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Customer Segmentation Using the K-Means Algorithm for Marketing Strategy Design: Case Study at the Icon Yasika Makassar

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Abstract: This research aims to segment customers of the Icon Yasika Makassar by implementing the K-Means clustering algorithm using the LRFM (Length, Recency, Frequency, Monetary) model. The purpose is to group customers based on their transaction behavior to develop targeted and data-driven marketing strategies. Using transaction data from February 2022 to June 2023, the study processed LRFM scores for each customer and applied K-Means clustering with Elbow and Davies-Bouldin Index methods to determine the optimal number of clusters. The results identified five distinct customer segments with varying characteristics, such as lost customers, core customers, and new customers. A dashboard was developed to visualize segmentation insights and support strategic marketing decisions. This study supports the application of Business Intelligence and behavioral segmentation in improving customer understanding and enhancing digital marketing effectiveness.

Keywords: *Customer Segmentation, LRFM, K-Means Clustering, Digital Marketing, Business Intelligence, the Icon.*

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I. INTRODUCTION

The rapid advancement of information technology has significantly transformed how businesses interact with their customers, including those in the culinary industry[1]. In an increasingly competitive market, gaining a deep understanding of customer behavior is crucial for designing precise and effective marketing strategies. One approach that can be utilized is Business Intelligence, which involves collecting, processing, and analyzing data to generate relevant insights for strategic decision-making[2].

The Icon Yasika Makassar, a business operating in the food and beverage sector, has implemented various promotional strategies, such as discount programs and loyalty schemes. However, transaction data indicates that these efforts have not been entirely effective in boosting sales. For example, despite special promotional events during February 2023 for the company's anniversary and Valentine's Day, sales continued to decline. This suggests that the current marketing approach may not align well with the actual characteristics of the customer base.

To address this issue, more targeted and personalized marketing strategies are needed. Customer segmentation offers a practical solution by classifying customers based on shared traits and behavioral patterns. Through the LRFM (Length, Recency, Frequency, Monetary) model, businesses can analyze transaction behavior with greater precision. This model is combined with the K-Means clustering algorithm, which enables the grouping of customers into homogeneous segments based on numerical data[3]. Previous studies have shown that data-driven segmentation methods can enhance the effectiveness of digital marketing. Grady and Suryani (2021) highlight the value of segmentation in identifying high-risk churn customers while Islam et al. (2021) emphasize the importance of digital approaches in fostering loyalty among new customers [4], Therefore, this study aims to implement customer segmentation using the K-Means algorithm based on the LRFM model to design more tailored digital marketing strategies for The Icon Yasika Makassar.

II. LITERATURE REVIEW

Marketing management is the process of planning and executing activities aimed at creating valuable exchanges between companies and customers. Kotler and Keller (2016)

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state that in an increasingly digital world, successful marketing strategies must be able to understand and fulfill customer needs in a more personalized and data-driven manner [5]. One approach that can support this is Business Intelligence (BI), which is a systematic process of collecting, storing, and analyzing data to support more effective decision-making [2].

In this context, behavioral segmentation is one of the primary methods for utilizing historical customer data. It classifies customers based on their activities and transaction patterns, such as how frequently they purchase, how much they spend, and when they last transacted [6]. The LRFM model (Length, Recency, Frequency, Monetary) is considered an effective behavioral segmentation approach, where customers are evaluated based on how long they have been with the company, how recently they transacted, how often, and how much they spent [7].

To ensure more accurate segmentation, analytical methods capable of processing numerical data and grouping customers into homogeneous segments are required. One widely used algorithm in this context is K-Means Clustering, which effectively clusters data based on the similarity of numeric values [8]. This method has been extensively applied in Customer Relationship Management (CRM) and marketing research to understand different customer groups [9].

Previous studies support the importance of data-driven customer segmentation in formulating marketing strategies. Grady and Suryani (2021) demonstrated that customers at risk of churn can be effectively identified through behavioral segmentation [10]. Perdana (2022) also emphasized that digital marketing strategies targeting new customers can enhance loyalty when implemented appropriately [11]. This finding is further reinforced by the research of Ashdaq et al. (2023), which shows that marketing through social media has a significant influence on customers' positive attitudes toward brands, especially among younger generations who are highly responsive to visual and interactive content [12]. Additionally, Chaffey and Ellis-Chadwick (2016) highlighted the importance of using visual content on social media as part of digital marketing strategies to enhance customer engagemen [13].

III. METHODOLOGY

This study adopts a quantitative approach using a descriptive research design. The objective is to describe patterns and behavioral characteristics of customers based on actual transaction data collected from The Icon Yasika Makassar. The data used are secondary data obtained directly from the company’s internal database, including information such as customer IDs, items purchased, unit prices, total transaction values, and transaction dates. The transaction data analyzed cover the period from February 2022 to June 2023.

In the initial stage, the data were cleaned and restructured to facilitate analysis. Subsequently, LRFM scores were calculated for each customer, with the following explanations: Length refers to the duration of the customer’s relationship with the business; Recency reflects the time since the last transaction; Frequency indicates how often the customer made purchases; and Monetary denotes the total spending within the observed period. After the LRFM scores were calculated, the data were normalized to equalize the scale before proceeding to clustering.

The clustering method used in this study is the K-Means algorithm, due to its efficiency in grouping numerical data into a predefined number of clusters [14]. The optimal number of clusters was determined using the Elbow Method, which visualizes the total within-cluster sum of squares (WCSS) against the number of clusters. The ideal K value is selected at the “elbow point” of the curve. The quality of the clustering results was validated using the Davies-Bouldin Index (DBI), where a lower DBI value indicates better cluster separation [15].

The resulting clusters were then analyzed to identify the characteristics of each customer segment. To facilitate the interpretation of the results and support managerial decision-making, a deep understanding of this segmentation will serve as the foundation for designing digital marketing strategies that align with each segment's profile since effective marketing must be based on mapping customer needs and behavioral patterns [16].

IV. RESULTS

This study successfully performed customer segmentation for The Icon Yasika Makassar using the K-Means algorithm based on the LRFM (Length, Recency, Frequency, Monetary) model. The data utilized consists of customer transactions recorded during the period from February 2022 to June 2023. It includes a total of 3,228 transactions conducted by members of The Icon, representing 1,228 unique member IDs. Each transaction contains seven main columns: Transaction Date, Receipt Number, Member ID, First Name, Last Name, Purchase Amount, and Payment Method. Additionally, the dataset includes a supplementary column, Full Name, which is derived from the combination of first and last names. The analysis process was conducted through several stages, including LRFM score calculation, data normalization, determination of the optimal number of clusters, and visualization of the segmentation results through an interactive dashboard.

- *LFRM Calculation*

In this study, the analysis of Lifetime, Frequency, Recency, and Monetary (LRFM) is employed to understand customer behavior based on four key dimensions. Lifetime represents the total number of days from a customer's first transaction to their most recent one. Frequency records the total number of transactions made by each customer during the specified period. Recency measures the number of days since the customer’s last transaction up to the final date of data collection. Monetary calculates the total monetary value spent by the customer on their transactions during the same period.

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Table 1 LRFM Calculation Results

Member ID	Lenght	Recency	Frequency	Monetary
0001	51	651	3	4954315
0002	31	662	2	2379762
0003	35	651	2	1574760
0004	105	547	6	3389769
0005	0	117	1	1372487
……	……	…….	…….	……
1349	0	8	1	1985445

Source: Data Processed by the Researcher, 2025.

Based on the transaction data provided by The Icon, the values of each LRFM component were calculated for every customer. The LRFM score calculation offers a quantitative overview of customer relationships and activity with The Icon Yasika Makassar. The variation in Length values reflects differences in the duration of customer engagement with the business, ranging from first-time buyers to those who have maintained interactions for over a hundred days. Frequency helps identify how actively customers make purchases, where higher Frequency values indicate a more consistent level of engagement. Meanwhile, a high Recency value suggests that the customer has not made a transaction in a long time, while a low Recency value indicates recent purchasing activity. Lastly, Monetary provides insight into each customer's financial contribution to the company, with values representing the total amount spent during the observation period. With this data, The Icon is able to evaluate the effectiveness of its past marketing strategies and design more personalized and relevant approaches based on actual customer behavior.

➢ *Normalized LRFM Score Results*

The purpose of this normalization process is to align the scale of values generated from the four LRFM components, ensuring that each dimension holds equal weight in the subsequent analysis. Normalization was carried out by dividing the computed scores into five categories based on unique quantiles. This scale assigns scores ranging from 1 to 5 for each dimension, where a score of 5 represents the highest value within that particular dimension.

Table 2 Normalized LRFM Scores

ID Pelanggan	Length	Recency	Frequency	Monetary
C001	0.75	0.20	0.80	0.90
C002	0.10	0.90	0.10	0.15
C003	0.50	0.40	0.45	0.60
C004	0.85	0.10	0.95	0.88
C005	0.30	0.60	0.30	0.40

Source: Data Processed by the Researcher, 2025.

This normalization process facilitates further segmentation analysis by producing standardized data that is comparable across all dimensions. Once normalized, the data becomes ready for clustering using algorithms such as K-Means, which groups customers based on their behavioral patterns according to the calculated LRFM scores.

➢ *Determining the Optimal Number of Clusters*

In this study, the K-Means algorithm was applied to segment The Icon's customers based on normalized LRFM (Length, Recency, Frequency, Monetary) values. To ensure the accuracy and reliability of the segmentation process, the optimal number of clusters must first be determined. One method used to identify the appropriate number of clusters is the Elbow Method. The Elbow Method works by analyzing the Sum of Squared Errors (SSE), which is the total squared distance between data points and the centroids of their respective clusters. Essentially, the K-Means algorithm aims to minimize the SSE value; the smaller the SSE, the better the resulting clustering.

The Elbow Method evaluates various numbers of clusters (k) and plots the relationship between k and the SSE values on a graph. On this graph, a significant decline in SSE is typically observed when the number of clusters is small, but after a certain point, the rate of decline begins to level off. The point where the curve forms a distinct bend or "elbow" represents the optimal number of clusters.

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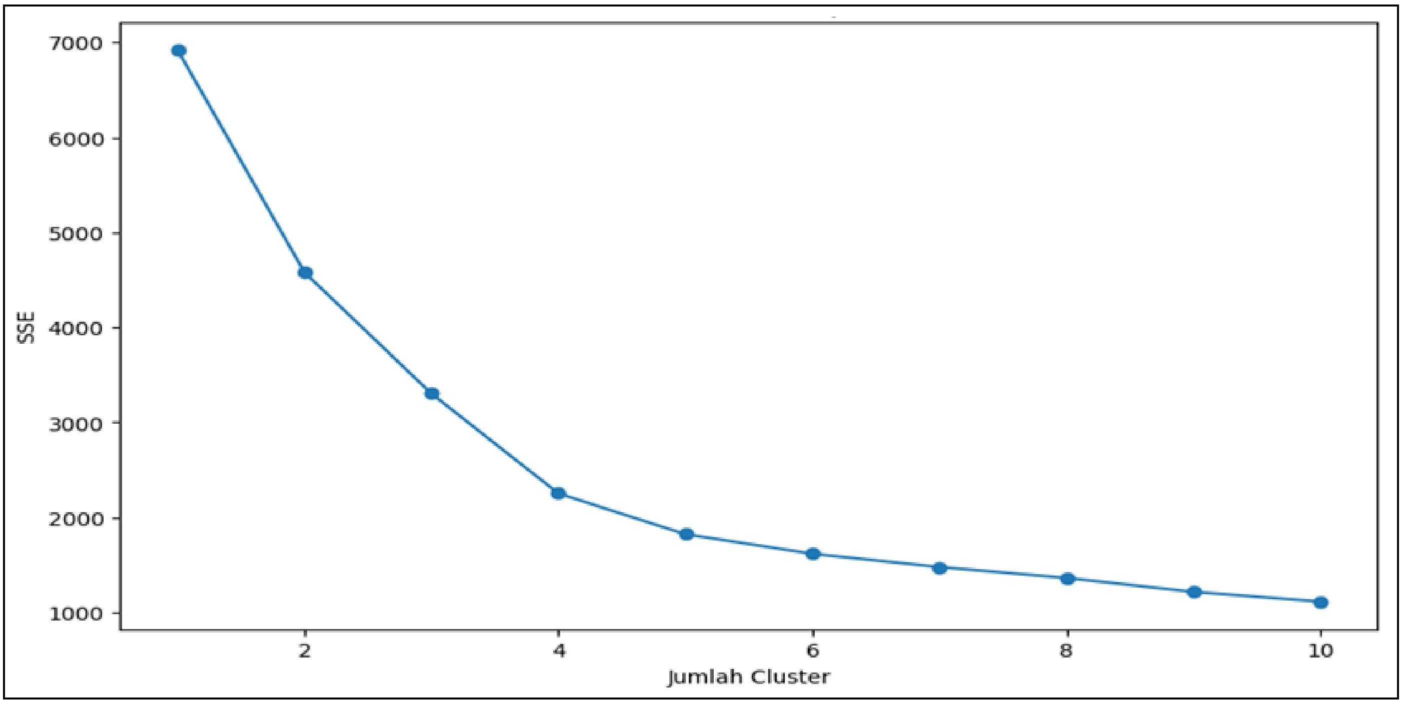

Fig 1 Elbow Method

Based on the Elbow graph analysis in this study, the optimal number of clusters was found at $k = 5$. The Elbow graph indicated a significant decline in SSE from $k = 1$ to $k = 5$; however, after $k = 5$, the curve began to flatten, indicating that adding more clusters beyond this point did not result in a substantial improvement in the SSE value.

➢ *Clustering Evaluation Using Davies-Bouldin Index*

The Davies-Bouldin Index (DBI) is an evaluation metric used to measure the quality of clustering in the K-Means algorithm. DBI assesses how well the clusters are formed by comparing the average distance among members within the same cluster (within-cluster distance) with the distance between different clusters (inter-cluster distance). A lower DBI value indicates better clustering quality, as it reflects high compactness within clusters and large separation between clusters.

Table 3 Davies-Bouldin Index for Various K Values

Cluster	**DBI Score**
DBI for 2 Clusters	1.3494173046618871
DBI for 3 Clusters	0.9403921851366462
DBI for 4 Clusters	0.7740137975213526
DBI for 5 Clusters	0.7025572457404367
DBI for 6 Clusters	0.9160234246810964

Source: Data Processed by the Researcher, 2025.

The analysis calculated DBI values for cluster numbers ranging from 2 to 6. The DBI value for 5 clusters was 0.7025, the lowest among all cluster configurations tested. This indicates that the configuration with five clusters provides the most optimal data partitioning. From this evaluation, it can be concluded that K = 5 is the best choice for clustering in this study, supporting the previous result obtained from the Elbow Method. The DBI serves as an additional validation to ensure that the clustering structure is not only based on changes in the Sum of Squared Errors (SSE) but also reflects deeper insights into the data distribution.

➢ *Segmentation Results and Cluster Characteristics*

Based on the data analysis using the K-Means algorithm, five customer groups (clusters) were identified with the following distribution: Cluster 1 consists of 311 customers, Cluster 2 includes 181 customers, Cluster 3 comprises 341 customers, Cluster 4 contains 205 customers, and Cluster 5 consists of 190 customers. In total, 1,228 customers were successfully segmented.

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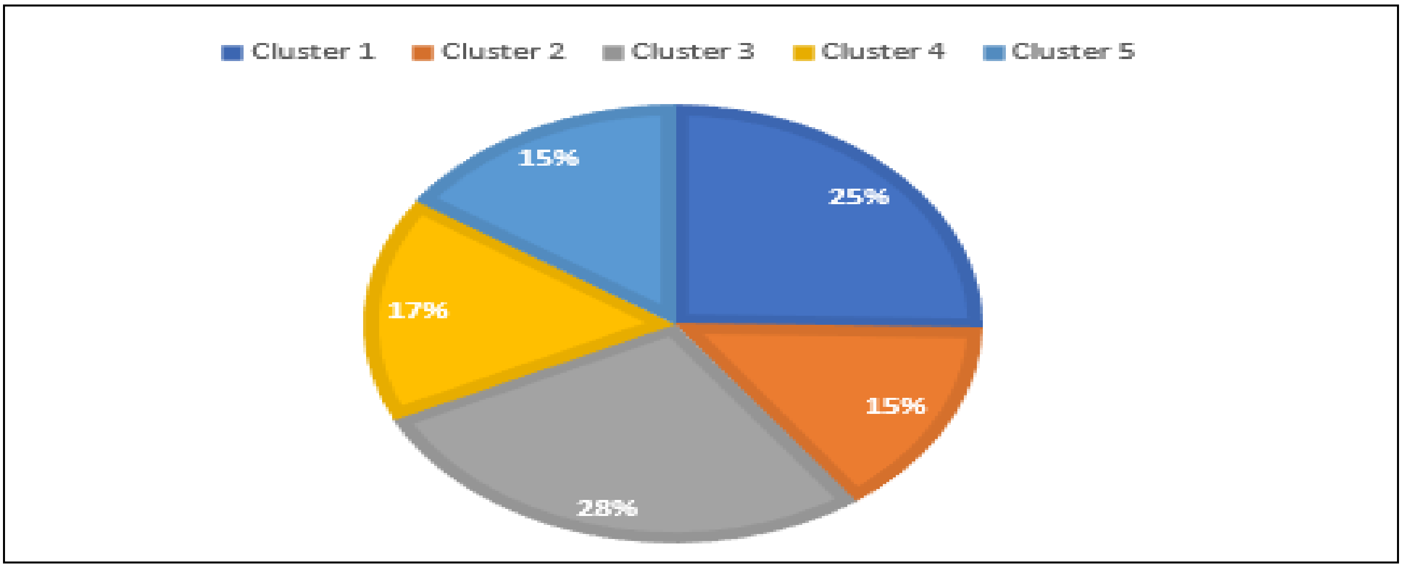

Fig 2 Cluster Distribution Percentage

Based on the pie chart in Figure 2, the customer segmentation results generated by the K-Means algorithm produced five clusters with varying proportions. Cluster 2 holds the largest share, accounting for 28% of the total customers, followed by Cluster 1 with 25%. Cluster 5 ranks third with a contribution of 17%, while Cluster 3 and Cluster 4 each represent 15%. This distribution indicates the dominance of Clusters 2 and 1, which can serve as the primary focus of marketing strategies, while the remaining clusters may require tailored approaches based on the specific characteristics and needs of each group.

Table 4 Cluster Characteristics

Cluster	Characteristics
1	1. *Lifetime: 0 – 266 days (average: 42)* 2. *Recency: 308 – 734 days (average: 537)* 3. *Frequency: 1 – 26 visits (average: 3)* 4. *Monetary: IDR 2,640,099 – IDR 43,754,076 (average: 4,791,771)* *Number of Members: 311*
2	1. *Lifetime: 164 – 710 days (average: 387)* 2. *Recency: 5 – 474 days (average: 167)* 3. *Frequency: 2 – 31 visits (average: 6)* 4. *Monetary: IDR 1,403,095 – IDR 61,729,882 (average: 9,841,097)* *Number of Members: 181*
3	1. *Lifetime: 0 – 254 days (average: 14)* 2. *Recency: 303 – 733 days (average: 532)* 3. *Frequency: 1 – 6 visits (average: 1)* 4. *Monetary: IDR 157,080 – IDR 2,633,400 (average: 1,874,835)* *Number of Members: 341*
4	1. *Lifetime: 0 – 405 days (average: 15)* 2. *Recency: 3 – 288 days (average: 114)* 3. *Frequency: 1 – 5 visits (average: 1)* 4. *Monetary: IDR 0 – IDR 3,655,518 (average: 2,152,065)* *Number of Members: 205*
5	1. *Lifetime: 0 – 157 days (average: 22)* 2. *Recency: 3 – 448 days (average: 221)* 3. *Frequency: 1 – 81 visits (average: 3)* 4. *Monetary: IDR 2,641,485 – IDR 114,307,653 (average: 7,439,468)* *Number of Members: 190*

Source: Data Processed by the Researcher, 2025.

After analyzing the characteristics of each cluster, the next step is to map the results into a Customer Loyalty Matrix to identify customer categories. This mapping is conducted by calculating the standard deviation and mean values of the LRFM variables based on the formed clusters [14]. Based on the clustering results, five customer groups were identified, each with distinct behavioral characteristics. A summary of the segmentation results is presented in the following table:

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Table 5 Cluster Segmentation and Characteristics

Cluster	Simbol LRFM	Cluster Name
1	L ↓ R ↑ F ↓ M ↓	Lost Customers
2	L ↑ R ↓ F ↑ M ↑	Core Customers
3	L ↓ R ↑ F ↓ M ↓	Lost Customers
4	L ↓ R ↓ F ↓ M ↓	New Customers

Source: Data Processed by the Researcher, 2025.

Cluster 2 (Core Customers) is the primary customer group with the highest purchase frequency (F = 11), low recency (R = 300 Cluster 2 (Core Customers) represents the core group of loyal customers, characterized by the highest frequency (F = 11), low recency (R = 300), and the highest transaction value (M = 18,954,215). Customers in this segment are high-value loyal customers, making them essential to retain through loyalty programs, exclusive services, and customer appreciation initiatives. This finding is consistent with Kotler and Keller's (2010) assertion that retaining existing customers is more cost-effective than acquiring new ones [17].

Clusters 1 and 3 (Lost Customers) are marked by very high recency values (R = 629 and 644), low purchase frequency (F = 5 and 2), and low transaction values. This indicates that customers in these groups have not transacted in a long time and contribute minimally to revenue. Therefore, re-engagement strategies such as special offers, personalized discounts, or digital reminder campaigns are necessary to reconnect with these customers.

Clusters 4 and 5 (New Customers) consist of customers who are still in the early stages of their relationship with the company. Cluster 4 shows low frequency and monetary values, reflecting minimal initial engagement. In contrast, Cluster 5 shows rapid growth with high frequency (F = 11) and a large transaction value (M = 19,076,573), indicating strong potential to become core customers if managed properly. Digital marketing approaches such as educational content, digital point programs, and active engagement on social media are highly recommended.

V. DISCUSSION

The customer segmentation results of The Icon Yasika Makassar using the K-Means algorithm with the LRFM model approach reveal that the five customer clusters formed exhibit distinct behavioral characteristics. These findings provide a deeper understanding of purchasing patterns, levels of customer engagement, and the loyalty potential of each group. This segmentation is not only beneficial for classifying customers but also serves as a foundation for designing more targeted and data-driven marketing strategies.

One particularly interesting finding is the existence of Cluster 5, which is classified as a new customer group, yet displays high values in both frequency and monetary. This indicates that, although customers in this cluster are relatively new (low Length), they immediately demonstrate active and significant purchasing behavior. Confirmation from The Icon revealed that these customers typically come in groups or place large orders for specific events such as birthday celebrations or community gatherings. They also tend to choose premium menu items, resulting in higher transaction values. This finding highlights the importance of implementing aggressive loyalty strategies for new high-potential customers to prevent them from switching to competitors.

On the other hand, Clusters 1 and 3 are categorized as lost customers, characterized by high recency, low frequency, and low monetary values. Customers in these groups have not made purchases for a long time and contribute minimally to revenue. Based on consumer behavior theory, this segment is at high risk of churn and thus requires appropriate re-engagement strategies such as retargeting ads and reminders through personalized communication channels. Meanwhile, Cluster 2, classified as core customers, demonstrates consistent purchasing behavior and high transaction values. Customers in this cluster are considered essential and must be retained through appreciation programs, personalized approaches, and consistent service. Efforts to retain loyal customers are proven to be more efficient than acquiring new ones [18].

This discussion also highlights that a data-driven approach through LRFM-based segmentation and K-Means clustering can provide sharper insights for businesses in designing personalized, relevant, and measurable digital marketing strategies. The findings of this study are supported by Rakib et al. (2023), who explain that product image is the perception and understanding that consumers have of a brand based on what they see, think, or imagine [19]. Their research shows that the effective implementation of digital advertising, particularly through social media, can build a positive product image in consumers' minds and expand the reach of small-scale businesses. In the context of The Icon Yasika Makassar, integrating segmentation results with digital strategies—such as personalized promotions, loyalty programs, and strengthened brand visualizations on social media—has strong potential to reinforce positive customer perception and enhance the effectiveness of ongoing marketing campaigns.

VI. CONCLUSION

This study demonstrates that the K-Means algorithm combined with the LRFM (Length, Recency, Frequency, Monetary) model is effective in segmenting customers of The Icon Yasika Makassar. By processing customer transaction data from the period of February 2022 to June 2023, the study successfully identified diverse consumer behavior patterns based on their interactions with the company. The analysis revealed that customers could be classified into five main clusters Core Customers, Lost Customers, and New Customers each characterized by LRFM attributes that represent their level of loyalty, financial contribution, and future engagement potential. Each cluster holds distinct strategic value in supporting business growth. Core Customers, with high Frequency and Monetary values and low Recency, are the primary targets for retention strategies and customer appreciation programs. Conversely, Lost Customers exhibit very high Recency and low purchasing activity, requiring intensive re-engagement approaches through promotional efforts and personalized communication. Meanwhile, New Customers, though relatively new, show strong potential to develop into loyal patrons if managed with the right, data-driven digital marketing strategies.

The optimal number of clusters in this study was determined using the Elbow Method and validated through the calculation of the Davies-Bouldin Index, where the lowest DBI value was found at K = 5. This indicates that the five-cluster configuration provides optimal separation among customer segments. Additionally, data visualization and segmentation results were presented in an interactive dashboard using Google Looker Studio, which enhances the understanding of customer distribution and supports real-time and efficient managerial decision-making. The integration of Business Intelligence, data mining techniques, and digital marketing strategies has proven to deliver valuable insights for the company, particularly in improving promotional targeting accuracy, managing customer relationships, and optimizing marketing budgets. This study contributes not only to the development of knowledge in the fields of information systems and marketing management but also demonstrates a practical application of a data-driven approach in the local food and beverage industry. In the future, similar approaches can be extended through the use of alternative algorithms or integration with CRM systems to develop marketing strategies that are more adaptive, predictive, and customer-oriented.

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