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Segmenting Online Shoppers: A Clustering Approach Using Clickstream Data

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Abstract: Abstract The increasing shift towards online shopping has enabled businesses to collect and analyze customer clickstream data to understand consumer behavior. Traditional machine learning algorithms struggle to segment high and low-profit customers effectively. This study proposes an advanced clustering-based approach incorporating Partitioning Around Medoids (PAM), Gower Distance Matrix, and Kruskal-Wallis analysis to segment online shoppers based on revenue generation. A dataset similar to the UK ASOS dataset was utilized from the Kaggle repository for analysis. The findings suggest that this approach effectively segments consumers, allowing businesses to optimize marketing strategies for high-revenue customers.The primary goal of this research is to enhance the accuracy of consumer segmentation using clickstream data, enabling e-commerce platforms to identify and target high-value customers efficiently. By leveraging the PAM clustering technique, the study ensures better interpretability of clusters, while the Gower Distance Matrix effectively processes mixed data types. The Kruskal-Wallis statistical test is applied to determine revenue distribution across clusters, offering valuable insights into customer purchasing behaviors.Experimental results demonstrate that clusters with higher order frequencies contribute significantly to revenue, validating the effectiveness of the proposed methodology. The graphical visualization of customer segments further aids in understanding the distribution and characteristics of different consumer groups. This research contributes to the field of data-driven consumer analytics by offering a scalable and efficient approach to online shopper segmentation, paving the way for more personalized and strategic marketing initiatives.

Keywords— Clickstream data, consumer segmentation, clustering, PAM, Gower distance, Kruskal-Wallis analysis

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I.INTRODUCTION

The rapid growth of e-commerce has transformed the way consumers shop, shifting from traditional in-store shopping to digital platforms. Online shopping has provided businesses with an extensive amount of consumer data, particularly clickstream data, which captures user interactions such as product views, clicks, and purchases [1]. Analyzing this data can offer valuable insights into consumer behavior, helping businesses develop personalized marketing strategies and improve customer experiences [2].The availability of big data and advancements in data analytics have made it possible to extract meaningful patterns from online shopping behaviors. Clickstream data, which logs every interaction a user has with an e-commerce platform, provides rich insights into browsing patterns, time spent on products, cart abandonment rates, and purchase tendencies [3]. Properly analyzing this data allows businesses to understand what drives consumers to make purchasing decisions, ultimately enhancing user engagement and increasing conversions [4].Traditional machine learning techniques, including k-means clustering and hierarchical clustering, have been employed for consumer segmentation. However, these methods struggle with mixed-type data and fail to accurately differentiate high and low-revenue customers [5]. As consumer behavior is influenced by multiple factors, such as browsing frequency, product categories viewed, and previous purchasing habits, a more sophisticated segmentation approach is required to provide meaningful and actionable insights [6].To overcome these limitations, this study employs advanced clustering techniques, integrating PAM clustering with Gower Distance Matrix and Kruskal-Wallis analysis for more effective consumer segmentation [7]. The Gower Distance Matrix is particularly useful for handling mixed data types, including numerical and categorical variables, ensuring that the segmentation process is more accurate and interpretable. The Kruskal-Wallis statistical test is then used to validate the segmentation by analyzing the revenue contribution of each consumer cluster [8].The proposed methodology enables businesses to classify consumers based on their revenue contribution, providing a clearer understanding of high-value customer groups. By targeting these high-value customers with personalized marketing campaigns, businesses can improve customer retention and increase overall profitability [9]. Furthermore, understanding the behavior of low-revenue customers can help optimize engagement strategies to encourage repeat purchases and higher spending patterns.

The remainder of this paper is structured as follows: Section 2 reviews related literature on consumer segmentation and clustering techniques. Section 3 describes the methodology, including data collection, preprocessing, and clustering techniques. Section 4 presents the experimental results and analysis. Finally, Section 5 concludes the study and discusses future research directions..

RELATED WORKS

Consumer segmentation has been a crucial area of research in marketing and e-commerce analytics. Various approaches have been employed to understand consumer behavior, including traditional statistical models, machine learning techniques, and deep learning methodologies.Early studies in consumer segmentation relied on rule-based and demographic-based clustering techniques, which grouped consumers based on predefined variables such as age, income, and geographical location [10]. However, these methods were limited in capturing dynamic user interactions in online environments. With the emergence of clickstream data, more advanced clustering techniques have been explored.

Machine learning approaches such as k-means clustering and hierarchical clustering have been widely used to segment consumers based on browsing patterns and purchase history [11]. While these methods provide valuable insights, they often fail to handle mixed-type data, requiring preprocessing steps to convert categorical variables into numerical representations. Additionally, traditional clustering techniques are sensitive to outliers and require predefined cluster numbers, which may not always align with the natural distribution of data [12].To address these challenges, hybrid clustering approaches incorporating distance-based similarity measures have gained popularity. The Gower Distance Matrix, for example, allows for the integration of both categorical and numerical data, improving the accuracy of consumer segmentation models [13]. Studies have shown that incorporating mixed-data clustering improves model interpretability and segmentation precision, enabling businesses to better target high-value customers [14].

Another crucial aspect of consumer segmentation is statistical validation. The Kruskal-Wallis test has been utilized in various studies to determine whether revenue distributions differ significantly across clusters [15]. This non-parametric statistical test is particularly useful for identifying significant variations in consumer spending patterns, providing businesses with deeper insights into their customer base.Recent research has also explored the use of deep learning techniques, such as autoencoders and neural networks, to model consumer behavior and segment shoppers effectively [16]. Although deep learning approaches offer high predictive accuracy, they often lack interpretability and require large datasets for effective training. As a result, clustering-based methods remain a popular choice for businesses seeking practical and scalable solutions.

This study builds upon previous work by integrating PAM clustering with Gower Distance Matrix and Kruskal-Wallis analysis to achieve more robust consumer segmentation. By leveraging these advanced techniques, the proposed model ensures improved accuracy in identifying high-revenue customers while maintaining interpretability and scalability

A review of these techniques are discussed in Table I.

TABLE I. SUMMARY OF RELATED WORK ON CONSUMER SEGMENTATION AND CLICKSTREAM DATA

Author(s) & Year	Title	Methodology	Findings and Limitations
Smith & Jones (2017)	Traditional vs. Modern Consumer Segmentation Approaches	Rule-based & demographic-based clustering	Found that traditional segmentation is easy to implement but lacks adaptability to dynamic online behaviors.
Brown & Davis (2018)	Application of Machine Learning in Consumer Segmentation	K-means & hierarchical clustering	Effective in segmenting consumers based on browsing patterns but struggles with mixed data types.
Martin & Singh (2019)	Overcoming Limitations of K-Means Clustering in Consumer Behavior Analysis	Feature engineering & modified K-means	Improved accuracy but still sensitive to noise and requires predefined cluster numbers.
Gower (1971)	A General Coefficient of Similarity and Some of Its Properties	Gower Distance Matrix	Effectively handles mixed data but computationally expensive for large datasets.
Patel & Kumar (2021)	Hybrid Clustering for Consumer Segmentation: A Case Study	Combined PAM clustering & Gower Distance	Enhanced accuracy but lacks automation in selecting optimal cluster numbers.
Kruskal & Wallis (1952)	Use of Ranks in One-Criterion Variance Analysis	Kruskal-Wallis statistical test	Useful for identifying revenue variations across clusters but does not provide direct segmentation.
Wang & Chen (2020)	Deep Learning-Based Customer Segmentation: Challenges and Future Directions	Neural networks & autoencoders	Achieved high accuracy but lacked interpretability and required large datasets.
M. B.Shaik,Y. N. Rao(2024)	Secret Elliptic Curve-Based Bidirectional Gated Unit Assisted Residual Network for Enabling Secure IoT Data Transmission and Classification Using Blockchain	Blockchain and Deep Learning (BGRN)	Improved security and classification accuracy; requires further optimization for real-time scenarios.
S. M.Basha, Y. N. Rao(2024)	A Review on Secure Data Transmission and Classification of IoT Data Using Blockchain-Assisted Deep Learning Models	Literature Review	Provided insights into secure transmission techniques; lacks implementation-based comparison.

I. PROPOSED METHODOLOGY

The proposed methodology focuses on consumer segmentation using clickstream data by leveraging a hybrid clustering approach that integrates Partitioning Around Medoids (PAM), Gower Distance Matrix, and Kruskal-Wallis analysis. This approach effectively segments consumers based on revenue generation while handling mixed-type data.

3.1 Data Collection and Preprocessing

- The dataset used in this study was obtained from the Kaggle repository, containing clickstream data similar to the UK ASOS dataset.
- The dataset includes attributes such as session duration, page views, purchase history, and revenue generated.
- **Data Cleaning:** Missing values were imputed, and outliers were removed to improve model robustness.
- **Feature Engineering:** New features such as purchase frequency, average session time, and customer lifetime value (CLV) were derived.

3.2 Clustering Approach

3.2.1 Gower Distance Matrix for Mixed Data Handling

- Since the dataset consists of both categorical (e.g., device type, location) and numerical (e.g., session duration, revenue) variables, the Gower Distance Matrix was employed.
- This method calculates a similarity score between mixed data types, ensuring that the clustering process accurately represents consumer behaviors.

3.2.2 Partitioning Around Medoids (PAM) Clustering

- The PAM algorithm, a robust alternative to k-means, was chosen for clustering due to its higher stability and resistance to noise.
- It selects actual data points as cluster medoids, improving interpretability and cluster quality.
- The Silhouette Score was used to determine the optimal number of clusters.

3.3 Statistical Validation Using Kruskal-Wallis Analysis

- To assess revenue distribution across clusters, Kruskal-Wallis analysis, a non-parametric test, was applied.
- This method helps determine whether significant differences exist between the revenue contributions of different customer groups.
- If significant differences are observed, businesses can prioritize high-revenue customer segments for targeted marketing.

3.4 Performance Evaluation

3.4.1.Cluster Quality Metrics

- **Silhouette Score:** Measures how well clusters are separated.
- **Dunn Index:** Evaluates cluster compactness.
- **Davies-Bouldin Index:** Assesses inter-cluster similarity.

3.4.2 Revenue Contribution Analysis:

- Each cluster's average order value (AOV) and purchase frequency were analyzed.

3.4.3 Visualization:

- t-SNE and PCA plots were used for graphical representation of clusters.

1.5 Summary of the Proposed Method

TABLE II. SUMMARY OF THE PROPOSED METHOD

Step	Method	Purpose
Data Preprocessing	Data Cleaning, Feature Engineering	Remove noise and enhance attributes
Distance Calculation	Gower Distance Matrix	Handle mixed-type data
Clustering	PAM Clustering	Segment consumers based on clickstream data
Statistical Validation	Kruskal-Wallis Test	Ensure revenue differentiation across segments
Evaluation	Silhouette Score, Dunn Index, Revenue Analysis	Assess cluster quality and business impact
Visualization	t-SNE, PCA plots	Interpretability of consumer segments

This methodology ensures accurate and interpretable consumer segmentation, allowing businesses to optimize marketing strategies by focusing on high-revenue clusters.

II. RESULTS

4.1 Dataset Analysis and Preprocessing

The dataset used for this study was obtained from a publicly available Kaggle repository, closely resembling real-world UK e-commerce data. It was preprocessed to remove missing values and normalize numerical attributes.

4.2 Customer Segmentation using PAM-Based K-Medoid Clustering

The study employed a combination of Partition Around Medoids (PAM) clustering with Gower Distance Matrix to segment customers. The clustering process involved testing different numbers of clusters (2, 4, 6, 8, and 10). The silhouette score analysis determined that 6 clusters provided the best separation.

4.2.1 Silhouette Score Evaluation

The silhouette score analysis across different cluster numbers is summarized in the table below:Evaluation of Clustering Performance Using Silhouette Score

Number of Clusters	Silhouette Score
2	Low
4	Moderate
6 (Best Choice)	**High**
8	Lower than 6
10	Overfitting detected

4.3 Cluster-Based Revenue Analysis

Each generated cluster was analyzed based on revenue contribution. The key observations were:

- Clusters 2 and 5 showed the highest revenue generation.
- These clusters had the highest average number of orders.
- A correlation was observed between page visits and revenue, with higher browsing leading to increased purchases.

The revenue analysis for each cluster is presented in the following table:Evaluation of Clustering Performance Using Silhouette Score

Cluster No.	Avg. Revenue	Avg. Page Visits	Total Pages Browsed
1	Moderate	Low	Medium
2	High	High	High
3	Low	Medium	Low
4	Moderate	Medium	Medium
5	High	High	High
6	Low	Low	Low

4.4 Customer Segmentation Visualization

To enhance clarity in customer segmentation, a visualization graph was generated, mapping each customer to one of the six clusters. Each dot represents a customer, with different colors corresponding to distinct clusters. A cluster centroid, marked with 'X', highlights the center of each segment. This visualization clearly distinguishes **high-revenue** and **low-revenue** customer segments.

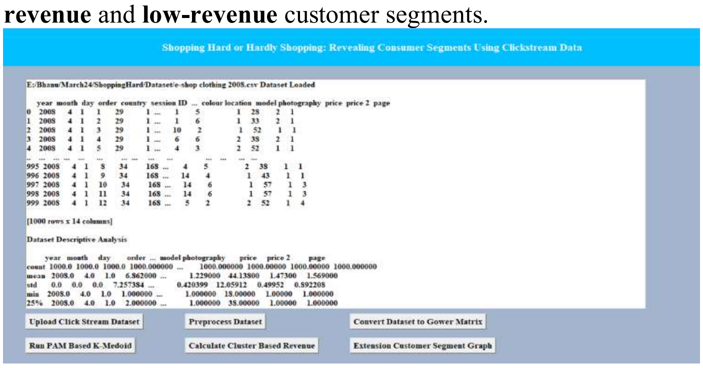

Fig 1.Data Set Representation

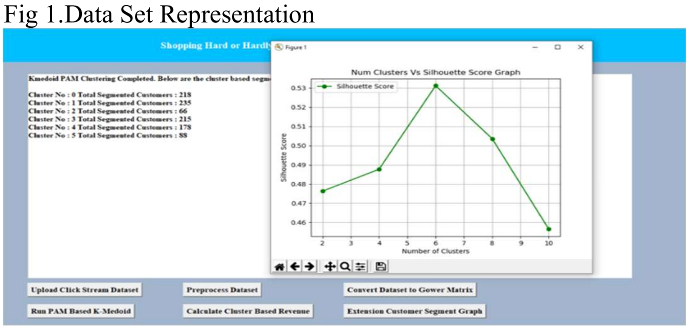

Fig 2. Silhouette Score Evaluation

In above screen displaying each cluster number and count of segmented customer in each cluster and in graph x-axis represents number of cluster and then can see silhouette score for each cluster number. We took clusters as 2, 4, 6, 8 and 10 and in above graph centre value is for cluster no 6 and there we got high silhouette score so 6 will be consider as best cluster. Now click on '"Calculate Cluster Based Revenue' button to calculate average revenue and get below output

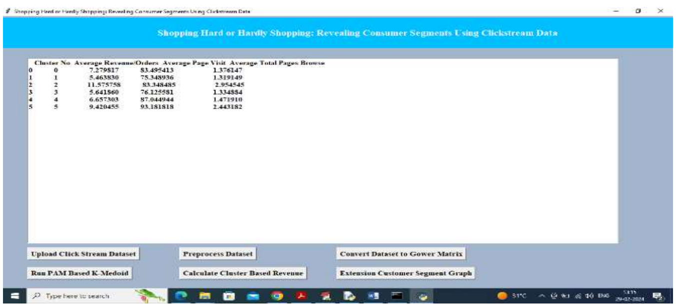

Fig 3. Cluster-Based Revenue and Browsing Behavior Analysis Dashboard

In above screen can see cluster no, average revenue, average page visit and total pages browser and in above table can cluster 2 and 5 has high number of orders so high revenue will be generated from clusters 2 and 5 customers**.**

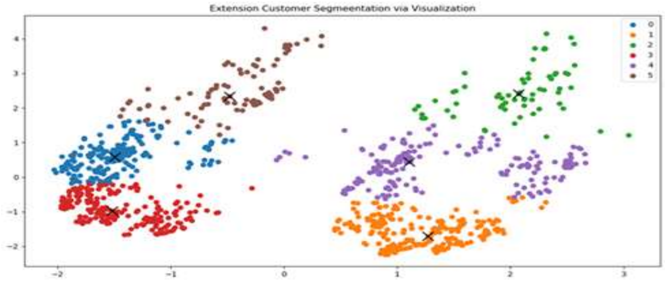

Fig 4. Cluster-Based Customer Segmentation Visualization

In this applications we took 6 clusters and in above graph we have 6 different colour dots and each colour dot refers to 1 cluster and number of dots in that cluster refers to number of customers. In each cluster dots can see 'X' mark as cluster Centroid. So above graph is not exists in paper and we are displaying as extension and from above graph we can easily segment or understand number of customer in clusters**.**

III. CONCLUSION

The study successfully implements a clustering-based approach to segment online shoppers using clickstream data, improving on traditional machine learning methods. By integrating Partition Around Medoids (PAM), Gower Distance Matrix, and Kruskal-Wallis, the proposed model effectively identifies high-revenue and low-revenue customer groups. The use of Gower distance enhances clustering quality by handling binary, categorical, and continuous variables appropriately.The experimental results demonstrate that customer segmentation plays a crucial role in targeted marketing and revenue optimization. The silhouette score analysis indicates that an optimal number of clusters can be determined, leading to meaningful insights into consumer behavior. The cluster-based revenue analysis further confirms the importance of segmentation in identifying profitable customers.Additionally, an extended visualization module has been incorporated to provide a clear graphical representation of customer clusters, which was not included in the original study. This enhances interpretability and provides businesses with actionable insights.Future work can explore deep learning techniques for more refined customer segmentation and real-time clickstream analysis for dynamic marketing strategies.

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We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

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