

## DERIVING CUSTOMERS PREFERENCES FOR HOTELS FROM UNSTRUCTURED DATA

Nasa Zata DINA \*

Universitas Airlangga, Faculty of Vocational Studies, Surabaya, Indonesia, e-mail: nasazatadina@vokasi.unair.ac.id

Nyoman JUNIARTA

Université de Lorraine, Faculty of IAEM, Nancy, France, e-mail: nyoman.juniarta@yahoo.com

---

**Citation:** Dina, N.Z., & Juniarta, N. (2022). DERIVING CUSTOMERS PREFERENCES FOR HOTELS FROM UNSTRUCTURED DATA. *GeoJournal of Tourism and Geosites*, 43(3), 872–877. <https://doi.org/10.30892/gtg.43305-899>

---

**Abstract:** Hotel management uses customers' online reviews to uncover the most essential criteria for hotel selection to support sustainable tourism development and strengthen their marketing strategy as well as decision-making. This study implemented the Multi-Criteria Decision-Making (MCDM) to identify customers' satisfaction and preferences. Data were collected from online reviews on eight hotels in Ubud, Bali Islands, submitted on TripAdvisor. The findings demonstrate that customers have varying levels of satisfaction when it comes to dissimilar preferences. Five major criteria influence their choices, namely price, cleanliness, location, facility, and food. The result of this study will help hotel management to set priority instructions for improving the corresponding hotel features.

**Key words:** customers' review, multi-criteria decision making, hotel selection, sustainable tourism development, sustainable tourism, tourism economics, tourism, and economic growth

\* \* \* \* \*

### INTRODUCTION

Among all the diverse regions, Bali Island is one of the popular tourist attractions located at the center of Indonesia. This area is famous for its lush greenery, scenic lakes, gorgeous waterfalls, iconic rice fields, flower gardens, gushing sacred rivers, and secret canyons. Therefore, it plays an important role in providing tourism potential, and this has led to massive development such as hotels and villas to accommodate these tourists.

Hotel businesses are continuously trying to satisfy their clients by meeting their respective needs, and the valuable feedbacks serve as a measure of customers' satisfaction. Therefore, the management aims to identify these preferences, which are divided into several aspects such as price, cleanliness, location, facility, food, etc, by adopting a supportive marketing strategy. Presently, customers express their opinions through online reviews posted on the hotels' platforms such as TripAdvisor, Expedia, Agoda, which determines their satisfaction and preference rates. Herrera et al., 2014 used numerical ratings from each attribute of specific hotels on the website to calculate average scores.

This was realized using five-point or ten-point ratings on the website, and users made certain comparisons based on the ratings assigned to the specific attributes. Therefore, (Fan et al., 2018), converted this measure into a discrete percentage distribution and ranked these hotels using PROMETHEE-II. Zhao et al. (2021) integrated numerical ratings from multiple sources to help customers select suitable hotels using the Probabilistic Linguistic Term Set (PLTS). Customers turn used the information obtained from different sources to determine the PLTS similarities. Guo et al. (2017), stated that numerical rating cannot be used to determine customers' emotional preferences and user satisfaction. Dina (2020) developed a word cloud to illustrate the frequently used words, but they needed to be tagged part-of-speech and categorized as aspects. Subsequently, Dina et al. (2021) Stanford taggers to separate part-of-speech and calculated TF-IDF of each frequent word that appeared by constructing a matrix to measure preferences.

Both studies focused on extracting wording from the unstructured customers' reviews even though it was recommended to measure their satisfaction and not numerical rating. Ahani et al. (2019) used a soft-computing approach to categorize these travelers into 4 market segments, namely "highly satisfied", "satisfied", "moderately satisfied", and "unsatisfied" travelers based on previous reviews on TripAdvisor.

In the age of customer-based service, customer satisfaction boosts loyalty (Chou et al., 2008) and it serves as strategic importance for hotel management in the long run. Therefore, a method for identifying the most valued criteria is essential for hotel management to increase its competitive advantage, which led to the use of the VIKOR procedure. It is one of the multiple criteria decisions making (MCDM) algorithm to determine the preferred ranking from a set of alternatives (Huang et al., 2009). In addition, VIKOR is used to extract, analyze and rank reviews from different hotels. Kundakcı et al. (2015), studied location selection and its impact on business activities, income, and the number of customers. The MCDM method was employed based on 3 main criteria namely geographical condition, operation management, and transportation facilities. Meanwhile, Yadegaridehkordi et al. (2021) used these reviews to segment the customers that prioritized eco-friendly hotels. MCDM was used to make future predictions and determine important factors that affect its selection, however, it

---

\* Corresponding author

was proven that quality sleep is one of the major criteria. Both studies employed this approach to select and sort data, including overall assessment. Also, a variety of MCDM methods have been extensively used in diverse disciplines to solve complex problems. These versatile approaches are used for evaluation and selection processes. Based on these advantages, MCDM was employed to identify certain criteria and rank the hotel based on users' reviews.

In general, this study aims to evaluate the quality of hotel services by developing a decision-support framework. The output is based on key aspects such as customers' reviews and hotel ranking lists. Furthermore, the following objectives (1) to identify customers' preferences and segment the hotel based on online reviews and ratings on TripAdvisor, and (2) to rank this aspect using the MCDM approach were addressed. Consequently, the hotel's management tends to identify these preferences by adopting marketing strategies to meet the customers' needs.

**MATERIALS AND METHODS**

The proposed method is shown in Figure 1, in addition, data was collected from the TripAdvisor website. The reviews were extracted from 8 five-stars-hotels in Ubud, Bali. Then, the pre-processed data, experienced a series of phases to make them suitable for mining and analysis, with vectors as the keyword. In the subsequent phase, these are turned into a decision matrix, while in the final, the VIKOR approach as an aspect of MCDM is run through the data.

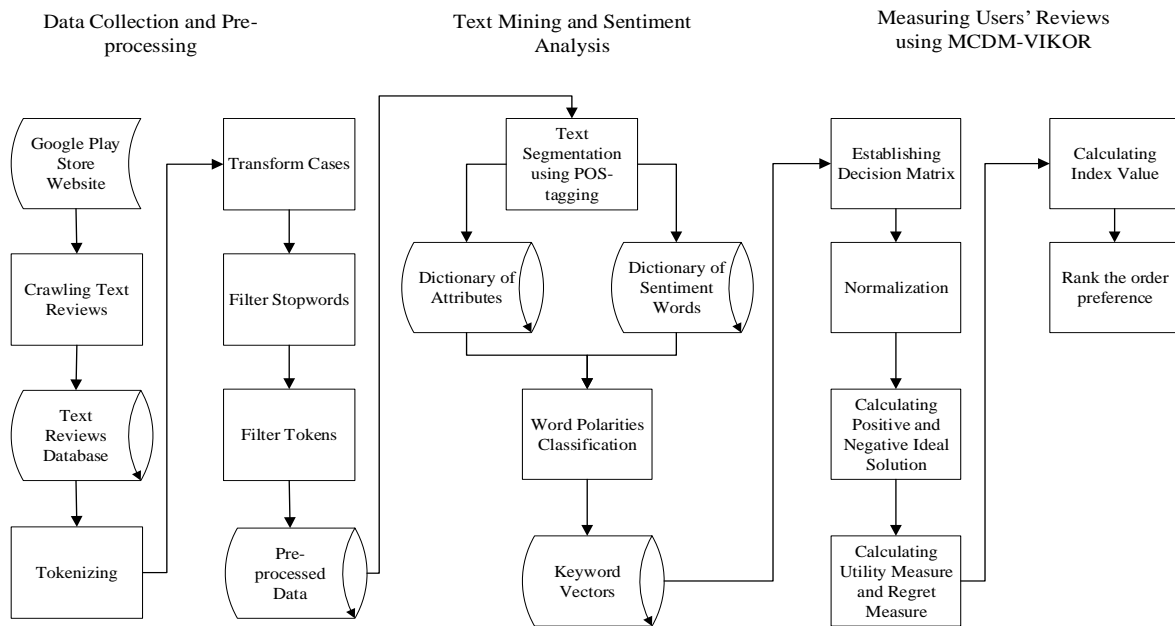


Figure 1. Proposed Method

**Data collection**

The data were collected by considering similar features. Common aspects were extracted from the 5413 reviews and used to measure and compare user satisfaction. An example is shown in Table 1, while Figure 2 is the interface from the TripAdvisor website. Each review comprises of date of stay, username, title, review, and star rating attributes.



Figure 2. Example of users' review from TripAdvisor

**Data Pre-processing**

The pre-processing phase involves the transformation of unformatted data into an understandable format, which is further analyzed in subsequent phases, starting from the elimination of irrelevant or noisy data. The second phase is data transformation which includes tokenizing, case folding, stop words filtering, and stemming. The result obtained from the pre-processing phase is a collection of stem words.

**Text Mining**

The text-mining process usually consists of segmentation, summary extraction, keyword identification, topic detection, term clustering, and document categorization. This aims to compile dictionaries that consist of attributes and sentiment-

related words, which differs from the method proposed by Dina et al. (2021). The feature-sentiment words were considered as pairs and the polarities are determined from the pairs. However, when there is a positive-sentiment word then its pair is also positive-labelled word, and vice versa. However, in this research, the words are not considered as a pair.

Table 1. Online review examples from 8 hotels

Hotels	Title	Review	Star
Hotel-A	Stunning Rooms and Fantastic Service	We stayed at Hotel-A for four nights in a One Bedroom River Front Pool Villa. We have traveled to many luxurious places and this may be the most amazing room we have ever stayed in, mind you it is certainly a splurge. The butler service and housekeeping was excellent. The food was good and we really enjoyed our dinner at Kubu in a Cocoon - next time I would opt to order a la carte rather than the tasting menu but otherwise a very special experience not to be missed. The lunch menu and other dinners were inconsistent and the room service was actually disappointing for a resort of this caliber. One of our best meals was taking the shuttle into town and dining at a local Mexican restaurant and we regretted not having thought of doing this earlier.	5
Hotel-B	Nothing Special	I had HUGE expectations for this property- and perhaps this is why it fell spectacularly short. Yes. The location is beautiful. The hotel itself is well designed. The rooms are spacious and well appointed. I'm not normally someone who often writes negative reviews. However being a frequent traveller- there are a few things you eventually grow accustomed to. The average price of the hotel from my experience as an industry professional is around the 350-400 mark/night. Occasionally you'll catch an earlybird or off peak deal which is by far more appropriate. Frankly you can get alot more bang for your buck at the average prices, especially in Bali. If you're paying peak period rates here- you're a fool. I found the recommendations of the local area by the staff to be poor.	3
Hotel-C	Peace and Quiet	The Hotel-C at Sayan was a perfect antidote to Jakarta's pandemic life - rural, clean air, and space to walk and relax. The hotel ticks all the boxes. It's an organic blend of luxury without pomp or showiness - they get it right down to turndown (i.e., a second full clean at night) the minute we left for dinner each evening. After 20 some odd years, the buildings are still stunning, blending with the jungle, and situated on a sprawling property unmatched for the area. We took a Sayan villa high on the ridge above the resort; the advantage, more space and a pool that pushes full size. The River Villas are equally lovely, with smaller plunge pools and a smaller living area but immediately on the Ayung River and deep in the valley. F&B in the pandemic was a good as ever.	5
Hotel-D	Unaccommodative treatment	Upon arrival I was shown around a small part of the hotel grounds by a very nice young employee. However he seemed embarrassed to tell me that I wasn't allowed to enjoy my coffee in the bar/restaurant area unless spending a minimum of 350,000 rupiah (!) I explained that I just had lunch in Ubud and, being on my own and expecting my driver within one hour, had no desire or occasion to spend this amount. Thus, the only option I was left with was to wait in the reception area - not a very accommodating treatment from a high-end hotel to say the least.	1
Hotel-E	Favorite place to stay in Bali	I don't even know where to begin with how awesome this place is. Everyone who works there is so authentically kind and work hard for the best customer experience. If you want to stay in Ubud but be close to town, yet in the jungle (like Hanging Gardens) this is the place! We also stayed at Hanging Gardens after Kayon and Kayon is giving HG a run for its money (it's closer to UBUD and the service, offerings and pricing is better). HG has a slightly better view, but I heard Hotel-E is opening a second location in August deeper in the jungle/ more north with a three tier Hanging pool! The massage my new husband and I received from Kayons spa was the best we had on the trip and in general ( I get a lot at home in NYC due to chronic back pain). I recommend the Balinese all the way!	5
Hotel-F	Both highlights and lowlights	We arrived at the Hotel-F Bali at 11.15 pm after 18 hours flight. Everything dark and everybody went to sleep already! The airport driver brought us with the luggage to our villa and told us we can do the check in tomorrow. This impression turns around by 180 degrees as soon as you are sitting on the next morning in the restaurant for breakfast in the middle of a rice field. Breathtaking! Everybody in the hotel offers very friendly and helpful service. The landscaping in the hotel area is just wonderful. Take the time for yoga in the morning or a walk through the rice fields with your butler. The villas, the fitness center and most of the hotel equipment has seen their best ages years and years ago. Very disappointing!	3
Hotel-G	Room smelt strongly of mold	Stayed here a couple of nights in the garden suite on the ground floor. The resort and room looked very nice but I could not get over the smell of mold in our room. I asked if we could swap rooms but the resort was booked out. The staff were apologetic and brought a dehumidifier but it did not get rid of the smell and I had a headache the entire time. My friend's room on the top floor also smelt strongly of mold. The staff informed me it rains a lot in Ubud, however, the way the resort is built allows no natural sunlight to filter into the rooms. Would not recommend this resort.	3
Hotel-H	Phenomenal Resort with great customer service!	My husband and I just stayed at the Hotel-H and had an incredible experience there. My husband mentioned that it was our honeymoon and that I was also celebrating my birthday during our stay. The staff went out of their way to make each day special by making me desserts, singing me happy birthday, and decorating our entire room. Each time we came back to the hotel we were greeted warmly by the staff and made to feel as though we were part of a family. The resort grounds are gorgeous and our room was stunning! The hotel also offers a free shuttle every hour to and from the downtown area - we used the shuttle every night and it was seamless! This was our favorite place to stay over our 5 week vacation.	5

Following the data pre-processing phase, the stem words are extracted. After that, Part-of-Speech (POS) tagging is conducted. It is a process that categorize word based on its parts. There are five parts of speech which are adjectives, adverbs, nouns, numerals, and verbs. Toutanova et al. (2003), developed the use of Stanford POS-tagger to identify those five parts of POS tagging. To measure user satisfaction, there are five categories selected, namely price, cleanliness, location, facilities, and food, besides, these were determined based on functionality, reliability, and usability (Djouab and Bari, 2016). Afterward, the five polarities were classified into five, they were strong positive, positive,

neutral, negative, and strong negative. Usually, there are only three types of polarities: positive, neutral, and negative. There were several studies which were used three polarities. For instance, Dina (2020) and Prastyo et al. (2020) used three mentioned polarities. They analyzed the sentiments to discover the experiences of hotel customers through the most frequent words. Different from previous studies, five polarities are used in this research in order to be more specific and accurate. Its values are between 2 and -2. Finally, assuming no sentimental words appeared, then the value is 0. The value is used to construct keyword vectors of the user reviews. The value will be obtained by multiplying the occurrence with the polarity value to construct keyword vectors (Dina et al., 2021).

### Measuring user satisfaction using Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR)

In the previous subchapter, the following categories price ( $C_1$ ), cleanliness ( $C_2$ ), location ( $C_3$ ), facility ( $C_4$ ), and food ( $C_5$ ) were mentioned, and these are represented by  $C_1$  to  $C_5$ . VIKOR stands for Visekriterijumska optimizacija I kompromisno resenje. It was initially established by Serbians (Dincer and Hacıoglu, 2013), and is also perceived as one of the MCDM approaches. This method aids in the solution of an issue by taking into account the procedure created by Haleh and Hamidi (2011). It compares the proximity of each criterion using a multicriteria ranking index, resulting in an ideal alternative. According to Liou et al. (2011), a ranking index is obtained by calculating the maximum group utility ( $S_j$ ) and minimum individual regret ( $R_j$ ). Several steps are completed using VIKOR, and they are stated as follows:

#### Step 1: Establishing the decision matrix

The decision matrix is made up of keyword vectors, or it may be simply defined as the multiplication of the occurrence of attributes and their polarity values. The number of attribute instances for each category is then counted. The decision matrix's structure is shown below according to Liou et al. (2011).

$$X = \begin{matrix} A_1 \\ A_i \\ A_m \end{matrix} \begin{bmatrix} SN_{11} & SN_{1j} & SN_{1n} \\ SN_{i1} & SN_{ij} & SN_{in} \\ SN_{m1} & SN_{mj} & SN_{mn} \end{bmatrix} \quad \text{Where } \begin{matrix} A_i & : & i\text{-th alternative,} \\ SN_{ij} & : & \text{the value of } j\text{-th aspect for } i\text{-th alternative.} \end{matrix}$$

#### Step 2: Calculating the normalized values and putting them into a decision matrix

In Step 1, the attribute occurrence ( $x$ ) from each category is normalised to a value between 0 and 1. Equation (1) as mentioned by Liou et al. (2011) shows the stated normalisation, as well as the weighting technique that was used to the data to determine the weight of each category ( $w_k$ ). Equation (2) was used to determine this, with  $n_k(d)$  equaling the number of times the  $k$ -th category appears in document  $d$  (Liou et al., 2011),

$$x^* = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1) \quad w_k = \frac{n_k(d)}{\sum_{k=1}^m n_k(d)} \quad (2)$$

where:  $d$  = document;  $w_k$  = weight of each category;  $n_k(d)$  = number of times the  $k$ -th category appears in document  $d$ .

#### Step 3: Calculating the best $f_j^*$ and worst $f_j^-$ of all criteria

Liou et al. (2011) compiled equation (3) that obtains the positive ( $f_j^*$ ) and negative ( $f_j^-$ ) ideal solution.

$$f_j^* = \max_i f_{i,j} \quad \text{and} \quad f_j^- = \min_i f_{i,j} \quad (3)$$

#### Step 4: Calculating new decision matrix with the weight ( $w_j$ )

Equation (4) assigns assign the weight ( $w_j$ ) for a new decision matrix (Liou et al., 2011) as follows,

$$\frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \quad (4) \quad \text{where: } w_j = \text{weight of the category; } f_j^* = \text{positive ideal solution,} \\ f_j^- = \text{negative ideal solution.}$$

#### Step 5: Calculating the values of the group utility ( $S_i$ ) and individual regret ( $R_i$ )

Equation (5) and (6) according to (Liou et al., 2011) calculate the utility measure ( $S_i$ ) and regret measure ( $R_i$ ) as follows,

$$S_i = \sum_{j=1}^n \frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \quad (5) \quad R_i = \max_j \left[ \frac{w_j(f_j^* - f_{ij})}{f_j^* - f_{ij}^-} \right] \quad (6)$$

where:  $w_j$  = weight of the category;  $S_i$  = utility measure;  $R_i$  = regret measure;  $f_j^*$  = positive ideal solution;  $f_j^-$  = negative ideal solution.

#### Step 6: Calculating the index value ( $Q_i$ )

The following equation according to (Liou et al., 2011) obtains index value ( $Q_i$ ), where  $S^*$  = maximum value of  $S_i$ ,  $S^-$  = minimum value of  $S_i$ ,  $R^*$  = maximum value of  $R_i$ ,  $R^-$  = minimum value of  $R_i$ ,  $v$  = index weight value

$$Q_i = v \left[ \frac{S_i - S^*}{S^- - S^*} \right] + (1 - v) \left[ \frac{R_i - R^*}{R^- - R^*} \right] \quad (7)$$

where:  $Q_i$  = index value;  $S^*$  = maximum value of  $S_i$ ;  $S^-$  = minimum value of  $S_i$ ,  $R^*$  = maximum value of  $R_i$ ;  $R^-$  = minimum value of  $R_i$ ;  $v$  = index weight value.

#### Step 7: Ranking the order preference of index value ( $Q_i$ )

The smaller the index value ( $Q_i$ ), the better the solution, vice versa (Liou et al., 2011).

**RESULTS AND DISCUSSION**

Table 2 shows the calculated score for all categories ( $C_n$ ), while the last row illustrates the number of term instances in each. Table 3 was generated from Table 2 with the normalized score obtained by applying the formula in equation (1) while the weight from the last row was calculated using (2).

Table 2. Calculated Scores

Hotels	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
Hotel-A	123	56	773	2109	537
Hotel-B	39	92	800	1526	435
Hotel-C	69	139	687	2065	596
Hotel-D	85	39	613	1994	558
Hotel-E	56	31	693	1898	618
Hotel-F	145	97	1604	3882	997
Hotel-G	74	49	966	2321	545
Hotel-H	80	112	974	2174	645
Term presence	274	435	7354	10658	3396

Table 3. Normalized Scores

Hotels	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
Hotel-A	0.024	0.006	0.193	0.540	0.131
Hotel-B	0.002	0.016	0.200	0.388	0.105
Hotel-C	0.010	0.028	0.170	0.528	0.147
Hotel-D	0.014	0.002	0.151	0.510	0.137
Hotel-E	0.006	0.000	0.172	0.485	0.152
Hotel-F	0.030	0.017	0.408	1.000	0.251
Hotel-G	0.011	0.005	0.243	0.595	0.133
Hotel-H	0.013	0.021	0.245	0.556	0.159
Weight	0.012	0.020	0.333	0.482	0.154

Table 4. Positive Ideal Solution

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$f_j^*$	0.030	0.028	0.408	1.000	0.251
$f_j^-$	0.002	0.000	0.151	0.388	0.105

Table 5. Normalized Decision Matrix with Weight

Hotels	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
Hotel-A	0.003	0.015	0.279	0.363	0.126
Hotel-B	0.012	0.009	0.270	0.482	0.154
Hotel-C	0.009	0.000	0.308	0.372	0.110
Hotel-D	0.007	0.018	0.333	0.386	0.120
Hotel-E	0.010	0.020	0.306	0.406	0.104
Hotel-F	0.000	0.008	0.000	0.000	0.000
Hotel-G	0.008	0.016	0.214	0.319	0.123
Hotel-H	0.008	0.005	0.211	0.349	0.096

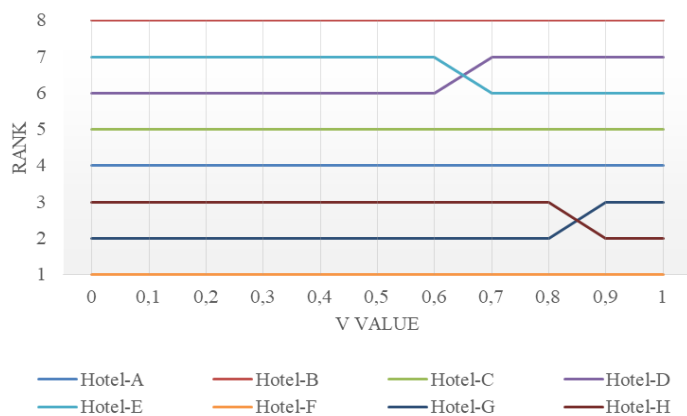


Figure 3. Sensitivity Analysis

Table 6. Q values

Hotels	$S_i$	$R_i$	$Q_i$										
			$v=0$	$v=0.1$	$v=0.2$	$v=0.3$	$v=0.4$	$v=0.5$	$v=0.6$	$v=0.7$	$v=0.8$	$v=0.9$	$v=1$
Hotel-A	0.785	0.363	0.749	0.758	0.768	0.778	0.788	0.797	0.807	0.817	0.827	0.836	0.846
Hotel-B	0.926	0.482	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hotel-C	0.798	0.372	0.768	0.777	0.786	0.795	0.805	0.814	0.823	0.832	0.842	0.851	0.860
Hotel-D	0.864	0.386	0.798	0.812	0.825	0.838	0.852	0.865	0.879	0.892	0.905	0.919	0.932
Hotel-E	0.845	0.406	0.840	0.847	0.854	0.861	0.868	0.876	0.883	0.890	0.897	0.905	0.912
Hotel-F	0.008	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Hotel-G	0.682	0.319	0.657	0.665	0.672	0.680	0.688	0.695	0.703	0.711	0.718	0.726	0.734
Hotel-H	0.669	0.349	0.721	0.721	0.721	0.721	0.721	0.721	0.721	0.720	0.720	0.720	0.720

Equation (3) was used to find the optimum answers that are both positive ( $f_j^*$ ) and negative ( $f_j^-$ ) ideal solutions. Comparing the normalized value in Table 3 yielded the positive. Both values, including the outcomes of the new decision matrix after the normalized values have been multiplied by the weight, are shown in Table 5. Each app's rank is determined by its index value ( $Q_i$ ) based on (7). The lowest index number indicates the highest level of user satisfaction across all categories. The  $Q_i$  value is based on the utility measure ( $S_i$ ) and regret measure ( $R_i$ ), calculated using equations (5) and (6). With reference to their  $R_i$  values in Table 6, it is clear that the specific criteria that need to be improved are location ( $C_3$ ), facility ( $C_4$ ), and food ( $C_5$ ). Based on the appearance of the terms in the review, Table 2 shows that the order of the criteria frequently mentioned were facility, location, food, cleanliness, and price. The hotel's management has to pay more attention to customers' preferences to create market segments and adopt strategies to meet their clients' needs.

The sensitivity analysis was performed to rank the top and lowest index values of 8 hotels in Table 6, and the v-value ranged from 0 to 1. Figure 3 shows that Hotels F, A, C, and B rankings are not affected by the v-value. Hotel-A was named the best, while Hotel-B was named the worst. It means that Hotel-F has a high level of user satisfaction in terms of highest collective benefit and least individual regret, whereas Hotel-B has the inverse. The v-value is graded higher than the Hotel-G and Hotel-D. Furthermore, both Hotels-G and D are projected to have improved user satisfaction if they focus on minimizing individual regret. When the v-value is increased, however, Hotels-E and H rank higher. It simply indicates that as the maximum group utility is enhanced, their user satisfaction scores tend to rise. However, this study has several limitations such as only 8 hotels were used as case studies. Increasing this number tends to improve the robustness of this analysis. The total number of reviews crawled from the internet was only 5413, and given the enormous volume online, the number of texts needed to accurately capture the trends needs to be raised. Future research will undoubtedly benefit from

adopting the VIKOR technique to combine star ratings and text reviews to create a more holistic measurement system. To ensure that these findings are corroborated, a comparison analysis including additional approaches must be carried out.

## CONCLUSION

The problem of selecting tourism product with online review has extensive practical application background. With respect to evaluating and selecting hotels, a decision support system is provided in this study based on data processing method and VIKOR. In the proposed method, the text is processed into data pre-processing, stem words extraction, word categorization based on its part-of-speech, word categorization and sentiment classification. Then, data is measured and obtain the ranking index for each hotel. This study utilized the user review from 8 hotels in Ubud, Bali.

The data used is the actual user reviews from TripAdvisor, and it was revealed that 5 major aspects influenced the customers' decisions in terms of selecting these hotels. These are price, cleanliness, location, facility, and food. It was concluded that Hotels F and B exhibited the highest and lowest satisfaction, respectively.

For future research, it is worth saying that the attainment for evaluation feature associated with alternatives could be further investigated from online reviews. The number of crawled data needs to be added to improve the attribute and sentimental directory; besides, the categories also need to be more than the five analyzed in this study.

## REFERENCES

- Ahani, A., Nilashi, M., Yadegaridehkordi, E., Sanzogni, L., Tarik, A. R., Knox, K., Samad, S., & Ibrahim, O. (2019). Revealing customers' satisfaction and preferences through online review analysis: The case of Canary Islands hotels. *Journal of Retailing and Consumer Services*, 51, 331–343. <https://doi.org/10.1016/j.jretconser.2019.06.014>
- Chou, T. Y., Hsu, C. L., & Chen, M. C. (2008). A fuzzy multi-criteria decision model for international tourist hotels location selection. *International Journal of Hospitality Management*, 27(2), 293–301. <https://doi.org/10.1016/j.ijhm.2007.07.029>
- Dina, N. Z., Yunardi, R. T., Firdaus, A. A., & Juniarta, N. (2021). Measuring User Satisfaction of Educational Service Applications Using Text Mining and Multicriteria Decision-Making Approach. *International Journal of Emerging Technologies in Learning*, 16(17), 76–88. <https://doi.org/10.3991/ijet.v16i17.22939>
- Dina, N.Z., Yunardi, R. T., & Firdaus, A. A. (2021). Utilizing Text Mining and Feature-Sentiment-Pairs to Support Data-Driven Design Automation Massive Open Online Course. *International Journal of Emerging Technologies in Learning*, 16(1), 134–151. <https://doi.org/10.3991/IJET.V16I01.17095>
- Dina, Nasa Zata. (2020). Tourist sentiment analysis on TripAdvisor using text mining: A case study using hotels in Ubud, Bali. *African Journal of Hospitality, Tourism and Leisure*, 9(2), 1–10.
- Dina, Nasa Zata, Triwastuti, R., & Silfiani, M. (2021). TF-IDF Decision Matrix to Measure Customers' Satisfaction of Ride Hailing Mobile Application Services: Multi-Criteria Decision-Making Approach. *International Journal of Interactive Mobile Technologies*, 15(17), 104–118. <https://doi.org/10.3991/ijim.v15i17.22509>
- Dincer, H., & Hacioglu, U. (2013). Performance evaluation with fuzzy VIKOR and AHP method based on customer satisfaction in Turkish banking sector. *Kybernetes*, 42(7), 1072–1085. <https://doi.org/10.1108/K-02-2013-0021>
- Djouab, R., & Bari, M. (2016). An ISO 9126 Based Quality Model for the e-Learning Systems. *International Journal of Information and Education Technology*, 6(5), 370–375. <https://doi.org/10.7763/ijiet.2016.v6.716>
- Fan, Z. P., Xi, Y., & Liu, Y. (2018). Supporting consumer's purchase decision: a method for ranking products based on online multi-attribute product ratings. *Soft Computing*, 22(16), 5247–5261. <https://doi.org/10.1007/s00500-017-2961-4>
- Guo, C., Du, Z., & Kou, X. (2017). Mining online customer reviews for products aspect-based ranking. In *Communications in Computer and Information Science* (Vol. 780). [https://doi.org/10.1007/978-981-10-6989-5\\_13](https://doi.org/10.1007/978-981-10-6989-5_13)
- Haleh, H., & Hamidi, A. (2011). A fuzzy MCDM model for allocating orders to suppliers in a supply chain under uncertainty over a multi-period time horizon. *Expert Systems with Applications*, 38(8), 9076–9083. <https://doi.org/10.1016/j.eswa.2010.11.064>
- Herrera, F., Martínez, L., Torra, V., & Xu, Z. (2014). Hesitant Fuzzy Sets: An Emerging Tool in Decision Making. *International Journal of Intelligent Systems*, 29, 493–494. <https://doi.org/10.1002/int>
- Huang, J. J., Tzeng, G. H., & Liu, H. H. (2009). A revised vikor model for multiple criteria decision making - The perspective of regret theory. In *Communications in Computer and Information Science* (Vol. 35). [https://doi.org/10.1007/978-3-642-02298-2\\_112](https://doi.org/10.1007/978-3-642-02298-2_112)
- Kundakci, N. K., Adali, E. A., & Isik, A. T. (2015). Tourist Hotel Location Selection with Analytic Hierarchy Process. *Journal of Life Economics*, 2(3), 47–58.
- Liou, J. J. H., Tsai, C. Y., Lin, R. H., & Tzeng, G. H. (2011). A modified VIKOR multiple-criteria decision method for improving domestic airlines service quality. *Journal of Air Transport Management*, 17(2), 57–61. <https://doi.org/10.1016/j.jairtraman.2010.03.004>
- Prastyo, P. H., Sumi, A. S., Dian, A. W., & Permanasari, A. E. (2020). Tweets Responding to the Indonesian Government's Handling of COVID-19: Sentiment Analysis Using SVM with Normalized Poly Kernel. *Journal of Information Systems Engineering and Business Intelligence*, 6(2), 112–122. <https://doi.org/10.20473/jisebi.6.2.112-122>
- Toutanova, K., Klein, D., Manning, C. D., & Singer, Y. (2003). Feature-rich part-of-speech tagging with a cyclic dependency network. *Proceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, HLT-NAACL 2003, June*, 173–180. <https://doi.org/10.3115/1073445.1073478>
- Yadegaridehkordi, E., Nilashi, M., Nizam Bin Md Nasir, M. H., Momtazi, S., Samad, S., Supriyanto, E., & Ghabban, F. (2021). Customers segmentation in eco-friendly hotels using multi-criteria and machine learning techniques. *Technology in Society*, 65, 101528. <https://doi.org/10.1016/j.techsoc.2021.101528>
- Zhao, M., Li, L., & Xu, Z. (2021). Study on hotel selection method based on integrating online ratings and reviews from multi-websites. *Information Sciences*, 572, 460–481. <https://doi.org/10.1016/j.ins.2021.05.042>