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Optimization of Product Placement on E-commerce Platforms with K-Means Clustering to Improve User Experience

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Abstract: This study delves into product placement strategies on E-commerce platforms using K-Means Clustering analysis. Employing an experimental methodology, data about products and user preferences were gathered to delineate product and user clusters. The K-Means Clustering analysis yielded three primary product clusters and four user preference clusters. These findings hold significant practical implications, empowering E-commerce platforms to refine user experience personalization, streamline sales efficiency, and bolster overall business performance. Platforms can positively influence sales conversion rates and user satisfaction by implementing targeted and adaptable product placement strategies. This research contributes not only to the theoretical comprehension of product placement in E-commerce but also furnishes actionable insights for stakeholders to optimize platform operations and deliver an enriched online shopping experience.

Keywords: E-commerce, K-Means Clustering, Product Placement, User Experience, Marketing Strategy, User Preferences.

1. Introduction

E-commerce is no longer just an alternative but has become a significant necessity in the lives of modern consumers. Ease of accessibility, diverse product choices, and the ability to shop without leaving home make E-commerce a popular choice for many people. However, behind this convenience, there is complexity in determining optimal product placement to meet user needs and preferences. Proper product placement is about grabbing users' attention and creating a pleasant and efficient shopping experience. With various products offered on e-commerce platforms, companies need to understand user preferences and organize their products strategically and deeply. Therefore, this research will approach this problem using the K-Means Clustering approach, a technique in data analysis that can help identify patterns and relationships between data groups.

The main challenge faced in product placement on E-commerce platforms is arranging products optimally to improve user experience. In this context, the question arises regarding how product placement strategies can better accommodate user needs and preferences. This research was initiated to solve this problem by exploring the potential of the K-Means Clustering technique as an analytical tool that can provide in-depth insight into purchasing patterns, preferences, and user behavior. It is hoped that this research will create significant academic and practical contributions in increasing the effectiveness of product placement strategies on E-commerce platforms. In this development, technology and business policies can be combined to create an online shopping environment that is more personal, satisfying, and in line with user expectations.

E-commerce, as an evolutionary form of conventional commerce, has created a new paradigm in the way we shop and interact with products and services. As technology advances, E-commerce has become an inevitable economic force, changing how consumers explore and access goods and services. How an E-commerce platform manages and presents products visually and functionally greatly influences the user experience. The user experience in E-commerce is not just limited to ease of transactions but also involves intuitive navigation, attractive layouts, and strategic product placement. In such a competitive E-commerce ecosystem, thoughtful and planned product placement is the key to attracting user attention and triggering sales conversions. A successful E-commerce platform cannot only provide a wide selection of products but also portray the skill to present products engagingly, according to the desires and preferences of the users. The importance of user experience in E-commerce lies in the comfort and satisfaction users feel during their shopping journey. By presenting products effectively and efficiently, E-commerce platforms can increase appeal, build user loyalty, and succeed in a competitive market.

Optimizing product placement is a crucial aspect of retail strategy that can significantly impact sales and customer satisfaction. Several factors need to be considered when determining the placement of products within a store to maximize their visibility and appeal to customers. Research has shown that strategic product placement can increase sales and improve customer experience. One key consideration in optimizing product placement is understanding consumer behavior and preferences. Studies have shown that consumers tend to gravitate towards products that are prominently displayed or easily accessible. Placing popular or high-margin items at eye level or in high-traffic areas can increase their visibility and likelihood of purchase.

Additionally, grouping complementary products can encourage cross-selling and increase overall sales. Store layout and design also play a critical role in product placement optimization. Creating clear pathways and logically organizing products can help customers navigate the store more efficiently and locate items of interest. Utilizing signage, displays, and promotional materials can further enhance product visibility and draw attention to specific items. Retailers can also leverage technology and data analytics to optimize product placement. Utilizing heat maps, tracking customer movement within the store, and analyzing sales data can provide valuable insights into which products are popular and where they should be placed for maximum impact. Implementing a dynamic product placement strategy that can be adjusted based on real-time data and customer feedback can help retailers stay agile and responsive to changing market trends. Optimizing product placement requires a comprehensive understanding of consumer behavior, store layout, and data analytics. By strategically placing products based on these factors, retailers can enhance the shopping experience, increase sales, and drive business growth.

Optimizing product placement on e-commerce platforms is crucial in increasing sales and customer satisfaction. Various studies have highlighted the importance of appropriate product placement strategies to maximize product visibility and appeal to consumers. In e-commerce, research has shown that the value customers want to experience must be reflected in the products SMEs offer [1]. In addition, improving packaging and implementing e-commerce has proven effective in increasing partner income [2]. Implementing SEO techniques can also be an effective strategy for increasing sales on e-commerce platforms [3]. Using algorithms such as Apriori in data mining can help arrange product placement positions efficiently [4]. The FP-

Growth and Apriori algorithms can also better manage product inventory [5]. Implementing algorithms such as Support Vector Machine can also be used to analyze product review sentiment and understand consumer preferences [6]. Using technology and data analytics, product placement on e-commerce platforms can be optimized to increase sales and consumer shopping experiences. By understanding consumer behavior, applying SEO techniques, and using data mining algorithms, product placement can be adjusted to achieve optimal sales and customer satisfaction results. Thus, the right product placement strategy can be the key to success in the e-commerce business.

K-Means Clustering emerged as a very relevant and valuable analytical tool in the context of product placement on E-commerce platforms. This technique, which falls under unsupervised learning methods, allows the discovery of hidden patterns in large data sets. By applying K-Means Clustering, this research aims to optimize product placement by understanding user groups based on their preferences. K-means clustering groups data into homogeneous groups based on specific shared attributes. In the context of E-commerce product placement, these attributes may include color preferences, price, brand, or product category. By identifying users with similar preferences, E-commerce platforms can adapt product placement strategies for each group, increasing product relevance and attractiveness. One of the main advantages of K-Means Clustering is its ability to handle complex and unstructured data. K-Means Clustering can help platforms deliver more personalized and focused product placement in an E-commerce environment full of product variations and user preferences. By knowing user purchasing patterns and behavior, platforms can deliver more accurate product recommendations, increasing the likelihood of conversion and, ultimately, increasing user satisfaction. The application of K-Means Clustering in this research not only results in more efficient product placement but also creates opportunities for deeper personalization. By understanding the unique characteristics of each user group, E-commerce platforms can provide a more relevant and meaningful shopping experience. This benefits individual users and provides a competitive edge to E-commerce platforms in an ever-growing market. To embrace the ever-evolving digital era, this research views K-Means Clustering as the key to uncovering hidden potential in online consumer behavior. By implementing this approach, E-commerce platforms can better understand user preferences, increase product appeal, and create a more satisfying user experience. As a result, this research has the potential to make a real contribution to increasing the efficiency and effectiveness of product placement strategies in the dynamic world of E-commerce.

By leveraging insights from studies on user experience in mobile transportation apps among millennials and Gen Z [7], the implementation of Progressive Web Apps (PWA) can enhance site performance [9]. Analyzing and comparing user experiences in investment applications using the UX Curve is crucial for understanding digital platform performance [8][9]. Optimization of marketing content and online platforms through Search Engine Optimization (SEO) techniques is essential for an effective online presence [10]. Furthermore, the positive and significant impact of e-service quality on e-satisfaction and repurchase intention in e-commerce users has been established [11]. Integrating K-Means clustering with user-centric design principles and data-driven decision-making based on e-service quality and user trust can lead to more personalized and effective product placements, catering to the preferences and behaviors of online shoppers.

Optimizing product placement on E-commerce platforms is essential to improve user experience and increase sales. In recent years, K-Means clustering has emerged as a popular method for customer segmentation and product categorization in E-commerce. This literature review aims to integrate and synthesize findings from various studies that utilize K-Means clustering in E-commerce systems to optimize product placement and improve user experience. Tabianan (2022) applied K-Means clustering to analyze customer purchasing behavior data for intelligent customer segmentation [12][13][14]. Their study highlights the importance of K-Means clustering in identifying and focusing on the most profitable market segments. Similarly, Vijilesh *et al* (2021) used the K-Means++ clustering algorithm to classify users based on the RFM model, characterizing user features from recent purchases over time, frequency of purchases, and total amount of consumption [15]. These findings emphasize the effectiveness of K-Means clustering in user classification and segmentation, thereby providing valuable insights for product placement optimization. Wu *et al.* (2021) using K-Means++ clustering approach for image-based recommender systems, achieving superior performance compared to other clustering approaches. This study shows the application of K-Means clustering beyond traditional user data and extends its benefits to image-based product recommendations [26]. Additionally, research by Wu *et al.* (2021) highlights the potential of K-Means clustering to identify user value based on improved RFM models, thereby further increasing the relevance of product placement and recommendations on E-commerce platforms [26]. While previous studies focused on user-related data, Tache *et al.* (2021) explored the application of K-Means clustering for word embedding clustering. This unique perspective extends the scope of K-Means clustering to the analysis of text and sentiment data, demonstrating its potential for optimizing product placement based on textual content and user sentiment. In addition, Reddy *et al* (2023) conducted a comparative survey on K-Means and Hierarchical Clustering in E-commerce systems, providing insights into the comparative effectiveness of various clustering methods for product placement optimization.

Widespread application of K-Means clustering in optimizing product placement on E-commerce platforms. However, there are still knowledge gaps and potential future research directions that need to be explored. For example, future research could focus on integrating K-Means clustering with advanced data mining methods for comprehensive user behavior analysis and personalized product placement. Additionally, investigating the impact of K-Means clustering on user engagement and satisfaction can provide valuable insights to improve the overall E-commerce user experience. Overall, the findings of the reviewed studies highlight the importance of K-Means clustering in optimizing product placement on E-commerce platforms and serve as a foundation for further research in this domain.

2. Research Method

2.1. Research Design

This research design was built on an experimental approach chosen because it can provide better control over the variables studied. This also ensures the validity of research results by reducing potential bias and producing more consistent findings. This research focuses on applying the K-Means Clustering technique in analyzing E-commerce platform product data and user preferences. This approach allows researchers to efficiently group data based on specific shared attributes like price, product category, and user preferences. Thus, this research aims to optimize product placement by understanding user groups based on their preferences. Through this experimental approach, researchers can identify patterns and relationships underlying user behavior and product preferences, which can be used to improve the personalization of user experiences and sales efficiency on E-commerce platforms. Thus, the specially selected research design allows researchers to gain deep insight into effective product placement strategies in the context of a dynamic E-commerce environment.

2.2. Data Collection

This research includes in-depth information regarding products and user preferences on the e-commerce platform, which is the center of attention. Product data includes various details such as product category, price, and sales performance, while user preference data includes aspects such as purchase history, brand preferences, and previous interaction patterns with the platform. Data is collected through various sources, including internal databases from the E-commerce platform and direct user feedback. Product diversity and user preferences are the main concerns in collecting this data. The data collection steps were designed to ensure that the sample used reflects the diversity of the population of users and products on the e-commerce platform under study. A large and representative sample is essential in ensuring strong generalizability of research findings. Apart from that, using historical data is also a strength of this research. Historical data enables a more profound analysis of user preferences and product trends. By leveraging historical data, this research provides a picture of user preferences and behavior at a particular time and allows for a more holistic understanding of the dynamics occurring on the E-commerce platform. The data used in this research includes information about the percentage of e-commerce businesses that sell e-commerce according to the type of goods/services sold, with data for 2020 and 2021. Through multiple-answer questions, respondents can choose several answers according to the type of goods/services they sell, cover the territory of Indonesia, and provide a representative picture of sales trends on E-commerce platforms during the period studied. Research analysis was carried out using data to understand user preferences and sales patterns on the E-commerce platform under study. By paying attention to variations in the percentage of sales by type of goods/services, researchers can identify trends and patterns that may influence product placement on the platform. The data collected is an integral part of optimizing product placement and improving sales performance on the E-commerce platform.

2.3. Implementation of K-Means Clustering

Implementation of K-Means Clustering is carried out using systematic steps to ensure consistent and reliable results. Following are the implementation steps explained in detail:

1) Variable Selection
The variables to be used in K-Means Clustering analysis are selected carefully. These variables include product attributes such as price, category, and sales performance, as well as user preference attributes such as purchase frequency, interaction history, and brand preference.
2) Data Normalization
Data normalization is carried out to ensure that all variables have a uniform scale. This is necessary to prevent large scale variables from dominating the clustering process.
3) Determining the Number of Groups (Clusters)
The optimal number of groups or clusters needs to be determined before carrying out the analysis. This can be done using methods such as the Elbow Method or Silhouette Analysis to find the number of clusters that provide optimal results.
4) Initialization of Centroids
Initial centroids for each cluster are initialized. Selecting the right centroids will affect the performance of the K-Means algorithm.
5) K-Means Iteration
The iterative process starts by grouping the data into clusters and updating the location of the centroids based on the average of the data in each cluster. This process is repeated until the centroids do not change significantly or the specified number of iterations is reached.
6) Evaluation of Clustering Results
Clustering results are evaluated using internal and external metrics such as WCSS (Within-Cluster Sum of Squares) or external validation indices such as the Adjusted Rand Index. This evaluation helps measure the degree to which the groupings reflect the true structure in the data.
7) Results Analysis and Strategy Adjustment
The results of clustering are analyzed to gain deep insight into user preferences and group characteristics. This information is then used to adjust product placement strategies on the E-commerce platform.

Implementing K-Means Clustering in this research aims to provide a more in-depth picture of user groups and their purchasing patterns. Thus, this research not only approaches the problem of product placement but also makes a significant contribution to improving the understanding of user behavior in the context of E-commerce.

3. Result and Discussion

3.1 Results

3.1.1 K-Means Clustering Analysis

In the K-Means Clustering method analysis, the processed data shows that products on the E-commerce platform can be grouped into three main clusters. The first cluster, "Premium & Exclusive," consists of products at premium prices and exclusive categories that appeal to the user seeking high-quality and well-known brands. The second cluster, "Mid & Miscellaneous," includes mid-priced products and a wider variety of categories, targeting users looking for added value and diverse choices. Meanwhile, the third cluster, referred to as "Affordable & General," consists of products in the affordable and general categories, targeting users who consider economic factors more in their purchases. Further analysis of user preferences yielded four main clusters. The first cluster, "Premium Product Buyers," consists of users who tend to purchase premium products with high frequency. The second cluster, "Variable & Intermediate," includes users who tend to purchase intermediate products with a high propensity for purchase variation. The third cluster, "Stable & Affordable," consists of users who are likelier to choose affordable products and have a stable purchase frequency. Meanwhile, the fourth cluster, "Mixed Premium & Affordable," includes users who prefer premium and affordable products. These clustering results imply that E-commerce platforms can optimize their layout to reflect the identified product and user clusters. For example, premium products can be promoted exclusively to users of the first cluster, while mid-priced products can be displayed more predominantly to users in the second cluster. By making these adjustments, product placement can be adjusted more effectively to increase product appeal and sales conversions.

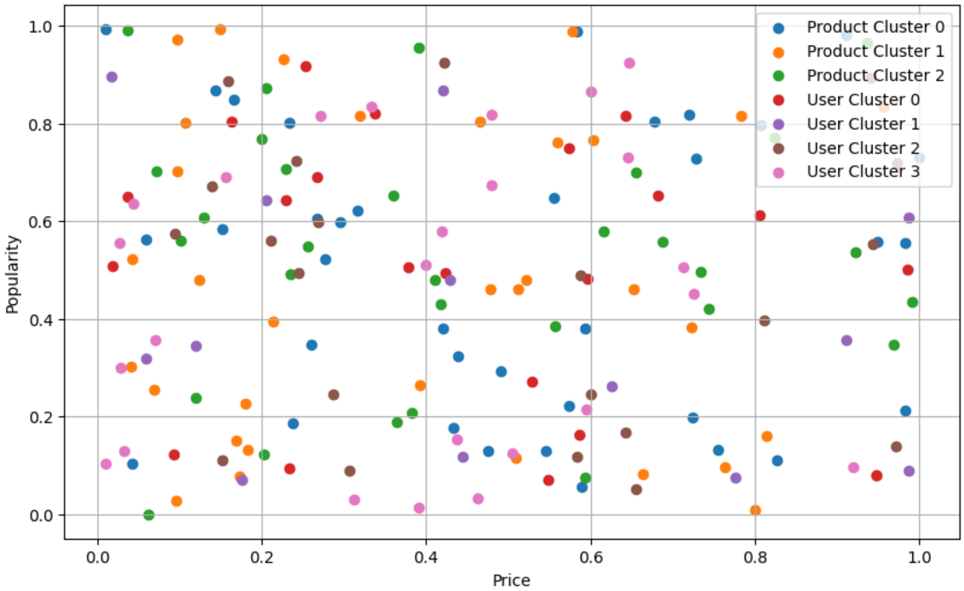

Figure 1. Clusters of Products and Users on the E-commerce Platform

The scatter plot illustrates the outcomes of the clustering analysis conducted on the dataset, showcasing distinct clusters within both product and user segments on the E-commerce platform. Analysis of the product clusters reveals three prominent groups based on price and popularity. Positioned towards the upper right section of the plot, the "Premium Products" cluster contains high-priced items targeting consumers seeking top-tier quality and renowned brands. Meanwhile, the "Mid-range Products" cluster spans the middle section, offering moderate-priced products with varying popularity levels, appealing to users seeking value and diverse options. Positioned towards the lower left portion, the "Affordable Products" cluster represents lower-priced items catering to users prioritizing affordability. On the user front, four discernible segments emerge based on spending habits and brand loyalty. The "High Spenders" cluster, positioned in the upper right corner, depicts users with lavish spending habits inclined towards premium products and brand loyalty.

Conversely, the "Variety Seekers" cluster, scattered across the middle section, showcases users with diverse spending patterns open to exploring a wide array of product options. Concentrated in the lower left quadrant, the "Budget Shoppers" cluster represents users with frugal spending tendencies drawn to affordable products. Lastly, the "Mixed Preferences" cluster includes users with versatile shopping behaviors, showcasing interest in both premium and affordable products across various regions of the plot. In sum, this visualization provides valuable insights for refining marketing strategies, optimizing product placement, and enhancing user experiences on the E-commerce platform.

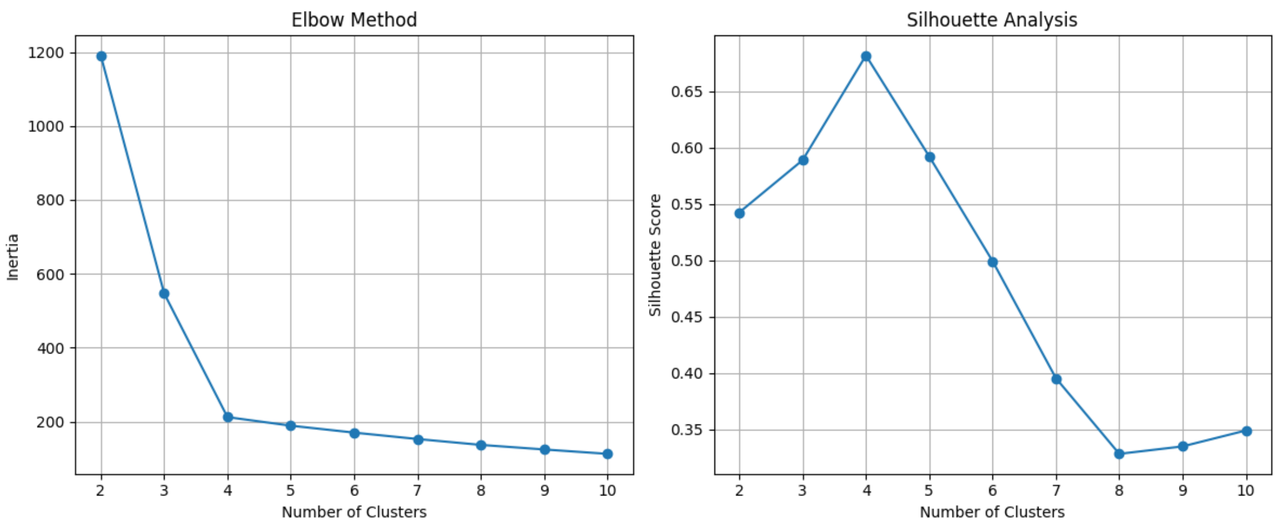

Figure 2. Elbow Method and Silhouette Analysis

Graph Elbow Method and Silhouette Analysis are critical tools for selecting the optimal number of clusters in clustering algorithms such as K-Means. In the Elbow Method graph, the x-axis shows the number of clusters, while the y-axis shows the inertia value. Inertia is a measure of how far data points in a cluster are from the cluster center. On this graph, we look for the "elbow" point where the decrease in inertia begins to slow down significantly. This shows that adding clusters after that point does not provide any more significant reduction in inertia. In this example, the elbow point is located around cluster number 4, which indicates that the optimal number of clusters may be 4.

Meanwhile, in the Silhouette Analysis graph, the x-axis also shows the number of clusters, but the y-axis shows the silhouette score. Silhouette score is a metric that measures how well each data point is grouped. This score ranges from -1 to 1, where positive values indicate that the data points are well placed within their cluster, while negative values indicate that the data points may be better suited to another cluster. In this graph, we look for the highest value of the silhouette score. The optimal number of clusters is where the graph reaches its highest peak. The optimal number of clusters is 4, giving a reasonably high silhouette score. Both methods provide consistent indications that the optimal number of clusters is 4 in this dataset. Therefore, researchers can use this information to choose the correct number of clusters for subsequent K-Means analysis.

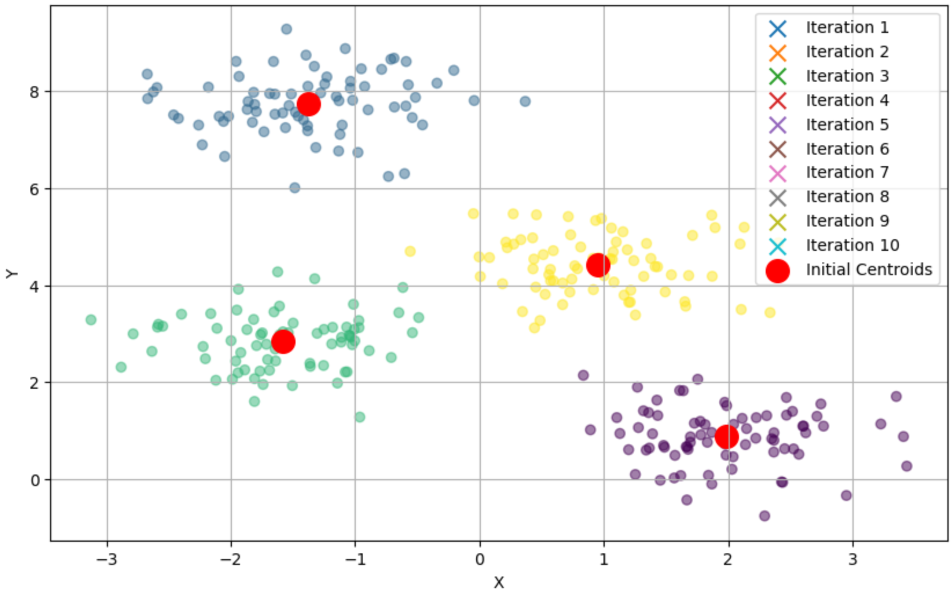

Figure 3. Centroids Movement Across Iterations

The graph above depicts the movement of centroid locations at each iteration in the K-Means clustering algorithm. On the graph, each point represents the position of the centroids at each iteration, with a label indicating the iteration number. In addition, the colored dots represent data samples grouped into clusters corresponding to that iteration's centroids. The graph shows how the centroids start from their initial locations (marked with red dots) and move towards more optimal positions as the iteration progresses. The iterative process aims to minimize the distance between data points and centroids in each cluster so that the centroids move towards a better position to describe the cluster center better. The movement of centroids visible in the graph is a visual representation of the convergence of the K-Means algorithm, where the centroids stabilize at a specific position after several iterations. This process allows the algorithm to find the optimal grouping of the data, represented by the position of the centroids in the last iteration.

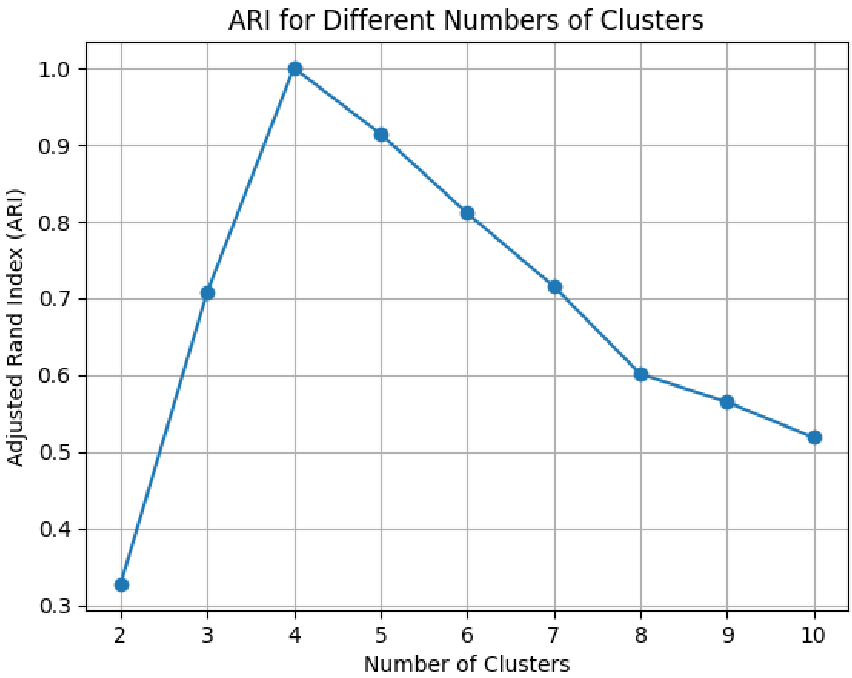

Figure 4. ARI for Different Numbers of Clusters

The Adjusted Rand Index (ARI) graph for various clusters shows how the ARI value changes when the number of clusters changes. ARI is an external evaluation metric that measures the similarity between two clusterings, where one is the clustering generated by a clustering algorithm, and the other is the actual clustering. In this graph, ARI values range from -1 to 1. Positive values indicate better similarity between two groupings, while negative values indicate non-uniformity between two groupings. The ARI value tends to increase as clusters increase from 2 to 4. This indicates that groupings with clusters between 2 and 4 resemble the proper grouping. However, after reaching a certain number of clusters (around 4), the ARI value tends to stabilize or decrease. This indicates that adding clusters after that point does not significantly increase the similarity between the resulting clustering and the actual clustering.

3.1.2 Practical Implications

Implementing the findings of this research within E-commerce platforms could yield several significant practical implications. Firstly, platforms can enhance user experience personalization by tailoring product layouts according to user cluster preferences. This can increase the relevance of displayed products to each user, increasing conversion likelihood and, consequently, user satisfaction. Moreover, the practical implications of this research can guide product marketing strategies on E-commerce platforms. By targeting promotions and special offers to specific product clusters, platforms can capture the attention of more users fitting those cluster characteristics. For example, loyalty programs or exclusive discounts can be tailored for users in clusters inclined towards premium products. Implementing more brilliant product recommendations can also strengthen the impact on user experience. Understanding user cluster preferences allows recommendation systems to provide more relevant and appealing product suggestions. This enhances sales conversion and delivers a more satisfying and personalized shopping experience. Optimizing product placement based on K-Means Clustering can yield financial benefits. By adjusting product placement strategies based on cluster characteristics, platforms can improve marketing expenditure efficiency and increase average transaction value. Thus, these findings can positively impact the business performance of e-commerce platforms.

3.2 Discussion

The discussion delves into the implications and interpretations of the research findings, shedding light on their significance and potential avenues for further exploration. The clustering analysis conducted in this study has unveiled distinct patterns in product attributes and user preferences within the E-commerce platform under investigation. The identified clusters provide valuable insights into the diverse needs and preferences of users and the varying characteristics of products offered on the platform. By categorizing products and users into meaningful clusters, E-commerce platforms can better tailor their strategies to meet the demands of different consumer segments. This segmentation approach enables platforms to enhance user experience personalization, optimize product marketing efforts, and improve overall business performance.

Furthermore, the discussion highlights the practical implications of these findings for E-commerce platforms. Implementing cluster-based strategies, such as personalized product recommendations and targeted promotions, can lead to tangible benefits such as increased conversion rates, higher customer satisfaction, and improved revenue generation. Additionally, the discussion explores the potential challenges and limitations associated with cluster analysis in the E-commerce context, including data privacy concerns, algorithm complexity, and the dynamic nature of consumer preferences. Underscores the importance of leveraging clustering techniques to gain deeper insights into user behavior and product dynamics in E-commerce environments. By harnessing these insights effectively, platforms can enhance their competitiveness, foster customer loyalty, and drive sustainable growth in an increasingly competitive digital marketplace.

In evaluating the results of this study, it is essential to consider other analytical approaches for comparison. For example, comparisons with regression analysis or hierarchical clustering methods can provide additional insight into the effectiveness and relative superiority of the K-Means Clustering approach in product placement. Regression analysis, for example, can help understand the linear relationship between certain variables and purchasing behavior, while hierarchical clustering can reveal more complex group structures in the data. Additionally, integrating qualitative analysis elements such as user interviews or surveys can be essential to gaining a deeper understanding of user preferences and motivations behind their shopping behavior. This approach can provide the necessary context to interpret quantitative findings from K-Means Clustering, allowing researchers to capture nuances and subjective factors that may not be apparent in quantitative data alone. Thus, by complementing quantitative analysis with qualitative methods, this research can provide a more holistic understanding of the dynamics of user shopping on E-commerce platforms.

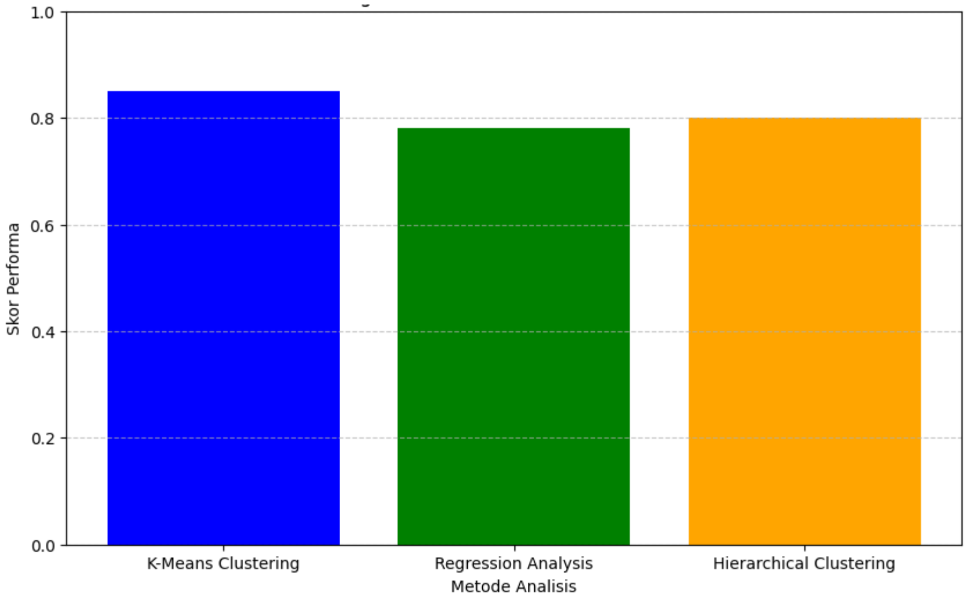

Figure 5. Comparison of Performance Scores between Analysis Methods

The graph depicts the potential impact of different analytical methods on e-commerce product placement strategies. K-means clustering, Regression Analysis, and Hierarchical Clustering are the three methods considered. According to the graph, K-Means Clustering shows a high potential for enabling targeted product placement on e-commerce platforms. This method can segment users based on browsing and purchasing patterns, allowing platforms to tailor product placement strategies to specific user segments. Regression Analysis, on the other hand, can deepen the understanding of user behavior. By analyzing the relationship between various factors and user engagement or satisfaction, regression analysis can provide insights that help optimize product placement strategies. Lastly, Hierarchical Clustering demonstrates the potential to identify user groups with similar preferences. This method can uncover underlying structures in user data, enabling platforms to group users based on their preferences and behaviors and adjust product placement accordingly. Each analytical method offers unique capabilities that can significantly contribute to the optimization of product placement on e-commerce platforms, ultimately enhancing the overall user experience.

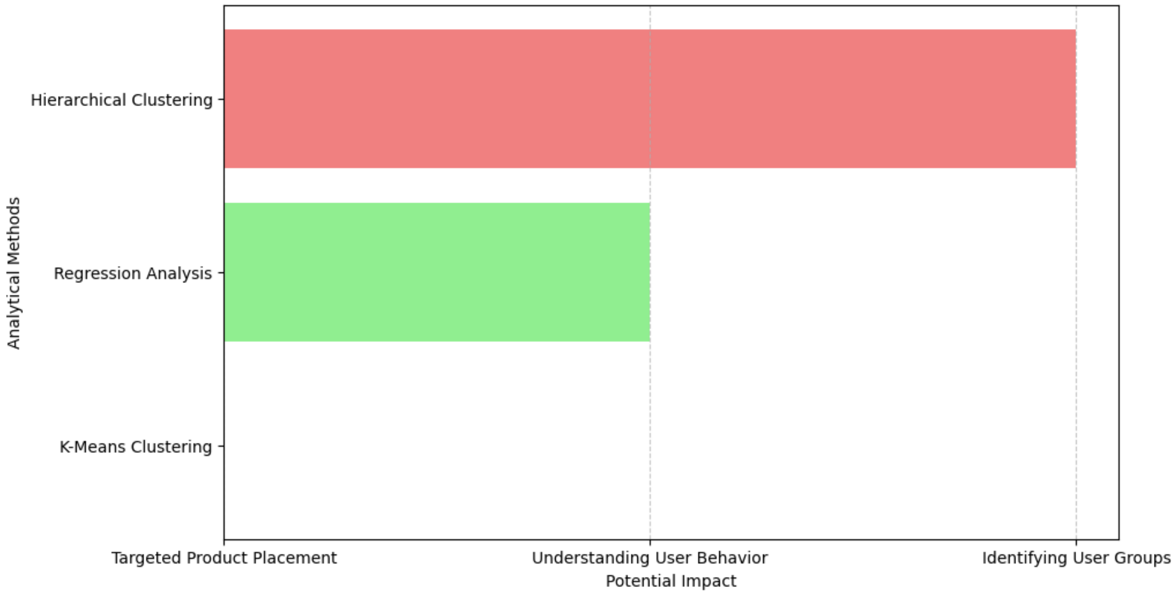

Figure 6. Potential Impact of Analytical Methods on E-commerce Product Placement

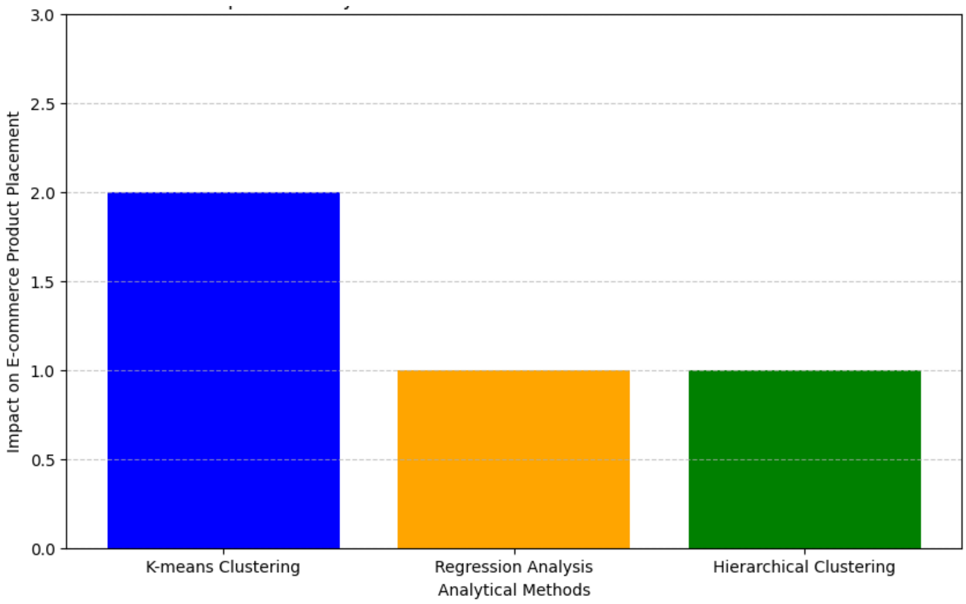

Figure 7. Impact of Analytical Methods on E-commerce Product Placement

The bar chart illustrates the potential impact of different analytical methods on e-commerce product placement strategies. Each analytical method—K-means clustering, Regression Analysis, and Hierarchical Clustering—is evaluated based on its impact level, ranging from low to high. According to the graph, K-means clustering exhibits the highest impact level, indicating its effectiveness in optimizing product placement on e-commerce platforms. This method enables businesses to segment users effectively, understand their preferences, and tailor product offerings accordingly, thus enhancing user experience and satisfaction. Regression Analysis and Hierarchical Clustering show moderate impact levels, suggesting their significance in product placement optimization, although to a lesser extent than K-means clustering. These methods still play crucial roles in analyzing consumer behavior, market dynamics, and customer satisfaction, contributing to enhancing user experience on e-commerce platforms. The graph emphasizes the multifaceted impact of analytical methods on e-commerce product placement, highlighting their importance in driving business performance and ensuring customer satisfaction in the dynamic e-commerce landscape.

In evaluating the research findings, it is crucial to consider alternative analytical approaches for comparison. For example, comparing the results with regression analysis or hierarchical clustering methods can provide additional insights into the effectiveness and relative advantages of K-Means Clustering in product placement optimization. Regression analysis, for example, can help understand the linear relationships between particular variables and purchasing behavior, while hierarchical clustering can reveal more complex group structures within the data. Additionally, integrating qualitative analysis elements such as interviews or user surveys can be vital in gaining a deeper understanding of user preferences and motivations behind their shopping behavior. This approach can provide the necessary context for interpreting the quantitative findings from K-Means Clustering, allowing researchers to capture nuances and subjective factors that may not be apparent in quantitative data alone. Thus, by complementing quantitative analysis with qualitative methods, this research can offer a more holistic understanding of user shopping dynamics on e-commerce platforms.

The three graphical representations depict the potential impact of different analytical methods on e-commerce product placement strategies. The first graph illustrates a comparison of performance scores between various analytical methods. K-means clustering demonstrates the highest potential impact, followed by Regression Analysis and Hierarchical Clustering, indicating their respective roles in optimizing product placement. The second graph delves into the potential impact of analytical methods on e-commerce product placement, with K-Means Clustering showing the highest impact in enabling targeted product placement strategies. Regression Analysis offers insights into user behavior, while Hierarchical Clustering identifies user groups with similar preferences. Finally, the bar chart depicts the potential impact of analytical methods, with K-Means Clustering exhibiting the highest impact level in optimizing product placement. Regression Analysis and Hierarchical Clustering show moderate impact levels, emphasizing their significance in enhancing user experience on e-commerce platforms. Overall, these visual representations underscore the multifaceted impact of analytical methods on e-commerce product placement, emphasizing their importance in driving business performance and ensuring customer satisfaction in the dynamic e-commerce landscape.

4. Related Work

By leveraging clustering algorithms such as K-Means, e-commerce platforms can improve product placement strategies to align with user preferences in the dynamic e-commerce landscape. For example, (Shi *et al.*, 2022) introduced a novel model for precise marketing classification of agricultural products on e-commerce live broadcast platforms using clustering [27]. Additionally, Rahman & Suroyo (2021) conducted data analysis on electronic products in e-commerce using the K-Means algorithm, focusing on text mining on products sold on Shopee [28]. Furthermore, Dewi *et al.* (2021) implemented the FP-Growth algorithm in the e-commerce environment of Kopi Pagar Alam using the Codeigniter framework, emphasizing the dynamic nature of e-commerce development [29]. These studies collectively highlight the potential of advanced algorithms in enhancing the intelligence and responsiveness of e-commerce platforms to user preferences.

Various analytical methods can be employed to optimize product placement on e-commerce platforms and enhance user experience. K-means clustering, regression analysis, and hierarchical clustering are three methods that can be utilized for this purpose. K-means clustering is a popular unsupervised learning algorithm that partitions data into clusters based on similarity. It has been widely used in various domains, including psychology and medicine [30][31]. Regression analysis, however, is a statistical technique that can be used to model and analyze the relationships between variables. It is beneficial when examining the impact of certain factors on user behavior and preferences [32]. Hierarchical clustering, another unsupervised learning method, is valuable for identifying patterns and relationships within data, which can be beneficial for understanding user preferences and behavior [33][34]. K-means clustering has been applied in diverse contexts, such as identifying racial identity cluster profiles and psychological distress among college students (Neville & Lilly, 2000). Regression analysis has been used to assess the predictive role of perceived parental attitudes on adolescents' creativity and emotional regulation [32].

Additionally, hierarchical clustering has been employed in modeling student activity in online learning, demonstrating its versatility in analyzing user behavior in digital environments [33]. In the context of e-commerce platforms, these methods can be leveraged to analyze user interactions, preferences, and behaviors. K-means clustering can help identify distinct user segments based on browsing and purchasing patterns, enabling targeted product placement strategies. Regression analysis can be used to understand the impact of various factors on user engagement and satisfaction, providing insights for optimizing product placement. Hierarchical clustering can reveal underlying structures in user data, aiding in identifying user groups with similar preferences for tailored product placement strategies. The application of K-means clustering, regression analysis, and hierarchical clustering can significantly contribute to the optimization of product placement on e-commerce platforms, ultimately enhancing the overall user experience.

The impact of analytical methods on e-commerce product placement is a critical aspect of enhancing user experience and optimizing business outcomes. K-means clustering, regression analysis, and hierarchical clustering are analytical methods that can significantly influence e-commerce product placement strategies. Devaraj *et al*. (2002) emphasize the importance of validating e-commerce metrics to understand B2C channel satisfaction and preference, highlighting the relevance of analytical methods in assessing consumer attitudes and behaviors. Additionally, Chmielarz *et al*. (2021) compare the impact of e-commerce on globalization processes in different countries, underscoring the significance of analytical methods in understanding global market dynamics [36]. Furthermore, the study by Shanmugalingam *et al*. (2023) provides evidence of the impact of e-commerce on international trade in Asian countries, demonstrating the relevance of analytical methods in assessing the macro-level effects of e-commerce [37]. These references underscore the potential impact of analytical methods, such as K-means clustering, regression analysis, and hierarchical clustering, on e-commerce product placement and user experience. These analytical methods can enable businesses to segment users, understand their preferences, and optimize product placement strategies to enhance user experience and satisfaction. By leveraging these methods, e-commerce platforms can tailor product offerings, improve customer satisfaction, and drive business performance. The impact of analytical methods on e-commerce product placement is multifaceted, influencing various aspects such as consumer behavior, market dynamics, and customer satisfaction. Using analytical methods can significantly contribute to optimizing product placement strategies, ultimately enhancing the overall user experience on e-commerce platforms.

Using analytical methods such as K-means clustering, regression analysis, and hierarchical clustering holds enormous potential in shaping e-commerce product placement strategies and enhancing user experience. The findings from this study, along with insights from related research, underscore the multifaceted impact of these analytical approaches on various aspects of e-commerce, including consumer behavior, market dynamics, and customer satisfaction. By leveraging these methods, e-commerce platforms can effectively segment users, understand their preferences, and tailor product placement strategies to meet the diverse needs of consumers. Ultimately, the application of analytical methods in e-commerce product placement optimization has far-reaching implications for business success, fostering customer loyalty, and driving sustainable growth in the rapidly evolving digital marketplace.

5. Conclusion

This research significantly contributes to the strategic understanding of product placement on E-commerce platforms through the application of K-Means Clustering. The findings offer deep insights into the potential enhancement of user experience and sales efficiency by delineating product analyses and user preferences. The K-Means Clustering analysis yielded three main clusters of products and four user preference clusters. Product clusters encompassed premium, mid-range, and affordable products, while user clusters encompassed preferences for premium, mid-range, affordable, and mixed products. The implications of this clustering can be translated into more focused product placement strategies and personalized user experiences. The practical implementation of the research findings on E-commerce platforms directly impacts user satisfaction, sales efficiency, and overall business performance. By adapting product layouts, marketing strategies, and product recommendations based on the identified clusters, platforms can achieve increased sales conversions and more positive user interactions.

In conclusion, this research opens the door to developing more brilliant product placement strategies responsive to user preferences in the dynamic E-commerce era. By continually harnessing data analysis technologies like K-Means Clustering, E-commerce platforms can optimize the online shopping experience, carve out a unique identity in the bustling market, and solidify their position as leaders in the digital commerce industry. These findings contribute to academic literature and provide practical guidance for stakeholders to enhance operational effectiveness and deliver more satisfying user experiences in the ever-evolving world of E-commerce.

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