Potential Customer Analysis Based on Gender, Age, Retention, Motivation Using K-Means and Octalysis Gamification Approach

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Abstract **– This study aims to analyze the role of gender, age, retention, and motivation on the high and low opportunities of potential customers using the K-means clustering approach and gamification octalysis. This research resulted in several new knowledge contributions. Female customers are the most potential customers in a retail company. On the other hand, male customers are the least potential customers. The motivation to buy is relatively high across all genders and ages, as evidenced by the average "core drive" score, which tends to be high in the customer cluster segment with various age groups. The amount of customer motivation to buy products does not affect purchase retention, which several factors outside this study can cause. Based on customer expectation and** ***customer impression data, low-price offers and product discount offers are dominantly in demand by customers, and this is also in line with the core drive "development" and "scarcity" scores which tend to be high. The age maturity of customers is directly proportional to purchase retention, and this is entirely rational when considering the buying ability of customers where the more mature age group has a higher purchasing power.***

Keywords **– Potential customer, small medium enterprise, k-means, octalysis gamification framework.**

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1. Introduction

Small Medium Enterprise (SME) is one of the foundations of the country's economy, therefore it is essential to focus on solving SME problems [1], [2], [3]. One of the important SME problems is extracting and analysing data to become useful, new knowledge [2], [3]. This activity has been carried out in many previous studies, but along with the increasing number of SMEs and their products, the problem continues to grow [1], [2]. Therefore, the study of extracting SME data to generate new knowledge still needs to be developed with various approaches [2], [4], [5], [6]. In the last few years, much research has been conducted on developing various approaches to support SMEs in making strategic decisions. Some of the approaches taken include a recommendation system [7], data mining [1], [3], [8], expert systems [9], and others. Solving these problems has used various methods and algorithms available. One of the expected results from extracting this data is predicting and analysing potential customers [10], [11].

Potential customer analysis is collecting and processing customer data to understand and predict potential customer opportunities [12], [13]. The purpose of this analysis is to identify customers who have a high probability of becoming potential customers in the future [12], [13], [14]. This information is essential for companies, especially retail, to maintain the stability of turnover and even increase it. Analysis of potential customers is important to do by considering several urgencies. Customer analysis can potentially help identify new business opportunities [15], [16].

By understanding potential customers' preferences, needs, and behavior, companies can develop appropriate marketing strategies to attract and retain customers [15], [16]. This analysis is also the basis for understanding better what customers want and expect. It allows companies to improve their products, services, and overall customer experience.

Besides that, potential customer analysis also helps companies understand the most potential and deep market segments [13], [14]. With this understanding, companies can develop relevant and effective marketing strategies to reach customers at the right time and through the right channels. Another urgency of this analysis is that companies can collect relevant data and make better decisions based on accurate information [15], [16]. It helps companies reduce inaccuracies in decision-making and avoid ineffective or unnecessary spending [15], [16]. This analysis also can potentially provide a competitive advantage to the company[17],[16],. Companies can develop better strategies by understanding customers and markets than their competitors. Various efforts need to be made to obtain information and increase the potential or opportunities of these potential customers [13], [14]. Several indicators related to potential customer analysis include gender, age, retention, and motivation [13], [14], [18]. The data related to these indicators can be used to analyze potential customers.

The analysis process can be started by segmenting some of the item sets involved with the data mining approach, especially the clustering method. The clustering work system is grouping data into groups that are similar to the group [13]. Clustering is a method in data mining that works by grouping datasets on various platforms into specific clusters according to the level of similarity in which the number of clusters to be generated is determined, and then the centroid is determined [14]. Various fields apply clustering to solve data grouping analysis problems, such as exploring customer behavior, customer segmentation, potential customers, the best suppliers, customer profitability opportunities, and other analysis needs. Clustering has several algorithms, such as Self Organizing Map (SOM), Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Clustering k-means, and others. The most commonly used and recommended algorithm is k-means [3]. K-means has several advantages, some of which are that the calculation process is relatively fast and easy to learn [3].

In this study, gender, age, and retention are grouped using k-means as potential customer analysis material. Meanwhile, motivational data is also an important element that needs to be explored in more detail to support the analysis.

A gamification is an alternative approach that can be used to observe motivation. Gamification can potentially increase motivation and user retention and has a framework that can measure the amount of motivation [19], [20]. Gamification is an approach/method/model that is the game field approach to solving problems related to business, education, economics, society, entertainment, and others. The primary purpose of gamification is to motivate and stimulate system users to be more involved in the gamified system [21], [22]. There have been many studies related to gamification in several fields, including education [19], [20], health [23], and business [24]. Gamification develops multiple frameworks. The basic framework for gamification is Mechanics Dynamics Aesthetics (MDA), then developed into Mechanics Dynamics Emotional (MDE). Sustainable Gamification Design (SGD) is also a development framework for gamification, and one that is quite popular today is Octalysis [25], [26], [27], [28]. The Octalysis framework has the specificity of being able to measure the amount of user motivation by exploring motivation in 8 "core drives," which are believed to be the background of someone taking action [29], [30], [31]. For this reason, Octalysis provides a mechanism for measuring motivation through an octalysis scale consisting of "8 core drives", whose purpose is to measure customer motivation in more detail [25], [26], [27], [28].

Until now, few studies still observe how customer motivation in detail causes loyalty to the company or vice versa. Previous research also rarely discusses the role of gender, age, customer retention, and motivation data in supporting the analysis of potential customers. It is a research opportunity. For this reason, this study focuses on analyzing the relationship between gender, age, customer retention, and motivation in analyzing potential customers so that company evaluation materials can be used to increase product sales volume.

2. Research Method

This research methodology combines the k-means clustering data mining approach and gamification octalysis to analyse potential customer opportunities. The method is depicted in Figure 3 below.

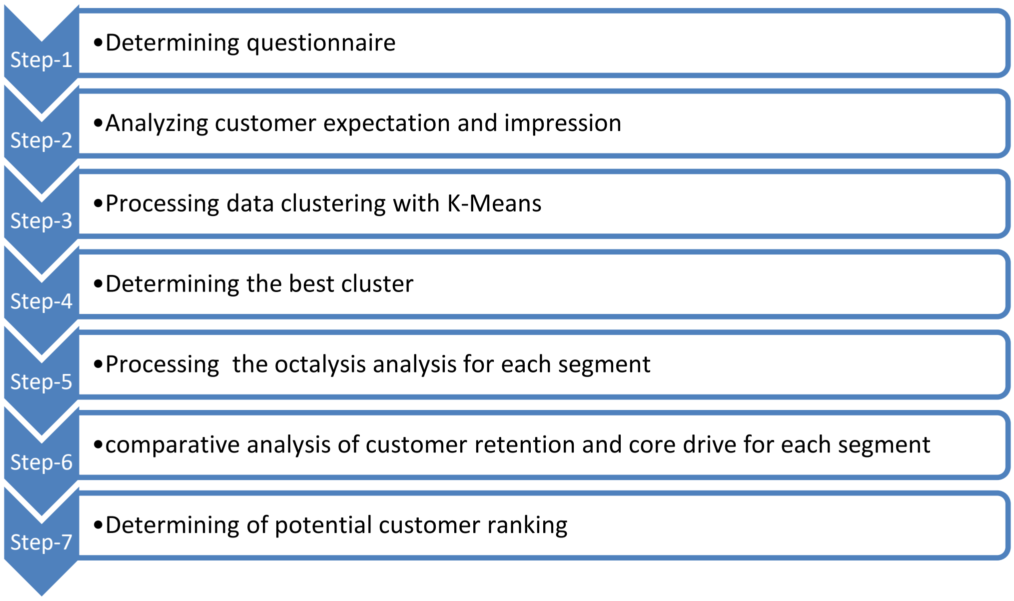

Figure 3. Research methodology

Determining of Questionnaire [1]

In this stage, the data were grouped by distributing questionnaires to 100 customer respondents sampled from the retail SME network spread across East Java - Indonesia. Then do the process of weighting the questionnaire with a Likert scale [32] with 5 ordinal scales. Calculation of the number of samples following Slovin's guidelines [32].

$$n = \frac{N}{1+Ne^2} \quad (1)$$

with notation:
n = sample,
N= population,
E = standar deviation 5%.
Then the result of calculating the determination of the sample from the two samples (N = 144) is n = 100. Questions were divided into 2 groups, namely No. 1 to 13, exploring data on gender, age, retention, eight core drives octalysis, and customer expectations and impressions. Questionnaire answers were tabulated, normalized, and totaled according to the weight of the answers.

Analyzing customer expectations and impressions [2]

This stage is to present tables and graphs comparing the questionnaire results regarding customer expectations and impressions of the choices offered in the questionnaire. Comparisons were made in percentages and then analyzed.

Processing cluster data with k-means [3]

First, determine the criteria, namely gender, age, retention, and the number of clusters (K = n). Then determine the center point of each centroid, calculate the shortest distance and carry out the iterative process until it has finished.

Determining the best clusters [4]

Determining the best cluster using the Elbow and Some Squares Error (SSE) method [3]. The best cluster is generated from the most concave angle of the elbow graph and the lowest value of SSE. The results of this determination are the cluster guidelines that will be applied in the analysis.

Processing the octalysis analysis for Each Segment [5]

This step calculates the questionnaire results on the core drive group using a Likert scale. Then the questionnaire data were grouped into five groups referring to the range of the multiplication difference between the number of respondents and the weight of the criteria. After the group is formed, compare the actual and target values of the core drive octalysis by combining the results of the Likert scale test from the eight calculated core drives. Then carry out the process of converting the octalysis scale value to the Likert scale results, and the conversion results are used to measure the octagon pattern with the resulting core drives value guideline. The final result of this stage is a comparison between the octalysis target octagon pattern and the actual octagon pattern that is formed.

Comparative analysis of customer retention and core drive for each segment [6]

This stage performs several calculations from gender, age, retention, and motivation data in 8 core drive octalysis. The data is added to calculate the average retention, core drive, age, and gender segmentation. This stage aims to find valuable analytical results for companies from the relationship between gender, age, retention, and motivation to potential customer opportunities.

From this stage, potential customers can be analyzed based on gender and age and how the relationship between motivation and customer retention contributes to the strength of potential customers.

Determining potential customer ranking [7].

This stage determines the ranking of potential customers by adding up the average retention and core drive catalysis values. In this stage recommendations for potential customer groups are generated from all the clusters produced.

3. Result and Discussion

a. Determining The Questionnaire

The process begins with collecting data and distributing questionnaires that accommodate gender, age, retention, customer expectations, customer impressions, and 8 core drives octalysis. The measurement scale consists of 5 ordinal scales: the lowest score is 1, and the highest is 5. Then the data are grouped for three different analysis purposes. The first group grouped the data for analysis of customer expectations and impressions. The second group collected data on gender, age, and retention as criteria data which were analyzed using the K-Means algorithm. The third group collected data related to eight octalysis drive cores.

b. Analyzing Customer Expectation

The result of the analysis of the survey data is a description of the customer's impression of the company's services. In this data network, customers can choose more than one option. As described in Table 1 and Figure 1, the customer's biggest impression is the choice of affordable price (65.06%) and affordability of place (59.43%). A large percentage of both is possible because the two options are generally what most people are interested in. On the other hand, company services tend to be minor, including availability many of souvenirs is 2.83%, availability much of discounts is 7.55%, convenient shopping place is 27.36%, and "Ease of finding items" is 23.58%. This analysis indicates that customers seem dissatisfied with the programs offered related to customer service.

Table 1. Percentage of customer impression

No	Options	Percentage
1	Affordable price	65.09
2	Availability Many of Souvenirs	2.83
3	Availability Much of discounts	7.55
4	Affordability of place	59.43
5	Convenience shopping place	27.36
6	Ease of finding items	28.30
7	Neutral	2.83
8	No Response	0.00

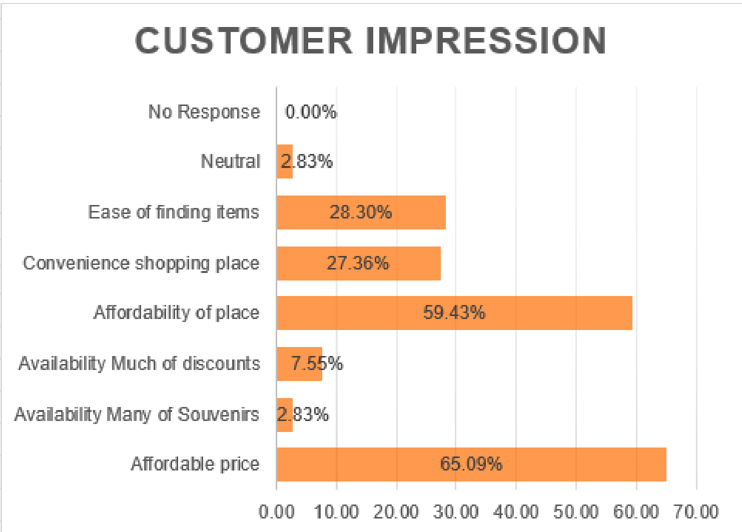

Figure 1. Graph of customer impression

While the analysis of customer expectations is described in Table 2 and Figure 2, the questions consist of five items with the theme of service programs. In data networking, customers can choose more than one option. From the screening results, all options have a value and are almost the same, from 19.81% to 23.58%. The thing that can be analyzed is customer expectations for the service improvement programs offered, although manageable.

In contrast, this data is quite inversely proportional to the "Customer impression" data which significantly describes customer impressions of small services, which means that current customer service is less than optimal. For this reason, it is necessary to carry out more profound research, one of which is to explore customer motivation in detail and the impression felt towards customer service with a better method or approach.

However, referring to Table 2 and Table 3, there are three dominant options chosen by respondents, which are proven to have a high percentage, including affordable price, convenient shopping place," and availability much of discount. This condition can be a supporting material for the overall analysis of this research.

Table 2. Customer expectation percentage

No	Options	Percentage
1	Items are Well available	22.64
2	Member cards are well available	19.81
3	Customer motivation programs are well available	20.75
4	Discount are well available	33.02
5	Ease of finding items	23.58
Average		23.96

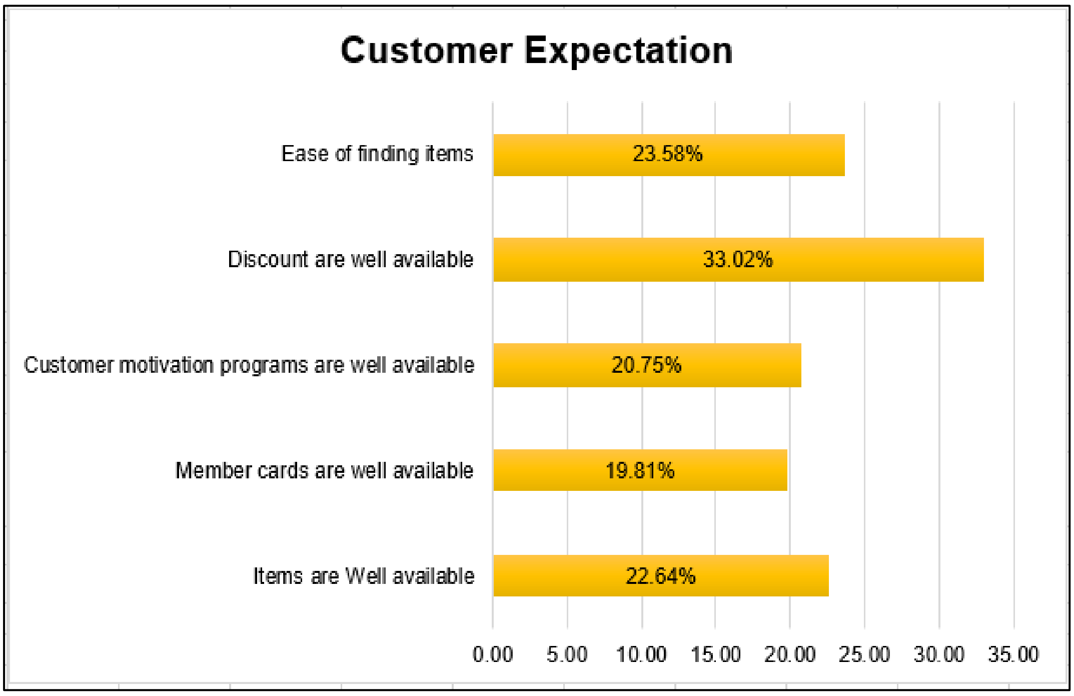

Figure 2. Graph of customer expectation

c. Processing Data Clustering with K-Means and Determining the Best Cluster

This stage performs the process of grouping with the k-means algorithm from 100 data. The number of clusters is determined by several K = 5. The grouping results produce 5 data clusters. Table 3 shows the resulting cluster data with membership in each segment and the resulting SSE value that form the elbows on the elbow chart [3]. Referring to Figure 3 that the best cluster is Cluster 4

Table 3. Five clusters result

Cluster	Number of Segment	SSE Value
1	Segment = 100	238.2
2	1-Segment = 35	186.7
	2-Segment = 65	
3	1-Segment = 20	134.9
	2-Segment = 50	
	3-Segment = 25	
4	1-Segment = 25	65.4
	2-Segment = 29	
	3-Segment = 23	
	4-Segment = 23	
5	1-Segment = 50	101.9
	2-Segment = 10	
	3-Segment = 17	
	4-Segment = 23	
	5-Segment = 0	

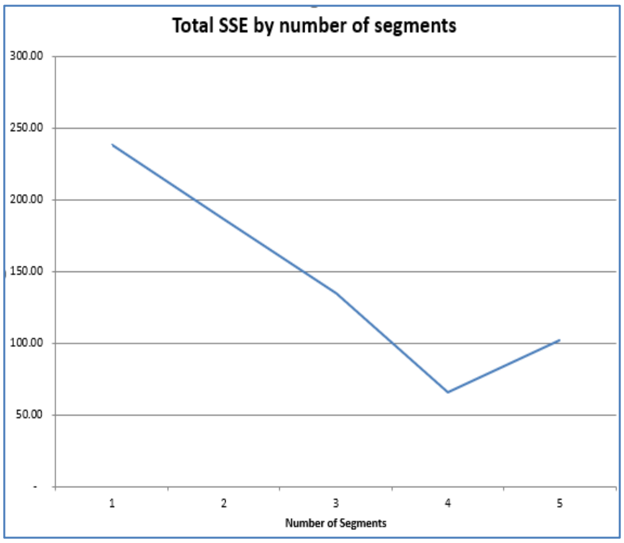

Figure 3. Graph elbow method

Thus, Cluster 4 becomes the data reference for further analysis. Cluster 4 consists of 4 segments with membership of Segment-1 = 25, Segment-2 = 29, Segment-3 = 23, and Segment-4 = 23. The visualization of Cluster-4 has been described in Figure 4.

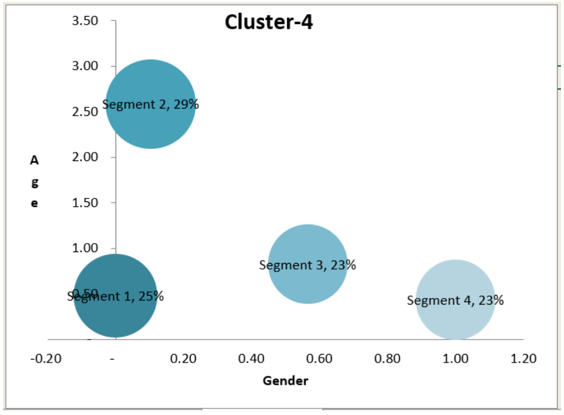

Figure 4. Visualization of Cluster-4

d. Processing the Octalysis Analysis for Each Segment

This stage begins by calculating the average octalysis value for eight core drives. The maximum value of the questionnaire score is five, so the highest average value is the maximum value of the questionnaire. The average value will be compared with the target octalysis value of 10 for each core drive. Therefore, the mean value of the questionnaire is multiplied by 2 to balance the octalysis target value. The results of calculating the core drive of the four segments have been described in Table 4.

Table 4. Octalysis value of 4 segments

Core Drives	Octalysis Score				
	Target	2-Segment	2-Segment	3-Segment	4-Segment
Core Drive of Epic Meaning and Calling	10	8	10	10	8
Core Drive of Development and Accomplishment	10	8	8	8	8
Core Drive of Empowerment and Creativity	10	8	8	8	8
Core Drive of Ownership and Possession	10	8	8	8	8
Core Drive of Social Influence and Relatedness	10	8	8	8	8
Core Drive of Scarcity and Impatience	10	8	8	8	8
Core Drive of Unpredictability and Curiosity	10	8	8	8	8
Core Drive of Loss and Avoidance	10	8	8	8	8

From the resulting octalysis score, an octagon graph of each segment can be visualized. Figures 5, 6, 7, and 8 state that the blue color shows the target octagon while the red color is the actual score. From the visualization, almost all core drives tend to achieve high values, although they have not yet reached the target of the maximum octalysis value.

The value of each core drive is also quite balanced, which is in the range of eight. It means that customers have high and diverse motivations to buy products. From these results, companies need to analyze the meaning of each core drive in more detail as a basis for making the right decisions for promo strategies.

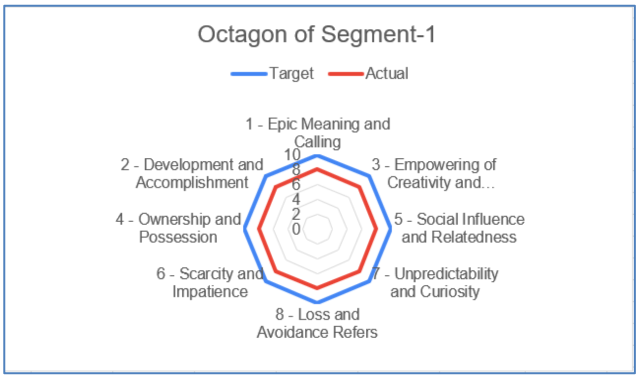

Figure 5. Octagon graph of Segment-1

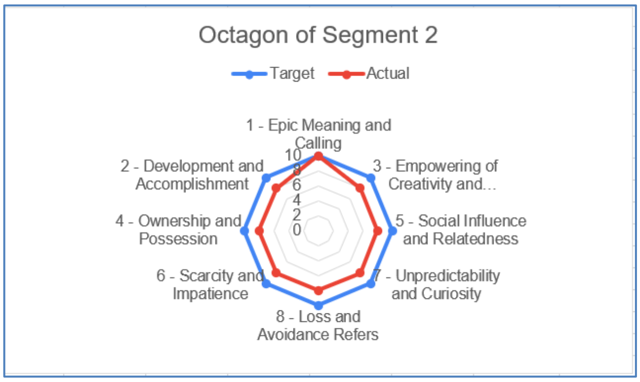

Figure 6. Octagon graph of Segment-2

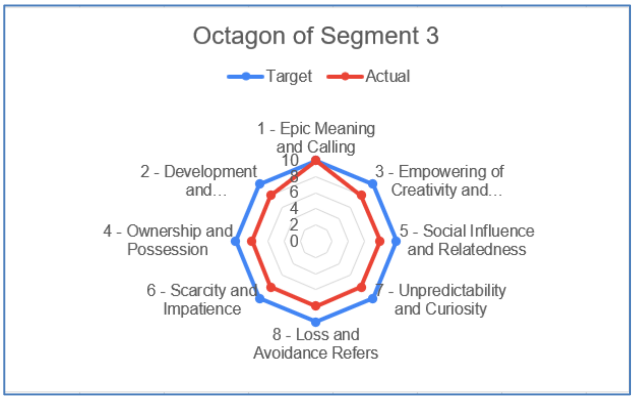

Figure 7. Octagon graph of Segment-3

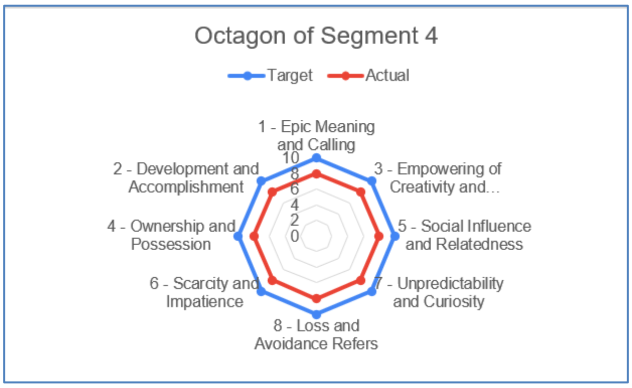

Figure 8. Octagon graph of Segment-4

d. Comparative Analysis of Customer Retention and Core Drive for Each Segment

This stage processes data on gender, age, retention, and octalysis value into several analysis results that become recommendations regarding potential customers. Each segment is classified in more detail in Table 5 and Table 6. In Table 5, gender is classified into two categories: male and female. Age is classified according to the grouping in the questionnaire, which is divided into five groups. In Table 6, retention is generated from the average number of questionnaire data so that the final result is a percentage. Table 6 also lays out the core drive data for each segment. Based on researches [13], [14], [18] retention and motivation are part of the indicators to determine potential customers. Then the value of potential customers can be determined for the four segments by adding up the average retention and core drive values.

Table 5. Classification of the segment on gender and age

Segment	Gender		Age				
	Male	Female	15-27	28-35	36-45	46-55	>55
1	0	100%	46.88%	53.13%	0	0	0
2	0	100%	0	0	65.52%	24.14%	10.34%
3	100%	0	0	35.71%	35.71%	21.43%	7.14%
4	100%	0	100%	0	0	0	0

Table 6. Classification of the segment on retention, core drive and potential customer value

Segment	Retention	Core Drive Value	Potential Customer Value
1	26.55%	8	34.55%
2	26.21%	8.25	34.46%
3	23.79%	8.25	32.04%
4	23.45%	8	31.45%

From Table 6, a graphical visualization of the composition of the retention levels of each segment can be visualized. Figure 9 describes Segment-1 as at its highest point, whereas Segment-4 is at its lowest point. If observed, the difference in retention values in Segment-1 and Segment-2 is not far adrift, as well as in Segment-3 to sSgment-4. However, there is a significant difference in value between Segment-2 and Segment-4, so it can be said that these four segments tend to become two groups that tend to be high (Segment-1 and Segment-2) and two groups that tend to be low (Segment-3 and Segment-4). Referring to Table 5, Segment-1 and Segment-2 have 100% female customers, while Segment-3 and Segment-4 have 100% male members. So the knowledge obtained in this analysis is that female customers have a greater chance of purchase retention than male customers.

Figure 9. Customer retention graph

Based on Figure 10 and Table 6, the graph compares the retention and core drive values. The movement of the retention value is not related to the value of the core drive. Based on this research, the retention in the level of motivation to buy a product does not guarantee high retention. It is an exciting piece of knowledge, meaning it is necessary to learn more about the factors that affect retention and how to encourage motivated customers to continue buying the product.

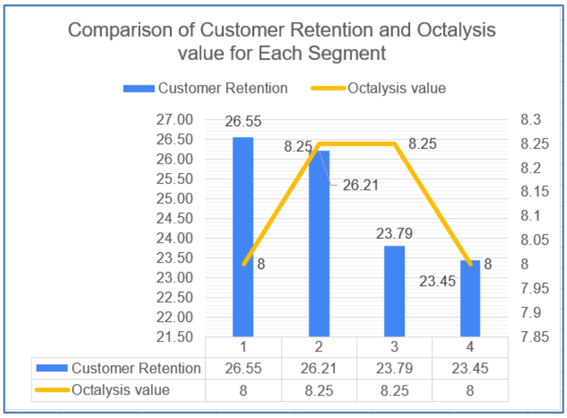

Figure 10. Comparison graph of retention and octalysis

e. Determining of potential customer ranking

This stage determines the ranking of potential customers. In Tables 5, 6, and Figure 11, a graph of potential customer ranking has been visualized based on retention value and core drive. The first rank for potential customers is the female customer segment with an age range of 15 to 35 years, followed by Segment-2, namely female customers with an age range of 36 years and over. Male customers tend to have lower retention, especially those under the age range of 28 years. These findings can be a consideration for retail companies to increase sales volume.

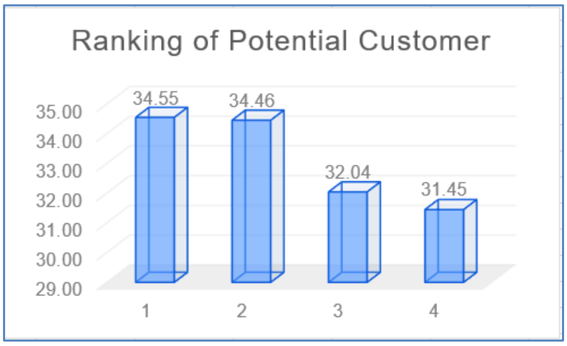

Figure 11. Ranking of potential customer

4. Finding

Several findings have resulted from this experiment. The highest retention is the segment with the most gender of women in the age range of 15-35 years, as evidenced by Segment-1, which has 100% female members consisting of the age range of 15-27 years of 46.88% and the age range of 28-35 years of 53.13%. Segment-1 has a customer retention value of 26.55%, the largest compared to the other three segments. Likewise, the second highest retention is Segment-2, with gender 100% females with an age range of over 35 years. The retention value of Segment-2 is 26.21%, meaning that this value is close to the retention value of Segment-1. These findings conclude that in retail companies, female customers from various age groups contribute the most and have the most potential to become potential customers.

In the octalysis value test, it was found that the distribution of gender and age groups that were more diverse had higher core drive values than those that did not vary, as evidenced in Segment-2 and Segment-3 having higher core drive values (each of 8.25) compared to Segment-1 and Segment-4 (each by 8). It can be said that customers with various age and gender segments own the motivation to shop. It also means that all of these customers have the potential to shop and, of course, have the opportunity to become potential customers.

Meanwhile, Segment-3 and Segment-4 consist of 100% male customers. In Figure 10, these two segments have significantly lower retention values than Segment-1 and Segment-2. However, Figure 10 and Table 5 also describe Segment-3, which has the most male customers and achieves high core drive scores. These findings provide important information for retail companies to pay more attention to promo strategies and find reasons why male customers have little retention. This data also indicates that high motivation does not guarantee high retention. Many factors affect loyal customers and have significant retention [14], [18], so these factors need to be investigated so that male customers can potentially become potential customers.

The most potential customers based on retention value and core drive are women with an age distribution ranging from 35 years to over 55 years, as evidenced by Segment-2 having a high retention value of 34.46% and a core drive value of 8.25. These findings provide information that customers in this segment need to investigate the causes or reasons that move them to buy internally and externally so that it can serve as a reference for implementing promos in other segments.

Based on the data obtained, the value of core drive motivation is not directly proportional to customer retention. However, customers who are more varied in age distribution and balanced gender distribution have more core drives. It is evidenced by Segment-2 and Segment-3. This finding proves that high motivation does not guarantee a customer's tendency to buy, and buying decisions can be influenced by other factors that have not been investigated. Several factors, including age and gender, may also influence retention that is not always directly proportional to core drive. The value of the core drive is influenced by the diversity of the age distribution, where the distribution of various ages has a more considerable value of the core drive. However, the size of the core drive does not affect the retention amount and vice versa.

From the results of ranking the total retention weight and core drive, a potential customer value has been generated, with the first ranking being the dominant gender group of women in the age range of 15 to 35 years, the second being the group with the dominant gender of women in the age range of 35 to 55 years and over, the third the group with the dominant gender is male at the age of 28 to 55 years and over, and the fourth is the group with the dominant gender male at the age of 15-27 years. These findings show that age maturity is directly proportional to retention value. It is due to buying ability and needs [12], [13].

Based on customer expectations and impressions data, other factors influence customers' buying, such as low prices, discounts, ease of finding goods, availability of products, and convenience of place. Based on the survey results, low-price offers and product discount offers that have been predominantly in demand by customers are also in line with the "core drive," "development," and "scarcity" scores which tend to be high.

5. Conclusion

Gender, age, retention, and motivation are four indicators that can be considered to determine potential customers. Gender, age, and retention data are processed with the k-means clustering algorithm to form data segments that can be used as material for the analysis of potential customers. In line with that, the gamification octalysis framework can explore motivation in more detail, especially to investigate why customers want to buy a product. The results of the core drive test, which stated high "development" and "scarcity," were in line with the customer expectation survey data and the impression that dominant customers chose to buy products with low-price offers and applied discounts. This study concludes several findings that contribute to potential customer tracking. The female customer group of various ages has the highest chance of becoming a potential customer, especially those aged 35 and over, who are the strongest. It could be because, in this age range, customers have a higher buying ability than those under the age group. These findings can be used as a reference for companies in optimizing it, for example, by conducting product promos that customers usually consume under the age of 35 at a lower price for consumers.

This research also found that male customers of various age segments have relatively low retention, making them less likely to become potential customers, and referring to several previous studies that many indicators can contribute to getting potential customers. It is necessary to carry out more studies to investigate this so that male customers also have a high chance of becoming potential customers. Based on the octalysis test, it was found that male and female customers have high motivation in buying products, where this high motivation exists in the diversity of age layers. However, the amount of motivation does not guarantee high purchase retention. It is an exciting finding, and for future research, a more detailed investigation is needed and involves many indicators to identify the cause of this condition.

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