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Mapping the Wuling vehicle market with K-Means Clustering: An effective digital marketing strategy

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ABSTRACT

This study focuses on Indonesia's automotive industry sector, which is currently experiencing growth, particularly in terms of Wuling's contribution to the economy through sales. The aim is to identify customer clusters for Wuling vehicle and the marketing mix strategy after the most dominant customer cluster for Wuling vehicle. The research method used was a quantitative survey, which involved collecting data from 111 potential Wuling customer using purposive sampling and data collection through questionnaires. The analysis included an F-Test to examine the differences between clusters. The results show that the clustering of Wuling customer using the K-Means Clustering method successfully divided them into three different clusters, namely Perfectionist, Easy Going, and Beginner, with the Easy Going being the most dominant. Therefore, it is necessary to adjust marketing strategies to focus more on the needs and preferences of the Easy Going, including optimizing the use of promotion channels that have been proven effective, such as direct marketing and sales websites. Thus, this study emphasizes the importance of applying the K-Means Clustering method in automotive market segmentation, providing valuable insights for Wuling to formulate more effective and relevant marketing strategies to meet the diverse needs of customer in a dynamic market.

1. Introduction

The Indonesian automotive industry has experienced significant growth, contributing substantially to the national economy (Chakraborty et al., 2020). It comprises 22 companies in the automotive sector and 26 companies in the two and three-wheeler industries. This sector employs tens of thousands of workers and invests trillions of rupiah, producing millions of vehicles annually. Vehicle sales have rapidly increased owing to the growth of the middle class and infrastructure development (Meszaros et al., 2020; Hardman et al., 2021).

Through the Roadmap Making Indonesia 4.0, the Indonesian government aims to prioritize the automotive industry, focusing on developing electric vehicles and positioning Indonesia as a vehicle export hub (Maghfiroh et al., 2021). The Association of Indonesia Automotive Industries (AIAI) recorded an increase in car sales, with 851.430 units sold in 2018 up to 10.85% from 2017. The low-cost green car segment significantly contributed to total sales. Based on data from the AIAI in 2019, the number of Indonesian car exports in 2018 reached 187.752 units, an increase of 10.4% from the previous year, excluding exports of car components and accessories. 2022 data from the AIAI in the first quarter of 2022 shows car sales in Indonesia reached 263.822 units. The national automotive industry is expected to serve the domestic, regional, and global markets, supporting Indonesia's position as the second-largest economy in Association of Southeast Asian Nations (ASEAN) manufacturing (Darwis et al., 2020). This indicates that the national automotive industry has bright future potential, making it an important topic for further research.

This study focuses on digital marketing, which has become crucial for the automotive industry because of its ability to efficiently and effectively enhance reach and interaction with customer. Through strategies such as social media marketing, content marketing, and online advertising, automotive companies can increase product visibility, build relationships with customer, and provide relevant information that assists customer in the purchasing decision-making process (Verhoef et al., 2021). Additionally, digital marketing offers measurable data, allowing companies to analyze campaign performance and optimize marketing strategies for better results (Purnomo, 2023). In the context of analyzing and optimizing digital marketing strategies, the use of data analysis methods, such as K-Means Clustering, has become highly relevant. K-Means Clustering is an unsupervised machine learning algorithm used to cluster data into several clusters based on the similarity of characteristics (Ahmed et al., 2020). It works by randomly determining the number of clusters as initial centroid points and then calculating the distance between each data point and all centroids (Alibuhtto & Mahat, 2020). Each data point is clustered into a cluster with the nearest centroid. This process was repeated with the centroid positions updated based on the average of the data points in the cluster until the centroid positions no longer changed (Kasim et al., 2021). This method is highly useful in data analysis for identifying patterns or segments in large datasets with diverse applications, ranging from market segmentation and document clustering to image analysis (Chaudhry et al., 2023).

The digital marketing mix is an evolution from the traditional 4P marketing model (product, price, place, promotion) and the expanded 7P model, which adds people, processes, and physical evidence to adapt to the changing dynamics of the digital era (Othman et al., 2021; Tsygankova & Gordieieva, 2023). In the digital age, online interactions, digital credibility, digitally oriented distribution, and promotion strategies are key to attracting customer (Hall & Towers, 2017; Paiola & Gebauer, 2020). With the increasing use of digital platforms and social media, companies are now focused on creating engaging content (Goyal et al., 2021), and interactive social media marketing campaigns to enhance customer engagement (Ting et al., 2020). Moreover, digital credibility through online reviews and testimonials has become a crucial aspect in building trust and influencing customer purchasing decisions (Shaheen et al., 2020). Distribution and promotion strategies also adopt broader and more diversified digital channels, enabling companies to reach their target markets more effectively and efficiently (Katsikeas et al., 2020). Therefore, the digital marketing mix integrates technology and data analysis to understand customer behavior, personalize messages, and optimize marketing strategies to create value for customers and companies.

Various studies have explored the use of K-Means Clustering in diverse contexts, showing both similarities and differences with this study, which focused on the market segmentation of Wuling vehicle. For instance, Chen et al. (2022) applied K-Means Clustering in the context of public transportation, similar to the approach used in this study, but focusing on different customer patterns. On the other hand, Chandrashekar et al. (2021) also used K-Means Clustering in the transportation sector but concentrated on optimizing the performance and energy consumption of electric rickshaw drivers. Their approach, involving real data collection from urban and rural environments and the use of random sampling techniques, provides a new perspective in transportation studies.

Niroomand et al. (2021) distinguished themselves by using a different clustering method, namely Fuzzy C-Means and Non-Fuzzy Clustering, to classify passenger cars based on dimensions. This is a significant difference from this study, which emphasizes market segmentation and marketing strategy aspects, showing a difference in application focus despite using a similar methodology. Ran et al. (2021) introduced innovation by incorporating a noise algorithm into the use of K-Means Clustering, creating another difference from the approach taken in this study. This study is unique because it uses K-Means Clustering to map the Wuling vehicle market by collecting data from potential customers and clustering them into clusters with similar characteristics. This differs from the results of the study by Ran et al. (2021) and Chen et al. (2022) used K-Means Clustering to analyze vehicle travel and urban congestion patterns, respectively. Conversely, Chandrashekar et al. (2021) combined K-Means Clustering with the Recency, Frequency, Monetary Model to analyze the profiles of public transportation, whereas Niroomand et al. (2021) compared the performance of K-Means Clustering with Fuzzy C-Means Clustering in categorizing passenger cars based on dimensions. Nonetheless, clustering approaches generally need help in determining the optimal number of clusters and in addressing the complexity of high or unstructured data, which is a relevant weakness across various applications (Nwogbaga, 2020). In the context of digital marketing, K-Means Clustering offers substantial benefits. The algorithm enables companies to better understand customer preferences and behavior through effective market segmentation, allowing for customization of marketing strategies to enhance the relevance and appeal of campaigns (Alawadh & Barnawi, 2024). Moreover, identifying customer clusters with similar characteristics facilitates the personalization of marketing messages and increases customer engagement and responses to campaigns (Yusnidar et al., 2023). Thus, K-Means Clustering is a valuable tool for enhancing the efficiency and effectiveness of digital marketing strategies, asserting its uniqueness among diverse applications in related research.

Therefore, this study offers a new approach to analyze the Wuling vehicle market, explicitly focusing on customer clustering and relevant marketing mix strategies. Wuling customers were chosen as the research object because the brand has shown significant growth in the Indonesian automotive market, attracting customer attention through competitive and innovative product offerings. Moreover, Wuling has successfully penetrated the market with effective marketing strategies targeting diverse customer cluster, making it an interesting case for analyze customer behavior and the effectiveness of digital marketing strategies in the context of the automotive industry in Indonesia (Wahyudi & Mulyowahyudi, 2022). Uniquely, this research incorporates the K-Means Clustering algorithm, a method used in various transportation sectors, but has yet to be specifically applied to understand the market segmentation of Wuling vehicle. The main research question is "How are Wuling vehicle consumers clustered, and are the current marketing mix strategies optimal for reaching the most dominant consumer clusters?". Therefore, the aim of this research is to identify the clusters of Wuling vehicle customer and to understand the marketing mix strategies after determining the most dominant customer clusters for Wuling vehicle. This research contributes to the innovative application of clustering techniques in a specific context, enriching the literature on automotive industry marketing strategies, and providing

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practical insights for Wuling marketers in designing more targeted strategies. Thus, this study is expected to enhance the understanding of customer preferences and needs and facilitate the development of more personalized and effective marketing strategies to increase Wuling sales and customer loyalty.

2. Literature Review and Hypothesis Development

2.1. Theory of Planned Behavior

Theory of Planned Behavior (TPB) was developed from the Theory of Reasoned Action (TRA) and designed to understand and predict human behavior in various contexts by emphasizing the important role of behavioral intention as the primary determinant of behavior. According to this theory, an individual's behavioral intention are influenced by three main factors: attitude toward behavior, subjective norms, and perceived behavioral control (Damit et al., 2019). Perceived behavioral control, which is the main contribution of TPB to TRA, refers to an individual's perception of how easy or difficult it is to perform a specific behavior. This expands our understanding of predicting behavior and explains the importance of internal and external factors in shaping behavioral intention. TPB has proven helpful in explaining and predicting purchase intention, especially when shopping online. Buyers often face issues in online shopping that require them to use prior knowledge and experience. This helps form beliefs about attributes associated with online shopping, which assists in creating an overall attitude towards online shopping behavior.

Attitude toward a behavior is defined as an individual's positive or negative evaluation after considering performing a specific behavior. The main factor determining attitude is belief about the outcomes or benefits expected from the action. In that case, this can increase their likelihood of developing a positive interest in the behavior. Subjective norms refer to perceived social pressure or support from others in making a decision to act. Finally, perceived behavioral control relates to an individual's opportunities or obstacles. This could include factors such as access to relevant market information or availability of capital. Individuals who believe that they have greater control over this behavior are more likely to have the intention to act. TPB provides a comprehensive framework for understanding how attitudes, subjective norms, and perceived behavioral control influence an individual's intentions. This is highly relevant in contexts such as online shopping, where individuals must consider various factors before making decisions.

2.2. Market Segmentation Theory

Market segmentation is the primary marketing and planning strategy. Given the diversity of customer, satisfying every customer with only one product or service is impossible. Therefore, dividing the market into smaller, more uniform segments offers several advantages such as increased marketing efficiency, better financial performance, and high customer satisfaction. Market segmentation theory enables companies to divide a large market into smaller clusters of customer with similar needs, characteristics, or behaviors (Zhou et al., 2020). The goal is for companies to target their marketing efforts towards the clusters most likely to purchase their products or services, thus enhancing marketing efficiency and effectiveness. Segmentation can be based on geographic location, demographics, psychographics, or customer behavior, with each method offering different ways to identify and target specific customer sub clusters.

Market segmentation allows companies to design and implement more focused and personalized marketing strategies for specific customer cluster. Methods such as K-Means Clustering help identify customer cluster with similar characteristics, proving highly useful in developing more targeted digital marketing strategies and improving the effectiveness of marketing campaigns and customer satisfaction. Thus, market segmentation is crucial for classifying customers based on the similarity of their needs, characteristics, or purchasing behavior. This provides valuable insights for marketing research and enables the clustering of customers based on similar purchasing preferences or behaviors, thereby maximizing the relevance and effectiveness of marketing strategies.

2.3. Data Mining

Data mining is the process of searching through data to discover previously unknown relationships among user-interest data (Hou et al., 2021). This has become an established research field. Data mining also seeks and analyzes data to uncover implicit yet potentially useful information. This involves selecting, exploring, and modeling large amounts of data to reveal patterns that are previously unknown and, ultimately, information that can be understood from extensive databases (Hassani et al., 2020). Data mining uses various computational methods including statistical analysis, decision trees, neural networks, induction, rule refinement, and graphical visualization. Furthermore, data-mining techniques must be understood and carefully applied by frontline users. Data mining enables the search for valuable information from large volumes of data. The rapid growth of databases has created the need for technology that intelligently utilizes information and knowledge. Zhang and Han (2021) said that data mining is the computational process of analyzing data from different perspectives, dimensions, angles, and summarizing it into meaningful information. Thus, data mining, known as knowledge discovery in databases is an essential process in modern data landscapes (Shu & Ye, 2023).

2.4. Digital Marketing Mix

The digital marketing mix, which expands from the traditional 4P concept (product, price, place, promotion) to include 7P, adding people, process, and physical evidence, has evolved significantly with advancements in digital technology (Badica & Mitucă, 2021). In the digital context, products are not limited to physical goods, but also encompass digital services and experiences that can be modified or expanded to meet specific market needs. Price in the digital world often adopts subscription or usage-based models, allowing companies to offer flexibility and personalization. Place is now more than just a physical location. It encompasses digital platforms that facilitate transactions anytime and anywhere, offering unprecedented accessibility to customer. Promotion has evolved to include digital strategies such as social media marketing and influencer marketing, allowing brand messages to reach a broader and more segmented audience. The elements of people, process, and physical evidence emphasize the importance of human interaction in digital marketing, efficiency and transparency of processes, and design and functionality of digital platforms as tangible proof of the value offered (Othman et al., 2021).

Digital marketing changes how companies communicate with customer and extends the scope and effectiveness of the marketing mix. People in the digital context includes how staff interact with customer through digital channels, strengthening relationships and building trust. Process relates to how companies manage and streamline digital transactions and customer interactions, emphasizing the importance of a seamless user experience. Physical evidence in the digital world is often manifested through website and app design, ease of use, and online reviews, all of which contribute to perceived quality and reliability (Tsygankova & Gordieieva, 2023). The strategic implementation of each aspect of the digital marketing mix allows companies to not only meet but also exceed customer expectations, leveraging technology to create added value, strengthen customer relationships, and ultimately drive growth and success in this highly competitive market.

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3. Research Method

In this study, a quantitative survey method was employed. The population for this study was 152 individuals, with the research subjects being individuals with the potential to purchase Wuling vehicle, totalling 111 people. In the context of this research, the criteria include individuals with an interest in or potential to buy a Wuling car and brand awareness, those actively seeking information or visiting Wuling car exhibitions, those interested in innovative features, and the latest technology. The research instrument was a questionnaire that measured two main variables, perceived quality and purchase intention. This questionnaire was designed to collect data on the perceived quality and the purchase intention of Wuling vehicle (Carpino et al., 2019). The variables of purchase intention measured by nine indicators (Nerurkar et al., 2023). Meanwhile, the variables of perceived quality measured by 16 indicators (Ivanova & Moreira, 2023). Data were collected through the distribution of questionnaires to selected respondents. The collected data were processed using SPSS software for statistical analysis. Data analysis was performed using the K-Means Clustering technique to cluster respondents based on similarities in their characteristics.

In this research, the clustering technique used was K-Means Clustering, a method that attempts to cluster data into several clusters based on the similarity of characteristics among the data. Thus, a cluster is a collection of objects that are "similar" to each other and "dissimilar" to objects in other clusters (Mehta et al., 2020). The process begins by selecting the desired number of clusters, K, which may have been determined based on the research objectives or exploratory data analysis. After setting K, the next step is to initialize the centroids for each cluster, which can be done randomly or based on certain heuristics to improve the algorithm convergence. Then, for each data point in the dataset, this step was followed by calculating its distance to each centroid, and the data point was associated with the cluster with the nearest centroid (Alibuhtto & Mahat, 2020). This means that each data point is clustered based on its proximity to the centroid, reflecting the similarity in characteristics among members within the same cluster. After all data points are assigned to a specific cluster, the next step is to recalculate the centroid position of each cluster (Ahmed et al., 2020). This is performed by calculating the average of all data points within the cluster, which then becomes the new position of the centroid.

The process of clustering and updating centroids is repeated in several iterations until convergence is achieved, when there is no significant change in the cluster membership or centroid positions between iterations (Kasim et al., 2021). In the context of this research, after clustering is complete, the collected data that have been clustered into specific clusters are analyse to understand the characteristics and behavior patterns of Wuling customers. These characteristics include purchase intention and perceived quality, which are the focus of this study. This analysis allows researchers to identify different customer segments, such as Perfectionist, Easy Going, and Beginners, based on their level of purchase intention and perceived quality towards Wuling products. The Perfectionist is identified with high purchase intention and high perceived quality, reflecting customer behavior that prioritizes perfection in the products they buy. This aligns with the research by Chen et al. (2023), which indicates that perfectionism is a personality trait that influences reluctance to buy imperfect products. Meanwhile, the Easy Going includes customer with medium purchase intention and perceived quality. They are not overly picky or brand-oriented but do not entirely ignore quality. Their purchase decisions are more flexible and are influenced by price, quality, and convenience. Research by Chin and Viriyasuebphong (2016) shows that, for this customer cluster, price reductions and promotions can increase purchase interest by lowering additional costs, making the purchase more attractive. Lastly, the Beginner is identified with low purchase intention and low perceived quality, reflecting customer who may be new to the market or lack information. Research by Septiani and Chaerudin (2020) found that low perceived quality can decrease customer trust and directly affect purchase intention. This highlights the importance of understanding and addressing the concerns and needs of the customer segment.

Subsequently, an F-test with ANOVA was used to validate the significant differences among the formed clusters, which measures the variance between clusters (MS Between) compared with the variance within clusters (MS Within). In the ANOVA table, MS Between is marked by the Means Square value in the Cluster column, while MS Within is marked by the Means Square value in the Error column (Badri & Habibi, 2022). The results of this F test assist in the structural validation of the clusters generated, providing evidence that the formed clusters indeed have significantly different characteristics from one another. This allows researchers to interpret and describe each cluster specifically, as done in this study, by identifying three customer personas.

4. Result and Discussion

4.1. K-Means Clustering Result

SPSS initially processed the data using three clusters, resulting in zero salvage after seven iterations. This was checked and validated in Excel format and then executed using the SPSS program. The number of segmented clusters was three.

Table 1. Initial Cluster Centers

	Cluster 1 (Perfectionist)	Cluster 2 (Easy Going)	Cluster 3 (Beginner)
Z-Score (Sum Z)	1.991	-1.856	-0.146
Z-Score (Sum Y)	1.452	0.983	-2.764

Source: Processed Primary Data (2023)

Table 1 lists the initial cluster centers from the analyzed data. Cluster 1 (Perfectionist) has high Z-Score for purchase intention (1.991) and perceived quality (1.452), indicating that this cluster has a strong desire to buy and high standards for product quality. Cluster 2 (Easy Going) shows moderate Z-Score in purchase intention (0.983) and perceived quality (-0.146), indicating a less hurried approach to purchase and more flexible standards for product quality. Cluster 3 (Beginner) has low Z-Score in both purchase intention (-1.856) and perceived quality (-2.764), indicating a weaker purchase desire and lower quality standard. These distinct customer cluster based on purchase intention and perceived quality can help companies to target their marketing strategies more effectively for each cluster.

Table 2 shows the iteration history in the K-Means Clustering process for Wuling vehicle market mapping. Seven iterations were conducted, with changes in the values at each iteration. The first iteration changes from 1.324 to 1.313 in the last column. The second and fifth iterations showed significant decreases towards 0.000, indicating cluster stabilization. The third, fourth, and sixth iterations also showed consistent decreases, with the final values reaching 0.000, indicating convergence. In the seventh iteration, no value changes occurred, with all values in the column being 0.000. This indicates that the cluster centers did not change further, thereby achieving full convergence. These results indicate the effectiveness of clustering and potential for tailored digital marketing strategies based on identified market segmentation. In addition, the minimum distance between the initial centers was 3.877, indicating a diverse initial cluster distribution.

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Table 2. Iteration History

Iteration	1	2	3
1	1.324	1.489	1.313
2	0.077	0.168	0.334
3	0.095	0.050	0.000
4	0.910	0.450	0.000
5	0.029	0.013	0.000
6	0.420	0.020	0.000
7	0.000	0.000	0.000

Convergence achieved due to no or small change in cluster centers. The maximum absolute coordinate change for any center is 0.00. The current iteration is 7. The minimum distance between initial centers is 3.877.
Source: Processed Primary Data (2023)

Table 3 shows the Wuling vehicle market mapping using K-Means Clustering reveals the analysis results of three different clusters. Cluster 1 stands out with a high positive Z-Score (Sum Z) of 1.195 and a positive Z-Score (Sum Y) of 0.751, significantly differing from the other two clusters in certain aspects. In contrast, Clusters 2 and 3 had negative Z-Score (Sum Z) of -0.996 and -0.758, respectively, and significantly differing Z-Score (Sum Y): 0.236 for Cluster 2 and -1.636 for Cluster 3. These results indicate that Clusters 2 and 3 have characteristics different from Cluster 1 and also differ from each other, with Cluster 2 having more neutral characteristics than the negative extremes of Cluster 3. This information is crucial for determining the effective digital marketing strategies for each market segment represented by these clusters.

Table 3. Final Cluster Centers

	Cluster 1 (Perfectionist)	Cluster 2 (Easy Going)	Cluster 3 (Beginner)
Z-Score (Sum Z)	1.195	-0.996	-0.758
Z-Score (Sum Y)	0.751	0.236	-1.636

Source: Processed Primary Data (2023)

Table 4 shows the results of the Wuling vehicle market mapping using the K-Means Clustering method. The analysis, based on a survey of 111 respondents, resulted in three different clusters. The first cluster (Perfectionist) involving 29 respondents. This cluster is characterized by high purchase intention and high perceived quality, indicating that customer in this cluster are selective and prioritize quality when choosing a car. They are likely to seek premium features and the latest innovations, and will probably be influenced by quality aspects in their purchase decisions. The second cluster (Easy Going), the largest with 60 respondents. The main characteristics of this cluster were moderate purchase intention and perceived quality. This indicates that they might be more flexible in their choices, not too demanding in terms of features or innovations, and more focused on basic aspects, such as price and reliability. The third cluster (Beginner) with 22 respondents had low purchase intention and perceived quality. This could indicate that they are new customer in the car market or possibly those with budget limitations. They tend to focus less on features and consider the cost aspects more when choosing a car. All the respondents involved in this survey were valid, with no missing or incomplete data.

Table 4. Number of Cases in Each Cluster

Cluster	Result
Perfectionist	29
Easy Going	60
Beginner	22
Valid	111
Missing	0.000

Source: Processed Primary Data (2023)

Table 5 shows both were analyse using ANOVA to determine whether there were significant differences between clusters for each variable. Z-Score of perceived quality has a mean square of 29.750 with two degrees of freedom (DF) in the cluster and a mean square of 0.468 with DF 108 in error. An F-Value of 63.623 with significance (Sig.) of 0.000 indicates a significant difference between clusters in terms of perceived quality. In other words, the perceived quality differed significantly among the studied clusters. Z-Score of purchase intention has a mean square was 39.323 with DF 2 in the cluster, and the mean square was 0.290 with DF 108 in error. A very high F-Value of 135.449 and a significance (Sig.) level of 0.000 indicate a significant difference between the clusters in terms of purchase intention. This means that purchase intention varies significantly among the different clusters. Thus, the ANOVA results show that there are significant differences in perceived quality between clusters, with high F-Value and low significance (Sig.) levels, indicating significant differences in perceived quality among the studied clusters. Similarly, the results for purchase intention indicate significant differences between clusters, with very high F-Value and low significance (Sig.) levels, indicating significant variations in purchase intention among different clusters.

Table 5. F-Test Results with ANOVA

	Cluster		Error		F	Sig.
	Mean Square	DF	Mean Square	DF		
Z-Score (Sum Z)	29.750	2	0.468	108	63.623	0.000
Z-Score (Sum Y)	39.323	2	0.290	108	135.449	0.000

The F test should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.
Source: Processed Primary Data (2023)

Figure 1 shows the result of K-Means Clustering analysis processed using the SPSS program. The graph shows the data division into three clusters based on the distribution of purchase intention (Y-Axis) and perceived quality (Z-Axis). The first cluster, marked in red, shows a cluster of data points that are relatively close together, indicating similarity among individuals in terms of lower purchase intention and perceived quality. The second cluster, in green, encompasses data on mid-range purchase intention and perceived quality. The third cluster, in blue, consists of individuals with higher values of purchase intention and perceived quality. This distribution pattern indicates clear differences in purchase intention and perceived quality among the three clusters.

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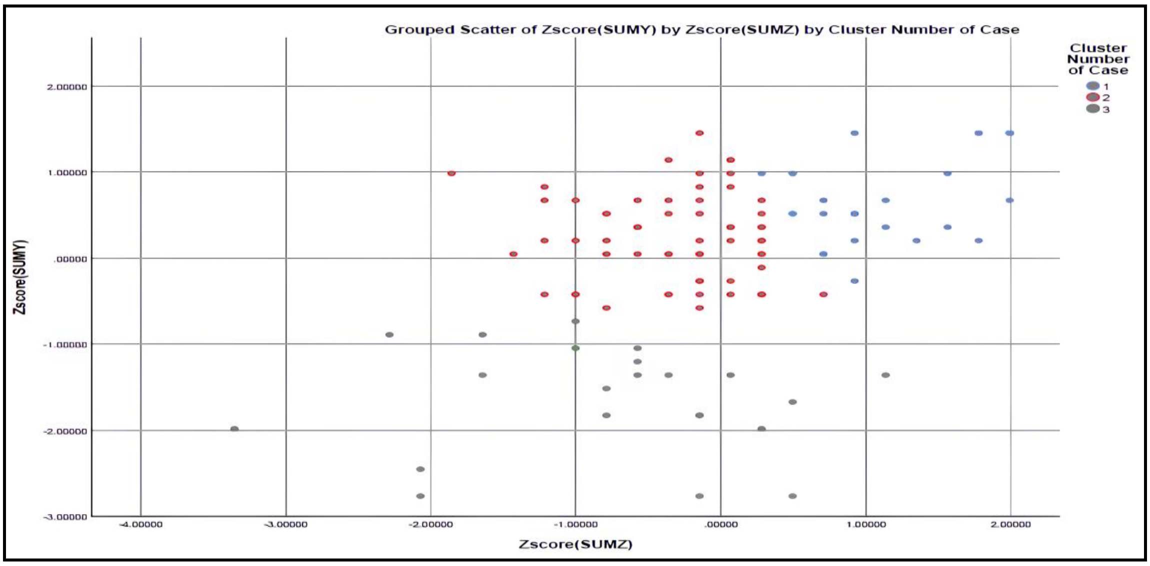

Figure 1. Cluster Distribution Graph of Purchase Intention (Y) and Perceived Quality (Z)

Figure 2 shows significant variation in the purchase intention and perceived quality resulting from various promotional channels such as Facebook, Instagram, Friends, Banners, Television, Websites, and YouTube. The horizontal axis represents perceived quality, whereas the vertical axis represents purchase intention. Points scattered around the centre of the graph indicate an average combination of purchase intention and perceived quality, whereas points far from the centre indicate combinations far from the average. For example, promotions through direct marketing and website sales appear to result in higher-than-average purchase intention and perceived quality, whereas public relations and brand comparison are below average in both aspects. This graph demonstrates that the choice of promotional channel can have different impacts on how customer perceived quality and the extent of their purchase intention, thus providing strategic insights for marketers in tailoring their campaigns for optimal results.

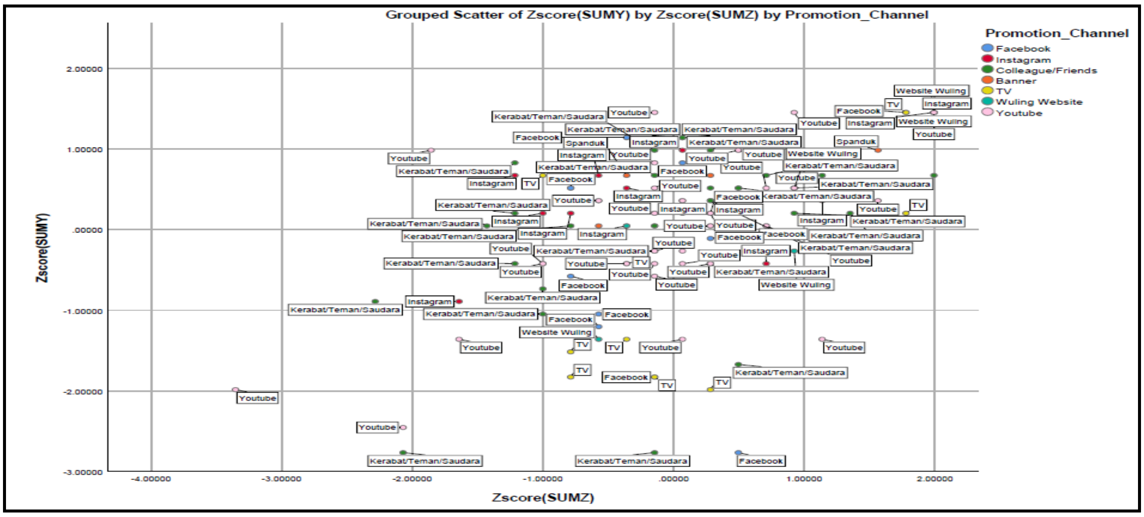

Figure 2. Scatter Graph of Cluster Distribution of Purchase Intention and Perceived Quality Based on Used Promotion Channels

4.2. Discussion

The clustering of Wuling vehicle customer using the K-Means Clustering method divides them into three distinct clusters, that is Perfectionist, Easy Going, and Beginner. Effective market segmentation allows companies to identify and meet customer needs more specifically, which is the key to marketing success. For example, the Perfectionist Cluster shows high purchase intention and high perceived quality. On the other hand, the Easy Going Cluster is characterized by moderate purchase intention and perceived quality. Meanwhile, the Beginner Cluster exhibited low purchase intention and perceived quality. Previous research on market segmentation and automotive marketing often emphasizes the importance of identifying different customer cluster to target more effective marketing strategies. For instance, Wardana et al. (2023) found that dividing the market based on preferences and purchasing behavior can enhance the effectiveness of marketing strategies. This is relevant for the use of K-Means Clustering in the segmentation of Wuling customer.

This study's data analysis showed that the current marketing mix strategy is not optimized to reach the most dominant customer cluster. The F-Test results shows a significant difference between the clusters regarding these two variables. This suggests that each cluster has distinct characteristics that require a tailored marketing approach. To improve the marketing approach for these clusters, it is important to focus on basic aspects, such as price and reliability, which are the main factors in their purchase decisions, rather than emphasizing premium features or the latest innovations. This approach is supported by previous research, indicating that customer with moderate purchase intention and perceived quality tend to be more responsive to marketing strategies that highlight value and practicality over innovation or premium features (Dwivedi et al., 2021; De Silva et al., 2021; Luo et al., 2022).

According to the K-Means Clustering analysis, the most dominant customer cluster for Wuling vehicle is the Easy Going Cluster. With 60 respondents, they formed the largest cluster, indicating a significant presence in the market. The characteristics of this cluster included moderate purchase intention and perceived quality, showing a more practical and flexible attitude toward purchase. This phenomenon aligns with the research by Zhang and Dong (2020), who found that customer in the automotive market segment often place practical and economic factors above other attributes when considering vehicle purchases. This confirms that car purchase decisions are driven by prestige or advanced technology factors, as well as practical considerations and efficiency.

Referring to the clustering results, a more effective marketing mix strategy recommendation for Wuling vehicle should focus on the Easy Going Cluster. This strategy should include marketing messages that emphasize value, reliability, and cost efficiency in line with the cluster moderate purchase intention and perceived quality. Furthermore, considering the cluster scatter plot based on promotional channels, there seems to be an opportunity to optimize the use of certain channels like direct marketing and selling website, which show positive results in perceived quality and purchase interest. It's also important to tailor messages across these channels to target the specific needs of the Easy Going Cluster. Additionally, given the differences in customer cluster characteristics, a personalized approach and more focused segmentation will enhance the overall effectiveness of the marketing mix.

The advantages of previous studies lie in their particular application in automotive marketing (Chandrashekar et al., 2021; Niroomand et al., 2021; Ran et al., 2021; Chen et al., 2022). This study identifies customer cluster and integrates cluster results with marketing mix strategies, providing deeper insights and directly applicable knowledge for enhancing marketing strategies. By clustering customer based on their preferences and purchasing

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behavior, this research offers a more focused approach to identifying and targeting different market segments, which is crucial in the highly competitive automotive industry. This differs from other studies that focus on travel pattern analysis, vehicle performance, or vehicle classification based on dimensions.

Thus, identifying three different customer clusters provides deep insights into the needs and preferences of each segment, enabling Wuling to tailor its marketing strategies more effectively. Moreover, this study highlights the importance of leveraging analytical data to optimize distribution and promotion, reinforcing the relevance of data-based strategies in automotive marketing. Therefore, this study not only assists Wuling in improving marketing effectiveness but also provides a model for other automotive industries to understand and respond to dynamic market needs.

5. Conclusion

The classification of Wuling vehicle customer using the K-Means Clustering method successfully identified three distinct clusters: Perfectionists, Easy Going, and Beginners, each with diverse purchasing characteristics and preferences. The results indicate that the current marketing mix strategy needs to be fully optimized to reach the most dominant customer cluster, Easy Going. Being the largest, this cluster exhibits moderate purchase intention and perceived quality, indicating the need for a marketing approach that emphasizes value, reliability, and cost efficiency. Therefore, a marketing strategy adjustment is necessary to focus more on the needs and preferences of the Easy Going Cluster, including optimizing the use of promotional channels that have proven effective, such as direct marketing and sales websites, to enhance the overall effectiveness of the marketing mix in attracting this market segment. This study offers a model that other automotive industries can apply to understand and respond to dynamic market needs. Moving forward, this research opens opportunities for further studies to optimize data-based digital marketing strategies and the potential application of similar methods in other market and industry contexts.

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