LEVERAGING DATA-DRIVEN ANALYSIS TO EXPLORE RESTAURANT'S MARKET SEGMENTATION IN INDONESIA

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ABSTRACT

Background: The internet and Electronic Word of Mouth (eWOM) have transformed consumer behavior in choosing dining options in Indonesia's culturally diverse culinary landscape, yet research leveraging eWOM data to understand consumer preferences remains limited.
Purpose: This research is conducted to develop the restaurant's market segments based on customer ratings in Indonesia using a data-driven approach.
Design/methodology/approach: The data is crawled from notable review sites in Indonesia which consist of 35.811 restaurants across Indonesia. Two clusters were generated using TripAdvisor data, encompassing users' ratings for Food, Service, Value, Atmosphere, and overall satisfaction. The research successfully segmented the Indonesian restaurant market based on customer ratings using the K-Means clustering approach.
Findings/Result: Cluster 1 valued food quality and cared about service and value. Meanwhile, Cluster 2 focused more on good service, followed by food and the restaurant's atmosphere.
Conclusion: The research successfully segmented the Indonesian restaurant market based on customer rating, helping restaurant managers understand what customers prefer in Indonesia's varied food scene. This can assist marketers in creating effective marketing strategies, such as advancing product development, enhancing food quality, and optimizing service offerings to better fulfill the needs and expectations of their target audience.
Originality/value (State of the art): This study can pave the way for further investigation into market segmentation in Indonesia's restaurant sector. While similar approaches have been applied in studies of other countries, the Indonesian market is unique and has distinctive features that haven't been examined in previous research. Therefore, these insights can illuminate the segmentation of the restaurant market in Indonesia.

Keywords: consumer rating, customer segmentation, digital marketing, k-means clustering, big data

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INTRODUCTION

The perpetual development of the digital business phenomenon has revolutionized how people behave, especially their buying behavior (Ahmad & Nasution, 2020) . Those phenomena surged the numbers of online buyers as well as the sellers which create a massive economy in one country. Buying behavior has shifted from evaluating the physical product in the store to reading the consumer review in order to reduce risk and making decisions when buying online. There are two primary stakeholders expressing considerable interest in consumer review, they are the consumers for their purchasing, and the merchants for their business sustainability. This review can be identified as Word of Mouth (WoM) where sharing ideas and opinion surged (Huete-Alcocer, 2017; Ngoma & Ntale, 2019), especially, electronic rating which arise on online platforms like ecommerce. In the digital domain, online consumer review, which is typically provided by online marketplace, can be viewed as one form of eWOM (Godes & Mayzlin, 2004). According to (Biyalogorsky et al. 2001; Brown & Reingen, 1987; Shi, 2003), electronic word of mouth (eWOM) can reach far beyond the traditional WOM which only spread across local communities, because the internet can be accessed by the consumer all over the world.

Compared to traditional WOM, electronic WOM is far more powerful in the context of accessibility and the message diffusion speed (Huete-Alcocer, 2017; Hussain et al. 2018). In several industries, Online Rating has significant impact on Offline purchase behaviour (Comscore and The Kelsey Group, 2007). According to its survey, around 83% of readers of online reviews of restaurants, travel services and hotels had been influenced by their purchase behaviour. E-WOM in restaurants has brought 41% of review's readers into consumers who visit the reviewed place. Another study conducted by (Kim et al. 2016) that specifically concerns the culinary industry found that online reviews had a positive impact on net sales, number of visitors, and average check which relates with restaurant financial accomplishment. Therefore, online rating and review plays an important role in Marketing because it can be easier to share a customer's personal experienve about a product or company through the Internet especially in food industries (Hussain et al. 2018).

The capability in obtaining and analyzing consumer information is the key to win the market competition, but it is not an easy task since the consumer (personal or collective) has distinct criteria and expectations (Hogan et al. 2002). The solution to tackle this problem is by having an information-based marketing strategy to allow effective and sustainable decision making based on data. Describing and analyzing big (terabytes to exabytes) and complex (sensor to social media) data sets can be used in big data analytics. This method requires several techniques such as web crawling, machine learning, and statistical analysis to obtain, analyze and explain distinct phenomena for business needs (Chen et al. 2012; Xiang et al. 2017). On this research context focusing in culinary, several study that use big data in food has been conducted by several researchers. Nilashi et al. (2021), focused on customer segmentation and preference forecasting at a vegetarian restaurant, highlighting the value of analyzing online review using text mining. Fahira et al. (2020), developed a system to classify traditional foods, finding that the Random Forest classifier performed the best. Yanfi et al. (2022), conducted sentiment analysis on Indonesian food and beverage reviews, with Support Vector Machine (SVM) showing the highest accuracy. Laksono et al. (2019) analyzed Surabaya restaurant reviews, finding Naïve Bayes to be more accurate. Tama (2015), studied customer satisfaction in fast-food restaurants, with both Decision Trees and Neural Networks achieving over 80% accuracy. These studies collectively demonstrate the effectiveness of advanced analytics in understanding consumer behavior and enhancing customer satisfaction in the food industry. While the use of big data in marketing research has made significant strides, there remains a lack of focus on clustering consumer rating data to develop a fundamental marketing strategy known as market segmentation. This approach categorizes the market into segments of customers with unique characteristics, traits, personalities, or behaviors that may require distinct marketing strategies (Kotler & Armstrong, 2009).

We choose Indonesia as the scope of this research. Indonesia is the fourth most populous country in the world after China, India, and America, with more than 273 million citizens, living spread across 16.771 islands from Sabang in Weh Island, the westernmost side, to the easternmost side, Merauke. It is a unique country containing thousands of cultures and languages which then make Indonesia rich of culinary. There are many

Indonesian food review websites that provide millions of data indicating the diversity of the market, the type of foods, as well as the consumer preferences themselves reflected from Indonesian rich culture. This massive data on the internet regarding the consumer satisfaction of food products in Indonesia can be analyzed into fruitful information to shed light especially for Indonesian food practitioners which grow bigger from time to time.

This research addresses how eWOM have transformed consumer behaviour in the Indonesia culinary industry with diverse food culture. There is a lack of comprehensive research utilizing eWOM data to understand customer preferences and segment the market effectively. To solve this lack of comprehensive research utilizing eWOM data to understand customer preferences and segment the market effectively, this study employs a data-driven approach, starting with web crawling to gather eWOM from popular review sites about Indonesian restaurant. This dataset undergoes reprocessing to ensure the data quality and accuracy uses K-Means clustering to groups the segment based on customer ratings across key dimensions such as food, service, value, and atmosphere. This approach aims to find out what different groups of customers clusters within the Indonesian culinary industry. The research expects to find two or more groups of customers with different preferences for Indonesian restaurant. Cluster analysis will reveal insight into whether consumers prioritize food quality, service excellence, value of money, or atmospheric experience. This information will help restaurant managers improve their services and meet customer expectations. Additionally, this study aims to contribute valuable knowledge in the field of culinary market segmentation in Indonesia.

METHODS

In this research, we aimed to develop the restaurant's market segments based on customer satisfaction in Indonesia using a data driven approach. The proposed method is shown in Fig. 1. It is started by data crawling method which acquires the dataset from TripAdvisor, comprising Electronic Word of Mouth (e-WOM) data from 35,811 Indonesian restaurants. The crawled data then underwent a comprehensive pre-processing phase by cleaning the data. This step is crucial to ensure data quality and suitability for subsequent analysis, involving the identification and handling of missing values, addressing noisy data, and resolving inconsistencies. To execute these tasks, the research employs the versatile tools RStudio. Following the pre-processing steps, the data is then figured in several bar charts and histograms to make it understandable before K Means Clustering is performed. K-Means, an unsupervised machine learning algorithm, facilitates the clustering of similar data points based on distinct features. The Elbow and Silhouette approach needs to be used to determine the ideal number of clusters for the study before a logarithm is used (Saputra et al. 2020). The outcomes of this clustering technique are then analyzed to provide important insight into various customer groups that make up the Indonesian culinary market, revealing the preferences and behaviors of participants in this dynamic sector.

The number of clusters the algorithm should identify inside the dataset is denoted by "k" in the context of K-Means (Nainggolan et al. 2019). The algorithm's objective is to minimize the sum of the squared distance between data points and the corresponding cluster centroids for each cluster, which are represented by centroid values (Erisoglu et al. 2011). Finding the optimal number of clusters, represented by "k" is a crucial step in the K-Means clustering process. An approach that's frequently utilized for this is the elbow method. Plotting the sum of squared distance – also referred to as the "inertia" or "within-cluster sum of square" – for each k involves applying the K-Means algorithm with various values of k. The elbow technique helps in finding the ideal number of clusters by weighing the trade-off between performance and model complexity. Finding the ideal balance is essential to getting significant and applicable clustering results.

This study emphasizes the evaluation provided by customers for a dataset that comprises 35,811 restaurants located in various parts of Indonesia. The main goal is to do a clustering analysis based on three essential dimensions: Atmosphere, Value, Food, and Service. The analysis uses geographic restaurant classification to identify regional preferences and unique culinary trends User-rated clustering provides insight on evaluation trends for restaurants and makes it easier to find groupings that have comparable levels of customer satisfaction. Furthermore, the inclusion of restaurant amenities like ambiance and serving in the filtering process makes it possible to identify recurring themes that impact customer feedback. This method seeks to identify subtle patterns in the dataset by using machine learning techniques, namely the K-Means clustering algorithm. Businesses can utilize these clusters by gaining actionable insight into popular restaurant attributes in particular areas features associated with higher ratings, and areas where restaurant facilities need to be improved. Finally, the analysis leads to a thorough understanding of consumer preferences, enabling businesses to adjust their strategies to specific customer segment in the unique culinary scene of Indonesia.

This study examined customer purchase behavior in Indonesia's culinary sector using an examination of TripAdvisor data. Leveraging machine learning techniques, the primary objective is to segment food consumer preferences. The dataset comprises Electronic Word of Mouth (e-WOM) with specific rating attributes such as value, atmosphere, service, and food. This rich data set offers a detailed perspective on customer experiences within the culinary domain (Figure 1). Acknowledging concerns about potential inaccuracies due to the dataset's massive size, the research emphasizes a thoughtful approach to data selection and analysis. The central goal of the research is to conduct clustering in the Indonesian Customer Online Rating, aiming for Customer Segmentation based on the Satisfaction Determinants in restaurants. Considering Indonesia's diverse culinary landscape, with contributions from various cultures, the culinary industry presents significant market potential. The clustering process seeks to group related categories, constructing a representative sample to gain insights into the preferences and behaviors of different consumer segments. While specific sampling criteria are yet to be defined, the research anticipates utilizing the gathered data for visualizing patterns and trends. Presumably illustrating a sample of the dataset in Figure 2. The expected outcome of the clustering and analysis process is to gain valuable insights into leveraging e-WOM data for segregating consumers and understanding their preferences across different segments. Ultimately, the research aims to address the existing gap in clustering the Indonesian market using machine learning within the realm of Artificial Intelligence.

RESULTS

From the analyzed dataset, the prolification of restaurant's variable can be summarized as represented in the Data Overview (Figure 3). Top-left histogram provides a visual representation of the Top 10 cities in Indonesia with the densest concentration of restaurants. In the illustration, each city is assigned a numeric value based on the frequency of restaurant data. It is noteworthy that the dataset originally encompassed over one hundred cities, prompting the need for a focused analysis that involved slicing the data to highlight the 10 cities exhibiting the highest frequency. The findings reveal a distinct geographic segmentation, highlighting Jakarta as the city with the highest concentration of restaurants. The number of restaurants in Jakarta surpasses that of other major cities in Indonesia, including Bandung, Surabaya, and Denpasar. This disparity suggests that Jakarta boasts a larger restaurant market compared to other cities in Indonesia. This refined presentation not only facilitates a more accessible comprehension of the information but also underscores the prevalence and distribution of restaurants across various cities in Indonesia. On the right side of it, there is a bar chart showing the types of cuisines that restaurants most commonly offer. This chart gives a straightforward visual representation of which cuisines are popular among the restaurants in the dataset. Each bar on the chart represents a specific type of cuisine, and the height of the bars indicates how often that cuisine appears in the dataset. In line with the segmentation analysis, Asian and Indonesian cuisines emerge as the most popular menu options based on the data. This observation reflects the psychographic segmentation of the market, indicating preferences related to food. The popularity of Asian and Indonesian cuisines is unsurprising, given their alignment with local taste preferences. Chinese cuisine, in particular, holds a notably larger share than international cuisines in the Indonesian market, highlighting the substantial influence of Chinese culinary heritage.

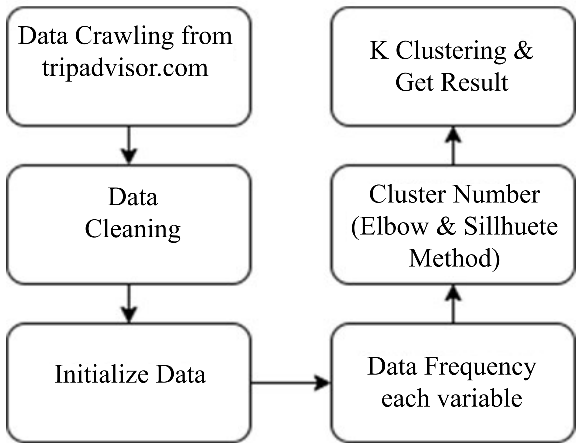
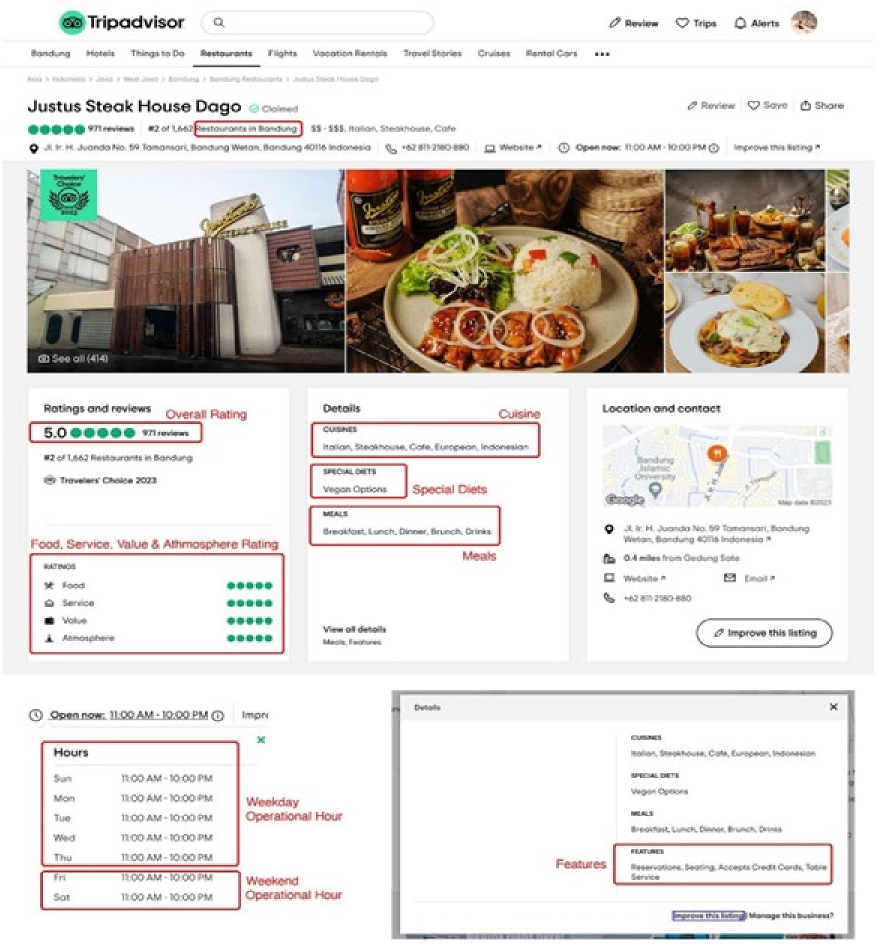


Figure 1. Methodology flow chart



Data	
con	Formal class PostgreSQLConnection
Data	35811 obs. of 39 variables
drv	Formal class PostgreSQLDriver
Values	

Figure 2. Data crawled from trip advisor and total data set

The following Figure 4 the densest concentration of restaurants histogram, it represents behavioural segmentation of the restaurant's features in Indonesia. It displays the features of restaurants which predominantly including reservation, seating, takeout, and table service. Looking to the right side, it illustrates the variety of meals and special diets provided by restaurants. It shows that dinner and lunch are the most commonly served meals, while vegan and vegetarian options are the most frequently available special diets. At Figure 3, it provides a visual breakdown of restaurant operating hours, showing that most restaurants are open from 10 AM to 10 PM. These charts give a clear picture of the variety of restaurant offerings and operational hours within the dataset, which also serves as a representation of customer behavioral segmentation. By looking at these figures, we can easily understand the different features, meal options, special diets, and operational patterns that characterize the restaurants being studied.

Figure 4 shows histograms that specifically depict visual representations of how ratings are distributed across key aspects: food, service, value, and atmosphere. From the data presented, the atmosphere rating has a wider distribution compared to other variables. While eight hundred customers rated the restaurant's atmosphere 4.5 stars, around 350 customers rated it 3 stars. On the other hand, most customers gave 4.0 and 4.5 stars for the food quality, with significantly fewer lower ratings. The distribution trends for service and value are slightly different, with 4.0 stars dominating the customer ratings, followed by 4.5, 3.5, and 5.0 stars consecutively.

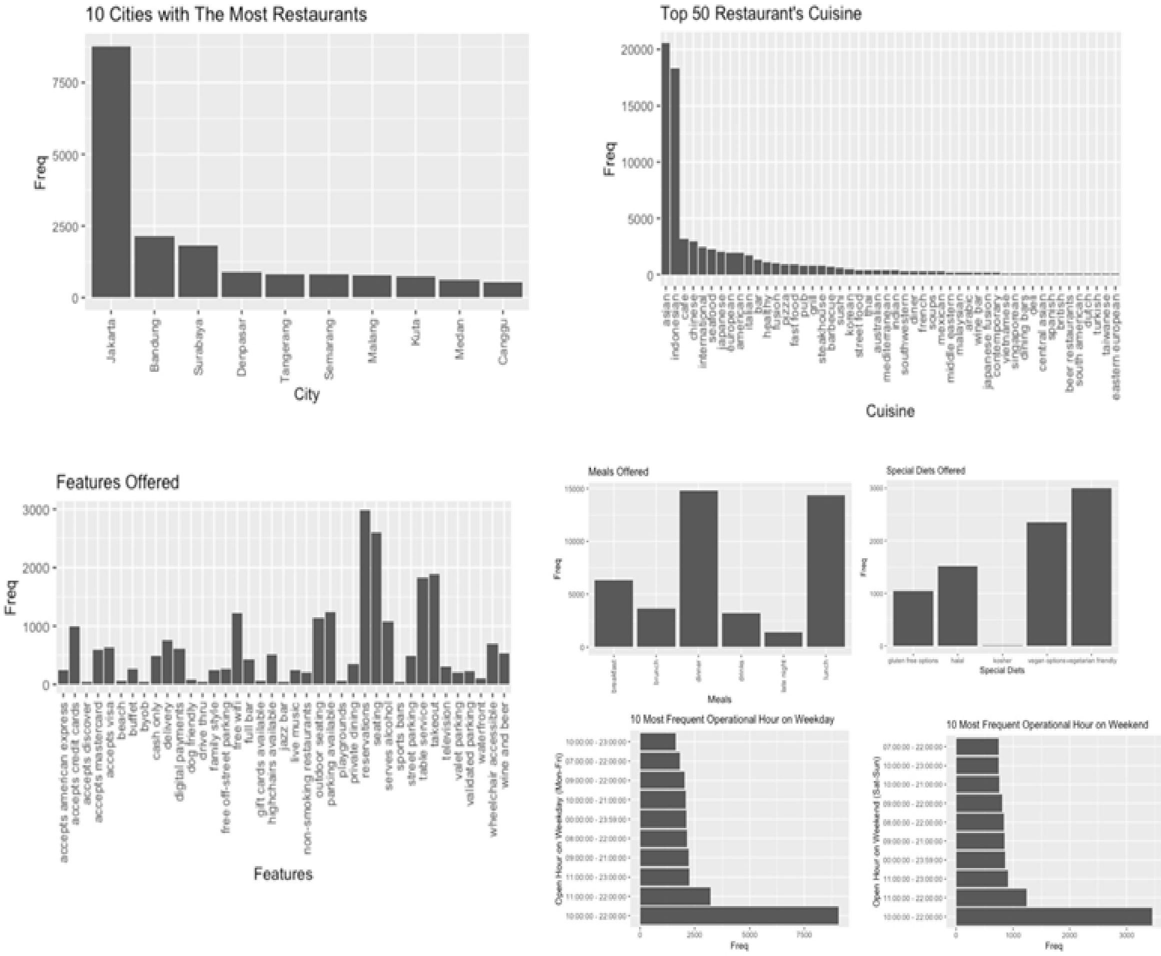


Figure 3. Bar chart of data overview

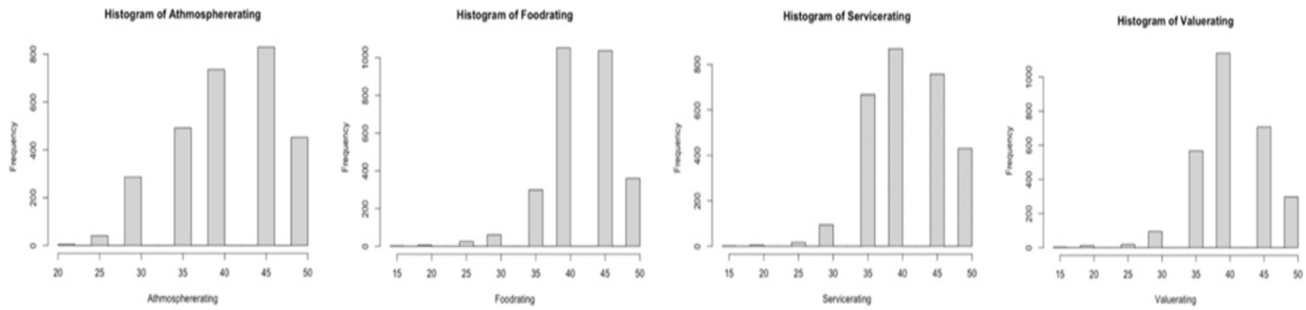
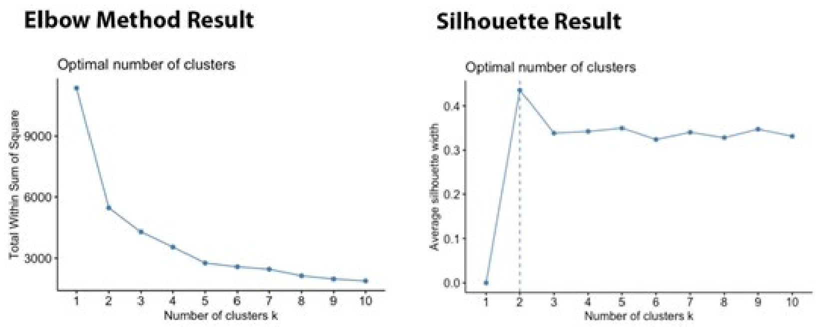


Figure 4. Histogram of restaurant's rating

Figure 5 shows the outcome of elbow method, silhouette, and also K-Means Clustering result. The elbow method is a technique for finding the optimal number of clusters in a dataset (Syakur et al. 2018). This code visually guides users through the steps of implementing the elbow method and interpreting the results. Moving on the right side of the graph, it presents the result of the silhouette method, another approach to assess the appropriateness of clustering. Based on those two results, the optimal number of clusters is two which then was implemented on the next process of clustering. Below those graphs, the application of the K-Means code in R studio is visually represented, specifically applied to columns 4 to 7 with a designated k value of 2. This strategic application of the algorithm aims to segment the dataset into two distinct clusters, unraveling inherent patterns and relationships within the data. The subsequent picture provides additional insights, presenting the centroid in each cluster. This centroid delineating the center distance for each cluster, meticulously specifies the data point to which it belongs based on the distance to its centroid. Lastly, the bottom picture offers a scattered plot of k-means result. These detailed data serve to illuminate the internal cohesion of clusters, their relative dispersion, and the overall distribution of data points, contributing to a more nuanced understanding of the algorithm's effectiveness in delineating distinct patterns within the dataset.

The primary focus of this research centered on a comprehensive understanding of the restaurant rating platform, with a specific emphasis on the evaluation of the K-Means clustering algorithm for customer segmentation. Through extensive research, it was determined that the K-Means clustering algorithm emerged as the most fitting method for achieving the study's objectives. The efficacy of the selected algorithm was effectively demonstrated through its application to customer ratings.



K-Clustering Code with 2 Clusters

```
fviz_nbclust(ratingrestofiltered, kmeans, method = "wss")
fviz_nbclust(ratingrestofiltered, kmeans, method = "silhouette")

Clustering=kmeans(ratingrestofiltered,centers=2,nstart=25)
Clustering
fviz_cluster(Clustering, geom = "point", data = ratingrestofiltered)+ggtitle("k=2")
```

Centroid Each Clusters

```
Cluster means:
  ratings_food ratings_service ratings_value ratings_atmosphere
1     39.15159        37.29881      37.45789           37.04304
2     46.09223        46.27832      45.01214           45.96683
```

K-Means Result

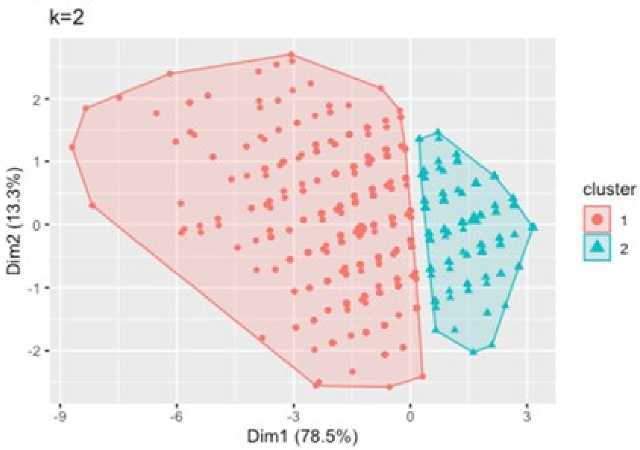


Figure 5. Elbow Method, Silhouette, and K-means clustering result

Employing K-Means clustering on the available data led to the formation of distinct clusters based on customers' evaluations of restaurants. Specifically, the TripAdvisor data were utilized to create two clusters, incorporating users' ratings on various dimensions such as Food, Service, Value, Atmosphere, and overall satisfaction. Each cluster shed light on the pivotal factors influencing customer satisfaction. Notably, Cluster 1 revealed a preference for individuals who prioritize the significance of food, followed by considerations for the value and quality of service. On the other hand, Cluster 2 comprised customers for whom service was the primary influencing factor, followed by considerations for food and atmosphere. The distinctiveness of Cluster 2 lies in its status as a lucrative segment, marked by consistently high average ratings, suggesting a considerable potential for financial gain.

The insights gleaned from these clusters offer invaluable information regarding customer preferences within the realm of Indonesian restaurants. This result effectively addresses the research question aimed at segmenting the Indonesian restaurant market, leading to the identification of two distinct clusters, each characterized by unique attributes. Furthermore, it is essential to highlight that this study employed authentic data for evaluating the proposed methodology. In the contemporary landscape, the utilization of advanced learning approaches for the analysis of social data can provide business managers with enhanced capabilities in discerning distinct customer segments. This, in turn, has the potential to significantly bolster their competitive advantages within the market.

Managerial Implication

Understanding the clustering analysis of Indonesian food consumer preferences also offers valuable insights for restaurant practitioners to optimize their operations, provide actionable strategies for restaurant managers, and effectively drive business growth based on customer satisfaction. By understanding different customer preferences, restaurants can customize their advertising approaches. If most customers are more concerned about food quality (Cluster 1), restaurants can focus on promoting the uniqueness of their dishes and the use of high-quality ingredients. But if the customer prioritizes service (Cluster 2) the restaurant can emphasize friendly staff and speedy service in their promotion. The manager of the restaurant can also allocate their resources more wisely by knowing which customer groups tend to spend more. If Cluster 2 usually gives high ratings, restaurants can invest more in improving service quality, and the atmosphere of the restaurant. The restaurant manager can also develop the menu and pricing strategies based on the analysis result. For Cluster 1, restaurants can offer luxurious dishes at higher prices as these customers highly value food quality. Restaurants practitioners can also improve their operational by listening to feedback from each customer group, making each customer group feel special so restaurant can enhance overall satisfaction, offering exclusive deals based on their likes, or creating themed experiences for their visits. Restaurants need to continuously learn from customers as preferences change over time. By utilizing new tools to understand customers better. By adhering to this insight from the analysis, restaurants in Indonesia can improve their business performance, enhance customer satisfaction, and greater profitability in the competitive market.

CONCLUSIONS AND RECOMENDATIONS

Conclusions

The objective of this research is to cluster the segmentation of the Indonesian food market based on consumer reviews from the internet which focuses on the segmentation of a diverse cohort based on consumer data, predominantly in the form of ratings, derived from a wide array of restaurant types scattered across Indonesia. This research endeavors to contribute valuable insights to researchers and stakeholders within the restaurant industry by undertaking a comprehensive comparative analysis of the structuring and grouping of customer preferences in Indonesia across various geographic areas in Indonesia. Building on previous studies in the context of big data, this research can serve as a steppingstone for further exploration of Indonesian market segmentation, particularly in the restaurant sector. Although similar methods have been used in studies of other countries, the Indonesian market is distinct and possesses unique characteristics that have not been explored in earlier research. Consequently, these findings can shed light on the segmentation of the restaurant market in Indonesia.

To accomplish this, the study meticulously examined a dataset comprising over 35,811 entries from restaurants situated in major cities in Java and several cities in Bali. The deliberate choice to concentrate on tourist-centric cities was made to align with the preferences of TripAdvisor users, acknowledging, however, the limitation in generalizing findings to the broader restaurant market. The analysis primarily centered around four rating factors, providing a foundational understanding of the disparities between highly profitable and less profitable variables within the restaurant landscape.

The primary focus of this research is to explore the Indonesian market segment on the digital platform Trip Advisor, which has not been extensively studied in other research. The study utilizes a quantitative approach to gather data and analyze the impact of various elements on the outcome. The key findings indicate that there are two distinct segments representing the Indonesian market in the restaurant sector. The research delves into Indonesian market segmentation by analyzing data from TripAdvisor, an area that has previously remained unexplored. This study offers novel insights into consumer behavior and preferences within the Indonesian market. The findings revealed the generation of two clusters, each exhibiting distinct preferences for scoring restaurants in Indonesia. Cluster 1 showed a preference for those who prioritize the food itself, while also considering service value and quality, whereas Cluster 2 consisted of customers who valued service as the most important, followed by considerations for food and atmosphere. This can significantly aid marketers in devising effective marketing strategies, such as enhancing product development, improving food quality, and refining service offerings to better meet the needs and expectations of their target audience. By leveraging this untapped data, businesses can gain a competitive edge and tailor their approaches to align with the specific demands of Indonesian consumers.

Recomendations

For further study, there is room for improvement in analyzing not only the ratings but also the testimonials or comments to gain a deeper understanding of customer sentiment which potentially exploring more detailed facets such as psychological or behavioral segmentation. Such a nuanced approach could directly inform and enhance strategic decision-making for restaurant practitioners, paving the way for a more targeted and effective market strategy. This is important because the clusters derived from this analysis may be considered as generalized in their applicability to managerial decision-making. This research encompasses a broad scope of rating factors and focuses on tourist-centric cities, serving as an important starting point. In addition, since the proportion of restaurants is concentrated around Java and Bali, especially in big cities, the clustering cannot be generalized to Indonesian customers as a whole. It needs to be explored further in other cities particularly in eastern Indonesia.

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