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Combining RFM-based Clustering and GIS-based MCDM for Effective Promotion Location Selection in Higher Education Marketing

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Abstract. This study proposes a novel approach for identifying potential promotion locations for higher education institutions (HEIs) by combining Recency-Frequency-Monetary (RFM)-based clustering and Geographic Information System (GIS)-based multi-criteria decision-making (MCDM). The author uses historical student enrollment data from an Indonesian university to demonstrate the effectiveness of the proposed method. The study aims to extend RFM-based targeting analysis with suitability analysis using the GIS-based MCDM method to determine potential areas for HEI promotional activities. The author applies K-means clustering to identify high-value feeder schools as the target segment and then uses GIS-based MCDM with a weighted linear combination (WLC) to select the most potential areas for promotion based on three criteria: accessibility, market potential, and market concentration. The results show that by focusing on a small number of high-value feeder schools in selected areas, the university can potentially gain a significant portion of its enrolled students while optimizing resource allocation for promotional activities. The proposed approach contributes to the field of higher education marketing by providing a data-driven method for determining promotion target markets and locations.

Keywords: clustering, GIS, MCDM, RFM model, suitability analysis

1. Introduction

Even though the COVID-19 pandemic has passed, its impact on various aspects of life is still felt today. In the field of education, apart from changes in learning paradigms, there has also been a decline in the number of students enrolling in higher education (Fields, 2022), which needs attention from higher education management. According to the National Student Clearinghouse Research Center (NSCRC), undergraduate college enrollment in the United States fell by around 6% (16,152,005 to 15,248,077) between Fall 2019 and Fall 2023 (Welding, 2024). In Indonesia, according to University World News, the COVID-19 pandemic had a significant influence on private universities, with enrollment dropping sharply and student dropout rates rising (Yamin, 2021). Although the decline has started to slow down (Korotchenko & Dobbs, 2023), from 6.55% in 2021, 6.68% in 2022 to 5.60% in 2023 when compared to undergraduate enrollment data in 2019 (Welding, 2024), higher education institutions (HEIs) must generate stable income flows to maintain financial sustainability, which allows them to achieve their goals and invest in future academic and research activities (Sazonov et al., 2015). The high competition also has made them recognize that a successful marketing strategy implementation in HEIs is important to increase student enrollment (Wright, 2017). Many HEIs have adopted a marketing strategy that has been proven successful in business to overcome the increased competition among colleges to attract students (Kuiper, 2018). One element of marketing applied in HEIs is promotion. To build a promotion plan, HEI must first identify the target market and potential promotion locations.

Understanding a target market is crucial for developing successful marketing plans and campaigns. A well-defined target market and an effective marketing strategy can assist organizations retain existing customers while also increasing new customer involvement. Market segmentation is a popular approach for selecting a target market. It differentiates customer groups based on customer characteristics (Abbasimehr & Shabani, 2019) and is used to identify and develop consumer segment profiles, from which one or more groups are chosen as target segments. The target segment consists of potentially valued customers to whom the focused promotional efforts may be applied (Roshan & Afsharinezhad, 2017).

Previous research has extensively used the Recency-Frequency-Monetary (RFM) model for market segmentation and targeting (Christy et al., 2021; Firdaus & Utama, 2021; Hwang & Lee, 2021; Kit et al., 2021; Sarkar et al., 2024; Wu et al., 2020) because RFM is a powerful marketing analysis method (Gustriansyah et al., 2020) and has a high ability to find potential customers (Hwang & Lee, 2021). The RFM model contains three variables: recency, frequency, and monetary. Recency indicates the recentness of customer interactions, frequency represents the number of customer transactions, and monetary measures the amount customers paid throughout the analysis period. Customers who transact more frequently, pay more money, and have just completed a transaction are more valuable. However, the RFM model solely examines customers based on their transaction behavior and does not consider their location. Ernawati et al. (2022a) and Purfini & Yunanto (2019) applied the RFM model and data mining technique to identify potential schools as a target market. However, they did not use location information so the studies could only get the market segments and their characteristics but could not capture regional preferences, making it difficult for HEIs to properly target their marketing efforts geographically.

Nowadays, market analysis incorporates spatial dimensions into problem-solving (Guarda & Augusto, 2019). The location variable is important when developing regional marketing plans (Libório et al., 2020), such as when expanding into new markets and deciding where to run campaigns or promotions. Understanding customer locations is critical in marketing because organizations have limited resources and must carefully choose which areas to focus their marketing efforts in. Firms typically focus their efforts in areas where their target audiences and consumers are concentrated, while also considering competitor concentration and proximity to the distribution channels (Guarda & Augusto, 2019). Therefore, after identifying the target segment, location selection is required. Several previous RFM studies considered geographic information such as area and city (Beheshtian-Ardakani et al., 2018; Carneiro & Miguéis, 2021; Hidayat et al., 2020; Kadir & Achyar, 2019), but they were not analyzed spatially using Geographic Information System (GIS). Some researchers who studied RFM used GIS to consider customer location, such as Buenoa et al. (2022), Ernawati et al. (2022b), and Rahadian & Syairudin (2020). However, location selection has not been explicitly carried out in these studies.

Location selection is the process of finding the most suitable locations with desired conditions based on some variables. Because multiple criteria influence site selection decisions, the multi-criteria decision-making (MCDM) method typically be utilized to deal with location selection problems. The concept of location is related to geography, so many location selection solutions incorporate MCDM with GIS (Aryaee, 2019; Ernawati et al., 2021; Herlawati et al., 2020; Islam et al., 2022). GIS-based MCDM produces beneficial outcomes because it involves geographic information in decision-making (Herlawati et al., 2020) and the capabilities of GIS can help decision-making through visualization. One of the popular GIS-based MCDM applications is suitability analysis. The concept of suitability analysis refers to discovering sites or regions using a set of variables. The outcome of the analysis is a thematic map, which depicts whether sites or places are suitable for particular objectives (Flitter et al., 2013). In the education domain, Lagrab & Aknin (2017) used GIS to perform a suitability analysis to determine the best location for a new elementary school as well as alternate locations for existing elementary schools. Ernawati et al. (2021) used GIS-based MCDM to uncover possible areas for HEI promotion targets. The study proposed a two-stage clustering and GIS-based MCDM approach to support HEI decision-making. However, these studies did not employ the RFM model. Furthermore, there has been little data analytics research on location selection applied in the education domain, particularly with the RFM model and the GIS-based MCDM method. Therefore, this present study fills the gap by combining the RFM model with suitability analysis to select HEI promotional locations. The objective of this research is to expand RFM-based targeting analysis with the GIS-based MCDM model to determine suitable locations as promotional targets based on specified criteria. This study conducts an empirical study to determine an HEI target market using the RFM model and then performs a suitability analysis to select the potential locations for HEI promotional activities using data obtained from an Indonesian university. The present study investigates the following research questions: 1. What are the university target segment's characteristics? 2.) Which feeder schools and in which locations should the institution concentrate its promotional efforts?

Prospective HEI customers are high school graduates. However, parents and high school teachers/counselors significantly influence students' decisions in choosing a university (Jati et al., 2021). Hence, in addition to reaching out to students, many HEIs target students' parents and teachers/counselors as influential decision-makers for promotional targets. According to Beneke & Human (2010), the relationship between HEI with high school students and their parents is the weakest in the student recruitment triangle. Fortunately, HEI can develop a strategy to win students through its feeder schools by leveraging the power of the relationship between the schools and their students (Beneke & Human, 2010). Therefore, this study takes feeder schools as the research object in determining the promotion target market using the RFM-based model and conducting suitability analysis for selecting promotion locations using the GIS-based MCDM method. The study's findings can help HEI management develop promotion strategies, especially for determining promotion target markets and locations and allocating promotional resources. The contribution of this study is expanding the RFM-based targeting analysis with suitability analysis using the GIS-based MCDM method to determine potential areas for HEI promotional activities.

The remainder of this paper is structured as follows. Section 2 summarizes the literature review on RFM and GIS-based MCDM. Section 3 describes the methods that are used in this study. Section 4 focuses on the empirical findings and analysis, and the final section presents a brief conclusion.

2. Literature Review

One of the vital marketing decisions is determining the appropriate target market (Aghdaie & Alimardani, 2015). Recognizing customer characteristics through customer segmentation and determining customer groups as target markets are the initial steps in preparing a marketing plan, including promotional activities. One approach that is widely used in selecting target markets is the customer segmentation method using an RFM-based model in collaboration with data mining techniques (Ernawati et al., 2022a). RFM-based models are popular among decision-makers because they are simple, easy to execute, and understandable (Maryani et al., 2018; Peker et al., 2017; Sarvari et al., 2016). RFM also has good capabilities in identifying potential customers (Hwang & Lee, 2021). Furthermore, RFM-based models are frequently integrated with data mining techniques, particularly clustering (Ernawati et al., 2022a), because they can increase accuracy (Lu et al., 2019).

Firdaus & Utama (2021) modified RFM into RFM+B by including the bank customer balance (B) variable for bank customer segmentation. Using the K-means clustering algorithm, the customer segment can be determined and used as a reference for business units when evaluating marketing and customer growth strategies based on targets. Handojo et al. (2023) introduced a multi-layer RFM method that considers the time-period factor when determining customer priority in online transactions. The proposed approach is effective for evaluating the dynamic nature of customer behavior in online businesses. Kit et al. (2021) used the LRFMP model and K-means algorithm to generate online retail customer profiles. It improves retailers' understanding of their customers and lays the groundwork for them to make informed decisions in a variety of business areas, including product selection and marketing tactics. Sarkar et al. (2024) used the RFM model and the K-means algorithm to segment customers in an online retail company. The study findings, which achieved a 95% accuracy rate, gave significant information and a trustworthy tenet for online retail organizations to understand and target certain client categories more efficiently. It can assist in designing tailored marketing strategies, personalized recommendations, and consumer-centric techniques, which can improve customer satisfaction and corporate performance. Wassouf et al. (2020) transformed the RFM model into the time, frequency, and monetary (TFM) model to segment and target telecom customers. They used classification algorithms to identify the causes and influential factors of loyalty and to categorize new users. Wu et al. (2020) used the RFM and K-means algorithms to segment customers and analyze their values using online transaction data. The customer grouping allows the extraction of purchasing habits for each group of customers, which can then be used to develop accurate marketing strategies. RFM-based segmentation and data mining have been applied in the education sector as well, specifically for HEI marketing and student recruitment (Ernawati et al., 2022a; Purfini & Yunanto, 2019). However, because these studies did not use customer location information, they can only show customer group characteristics and cannot capture regional preferences, making it difficult for HEIs to properly target their marketing efforts geographically.

The location factor is an important consideration when making business decisions, such as in choosing a business or marketing location. Estimation of potential market areas is important because many businesses face the challenge of selecting the best territories and allocating their market budget optimally among them. According to the previous study, HEI students come from many feeder schools spread across different districts. However, the feeder schools are not distributed randomly but rather clustered in specific areas (Ernawati et al., 2022b). Therefore, identifying the areas as potential targets for promotion and student recruitment is essential. Location is related to an object's geographic position on the earth's surface. Marketing strategies that involve location analysis or spatial analysis are known as geomarketing. GIS, a commonly used geomarketing tool, is a framework for gathering, storing, and mapping spatial data, assessing it using spatial analysis methods, and reusing it in other applications (Cliquet & Baray, 2020). GIS is an effective tool for spatial decision-making because it provides comprehensive and visual information (Chacón-García, 2017; Jurišić et al., 2016; Oliveira et al., 2020). One of the GIS applications is to solve location selection problems. Several previous RFM studies considered geographic information such as area and city (Beheshtian-Ardakani et al., 2018; Carneiro & Miguéis, 2021; Hidayat et al., 2020; Kadir & Achyar, 2019), but they were not analyzed spatially using GIS.

Some researchers who studied RFM used GIS to consider customer location, such as Buenoa et al. (2022), Ernawati et al. (2022b), and Rahadian & Syairudin (2020). Rahadian & Syairudin (2020) used the RFM model to analyze non-formal education institutions' customer payment patterns and transaction data. Customers in each segment were visualized on a map to assist decision-makers in analyzing their locations. The study used GIS to map customers' addresses. Buenoa et al. (2022) used the RFM model, which was modified into a Recency-Frequency-Helpfullness model, in conjunction with a Fuzzy 2 Tuple model, to determine tourist satisfaction with hotels in a variety of geographic locations using online user reviews. The results were visualized using GIS, allowing customer satisfaction with the hotel group to be distinguished based on the city in which the hotel is located. These findings provide an opportunity for hotels, restaurants, and other service businesses with locations in multiple cities for service improvement and change, to attract and retain customers. Ernawati et al. (2022b) proposed an RFM-based framework to help HEI management identify target markets. The study determined an institution's promotional target markets for recruiting students and devised a geomarketing plan. GIS was used in the study for spatial analysis using Moran's I test and heatmap so that it can be concluded that there are differences in the market potential of each region. The district potential variable was integrated into the RFM-based model which is used to select valuable market targets based on the RFM-based model and its regional potential. However, these studies have not specifically conducted location selection.

Lagrab & Aknin (2017) employed GIS in the field of education to conduct a suitability analysis. The study aimed to identify the best site for a new elementary school, as well as alternative locations for existing primary schools. The school's locations were evaluated based on their proximity to fuel stations, existing schools, industrial areas, study area elevation, and open space. Ernawati et al. (2021) employed GIS-based MCDM to identify potential locations for HEI's promotion activities. The study suggested a two-stage clustering and GIS-based MCDM approach. Nevertheless, the earlier studies did not utilize the RFM model. In addition, there has been a scarcity of data analytics research focused on location selection in the field of education, specifically using the RFM model and the GIS-based MCDM method. Thus, this study addresses the gap by integrating the RFM model with suitability analysis to determine the suitable location for HEI promotional locations.

3. Research Methods

This research performed data analytics in four major stages to discover suitable locations for an HEI promotion: data collecting, data preprocessing, data processing and analysis, and evaluation, as illustrated in Fig. 1.

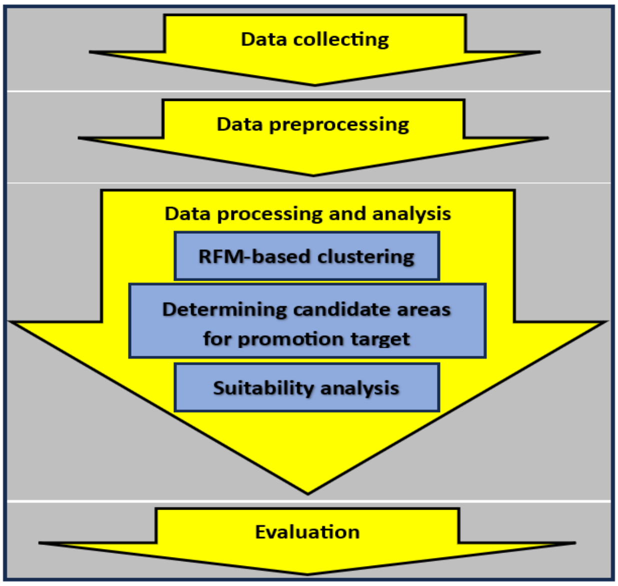

Fig. 1: Methodology

The first stage involved the collection of secondary data from a university. Five years (2014-2018) of enrollment data were gathered for empirical study. The student enrollment data, specifically the student identity, enrollment year, and high school origin were recorded. The high schools' locations and the shapefile of the study area were also gathered for implementation in the GIS environment. This study took Indonesia as the study area. School locations in the form of their latitude and longitude were gathered from Sekolah Kita (https://sekolah.data.kemdikbud.go.id/), the Indonesian Ministry of Education and Culture's official website regarding Indonesian schools, as well as from Google Maps. At the same time, the shapefile for the Indonesian cities/regencies was downloaded from Indonesia's geospatial site (www.tanahair.indonesia.gov.id).

In the second stage, data preprocessing was employed to make data ready for processing. The collected data were integrated and cleaned. Following that, data aggregation was conducted to convert the data into a suitable form for analysis. The enrolled student data were aggregated by high school.

Data processing and analysis were performed in the third stage. This stage involves three steps, namely:

a. Determining a target market using RFM-based clustering.

   Since not all high schools contribute the same value to a university as a target market, RFM analysis was used to identify high-value feeder schools. The RFM variables used in this study were modified to fit the context of higher education marketing (Ernawati et al., 2022c), and redefined as written in Table 1. Feeder school segmentation was carried out utilizing clustering, a data mining technique, based on the revised RFM variables. The simplest clustering algorithm, K-means, was used to group the feeder schools because it is easy to understand, interpret, and apply, as well as fast and efficient in execution (Davari et al., 2018; Peker et al., 2017), making it appropriate for large dataset or big data (Li and Li, 2018; Lu et al., 2019). K-means is also widely used in customer segmentation (Ansari, 2021) and RFM analysis (Sheikh et al., 2019). However, for applying K-means algorithm, the number of clusters must be determined at the beginning, hence the Elbow method was employed in this study to determine the optimal number of clusters (Firdaus and Utama, 2021; Kit et al., 2021). Elbow method is a popular method for determining the optimal number of clusters (Wu et al., 2020). To assess clusters quality, the Silhouette index was applied since it performs well under a variety of conditions (Dalmaijer et al., 2022). Based on the clustering results, high-value feeder schools were identified as the target segment for promotion.

Table 1: The RFM variables definition

Variable	Definition
Recency (R)	The novelty of the most recent graduate of a feeder school enrolling in the university.
Frequency (F)	The number of times within the analysis period that graduates from a feeder school enrolled in the university.
Monetary (M)	The total number of graduates from a feeder school who enrolled at the university in the analysis period.

b. Determining candidate areas for promotion target.
According to the results of the RFM-based clustering, the locations of high-value feeder schools were mapped and aggregated by their city/regency to generate candidate areas for the suitability analysis process.

c. Conducting a suitability analysis to select potential locations for HEI promotion targets.
This suitability analysis aims to determine suitable cities/regencies to become the main targets for a university promotion. The criteria chosen to determine suitable areas are the proximity of the city/regency to the university, the number of high-value feeder schools in the city/regency, and the number of enrolled from the city/regency. They are chosen based on the practices carried out by AB University. These three variables assess a location's potential as a promotion target based on: the ease of access to the market and budget/resource required, the market potential, and the market concentration in the area where the target audiences are concentrated (Guarda & Augusto, 2019). Every variable was classified into five categories (1-5) according to its values. This suitability analysis used weighted linear combination (WLC), which was implemented in vector-based maps (Wigati et al., 2023), in the form of polygons/areas showing their potential for promotion locations. The FUCOM method (Pamučar et al., 2018) was used to calculate the criteria weights. The FUCOM method employs three steps for determining the weight of variables (Ernawati et al., 2022a; Pamučar et al., 2018): 1. Decision makers rank variables in order of importance ($V_1 > V_2 > \ldots > V_k > \ldots > V_m$) and establish each variable's priority in comparison to the most important variable. 2. Comparative priority ($\varphi_{k/(k+1)}$) is determined by comparing the V_{k+1} priority scale to the V_k. 3. The variables' weight ($W_1, W_2, ..., W_m$) and deviation from full consistency (DFC(χ)) were determined following two criteria: the weight coefficients' ratio is equal to the relative priority among the employed variables:

$$\frac{w_k}{w_{k+1}} = \varphi_{k/(k+1)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

and satisfies the mathematical transitivity property.

$$\frac{w_k}{w_{k+2}} = \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \quad \ldots\ldots\ldots\ldots\ldots \quad (2)$$

Following that, based on the results of the WLC method, the candidate areas were classified into three categories: the most potential, potential, and least potential for promotion locations.

Finally, in the fourth stage, a comprehensive evaluation was carried out to assess the proposed approach. A sensitivity analysis was conducted to assess the robustness of the results by changing the criteria weight.

4. Results and Discussion

4.1. Data collecting and preprocessing

For the empirical study, this research employed student enrollment data from an Indonesian private university (called AB University). It only examined students from Indonesian high schools as the university feeder schools; thus, international students were excluded. This study collected five years (2014-2018) of enrolled student data (11,861 students). After preprocessing, 11,199 student records remain. Following aggregating by their high school origin, they come from 1,799 feeder schools scattered over 338 Indonesian cities/regencies (90 cities and 248 regencies). The latitude and longitude of the feeder schools were gathered from Sekolah Kita (https://sekolah.data.kemdikbud.go.id/) and Google Maps. At the same time, the shapefile for the Indonesian cities/regencies was obtained from Indonesia's geospatial site (www.tanahair.indonesia.gov.id). The distribution of AB University's feeder schools is depicted in Fig. 2.

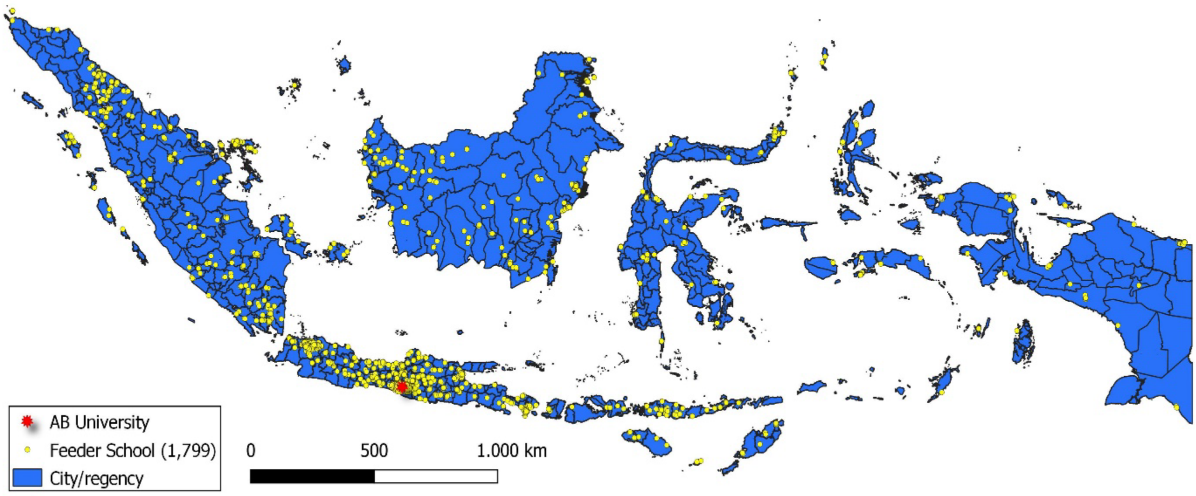

Fig. 2: AB University's feeder schools

4.2. Data processing and analysis

Before the clustering process was carried out, the recency (R), frequency (F), and monetary (M) values for each feeder school were calculated according to the RFM variables definition in Table 1. The student enrollment data was collected over 5 years, so the recency value is coded as 1 to 5, with 5 indicating that the feeder school' graduate was still enrolled at AB University in the last year of the analysis period, and 4 indicating that the feeder school's recent graduate enrolled at AB University one year before the last-year of the analysis period. While 1 indicates that the feeder school last sent students to AB University in the first year of the analysis. Similarly, the F value was coded from 1 to 5, indicating how frequently the feeder school sent graduates to AB University over the 5-year analysis period. A score of 5 indicates that the feeder school sends its students to AB University every year; a score of 4 indicates that the feeder school sends four times in five years; and a score of 1 indicates that the feeder school sends just once in five years. The M value is the total number of students from each feeder school who enrolled at AB University during the analysis period. The empirical data show that the M value ranges from 1 to 439. Table 2 presents a statistical summary of the 1,799 feeder schools' RFM values. The RFM data were then standardized using Z-Score normalization, making them ready for clustering.

Table 2: Statistics summary of the RFM variables

Statistics	Recency (R)	Frequency (F)	Monetary (M)
Minimum	1	1	1
1st Quartile	2	1	1
Median	4	1	2
Mean	3.54	2.09	6.23
3rd Quartile	5	3	5
Maximum	5	5	439
Standard deviation	1.46	1.40	21.98

4.2.1. RFM-based clustering for selecting target segment

The results of RFM-based clustering using the K-means algorithm are displayed in Table 3. The dataset was grouped into six clusters as suggested by Elbow method displayed in Fig. 3.

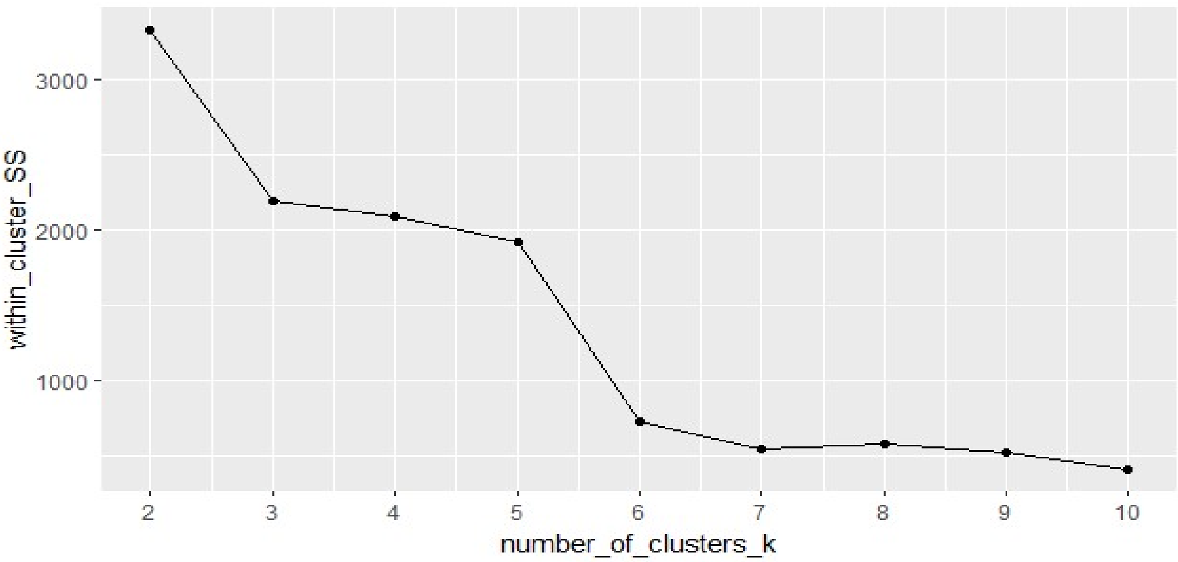

Fig. 3: Elbow method for determining the number of clusters

Table 3 displays the distinctive features of each cluster, as indicated by the mean value of each RFM variable, and the number of feeder schools within each cluster. The clustering findings were validated by employing the Average Silhouette score, as depicted in Fig. 4. The Silhouette score is 0.56, which exceeds the Silhouette threshold of 0.5 (Dalmaijer et al., 2022). It indicates that the clustering outcomes exhibit good cluster quality.

Table 3: RFM-based clustering' result

Variable	Dataset	1st cluster	2nd cluster	3rd cluster	4th cluster	5th cluster	6th cluster
Recency	3.54	3.00	2.00	4.80	4.53	5.00	1.00
Frequency	2.09	1.42	1.21	4.06	1.42	5.00	1.00
Monetary	6.23	1.85	1.45	14.43	1.72	360.40	1.18
Cluster's member	1,799	251	278	510	518	5	237

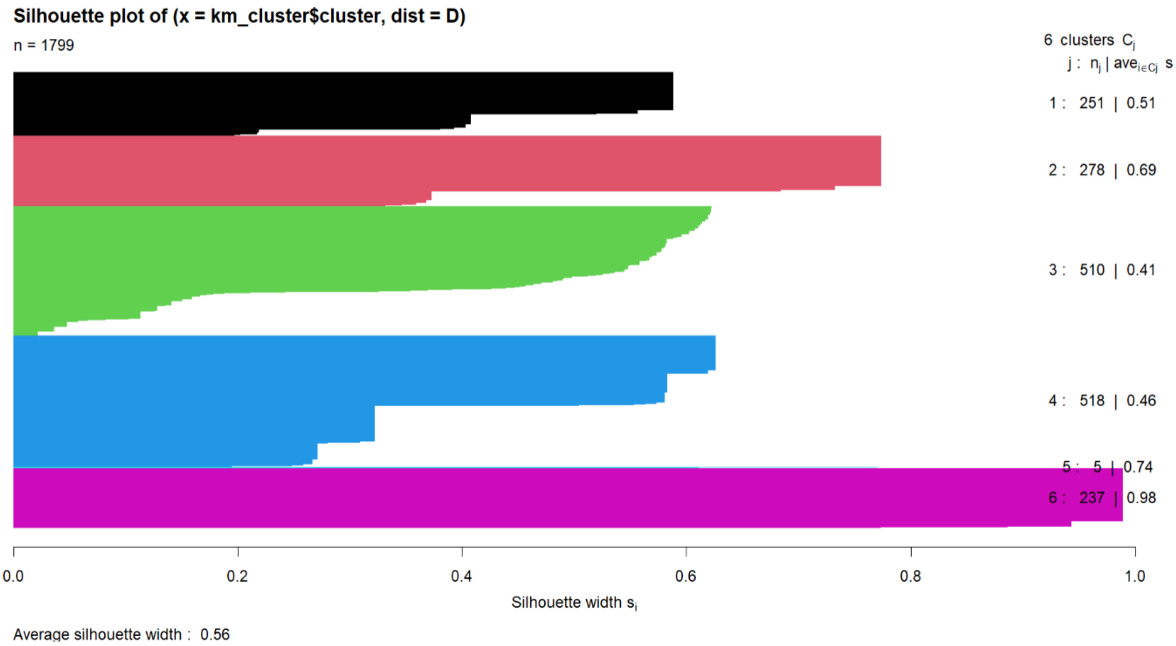

Fig. 4: Silhouette score for assessing the quality of the clusters

Comparing the R, F, and M mean values, the 1st, 2nd, and 6th clusters have R, F, and M mean values lower than the dataset mean values for respective variables, with the 6th cluster having the lowest RFM value, followed by 2nd and 1st clusters. The R-value in Table 3 indicates that feeder schools in these clusters did not send students enrolled at AB University relatively longer than other clusters. The M-value and F-value show that feeder schools in the 6th cluster only sent one student once during the analysis period, while feeder schools in the 1st and 2nd clusters sent 1-2 students 1-2 times. Meanwhile, although feeder schools in the 4th cluster relatively have students performing enrollment at AB University recently, the schools only sent 1-2 students 1-2 times during the study period. So, feeder schools in the 4th cluster have a low value for AB University. Therefore, these four clusters were not chosen as the target segment. In contrast, the 5th cluster which contains 5 feeder schools, has the highest average R, F, and M values. The RFM values reveal that every year until the end of the analysis period, they regularly send a very large number of students enrolled at AB University during the analysis period, followed by feeder schools in the 3rd cluster as the second valuable feeder school cluster. Because the highest value cluster (the 5th cluster) only contains five schools, so for this case study, the second valuable cluster (the 3th cluster), which includes 510 feeder schools was also chosen as the target market. As a result, this study assigns 515 high-value feeder schools in the 5th and 3rd clusters as the target segment for AB University. The average R, F and M values of the 515 high-value feeder schools are 4.81, 4.07, and 17.79 respectively. It means these high-value feeder schools have been sending a large number of students to AB University four to five times within a five-year analysis period until recently. Of the 515 high-value feeder schools, 488 are senior high schools, 26 vocational high schools, and one Madrasah school. According to their type, 280 are public schools, while 235 are private. The average cumulative grade point average (CGPA) at the end of the fourth semester of 9,162 enrolled students at AB University from these 515 schools was 2.98. Thus, the first research question regarding the characteristics of AB University's target segment has been addressed.

4.2.2. Determining candidate areas for promotion target

After aggregating and mapping the 515 high-value feeder schools, it recognizes that they are scattered over 68 cities and 106 regencies in 30 Indonesia's provinces. Fig. 5 depicts a distribution map of high-value feeder schools, which are AB University's target segment, while Fig. 6 presents a heatmap indicating the concentration of these schools. The maps indicate that the majority of the high-value feeder schools are located on Java island, particularly in the Jawa Tengah and Daerah Istimewa Yogyakarta Provinces.

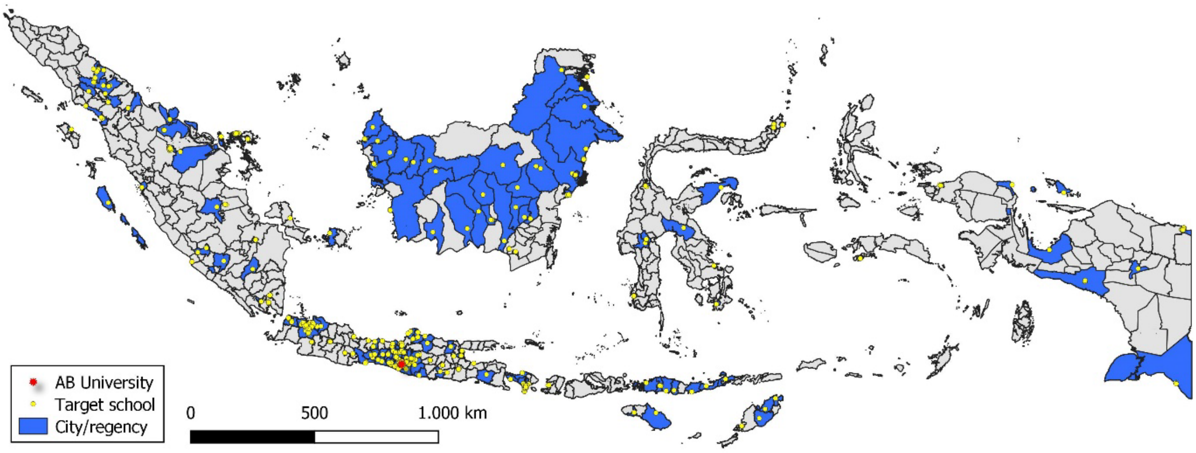

Fig. 5: High value feeder schools distribution

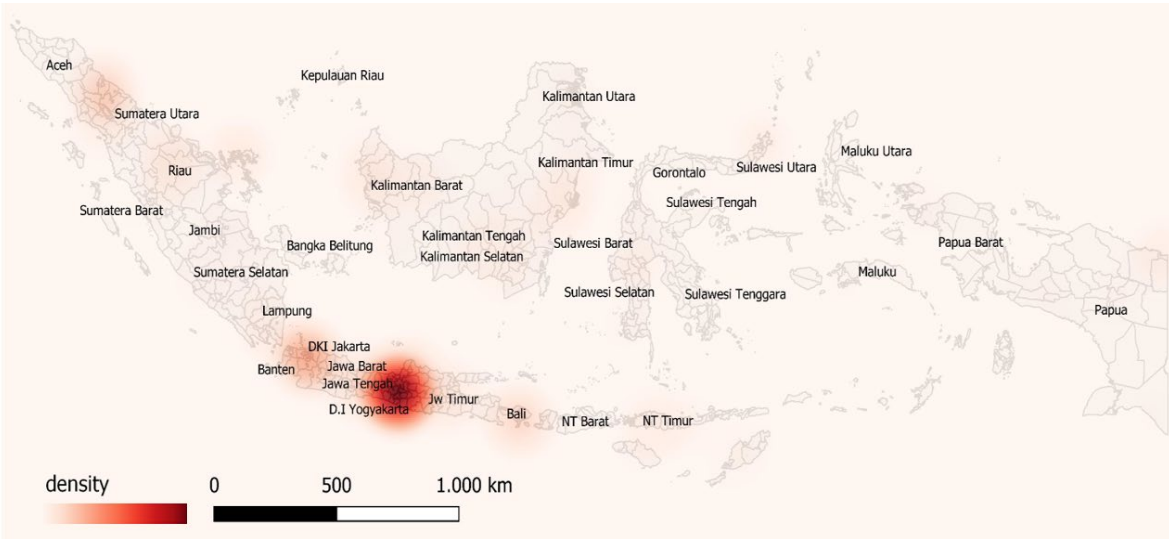

Fig. 6: High-value feeder schools heatmap

Fig. 7 shows the number of high-value feeder schools in each province. Most feeder schools (109) are situated in Jawa Tengah Province, the closest province to AB University's province. In second place is the Province of Daerah Istimewa Yogyakarta (67), where AB University is located. Sumatera Utara takes the third position (38). Despite having fewer feeder schools, Daerah Istimewa Yogyakarta Province has more enrolled students in AB University than Jawa Tengah Province, as shown in Fig. 8. These two provinces are the largest source of AB University students.

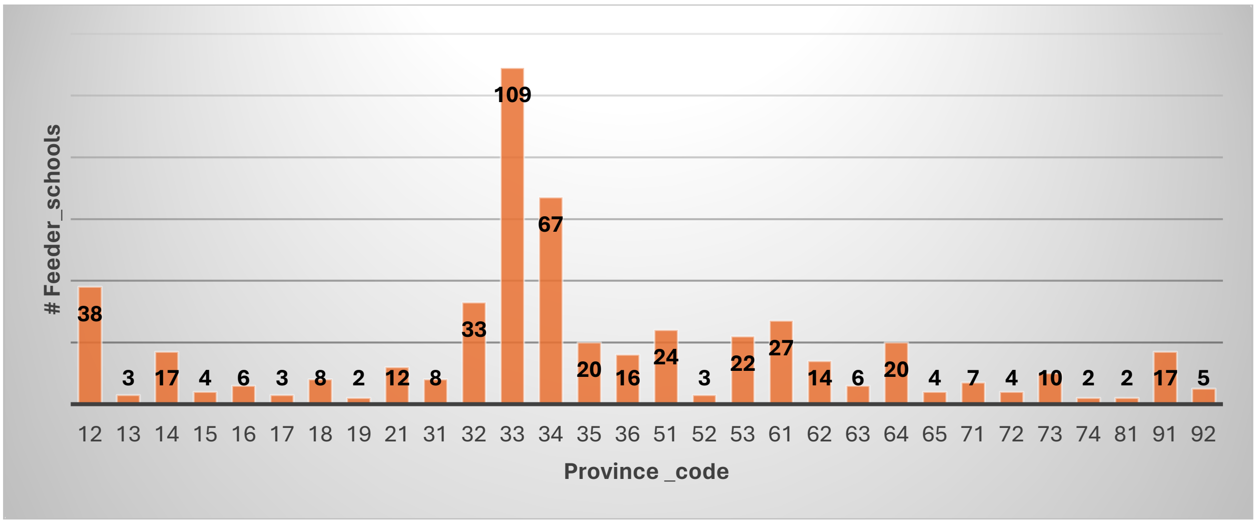

Fig. 7: Number of high-value feeder schools by province

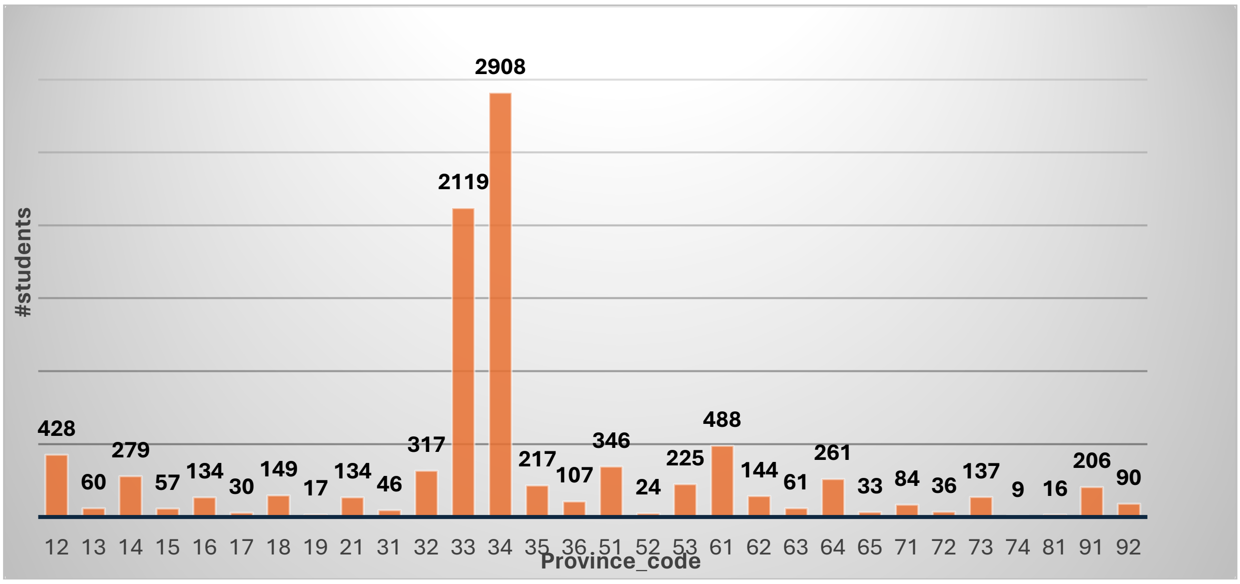

Fig. 8: Number of enrolled students by province

According to Chase et al. (2019), personal contacts, such as campus visits and recruitment officers visiting high schools, influence students' university selection decisions, and campus visits are the most effective student recruitment promotion strategy. However, due to Indonesia's vast territory, it is not easy for high school students from all over Indonesia to visit AB University. Therefore, AB University must proactively promote itself by sending recruitment officers to high schools.

Jati et al. (2021) found that promotion is one of the most important factors for Indonesian parents when choosing private universities for their children, and most institutions promote through high school visits besides websites, and exhibitions. To visit all high-value feeder schools spread across 174 very wide regions in Indonesia, of course, requires significant resources so it is necessary to determine which areas should be prioritized as promotion target locations. Therefore, this study conduct a suitability analysis and assigns these 174 cities/regencies as candidate areas for further suitability analysis in the following step.

4.2.3. Suitablity analysis

The purpose of this suitability analysis is to determine appropriate cities/regencies to become primary promotion targets for AB University. This study bases its suitability analysis on three criteria: proximity which measures how close a candidate area is to the university, the number of high-value feeder schools as promotion targets in the candidate area, and the number of enrolled students who came from the candidate area. The statistics of these variables are presented in Table 4. For performing the analysis, each variable was discretized into five classes as shown in the last column in Table 4.

Table 4: Criteria used for suitability analysis

Criteria	Empirical data statistics			Classification
	Minimum	Mean	Maximum	
Proximity	5.21 km	1,179.17 km	3,401.50 km	5: distance ≤ 100 km 4: 100 km < distance ≤ 500 km 3: 500 km < distance ≤ 1000 km 2: 1000 km < distance ≤ 1500 km 1: distance > 1500 km
Number of high-value feeder school (TS)	1	2.96	31	5: TS > 5 4: 4 ≤ TS ≤ 5 3: TS = 3 2: TS = 2 1: TS = 1
Number of enrolled students (ES)	3	61.52	2,113	5: ES > 64 4: 32 < ES ≤ 64 3: 20 < ES ≤ 32 2: 11 < ES ≤ 19 1: ES ≤ 11

Proximity was determined by calculating the distance from the centroid of each candidate area (in this case: city/regency) to AB University using the distance matrix tool available in QGIS software. The proximity was categorized into a value of 1 to 5. The closer the area is to AB University, the higher the proximity value. The higher the proximity value, the more potential the area is to become a promotional target location. The city/regency's proximity classification was visualized in the vector-based thematic map as shown in Fig. 9.

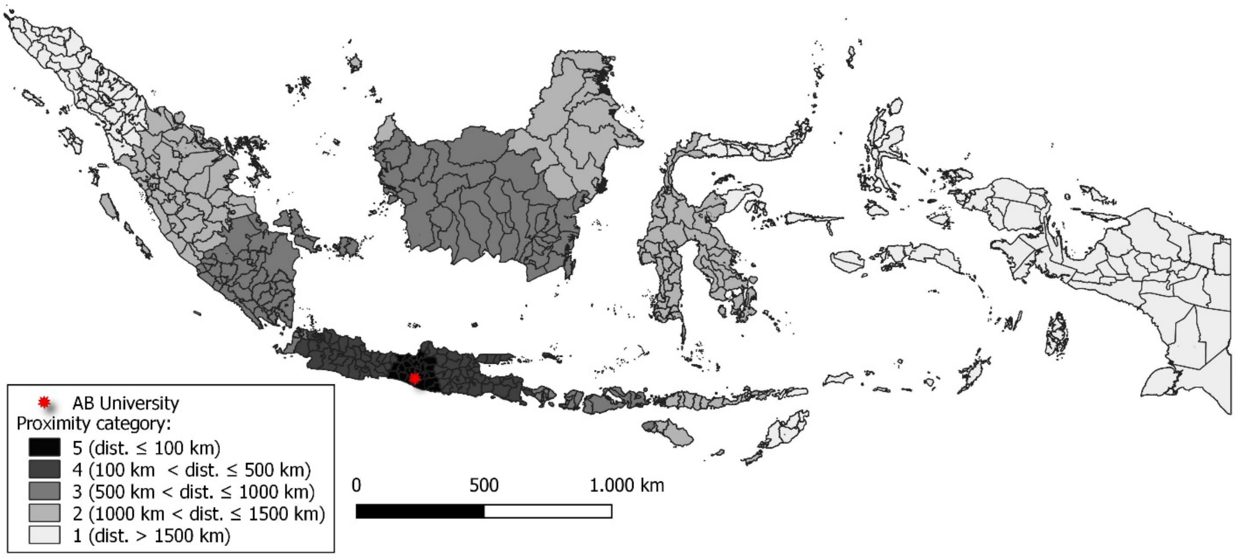

Fig. 9: City/regency's proximity classification

The number of high-value feeder schools in a city/regency as the target segment (TS) demonstrates its market potential. This variable was divided into five values (1-5). The greater the TS value of a city/regency, the more likely it is to become a promotional target area. Fig. 10 displays the city/regency's classification based on the number of high-value feeder schools.

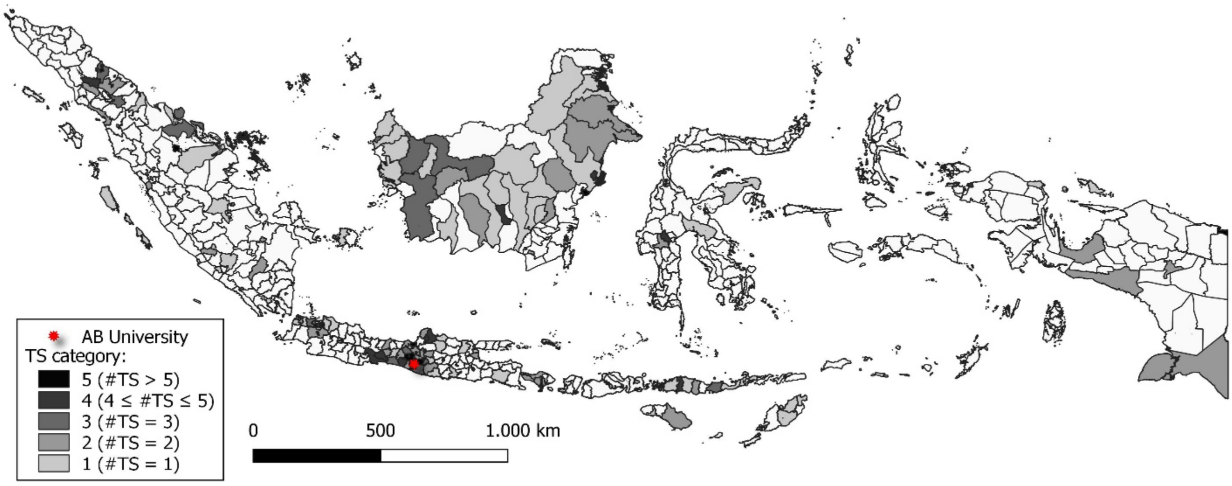

Fig. 10: City/regency's classification based on the number of high value feeder schools

The number of enrolled students (ES) at AB University from cities/regencies during the analysis period reflects market concentration. The ES values are assigned from 1 to 5. The greater the number of enrolled students from the city/regency, the higher the market concentration, hence the greater the possibility for the area to become a promotional target. Fig. 11 depicts a thematic map of the city/regency's classification based on students enrolled at AB University.

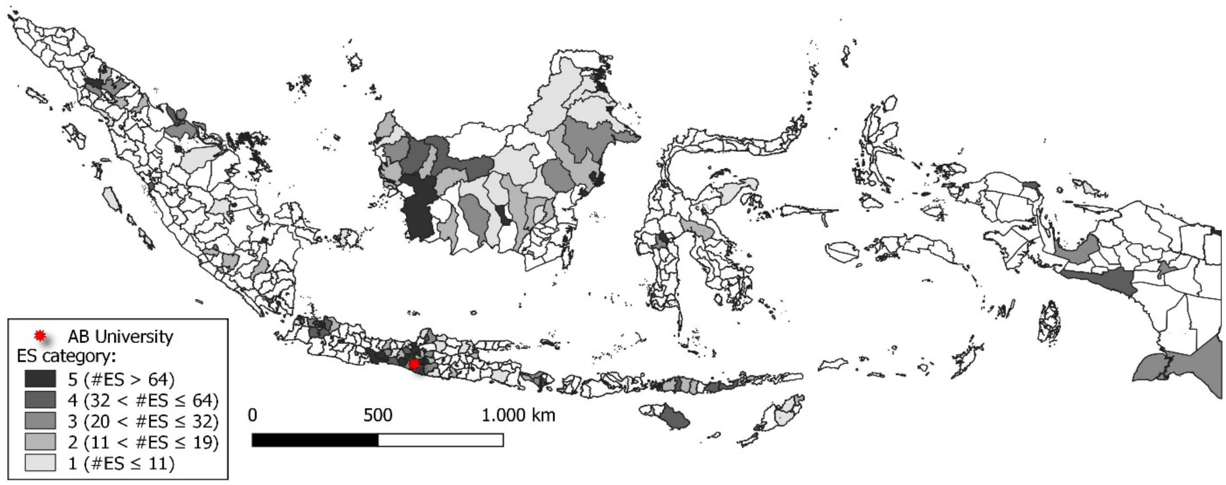

Fig. 11: City/regency's classification based on its students enrolled at AB University

To implement GIS-based MCDM, the weights for each criterion were determined using the FUCOM approach (Ernawati et al., 2022a; Pamučar et al., 2018) in three steps: 1. Based on the university experience, the second criterion (TS) was chosen as the most important variable, followed by the third criterion (ES) and the first criterion (Proximity), resulting in a variable ranking of TS > ES > Proximity, while the relative variables' priorities are set as 1, 1.5, and 1.5, respectively. 2. After comparing the variables' priority to the most important variable (TS) priority, we found the comparative priority vector = (1.5/1, 1.5/1.5) = (1.5, 1). 3. By applying the constraints in Equations 1 and 2, the following equation system was obtained:

$$\begin{aligned} 2w_{TS} - 3w_{ES} \quad &= 0 \\ w_{ES} - w_{Proximity} &= 0 \\ 2w_{TS} \quad - 3w_{Proximity} &= 0 \\ w_{TS} + w_{ES} + w_{Proximity} &= 0 \end{aligned}$$

After solving the equation system, we yielded the variable weights (W_{TS}, W_{ES}, $W_{Proximity}$) = (0.42, 0.29, 0.29) with DFC(χ) = 0.

Each of the 174 candidate areas was scored using the WLC approach. The candidate score was computed by multiplying the value of each criterion by its weight and then summing the results. The prospective areas were classified into three categories based on the score: most potential for promotion target (score ≥ 4), potential (3 ≤ score < 4), and least potential (score < 3). The final suitability map of the candidate locations was created and shown in Fig. 12. The most potential area includes 27 cities/regencies, followed by 37 in the potential category and 110 in the least potential group.

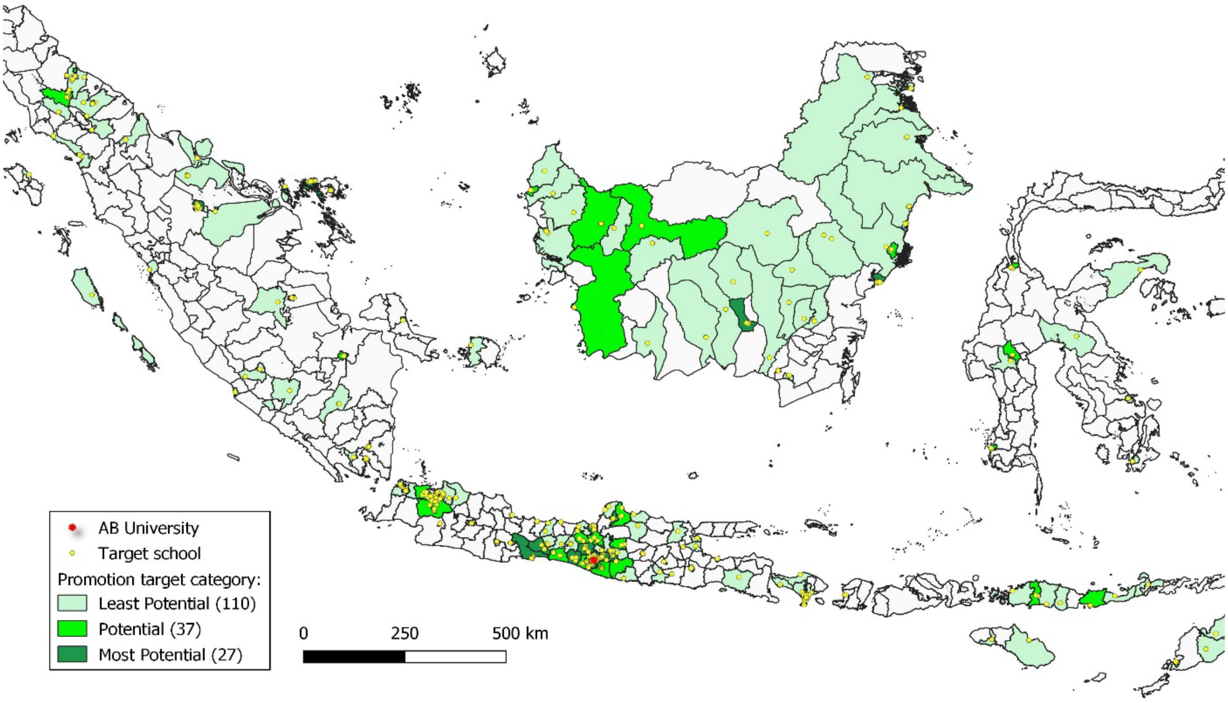

Fig. 12: Suitability map of cities/regions as promotion locations

The most potential area consists of 17 cities and 10 regencies which are spread over 13 provinces. Fig. 13 shows that most of these cities/regencies (19 of 27) are on Java Island, the most populated island in Indonesia. Jawa Tengah Province contains ten cities/regencies, Daerah Istimewa Yogyakarta Province contains three cities/regencies, Jawa Barat Province contains two cities, Jawa Timur Province has two cities, Jakarta Province comprises one city, and Banten Province contains one city. The remaining are located outside of Java Island, with most being provincial capitals.

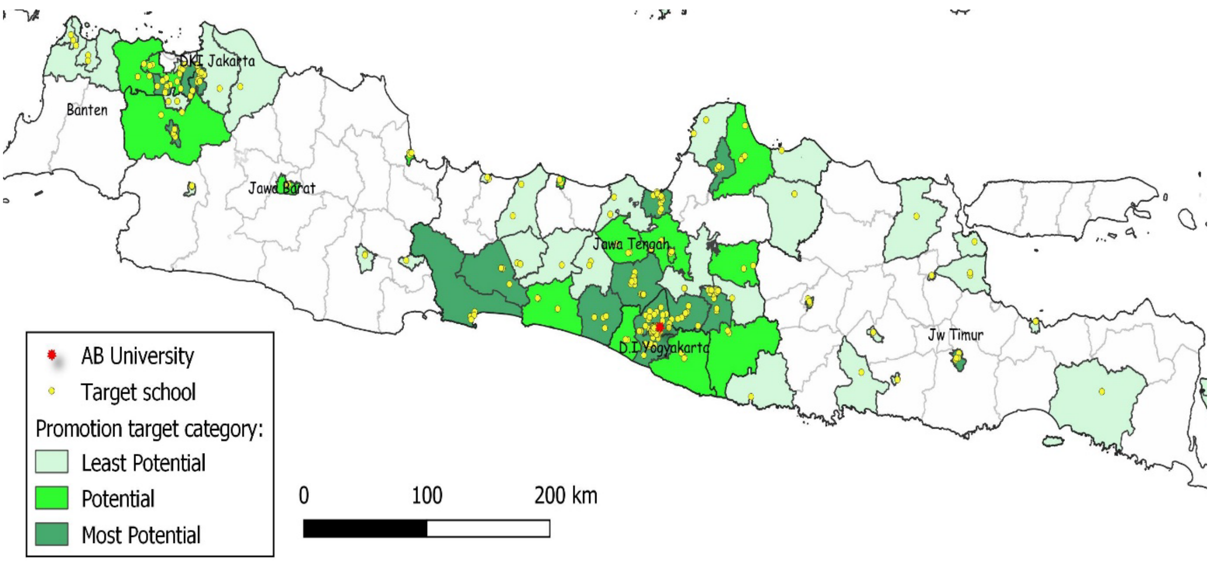

Fig. 13: The suitable cities/regions on Java Island

The findings indicate that by concentrating on the 27 most potential cities/regencies (which make up 7.99% of AB University's catchment areas), there are 226 feeder schools of high value (accounting for 12.56% of AB University's feeder schools) that can be specifically targeted for promotional campaigns. As a result, AB University is expected to gain more than half of its total enrolled students (5,940 or 53.04%) during the analysis period. The total distance needed to get to all 27 cities/regencies is roughly 9,750.42 kilometers.

Fig. 14 compares the total number of feeder schools to the number of high-value feeder schools in each of the most potential cities/regencies. Meanwhile, Fig. 15 shows the contrast in number of enrolled students when the university reaches all of the feeder schools in each city/regency compared to when it focuses only on the high-value feeder schools in the city/regency. Of the 529 feeder schools located in the most potential area, by concentrating on the 226 high-value feeder schools, the university could recruit 5,940 out of 6,453 students from the most potential cities/regencies. So even though the number of schools targeted for promotion is smaller, the number of enrolled students that can be obtained remains relatively large. The average CGPA at the end of the fourth semester of the 5,940 enrolled students at AB University from these 226 schools was 3.03. These schools' average R, F, and M values are 4.84, 4.19, and 26.28 respectively. The M value indicates that the chosen schools sent more students to AB University, while the R and F values show that the schools regularly sent their students four to five times within a five-year analysis period until recently. Of the 226 high-value schools, 203 are senior high schools, 22 vocational high schools, and one Madrasah school. Furthermore, 120 of these schools are public, while the remaining 106 are private.

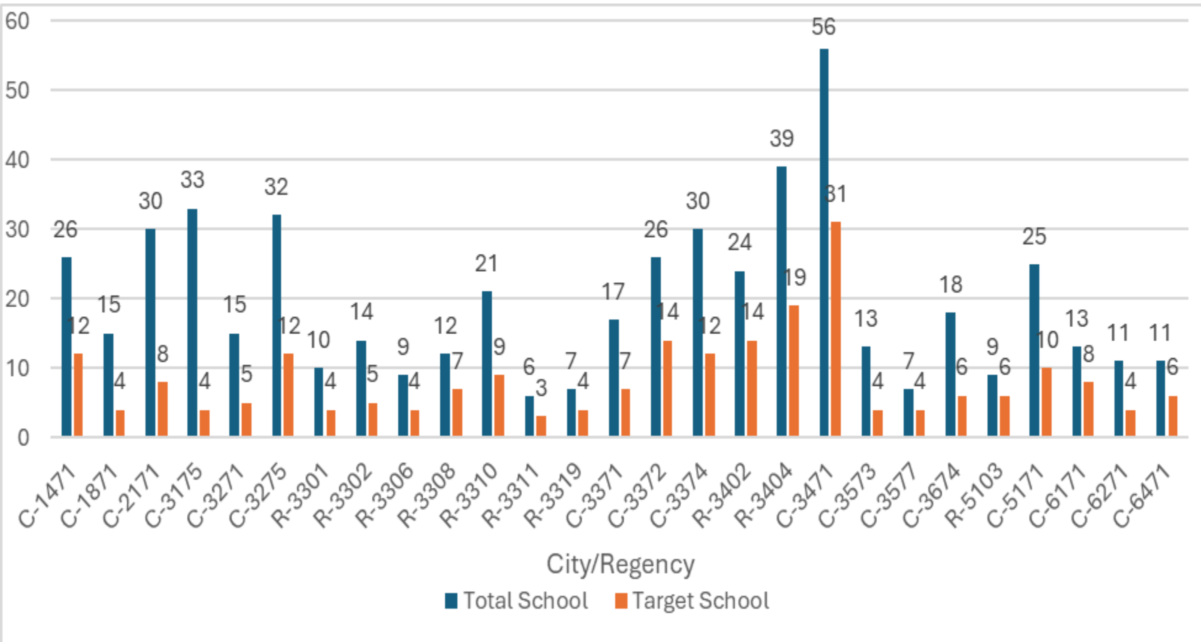

Fig. 14: Total number of feeder schools and high-value feeder schools in the most potential cities/regencies

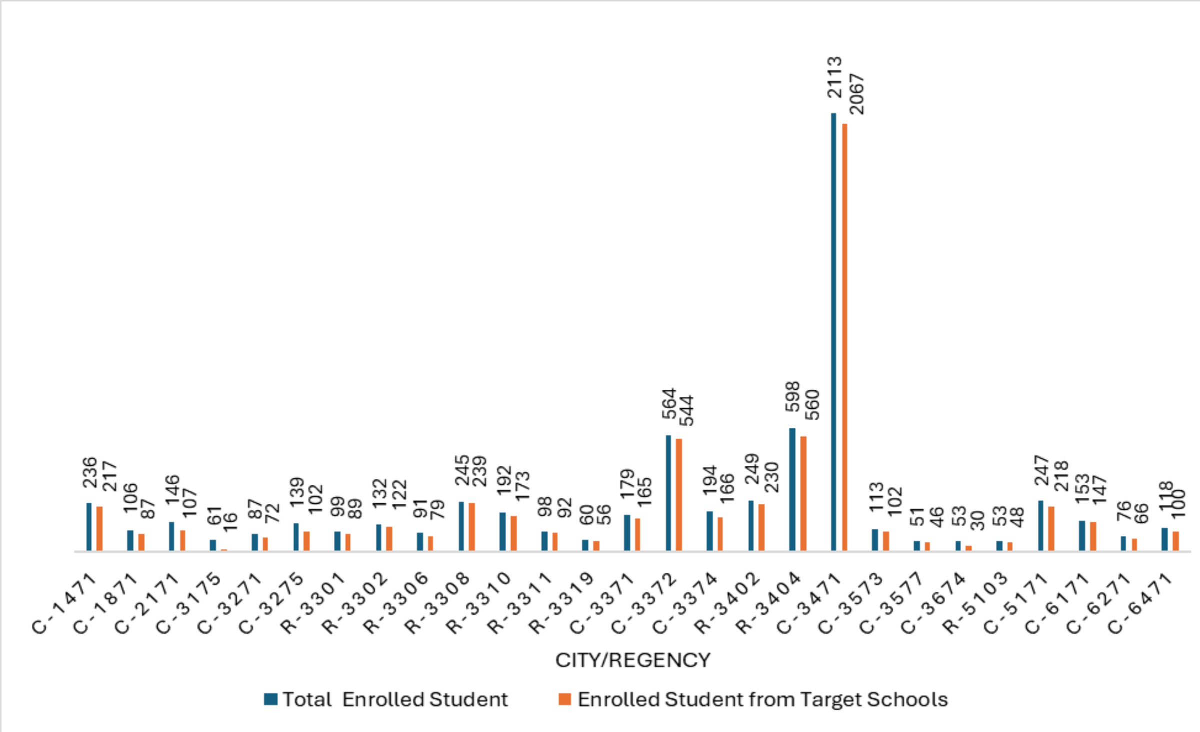

Fig. 15: Total number of enrolled students and enrolled students from high-value feeder schools in the most potential cities/regencies

Based on the findings, to answer the second research question, this study suggests AB University should concentrate its marketing efforts and resources on the 27 cities/regencies in Indonesia that have the highest potential, instead of targeting all cities/regencies. Most cities/regencies are located on Java Island, where AB University is also located. This proximity enables cost savings and minimizes the requirement for promotional team personnel. Furthermore, most of the promotional targets situated beyond Java Island are provincial capitals, making them easily accessible by air travel. This allows the promotional teams to optimize time in reaching the locations. In addition, AB University should prioritize targeting the 226 high-value feeder schools in these cities/regencies to attract more students. Since AB University currently focuses its marketing effort more on private schools, it should broaden to public schools, since the results show that the number of potential public schools is greater than private schools.

4.2.4. Evaluation

Table 5 summarizes the proposed approach's results after performing RFM-based clustering followed by the suitability analysis. Using RFM-based clustering to choose high-value feeder schools as the target market, this study recommends targeting 515 schools from which 81.81% of AB University's students came during the analysis period. The table demonstrates that RFM-based clustering significantly reduces the number of feeder schools (from 1,799 to 515). It also helps in selecting high-value schools. Of the 1,469 feeder schools in 174 candidate areas as promotion targets, from which 10,705 enrolled students came, 515 targeted schools were chosen, which sent 9,162 students. However, these 515 schools are distributed in 174 cities/regencies with a total distance of 151,080 kilometers from AB University, requiring enormous resources to reach them.

Fortunately, by extending the selection process with suitability analysis, this study could find a small number of areas, namely 27 cities/regencies with a total distance of 9,750.42 kilometers from AB University as promotion target locations. There are 226 high-value feeder schools in these areas, where 5,940 (53.04%) students came. At this step, it is possible to reach 92.05% of the 6,453 students from the 27 cities/regencies by targeting only 226 (42.72%) feeder schools in the areas as promotion targets.

Thus, by implementing the proposed approach, this study suggests AB University conduct promotion to 27 (7.99%) cities/regencies with a total distance of about 9,750.42 kilometers (2.90%) and target 226 (12.56%) feeder schools where 5,940 (53.04%) AB University's students came from. Therefore, it can be concluded that integrating RFM-based clustering and GIS-based MCDM suitability analysis is effective for choosing promotional target locations. In the case of determining HEI promotional locations, it also can be used to select high-value feeder schools as target markets.

Table 5: Summary of the proposed approach's results

	Number of areas	Total distance to the areas (km)	Number of feeder schools in the areas	Number of enrolled students from the areas	The proposed approach's results	
					#TS	#ES
Initial condition	338	336,431.01	1,799	11,199	-	-
RFM-based clustering	174	151,080.86	1,469	10,705	515	9,162
Suitability analysis	27	9,750.42	529	6,453	226	5,940

This study performed a sensitivity analysis to evaluate the robustness of the proposed approach's results by altering the weight of the criteria. Since this research uses the FUCOM method in determining the criteria weights, for varying the criterion weights, 10 other scenarios were created, each with a distinct variable order of importance and variable relative priority, as presented in Table 6.

Table 6: Weight variation used for conducting sensitivity analysis

Scenario	Variable order of importance and relative priority	W_{TS}	W_{ES}	$W_{proximity}$
S1	TS > ES > P; 1 : 1.5 : 2	0.46	0.31	0.23
S2	TS > ES > P; 1 : 2 : 3	0.55	0.27	0.18
S3	ES > TS > P; 1 : 2 : 3	0.27	0.55	0.18
S4	ES > TS > P; 1 : 1.5 : 2	0.31	0.46	0.23
S5	ES > TS > P; 1 : 1.5 : 1.5	0.29	0.42	0.29
S6	ES > P > TS; 1 : 2 : 3	0.18	0.55	0.27
S7	ES > P > TS; 1 : 1.5 : 2	0.23	0.46	0.31
S8	ES > P > TS; 1 : 1 : 2	0.2	0.4	0.4
S9	ES > P > TS; 1 : 1 : 1.5	0.25	0.375	0.375
S10	TS = ES = P; 1 : 1 : 1 (equally weighted)	0.333	0.333	0.333
Implemented	TS > ES > P; 1 : 1.5 : 1.5	0.42	0.29	0.29

Fig. 16 presents the outcomes of the sensitivity analysis. This analysis compares the ranks of the 27 recommended cities/regencies in the implemented scenario with those of other scenarios. The figure shows that the top eight rankings across all scenarios are identical, while the other ranks exhibit some variations. However, these discrepancies in the ranking are still relatively not very big, with the largest discrepancy being 23, for the R-5103 regency between scenarios S2 and S6. Meanwhile, compared to the implemented scenario, the maximum ranking difference is 18 with the S6 scenario. The analysis found that the proximity variable was most sensitive to changes in weight. As a result, the disparity in rankings for cities/regencies far from AB University was relatively larger. Nevertheless, the proposed approach yields satisfactory results since all scenarios rank the recommended cities/regencies inside the top 40 out of the total 174 rankings.

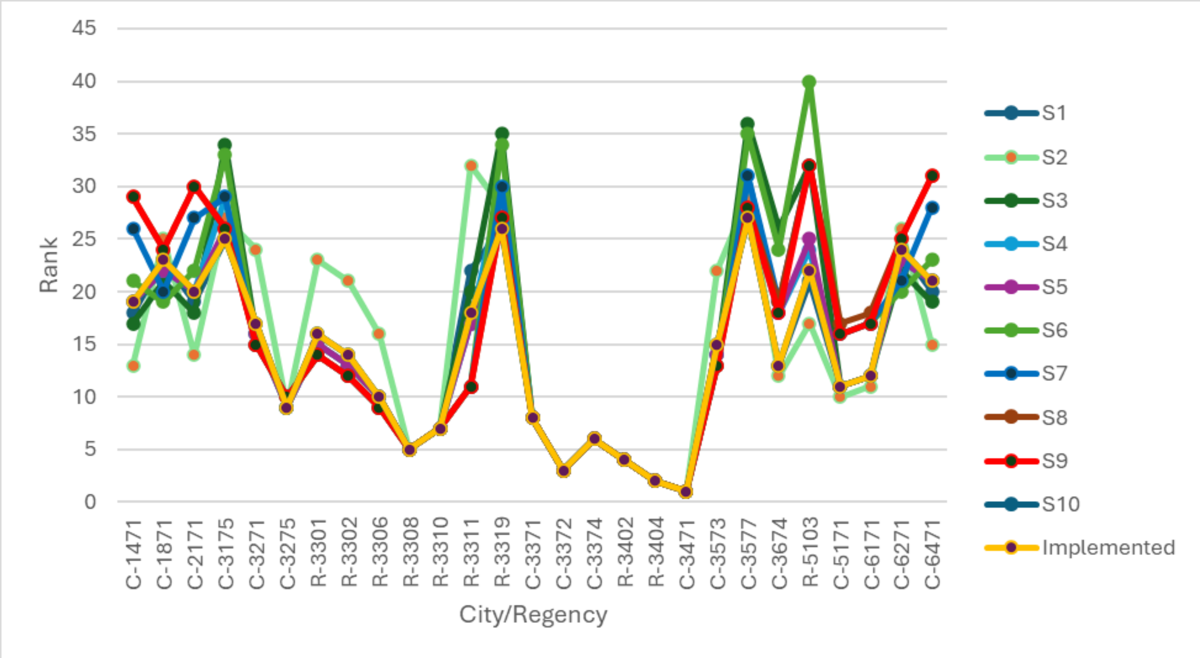

Fig. 16: Sensitivity analysis using different weights of criteria

This study conducted a comparative evaluation by contrasting the outcomes of the proposed approach with those of a prior study (Ernawati et al., 2021). Both studies utilized the same dataset to identify possible regions for university promotion targets but employed distinct methodologies and criteria. The previous study classified the regions into different groups based on the enrolled students' pattern categories, the consistency in sending students, CGPA, and dropout (DO) rate using the K-prototype algorithm. The study identified 26 cities/regencies from 15 provinces that contributed 6,388 (57.04%) students with good academic performance (CGPA of 2.98 and DO rate of 3.44%) as the university promotion targets. In contrast, the proposed approach suggested 27 cities/regencies distributed among 13 provinces that provided 6,453 (57.62%) students. Both studies recommend 20 cities/regencies that are identical. The total distance to catch the 27 cities/regencies is 9,750.42 km, smaller than the total distance to the 26 cities/regencies suggested in the previous study (16,974.98 km. In addition to its ability to determine cities/regencies for university promotion targets as in the previous study, the suggested approach can also identify high-value feeder schools in the recommended cities/regencies. Regarding student performance, this study recommended the 226 high-value feeder schools with a higher average CGPA (3.03), although with a slightly worse DO rate (4.11%) as promotional targets. The comparative evaluation shows that the proposed approach is effective in identifying the appropriate cities/regencies and high-value feeder schools that should be prioritized for promotional targets.

5. Conclusion

In conclusion, this study presents a novel approach for identifying potential promotion locations for HEIs by combining RFM-based clustering and GIS-based MCDM. The proposed method demonstrates the effectiveness of using data-driven techniques to optimize resource allocation and promotional strategies in higher education marketing. The author uses historical student enrollment data from an Indonesian university to identify high-value feeder schools as the target segment and select the most potential areas for promotion based on accessibility, market potential, and market concentration. The results show that by focusing on a small number of high-value feeder schools in selected areas, the university can potentially gain a significant portion of its enrolled students while minimizing the resources required for promotional activities. The proposed approach contributes to the field of higher education marketing by providing a systematic and data-driven method for determining promotion target markets and locations. The proposed methodology utilizes criteria categorized on a scale that spans from 1 to 5, perhaps leading to less accurate decision-making results. Alternatively, it can utilize actual numerical values. Future challenges may involve the utilization of fuzzy variables which which enable the employment of natural language terms and may effectively manage ambiguity. This facilitates decision-makers in interpreting and making judgments with more ease. Furthermore, future research could explore the generalizability of the proposed approach to other HEIs or educational contexts, incorporate additional criteria, or investigate the use of other data mining techniques for target market identification. The findings of this study have important implications for HEI management in terms of resource allocation, promotional strategies, and decision-making processes in an increasingly competitive higher education landscape.

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