networks, help companies segment customers based on a number of variables (Tsai, 2020). Natural Language Processing (NLP) examines customer reviews, feedback, and social media to decipher sentiment and segment customers based on it (Cambria, 2017).Deep Neural Networks helps is advanced deep neural networks allow businesses to uncover hidden patterns within customer data and create hyper-personalized experiences (Goodfellow, 2016) Reinforcement Learning provide that the AI learns customer behavior in real-time and dynamically optimizes segmentation models (Sutton, 2018).

Personalized Recommendations

Customer segmentation has evolved from rule-based approaches to AI-driven models that analyze consumer behavior in real time (Ricci, 2015). Early recommendation systems used collaborative filtering (CF) and content-based filtering (CBF) to provide generic customer segmentation (Schein, 2002).However, deep learning (DL), natural language processing (NLP), and reinforcement learning (RL) have enabled more accurate, scalable, and context-aware personalized recommendations (Jannach, 2019).Recent research highlights the shift toward hybrid recommendation models that integrate customer segmentation techniques, big data, and AI-driven decision-making (Zhou, 2020)

Industry Applications of Personalized Recommendations in Customer Segmentation

Retail and E-commerce aligns with amazon and alibaba use AI to analyze purchase history and browsing behavior to recommend products (McAuley, 2015).Streaming and Entertainment use netflix and spotify both apply AI segmentation to make personalized recommendations. (Gomez-Uribe, 2016) Finance and Banking allows the banking sector to provide customized loan offers, investment recommendations, and credit card offers (Li, 2020). Health and Wellness assists in tailored treatment regimens, exercise recommendations, and preventive healthcare segmentation (Topol, 2019).Online Education & Learning offer customized learning content and courses according to student behavior (Zhou, 2020).

AI-driven Predictive Analytics in Marketing

AI helps businesses track customer engagement across various channels and adjust strategies in real-time. For example, AI can: (a) identify when customers are about to abandon their online shopping carts and send targeted offers to increase conversions.(b) Enable dynamic pricing models that adjust prices based on consumer demand and behavior, maximizing revenue. This provides businesses with advanced insights to optimize their marketing strategies and boost sales. (Researcher, 2024) AI-driven predictive analytics uses historical data to forecast future consumer behavior. This allows businesses to tailor their marketing

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strategies and stay ahead of the curve. By analyzing data trends and patterns, AI can identify current preferences and predict future trends, providing valuable insights. This shift from descriptive to predictive analytics is a significant evolution in market research, enabling businesses to anticipate what will happen rather than just understanding what happened. (Islam., 2024)

Challenges in AI-Driven Customer Segmentation

The integration of customer data in AI systems raises significant concerns regarding data privacy and compliance (Lipton, 2018). Furthermore, AI segmentation can perpetuate biases if the training data is imbalanced, leading to unfair outcomes (Mehrabi, 2021). Additionally, the lack of transparency in deep learning models and other AI systems, often referred to as "black boxes," poses interpretability issues, making it challenging to understand the decision-making processes (Barredo Arrieta, 2021).

Future Actions for AI-Driven Customer Segmentation

To make AI-driven customer segmentation better, future research should focus on keeping customer data safe using secure AI methods like federated learning (Gao, 2024) AI should also be fair so that it does not treat some customer groups unfairly (Kesswani, 2024). Making AI easier to understand will help businesses trust AI decisions. AI should also be combined with human knowledge to make marketing more effective, and cheaper AI solutions should be developed so that small businesses can also use them. (Islam, 2024).

Research Objective
1. To examine how gender influences grocery spending and how lifestyle choices vary across different geographical regions
2. To develop AI-ML models for predicting consumer spending patterns

RESEARCH GAP

AI helps overcome several weaknesses of traditional customer segmentation. First, traditional methods struggle to identify hidden patterns because they rely on straightforward criteria like age, income, or past purchases instead of analyzing deeper connections. AI resolves this by identifying intricate connections in data. Second, traditional approaches don't have predictive segmentation, which means they don't forecast future behavior they just examine historical behavior. AI fills this gap by forecasting trends and helping businesses plan ahead. Lastly, traditional methods cannot fully process unstructured data like social media, reviews, and images, while AI can analyze this information for deeper insights using AI tools like Meta Business Suite. These improvements make AI-driven segmentation more accurate and effective.

Hypothesis
H1: There is a significant difference in vegetable spending between males and females. H2: There is no significant difference in milk spending between males and females.
H3: There is no significant difference in grocery spending between males and females.
H4: There is a marginally significant difference in frozen item spending, with females tending to spend more.
H5: There is an association between Regions and Lifestyle.

RESEARCH METHODOLOGY

This study employed a **quantitative research design** using **secondary data** to analyze the relationship between gender and spending habits on various grocery categories, as well as the association between lifestyle and regions. The objective was to examine whether significant differences exist in spending patterns based on demographic factors and to determine the relationship between geographical factors and psychographic factors.

The study utilized **secondary data** obtained from existing datasets related to consumer spending. The dataset comprised information on consumer demographics, spending on vegetables, milk, grocery, and frozen items, as well as lifestyle classifications and regional distributions. After cleaning and preprocessing, the final dataset was analyzed using statistical methods.

For data analysis, **IBM SPSS Statistics (Version 23)** was used to conduct **independent t-tests** and **chi-square tests**: The independent t-test was used to examine whether there were significant differences in spending on vegetables, milk, grocery, and frozen items between male and female consumers. This test helped determine if gender had a statistically significant impact on spending behavior. The chi-square test was conducted to analyze the association between lifestyle categories and regions, assessing whether there was a significant relationship between consumers' lifestyle choices and their geographical locations. The dataset for this study was obtained from the UCI Machine Learning Repository.

Data Analysis and Interpretation Reliability of the variables

Table: 1 Reliability Statistics

Cronbach's Alpha	N of items
.643	13

Cronbach's Alpha was calculated to assess the internal consistency of the **data**, yielding a value of **0.643**, indicating **moderate reliability**.

Table: 2 Mean difference for Vegetable, Milk, Grocery, Frozen with respect to Gender

Variable	Male		Female				
	M	SD	M	SD	Mean Difference	t	p
Vegetable	10809.82	10939.65	13257.53	14147.866	-2447.714	-2.022	0.042
Milk	5668.62	7195.187	5931.07	7585.610	-262.451	-.372	0.710
Grocery	7778.70	8675.051	8133.53	10323.313	-354.834	-.391	0.696
Frozen	2678.15	3735.729	3487.79	5787.395	-809.635	-1.753	0.080

H1: Gender → Vegetable Spending (Supported, p = 0.042)

The hypothesis that gender plays a significant role in vegetable spending holds well (p = 0.042). The results indicate that female spend much more on vegetables when compared to male. Since the p-value is less than the conventional value of 0.05, we can conclude that gender has a significant statistical effect on vegetable spending.

H2: Gender → Milk Spending (Not Supported, p = 0.710)

There is no evidence of a correlation between milk expenditure and gender (p = 0.710). This high p-value indicates that the difference in milk expenditures between males and females is not statistically significant. The findings suggest that milk purchases are not significantly influenced by gender.

H3: Gender → Grocery Spending (Not Supported, p = 0.696)

There is no evidence to support the hypothesis that grocery spending is influenced by gender (p = 0.696). There is no statistical evidence to support a significant difference between the grocery spending habits of male and female because the p-value is significantly higher than the 0.05 significance level.

H4: Spending on Frozen Goods → Gender (Marginally Supported, p = 0.080)

Spending on frozen foods and gender have a marginally supported relationship (p = 0.080). Despite not being statistically significant at the 0.05 level, this result is close and may indicate a trend in which female spend more money on frozen goods than male. To verify this possible discrepancy, more investigation with a bigger sample size might be required.

Table: 3 Cross tabulation between Lifestyle and Region

	Region		
Lifestyle	Urban	Semi-Urban	Rural
Vegan	80	49	22
Organic	71	46	33
Sustainability	72	36	31

The information demonstrates that regional differences exist in lifestyle choices. Urban areas have   the highest percentage of vegans (80), while semi-urban (49) and rural (22) areas have significantly lower rates. Because fresh produce is more readily available in rural areas, organic living is more widely distributed, with 71 people living in urban areas, 46 in semi-urban areas, and 33 in rural areas. Additionally, urban areas are the most popular for sustainability (72), followed by semi- urban (36) and rural (31).

All three lifestyles are most widely adopted in urban areas, whereas rural areas are less interested in sustainable and vegan lifestyles. Organic living, however, is more evenly distributed throughout   the world. These results imply that lifestyle choices are influenced by urbanization, with cities offering more sustainable and vegan options.

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Table: 4 Chi-Square

	Value	df	Sig
Pearson Chi-Square	4.027	4	.402
Likelihood Ratio	4.168	4	.384
Liner-by-Linear Association	.766	1	.381

There is no statistically significant correlation between lifestyle and region, according to the results of the Chi-Square test (Table 4; p-value = 0.402, > 0.05). This implies that regional variations (Urban, Semi-Urban, Rural) have no impact on lifestyle choices (Vegan, Organic, and Sustainability). This implies that lifestyle adoption may be more influenced by other factors than location, such as socioeconomic status, information availability, or personal values. (Williams, 2017)

Cluster Analysis on Spending (Low, Medium, High)

To further analyze spending behavior, a K-Mean was applied to segment consumers into three clusters: Low, Medium, and High spenders. The segmentation was based on the total spending variable.
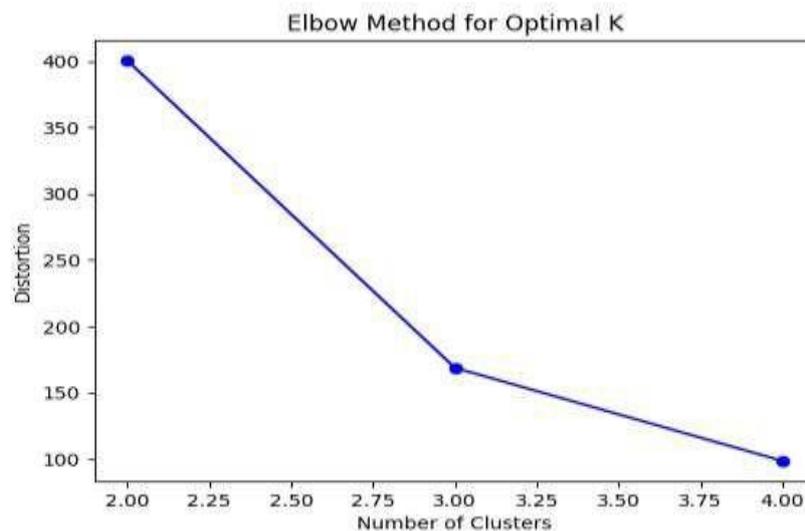
The ideal number of clusters for the dataset was determined using the Elbow Method. The plot indicates that the distortion reduces with an increase in the number of clusters. But at K = 3, the rate of decline slows considerably, creating an "elbow" point. This implies that the optimal balance between simplicity and accuracy is offered by three clusters. As a result, the ideal number of clusters for this investigation is K = 3.

Table: 5 No. of cluster in each clusters

0	19198.12
1	48691.12
2	135674.00

The clustering results show three customer groups based on spending. **Cluster 0 (Low Spending)** has **19,198.12** customers, making it the smallest group. **Cluster 1 (Medium Spending)** includes **48,691.12** customers, forming a moderate-sized segment. **Cluster 2 (High Spending)** is the largest, with **135,674.00** customers. This means most customers are high spenders, while fewer belong to the low-spending group. These insights can help businesses create better marketing strategies, such as offering discounts to low spenders and loyalty rewards to high spenders.

FINDINGS

The analysis conclusions provides on the relationships between lifestyle and geography as well as the relationship between gender and spending on different food categories. The findings provide insight into patterns of consumer behavior by highlighting significant, marginal, and non- significant relationships.
According to the findings, there is a trend that is statistically significant between gender and vegetable

spending **(p = 0.042)**, indicating that women spend more money on vegetables than men do. It can be inferred that gender significantly influences vegetable purchases because the p-value is less than the conventional of 0.05. This is consistent with earlier research that indicates women are more likely to buy fresh produce and make healthier food choices (Smith L. C., 2019)

On the other hand, no significant correlation between gender and milk expenditure was discovered (p = 0.710), suggesting that there is not a significant variation in milk expenditure between males and females. In line with the results of earlier research, this implies that household consumption habits may have a greater impact on milk consumption patterns than individual gender differences (Brown, 2018). Men and women spend similarly on general grocery items, as gender has no significant impact on grocery spending (p = 0.696). The lack of a significant difference implies that household size, income, and frequency of shopping may have a greater impact on grocery spending than gender alone (Jones, 2020)

A marginal relationship was observed between gender and spending on frozen good**s** (p = 0.080), indicating a possible trend where females may spend slightly more on frozen products compared to males. Although the result is not statistically significant at the 0.05 level. This finding is in line with studies suggesting that women may prefer convenience foods, including frozen items, due to time constraints and household responsibilities. (Lee, 2021)

Overall, these findings provide valuable insights into consumer spending behaviors and lifestyle choices. While gender significantly influences vegetable spending, it has little to no impact on milk, grocery, or frozen food expenditures. Additionally, lifestyle preferences appear to be independent of geographic location, indicating that external factors such as personal beliefs and economic conditions may play a more significant role in shaping consumer behavior.

CONCLUSION

The demand for AI-driven customer segmentation is expected to grow as businesses seek better ways to personalize marketing and improve customer retention. AI's ability to analyze large amounts of data will help companies make smarter, data-driven decisions. This study found that gender affects vegetable spending, with females spending more, but it has no significant impact on milk, grocery, or frozen food spending. Additionally, lifestyle choices are not influenced by region, suggesting that personal values and socioeconomic factors play a bigger role than location.

These findings show that consumer behavior is complex and influenced by multiple factors. AI-driven segmentation can improve accuracy by going beyond basic demographics, helping businesses create more personalized and effective marketing strategies.

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