
Segmentation of Hikers Preferences for Hiking Boot Recommendations Using K-Means and SAW

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Article History

Submitted : 07-07-2026

Revised : 27-07-2026

Accepted : 29-07-2026

Published : 18-09-2026

DOI: 10.32664/smatika.v16i03.2468

Keyword

Hiking Shoes; Hiker Preference; K-Means; Multi-Criteria Decision Making; Simple Additive Weighting

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Abstract

The increasing number of mountain climbers in Indonesia, particularly beginners, has led to issues in selecting the right hiking shoes. Without data-driven guidance, shoe selection tends to be influenced solely by brand popularity rather than suitability with physical needs and trail characteristics, which potentially increases the risk of injuries such as blisters or sprains. This problem is exacerbated by the lack of a system capable of accommodating differences in preferences among climber segments, considering that the needs of technical trail climbers differ significantly from those doing light hikes (day hikes). This research aims to identify mountain climbers' preference patterns and build a decision support system for hiking shoe recommendations based on user segmentation. The approach used is the integration of the K-Means Clustering method to group climbers based on shoe attribute preferences, and the Simple Additive Weighting (SAW) method to generate objective brand recommendation rankings based on weights extracted from the clustering results. Data was collected from 154 climber respondents on Mount Buthak and Mount Penanggungan, East Java, using a ranking-based preference questionnaire. The clustering results with the best performing though still suboptimal, configuration of K=2 (Silhouette Score 0.4506) produced two segments: Cluster 0, which prioritizes comfort and durability (80 respondents), and Cluster 1, which is oriented towards Brand and shoe Weight (74 respondents). The application of SAW yielded different recommendations for each segment, with Consina being the top recommendation for Cluster 0 (score 0.8663) and Nineten for Cluster 1 (score 0.8810). These results prove that the integration of K-Means and SAW can produce more objective and personalized recommendations compared to approaches based solely on brand popularity, while also serving as a foundation for market segmentation strategies for outdoor equipment manufacturers.

1. Introduction

Mountain climbing has become an increasingly popular form of outdoor recreation among Indonesians, driven by growing interest in nature tourism, active lifestyles, and the role of communities and social media in introducing this activity to a wider audience [1]. For example, the number of climbers visiting Mount Semeru rose from 141,327 in 2014 to 669,422 in 2019, while the number of hikers visiting Mount Gede Pangrango rose from 167,514 to 345,861 during the same period [1]. Data from the Indonesian Mountain Guides Association

(APGI) even indicates that there were approximately three million active hikers in Indonesia as of 2019, and this number is expected to continue growing in line with post-pandemic trends in nature tourism [2]. This growth has also been accompanied by an increase in the number of beginner hikers, who often lack sufficient knowledge about choosing hiking gear, particularly hiking boots [3].

Hiking boots play a crucial role in ensuring hikers' safety and comfort, as they are used on varied terrain and in challenging environmental conditions. Choosing the wrong boots can potentially lead to injury; a systematic review of 17,757 cases of hiker injuries found that the most common site of injury was the lower extremities, accounting for 49% to 100% of all cases, with the most common types of injuries being blisters and ankle sprains [4]. The problem is that choosing hiking boots is not a simple decision. Consumer preferences are influenced by various technical attributes such as material durability, weight, comfort, design, and the product's basic functionality [5], while the multitude of brands and types of boots with differing characteristics often makes it difficult for users to determine the most suitable choice [3]. This complexity is further compounded by the fact that every hiker has different characteristics and needs, ranging from age, hiking intensity, and type of activity to budget constraints [6].

However, the information and recommendations currently available for choosing hiking boots remain general in nature and do not take into account the specific differences in hikers' characteristics. Previous research on consumer preferences for hiking boots, for example, tends to stop at identifying attributes considered important in aggregate without linking them to the segmentation of user needs [5], [7]. On the other hand, the K-Means Clustering method has been widely proven effective for performing segmentation without requiring initial class labels, [8] and its combination with the Simple Additive Weighting (SAW) method has been shown to improve the relevance and accuracy of product recommendation systems in other contexts, such as e-commerce. [9] Nevertheless, the combination of these two methods has not been extensively explored specifically in the context of selecting hiking boots based on hikers' preference segmentation this gap is the primary motivation for this study.

Based on these issues, this study aims to identify the preference patterns of mountain climbers and group them into homogeneous segments using the K-Means Clustering method, and to develop a decision support system based on Simple Additive Weighting (SAW) to generate recommendations for hiking shoe brands that align with the characteristics of each segment, particularly for beginner climbers. Unlike conventional approaches that assign criterion weights subjectively or standardize them for all users, this study objectively extracts SAW criterion weights from the clustering results, ensuring that the resulting recommendations adapt to the differing priorities of each segment of hikers [10].

Research data was collected from 154 hikers on Mount Buthak and Mount Penanggungan in East Java through a ranking-based preference questionnaire covering five attributes of hiking boots: comfort, price, durability, weight, and brand. Clustering results with the best performing configuration of $K=2$ yielded two segments of hikers with contrasting needs, which were subsequently used as the basis for weighting in the SAW model to generate different brand recommendation rankings for each segment. Thus, this study is expected to bridge the gap in previous research by producing a hiking boot recommendation model that is more personalized, objective, and relevant to the real needs of each group of hikers.

2. Research Method

2.1 Research Phases

This study employed a quantitative approach based on primary data collected via an online questionnaire. The study subjects were mountain climbers who had climbed Mount Buthak or Mount Penanggungan in East Java at least once. The questionnaire was distributed online to the mountain climbing community in East Java and successfully gathered 154 respondents who met the inclusion criteria.

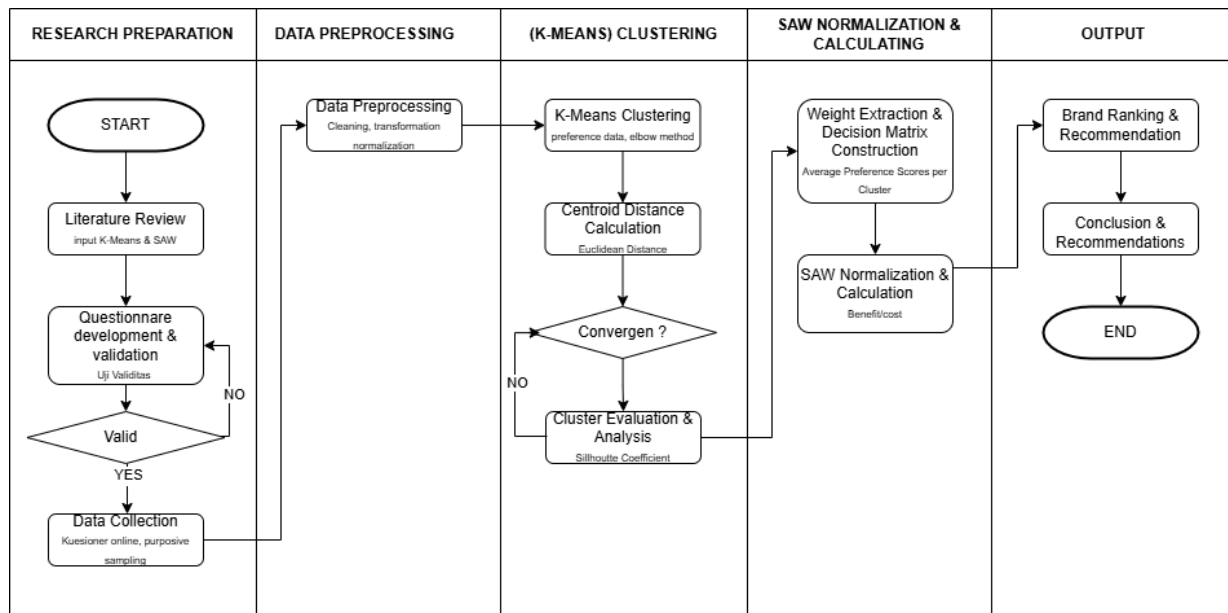


Figure 1. Flowchart of the research stages

Table 1. Demographic result from respondent

Demographic	Category	Percentage
Gender	Female	49.35%
	Male	50.65%
Age	< 20	7.14%
	20-25	48.05%
	25-30	35.71%
	> 30	9.09%
Hiking Frequency	1-2 times	20.13%
	3-5 times	30.65%
	6-10 times	34.42%
	>10 times	14.94%
Types of Activities	Fast Hiking (tektok)	42.86%
	Camping	38.96%
	Trail Running	18.18%
Boot Budget	< Rp 300.000	6.49%
	Rp 300.000-Rp 600.000	35.71%
	Rp 600.000-Rp1.000.000	39.61%
	> 1.000.000	18.18%

The questionnaire used a ranking-based format, in which respondents were asked to rank five attributes of hiking boots (comfort, weight, durability, price, and brand) from most important (rank 1) to least important (rank 5). This format was chosen because it minimizes the response bias commonly found in conventional Likert scales, while also yielding preference data that better distinguishes between criteria [11].

2.2 Data Preprocessing and Normalization

Before the data is used in the clustering process, two preprocessing steps are performed. The first step is data cleaning, which involves checking the completeness and consistency of respondents' answers. Respondents who did not complete the questionnaire in full or provided duplicate ratings for more than one criterion were excluded from the analysis. The second stage is the transformation of the ranking data so that the direction of

the scores is uniform for further processing, since ranking-based data has ipsative characteristics and requires special treatment before analysis [12]. The original ranking scale is inverted using a linear complementary formula so that the highest value represents the highest priority. This is necessary because in ranking-based questionnaires, rank 1 (most important) has the lowest numerical value, so it must be reversed before further processing.

After transformation, the data is normalized using MinMaxScaler to a range of 0 to 1 using the following equation [13]:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where x' is the normalized value, x is the original value, x_{min} is the minimum value, and x_{max} is the maximum value of each variable. This normalization ensures that all variables are on an equivalent scale so that no single criterion dominates the clustering process due to differences in the range of values.

2.3 K-Means Clustering Method

K-Means is a non-hierarchical clustering algorithm that partitions data into one or more clusters, so that data with similar characteristics are grouped into the same cluster, while data with different characteristics are grouped into other clusters [13].

Clustering techniques such as K-Means are increasingly used to group data based on diverse behavioral attributes [14]. In this study, K-Means was applied to hikers' preference data to group respondents based on the similarity of their priority patterns regarding hiking shoe attributes. Each respondent is treated as a single data point in a multidimensional space, represented by preference scores for each criterion: comfort, price, durability, shoe weight, and brand [8].

The distance between each data point and its centroid is calculated using Euclidean distance, with the following formula:

$$d(x, y) = \sqrt{\sum (x_i - Y_i)^2} \quad (2)$$

In the application of K-Means, one of the parameters that must be determined is the number of clusters (k) to be used. To help determine the most appropriate number of clusters, the Elbow Method is used, which involves analyzing the Within-Cluster Sum of Squares (WCSS) for various numbers of clusters. The optimal value of k is determined at the point where the decrease in WCSS begins to slow down, forming an elbow-like pattern [15].

To ensure that the resulting clustering has good quality, the Silhouette Coefficient is used as a cluster evaluation method, which measures the degree to which a data point belongs to its own cluster compared to the nearest other clusters [16]. The formula for the Silhouette Coefficient for each data point i is as follows:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (3)$$

Let $S(i)$ be the silhouette coefficient for the i -th data point, $a(i)$ be the average distance of the i -th data point from all other data points in the same cluster, and $b(i)$ be the average distance of the i -th data point from data points in the nearest other cluster.

The value of $S(i)$ ranges from -1 to 1. The closer it is to 1, the more accurately the data is placed in its cluster, while a value close to 0 or negative indicates that the clustering is less appropriate. As a general guideline, a value above 0.70 indicates good clustering results; a value of 0.50-0.70 indicates satisfactory results; a value of 0.25-0.50 indicates suboptimal results; and a value below 0.25 indicates that the clustering does not produce a clear pattern [17].

As a complementary evaluation metric, the Davies-Bouldin Index (DBI) was also computed, where lower values indicate better cluster separation [18]. The clustering results obtained through the K-Means method are then used as additional input in a Decision Support System (DSS), specifically as the basis for determining criterion

weights in the Simple Additive Weighting (SAW) method, so that the resulting product recommendations are more relevant and aligned with the preference characteristics of each cluster.

2.4 Simple Additive Weighting (SAW) Method

Simple Additive Weighting (SAW) is a decision-making method that works by summing the performance values of each alternative across all criteria which have been normalized and multiplied by the importance weights of each criterion. The advantage of SAW lies in the transparency of its calculations, which are easy to interpret, making it a suitable choice for multi-criteria product recommendation systems [19].

The steps for applying SAW in this study are as follows. First, the criterion weights (W) are obtained objectively from the normalized centroid values of each cluster resulting from the K-Means algorithm, rather than being determined subjectively by the researcher. Second, the performance scores of the shoe brand alternatives (r_{ij}) are obtained from the average of respondents' ratings for each brand on each criterion. The decision matrix is normalized using the following equation for the benefit criterion [20]:

$$r_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \quad (4)$$

Where x_{ij} is the value of alternative $k-i$ for criterion j , and $\max_i x_{ij}$ is the maximum value for that criterion. The final preference score for each alternative is calculated as follows:

$$V_i = \sum_{j=1}^n w_j \cdot r_{ij} \quad (5)$$

V_i is the final preference value for alternative i , w_j is the weight of criterion j , and r_{ij} is the normalised value of alternative i for criterion j [4]. The alternative with the highest V_i value is designated as the primary recommendation for that cluster.

The brand alternatives evaluated in the SAW model are the five brands with the highest frequency of mention by respondents, namely Eiger, Arei, Consina, Nineten and Hoka. The criteria used in the SAW evaluation include comfort, shoe weight, durability and price, whilst the brands are positioned as alternatives. The entire computational process was carried out using the Python programming language with the scikit-learn library for K-Means and structured manual calculations for SAW.

2.5 Data Validity and Reliability Testing

The data on hiking shoe preference criteria in this study were obtained through a strict ranking procedure from 1 to 5 by each respondent (forced-choice design). The nature of this ranked data results in ipsative data, in which the assessment of one criterion depends on the assessment of other criteria.

According to modern statistical literature, the use of Pearson's product-moment correlation and Cronbach's alpha on ipsative data is not applicable, as it can lead to spurious correlations and violate the assumption of independence among variables [12],[21]. Therefore, the instrument validity test in this study was conducted using a discrete choice modeling approach, namely the Rank-Ordered Logit Model (Plackett-Luce Model).

The use of the Plackett-Luce Model is based on its effectiveness in estimating and validating the probability of the ordering structure among variables based on ranked data [21]. This test serves as a global model validity test to ensure that all ranking data provided by respondents exhibit consistent, logical, and statistically significant preference patterns, rather than being the result of random guessing.

This model assumes that the ranking process by respondents occurs as a series of sequential, step-by-step decisions (exploded logit). The probability that a respondent will choose a particular ranking order of criteria is formulated as follows:

$$P(\text{Ranking}) = \prod_{i=1}^{k-1} \frac{\exp(\beta_i)}{\sum_{j \in A_i} \exp(\beta_j)} \quad (6)$$

P is the probability of selecting the entire sequence of criteria; k is the number of ranked criteria ($k = 5$); β_i is the utility coefficient (selection weight) for the i -th criterion; A_i is the set of alternative criteria still available at the i -th selection stage; and $\exp$ is the exponential function with the natural logarithm as its base.

Model parameter estimation was performed using the Maximum Likelihood Estimation (MLE) method, with the assistance of the Python programming language via Google Colab. The preference data instrument was deemed valid and suitable for proceeding to the next analysis stage (K-Means and SAW) if it met two main criteria. First, model convergence, meaning the optimization algorithm successfully reached a point of convergence with a stable log-likelihood value. Second, the parameter significance test (P-value), where the significance value ($P > |z|$) for the dominant criterion variable falls below the critical threshold of $\alpha = 0.05$ ($P < 0.05$), indicating that differences in preferences among criteria are statistically significant and consistent across the entire sample of respondents.

To minimize errors in filling out the forced-choice scale, the questionnaire included clear instructions that each ranking value could be used only once. Data that did not comply with these instructions were excluded from the analysis. The Plackett-Luce validity test was conducted on the original (data raw) ranking scale, prior to the reversal and normalization applied in section 2.2 for the cluster stage.

3. Result and Discussions

3.1 Result of the Plackett-Luc Validity Test

A global validity test of the preference data from 154 respondents was conducted using the Conditional Logit model as a representation of the Rank-Ordered Logit (Plackett-Luce) framework. The estimation results show that the model successfully converged at a log-likelihood value of -731.80. Three of the five criteria tested showed a significance level of $P < 0.05$, namely shoe weight ($P = 0.002$), price ($P = 0.034$), and comfort ($P = 0.049$), as shown in Figure 2. These results indicate that the respondents' preference data are statistically consistent and valid, making them suitable for the next stage of analysis.

Conditional Logit Model Regression Results						
=====						
Dep. Variable:	chosen	No. Observations:	2156			
Model:	ConditionalLogit	No. groups:	616			
Log-Likelihood:	-731.80	Min group size:	2			
Method:	BFGS	Max group size:	5			
Date:	Tue, 07 Jul 2026	Mean group size:	3.5			
Time:	00:22:17					
=====						
	coef	std err	z	P> z	[0.025	0.975]

d_kenyamanan	0.2982	0.152	1.967	0.049	0.001	0.595
d_harga	0.2981	0.140	2.122	0.034	0.023	0.573
d_daya_tahan	0.1846	0.146	1.263	0.207	-0.102	0.471
d_berat_sepatu	0.4274	0.138	3.094	0.002	0.157	0.698

Figure 2: Results of the Validity Test for the Rank-Order Logit Preference Model

The Plackett-Luce model assumes that each criterion has a preference strength value (worth parameter) represented by the parameter λ , where a larger value of λ indicates that the criterion is prioritized more frequently by respondents. Parameter estimation was performed using the Maximum Likelihood Estimation (MLE) method and successfully converged at the 13th iteration.

Hasil Plackett-Luce:			
Peringkat	Kriteria	Parameter λ	Probabilitas
#1	berat_sepatu	1.1922	0.2384
#2	kenyamanan	1.0478	0.2096
#3	harga	1.0473	0.2095
#4	daya_tahan	0.9352	0.1870
#5	merek	0.7775	0.1555

Figure 3: Results of the Plackett-Luce Model Validity Test

The results of the Plackett-Luce model estimation, as shown in Figure 3, indicate that the aggregate order of consumer preferences (before the data were grouped into their respective clusters) is shoe weight (23.84%; $\lambda = 1.1922$), comfort (20.96%), price (20.95%), durability (18.70%), and brand (15.55%; $\lambda = 0.7775$). These findings indicate that shoe weight is the attribute most prioritized by mountain climbers when choosing hiking shoes, while brand is the attribute with the lowest overall priority.

3.2 Results of Data Preprocessing and Normalization

The data collection process yielded 154 valid respondents who met the study's inclusion criteria. All respondents were active hikers with at least one previous hiking experience on Mount Buthak or Mount Penanggungan in East Java. The raw data consisting of respondents' preference rankings for five hiking boot attributes underwent two stages of preprocessing before being used in the clustering process.

In the transformation stage, the original rating scale (1-5) was inverted using the complementary formula so that the highest value represented the highest priority. The transformation results were then normalized using MinMaxScaler to a range of 0-1 according to Equation (1). Figure 4 shows an example of the normalized data results from the first ten respondents to illustrate the data structure used in the clustering process.

	kenyamanan	harga	daya_tahan	berat_sepatu	merek
count	154.000	154.000	154.000	154.000	154.000
mean	0.458	0.497	0.549	0.466	0.531
std	0.399	0.320	0.307	0.294	0.425
min	0.000	0.000	0.000	0.000	0.000
25%	0.000	0.250	0.250	0.250	0.000
50%	0.500	0.500	0.500	0.500	0.750
75%	0.750	0.750	0.750	0.750	1.000
max	1.000	1.000	1.000	1.000	1.000

Figure 4. Results of the Normalization of Respondent Preference Data

3.3 Results of K-Means Clustering

The best performing value of K was determined using two evaluation methods simultaneously. The results of the Elbow Method showed a significant decrease in the SSE value from K=1 to K=2; after that, the curve began to flatten, indicating that adding more clusters beyond K=2 did not result in a significant improvement in separation quality.

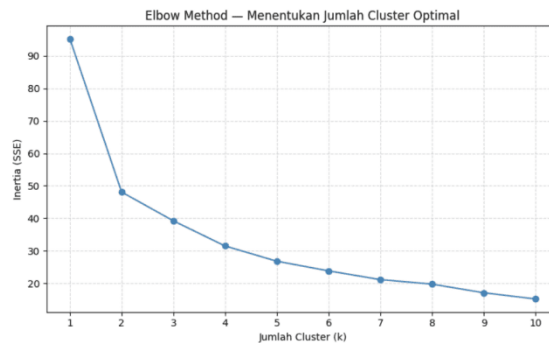


Figure 5. Graphical Results of the Elbow Method

Confirmation was obtained from the Silhouette Score results presented in Figure 6. The highest Silhouette Score was achieved at K=2 with a score of 0.4506, which then consistently decreased at K=3 (0.3861) and K=4 (0.3443). Although the value of 0.4506 falls into the "suboptimal" category according to standard criteria, it remains the best configuration achievable from the data structure of this study and is still accepted as a valid basis for segmentation [22].

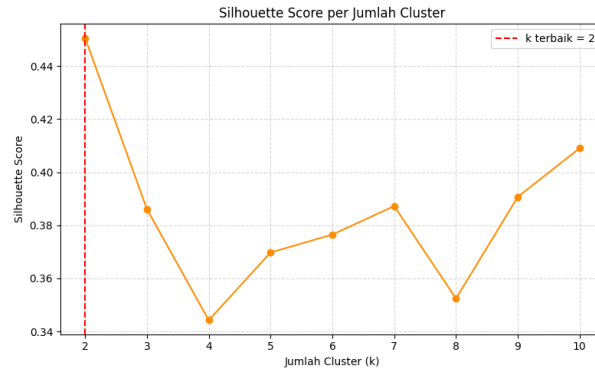


Figure 6. Silhouette Score Results by Number of Clusters

As a complementary metric, the Davies-Bouldin Index (DBI) was also calculated across the same range of K, where lower values indicate better cluster separation.

Table 2. Comparison of Silhouette Score and Davis Bouldin Index Across different values of K

Result	Value of K								
	2	3	4	5	6	7	8	9	10
Silhouette	0.4506	0.3861	0.3443	0.3698	0.3765	0.3873	0.3524	0.3907	0.4091
Davies-Bouldin Index	0.9557	1.1044	1.2756	1.0951	1.0404	1.0247	1.0390	1.0405	0.9430

The DBI reached its lowest value at K=10 (0.9430), only marginally better than K=2 (0.9557). Although DBI's global minimum falls at K=10, such a large number of clusters is impractical for this study's segmentation purpose and risks producing overly fragmented, less generalizable segments rather than meaningful hiker typologies. Given that K=2 performs strongly on both metrics clearly best on Silhouette Score and a close second on DBI it was retained as the more interpretable and practically justified choice, consistent with the two-segment structure used in the subsequent SAW-based recommendation model.

Derived from three evaluation methods, K=2 was determined to be the best performing number of clusters, and all subsequent analysis were conducted using this configuration. The K-Means process with K=2 yielded two groups of hikers with the following distributions and characteristics:

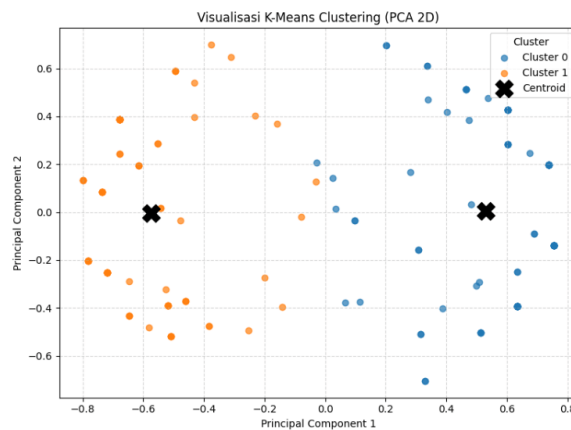


Figure 7. Result Visualization K-Means Clustering

To provide a more intuitive visualization of the cluster separation, dimensionality reduction was performed using Principal Component Analysis (PCA), reducing the five criterion variables into two principal components

(PC1 and PC2). Together, PC1 and PC2 explained 76.6% of the total variance, indicating that the two dimensional projection retained most of the information contained in the original five dimensional data. Figure 7 shows the distribution of respondent data in this two-dimensional space, with Cluster 0 represented by blue points and Cluster 1 by orange points, while the black cross markers indicate the centroid position of each cluster.

Based on this visualization, both clusters show a fairly distinct grouping tendency, with Cluster 0 (blue) predominantly distributed on the right side of the plot (positive PC1 values), while Cluster 1 (orange) is mostly distributed on the left side (negative PC1 values). Although slight overlap between clusters is observed in the middle region of the plot, the visible separation along the PC1 axis indicates that the two clusters possess sufficiently distinct preference characteristics, suggesting that the resulting K-Means segmentation is reasonably representative in distinguishing preference patterns among respondent groups. A conclusion further supported by the relatively high combined variance (76.6%) capture by two principal componets used for this visualization.

Table 3. Distribution and Centroid Profile for Each Cluster

Cluster	Atribut					
	Comfort	Shoe weight	Durability	Price	Brand	Amount of respondent
Cluster 0	0,153	0,550	0,350	0,538	0,909	80
Cluster 1	0,787	0,439	0,764	0,389	0,122	74

Based on the centroid values in Table 3, the two clusters exhibit contrasting preference characteristics:

Cluster 0, Comfort and Durability Segment (80 respondents, 51.9%): This group prioritizes comfort above all else (0.153), followed by durability (0.350). The criteria of shoe weight and price received low weights, indicating that this group is willing to overlook economic factors and shoe weight in order to achieve the best performance. This profile is typical of hikers who engage in multi-day hikes or climb technical trails that demand high physical endurance.

Cluster 1, Trend and Efficiency Segment (74 respondents, 48.1%): This group prioritizes Brand (0.122) and price (0.389) as their two main criteria. Comfort and durability are given lower weightings, reflecting the profile of hikers who are efficiency-oriented and have budget constraints. These characteristics are commonly found among young hikers who frequently go on day hikes or short hikes.

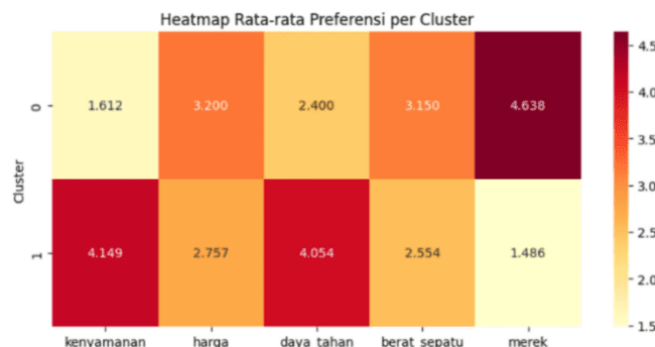


Figure 8. Visualization of the Preference Profiles for Each Cluster

Figure 8 shows the average preference scores for each criterion across the two K-Means clusters on the original ranking scale (1-5), consistent with the centroid profiles in Table 3, which were calculated on a normalized scale (0-1). Cluster 0 (80 respondents, 51.9%) has the lowest scores for comfort (1.612) and durability (2.400), indicating that this group prioritizes comfort and physical performance over price and brand; this profile is commonly found among multi-day hikers or those tackling technical trails. Cluster 1 (74 respondents, 48.1%) has the lowest scores for brand (1.486) and price (2.554), reflecting a group that is trend-oriented and budget-conscious a profile commonly found among young hikers on day hikes. These contrasting preference patterns form the basis for applying different SAW weights to each cluster (cluster-specific weighting).

3.4 Results of the SAW Implementation

The SAW criterion weights for each cluster are derived directly from the normalized centroid values obtained from the K-Means algorithm. The centroid values for the four technical criteria (comfort, weight, durability, and price) were renormalized so that the total weights sum to 1.00, while the brand criterion was excluded from the SAW calculation because it was treated as an alternative option rather than an evaluation criterion. Table 4 presents the final weights used in the SAW calculation.

Table 4. SAW Criteria Weights by Cluster

Cluster	Comfort	Price	Durability	Shoe Weight
0	0.3217	0.2053	0.2640	0.3286
1	0.1765	0.3093	0.1856	0.3286

The performance scores for each brand alternative under each criterion were derived from the average ratings of all respondents and then normalized using Equation (4) for the benefit and cost criteria. Figure 9 presents the normalized decision matrix used as input for the final SAW calculation.

	kenyamanan	daya_tahan	harga	berat_sepatu
rekommendasi_brand				
eiger	0.8880	0.8579	0.8945	0.7715
arei	0.9821	0.6482	1.0000	0.9091
consina	0.9143	0.8171	0.8542	0.8117
nineten	1.0000	0.8755	0.8969	0.7761
hoka	0.7273	1.0000	0.6128	1.0000

Figure 9. Normalized Decision Matrix

The final preference values (V_i) for each brand alternative were calculated using Equation (5), with different weights for each cluster. The complete ranking results are presented in Table 5.

Table 5. SAW Ranking Results by Cluster

Rank	Cluster 0	Skor	Cluster 1	skor
1	Consina	0.866314	Nineten	0.881039
2	Eiger	0.858647	Arei	0.843016
3	Hoka	0.851567	Consina	0.821954
4	Arei	0.844521	Hoka	0.817269
5	Nineten	0.828553	Eiger	0.803917

The results in Table 5 show that Consina is the top recommendation for hikers in Cluster 0 with the highest SAW score of 0.8663, while Nineten is the top recommendation for Cluster 1 with a score of 0.8810. An interesting phenomenon is the significant reversal in rankings between the two clusters: Consina, which ranked first in Cluster 0, dropped to third place in Cluster 1, while Nineten, which ranked fifth in Cluster 0, actually came out on top in Cluster 1. This reversal directly reflects the differences in weighting structures between clusters and validates that the recommendation system built is sensitive to differences in user preferences.

3.5 Discussion

The results of this study reveal three main findings that complement one another. First, K-Means-based segmentation successfully identified two groups of hikers with preference patterns that are contextually plausible and empirically explainable. Cluster 0 represents hikers who prioritize comfort and durability above all else characteristics aligned with the needs of technical trail hikers or those embarking on multi-day hikes, where foot protection is crucial to preventing injuries such as blisters or sprains. Cluster 1 represents hikers who are brand- and weight-conscious, reflecting the trend of lightweight hiking or fast hiking (tektok), which

is popular among young hikers with limited budgets and a preference for dynamic movement. These two groups reflect two widely recognized typologies of hikers within the Indonesian hiking community: safety-oriented hikers and lifestyle-oriented hikers.

Second, integrating the K-Means results into the SAW was shown to produce recommendations that differed significantly across clusters. Consina ranked first in Cluster 0, while Nineten ranked first in Cluster 1. This reversal in rankings serves as empirical evidence that criterion weights derived objectively from the average value (centroid) of each cluster rather than from the researcher's subjective assumptions can produce an adaptive and personalized recommendation system that adapts to shifts in behavior and the specific needs of each hiker segment. This approach yields a more personalized system compared to the conventional SAW approach, which assigns uniform weights to all users. This finding is consistent with the results of Pradana et al. [9], who concluded that integrating user segmentation into a recommendation system significantly improves the relevance of recommendation results.

Third, the most striking finding of this study is Eiger's position in the SAW results. Eiger was the brand most frequently used by respondents, cited by 37 out of 154 respondents (24%). Despite this popularity, it ranked only second in Cluster 0 and last in Cluster 1 based on the SAW calculations. This discrepancy suggests that Eiger's dominance in the field is driven more by brand awareness and trust. These have long been established within Indonesia's mountaineering community. They appear to matter more than objective performance advantages based on the criteria each segment prioritizes most. This phenomenon is consistent with the findings of Alam et al. [7]. They found that consumers' purchasing decisions regarding outdoor gear are often not entirely based on evaluations of technical criteria. This aligns with Wardhana's concept of a brand, which defines a brand as a name, term, design, symbol, or service that distinguishes a product from its competitors. A brand is more than just a visual identity. It represents consumers' perceptions of value and experience, and plays a crucial role in building image, trust, and loyalty [23].

In practical terms, the system developed in this study offers benefits in two ways. For hikers, this system can reduce the time spent searching for products amid information overload and minimize the risk of making the wrong purchase especially for beginner hikers who tend to choose shoes based on brand popularity without considering whether the specifications match their physical needs on the trail. For manufacturers and the outdoor gear industry, these segmentation results provide a strategic advantage in positioning products in the eyes of consumers; for example, Nineten can strengthen its marketing strategy in the lightweight segment (Cluster 1), while Consina can maintain its position as a provider of highly durable products for the functional segment (Cluster 0).

A comparison with previous studies highlights the unique contribution of this research. Husein et al. [24], who used SAW without segmentation, produced a single set of brand rankings applied uniformly to all users, thereby failing to capture the differing needs among groups of hikers. This study addresses this limitation by integrating K-Means as a pre-weighting stage that generates dynamic weights per cluster. Compared to Yunita et al. [25], who integrated K-Means and SAW in the context of public policy, this study applies a similar integration to the realm of consumer product recommendations, taking into account the more complex dynamics of user preferences.

The limitations of this study must be openly acknowledged. A Silhouette Score of 0.451 indicates that the separation between clusters is not yet entirely distinct, which is likely due to the similarity in preference patterns among most beginner hikers. Furthermore, this study is limited to the five brands most frequently mentioned by respondents and five product attributes; thus, other brands and attributes such as design, warranty, or availability of spare parts have not been taken into account.

The study's scope, limited to respondents from two mountains in east java (mount buthak and mount penanggungan), also restricts the generalizability of the findings to Indonesia's broader hiking population. In addition, the sample was self-selected through an online questionnaire distributed to hiking communities and social media, which may have skewed participation toward hikers who are more socially connected or tech savvy and may therefore not fully represent the wider population of Indonesian mountain climbers. Future research is encouraged to consider adding variables and testing alternative clustering methods to achieve a sharper separation of groups.

4. Conclusions and Future Works

This study successfully developed a decision support system for recommending hiking boots based on the integration of K-Means Clustering and Simple Additive Weighting (SAW), using empirical preference data from 154 hikers on Mount Buthak and Mount Penanggungan in East Java. The K-Means process, with an best performing configuration of K=2 (Silhouette Score 0.4506), successfully identified two hiker segments that are significantly different in context: Cluster 0, which prioritizes comfort and durability, and Cluster 1, which prioritizes brand reputation and shoe weight. This segmentation demonstrates that mountain hikers are not a homogeneous group but rather consist of diverse typologies with varying needs and priorities.

Integrating the objective preference weights from the K-Means results into the SAW method yields adaptive brand recommendations that differ across clusters, with Consina as the top recommendation for Cluster 0 with a score of 0.8663 and Nineten for Cluster 1 with a score of 0.8810. The reversal in rankings observed between the two clusters empirically validates that the developed system is capable of sensitively capturing differences in user preferences something that cannot be achieved by recommendation systems with uniform weights. The finding that Eiger which dominates actual usage in the field does not always perform better mathematically underscores the need for a data-driven approach in decision-making regarding the selection of climbing gear, rather than relying solely on brand popularity.

This study has several limitations that should be considered for future development. The Silhouette Score of 0.4506 indicates that the separation between clusters is not yet fully optimal, suggesting the need to explore alternative clustering methods, such as DBSCAN or Fuzzy C-Means, in future research. The study's scope, which was limited to two mountains in East Java, also restricts the generalizability of the findings. Future research is recommended to expand the data collection area, add more product attribute variables, and develop this system into a prototype application that can be used directly by the Indonesian hiking community.

5. Declarations

Author Contributions

D.F.I.M.: Conceptualization, Methodology, Software, Data Curation, Formal Analysis, Writing - Original Draft; D.M.P.: Conceptualization, Validation, Investigation, Writing - Review & Editing, Supervision.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Use of Artificial Intelligence (AI)

During the preparation of this work, the authors used ChatGPT to improve the language clarity and grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Ethical Clearance

Ethical clearance was not required for this study as it was non-experimental and involved low-risk, voluntary preference survey data from human participants.

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