SMART method for recommender system towards smart tourism and green computing

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Abstract. Smart tourism is one component of smart village or smart city that aims to improve service quality of tourism. Smart tourism is expected to provide a better tourist experience for tourists by utilizing information technology. The purpose of this study is to develop for a culinary recommendation application to support smart tourism. Simple Multi-Attribute Rating Technique (SMART) was employed to develop the application which is based on geographic information systems. The application gives culinary places’ recommendation by considering several attributes, such as facilities, prices, menu variations, and distances (most recommender systems of culinary places do not use distance as the main attribute). In addition, this recommendation system is also one of the solutions in implementing green computing, namely "telecommuting" by reducing transportation emissions. Two test scenarios, namely user acceptance, and accuracy testing have been carried out. The user acceptance testing yielded 75.2% which indicated that the application was good, while the result of the accuracy testing was 83.33% which was considered high.

1. Introduction

The emerge of smart tourism has been gaining more attention from practitioners and scholars when information and communication technology (ICT) is massively leveraged nowadays [1]. Smart tourism is influenced by four main technologies, such as the Internet of Things, Mobile Communication, Cloud Computing, and Artificial Intelligence [2]. Smart tourism provides an interesting experience for tourists and gives benefits to stakeholders in a city or place that utilizes ICT [3].

Culinary, hotel, and travel agent entrepreneurs are stakeholders who contribute to the growth of tourism in both urban and rural areas. The stakeholders use ICT to promote their businesses while tourists use ICT to make it easier to arrange an itinerary. However, the massive amounts of information on the internet can make tourists hard to determine their choices. A recommender system can be an alternative system to assist the tourists in selecting desired culinary places, hotels, and other places as a tourist destination. The recommender systems usually suggest relevant items to users so that the attributes should meet what users are expected. In addition, by using this recommendation system, tourists no longer need to use vehicles to search for places of their choice that can increase...
transportation emissions. As we know that one of the solutions in implementing green computing is "telecommuting" by reducing transportation emissions [4].

Several studies have used various multi-attribute decision making (MADM) techniques as an alternative method to figure out a final ranking, screening, or selection. Table 1 presents some previous studies related to the selection of a location in the tourism industry such as the selection of hotels, restaurants, and coffee and tea shops. Table 1 presents some related studies which concern a recommender system and shows that the recommender system can help the stakeholder to determine the location of the business and the user to determine the choice of hotel or culinary place.

| Author          | Method         | Attribute                                      | Summary                                                                 |
|-----------------|----------------|-----------------------------------------------|-------------------------------------------------------------------------|
| Roy et al (2019) [5] | Copras        | Location, Hospitality, Facilities, Cleanliness, Food, Price. | Implement Copras to produce a web-based application to recommend the selection of 30 popular hotels in Delhi, India. |
| Pahari et al (2018) [6] | Fuzzy TOPSIS  | Geographical Location, Facilities, food quality, and price. | Hotel recommendation is based on online reviews on the tourism web site TripAdvisor.com. The review is made in five categories: excellent, good, average, poor, and terrible. 3 hotels in TripAdvisor.com are selected |
| Yu et al (2017) [7] | VIKOR         | Sleep quality, location, room, service, and score of cleanliness. | This study produces a recommender system using VIKOR which is based on reviews from several groups so that it helps visitors in selecting 10 popular hotels in Shanghai through Tripadvisor.com. |
| Park et al, (2015) [8] | AHP dan Bayesian Network | Type of restaurant, Price, mood, and distance. | This study develops a recommender system in order to recommend several prioritized restaurants from 90 restaurants in Korea by considering several references from many users. |
| Yildiz (2015) [9] | AHP dan TOPSIS | Responsiveness, experience, loyalty, food quality, price, ambiance, empathy, assurance. | This recommender system is used to find out which mostly influenced variables in improving restaurant service. The result of the system recommends that “the quality of food” is the most vital variable. |
| Ho (2013) [10] | AHP and MCGP   | Commercial area, cost, transportation, environment | This recommender system which is produced is to help the decision maker to decide the location of the restaurant and coffee shop toward 10 alternative locations. |
| Chen (2018) [11] | EDAS dan WASPAS-N | Rent cost, property area, public transportation, parking capacity, number of competitors. | This recommender system is used to help the decision maker to decide the outlet location of tea shop toward 6 alternative locations in Lithuania. |
This study aims to develop a recommender system that enables recommend culinary places, such as restaurants, coffee shops, and tea shops which are located in Kupang-Indonesia. The Simple Multi-Attribute Rating Technique (SMART) was used in this study. The SMART model has the advantage diminishing the value of lesser attributes when assessing the overall utility of the solution [12]–[14]. The recommender system used a geographic information system to collect data, particularly the distance attribute to display nearby culinary places.

2. Proposed Model

Figure 1 shows a proposed model used in the recommender system. The whole process is divided into 3 parts: (1) user preferences, (2) multi-attribute decision process, and (3) recommendation results.

2.1. User preference
This recommender system is built based on user preferences. The users give preference to such attributes which are most important to them. If user prefers the distance attribute, then the system will provide a recommendation for culinary places that are near to the user's position although they have high prices. In addition to the preferences, the coordinate position of the users will also be recorded automatically or manually.

2.2. Multi-attribute decision process
Multi-attribute decision process is a process that compares among all available alternatives and the attributes and recommends the most suitable alternative [15]. The application of the recommender system uses four attributes like price, menu variation, facilities, and distance.

The price attribute shows the level of price of the menus at the culinary place; the menu variation attribute shows the number of available menus; the facility attribute shows the availability of facilities that provide a comforting effect; then the distance attribute gives information on the exact number of the distance between culinary places and the users. In this recommender system, each attribute has a class. The decision of the class of each attribute is given by experts or professionals who have experience in assessing the quality of culinary places.

2.3. SMART method
SMART (Simple Multi-Attribute Rating Technique) is one of the multi-attribute decision-making methods which was developed by Edward in 1977 and is a method that uses multi-attribute utility measurement in decision making [13].
Figure 2 shows the six steps of the SMART model, as follows [16]:

1) Identifying attributes that are used in making decisions.
2) Giving weight to each attribute.
   This stage is about giving scores to all attributes for each alternative. In this field, an expert estimates alternative score on a scale: 0-100, that 0 is the minimum score while 100 is the maximum score.
3) Calculating the normalized weight of the attribute.
   The weight is normalized by dividing the weight of each attribute with the total number of weights. The normalization formula is given in equation (1):
   \[
   \text{Normalization} = \frac{w_j}{\sum_{j=1}^{n} w_m} \quad \text{.......................................................... (1)}
   \]
   \begin{align*}
   w_j & : \text{score of the attribute to } j \\
   m & : \text{total attribute} \\
   w_m & : \text{score of the attribute to } m
   \end{align*}
4) Giving score to attribute for each alternative.
   The attribute score for each of these alternatives can be in the form of quantitative data (numeric) or qualitative data. For example, the price attribute scores are definitely in numeric while the facility attribute values are in qualitative data form using a three-point scale from very complete to incomplete (scored from 3 to 1).
5) Calculating or determining the utility value.
   Determining the value of the utility can be done by converting the attribute score on each attribute into the standard data of the attribute score. The score of this utility depends on the nature of the attribute itself.
   a) Cost attributes are attributes one wants to be as low as possible.
      The equation is:
      \[
      u_i(a_j) = \frac{c_{\text{max}} - c_{\text{out}}}{c_{\text{max}} - c_{\text{min}}} \times 100\% \quad \text{.......................................................... (2)}
      \]
   b) Benefit attributes are attributes one wants to be as high as possible.
      The equation is:
      \[
      u_i(a_j) = \frac{c_{\text{out}} - c_{\text{min}}}{c_{\text{max}} - c_{\text{min}}} \times 100\% \quad \text{.......................................................... (3)}
      \]
      \[u_i(a_j) : \text{score of utility attribute to } i \text{ for every } a \text{ to } i\]
6) Determine the final score of every alternative by multiplying the scores from the normalization of the standard data attribute value with the of the attribute weights. Then add up the value of the multiplication.

\[ u(a_i) \sum_{j=1}^{m} w_j u_i(a_i) \]

\( u(ai) \): alternative total score from every \( a \) to \( i \)
\( w_j \): the result of normalizing the weight attribute from \( w \) to \( j \)
\( u_i(a_i) \): the result of determining the utility value of each \( u \) to \( i \) with respect to \( a \) to \( i \)

### 2.4. Illustration of Model Implementation

This section illustrates a calculation in order to obtain recommendations when selecting culinary places. To simplify this illustration, we take 7 alternatives, namely: A1, A2, A8, A12, A29, A34, and A37 with four attributes in sequence: price, menu variation, distance, and facilities.

1) Giving preference weight.

The weight of preference is given based on the subjective view of the user. In this study, the scale was from 10 to 40. The highest number indicates the highly prioritized level of use for these attributes. In this illustration we give preference weight to four attributes in a sequence:

\( (W) = (40, 30, 20, 10) \)

2) Normalizing the preference weight.

The result of normalization from preference weight is \( (W) = (0.4, 0.3, 0.2, 0.1) \)

3) Giving the score of each alternative to each attribute.

Table 2 shows the class and score of each attribute. Classes of price attributes, menu variations, and facilities are obtained from a survey for 39 alternatives. As for the distance attribute, the class is obtained from the real distance of the culinary location to the reference location.

| Attribute     | Class            | Score |
|---------------|------------------|-------|
| Price         | Cheap            | 3     |
|               | Medium           | 2     |
|               | Expensive        | 1     |
| Variation of  | Few (≤ 50)       | 1     |
| Menu          | Enough (51 - 100)| 2     |
|               | Many (> 100)     | 3     |
|               | Very near (≤ 1km)| 4     |
| Distance      | Near (1km < location ≤ 3km)| 3|
|               | Middle (3km < location ≤ 5km)| 2|
|               | Far (> 5km)      | 1     |
|               | None             | 1     |
| Facility      | WiFi or live music| 2   |
|               | WiFi and live music| 3|

Score or class in distance attribute is obtained from the distance between an alternative location and a certain location. We used this point (-10.167759, 123.641701) as a reference. Coordinate point of alternative locations were -10.161846, 123.622968; -10.173121, 123.600527; -10.160273, 123.584486; -10.158893, 123.605360; -10.155001, 123.603467; -10.157773, 123.632029; -10.160171,
123.610684. By using *Google Maps*, there were several reference locations with some sequenced alternatives, like: 4.4 km; 6.2 km; 9 km, 5.5 km, 6.4 km; 2.3 km; 4.8 km.

Table 2 is a reference to make a scoring matrix of each alternative to each attribute. In this illustration, this matrix is shown in Table 3.

| Table 3. Scoring matrix of each alternative to each attribute |
|---------------------------------------------------------------|
| Alternative | Price | Variation of Menu | Distance | Facility |
|-------------|-------|--------------------|----------|----------|
| A1          | 2     | 1                  | 2        | 1        |
| A2          | 2     | 2                  | 1        | 3        |
| A8          | 2     | 3                  | 1        | 3        |
| A13         | 3     | 3                  | 1        | 3        |
| A29         | 2     | 2                  | 1        | 2        |
| A34         | 1     | 3                  | 3        | 2        |
| A37         | 2     | 3                  | 2        | 2        |

4) Calculating Utility Scores.

The utility score is obtained using equation 2. Table 4 shows the results of the calculation of the utility score.

| Table 4. Utility score for every alternative |
|---------------------------------------------|
| Alternative | Price | Variation of Menu | Distance | Facility |
|-------------|-------|--------------------|----------|----------|
| A1          | 0,5   | 0                  | 0,67     | 0        |
| A2          | 0,5   | 0,5                | 1        | 1        |
| A8          | 0,5   | 1                  | 1        | 1        |
| A13         | 0     | 1                  | 1        | 1        |
| A29         | 0,5   | 0,5                | 1        | 0,5      |
| A34         | 1     | 1                  | 0,33     | 0,5      |
| A37         | 0,5   | 1                  | 0,67     | 0,5      |

5) Calculating the final score of each alternative.

The final score of each alternative is calculated using equation 4. Table 5 presents the results of the calculation of the final score of each alternative.

Table 5 shows that Excelso is the first recommendation while Kikikaka is the last recommendation.

| Table 5. Final Score of each alternative |
|------------------------------------------|
| Alternative | Final score |
|-------------|-------------|
| A1          | 0,33        |
| A2          | 0,65        |
| A8          | 0,80        |
| A13         | 0,60        |
| A29         | 0,60        |
| A34         | 0,82        |
| A37         | 0,68        |
3. Results and Discussion

The recommender system as shown in Figure 1, the user chooses such attributes which are prioritized according to the level of importance. The user then determines each class from the four attributes. The user’s input is processed using the SMART method. Next, the application provides five recommended culinary choices. This recommendation system also provides a visualization of the distance from the user's position to his culinary choice (see Figure 3).

Two test scenarios have been carried out in this study. The first scenario was testing user acceptance toward the application of the model. The second scenario was testing the accuracy of the application.

![Figure 3. The result of recommendation and distance visualization](image)

3.1. User Acceptance Testing

In this study, there are five evaluation categories to measure the user acceptance including assessment of usefulness (I), ease of use (II), informative (III), need for further developed (IV), and has an interesting of graphical user interfaces (GUI) (V). Technology Acceptance Model (TAM) was used as a baseline to determine these factors [17], [18]. Based on the survey to 20 respondents, the first category gets 68%, the second category gets 75%, the third category gets 70%, the fourth category gets 89% and the fifth category gets 74%. The percentages were obtained using the concept of a Likert scale [19].

| Respond                          | Score | I  | II | III | IV  | V  |
|----------------------------------|-------|----|----|-----|-----|----|
| Strongly Agree/very satisfied    | 5     | 4  | 7  | 5   | 12  | 6  |
| Agree/satisfied                  | 4     | 4  | 6  | 5   | 5   | 5  |
| Neither agree nor disagree /     | 3     | 9  | 4  | 7   | 3   | 6  |
| neither satisfied nor satisfied  |       |    |    |     |     |    |
| Disagree/dissatisfied            | 2     | 2  | 1  | 1   | 0   | 3  |
| Strongly Disagree/very dissatisfied | 1   | 1  | 2  | 2   | 0   | 0  |
| Percentages                      |       | 68%| 75%| 70% | 89% | 74%|

Table 6 shows the percentages of each question category and the distribution of the response. From these percentages, it appears that the users were satisfied with the usefulness, ease of use, received information, and the GUI. For the question of category IV, need for further developed, users strongly agreed to be further developed of application. However, in general, the result of this test reaches a percentage of 75.2%. This shows a good level of user acceptance to the model that has been applied.

3.2. System Accuracy Testing

System accuracy testing was done by comparing the results of the recommendations from the system and the experts (observers). Each result consisted of three best recommendations from 39 alternatives.
(A1-A39). This test was done by determining the main priorities of the existing attributes, namely distance (C1), price (C2), menu variations (C3) and facilities (C4) of 5 locations in Kupang such as Liliba (L1), Oesapa (L2), Kayu Putih (L3), Fatululi (L4), Kuanino (L5).

| Location | Recommendation from System | Recommendation from Experts | Accuracy Percentage |
|----------|----------------------------|-----------------------------|---------------------|
|          | C1 | C2 | C3 | C4 | C1 | C2 | C3 | C4 | C1 | C2 | C3 | C4 | C1 | C2 | C3 | C4 |
| L1       | A34 | A3 | A25 | A25 | A34 | A3 | A25 | A25 | 1 | 1 | 1 | 1 |     |     |     |     |
| L2       | A25 | A1 | A4 | A12 | A25 | A1 | A4 | A12 | 1 | 1 | 1 | 1 |     |     |     |     |
| L3       | A17 | A13 | A6 | A6 | A17 | A13 | A6 | A6 | 1 | 1 | 1 | 1 |     |     |     |     |
| L4       | A17 | A13 | A6 | A6 | A17 | A13 | A6 | A6 | 1 | 1 | 1 | 1 |     |     |     |     |
| L5       | A25 | A4 | A4 | A34 | A25 | A13 | A13 | A34 | 0 | 0 | 0 | 1 |     |     |     |     |
| L6       | A11 | A10 | A25 | A10 | A10 | A10 | A25 | A10 | 0 | 1 | 1 | 1 |     |     |     |     |
| L7       | A13 | A12 | A28 | A28 | A13 | A28 | A28 | A28 | 1 | 1 | 1 | 1 |     |     |     |     |
| L8       | A25 | A4 | A12 | A28 | A4 | A4 | A12 | A4 | 1 | 1 | 1 | 1 |     |     |     |     |
| L9       | A25 | A4 | A12 | A28 | A4 | A4 | A12 | A4 | 1 | 1 | 1 | 1 |     |     |     |     |
| L10      | A25 | A4 | A12 | A28 | A4 | A4 | A12 | A4 | 1 | 1 | 1 | 1 |     |     |     |     |
| Percentage of accuracy for every attribute (%) | 73.33 | 66.67 | 93.33 | 100 |

The accuracy of the system can be calculated using the average score of all accuracy testing that has been done.

\[
\text{Accuracy of the system} = \frac{(73.33\% + 66.67\% + 93.33\% + 100\%)}{4} = 83.33\%
\]

Table 7 shows that the smallest percentage of accuracy is on the price attribute (C2). This occurs because the price attribute is difficult to be measured. Classification on C2 can only be taken in general terms. As an example, the price of one cup of Espresso in Kikikaka is cheaper than the price of that in Beta. It could be that the price of one cup of Cappuccino in Kikikaka is more expensive than the price of that in Beta. This also happens for menus in comparison to those in other culinary places. Contrariwise, the other three attributes are relatively easier to be measured.

4. Conclusion

In this study, a recommender system has been used to support smart tourism which became a dimension of smart cities and villages. Testing to user acceptance of the application has been carried out using five categories. The test results show that the users feeling “satisfied” with the usefulness (I), ease of use (II), received information (III), and the GUI (V). For the question of category IV, user “strongly agree” to be further developed of application. Accuracy testing has also been carried out that level of accuracy reaches 83.33%. In general, applications using the SMART method have provided recommendations with a good degree of accuracy. This application can also indirectly reduce environmental pollution by reducing vehicle gas emissions because tourists no longer have to go around looking for places of their choice.

This study has limitations in the class of each attribute. For instance the price attribute, it is hard to determine an alternative culinary place for the cheap, medium, or expensive class. This occurs because
every culinary place has its strategy to set prices from each menu. In addition, only four attributes and 39 alternatives were considered in testing the model.

There are number of possibilities for further research on these topics. It could be developed by adding a method to overcome the problem to determine the complex price class. In addition, to maximize the given recommendations, it is necessary to identify the user's needs. This might be done by extracting the experience from the review in other recommender systems.

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References

[1] Yoo C W, Goo J, Huang C D, Nam K and Woo M 2017 Improving travel decision support satisfaction with smart tourism technologies: A framework of tourist elaboration likelihood and self-efficacy Technol. Forecast. Soc. Change 123 330–341
[2] Guo Y, Liu H and Chai Y 2014 The embedding convergence of smart cities and tourism internet of things in China: An advance perspective Adv. Hosp. Tour. Res. 2 54–69
[3] Jasrotia A and Gangotia A 2018 Smart cities to smart tourism destinations: A review paper J. Tour. Intell. Smartness 1 47–56
[4] Rajguru P, Nayak S, and More D 2010 Solution for Green Computing Int. J. Comput. Netw. Secur. 2 51–54
[5] Roy J, Sharma H K, Kar S, Zavadskas E K and Saparaukas J 2019 An extended COPRAS model for multi-criteria decision-making problems and its application in web-based hotel evaluation and selection Econ. Res. Istraz. 32 219–253
[6] Pahari S, Ghosh D and Pal A 2018 An Online Review-Based Hotel Selection Process Using Intuitionistic Fuzzy TOPSIS Method Adv. Intell. Syst. Comput., 710 785–793
[7] Yu S M, Wang J, Wang J Q and Li L 2017 A multi-criteria decision-making model for hotel selection with linguistic distribution assessments Appl. Soft Comput. J., 67 741–755
[8] Park H S, Park M H and Cho S B 2015 Mobile information recommendation using multi-criteria decision making with bayesian network Int. J. Inf. Technol. Decis. Mak. 14 317–338
[9] Yildiz S and Yildiz E 2015 Service Quality Evaluation of Restaurants Using the Ahp and Topsis Method J. Soc. Adm. Sci., 2 53–61
[10] Ho H P, Chang C T, and Ku C Y 2013 On the location selection problem using analytic hierarchy process and multi-choice goal programming Int. J. Syst. Sci., 44 94–108
[11] Chen J, Wang J, Baležentis T, Zagurskaite F, Streimikiene D and Makuteniene D 2018 Multicriteria Approach Towards the Sustainable Selection of a Teahouse Location with Sensitivity Analysis Sustain. 10 1–17
[12] Taylor J M and Love B N 2014 Simple multi-attribute rating technique for renewable energy deployment decisions (SMART REDD) J. Def. Model. Simul. Appl. Methodol. Technol. 11 227–232
[13] Risawandi and Rahim R 2016 Study of the Simple Multi-Attribute Rating Technique For Decision Support Int. J. Sci. Res. Sci. Technol. 2 491–494
[14] Patel M R, Vashi M P, and Bhatt B V 2017 SMART- Multi-criteria Decision-Making Technique for use in Planning Activities New Horizons in Civil Engineering (NHCE 2017), 1–6
[15] Sarraf R and McGuire M P 2020 Integration and comparison of multi-criteria decision making methods in safe route planner Expert Syst. Appl. 154 113399
[16] Goodwin P and Wright G, *Decision Analysis for Management Judgment*, 3rd ed., 49 John Wiley & Sons

[17] Davis F D, Bagozzi R P and Warshaw P R 1989 User Acceptance of Computer Technology: A Comparison of Two Theoretical Models *Manage. Sci.* 35 982–1003

[18] Kamal S A, Shafiq M, and Kakria P 2020 Investigating acceptance of telemedicine services through an extended technology acceptance model (TAM) *Technol. Soc.* 60 101212

[19] Shanafelt T D, Gorringe G, Menaker R, Storz K A, Reeves D, Buskirk S J, Sloan J A, Swensen S J 2015 Impact of organizational leadership on physician burnout and satisfaction *Mayo Clin. Proc.* 90 432–440