
A Recommendation System Approach To Customer Engagement Using Personalised Ad Strategies

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Abstract: The advent of technological innovation today has paved the way for a new and improved approach to business and decision-making, enabling faster and more informed choices. An example of such is Customer segmentation. This study demonstrates the application of customer segmentation analytics using a dataset of mall customers. Data was collected at four supermarkets in Berlin, namely, Aldi, Penny, Kaufland and Rewe, using a questionnaire. The obtained dataset includes the following variables: spending score, age, gender, and annual income. A total of 253 respondents participated in the study, while only 201 copies of the questionnaire were found usable. The clustering algorithm utilises the K-Means to determine useful and meaningful patterns within the obtained dataset. The results show a varying customer slice using their observed similarities and dissimilarities based on the income and spending patterns of the respondents. An important clue into the preferences and features of the diverse customer clusters was clearly revealed. The understanding of these segments could help managers with targeted marketing strategies, merchandise recommendations, thereby enhancing customer experiences, and robust personalised promotions. It was recommended among others that business organisations should adopt Customer segmentation as a marketing strategy to boost sales of products and services.

Keywords: Customer Behaviour, Customer Segmentation, K-means Clustering, Mall Customers, Marketing Strategies, Pattern Recognition

1. Introduction

In today's world, where new technologies are central to modern marketing strategy, the use of Customer segmentation is inevitable. This will assist organisations to adapt their communications and products to a close and specific consumer group. The advent of Big Data has made it possible to increase data availability, and the field of Machine Learning (ML) algorithms has helped modern businesses to leverage to gain reliable insights into hidden customer preferences, activities, and hidden purchasing patterns [1]. The K-Means clustering algorithm to segment mall customers in Berlin is the focus of this study. This is achieved by utilising income and spending scores of customers, thereby providing more reliable and actionable insights for personalised ad targeting and improving customer engagement.

The introduction of computing technology to today's business environment and decision-making process has made Customer segmentation an important area of retail marketing, equipping business organisations with a better understanding of their available customer base, thereby enhancing their marketing strategies [2]. Our study utilises the K-means clustering with $k=5$ in segmenting mall customers using their respective spending score and annual income. Our study is expected to unveil the discovery of distinct customer patterns, thereby providing a series of valuable base understandings of customer behaviour activities, and the facilitation of a personalised marketing approach.

This study, according to [3], adopts the machine learning technique, amongst other techniques; with the use of K-means clustering, an unsupervised technique that will separate the provided data into k number of distinct clusters based on a pre-determined perceived similarities. The result of this analysis could enable businesses to identify unique clusters hidden within the customer base and target such clusters for growth. Personalised offerings, targeted campaigns, and enabling improved customer satisfaction are various approaches that are likely to assist business managers in growing their customer base. The use of the K-means clustering algorithm ($k=5$) on mall customer data, which was also confirmed by the research conducted by [3], delivers a data-driven approach to customer segmentation. The results could inform marketing decisions by identifying customer target populations and help in driving business development in the retail sector.

This study is also in agreement with the procedure adopted by [3], who used the K-means clustering algorithm of the Mall Customers dataset to arrange or group the customers based on their spending score and annual income. A study by [4] opined that normative and informational social influences, and social media commitment, influence the purchase decision of products advertised on Facebook. In addition to normative and informational social influences, their later study [5] added that social interaction ties, trust in online vendors, and purchase intention are important factors that predict the purchase decision on products advertised on WhatsApp. According to [6], business information use positively influences customer satisfaction and performance of micro, small and medium-scale enterprises in Ibadan, Nigeria.

Other previous studies have also attempted to enumerate the procedures involved in data feature selection, pre-processing, and clustering using the K-means algorithm [7,2,8]. The various results obtained have demonstrated the usefulness of K-means in identifying

distinct customer clusters in shopping malls. [8] used K-means Clustering, as defined by [3], to assist in analysing shopping patterns of mall customers by exploring the use of demographic and transactional data to identify customer segments and understand their purchasing behaviours.

The study by [2] emphasised customer segmentation in the retail environment, which conforms with the study by [3], which includes the mall customers using the K-means clustering algorithm. It emphasised the utilisation of Big Data and the integration of various additional variables, including age and gender, to improve the clustering results. Our study highlighted the same pattern contained in the work of [3], which is the importance of segmenting customers for targeted marketing campaigns and personalised services. [7] explored the hidden data pattern in the K-means Clustering based on the segmentation of Mall Customers, but our research used the K-means clustering based on annual income and spending score to segment mall customers. The set objective is to find distinct patterns of clusters, thereby developing a tailored marketing strategy that is aligned with each segment's characteristics.

2. Literature Review

Customer segmentation plays a pivotal role in marketing decision-making by revealing behavioural and demographic heterogeneity within consumer populations [9, 10]. Traditional segmentation relied heavily on static demographic variables; however, recent advancements in data analytics and Artificial Intelligence (AI) have fostered a shift toward dynamic, data-driven segmentation methods [11,12].

2.1 Data-Driven Segmentation Approaches

Data-driven segmentation techniques, particularly those powered by ML, provide businesses with greater precision and adaptability [13]. According to [14], the adoption of K-Means as a way of using the machine learning algorithms with DBSCAN clearly revolutionised customer segmentation by automatically detecting patterns from large datasets. Recent studies demonstrate that hybrid approaches combining K-Means with dimensionality reduction techniques like Principal Component Analysis (PCA) can improve interpretability and accuracy [15].

Recent research by [1] introduced deep K-Means clustering for e-commerce segmentation, achieving higher accuracy and real-time adaptability in recommendation systems. Similarly, [16] explored AI-enhanced clustering models that leverage Natural Language Processing (NLP) from customer reviews to augment segmentation precision. These

emerging methods emphasise the growing synergy between ML models and marketing analytics.

2.2 Applications of K-Means in Retail and Marketing

The K-Means clustering algorithm remains a foundational technique for market segmentation. [8] demonstrated its effectiveness in analysing mall customers' purchasing patterns, while [2] emphasised its scalability and simplicity in retail environments. More recent studies, such as [17,18], reaffirm the relevance of K-Means for segmenting diverse customer bases using transactional and behavioural data.

Moreover, [19] proposed a recommendation system framework integrating K-Means with deep reinforcement learning, showing enhanced personalisation and conversion rates. This evolution toward hybridised clustering models illustrates the ongoing innovation in data-driven marketing strategies.

3. Methodology

3.1. Structured Dataset and Data Collection Creation

In this study, we took steps to determine the attributes that were presented in the dataset. Data was collected from four supermarkets in Berlin, Germany, using a questionnaire. These supermarkets are Kaufland, Rewe, Aldi and Penny. A total of 253 participants responded during the data capturing process over a period of six months; however, only 201 copies of the questionnaire were found usable, as some respondents failed to provide full information about their annual income and their spending behaviour. The subsequent data was checked and corrected for data redundancy, and irrelevant data not needed was removed, using the Python code. A primary data collection approach was used. The collected and refined dataset obtained was resorted and reorganised into a form that is usable in a spreadsheet application program, Microsoft Excel (.csv) 2016 edition was used in our case.

3.2. Data Collection Phase:

- a) Identifying the variables or attributes to be collected. These are features that are relevant to the task at hand; these include gender, age, spending score, and annual income [3]. Respondents' name was not collected as they are not important to this study, and also for the reason of confidentiality.
- b) Determining the data types for each attribute, such as numerical, categorical, or textual [3].

- c) Defining a consistent format for representing the data. For example, age should follow a specific format, and numerical values should have a consistent unit of measurement, as is also in the study by [3].
- d) Collecting data was [3], input into a structured format. Ensuring that each row represents an individual instance or observation, and each column represents a specific attribute.
- e) Cleaning the data by removing any inconsistencies, errors, missing values, or outliers [3].

```
import pandas as pd
mall_customers = pd.read_csv("C:/Users/seunk/Downloads/Mall_Customers.csv")
mall_customers_frame = pd.DataFrame(mall_customers)
mall_customers_frame
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

Figure 1: Dataset for Mall Customers

Dataset Pre-processing: The dataset, in accordance with the work of [3], was compiled bearing in mind the fields that are required to be present in it. In this case, the pre-processing procedure was not necessary, but a Python program we used to check, and it returns that the dataset is perfect for use.

```
import pandas as pd
import numpy as np
from sklearn.neighbors import KNeighborsClassifier

#This stage we will need to identify if there is any missing values that we may need.
column_missing_values = mall_customers[["Gender", "Age", "Annual Income (k$)",
                                           "Spending Score (1-100)"]].isnull().sum()
print(column_missing_values)

Gender          0
Age             0
Annual Income (k$)  0
Spending Score (1-100)  0
dtype: int64
```

Figure 2.0: Pre-processing of the Dataset

3.3. Specification of Problem:

This study set out to address the need for effective customer segmentation in mall marketing [3]. The study aimed at designing data-

driven techniques to resolve the issues surrounding many mall businesses around the world [3]. The study aims to deliver actionable understandings for retailers to organise their marketing strategies, advance customer satisfaction, and initiate business development in and around the mall environment [3]. Offering a robust segmentation model that boosts customer targeting and personalisation in the mall setting is an addition to the body of knowledge via this study.

3.4. Choosing an appropriate algorithm

In our study and also confirming the study carried out by [3], several factors were taken into account, including simplicity and interpretability, scalability, flexibility, cluster centroid representation, and the fact that they are widely used and well-studied. These factors have been considered twice to ensure their importance in the analysis for this study. K-means clustering in the literature has proven to be the widely used and well-studied algorithm in the field of machine learning (data mining). The choice of the K-means algorithm aligns with effectively segmenting mall customers based on their annual income and spending score.

4. Results

The use of clustering using the K-Means analysis revealed five distinct and meaningful customer segments consistent with findings from prior studies [9,17]. These segments include: (1) high-income, high-spending customers; (2) high-income, low-spending customers; (3) moderate-income, moderate-spending customers; (4) low-income, high-spending customers; and (6) low-income, low-spending customers. The resulting clusters align with the segmentation patterns observed by [2] and [18], confirming that income and spending scores remain critical determinants of consumer behaviour in retail markets.

The first cluster, as shown in Figure 4, is composed of high-income and high-spending customers, reflecting the premium consumer group described by [8], who are most receptive to personalised, high-value offers. The second cluster—high-income but low-spending customers—mirrors the conservative buyer behaviour identified by [2], highlighting the need for motivational campaigns and value-based marketing. Cluster three represents the middle-income segment with balanced spending patterns, similar to the findings of [14], indicating stability in purchase behaviour and responsiveness to loyalty-driven strategies.

Cluster four, as shown in Figure 4, consists of low-income yet high-spending individuals, supporting the observations of [19], suggesting that

emotional or impulsive purchase drivers influence spending behaviour 241
more than income levels. Lastly, the fifth cluster—low-income, low- 242
spending customers—corresponds with the cost-conscious groups 243
identified by [13], who prioritise affordability and value for money. 244

The high degree of separation achieved among the five clusters 245
demonstrates the robustness of the K-Means algorithm as previously 246
discussed by [15]. These results further substantiate the scalability and 247
interpretability of K-Means in modern marketing contexts, as highlighted 248
by [1] and [16]. By identifying behavioural distinctions across segments, 249
this study underscores the algorithm's value in guiding data-driven 250
advertising and customer retention strategies. 251

```
import matplotlib.pyplot as plt
# Extract the relevant columns for visualization
x = mall_customers['Annual Income (k$)']
y = mall_customers['Spending Score (1-100)']
cluster_labels = mall_customers['Cluster']

# Get unique cluster labels
unique_clusters = cluster_labels.unique()

# Create a scatter plot for each cluster
for cluster in unique_clusters:
    cluster_x = x[cluster_labels == cluster]
    cluster_y = y[cluster_labels == cluster]
    plt.scatter(cluster_x, cluster_y, label=f'Cluster {cluster}')

plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Clustering Visualization')
plt.legend()
plt.show()
```

Figure 3: Scatter Plot for Mall Customer Dataset

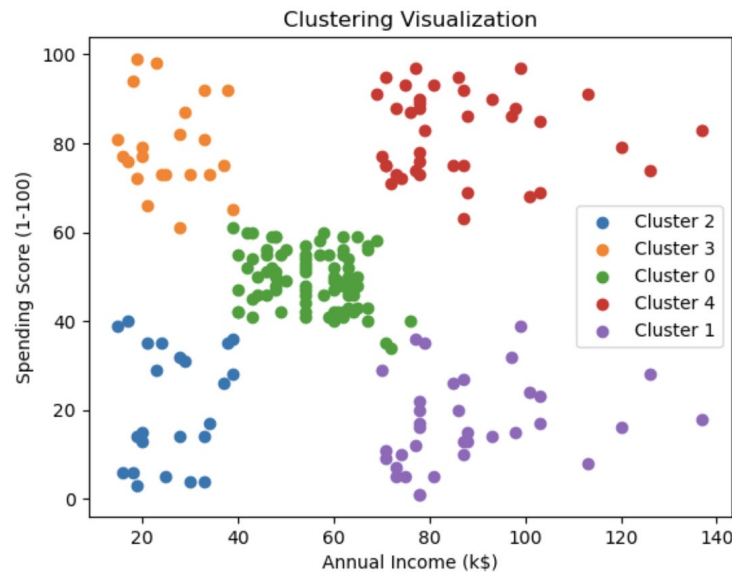


Figure 4: Clustering Visualisation for Mall Customers Dataset

The third segment (Cluster 2), as shown in Figure 4, encompasses average-income, average-spending customers who can be considered the average customer group. If we are able to analyse their buying patterns and preferences, we will gain access to identifying areas where we could use promotional offers to make them spend more. The fourth segment (Cluster 3) represents low-income, high-spending customers who prioritise certain products by exhibiting a higher propensity for impulse buying. Customers in this category are more easily retained by giving them a choice of alternatives that are affordable to them in terms of Loyalty offers and discounts on various products. The fifth segment (Cluster 4) includes low-income, low-spending customers who may have limited disposable income or prioritise saving. Building brand loyalty, providing value for money, and offering affordable product lines can cater to this segment effectively. Figure 4 shows the display of the visualisation of the entire clusters created at a go; different colours were used to easily identify the different clusters, with Figure 5 showing the Python codes for the model [3].

```
1 import pandas as pd
2
3 ads_data = pd.DataFrame({
4     'Cluster': [0, 1, 2, 3, 4],
5     'Ad_Title': ['Ad A', 'Ad B', 'Ad C', 'Ad D', 'Ad E'],
6     'Ad_Description': ['This is Ad A', 'Check out Ad B',
7     'Amazing Ad C', 'Get Ad D now', 'Special offer with Ad E'],
8     'Ad_Budget': [1000, 1500, 800, 1200, 2000]
9 })
10
11 print(ads_data)
12
```

	Cluster	Ad_Title	Ad_Description	Ad_Budget
0	0	Ad A	This is Ad A	1000
1	1	Ad B	Check out Ad B	1500
2	2	Ad C	Amazing Ad C	800
3	3	Ad D	Get Ad D now	1200
4	4	Ad E	Special offer with Ad E	2000

Figure 5: Clustering Ads Description for Mall Customers Dataset

In accordance with the study carried out by [3], five clusters have been decided and created for this assignment (Case k=5). K-means is computationally efficient and scalable, making it suitable for large datasets like the Mall Customers dataset. It can handle a substantial number of data points and features without significant computational overhead, enabling the analysis of large customer datasets efficiently. It provides meaningful insights into customer segments, aiding marketers in targeted marketing strategies and personalised customer experiences.

```

1 import pandas as pd
2 import numpy as np
3 from sklearn.metrics import confusion_matrix
4 # Extract the cluster labels from the DataFrame
5 cluster_labels = mall_customers['Cluster_Labels']
6 # Get the unique cluster labels
7 unique_labels = np.unique(cluster_labels)
8 # Generate the confusion matrix
9 confusion_mat = confusion_matrix(cluster_labels, cluster_labels)
10 # Create a DataFrame from the confusion matrix
11 confusion_df = pd.DataFrame(confusion_mat, index=unique_labels, columns=unique_labels)
12
13 # Display the confusion matrix
14 print(confusion_df)

```

	0	1	2	3	4
0	81	0	0	0	0
1	0	35	0	0	0
2	0	0	23	0	0
3	0	0	0	22	0
4	0	0	0	0	39

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Figure 6: Confusion Metrics for our Model

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Figure 6 confirms the work done by [3], specifying the matrix for our algorithm, but since the cluster label is comparing with itself, we will obtain a non-zero result on the diagonal, indicating the count of instances within each cluster label.

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Table 1: The values obtained and their various explanations

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Metric	Value	Explanations
Accuracy	[1.0] in all	This means we achieved a good arrangement of instances within each cluster.
Precision	[1.0] in all	This means there are no wrong positive assignments; correct cluster assignments were achieved.
Error Rate	[0.0] in all	This means there are no misclassifications or errors in cluster assignments
Prevalence	1.0	This means our model is well-balanced, clustered with equal proportions of instances.
Specificity	[1.0] in all	This means there is the correct identification of instances outside each cluster.
Recall	[1.0] in all	This means there is correct identification and assignment of instances to clusters.

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Table 1 confirms the results obtained from the study conducted by [3], which gives a summary of the values obtained and various explanations. The general meaning of all the values is that our algorithm was able to achieve a near-perfect classification with no misclassifications or errors. The clusters were well-balanced, and all the instances were correctly assigned to their respective clusters. Our model, in fact, correctly identified instances outside each cluster.

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Overall, these results suggest that the clustering model performed optimally based on the provided values [3].

In summary, the clustering results revealed five distinct customer segments: (1) high-income, high-spending; (2) high-income, low-spending; (3) moderate-income, moderate-spending; (4) low-income, high-spending; and (5) low-income, low-spending. Each cluster exhibited unique behavioural characteristics, providing a framework for designing personalised marketing campaigns.

5. Discussion of Findings

The results of this study reinforce the growing consensus that K-Means clustering remains an effective and interpretable approach for customer segmentation [9]; [14]. The five identified segments align with findings from [17] and [18], who both reported that income and spending patterns serve as robust predictors for understanding customer heterogeneity in retail environments.

In particular, the presence of high-income but low-spending clusters parallels observations by [2], who noted that conservative spenders often prioritise long-term brand loyalty over impulsive consumption. Similarly, the identification of low-income yet high-spending customers resonates with [19], who demonstrated that targeted promotional offers and personalised ad recommendations can increase retention and spending among such clusters.

The use of five clusters in this study corresponds to optimal segmentation levels in comparable works [15,13]. The precision of the K-Means algorithm in separating customers by spending score and income validates its continued relevance even amid emerging AI-driven alternatives. A study by [20] showed that socioeconomic factors positively influence the adoption and use of e-commerce. However, integrating complementary models such as PCA or deep K-Means [1,16] could further enhance interpretability and predictive capacity.

Moreover, the findings underscore the practical applicability of data-driven segmentation in improving customer engagement, consistent with [9] and [11]. By identifying distinct behavioural groups, marketers can design highly targeted and data-informed campaigns. For instance, high-income clusters can be approached with premium offerings, while moderate-income groups can receive loyalty-driven promotions. This approach aligns with [19], who demonstrated that combining reinforcement learning with K-Means segmentation yields dynamic, real-time recommendation capabilities.

Overall, the clustering results affirm that leveraging K-Means in conjunction with modern AI techniques can significantly upscale the quality of marketing insights, leading to improved customer satisfaction and long-term brand engagement.

6. Conclusion

K-Means clustering adoption has proved helpful for business managers who seek to have a better understanding and willingness to target customer clusters effectively. Partitioning our dataset correctly on annual income and spending scores has revealed distinct customer groups with varying characteristics and preferences. These perceptions empower business managers in developing tailored strategies for each segment, eventually helping in enhancing marketing efforts and customer involvement [3].

The result unveiled an exceptional customer segment based on annual income and spending scores, providing the mall owner with valuable insights into customer characteristics and preferences, thereby enabling the development of targeted marketing strategies, personalised promotions, and customised experiences. By understanding and catering to the specific needs of each segment, the mall can enhance customer satisfaction, loyalty, and overall performance [3].

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