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A Hybrid Multiple Attribute Decision Making Model for Measuring Image Scores of a Set of Stores

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Abstract

Evaluating store image is a challenging task as it incorporates with multiple attributes. Earlier quantitative studies paid minimal attention on assessing the stores based on their image scores and overlooked the interaction aspects between attributes in the process of identifying the optimal strategies for image enhancement. This paper proposes a hybrid multiple attribute decision making model for quantitatively performing image evaluation involving a set of stores. The model uses factor analysis to extract the large set of interacted attributes into fewer independent factors, Sugeno measure to characterize the interactions between attributes, Choquet integral to aggregate the interactive performance scores within each extracted factor, Mikhailov's fuzzy analytical hierarchy process to assign the factors' weights, and weighted average operator to aggregate the independent factor scores of each store into a single global image score. An evaluation involving three stores located at Pekan Sabak, Selangor was conducted in order to demonstrate the feasibility of the model. The ranking on three stores derived via proposed model matched with the benchmark ranking unlike the ranking yielded by a classical aggregation operator. The model will be supportive for the retailers to identify their relative positions with their competitors and to systematically implement potential strategies for image enhancement by taking into account the interactions between attributes.

Keywords: aggregation; Choquet integral; multiple attribute decision making; store image; weighted average

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1. Introduction

Store image defines the way a store is perceived by the customers [1] or the customers' total attitude towards a store [2]. Customers usually illustrate a store's overall image via their own post-purchasing experience, word-of-mouth sources, or through marketing communications such as advertisements [3]. Every retail store has its own image and it influences a customer whether to choose a store for purchasing [4]. A positive image usually leads to customer satisfaction and increases number of loyal customers [5]. If a store does not have a unique or favorable image, the customers would not find a reason on why they should purchase there [6]. Therefore, the retailers should timely analyze and enhance the store's image because a desirable store image appears as a determinant for a long-term business success in an increasingly competitive marketplace [7].

However, evaluating store image is somewhat challenging as it is normally measured by multiple attributes as presented in [8, 9, 10, 11]. Besides, the review on past literature discloses that there are only limited types of quantitative model have been recommended for assessing a store's image. Most of the past studies such as [12, 13] only employed factor analysis which enables the retailers to understand the main determinants of a store's image but failed to offer other crucial information such as the prioritization or weight age of the extracted factors. Moreover, to our knowledge, there are no any empirical studies which have compared or evaluated a set of stores by measuring their image scores or dealt with the interactions between attributes in the process of identifying the strategies for image enhancement. By owing to these gaps, this paper aims to propose a hybrid multiple attribute decision making (MADM) model which can be employed to analyze the images of a set of stores without disregarding the interactions between the attributes.

The paper is organized as follows. Firstly, the problem allied with store image evaluation is defined. Secondly, three basic phases in solving MADM problems through multiple attribute utility theory (MAUT) approach are explored where the main reviews are focused on the usage of fuzzy numbers and Choquet integral at the second and third phase respectively. Thirdly, the proposed model is introduced. Fourthly, the feasibility and performance of the model are presented by carrying out a real evaluation problem. Finally, the contributions of the paper and indications for future research are summarized.

2. Literature Review

2.1 MADM

MADMis a field that develops various quantitative techniques for selecting, ranking, or classifying a set of alternatives based on varied, usually conflicting, attributes [14]. Applying multiple attribute utility theory (MAUT) techniques appears as a well-accepted standard way for modeling MADM problems [15]. There are only three fundamental phases in implementing any of the MAUT techniques [16].

2.2 First phase

In the first phase, all the pertinent attributes for evaluating the alternatives under consideration are identified. The basic elements of a typical MAUT model comprised of a set of *m* alternatives denoted by $\boldsymbol{a_i} = \{\boldsymbol{a_1}, \boldsymbol{a_2}, \ldots, \boldsymbol{a_m}\}$ and a set of *n* attributes represented by $\boldsymbol{c_j} = \{\boldsymbol{c_1}, \boldsymbol{c_2}, \ldots, \boldsymbol{c_n}\}$.

2.3 Second phase and the usage of fuzzy numbers

In the following phase, the attributes' weights and performance score of each alternative with respect to each attribute are derived. Some preference values or judgments from the experts or respondents are normally required for this purpose [17]. In classical MAUT analysis, these experts or respondents are usually forced to express their exact preferences based on crisp scales. However, as humans are normally uncertain about their judgment [18], it is somewhat burdensome for them to express their exact or precise preferences [19]. In reality, due to uncertainty, humans tend to express their preferences in natural languages or linguistic terms [19] such as 'unimportant', 'important', 'very important' and 'extremely important' instead of using crisp numbers (1,2,3,⋯). Unfortunately, the traditional MAUT methods are based on crisp numbers and not based on linguistic terms. Thus, these models do not exactly represent the actual or natural human thinking style.

In order to deal with the aspect of uncertainty embedded in linguistic preferences, fuzzy set theory which was introduced by Zadeh[20] is usually applied into MADM environment. Through fuzzy analysis, the experts or respondents are permitted to express the required preferences in linguistic terms. These linguistic preferences are then converted or quantified with appropriate fuzzy numbers to mathematically represent the uncertainty embedded in linguistic estimations [21].

A fuzzy number is a generalization of basic numbers which consists of upper, lower and most optimal values that best represent a linguistic preference. Triangular fuzzy number (TFN) appears as one of the commonly used fuzzy numbers since its membership function is piecewise linear and arithmetic operations involving TFNs are comparatively simple [22]. A TFN, $\tilde{A}$ can be defined by a triplet $(l, m, u)$where $l, m,$ and u denote the lower, optimal, and upper value corresponding to the linguistic preference or set, A as portrayed in Fig. 1.Based on Figure 1, $\mu_A(x)$ indicates the degree of belongingness of element, x to the set or linguistic term, A. Assume $\widetilde{A_1} = (l_1, m_1, u_1)$ and $\widetilde{A_2} = (l_2, m_2, u_2)$ be two positive TFNs. Then, the basic fuzzy arithmetic operations on these fuzzy numbers can be expressed as follows [23]: $(\widetilde{A_1})^{-1} = (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1})$; $\widetilde{A_1} + \widetilde{A_2} = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$; $\widetilde{A_1} - \widetilde{A_2} = (l_1 - u_2, m_1 - m_2, u_1 - l_2)$; $k \times \widetilde{A_1} = (kl_1, km_1, ku_1)$ for $k > 0$; $\widetilde{A_1} \times \widetilde{A_2} = (l_1 l_2, m_1 m_2, u_1 u_2)$; $\widetilde{A_1} \div \widetilde{A_2} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right)$.

2.4 Third phase and the usage of Choquet integral

At this phase, a specific function known as aggregation operator is used to synthesize the set of attributes' weights and performance scores of each alternative into a single global score [24]. Based on these global scores, the alternatives can be ranked up where an alternative with highest global score signifies the most preferred alternative for the evaluation problem. Normally, additive operators such as weighted average (WA) are simply used for aggregation purpose. Unfortunately, these operators presume that the attributes are always independent to each other [25]. This assumption is irrelevant with real scenario where in many cases, the attributes hold inter active characteristics [26]. Therefore, the aggregation should not be always carried out via additive aggregators as they failed to model the interactions between attributes.

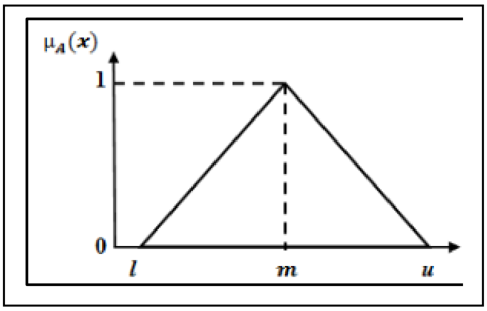

Fig. 1.TFN, $\tilde{A}$= (l,m, u)

However, with the aid of Choquet integral operator, the interactions aspects can be captured during aggregation [27]. The usage of Choquet integral requires a prior identification of monotone measure weights, g. Monotone measure weights not only represent the importance of each attribute but also the importance of all possible combinations or subsets of attributes [28, 29]. As a result, for a MADM problem comprising$n$ number of attributes, 2^nnumber of weights need to be identified prior to employing Choquet integral.

λ- measure which was introduced by Sugeno [30] emerges as one of the broadly used monotone measures due to its ease of usage, mathematical soundness and modest degree of freedom features[31].Let $c_j = (c_1, c_2, \dots, c_n)$ be a finite set. A set function $g_\lambda(.)$ defined on the set of the subsets of c_j,$P(c_j)$, is called a λ- measure if it satisfies the following conditions:

- $g_\lambda: P(c_j) \rightarrow [0,1]$, and $g_\lambda(\emptyset) = 0, g_\lambda(c_j) = 1$(boundary condition)
- $\forall A, B \in P(c_j)$, if $A \subseteq B$, then implies $g_\lambda(A) \leq g_\lambda(B)$ (monotonic condition)
- $g_\lambda(A \cup B) = g_\lambda(A) + g_\lambda(B) + \lambda g_\lambda(A) g_\lambda(B)$, for all $A, B \in P(c_j)$ where $A \cap B = \emptyset$ and $\lambda \in [-1, +\infty]$

According to Hu and Chen [32]:

- If $\lambda < 0$ then, it interprets that the attributes are sharing sub-additive (redundancy) effects. This means a significant increase in the performance of the target can be achieved by simply simultaneously enhancing some attributes in c_j which have higher individual weights.
- If $\lambda > 0$ then, it implies that the attributes are sharing super-additive (synergy support) effects. This means a significant increase in the performance of the target can be achieved by simultaneously enhancing all the attributes in c_j regardless of their individual weights.
- If $\lambda = 0$ then, it reflects that the attributes are non-interactive.

As $c_j = \{c_1, c_2, \dots, c_n\}$ is finite, then the entire λ- measure weights can be identified using the equation (1).

$$g_\lambda\{c_1, c_2, \dots, c_n\} = \frac{1}{\lambda} \left| \prod_{j=1}^{n}(1 + \lambda g_j) - 1, \right| for -1 < \lambda < +\infty (1)$$

where $g_j = g_\lambda(c_j)$, $j = 1, \dots, n$ denotes the individual weights of attributes. If $\sum_{j=1}^{n} g_j = 1$, $\lambda = 0$ whereasif$\sum_{j=1}^{n} g_j \neq 1$, the value of λ can be identified by solving equation (2).

$1 + \lambda = \prod_{j=1}^{n}(1 + \lambda g_j)$ (2)

The identified λ-measure weights and available performance scores can be then replaced into Choquet integral model to compute the global score of each alternative.

Let g_λ be a monotone measure on $c_j = (c_1, c_2, \ldots, c_n)$ and $x_j = (x_1, x_2, \ldots, x_n)$ be the performance score of an alternative with respect to each attribute in c_j. Suppose $x_1 \geq x_2 \geq \cdots \geq x_n$. Then, $T_n = (c_1, c_2, \ldots, c_n)$ and the aggregated score using Choquet integral can be identified using equation (3) [33].

$$\begin{aligned} & Choquet_{g_\lambda}(x_1, x_2, \ldots, x_n) \\ & = x_n . g_\lambda(T_n) + [x_{n-1} - x_n] . g_\lambda(T_{n-1}) + \ \ldots + [x_1 - x_2] . g_\lambda(T_1) \quad (3) \\ & = x_n . g_\lambda(c_1, c_2, \ldots, c_n) + [x_{n-1} - x_n] . g_\lambda(c_1, c_2, \ldots, c_{n-1}) + \cdots + [x_1 - x_2] . g_\lambda(c_1) \end{aligned}$$

where the arrangement of attributes in T_n parallel with the descending order of the performance scores.

For better understanding, presume that the scores of a student, x in three subjects (attributes), Mathematics (x_M), Physics (x_P), Biology (x_B) are 75, 80, and 50 respectively. Since $x_P \geq x_M \geq x_B$ then, $T_n = (P, M, B)$ and the aggregated score of the student using Choquet integral, $Choquet_{g_\lambda}(x_M, x_P, x_B) = x_B . g_\lambda(P, M, B) + (x_M - x_B) . g_\lambda(P, M) + (x_P - x_M) . g_\lambda(P)$. Figure 2 illustrates the idea of aggregation via Choquet integral.

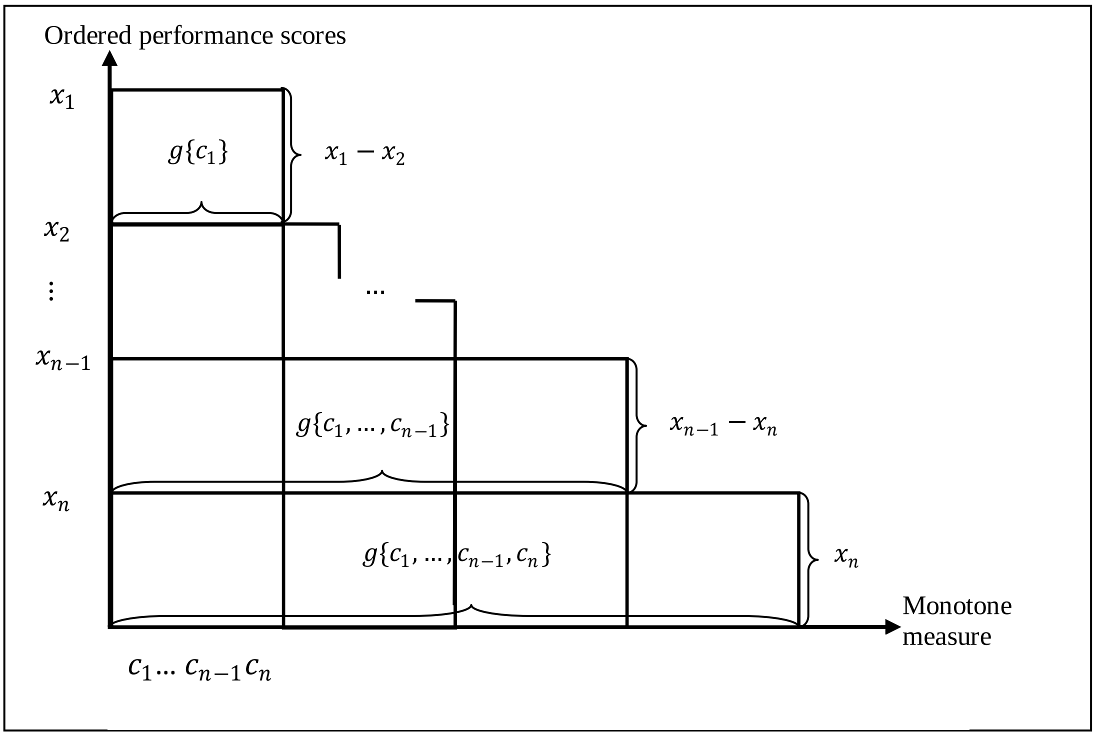

Fig. 2: Aggregation based on Choquet integral

3. Methodology

The proposed hybrid MADM model is developed with the combination of five main components namely factor analysis, Sugeno measure, Choquet integral, Mikhailov's fuzzy analytical hierarchy process (MFAHP), and AW operator. The nine main steps for implementing the proposed model are as follows.

3.1. Identification of store attributes

In step 1, each possible attribute that can be used to assess the image of the stores under consideration is identified. This could be the most time consuming process as omittingany crucial attributes would lead to distorted result.

3.2. Data collection by means of questionnaire

In step 2, questionnaires are used as a method to gather the data on the customers' satisfaction towards each store with respect to each image attribute. For the sake of convenient data offering and to deal with the usual uncertainty embedded in humans' estimations or preferences, the customers are allowed to express their satisfaction in linguistic terms. Therefore, the questionnaire should be designed based on a predetermined linguistic scale which comprised of a set of linguistic terms, $\boldsymbol{S_i} = (\boldsymbol{S_1}, \boldsymbol{S_2}, \dots, \boldsymbol{S_T})$together with their TFNs, $\widetilde{\boldsymbol{A}}_{\boldsymbol{i}} = (\widetilde{\boldsymbol{A}}_{\boldsymbol{1}}, \widetilde{\boldsymbol{A}}_{\boldsymbol{2}}, \dots, \widetilde{\boldsymbol{A}}_{\boldsymbol{T}})$ where$\boldsymbol{S_1}$ and $\boldsymbol{S_T}$denote "extremely unsatisfied" and "extremely satisfied" respectively and$\boldsymbol{T}$ implies the total number of linguistic term in the scale.

3.3. Deriving decision matrix: stores versus attributes

In step 3, the decision matrix of the evaluation problem which shows the performance score of each store with respect to each attribute is derived. For this purpose, firstly, the collected raw data are converted into fuzzified data by quantifying the linguistic scores in the raw data into their respective fuzzy scores based on the predetermined linguistic scale. Then, the fuzzy performance score of a store,$\boldsymbol{i}$ with respect to an attribute, $\boldsymbol{j}$ can be identified by averaging the scores obtained from $\boldsymbol{k}$ number of respondents. Each of these fuzzy performance scores is then converted into crisp scores by using centroid of area (COA) technique in order to obtain the required decision matrix (stores versus attributes). Assume a fuzzy performance score, $\widetilde{\boldsymbol{A}}_{\boldsymbol{ij}} = (\boldsymbol{l_{ij}}, \boldsymbol{m_{ij}}, \boldsymbol{u_{ij}})$. Then, its corresponding crisp value,$\boldsymbol{A_{ij}}$ can be identified using COA equation (4).

$$A_{ij} = l_{ij} + \left[\left(u_{ij} - l_{ij}\right) + \left(m_{ij} - l_{ij}\right)\right]/3 \quad (4)$$

3.4. Performing factor analysis

In step 4, the same collected raw data are utilized to perform factor analysis in order to extract the large set of store attributes into fewer independent factors. However, as the collected raw data encompass scores in linguistic forms then, they need to be transformed into valid forms where factor analysis can be performed. As the first stage of carrying out this transformation, the linguistic scores in the raw data need to be converted into their respective TFNs based on the same predetermined scale (but this stage can be actually bypassed as the fuzzified data should have been obtained in the process of deriving decision matrix). Secondly, each of these fuzzy scores is directly defuzzified into crisp scores using COA equation (4). Finally, each crisp score is translated into their equivalents in $\boldsymbol{T}$-point Likert scale which can be identified by multiplying the crisp score with number of linguistic terms in the predetermined scale, $\boldsymbol{T}$. By end of this stage, the data are ready to be factor analyzed.

3.5. Decomposing complex store evaluation problem into simpler hierarchy system

In step 5, based on the factor analysis result, the complex store evaluation problem is decomposed into simpler hierarchical structure that comprised of 'stores', 'attributes', 'factors', and 'goal' levels in order to conduct the analysis in a more systematic and interpretable means.

3.6. Identifying λ- measure weights within each factor

Since the attributes within each factor are being interactive, Choquet integral can be then employed in order to aggregate the performance scores within each factor. However, prior to employing Choquet integral, the monotone measure weights need to be identified. For this purpose, an approach applied in the [34] is utilized. The identification process can be simplified as follows.

Firstly, the experts are required to express the individual importance or contribution of each attribute towards its corresponding factor in linguistic terms. These linguistic importance are then quantified into their corresponding TFNs based on a preset scale. The scale should comprise a set of linguistic terms, $\boldsymbol{I} = (\boldsymbol{I_1}, \boldsymbol{I_2}, \dots, \boldsymbol{I_T})$ together with their respective TFNs, $\tilde{\boldsymbol{L}} = (\tilde{\boldsymbol{L}}_{\boldsymbol{1}}, \tilde{\boldsymbol{L}}_{\boldsymbol{2}}, \dots, \tilde{\boldsymbol{L}}_{\boldsymbol{T}})$ where $\boldsymbol{I_1}$ and $\boldsymbol{I_T}$ denote 'least important' and 'extremely important' respectively. Subsequently, the average fuzzy importance, $\tilde{\boldsymbol{L}}_{\boldsymbol{jp}}$ of an attribute, $\boldsymbol{j}$ corresponding to factor, $\boldsymbol{p}$ can be determined using equation (5).

$$\tilde{L}_{ij} = \frac{1}{z}\sum_{e=1}^{z} \tilde{L}_{j_e p} (5)$$

Suppose $E_e = \{E_1, E_2, \dots, E_z\}$ denotes the experts involved in the analysis. Then, based on equation (5), $\tilde{I}_{jep}$ represents the fuzzy importance of attribute, j with respect to factor, p that is derived from expert, e and z implies the total number of experts involved. The average fuzzy importance are then defuzzified into crisp importance via COA equation (4). These crisp importance actually represent the individual weights of attributes, $g_j = g_\lambda(c_j),\ j = 1,2, \dots, n$. Equation (2) and (1) can be then applied in order to find the interaction parameter, λ and monotone measure weights of each factor.

3.7. Aggregating interactive scores using Choquet integral

In step 7, the identified monotone measure and performance scores are replaced into Choquet integral model (3)to aggregate the interactive performance scores within each factor. As a result, by end of step 7, each store will have an aggregated score with respect to each factor (in other words, each store will have a set of factor scores).Hence, a new decision matrix, stores versus factors, can be constructed for further analysis.

3.8. Estimating weights of independent factors

In step 8, to assign the weights of independent factors, MFAHP [35] method is used as the consistency value of pair-wise comparison matrix and the weights of factors can be derived simultaneously by simply solving the suggested nonlinear optimization model (6). The execution of MFAHP with regards to the proposed model can be summarized as follows.

Firstly, the experts are required to linguistically express the relative importance of factors through a pair-wise comparison matrix based on Saaty's fuzzy AHP scale as shown in Table 1. For sake of simplicity, this paper suggests the experts to express their preferences via a single pair-wise matrix after achieving consensus. In order to avoid using reciprocal judgment (values between $\tilde{\mathbf{9}}^{-\mathbf{1}}$and $\tilde{\mathbf{1}}^{-\mathbf{1}}$) which could lead to rank reversal problem, MFAHP only requires the experts to provide assessment whenever factor,$\boldsymbol{f_a}$ is equally or more important than$\boldsymbol{f_b}$. If it is found that $\boldsymbol{f_a}$ is less important than $\boldsymbol{f_b}$ then, the evaluation should be done oppositely where $\boldsymbol{f_b}$ is compared to$\boldsymbol{f_b}$. It can be noticed that the reciprocal judgments are not offered in the Table 1 as they are not required in executing MFAHP.

Table 1: Saaty's fuzzy AHP scale

Linguistic terms	**Corresponding TFNs**	**Descriptions**
Equally important	$\tilde{1} = (1, 1, 2)$	Two elements contribute equally
Slightly important	$\tilde{3} = (2, 3, 4)$	One element is slightly favoured over another
Strongly important	$\tilde{5} = (4, 5, 6)$	One element is strongly favoured over another
Very strongly important	$\tilde{7} = (6, 7, 8)$	One element is very strongly favoured over another
Extremely important	$\tilde{9} = (8, 9, 9)$	One element is most favoured over another
The intermediate values	$\tilde{2} = (1, 2, 3)$, $\tilde{4} = (3, 4, 5)$,$\tilde{6} = (5, 6, 7)$, $\tilde{8} = (7, 8, 9)$	Used to compromise between two judgments

Secondly, the linguistic terms in the assessed pair-wise comparison matrix are converted into their corresponding TFNs. Finally, the suggested nonlinear optimization model (6) can be constructed based on the fuzzy pair-wise matrix and solved with the aid of EXCEL SOLVER to concurrently derive the consistency value of the matrix and the weights of the factors.

Maximize μ

Subject to;

$$(m_{ab} - l_{ab})\mu w_b - w_a + l_{ab} w_b \leq 0, \quad (6)$$

$$(u_{ab} - m_{ab})\mu w_b + w_a - u_{ab} w_b \leq 0,$$

$$\sum_{p=1}^{q} w_p = 1, w_p > 0, p = 1, \dots q$$

With respect to the proposed model,l_{ab}, u_{ab}, and u_{ab} represent the lower, upper and most probable values corresponding to the fuzzy judgment given by the experts when comparing factor, f_a to f_b. Meanwhile, w_p

denotes the weight of factor, f_p and μ represents the consistency index of the pair-wise comparison. If the value of μ is positive then, it indicates that the fuzzy pair-wise comparison matrix is being consistent. On the other hand, if the value is negative then, it implies that the comparison matrix is being inconsistent and re-evaluation on the pair-wise comparison is required.

3.9. Applying WAfor computing the global image score of each store

In step 9, after identifying the weight of each independent factor through MFAHP, WA operator(7) is applied to compute the global image score of each store.

$$\sum_{p=1}^{q}(w_p.y_p)(7)$$

wherew_p denotes the weight of factor, p and y_p denotes the score of a store with respect to factor, p. The stores can be then ranked based on their global scores where the store with the highest global score reflects the most preferred store by customers. The result or information derived from the model can be then utilized by the retailers to develop the optimal strategies for enhancing the images of their stores from the customers' perceptive. Figure 3 simplifies the steps involved in the proposed model.

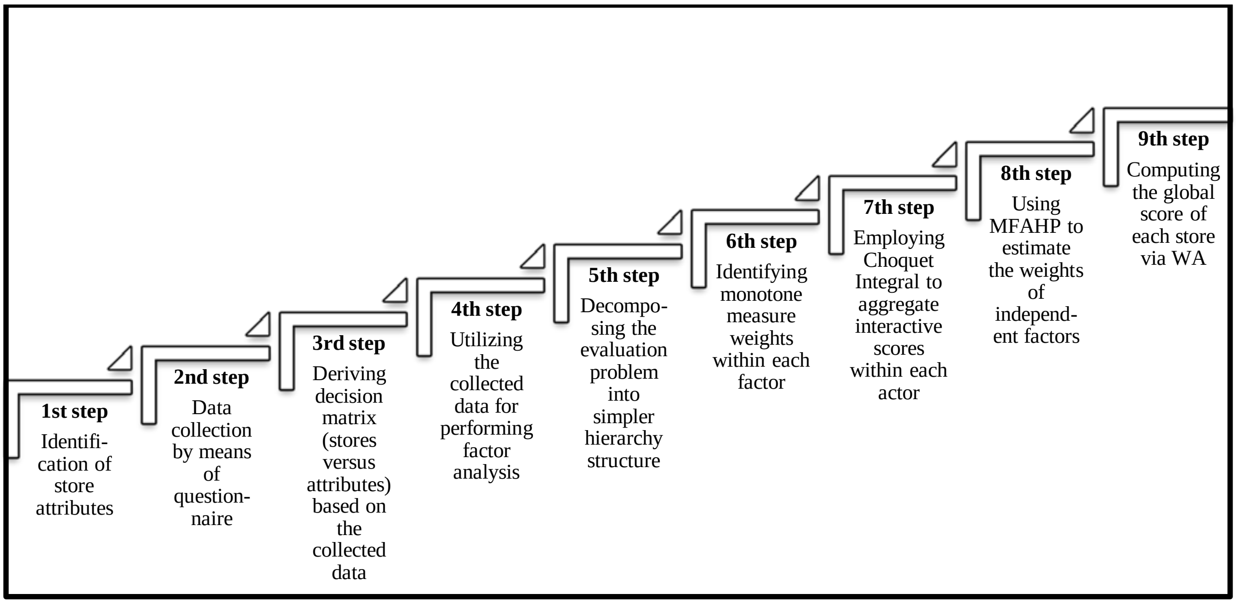

Fig. 3: Steps in executing proposed MADM model

4. Real Application

In this section, an evaluation involving three stores located at Pekan Sabak was conducted in order to verify the feasibility of the proposed model.

4.1. Background of the problem and stores under evaluation

Pekan Sabak is a subdivision of Sabak Bernam district, located at the northwest Selangor. It is a rural area, largely covered by traditional villages and plantation estates where most of the populace is engaged with agricultural activities. Alike other rural regions, Sabak has its own, progressing town which is locally known as 'Pekan Sabak'. The town has been experiencing a satisfying growth for the past few years. Mushrooming of new housing and shop lots projects, the presence of new banks, fast food franchise, new budget hotels, resort, and home-stays, mini convention centre, government community college and not to forget, the emergence of chain stores are reflecting the town's development for the past 15 years.

Focusing on the chain stores, there are three chain stores operating in Sabak Bernam namely Big Shop, 99 Speedmart, and Billion. Billion is the first chain store of the town then followed by 99 Speedmart and Big Shop. Both Billion and Big Shop are running their business in a double storey building whereas, 99 Speedmart is operating in a broad, single storey building. The main selling products of these stores are household items and foodstuffs. The main customers of these stores are the locals from the villages and plantation estates situated close to the town. It is essential for the retailers to analyze their stores' image from the viewpoints of these local people, so proper strategies can be organized to enhance their image as a way to boost the number of repetitive and loyal customers.

Nevertheless, in this study, we were only interested to measure the images of these three stores from the perception of the housewives living in Sabak Bernam Plantation Estate, which is located three kilometers away from the town. It has to be notified that housewives not only make purchase decisions for their own consumption but also influence family purchase decisions [36, 37].

4.2. Eliciting store attributes

With regards to this study, the two experts who involved in this analysis have initially extracted fifteen attributes from past literature which were believed to be significant for evaluating the image of stores located in small towns but latterly, after further consideration, two attributes ('long opening hour' and 'distance from home') were dropped out from the final list due to following reasons. The attribute 'distance from home' was discarded as the distance of the three stores from the estate is more or less same and the attribute 'long opening hour' was excluded as the three stores operate almost in a same time frame. The final list of store attributes used for this analysis was as presented in Table 2.

4.3. Data collection via questionnaire

A questionnaire was then designed based on a predetermined 9-point linguistic scale (refer Table 3) as an instrument to gather the perception of the housewives on each store. The questionnaire was mainly prepared in Malay and Tamil versions since it was understood that most of targeted respondents are only excel in their mother tongue. The questionnaire was organized into two major sections; $\boldsymbol{A}$and $\boldsymbol{B}$. Section $\boldsymbol{A}$ was dedicated to obtain some profiles of respondents such as age, race, period of residing in the estate, and total household income. Meanwhile, in Section $\boldsymbol{B}$, the respondents were requested to linguistically express their satisfaction towards each store with respect to the identified attributes based on the predetermined scale, ranging from 'absolutely unsatisfied' to 'absolutely satisfied'.

Table 2: Finalized list of store attributes

No.	Attributes	Description
1	Quality products (c_1)	The products sold at the store are in good quality, durable, function as expected and fresh (for foodstuffs)
2	Assortment (c_2)	The store carries different kinds or brands of products
3	Price(c_3)	The price of the products are reasonable and cheaper in comparison to other stores
4	Staff(c_4)	Store staff are neatly uniformed and always welcome the customers with friendly attitudes.
5	Fast checkouts(c_5)	I don't have to wait for so long in the queue at payment counters
6	Cleanliness(c_6)	The store is clean, neat, and tidy
7	Internal environment(c_7)	The internal atmosphere of the store always creates a pleasurable mood during purchasing activities
8	Store layout(c_8)	The design of store is spacious and makes shopping is easier and comfortable
9	Product display(c_9)	The products are displayed and arranged according to their usage and in an easy-to-find manner
10	Storefront(c_{10})	The store has attractive storefront with eye-catching decors, banners, or posters
11	In-store facilities(c_{11})	The store has satisfying level of necessary facilities within the stores such as such baskets, carriers, and fitting rooms
12	Parking facility(c_{12})	It is easy to get parking space around the store
13	Promotion(c_{13})	Good sales are offered timely

Table 3: 9-point linguistic scale for expressing satisfaction

Linguistic preferences	TFNs
S_1 = Extremely unsatisfied	$\tilde{A}_1 = (0,0,0.125)$
S_2 = Very unsatisfied	$\tilde{A}_2 = (0,0.125,0.25)$
S_3 = Unsatisfied	$\tilde{A}_3 = (0.125,0.25,0.375)$
S_4 = Somewhat unsatisfied	$\tilde{A}_4 = (0.25,0.375,0.5)$
S_5 = Neutral	$\tilde{A}_5 = (0.375,0.5,0.625)$
S_6 = Somewhat satisfied	$\tilde{A}_6 = (0.5,0.625,0.75)$
S_7 = Satisfied	$\tilde{A}_7 = (0.625,0.75,0.875)$
S_8 = Very satisfied	$\tilde{A}_8 = (0.75,0.875,1)$
S_9 = Extremely satisfied	$\tilde{A}_9 = (0.875,1,1)$

Prior to conducting the actual survey, the questionnaire was pre-tested with a group of 45 housewives from a housing area who were found to have purchasing experience at the designated stores. They were given three days to respond on the given questionnaire and also recommended to comment on the clarity of the questionnaire, puzzling terms, and overall format of the questionnaire. Based on the respondents' feedback, some alterations were made on the questionnaire especially some rare terms were replaced with simpler and straightforward words. Before embarking the actual survey, an approval from the estate management was obtained. The overall data collection procedure for this study can be summarized as follows.

- Target population: As mentioned formerly, this study was intended to understand the image of the stores from the view of female housewives who are dwelling in Sabak Bernam Estate. By interviewing the head of workers' union, it was discovered that around 51 houses in the area were occupied by Malaysian families (the remaining were occupied by few male bachelors and some foreign labors who were beyond of the study's focus). Therefore, the finalized population of this analysis was the 51 housewives from each of these families.

- Sampling procedure: Using the online calculator available at http://www.surveysystem.com/sscalc.htm, it was understood that the minimum sample size required to correctly represent the population of this study is 45 (in the case of 5% of confidence interval). However, in this analysis, no specific sampling procedure was applied as we believed that the overall population was small and thus, the perception from all the housewives can be obtained without any difficulties.
- Data collection process: With the help of two primary school teachers who are familiar with the local people, a house-to-house survey was conducted. For sake of caution, prior to offering the questionnaire, a screening question was asked to the respondents to ensure they had the purchasing experience at all the three stores. As expected, all of them had purchased at the three stores for at least once. In addition, in order avoid biased evaluation from the loyal customers, it was clearly explained to them that the intention of the survey is not to compare the performance of the stores. They were simply informed that the survey is being conducted to enhance the existing services and facilities within each store. Each of these 51 housewives was requested to express their perception on each item in the questionnaire with respect to each store. We assisted them throughout the answering process and assured that the questionnaires were fulfilled completely. The survey was scheduled and conducted after 5pm as most of the working women would be only available after this point of time. Therefore, it took almost a week to accomplish the survey. At the end of survey, a large data set comprising a total of 153 observations [number of observations on each store (51) × number of stores (3)] were obtained. Since the store image evaluation system constructed by 13 attributes, as per the rule of '10 observations per attribute', the total observation, N for this problem should be at least 130 to perform a meaningful factor analysis. This indicated that the total observation (N=153) gathered via this survey was enough to guarantee a trustworthy factor analysis result.

4.4. Deriving decision matrix (3 stores versus 13 attributes)

At this step, firstly, the collected raw data were converted into fuzzified data by quantifying the available linguistic scores into their corresponding TFNs based on the preset 9-point linguistic scale. Then, the fuzzy performance scores of each store with respect to each attribute was identified by averaging the scores obtained from the 51 respondents. Finally, these fuzzy performance scores were defuzzified into crisp scores using COA equation (4) in order to attain the decision matrix of the evaluation problem (3 stores versus 13 attributes) as presented in Table 4.

Table 4: Decision matrix (stores versus attributes)

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}
B	0.7271	0.7753	0.6291	0.5547	0.7418	0.7435	0.7288	0.6855	0.6462	0.6871	0.7263	0.7663	0.7132
S	0.8374	0.7247	0.7770	0.8521	0.7582	0.8685	0.8268	0.7549	0.8358	0.7255	0.7631	0.3374	0.4592
BS	0.6438	0.8137	0.6977	0.7541	0.7574	0.7002	0.6087	0.8080	0.8145	0.8113	0.8015	0.8668	0.8121

**B=Billion, S=Speedmart, and BS= Big Shop*

4.5. Factor analyzing the collected data

In order to assure the data are in valid forms to be factor analyzed, the scores in the fuzzified dataset which were obtained in the process of identifying decision matrix were directly converted into their crisp scores using COA equation (4) and finally into their equivalents in 9-pointLikert scale ($T = 9$). Prior to conducting factor analysis, the factor ability of the transformed data was investigated. The assessment on the correlation matrix disclosed the presence of several coefficients of 0.3 and above. Besides, by referring to SPSS output as in Table 5, it was noted that the KMO value was 0.662, surpassing the recommended 0.6 and Bartlett's Test of Sphericity reached statistical significance as the p-value, 0 is less than 0.05. These three circumstances clearly justified that the dataset was appropriate to be factor analyzed.

Table 5: KMO and Bartlett's Test for store image data

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.662
Bartlett's Test of Sphericity	Approx. Chi-Square	496.844
	df	78
	Sig.	.000

After factor analyzing the modified data via SPSS software, the large set of thirteen attributes was reduced into five independent factors. However, it has to be understood that the attributes within each extracted factor were still inter-correlated to each other. The result of factor analysis for this study can be further detailed as follows. Extraction through principal component analysis revealed the presence of five common factors with eigen values exceeding one, explaining 24.386 %, 16.679 %, 10.071 %, 8.269 %, and 7.705 % of the variance respectively as shown in Table 6. The total variance explained reached 67.110 %. To aid in the interpretation of these five common factors, varimax rotation was performed and the result as in Table 7 was obtained.

Four attributes c_7, c_6, c_3 , and $c_1$which had higher loading at factor 1 was renamed as 'in-store experience' factor (f_1) as it is believed pleasing internal environment, cleanliness level, price and quality of products could play significant roles in determining assenting in-store purchasing experience. Another four attributes c_9, c_4, c_{10} , and c_8 had higher loading at factor 2 and was labeled as 'first impression' factor (f_2) as the way the products are displayed and arranged, the appearance and attitude of staff, the exterior and layout of store are the first features which can be noticed by the customers even before purchasing the products. Meanwhile, attributes c_{13}, c_{12}, and c_{11} formed a new common factor which was then identified as 'customer care' factor (f_3) because usually, with a good sales promotion, sufficient facilities provided within the stores, and satisfactory parking facility, the customers believe the retailers are reflecting their appreciation and concern towards them. Both c_2 and c_5 did not show any relationships with other attributes and independently had higher loading at factor 4 and factor 5 respectively. Therefore, the name of these two factors were retained as 'assortment' (f_4) and 'checkout' (f_5).

Table 6: Total Variance Explained

Component	Initial Eigenvalues		
	Total	**% of Variance**	**Cumulative %**
1	3.170	24.386	24.386
2	2.168	16.679	41.066
3	1.309	10.071	51.137
4	1.075	8.269	59.405
5	1.002	7.705	67.110
6	.868	6.676	73.786
7	.783	6.022	79.809
8	.658	5.062	84.871
9	.563	4.333	89.204
10	.476	3.665	92.869
11	.346	2.658	95.527
12	.302	2.321	97.848
13	.280	2.152	100.000

*Extraction method: Principal component analysis

Table 7: Rotated component matrix

	Component				
	1	**2**	**3**	**4**	**5**
Environment(c_7)	.835				
Clean(c_6)	.760				.357
Price(c_3)	.750				
Quality(c_1)	.616				
Display(c_9)		.818			
Staff(c_4)		.694			
Storefront(c_{10})		.566	.314		
Layout(c_8)		.549		.389	
Promotion(c_{13})			.865		
Parking(c_{12})			.690	.386	
Facility(c_{11})	.335		.574		
Assortment(c_2)				.863	
Checkout(c_5)					.911

*Extraction Method: Principal Component Analysis
*Rotation Method: Varimax with Kaiser Normalization.
*Rotation converged in 25 iterations.

4.6. Simplifying complex store image evaluation problem into hierarchical structure

By adhering to the result of factor analysis, the complex store image evaluation system was decomposed into simpler and interpretable system which was helpful in conducting the further analysis gradually from one level to the others. Based on fig. 4, the first level of the hierarchical structure shows all the three stores under evaluation. The second level encompasses the groups of attributes that influence each of the extracted factors with their respective scores captured from the decision matrix. Meanwhile, the third level depicts the actual determinants or factors that affect the overall image of the stores and the fourth level reflects the goal of the MADM problem which was to assess the images of the three stores from the housewives' perspective.

4.7. λ-measure weights within each store image factor

As the first step of identifying the monotone measure values, the two experts expressed their independent perception on the individual importance of each attribute towards its factor based on a nine-point linguistic scale as shown in Table 8. The perception of the experts and the identification of individual weights of attributes within each factor via equation (5) and (4) are summarized into Table 9.

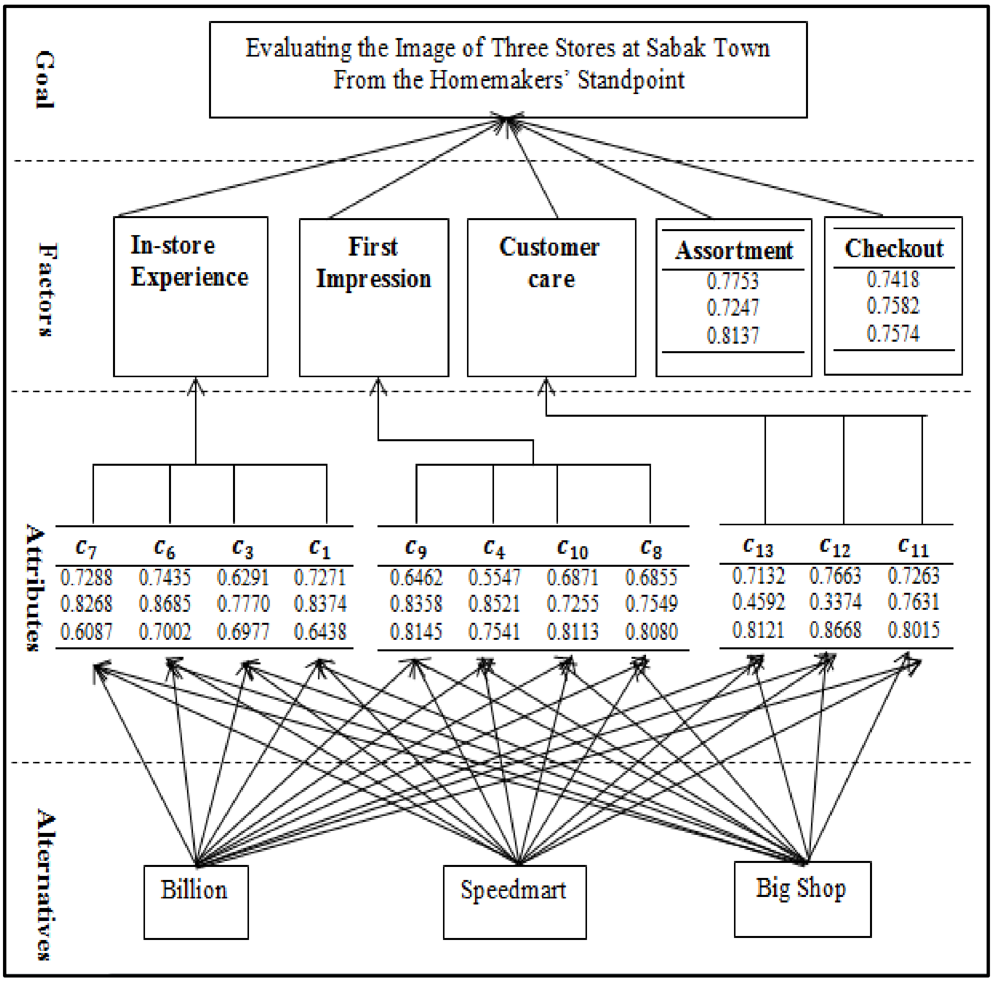

Fig. 4: Hierarchical system of the store image evaluation problem

Table 8: 9-point linguistic scale for expressing individual importance of attributes

Linguistic variables	TFNs
S_1 = Least important	$\tilde{I}_1$ = (0, 0, 0.125)
S_2 = Somewhat important	$\tilde{I}_2$ = (0, 0.125, 0.25)
S_3 = Important	$\tilde{I}_3$ = (0.125, 0.25, 0.375)
S_4 = Somewhat strongly important	$\tilde{I}_4$ = (0.25, 0.375, 0.5)
S_5 = Strongly important	$\tilde{I}_5$ = (0.375, 0.5, 0.625)
S_6 = Somewhat very stongly important	$\tilde{I}_6$ = (0.5, 0.625, 0.75)
S_7 = Very strongly important	$\tilde{I}_7$ = (0.625, 0.75, 0.875)
S_8 = Somewhat extremely important	$\tilde{I}_8$ = (0.75, 0.875, 1)
S_9 = Extremely important	$\tilde{I}_9$ = (0.875, 1, 1)

Table 9: Identification of individual weights within each store image factor

Factor	Attributes	Importance (Linguistic terms)		Fuzzy importance		Average fuzzy importance	Final individual weights
		1stE	2ndE	1stE	2ndE		
In-store experience	Environment	I	SI	(0.125,0.25,0.375)	(0,0.125,0.25)	(0.0625,0.1875,0.3125)	0.1875
	Clean	I	SI	(0.125,0.25,0.375)	(0,0.125,0.25)	(0.25,0.375,0.5)	0.3750
	Price	SI	SI	(0,0.125,0.25)	(0,0.125,0.25)	(0.1875,0.3125,0.4375)	0.3125
	Quality	STI	VSI	(0.375,0.5,0.625)	(0.625,0.75,0.875)	(0.5,0.625,0.75)	0.625
First impression	Display	I	SI	(0.125,0.25,0.375)	(0,0.125,0.25)	(0.0625,0.1875,0.3125)	0.1875
	Staff	SSI	I	(0.25,0.375,0.5)	(0.125,0.25,0.375)	(0.1875,0.3125,0.4375)	0.3125
	Storefront	SSI	I	(0.25,0.375,0.5)	(0.125,0.25,0.375)	(0.1875,0.3125,0.4375)	0.3125
	Layout	SI	SI	(0,0.125,0.25)	(0,0.125,0.25)	(0, 0.125, 0.25)	0.125
Customer care	Promotion	STI	SSI	(0.375,0.5,0.625)	(0.25,0.375,0.5)	(0.3125,0.4375,0.5625)	0.4375
	Parking	I	I	(0.125,0.25,0.375)	(0.125,0.25,0.375)	(0.125,0.25,0.375)	0.25
	Facility	SI	I	(0,0.125,0.25)	(0.125,0.25,0.375)	(0.0625,0.1875,0.3125)	0.1875

**E= expert, SI= somewhat important, I= important, SSI= somewhat strongly important, STI= strongly important, VSI= very strongly important*

The identified individual weights were then replaced into equation (2) in order to estimate the interaction parameter, λ of each factor. Finally, with the available individual weights and interaction parameters, λ, equation (1) was used to estimate the monotone measure weights within each factor. The identified interaction parameter, λ and monotone measure weights of each store image factor were as presented in Table 10.

As the proposed model consists of factor analysis, it is able to reduce the actual number of monotone measure weights which need to be identified by the retailers prior to applying Choquet integral from 8192 (2^{13}) weights to 40 (2^4+2^4+2^3) weights. Therefore, there was about 99.5% computational saving achieved in determining the weights of monotone measure for this specific problem. The percentage of computational saving relies on the result of factor analysis. In general, through the proposed model, the actual number of monotone measure weights can be reduced from 2^n to $\sum_{p=1}^{q} 2^{|f_p|}$ where $f_p = (f_1, f_1, \dots, f_q)$ set of extracted factors, q denotes the total number of factors, and $|f_p|$ represents the number of attributes within factor, p.

4.8. Applying Choquet integral to aggregate interactive performance scores

After identifying weights of monotone measure, Choquet integral model (3) was then applied to aggregate the interacted performance scores within each factor to obtain factor scores. The performance scores within each factor their aggregated scores via Choquet integral model are shown in Table 11.

Table 10: Monotone measure weights of each factor

In-store experience (λ= -0.7470)		**First impression (λ= 0.1922)**		**Customer-care attitude (λ= 0.5029)**	
Subsets	**Weights**	**Subsets**	**Weights**	**Subsets**	**Weights**
{}	0.0000	{}	0.0000	{}	0
{Environment}	0.1875	{Display }	0.1875	{Promotions }	0.4375
{Clean }	0.3750	{Staff}	0.3125	{Parking}	0.2500
{Environment, Clean}	0.5100	{Display, Staff}	0.5113	{Promotions, Parking}	0.7425
{Price }	0.3125	{Storefront}	0.3125	{Facility}	0.1875
{Environment, Price}	0.4562	{Display ,Storefront}	0.5113	{Promotions, Facility}	0.6663
{Clean, Price}	0.6000	{Staff, Storefront}	0.6438	{Parking, Facility}	0.4611
{Environment, Clean , Price }	0.7034	{Display , Staff, Storefront}	0.8545	{Promotions, Parking, Facility}	1.0000
{Quality}	0.6250	{Layout }	0.1250		
{Environment, Quality}	0.7250	{Display ,Layout }	0.3170		
{Clean ,Quality}	0.8249	{Staff, Layout }	0.4450		
{Environment, Clean ,Quality}	0.8969	{Display, Staff, Layout }	0.6485		
{Price, Quality}	0.7916	{Storefront, Layout }	0.4450		
{Environment, Price ,Quality}	0.8682	{Display, Storefront, Layout }	0.6485		
{Clean, Price, Quality}	0.9449	{Staff, Storefront, Layout }	0.7842		
{Environment, Clean , Price ,Quality}	1.0000	{Display ,Staff, Storefront, Layout }	1.0000		

Table 11: Factor scores of each store

Stores	**Attributes/performance scores**				**Factor scores**
	Environment	**Cleanliness**	**Price**	**Quality**	**In-store experience**
Billion	0.7288	0.7435	0.6291	0.7271	0.7234
Speedmart	0.8268	0.8685	0.7770	0.8374	0.8421
Big	0.6087	0.7002	0.6977	0.6438	0.6751
	Display	**Staff**	**Storefront**	**Layout**	**First impression**
Billion	0.6462	0.5547	0.6871	0.6855	0.6320
Speedmart	0.8358	0.8521	0.7255	0.7549	0.7910
Big	0.8145	0.7541	0.8113	0.8080	0.7913
	Promotions	**Parking**	**Facility**		**Customer care**
Billion	0.7132	0.7663	0.7263		0.7292
Speedmart	0.4592	0.3374	0.7631		0.4755
Big	0.8121	0.8668	0.8015		0.8230

Based on the factor scores, a new decision matrix, stores versus factors, was constructed as shown in Table 12. Note that the stores' scores with respect to assortment and checkout factor were elicited from the previous decision matrix (refer Table 4). Further evaluation was based on this newly constructed decision matrix.

Table 12: New decision matrix (stores versus factors)

	In-store experience	**First impression**	**Customer care**	**Assortment**	**Checkout**
Billion	0.7234	0.6320	0.7292	0.7753	0.7418
Speedmart	0.8421	0.7910	0.4755	0.7247	0.7582
Big	0.6751	0.7913	0.8230	0.8137	0.7574

4.9. Estimating weights of independent store image factors

MFAHP technique was then utilized in order to estimate the weights of independent factors. As the first step to employ MFAHP, the two experts involved in the analysis had a detailed discussion on the relative importance between the store factors. After achieving consensus, a single pair-wise matrix was assessed linguistically as shown in Table 13by using Saaty's fuzzy AHP scale. It can be noticed that since 'first impression' and 'customer care' were found to be less important than 'assortment' factor, the evaluation was done vice versa to avoid using reciprocal values as mentioned in section 3.8.

Table 13: Linguistic pair-wise comparison between store image factors

	In-store experience	**First impression**	**Customer care**	**Assortment**	**Checkout**
In-store experience	(1,1,1)	Slightly important	Somewhat strongly important	Somewhat slightly important	Somewhat strongly important
First impression		(1,1,1)	Somewhat slightly important		Somewhat slightly important
Customer care			(1,1,1)		Equally Important
Assortment		Somewhat slightly important	Slightly important	(1,1,1)	Slightly important
Checkout					(1,1,1)

The linguistic terms in the evaluated pair-wise matrix were then quantified into their corresponding TFNs.Based on the fuzzy pair-wise matrix, the suggested nonlinear optimization model (5) was constructed and solved with the aid of EXCEL Solver. Following result was obtained: weight of in-store experience factor,w_1 = 0.4091; weight of first impression factor,w_2 = 0.1532; weight of customer care factor,w_3 = 0.0937; weight of assortment factor,w_4 = 0.2503; weight of checkout factor,w_5 = 0.0937; consistency index, μ = μ =0.6340. The value of μ implied that the consistency of pair-wise matrix was satisfactory.

4.10. Computing global image score of each store

Finally, based on estimated weights of factors and available factor scores, the overall image of each store was computed via WA operator (7). The image score of each store and its corresponding ranking are summarized in Table 13.

Table 13: Image scores and ranking of stores

	In-store experience ($\boldsymbol{w_1 = 0.4091}$)	**First impression** ($\boldsymbol{w_2 = 0.1532}$)	**Customer care** ($\boldsymbol{w_3 = 0.0937}$)	**Assortment** ($\boldsymbol{w_4 = 0.2503}$)	**Checkout** ($\boldsymbol{w_5 = 0.0937}$)	**Global score**	**Ranking**
Billion	0.7234	0.6320	0.7292	0.7753	0.7418	0.7247	3
Speedmart	0.8421	0.7910	0.4755	0.7247	0.7582	0.7627	1
Big	0.6751	0.7913	0.8230	0.8137	0.7574	0.7492	2

4.11. Proposed model versus a conventional aggregation operator

In this section, the same stores' image problem was solved through a classical aggregator (to be specific, by only using the common WA operator) and the obtained result was compared with the result from the proposed model. The reason of choosing classical WA was to mainly illustrate the consequence of disregarding the interactions between attributes in analyzing the images of stores. As usual, the analysis was conducted by employing the basic three phases of MAUT as follows.

- Identifying the alternatives and attributes of problem: The same three stores and thirteen attributes were used to carry out the analysis. The problem was then decomposed into hierarchy structure comprising of 'alternatives' (three stores), 'attributes' (store attributes), 'goal' (evaluating the stores based on their image score) levels.
- Identifying performance scores of alternatives and weights of attributes: In order to make sensible comparison on the results (outputs) from two different MADM tools, same data (inputs) should be used. Therefore, in this case, the existing store image data were utilized to derive the local scores and weights required for the application of WA. In the process of obtaining the performance or decision matrix forthe evaluation using conventional WA, firstly, the linguistic scores in raw data were converted or represented with their equivalent crisp numbers in 9- point Likert scale (instead of quantifying into fuzzy numbers as required in the proposed model). Then, by averaging the crisp scores corresponding to each store, the performance scores were computed. As a result, a decision matrix as shown in Table 15 was attained. On the other hand, since WA assumes interdependency between attributes then, it is essential to ensure the sum of weights of the 13 attributes is being additive or equal to one. To derive the weights for WA, firstly, the individual weights of attributes within each factor were normalized to assure the sum of the weights is equal to one. These normalized weights were just implied the contribution or importance of attributes towards their respective factor. Therefore, the final weight of each attribute (contribution of attributes towards overall image) was then estimated by multiplying its normalized weight with the weight of respective factor. It has to be reminded that the weights of factors do not demand normalization as they were already in the additive state. Table 16 recaps the computational process of determining the additive weights of attributes for WA.

Table 15: Decision matrix for WA

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}	c_{13}
Billion	6.8431	7.2353	6.0392	5.4510	6.9608	7.0000	6.8824	6.5098	6.1961	6.5294	6.8431	7.1961	6.7451
Speedmart	7.8039	6.8235	7.2745	7.9412	7.1176	8.0588	7.7255	7.0980	7.7843	6.8431	7.1569	3.6667	4.6863
Big	6.1961	7.6078	6.6471	7.0980	7.1176	6.6471	5.8824	7.5686	7.6078	7.5686	7.4902	8.0784	7.6078

Table 16: Final additive weights for WA

Factors	Attributes	Individual weights	Normalized weights	Final weights
In-store experience (0.4091)	Environment	0.1875	0.1250	0.0511
	Clean	0.3750	0.2500	0.1023
	Price	0.3125	0.2083	0.0852
	Quality	0.625	0.4167	0.1705
	SUM	1.5000	1	
First impression (0.1532)	Display	0.1875	0.2000	0.0306
	Staff	0.3125	0.3333	0.0511
	Storefront	0.3125	0.3333	0.0511
	Layout	0.125	0.1333	0.0204
	SUM	0.9375	1	
Customer care (0.0937)	Promotion	0.4375	0.5000	0.0469
	Parking	0.25	0.2857	0.0268
	Facility	0.1875	0.2143	0.0201
	SUM	0.875	1	
Assortment (0.2503)	-			0.2503
Checkout (0.0937)	-			0.0937
SUM				1

- Aggregation: In this phase, the local scores of each store were composed into a global score using WA operator. Based on these global scores which represented the overall image, the stores were ranked up. Table 17 portrays the variation on the global scores and ranking of the stores derived from the proposed model and classical WA.

Table 17: Comparing the result from proposed model and conventional WA

Stores	Proposed model		Classical AHP	
	Global scores	Ranking	Global scores	Ranking
Billion	0.7247	3	6.6247	3
Speedmart	0.7627	1	6.2881	2
Big	0.7492	2	7.3283	1

Based on Table 17, it can be concluded that there was a significant disparity between the result generated through the proposed model and classical WA. For example, the proposed model assigned Speedmart as the store with the finest image but, based on classical WA, Big Shop appeared as the most preferred store. However, based on the data collected on the frequency of purchasing at each of the store (through section A of the questionnaire) which are summarized into Table 18, it was discovered that 82.85 % of the respondents purchase at Speedmart for at least twice in a month. Meanwhile, 72.55% of the same group of housewives purchase at Billion for at least twice in a month. Only 52.94% of the housewives purchase at Billion for at least twice a month.

Table 18: Frequency of purchasing at each store

Stores	Frequency of purchasing at each of the store	Percentage (%) of respondents
Billion	Once in a month	47.06
	Twice in a month	25.49
	More than twice in a month	27.45
	SUM	100
Speedmart	Once in a month	17.65
	Twice in a month	23.53
	More than twice in a month	58.82
	SUM	100
Big Shop	Once in a month	27.45
	Twice in a month	21.57
	More than twice in a month	50.98
	SUM	100

Obviously, in actual scenario, Speedmart appeared as their first choice store then followed by Big Shop and Billion. By using this order as the benchmark ranking, it can be concluded that the proposed model manage to yield a ranking which is closer to the actual ranking in comparison to the classical WA for this specific case study. It depends on the retailers either to choice the proposed model or to simply adhere to the common WA before conducting the evaluation. Nevertheless, if they believe that the attributes are interacted to each other then, the proposed model is recommended.

4.12. Discussion on the result

In this empirical study, the proposed model was applied in order to assess the image of three chain stores located in Pekan Sabak from the viewpoints of all the housewives who are residing at Sabak Bernam Plantation Estate. The result of the analysis can be summarized as follows.

Through the proposed model, the thirteen attributes which were finalized to characterize the image of the stores, were then clustered into five main factors namely in-store experience, first impression, customer care, assortment, and checkout factors. The prioritization on these five store image factors based on the proposed model was as follows. In-store experience (0.4091) ≥ assortment (0.2503) ≥ first impression (0.1532) ≥ customer care (0.0937) ≥ checkout (0.0937). It was understood that both in-store experience and assortment factors played major role in forming positive image on the stores from the housewives' perception. This showed that the retailer of each store should concentrate more on preserving satisfactory in-store experience and assortment aspects.

In addition, the interaction parameter of service factor, $\lambda = -0.7470$ indicated that in order to improve the image of a store in term of in-store experience, it is sufficient to simultaneously enhance some of the attributes which had higher individual weights such as quality of product (0.6250) and cleanliness (0.3750). In general, if the customers know that the products are being in good quality, the customer would consider the prices are reasonable and acceptable where they should be willing to pay the prices [38]. Besides, a clean store always plays a role in creating pleasing internal atmosphere for purchasing [39, 40] and encourages the customers to purchase longer or revisit the store [41]. In addition, the acceptance on the pricing could be high during purchasing if the internal environment of the specific store is clean and pleasurable as claimed in [42].

Meanwhile, the interaction parameter, λ= 0.1922 implied that in order to significantly improve the customers' first impression on a store, all the attributes such as products display (0.1875), staff (0.3125), storefront (0.3125), and layout (0.1250) have to be enhanced simultaneously regardless of their individual weights. The similar approach can be applied in order to augment the customer care factor as it had a positively valued interaction parameter, $\lambda = 0.5029$.

According to the proposed model, the ranking of the stores based on global image scores was as follows. Speedmart ≥ Big Shop ≥ Billion. Speedmart ruled the top position as it had satisfactory scores with respect to in-store experience factor, which was the main determinant of the stores' image. However, to retain the position and to form a greater image among the customers, the retailer could broaden the assortment of products (the second main determinant) in the store. From our observation, Speedmart does not carry much variety in food stuffs and there is no clothing section in the store in contrary to Billion and Big Shop. Big Shop has the potential to be in top position in future if the retailer puts major efforts on creating a satisfactory in-store experience by simultaneously assuring the quality of products is in high standard and ensure the store is always clean.

Meanwhile, Billion was identified as the store with most unfavorable image due to its unsatisfactory performance with respect to in-store experience and first impression aspects. Thus, appropriate strategies should be planned to achieve perfection in those aspects. With an average score in in-store experience factor, the retailer should focus on bringing in more quality products and assure the store is being cleaned timely and flawlessly. Besides, to improve the customers' first impression on the store, the retailer should simultaneously enhance all the attributes that influence the factor (display, staff, storefront, and layout), regardless of their individual weights.

The same problem was analyzed using a classical AW operator to demonstrate the consequence of ignoring the interactions between attributes. As a result, a dissimilar ranking as follows was obtained. Big Shop ≥ Speedmart ≥ Billion. However, it was discovered that the ranking generated by the proposed model was matching with the benchmark ranking. Yet, the choice of retailers between these two models depends on their interest whether to deal with the interaction aspects. It has to be notified that the paper was only interested to investigate the image of the stores from the viewpoints of housewives who are dwelling at Sabak Bernam Estate. The derived result was solely based on the perception of housewives staying in the estate. Therefore, the result is not a total representative of all the housewives living in Sabak.

5. Conclusion

The paper has finally presented a new hybrid MADM model which is tested and proven to be feasible in assessing the images of a set of stores from the customers' perspective. The model was developed by converging five main components namely factor analysis, Sugeno measure, Choquet integral, MFAHP, and WA operator. With the inclusion of the Choquet integral and its associated sugeno measure, the global image score of each store and strategies for image enhancement are identified by modeling and understanding the interaction aspects between store attributes. The presence of factor analysis and MFAHP helps the retailers to understand the actual determinants or factors contributing to a positive store image together with their priorities. Besides, the model enables the respondents or experts to provide or express their preferences in natural languages as way to deal with the usual uncertainty integrated with human's thought by utilizing the idea of fuzzy numbers. In addition, through the proposed model, the actual number of monotone measure weights which need to be identified prior to applying Choquet integral can be reduced from 2^n to $\sum_{p=1}^{q} 2^{|f_p|}$ where n represents the number of attributes,$f_p = (f_1, f_1, \ldots, f_q)$denotes the set of extracted factors, q is the total number of factors, and $|f_p|$ represents the number of attributes within factor, p.

To demonstrate the workability of the proposed model, a real image evaluation problem involving three stores in Pekan Sabak was performed using the model where some potential strategies have been proposed by adhering to the derived result. Besides, the ranking of the three stores yielded via the model was found to be matching with the benchmark ranking unlike the ranking generated by the classical aggregation model (AW operator) which assumes the attributes are independent to each other. Therefore, the retailers are recommended to utilize the proposed model in the scenario where they believe the attributes are interacted to each other,for a more trustworthy result.

For future studies, the proposed model can be employed in other real MADM problems occurring in different domains. Besides, the target population in the presented case study can be extended in future where the images of the stores can be investigated based on the viewpoints of all housewives dwelling in Sabak division by adhering to the same list of attributes. Further enhancing the proposed model is a commendable direction for future work. For example, as the proposed model could sometimes demand massive size of datasets to perform factor analysis, future research can focus on finding a simpler technique for clustering large set of attributes into fewer independent factors and swap it appropriately into the proposed model.

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