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Retailer Segmentation as A Strategy for B2B Marketing using A Two-Level Clustering Analysis

Prita Prasetya*, Mukhamad Najib, Febrina Mahliza*****
* School of Business and Economics, Universitas Prasetiya Mulya, Jakarta
** Departement of Management, IPB University, Bogor
***Faculty of Economics and Business, Universitas Mercu Buana, Jakarta

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ABSTRACT

This paper aims to explore the possibility of identifying retailer segments. Data is the foundation of segmentation that helps identify the critical value drivers, select the appropriate engagement level and decide the retailer engagement. This study proposes a new approach that considers two-stage clustering for retailer segmentation and behavioural analysis among building materials companies in Indonesia. The alignment could provide a practical managerial approach to finding competitive advantage and a better understanding of sales opportunities. Retailer segmentation can be done differently from the most relevant sales perspective. In this study, we propose an alternative method for retailer segmentation based on two-stage clustering. First, segmentation is based on three categories of the size of order: a very potential group of customers in which the order size is large, a middle group and a group where the order size is small. Second, segmentation based on personal value is a relational perspective that considers the behavioural analysis from the manufacturer-retailer relationship.

Kata Kunci:

Pengelompokan Dua-level,
Pengelompokan K-means,
Hierarki,
Segmentasi,
Pengecer

SARI PATI

Tujuan dari makalah ini adalah untuk mengeksplorasi kemungkinan mengidentifikasi segmen pengecer. Data adalah dasar segmentasi yang membantu mengidentifikasi pendorong nilai utama, memilih tingkat keterlibatan yang sesuai, dan memutuskan keterlibatan pengecer. Studi ini mengusulkan pendekatan baru yang mempertimbangkan pengelompokan dua tahap untuk segmentasi pengecer dan analisis perilaku di antara perusahaan bahan bangunan di Indonesia. Penyelarasan dapat memberikan pendekatan manajerial yang berguna untuk menemukan keunggulan kompetitif dan lebih memahami peluang penjualan. Segmentasi pengecer dapat dilakukan dengan cara yang berbeda dari perspektif penjualan dengan cara yang paling relevan. Dalam studi ini, kami mengusulkan metode alternatif untuk segmentasi pengecer berdasarkan clustering dua tahap. Pertama, segmentasi berdasarkan tiga kategori ukuran pesanan: kelompok pelanggan yang sangat potensial yang jumlah pesanannya tinggi, kelompok menengah, dan kelompok yang jumlah pesanannya rendah. Kedua, segmentasi berdasarkan nilai pribadi sebagai perspektif relasional yang mempertimbangkan analisis perilaku dari hubungan produsen-pengecer.

Corresponding Author:
Email:
prita.prasetya@pmbs.ac.id

INTRODUCTION

Segmenting the retailer is challenging but potentially highly rewarding. To be most effective with the prioritization, retailers need to be grouped or segmented. Manufacturers need to prioritize tasks with the right amount of attention and have a systematic approach to target their retailers to achieve optimal effectiveness. The attribute selection and scaling for retailer segmentation depend on the organization's or manufacturer's strategy. These can be considered an overall framework of segmentation. Challenges for segmentation in business-to-business markets are characterized in several ways that make them very different. An in-depth understanding of how-to segment is necessary to guide the best decisions leading to profitable targeting (Brotspies & Weinstein, 2019).

Organizations are looking for various strategies and ways to expand reach, efficiency, and loyalty to their customer base. Effective communication with customers reportedly had a positive impact on the company. Research and practice on marketing channel management have long proven the importance of managing relationships between people or organizations that perform distribution functions (Weitz and Jap 1995). Proper marketing channel management will result in targeted business performance (Rosenbloom, 2007). To achieve optimal business performance, the right marketing strategy is needed. One of the concepts currently widely applied in business-to-business marketing is relational marketing, which is to build, maintain and improve relationships with partners. Because in business interactions, it is infrequent for purely transactions to occur without relational relationships. In addition to identifying valuable and loyal business customers, customer classification can lead to a better understanding of the behaviour and preferences of different customer groups and help businesses design efficient strategies for each customer group (Dibb, 1998). As a result, many companies apply data-driven methods to find the characteristics of business customers to develop their market strategies. Systematic data analysis for identification and communication with retailers is an essential criterion in customer relationship management.

One of the most efficient approaches to analyzing business consumer behaviour utilizes data mining techniques that can help customer segmentation and develop appropriate policies for customer relationship management, especially in the relationship between manufacturers and retailers. Although many studies have used data mining techniques to assess the value of customers and their rankings in various industries, studies such as in the building materials industry and, in particular, retailers have been rare. The behaviour of retailers in the building materials industry in this study using personal value variables is the first to be carried out at the B2B level through a two-stage clustering method for retailer segmentation.

Identifying retailers is necessary for an efficient campaign plan and targeting profitable customers for a successful business. Clustering and segmentation are the two most important marketing and customer relationship management techniques. Most previous studies used various mathematical models to segment customers without considering the correlation between clusters and personal value variables as part of the concept of relationship marketing. Only through data mining techniques, it is possible to extract functional patterns and associations from potential data retailers. Data mining techniques such as clustering and associations can be used to find meaningful ways for future predictions.

In this study, two-level clusters were proposed to group retailers based on the most common data: retailer size of the order. Segmentation is based on the retailer size of the order, three categories of the size of order: a very potential group of customers in which the order size is large, a middle group and a group where the order size is small. Then the *retailer size of the order data cluster dataset* is reclassified based on questionnaire data filled out by retailers about personal value variables so that it can be known which category retailers have satisfaction data on personal value from the manufacturer. It is hoped that with a *two-level cluster* approach where at the beginning, the *cluster* will use the *k-means* method to process the initial data in the form of retailer sizes to form several *clusters*. In the second stage, the cluster result member data in the first stage will be used in the second phase *of the cluster* with the hierarchical clustering method to find the distance of similarity between retailers based on the questionnaire answers that have been submitted.

In its development, to group retailers into segments, it is not enough just to be based on monetary aspects, so it is necessary to conduct further analysis by testing the personal value of manufacturers to retailers. Personal value results are obtained from the processing of questionnaire data. Personal value in relationships is knowing detailed information about customers and maintaining good customer relationships. Customers will feel satisfied with marketers who can interact with customers and have the ability in social relationships to read customer feelings, attitudes and beliefs (Ulaga, 2003). Individuals play an essential role in any business relationship because they are managed by individuals (Ulaga, 2003). In the producer-distributor relationship, personal interaction refers to the interaction at the individual level between the distributor and the manufacturer's primary contact (Ulaga, 2003). Personal interaction will improve the performance underlying retailer satisfaction. Finally, satisfaction positively affects loyalty (Prasetya et al., 2020). These findings can help makers understand that personal value can directly affect business performance improvement.

Based on the background above, a problem can be formulated to determine the difference between in-retailer satisfaction levels based on personal value variables and manufacturers based on retailer size. A study was conducted that aims to build an application that applies a two-level clustering approach with k-means clustering and hierarchical clustering to determine retailer segmentation based on the level of satisfaction with the personal value of the manufacturer. A priori segmentation, that is, the most straightforward approach, uses the classification of schemes based on common characteristics, such as the size of the enterprise - to create different customer groups in its market. However, a priori market segmentation may not always be valid, as retailers of the same size may have very different needs. Value-based segmentation differentiates retailers based on the value they perceive, grouping retailers with the same value level into individual segments that can be targeted.

Indicators measure personal values such as friendliness, easy work and problem-solving (Ulaga, 2003; Nguyen and Nguyen, 2011). Businesses can use this data to divide customers into segments based on monetary aspects and personal value variables. Creating a retailer segment based on these variables highlights a clear marketing opportunity. This paper is structured as follows: part 2 discusses background research, and part 3 briefly reviews data mining and different grouping techniques. The proposed architecture, experiments and their results are discussed in section 4. Section 5 concludes the paper and advises on future work.

Size of Order, Personal Value and Relationship Marketing

The challenges of segmentation in business-to-business are characterized in several ways that make it very different between their consumers. B2B has a more complex decision-making unit than B2C. The problem is to identify the best variables for segmenting B2B customers. The criteria used are more complex, including company variables, situational factors, and personal characteristics. However, the approach must be adapted to the situation and circumstances of the individual. Almost all B2B markets show that customer distribution confirms the Pareto approach. A small number of customers dominate the sales ledger. One implication is that the B2B market generally has fewer needs-based segments than consumer segments – such a volume of data that achieving enough granularity for more than 3 or 4 segments is often impossible. B2B doesn't speak to thousands and millions of customers. Even in the company's largest B2B, it's not uncommon to have 100 or fewer customers who make a sales difference (Doraszelski, Ulrich & Draganska, 2006).

Segmentation is essential in the B2B market since often only a few distinguish one product from another. Segmentation is closely related to the positioning strategy of an enterprise. Historically, B2B was seen as segmentation between sellers and buyers by using a variety of segmentation bases, including demographics, firmographic, operating variables, purchasing approach, situational factors, and personal characteristics of buyers (Bonoma, T &T&Shapiro, 1983). B2B customer segmentation, also known as market segmentation, is the division of potential customers into a specific market group. That division is based on customers with enough in common (Figure 1). A priori segmentation is the most straightforward approach, using schema classification based on publicly available characteristics. However, a priori market segmentation may not always be so valid since companies in the same industry and of the same size may have very different needs. Segmentation by need is based on customers' differentiated and validated drivers (needs) for the specific product or service offered. Value-based segmentation differentiates customers based on their economic value, grouping customers with the same level of value into individual segments that can be targeted.

Apriori segmentation		**Need-based segmentation**	**Value-based segmentation**
Demographics	**Firmographics**		
• Geography • Gender • Age	• Size • Operation • Processes	• Performance • Security • Efficiency • Risk	• Personal value • Financial value • Strategic value
Identification	**Tactics**	**Strategy**	

Figure 1. B2B Customer Segmentation

Economists and business managers often use the Pareto's principle to describe the phenomenon of sales concentration. It has been applied to analyzing the city's population, sale of products, and salespeople. Pareto's principle states the 80:20 rule that a small percentage (for example, 20 per cent) of products on the market often generate most (for example, 80 per cent) of sales. Segmentation is an important activity in marketing, but its perspective has changed over time. Some authors view segmentation as closely related to the other primary thoughts of marketing, the concept of marketing (Kotler, 2000). The essence of the concept of marketing is that the best way to cope with customers is to satisfy their needs and desires. These needs and desires, therefore, need to be fully understood, and there are several ways to collect and analyze the necessary information. The method of use depends on the methodology and the guiding technique, but the approach to statistical analysis is the most common. Other authors do not see segmentation as a statistical analysis technique but as a tool for resource allocation.

Personal relationships are more critical in the B2-B market. The small customer base that regularly buys from business-to-business suppliers is relatively easy to discuss. Sales and technical representatives visit customers. Personal relationships and beliefs develop. It is not uncommon for business-to-business suppliers to have loyal and committed customers for many years. There are several implications of market segmentation here. First, although the level of focus of the relationship can vary from one segmentation to another, most segments in most B2B markets demand a personal level of service. The problem at the core of B2B segmentation is that everyone may want a personal relationship. Suppliers should make an unequivocal choice, deciding to offer relationships only to those who give more profit. On a practical level, this also means that market research must be done to understand how the relationship between the two is built fully.

Relationship marketing is an essential tool in marketing that can be used to create better synergies. Research in marketing channel management proves the importance of managing relationships between partners, individuals and organizations carrying out distribution functions (Weitz and Jap 1995). Almost all transactions have relationship elements that can coordinate channel activities and manage relationships between channel members. The motivation to establish mutual relations emphasizes the importance of cooperation, collaboration and coordination between organizations. Studi empirically suggests that there is potential for superior results due to the benefits of a close buyer-seller relationship (Cannon and Homburg 2001; Ganesan 1994; Nevins and Money 2008). An orderly about the business-to-business market explains that a company's performance can be improved by focusing on current customers rather than attracting new ones. Therefore, building long-term customer relationships is at the core of business-to-business marketing (Jap, 2012; Wolfgang Ulaga & Eggert, 2003).

Studies have shown that many companies move from discrete transactional exchanges to relational ones (Nguyen et al., 2007; Nguyen & Nguyen, 2011; Watson et al., 2015). The loyal customers will bring more profit to the company than price switchers who are sensitive and prone to transactions. In addition, committed relationships are the most durable because they are difficult for competitors to understand, copy, or move. As a result, scholars and practitioners agree that the collaborative relationship between buyers and sellers is a source of competitive advantage (Cannon & Homburg, 2001; Dwyer et al., 1987; Eggert & Ulaga, 2010; Morgan & Hunt, 1994).

The study of the relationship between aligned manufacturers and retailers is the key to success in business cooperation to improve performance. Thus in the Indonesian archipelago, the management of the marketing channels of these manufacturers remains a determining factor for business success (Prasetya & Wibawa, 2020). The high value of the relationship in the manufacturer-retailer relationship will improve the retailer's performance, in terms of sales, market share, and profit, based on the manufacturer's products. It benefits both parties. Retailers will be more likely to work more closely with the manufacturer, providing the opportunity to become a significant supplier and generating some benefits for both parties.

In business-to-business relationships between producers and distributors, personal interaction refers to interactions at the individual level between distributors and those of the manufacturer's primary contacts. Individuals play an essential role in any business relationship because they are managed by individuals (Wolfgang Ulaga & Eggert, 2003). The theory of interpersonal behaviour suggests that, in any relationship, people expect their opinions to be treated with respect and dignity, and many want to have the opportunity to voice their opinions. Thus, improving personal interaction between distributors and producers will benefit both parties through better communication and understanding of each party's goals and interdependence in the relationship, leading to more effective and efficient problem solving (Cater and Cater, 2009; Ulaga, 2003).

Personal value is defined as the circumstances in which one party certifies or accepts the other party's actions in unusual circumstances or whether or not they will be acceptable (Biggemann & Buttle, 2012). Meanwhile, Ford and McDowell (1999) define value as something related to one's personal beliefs. Barnes (2003) understands the value of the customer's emotional and emotional elements or understood as *emotional value*. Most individuals assign value to relationships limited to just personal interpretation. Studies have shown that personal interactions can be essential in distributors' supplier performance evaluation. Sometimes individuals assign value to relationships based solely on their values and personal interpretations of events. Research recognizes the importance of personal interaction in business relationships between manufacturers and distributors. Research (Nguyen & Nguyen, 2011) explores the role of personal interaction in the value of relationships and further in distributor performance in Vietnam's transition markets. The results of this study suggest that manufacturers should invest more time and effort in personal interactions with their primary distributors to increase the value of their relationship with those distributors.

METHODS

This section describes the methods used in this study, as shown in Figure 2. First, the preprocessing of data is described. Then by applying the data obtained, retailer segmentation is carried out with clustering techniques. The results of the clustering technique will be considered by looking at the Davies-Bouldin index for cluster validation. Davies Bouldin Index (DBI) validates clusters based on the ratio function of the number of distributions within the cluster for separation between clusters. Measurement using DBI aims to maximize inter-cluster distance. This study used DBI to perform data validation on each cluster. The system was built to group retailers based on demographic data and look for questionnaire patterns for each retailer cluster. The model used in this study is a two-level cluster model with the k-means method. This model is used to group retailers into clusters based on asset data and relationship age so that cluster result data can be reclassified based on questionnaire answers about personal values for each cluster member.

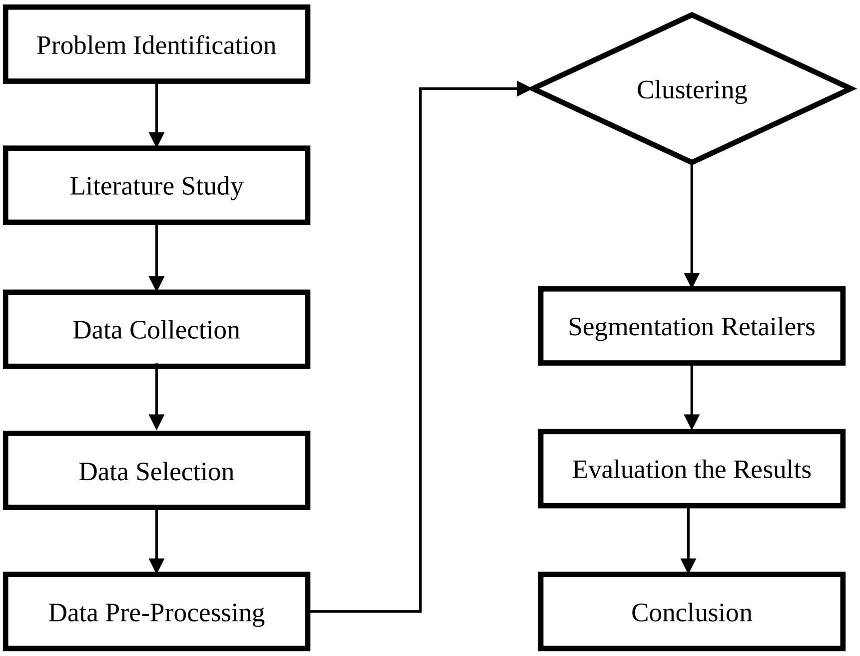

Figure 2. Proposed Approach

Problem Identification
Analyze the specified object, namely retailers in the building material industry, based on data and retailer segmentation problems.

Literatur Study
The study by Sheikh et al. (2019) proposes a new approach considering two-stage clustering and the LRFMP model (Length, Recency, Frequency, Monetary and Periodicity) simultaneously for customer segmentation and behaviour analysis. The study contributes to the customer segmentation and relationship management literature in B2B settings by proposing a new approach based on two-stage clustering methods that aid a deeper understanding of customer behaviour. We are looking for theories relevant to similar research that has been done before related to the segmentation method using two-stage clustering.

Data Collection
Data collection is carried out on industrial retailers of building materials. The types of data required are retailer profile data and questionnaire result data.

Data Selection
Process data selection on the data to select preference variables. Then the data is converted into .csv format for preprocessing data.

Data Preprocessing
Before the clustering process, it is necessary to preprocess data through data cleansing, outlier reduction, and data transformation with a Logarithmic process to transform the range of values

of each variable into smaller and Normalize Min-Max to change the range of values of each variable to 0 to 1. The preprocessing process to the clustering process is carried out using R software.

Clustering

The primary process, namely clustering, is then carried out through K-Means and Hierarchical Clustering. The K-Means method is done by intuitively determining the value of k with the Elbow method and the K-Means Clustering process. An agglomerative process carries out the Hierarchical Clustering method. Each observation begins in its cluster or segment, and these formed pairs of segments are combined as it ascends the hierarchy. After all the stages of the method have been applied, the cluster results are analyzed by denormalizing the data. The data that has been normalized and transformed is returned to its original value. This stage is carried out to facilitate cluster analysis by comparing personal value variables.

RESULTS AND DISCUSSION

Determination of cluster number

The value of k determines by using the Elbow Method. This method is used in cluster analysis to interpret and perform the consistency level of the right number of clusters by looking at the SSE value (Bholowalia and Kumar, 2014). The algorithm of the Elbow method in determining the value of k on K-Means is: (1). Initialization $ k = 1 $ (2). Start (3). increase in the value of $ k (4). Measuring SSE (5). If, at some point, the SSE drops drastically (6). It leads to the correct value of k (7). End of process. At some point, there will be a drastic decrease in the graph with a curve called the elbow criterion. That value then becomes the best k value or several clusters.

The results of the Elbow method graph are shown in Figure 3. From the plot, an elbow point is obtained between the two and four points; after point 4, there is no longer a significant decrease intuitively, so it can be concluded that the number of clusters according to the Elbow method is as many as 3 clusters. However, if recalculated with performance test calculations, the results were obtained that the optimal number of clusters was several 4 clusters, so the second point was chosen for re-clustering.

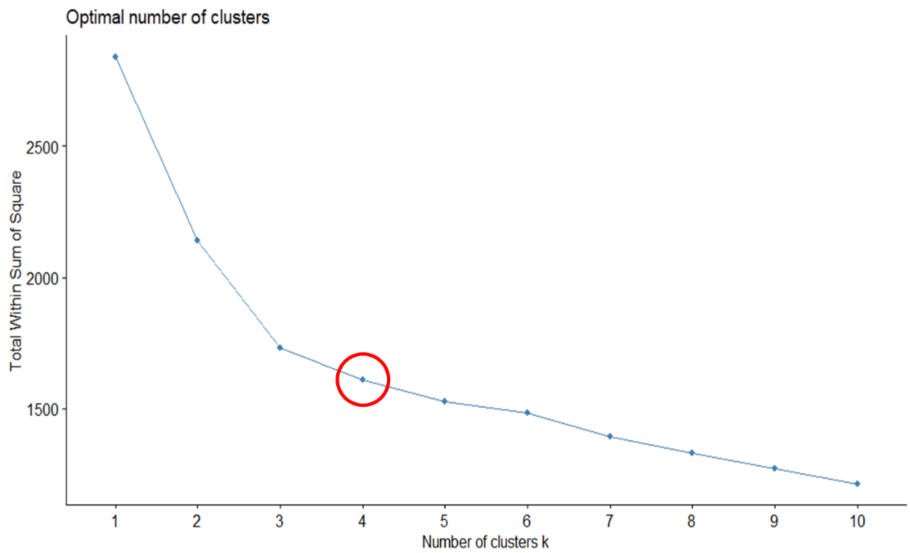

Figure 3. Result of Elbow Method to finding the optimal number of clusters for KMeans Clustering

K-means Clustering

Clustering is the practice of grouping data into similar groups. A cluster is a set of data with the closest similarity and proximity to each other in that cluster and is at least similar to data within another cluster (Khajvand et al., 2011). The K-Means algorithm is one of the most well-known clustering algorithms commonly used in customer grouping. The steps to implement this algorithm as applied in this study are as follows:

1. K points are selected as points from the centre of the cluster.
2. Each record is assigned to a cluster whose centre has the smallest distance to that data.
3. The centre of the new cluster is calculated based on the average points.
4. The 2nd and 3rd steps are repeated until there is no change in the cluster's centre.

Hierarchical Clustering

Hierarchical clustering is a method of cluster analysis that builds a hierarchy of data points as they move into or out of a cluster. Strategies for this algorithm are generally divided into two categories, Agglomerative and Divisive (Rokach, L. and Maimon, O., 2012). Agglomerative is a bottom-up approach in which each observation starts as an initial cluster and then merges into a cluster as they move up the hierarchy. Divisive is a top-down approach where at first, there is only one cluster and then broken down into more refined cluster groups as they move down the hierarchy. The merger and separation of these clusters took place. The hierarchical algorithm generates a dendrogram representing the grouping of nesting patterns and the degree of change of the grouping. One significant advantage of hierarchical grouping is that we don't need to know the exact number of previous clusters and can choose the clusters' formation when they merge. The dataset containing the retailer and its information is retrieved, just as it was used for the K Means algorithm, and an agglomerative hierarchical grouping is applied.

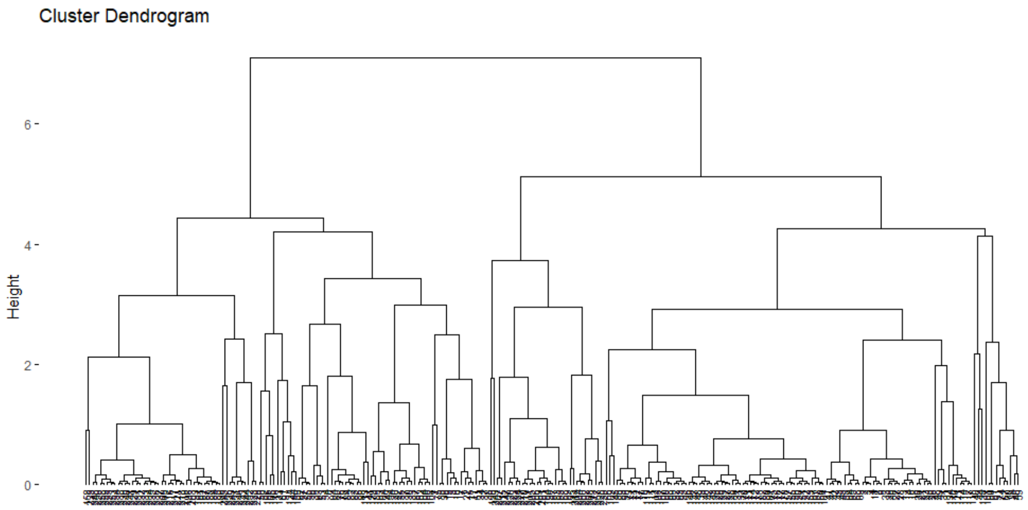

Figure 4. Visualization of the formation of clusters with the help of a dendrogram

Next, select the required number of clusters from the dendrogram by selecting the maximum distance and then placing the cut line in that position. It simply shows that the distance between the formed clusters is maximum, and differences can be made between them. Therefore, according to Figure 4, for satisfactory results, we can select three clusters (K = 3). The results of the visualization of the cluster dashboard are depicted as follows in Figure 5.

Dashboard Visualization Results

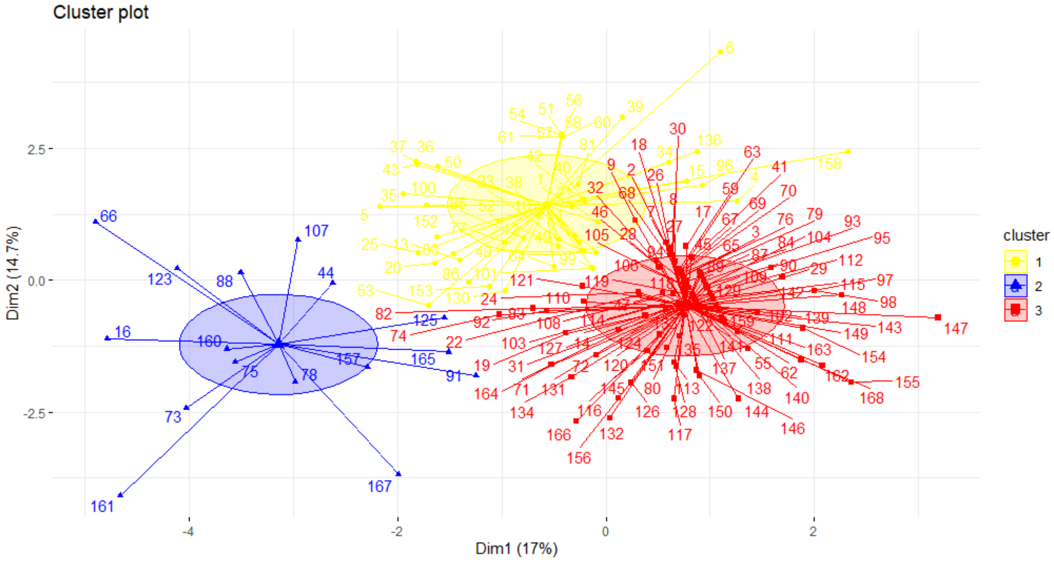

Figure 5. Clusters formed as a result of applying Hierarchical Clustering

The hierarchical grouping has been widely used for segmentation due to its ability to produce results visually (Rokach, L. and Maimon, O., 2012). It helps in determining the number of clusters for any analysis. It can be used for various datasets such as categorical, spatial and time series, with numeric data sets being the most common as they consist of data only as real numbers. The main advantage of Hierarchical clustering is that its output is in the form of a hierarchy in the form of a dendrogram that tells us precisely at what point the clusters are combined or separated. It is, therefore, easy to select and specify the number of clusters we want to retrieve by looking at the dendrogram (Sajana et al., 2016). In this method, the size and sequence of data impact the final result obtained. Nevertheless, one does not need to enter the number of clusters as input to the algorithm. Therefore we have different partition groups, the choice of which depends entirely on the end-user and the purpose of the clustering.

Analysis Hierarchical Clustering

At level 1, clustering aims to segment retailers based on an a priori approach with variables of the size of sales orders to manufacturers. This approach is the most common and straightforward way to perform segmentation. The retailer grouping at this stage uses transaction data to track purchase behaviour and create strategic business initiatives. The company wants to retain customers with high profits, high value, and low risk.

Table 1 shows that cluster 2, as a high sales order, is the most profitable, representing about 52 per cent of revenue but only 10 per cent of customers. The company doesn't want to lose these retailers because of their high value, so the strategy prioritizes retention to increase profitability. Cluster 1 is a segmentation of retailers with middle sales orders of 73 retailers (29 per cent), generating 32 per cent of the company's total revenue. Cluster 3 is a group of low-size order retailers with the most significant number of retailers, as many as 153 (16 per cent). From these results, it is possible to get several business strategies.

Table 1. Interpretation of Retailer Cluster

Cluster		Revenue (%)	Interpretation	Cluster	Interpretation
1	N = 73 st.dev = 0.97	32%	Middle size of order	1	Satisfied with personal value
				2	Moderates
				3	Dissatisfied with personal value
2	N=24 st.dev = 0.79	52%	High size of order	1	Satisfied with personal value
				2	Moderates
				3	Dissatisfied with personal value
3	N=153 st.dev = 0.30	16%	Low size of order	1	Satisfied with personal value
				2	Moderates
				3	Dissatisfied with personal value

At level 2, clustering uses a value-based segmentation approach. The previous segment variable focused on customer characteristics, but in recent years it has focused on customer benefits and value. In other words, variables have been created that focus on what benefits retailers get from the service. Cluster 1 is a satisfied group with personal values. This group is the company's most ideal and desirable type of retailer. The number of retailers is 140 (56 per cent), and they have the highest level of satisfaction.

Mathematical algorithms determine which groups in segmentation analysis have similar characteristics based on personal value variables. These variables are analyzed through quantitative information with questionnaires that make it possible to find common patterns in the data. Alat cluster analysis is performed based on a predetermined algorithm. It is essential to have a strong understanding of the composition of the algorithm and the elements in the clustering method to correctly determine the personal value variables and collect the data appropriately.

From these results, it is possible to get several high-level business strategies (Figure 6). It is clear to see that the best retailers are included in cluster 2. These retailers have a higher revenue value than other cluster retailers, as shown by the total revenue column. Cluster 2 is classified as a high-value cluster.

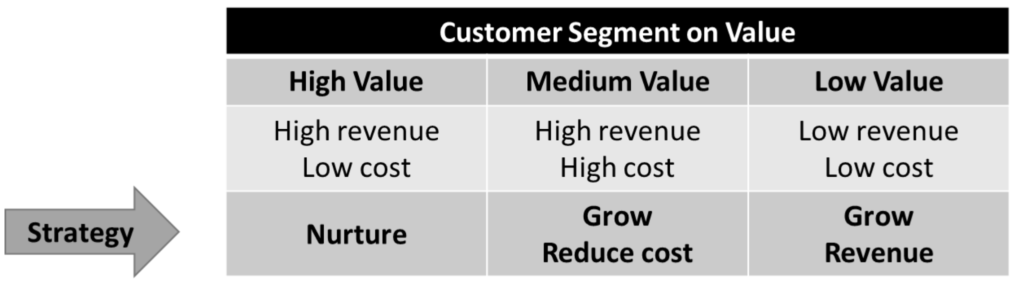

Figure 6. Business strategies for customer segment

Cluster 1 has a high income and cost and is classified as medium value. Cluster 2 has low income, low cost and is classified as low value.
Some possible strategies include:

1. The retention strategy for cluster 2 is for the best customers. This customer retention strategy is effective for increasing profits and helping to strengthen relationships. This strategy, of course, aims to increase profits.
2. The cross-sell strategy is for clusters 1 and 2. This strategy encourages retailers to purchase other additional products related to existing products. The main benefit of cross-selling is that it increases sales.
3. The relationship value strategy is for cluster 3. The potential of customers in this cluster needs to be studied more deeply. These retailers need to have closer personal relationships to collect enough data and determine strategies to increase sales.

MANAGERIAL IMPLICATION

The practical contribution of this study, firstly, the literature on the clustering approach to retailer segmentation has been further developed in this study which is based on personal value variables and retailer characteristics. Second, the practical results of this study expand the application of the two-level clustering model in the relationship of B2B in general and the context of the material building industry in particular. The application of this method will increase the efficiency of the marketing strategy. For restrictions, it should be noted that the data has been taken from active customers in the last two years. Future research could be built on more comprehensive data sets with extended timeframes. Further studies can also consider the implications of marketing strategies on the behaviour of each segment. It is also advisable to include more retailer data, for example, demographic and industry sectors, to evaluate retailer behaviour.

CONCLUSION

Understanding retailer behaviour is one of the more critical and current issues, a plan that organizations should consider in their interactions with their retailers. This knowledge can help organizations ensure the efficiency of their marketing, relationships, and retailer management. In this practitioner's note, retailers are segmented and analyzed by studying the criteria of retailers in the building material industry. The results showed that personal value variables could significantly help interpret and adjust marketing strategies for each group of retailers. In addition, a hierarchical grouping approach has been used to gain a deeper understanding and efficiency of marketing initiatives toward existing retailers. Preliminary results from this study suggest that it is possible and essential to find specific segments within the more general retailer segments that follow certain patterns and behaviours. Therefore, applying different strategies for this segment can result in knowledge, understanding, and management of the retailer segment that tends to be more accurate.

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