

DISCOVERING THE HOTEL SELECTION PREFERENCES OF HONG KONG INBOUND TRAVELERS USING THE CHOQUET INTEGRAL

ABSTRACT

Modeling MCDM requires the simultaneous consideration of multiple criteria but traditional statistical techniques can only evaluate these factors independently. As such, it is vital for managers to have a clear picture of customers' preferences in order to design more focused marketing strategies; whereas the existing body of work is unable to meet such a requirement. To tackle these challenges, we introduce a new technique based on deploying an aggregation function, the Choquet Integral (CI), in the tourism context. Focusing on a case study of the Hong Kong hotel industry, we demonstrate how this technique can be used to discover the preferences among travelers that affect their hotel selections. A set of criteria based on these preference profiles is then constructed. The findings are expected to benefit tourism managers worldwide.

Keywords: Hotel Preference, Data Mining, Travel Behavior, Choquet Integral, Aggregation Function, Fuzzy Measure, Interaction Index.

1. INTRODUCTION

The choice of accommodation is a high priority for most overseas travelers. It is also an example of a complicated decision-making process (Sohrabi, Raeesi, Tahmasebipur, & Fazli, 2012). A good understanding of travelers' behavior and preferences can assist tourism managers in strategic planning and decision making, which are the keys to business success (Rong, Vu, Law, & Li, 2012).

Hotel managers have long sought to identify the factors influencing travelers' selections (Matilla & O'Neill, 2003; Lockyer, 2005a). Many studies have been conducted to study the selection criteria that affect customers' choice intentions. For instance, Lockyer (2005b) identified factors such as location, price, facilities, and cleanliness as having a strong influence on travelers' hotel selections. Other criteria of interest to travelers are location, size of guest rooms, staff, facilities, and breakfast (Stringam, Gerdes, & Vanleeuwen, 2010). Recently, Merlo and de Souza Joao (2011) identified three attributes of the low-priced hotel segment that are more valuable in terms of improving consumer satisfaction: cleanliness, silence, and air conditioning. Ariffin and Maghzi (2011) demonstrated that expectations of hotels are influenced by personal factors such as gender, purpose of stay, nationality, culture, and the private domain of hospitality.

In fact, selection criteria preferences are significantly influenced by travelers' purpose (McCleary, Weaver, & Hutchinson, 1993) and background (Reisinger & Turner, 1997). Accordingly, there is a need to develop an insightful understanding of these factors and how they interact with travelers' preferences. With regard to background differences, Gilbert and Tsao (2000) used exploratory analysis to examine differences in the relationship between culture and hospitality marketing. They showed that Chinese customers care more about price and brand name whereas Western

customers focus more on quality and value for money. In studying the influence of trip purpose, Chu and Choi (2000) used importance-performance analysis to explore the perceived importance and performance of a range of selection factors in the context of the Hong Kong hotel industry, focusing on both business and leisure travelers.

In addition, attention has been paid to identifying the relative importance of each factor in determining travelers' overall satisfaction levels. Once these criteria have been identified and evaluated, managers can consider and develop their practices in order to focus on what is important to customers so that service quality as well as customer satisfaction can be improved (Israeli, 2000). For instance, using factor analysis, Choi and Chu (2001) showed that service quality, room quality, and value were the most influential factors in determining travelers' overall impression of the selected hotels. Aiming to identify the factors most likely to influence vacationers' perceptions, Shergill and Sun (2004) examined overall facilities, room facilities, and service in New Zealand hotels. More recently, Tsai, Yeung, and Yim (2011) used descriptive statistics and an independent-samples t-test to compare the importance ratings assigned to various hotel selection criteria by Mainland Chinese and foreign travelers to Hong Kong.

Despite the considerable research efforts in this area, hotel managers who want to understand travelers' behavior and decision making in order to inform effective planning still face the following two major barriers.

Travelers' Multiple-criteria Decision-making (MCDM) Process: Understanding this process is an effective strategy for improving products. For instance, one traveler may give a hotel a low rating for the room quality and service criteria but still selects it on the basis that it is clean. Other travelers may select a hotel only if it satisfies both the room quality and service criteria. An understanding

of how such criteria interact in guiding customers' decision-making intentions can provide managers with an insight into their preferences. Modeling MCDM requires the simultaneous consideration of multiple criteria; whereas most studies so far have focused mainly on evaluating these independently using various statistical techniques. Therefore, there is still a strong demand for a technique which will enable the exploration of travelers' MCDM process.

Travelers' Preference Profile: It is crucial for tourism managers to be able to identify their target customers so as to design more suitable products and to focus their marketing strategies. This task requires complete preference profiles to be compiled about, and for, different groups. However, few studies have evaluated either the factors influencing customers or customers' profiles (Tanford, Raab, & Kim, 2012), and no study has yet been able to provide a complete preference profile.

Over the past decade, fuzzy decision support has emerged as a means of providing effective tools and techniques for solving MCDM problems. Grabisch and Roubens (2000) used the aggregation function, a fuzzy decision-support technique, to support the MCDM process in a game theory context. Lu, Deng, Vroman, Zeng, Ma, and Zhang (2008) proposed a group MCDM method to evaluate nonwoven cosmetic product prototypes. Furthermore, a fuzzy system called Decider was implemented by Ma, Lu, and Zhang (2010); this system helps to increase overall satisfaction with a final decision across groups of respondents and deals with the uncertainty in solving an MCDM problem. Recently, more applications of fuzzy decision support for MCDM have been created (Deng, Vroman, Zeng, & Laouisset, 2010; Bazzari, Osanloo, & Karimi, 2011). Thus, it would be beneficial to consider the use of fuzzy decision-

support techniques in supporting business managers to understand travelers' MCDM process, particularly with regard to hotel selection.

In this study, we introduce a relatively new fuzzy decision-support technique based on an aggregation function named the Choquet Integral (CI) into the MCDM problem of hotel selection (Beliakov, Pradera, & Calvo, 2007). Our case study focuses on hotels in Hong Kong, a major Asian tourist destination. In 2010, Hong Kong attracted more than 36 million visitors, 21.8% more than in 2009 (HKTB, 2009). Over the same period, the average hotel occupancy rate in Hong Kong increased significantly, from 78% to 87%, with the average daily room rates for all hotels also experiencing remarkable growth (up 16.5% from \$960 to \$1,118) (HKTB, 2010). Such expansion has brought many new opportunities and challenges for researchers seeking to gain an insight into customers' behavior in order to support hotel managers in their business planning and decision making. Using the CI technique, the MCDM process of travelers can be modeled closer to reality, thus enabling a complete preference profile of travelers to Hong Kong to be constructed. This is a useful endeavor as the technique introduced here and the findings of this study will be valuable to hotel managers worldwide, and especially in Hong Kong, seeking to explore the potential of the growing tourism market.

Having set out the driver for undertaking this research, the rest of this paper is organized as follows. Section 2 reviews the existing work on the application of fuzzy decision-support techniques to modeling travelers' MCDM process, which is followed by a critical analysis of their limitations. Section 3 provides an overview of the concept of the aggregation function and related metrics used in this study. Section 4 describes the experimental design and data collection and then reports the results and analyzes

the findings with reference to customer preferences and preference changes. Section 5 summarizes the study and offers suggestions for future work.

2. RELATED WORK

In this section, we firstly review existing studies that have applied fuzzy decision-support concepts in modeling travelers' behavior. We then provide a critical analysis of their limitations and define our research objectives.

2.1. Fuzzy Decision Support for Decision Making Modeling

The field of tourism research has witnessed a number of attempts to apply fuzzy decision-support techniques to the modeling of MCDM process of travelers. In an early study carried out by Ngai and Wat (2003), a fuzzy expert system using fuzzy logic was developed to assist tourists in making their hotel selection. Later, Chou, Hsu, and Chen (2008) made use of the fuzzy analytic hierarchy process and triangular fuzzy numbers to consolidate decision makers' assessments of criteria weighting in identifying international tourists' hotel location selections in Taiwan. Similarly, Chen, Tseng, and Lin (2008) applied a fuzzy method called Dematel to linguistic information for group decision making and developed a cause and effect model for expectations of service quality at hot springs. Recently, Hsu, Tsai, and Wu (2009) combined fuzzy set theory with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to identify the factors influencing tourists' choice of destination and to evaluate their preferences. Using a fuzzy logic approach, Noor, Ahm, Ali, and Ismail (2010) proposed a prototype system called the Tourism Advisory System to assist tourists in planning their travel. Sohrabi, Raeesi, Tahmasebipur, and Fazli (2012) recently provided a fuzzy membership function based on the intrinsic vagueness of the selection process for

analyzing hotel selection factors. The models of the fuzzy membership function can be seen as logical models that use “if-then” rules to establish qualitative and quantitative relationships among variables. Because of the nature of rule-based models, the use of information can be expressed in the form of natural language statements, thus making the model transparent for interpretation (Vernieuwe, Georgieva, De Baets, Pauwels, Verhoest, & De Troch, 2005).

2.2. Problem Definition and Research Objectives

Some attempts have been made in general to use fuzzy decision-support techniques for preference analysis. However, only a limited number of these works were devoted to studying travelers’ hotel preferences. The recent work of Sohrabi, Raeesi, Tahmasebipur, and Fazli (2012), which assesses hotel selection factors, is probably the closest in this regard. In their work, the important hotel factors were identified using factor analysis from a survey dataset collected from travelers staying at selected hotels in Tehran. The limitation of this work is that the profile information of the respondents was not considered; the preferences between different travelers may not be the same but rather may depend on their travel purpose (McCleary, Weaver, & Hutchinson, 1993) and background (Reisinger & Turner, 1997). Thus, detailed knowledge about the preferences of each travel group has not been discovered. No study has yet resulted in the construction of a complete traveler preference profile, especially in relation to hotels, to address the challenges of modeling traveler decision-making process. Thus, there is still a high demand for studies on travelers’ hotel preferences.

In terms of methodology, techniques such as fuzzy logic, fuzzy rule, and fuzzy number have been incorporated into the analyses of travelers’ preferences. These techniques allow the assessment of preference through the weighting and aggregation

of criteria, which helps to identify the important criteria in the decision-making process of travelers. Nevertheless, these techniques have a limitation which derives mainly from their natural assumption that the input criteria are independent of each other. As shown by Chou, Hsu, and Chen (2008) as well as Hsu, Tsai, and Wu (2009), a weight is assigned for each input criterion in the modeling process and each criterion is interpreted independently. Such an assumption is not always true in reality, where the independence of criteria cannot be assumed and some interactions among different criteria, including *independence*, *complement*, and *correlation*, do exist (Grabisch & Roubens, 2000). For instance, two criteria which have a correlating relationship, such as *room quality* and *cleanliness*, may refer to the same concept. It is not possible to discover such interactions through an interpretation of their importance via the weight assigned to each criterion. In order to take all interactions among attributes into account, the use of a *fuzzy measure* in the calculation of aggregation function for MCDM modeling has been proposed. CI is one such technique which enables the importance not only of each criterion but also of each group of criteria to be considered (Beliakov et al., 2007). In addition, its properties, the Shapley value and the Interaction Index, offer good potential in terms of providing representations of the overall importance of each criterion and the interaction between the criteria.

With the aim of addressing the shortcomings of existing approaches in the hotel industry, the objectives of this study are as follows:

- To introduce a new aggregation function (the CI) into the hotel industry to provide more accurate modeling of travelers' MCDM process in relation to hotel selection. Using the Shapley value and the interaction index, the insights it offers into travelers' preferences and the interaction between criteria will be explored.

- To construct a preference profile of travelers to Hong Kong with respect to their purposes and backgrounds and to explore the interactions among selection criteria to arrive at an insightful understanding of travelers' decision-making process.

3. METHODOLOGY

This section firstly provides a formal definition of the aggregation function and then introduces the fuzzy measure that is used to compute the CI. Methods for computing the Shapley value and the interaction index are then described.

3.1. Aggregation Function

The MCDM process involves the comparison of two or more alternatives, each being evaluated against multiple or n criteria according to the decision maker's priorities. The degree to which an alternative satisfies a criterion corresponds to a utility value. The scores must then be combined in some ways to produce an overall rating for that alternative. Such a process is very similar to an *aggregation function*, which combines several inputs into a single representative output (Beliakov, Pradera, & Calvo, 2007). In this paper, the inputs and outputs are defined on the unit interval $[0,1]$; however, other choices are possible. Formally, an aggregation function is defined as a function of $n > 1$ arguments $f: [0,1]^n \rightarrow [0,1]$ with the following properties:

$$(3.1a) \quad f(x_1, x_2, \dots, x_n) = \begin{cases} 0, & \text{if } x_i = 0, \forall i \\ 1, & \text{if } x_i = 1, \forall i \end{cases}$$

$$(3.1b) \quad \mathbf{x} \leq \mathbf{y} \text{ implies } f(\mathbf{x}) \leq f(\mathbf{y}), \forall \mathbf{x}, \mathbf{y} \in [0,1]^n.$$

Equation 3.1a presents the boundary condition of this aggregation function. Equation 3.1b presents the monotonicity, which is understood component-wise, with an

output that does not decrease with increases in any of the inputs. Here, \mathbf{x} denotes a vector of input criteria $\{x_1, x_2, \dots, x_n\}$; thus $f(x_1, x_2, \dots, x_n)$ is equivalent to $f(\mathbf{x})$.

Aggregation functions can be assigned to classes with certain properties. One of the most widely used classes of functions is the averaging aggregation, which is bounded by its value by $\min(\mathbf{x}) \leq f(\mathbf{x}) \leq \max(\mathbf{x}), \forall \mathbf{x} \in [0,1]^n$. The term ‘‘average’’ is commonly employed in everyday language when referring to the *arithmetic mean* (AM). In case some criteria are considered as more important than others, it is common to consider the aggregation function to be additive and to take the form of a *weighted arithmetic mean* (WAM) (Torra & Narukawa, 2007), an *ordered weighted averaging* (OWA) (Yager, 1998).

The AM of n values is the function

$$(3.2) \quad M(\mathbf{x}) = \frac{1}{n} (x_1 + x_2 + \dots + x_n) = \frac{1}{n} \sum_{i=1}^n x_i$$

WAM is a linear function with respect to a positive valued weighting vector w with $\sum_{i=1}^n w_i = 1$:

$$(3.3) \quad M_w(\mathbf{x}) = w_1 x_1 + w_2 x_2 + \dots + w_n x_n = \sum_{i=1}^n w_i x_i$$

For a given weighting vector w with $\sum_{i=1}^n w_i = 1, w_i \geq 0$, OWA is defined by

$$(3.4) \quad OWA_w(\mathbf{x}) = \sum_{i=1}^n w_i x_{(i)}$$

The notion $(.)$ denotes that the arguments of x are arranged in a *non-decreasing* order $x_{(1)} \geq x_{(2)} \geq \dots \geq x_{(n)}$.

Although the WAM has been widely used, it can only be used in the presence of independent criteria, which is not appropriate for the aggregation of interacting

criteria in the MCDM process (Marichal, 2002). The OWA can, to some extent, account for the interaction among criteria, but it only considers the relative weighting of individuals; whereas the evaluation of the MCDM process is usually performed under conditions in which there are relative influences within groups of criteria. Hence, in this work, we chose another aggregation function, the CI, which is defined with respect to a fuzzy measure that takes into account the interplay of non-independent criteria (Torra & Narukawa, 2008).

3.2. Fuzzy Measures

This section introduces the fuzzy measure used to compute the CI. Let $N = \{x_1, x_2, \dots, x_n\}$ be a set of input criteria. A discrete fuzzy measure is a set function $v : 2^N \rightarrow [0, 1]$ which is monotonic (that is, $v(A) \leq v(B)$ whenever $A \subset B$) and satisfies $v(\emptyset) = 0$ and $v(N) = 1$. Since subset $A \subseteq N$ can be considered to be a *group of criteria*, $v(A)$ is able to represent its importance or weight. Note that the monotonicity condition implies that its weight is not decreased when new elements are added to a group. A fuzzy measure can be presented as an array based on a Hasse diagram (Beliakov et al., 2007). In the case $N = \{x_1, x_2, x_3\}$, the representation of fuzzy measures is shown as

$$\begin{array}{c}
 v(\{1,2,3\}) \\
 v(\{1,2\}) \quad v(\{1,3\}) \quad v(\{2,3\}) \\
 v(\{1\}) \quad v(\{2\}) \quad v(\{3\}) \\
 v(\emptyset)
 \end{array}$$

The discrete CI with respect to a fuzzy measure v is given by

$$(3.5) \quad C_v(\mathbf{x}) = \sum_{i=1}^n x_{(i)} [v(\{j | x_j \geq x_{(i)}\}) - v(\{j | x_j \geq x_{(i+1)}\})]$$

where $x_{(1)}, x_{(2)}, \dots, x_{(n)}$ is a non-decreasing permutation of the input \mathbf{x} , and

$x_{(n+1)} = \infty$ by convention.

Example 1. Given an input $\mathbf{x} = (0.4, 0.3, 0.8)$ and the fuzzy measure values

		1	
	0.5	0.6	0.9
	0.5	0.4	0.1
		0	

To calculate the CI, the input x is arranged in a non-decreasing order (0.3, 0.4, 0.8). Then, the result obtained from the input \mathbf{x} is

$$\begin{aligned}
 C_v(\mathbf{x}) &= 0.3[v(\{1, 2, 3\}) - v(\{1, 3\})] + 0.4[v(\{1, 3\}) - v(\{3\})] + 0.8v(\{3\}) \\
 &= 0.3(1 - 0.6) + 0.4(0.6 - 0.1) + 0.8(0.1) \\
 &= 0.3(0.4) + 0.4(0.5) + 0.8(0.1) \\
 &= 0.4.
 \end{aligned}$$

This value falls between the maximum and the minimum input expected in the bounding condition of averaging functions.

In this paper, we consider two special types of fuzzy measure:

- The *additive* fuzzy measure $v(A \cup B) = v(A) + v(B)$ whenever $A \cap B = \emptyset$.
- The *symmetric* fuzzy measure $v(A) = v(B)$ whenever $|A| = |B|$.

The CI corresponds to the WAM and OWA functions when it is defined by the *additive* and *symmetric* fuzzy measures, respectively (Beliakov et al., 2007). Typically, CI is a more general form of WAM and OWA, and it is more flexible for modeling the MCDM process.

In addition, we consider the issue of *k-additivity*, a recently developed concept for reducing the complexity of the fuzzy measure (Grabisch, 1997a). The interactions between criteria are only considered for subsets of k elements or less, which reduces the number of variables to define the fuzzy measure. It allows for a trade-off between modeling ability and complexity. A decision maker can decide how complex a fuzzy measure that s/he wishes to consider by selecting a *k-additive* value ($1 \leq k \leq n$). It

should be noted that the WAM is equivalent to CI defined by 1-additive fuzzy measure. The fuzzy measures are said to be unrestricted when $k = n$.

3.3. Shapley Value

The Shapley value is used to measure the overall importance of each criterion in terms of its contribution to the score of each *group of criteria*. It can enable a good estimate of the importance of each criterion to the MCDM of travelers to be constructed.

Let v be a fuzzy measure and $N = \{x_1, x_2, \dots, x_n\}$ be the set of criteria. The Shapley index for every input $x_i \in N$ is

$$(3.6) \quad \Phi_i = \sum_{A \subseteq N \setminus \{x_i\}} \frac{(n - |A| - 1)! |A|!}{n!} [v(A \cup \{x_i\}) - v(A)]$$

The Shapley value is the vector $\Phi(v) = \Phi_1, \Phi_2, \dots, \Phi_n$. The index Φ_i can be interpreted as a kind of average value of the contribution of criteria x_i in all groups of criteria. It also represents a true sharing of the total amount $v(N)$ as it must satisfy the condition $\sum_{i=1}^n \Phi_i = 1$.

3.4. Interaction Index

The interaction indices are interpreted as the behaviors of criteria in groups or as a measurement of the interaction among criteria in the decision-making process.

Let $N = \{x_1, x_2, \dots, x_n\}$ be the set of criteria, the interaction index for every set $A \subseteq N$:

$$(3.7) \quad I(A) = \sum_{B \subseteq N \setminus A} \frac{(n - |B| - |A|)! |B|!}{(n - |A| + 1)!} \sum_{C \subseteq A} (-1)^{|A \setminus C|} v(B \cup C)$$

It should be noted that $I(A) \in [-1, 1]$ can include all combinations of groups of criteria. However, the interaction index I_{ij} for each pair $A = \{x_i, x_j\}$ of criteria is

used most often due to its convenience of interpretation. For a pair of criteria x_i and x_j , if they have a positive interaction (*complement*), then $I_{ij} > 0$. Similarly, if x_i and x_j have a negative interaction (*correlation*), then $I_{ij} < 0$. When x_i and x_j have little or no interaction (*independence*), $I_{ij} \approx 0$. This measure is more than just the interaction between a pair of criteria themselves: Each pair is considered in the presence of all groups. It may be that two criteria interact positively in isolation but in larger groups make little contribution. Such behavior can be measured using an interaction index.

3.5. Justification

From the previous section, we can see that the advantage of CI lies in the fact that the fuzzy measure can account for the importance and the interaction between every subset of criteria. Let us take a simple example that is similar to the work of Marichal and Roubens (2006), to illustrate this advantage.

Example 2. A traveler wants to choose a hotel that is cheap, clean, and has good service. The options have been narrowed down to four choices with the following utility values:

	Price	Cleanliness	Service
Hotel A	0.7	0.6	0.9
Hotel B	0.6	0.7	0.9
Hotel C	0.6	0.7	0.4
Hotel D	0.7	0.6	0.4

The traveler starts the decision-making process by giving a ranking to the hotels. The traveler automatically suggests that Hotel A is ranked higher than Hotel D and Hotel B is ranked higher than Hotel C. Here, these rankings reflect some preferences over the criteria, and they follow the monotonicity of the preference

relation. Besides, the traveler realizes that some unobvious comparisons exist between hotel pairs A vs. B and C vs. D due to the interlacement of criteria (*price* and *cleanliness*). He/she might adopt the following reasoning: *If a hotel has good service, it is considered more important if it also has a good price, so Hotel A is ranked higher than Hotel B; if a hotel has poor service, then it is more important that it is clean, so Hotel C is ranked higher than Hotel D.* This leads to the ranking order $A > B > C > D$.

Here, the question arises: *Can an additive model, such as WAM, lead to this partial ranking?* Let w_1, w_2, w_3 be the weights of the hotel criteria of price, cleanliness, and service respectively. If the WAM model is used, the order $A > B$ holds when the weights satisfy $w_1 > w_2$ and the order $C > D$ holds when $w_1 < w_2$. We can see that there is no such weight for WAM to produce the proposed ranking order. The reasoning made by the traveler is an example of a complex decision-making process in a real situation. A model such as WAM cannot capture this well. This problem originates from the fact that the criteria are not mutually independent; rather, there are some interactions between them, and the weight of criteria should be considered in the group of criteria. The OWA also has a similar limitation to WAM, where only the weight of individuals is taken into account. It is proposed that a suitable fuzzy measure and the CI can solve this problem.

Suppose we use the CI to model the decision-making process of the traveler with an unrestricted fuzzy measure and it arrives at the solution below:

Group of criteria	Weight
$v(\emptyset)$	0
$v(\{\text{price}\})$	0.4
$v(\{\text{cleanliness}\})$	0.3
$v(\{\text{service}\})$	0.75

$v(\{\text{price, cleanliness}\})$	0.2
$v(\{\text{price, service}\})$	0.9
$v(\{\text{cleanliness, service}\})$	0.6
$v(\{\text{price, cleanliness, service}\})$	1

Here, a weight is assigned for each subset of criteria rather than for individual criterion. Following Equation 3.5, the CI values computed from this fuzzy measure are as follows:

	Hotel A	Hotel B	Hotel C	Hotel D
$C(.)$	0.73	0.7	0.59	0.58

The ranking based on the computed CI values satisfies the ranking order given by the traveler ($A > B > C > D$).

This example illustrates that the use of CI with an unrestricted fuzzy measure provides a flexible way of modeling the complex decision making of travelers. It allows consideration of the importance and interaction of all possible subsets of criteria, something which WAM and OWA cannot do.

3.6. Summary

In general, fuzzy measures and aggregation functions have been used in various applications such as multi-criteria evaluation (Jiang & Eastman, 2000), decision making (Grabisch & Roubens, 2000; Meyer & Roubens, 2006), and classification (Beliakov & James, 2011). In this paper, we explore its capability to analyze customers' attitudes by using two metrics for measuring the importance and interaction of criteria (the Shapley value and the interaction index).

We used a software package, *FMTtools* (Beliakov, 2007), to evaluate the CI and perform operations on fuzzy measures. *FMTtools* includes a fuzzy measure

estimation program, *fmfitting*, which is an executable file for MS Windows and Linux *i386*. It takes parameters from a configuration file. Some basic parameters for the input file are N (the number of input arguments), M (the number of data instances), *dataset* (name of a file containing empirical data), *output* (name of output file), and k (k -additive value). Given a dataset containing M records in pairs $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2) \dots, (\mathbf{x}_M, y_M)$, where \mathbf{x}_i is composed of n criteria $x_{i(1)}, x_{i(2)}, \dots, x_{i(n)}$, and y_i is the observed aggregated value. A fuzzy measure ν can be estimated from this dataset such that the corresponding CI predicts the output $f(\mathbf{x}_i) = C_\nu(\mathbf{x}_i)$ as close as possible to the observed value y_i . Then, other values, such as the Shapley value and the interaction index, can be computed following equations 3.6 and 3.7.

4. EXPERIMENT AND ANALYSIS

In this section, we firstly describe our experimental dataset, which was collected from online reviews of Hong Kong hotels. The experimental design and analysis of the results are then presented with reference to tables and figures of Shapley values and interaction indices. The last subsection contains a summary of the study setting out the managerial implications and providing suggestions to hotel managers on how to improve travelers' satisfaction with their businesses.

4.1. Data Collection

The data used in this study were collected from TripAdvisor (www.tripadvisor.com), a well-known travel review Web site frequently used for analyzing travelers' opinions (Blair-Goldensohn, York, Hannan, York, McDonald, Neylon, Reis, & Reynar, 2008; Wang, Lu, & Zhai, 2010). Each review contains ratings for popular hotel criteria, including value for money (*Value*), hotel location (*Location*),

quality of sleep (*Sleep*), quality of room (*Room*), room cleanliness (*Cleanliness*), and additional service (*Service*) as well as an overall rating. The ratings are reported on a scale from 1 (very unsatisfied) to 5 (very satisfied). We used professional data extraction software, Visual Web Ripper (www.visualwebripper.com), to extract user ratings together with demographic data about the reviewers such as travel type (business, family, couple) and country of origin. The software navigated through all listed hotels in Hong Kong and extracted all of the review ratings. Approximately 12,000 records were collected.

4.2. Experimental Design

In tourism research, it is suggested that people's behavior and decisions are guided by the profound effects of national culture (Reisinger & Turner, 1997), and hence there is a link between cultural values and hotel ratings (Leung, Lee, & Law, 2011). Furthermore, people from different continents come from different backgrounds (Khadaroo & Seetanah, 2008). Therefore, in this study, we grouped regions according to reviewers' continent of origin as a preparatory step in the profile-construction task. It was interesting to note that the majority of people who traveled to Hong Kong and posted review comments came from North America, Europe, Asia, and Oceania, with only a few people from South America and Africa; for this reason, only the first four continents are considered in this research.

We also noticed that most of the reviews on TripAdvisor for Hong Kong hotels were created in 2010 and 2011 and some reviewers did not provide ratings for all six criteria, resulting in missing values. We only took the reviews from the year 2011 into consideration and removed the records where data were missing. The data for the year 2011 was used because this is the latest dataset, thus the findings are more up-to-date.

This left us with 5,443 instances. Table 1 shows the structure of the collected dataset with respect to travel types and regions.

***** Please place Table 1 here *****

The aim of this study is to explore the hotel criteria preferences of travelers to Hong Kong. We analyzed the following cases:

- **Preference profile construction:** We constructed a detailed profile of hotel preferences with respect to both travel type and region of origin of travelers to Hong Kong by analyzing Shapley values.
- **Interaction Analysis of Selection Criteria:** Since a major advantage of the CI is its ability to assess the interaction between criteria, we demonstrate its usage by analyzing the interaction index for each traveler group as defined in the previous case.

Note that the input data values for the CI are in the range $[0, 1]$. Therefore, we normalized all hotel rating scores into this range before fitting them into the *fmfitting* function.

Since the CI claims to model the MCDM process of travelers better than previous typical methods, we aimed to evaluate its performance on these datasets. The mean absolute error (MAE) was adapted to measure the prediction error:

$$(4.1) \quad MAE = \frac{1}{M} \sum_{i=1}^M |y_i - f(\mathbf{x}_i)|$$

where M is the total number of instances to be evaluated, y_i is the value of the i^{th} input instance to be predicted and $f(\mathbf{x}_i)$ is the predicted value of y_i .

4.3. Results and Analysis

4.3.1 Model Evaluation

In this section, we evaluate the performance of the CI against other algorithms (AM, WAM, and OWA) in modeling travelers' decision making. Particularly for CI, we also consider the impact of *k-additive* by performing the experiment with different values of *k*. Each sub-dataset in Table 1 was inputted into these algorithms using the 10-fold cross-validation strategy. The algorithms are fitted to the data set so as to minimize the absolute difference between predicted and observed values. MAE values, reflecting the prediction error, are presented in Table 2.

*****Please place Table 2 here *****

As shown in Table 2, the overall MAE values indicate that the performance of CI (when $k > 1$) appears to outperform other algorithms. Its performance is similar to WAM only when $k = 1$, because the fuzzy measure was restricted to individual criterion, and for this reason, the CI was reduced to the WAM. Here, the overall values are the averages of the MAE values for each algorithm on the sub-datasets. The overall performance of CI increased as *k* increased, and it achieved the best performance when $k = 6$. This was the result of the fuzzy measure being less restricted, where more possible combinations of input criteria were considered. This evidence supports the claim that the use of the CI with less restricted fuzzy measures can model the MCDM process in a way that is closer to reality.

For each individual dataset, the best performance is indicated by the lowest MAE value, which highlighted by an underline. CI achieved the lowest prediction error on every sub-dataset. . Besides, we noticed that the performance of CI on each individual dataset is not necessarily increasing when *k* increases; its best performance is not always achieved with $k = 6$. This reflects the fact that the model is getting more complicated as *k* increases, while the available data for some sub-datasets are limited and may not fully cover the domain of the model. The use of $k < 6$ could be

considered in modeling the MCDM of travelers in different groups to reduce the complexity of the CI model. Even though, the overall performances of CI is still significantly better than the other algorithms when $k > 1$.

4.3.2 Preference Profile Construction

For business managers, the study of customer profiles is crucial in designing effective marketing strategies. In this case study, we constructed a hotel preference profile of travelers from different regions and with different traveling purposes. The collected dataset was divided into subsets according to travel type and region, as shown in Table 1, and inputted into the *fmfitting* function. The fuzzy measure was set to be unrestricted ($k = 6$) because, in general, this allows the CI to best model the MCDM process of travelers. The Shapley values, indicating the importance of hotel criteria for different travel groups, are shown in Table 3.

***** Please place Table 3 here *****

The hotel preference profile of visitors traveling to Hong Kong can be constructed as follows:

Business Group: In general, there are significant variations among the Shapley values of hotel criteria, and the preferences of people from different regions are also different. More specifically, Asian travelers care most about the service criterion while paying very little attention to room quality. On the other hand, European travelers value both room quality and service but do not care much about sleep quality and cleanliness. The sleep quality criterion is also considered as unimportant by North American travelers. For travelers from Oceania, the preferred criterion is value for money, whereas cleanliness and service are ranked as being of lowest importance. It is also interesting to see that while the service criterion is highly ranked by travelers from most

regions (as shown by its Shapley values of 0.25 or higher), travelers from Oceania do not care about this criterion at all (value of less than 0.1).

Couple Group: Since most of the Shapley values fall between 0.1 and 0.25, the preferences of couples are quite well-distributed across the criteria. However, it can be seen that Asian couples pay close attention to value for money when they are traveling with their partners and that cleanliness is relatively important to couples from North America and Oceania. North American couples pay the least attention to location criteria, and sleep quality is the least important criterion for couples from Oceania.

Family Group: Among travelers accompanied by their families, it appears that there is no significant preference; most of the Shapley values are below 0.25. Among Asian families, the sleep quality criterion is the lowest ranked, while the location criterion is the least important to European families. For all families except those from Oceania, hotel service is considered important but cleanliness is not.

4.3.3 *Interaction analysis of selection criteria*

Another advantage of the CI is its ability to provide insights into the interaction between criteria through the interpretation of interaction index. When the unrestricted fuzzy measure ($k = 6$) is used to model the MCDM process of travelers, the interactive indexes for every possible combination of selection criteria can be computed following equation 3.7. However, the interpretation of interaction indexes for more than 2 criteria is much more difficult; thus 2-additive fuzzy measures is suggested to be sufficient for a semantic analysis (Grabisch, 1997b). The sub-datasets were inputted into the *fmsfitting* function with $k = 2$, then interaction indices for every pair of criteria were computed. It should be noted that the overall modeling

capability of CI in this case is still better than other algorithms as demonstrated in Section 4.3.1. The pair-wise interaction indices corresponding to different travel groups (business, couple, and family) are presented in Tables 4, 5, and 6.

***** Please place Table 4 here *****

*****Please place Table 5 here *****

***** Please place Table 6 here *****

From the pair-wise interactions of the hotel criteria in the tables, we can see that there are some significant interactions between different criteria in the selection processes of travelers. The interactions are also quite different across groups. This indicates that people from different regions and with different travel purposes engage in different decision-making processes. Accordingly, we make the following observations:

Business Travelers: Hotel selection criteria appear to have some interactions for business travelers from Asia, but no considerable interaction was found. For business travelers from Europe, the service criterion appears to be correlated with the value for money. Travelers' preferences for a hotel do not increase even if it satisfies both of these criteria. On the contrary, the service criterion has a significantly positive interaction with room in the decision-making processes of North American business travelers. This positive index indicates that the preference of these travelers for a hotel will increase significantly only if it can satisfy all of those criteria. For business travelers from Oceania, there appears to be no interaction between most pairs of the criteria. Only except for the pair of value versus room quality, where a strong negative interactions were found, as shown by the strong negative interaction index.

Couple Travelers: It is interesting to see that, value for money shows strong redundancy with the room quality criterion for couples from all four evaluating continents. These are indicated by strong negative interaction indexes. Apparently, the preference for these travelers does not increase if such a hotel also offers good value for money and high quality rooms. In contrast, slight positive interactions were found between cleanliness and service for travelers from Asia and Oceania.

Family Travelers: Most of the hotel criteria pairs for this travel group show little interaction, as indicated by the low interaction indices. Only a few significant interactions were found. For instance, in the case of North American families, value for money has a slight negative interaction with the room quality criterion. For families from Oceania, cleanliness has a complementary effect on the service criterion.

4.4 Discussion

The detailed analysis of the preference profiles in section 4.3.2 highlights the important criteria for travelers from different regions and groups. To be specific, we found that room quality is significant for business travelers from Europe and couples from North America and Oceania. Additionally, service is the focus of businesspeople from Asia, Europe, and North America and families from Oceania. Thus, hotel managers should give a high priority for improving these aspects of their offering. As well, their marketing strategies should be carefully designed to draw travelers' attention. In addition, the value for money criterion is important to Asian couples and businesspeople from Oceania; thus, cheaper packages with extra benefits could be designed to attract more travelers from these groups.

On the other hand, as presented in Section 4.3.3, the advantage of the fuzzy decision-support technique using the CI is its power to assess the interaction between criteria. For instance, in Table 4, the positive interaction between the room and service criteria for business travelers from North America suggests that hotels must improve both of these criteria at the same time in order to satisfy the expectations of this group. On the other hand, it is not necessary to improve the value for money and room quality criteria as there appears to be strong negative interactions between them for most couples as shown in Table 5. Such information is useful in enabling hotel managers to decide what to focus on in order to achieve the best outcome with minimal effort.

5. CONCLUSIONS

The effective modeling of travelers' MCDM process has always been of interest to researchers working to support managers' strategic planning and decision making. Traditional methods, such as factor analysis, statistical tests, and descriptive statistics, are not suitable for MCDM modeling, and the critical analysis presented in Section 2 shows that the current fuzzy decision-support techniques (such as fuzzy logic, fuzzy rules, and fuzzy numbers) are unable to explore the MCDM process fully and accurately. In addition, the literature suggests that factors such as travel purpose and background should be taken into account because they can have significant influences on travelers' preferences. As such, this study has introduced a new fuzzy decision-support technique for constructing preference profiles of travelers, thus enabling a better understanding of the hotel selection behavior of travelers to Hong Kong, a major Asian travel destination.

In this work, we have introduced a new fuzzy decision-support technique which uses the CI to model the real-life MCDM process of travelers. The analysis of Shapley values for travelers from different groups and regions enables a more complete profile to be constructed. Moreover, consumer behavior can be more clearly understood through an analysis of the interaction indices between or among selection criteria. As a consequence, managers can allocate their limited resources to improve the aspects of their hotels which are significant to different groups of travelers. As a result, they can have more confidence in their decision making while reducing the investment risk. It should be noted that the CI is not a domain-specific fuzzy decision-support technique. Its use is not limited to the hotel industry but can be applied widely in many other areas.

A future extension of this work could take additional criteria into consideration to extend the traveler preference profile. Furthermore, trends in travelers' preferences can be identified when more data become available in later years (such as 2012, 2013, and so on). This can provide business managers with further valuable information and prediction capability for long-term business planning. In addition, we intend to investigate the extent to which applications in other sectors of tourism, such as airlines, restaurants, and shopping, can be explored. Readers who wish to learn more about the Choquet Integral are suggested to use the latest Choquet Integral toolbox, Rfmtool (<http://www.tulip.org.au/resources/rfmtool>), which is distributed as a standard R package containing source code files, data samples and a case study.

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Table 1. Hotel Rating Data Collection.

Travel Type	Region	Number of Instances	ID
Business	Asia	344 instances	D ₁
	Europe	349 instances	D ₂
	North America	176 instances	D ₃
	Oceania	86 instances	D ₄
Couple	Asia	828 instances	D ₅
	Europe	986 instances	D ₆
	North America	433 instances	D ₇
	Oceania	500 instances	D ₈
Family	Asia	995 instances	D ₉
	Europe	246 instances	D ₁₀
	North America	214 instances	D ₁₁
	Oceania	286 instances	D ₁₂
Total:		5,443 instances	

Table 2. MAE Values of the Evaluated Algorithms

Sub Dataset	AM	WAM	OWA	CI					
				$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
D ₁	0.0729	0.0739	0.0733	0.0740	0.0737	0.0740	0.0709	<u>0.0686</u>	0.0692
D ₂	0.0645	0.0638	0.0639	0.0639	0.0615	0.0514	0.0507	<u>0.0486</u>	0.0496
D ₃	0.0600	0.0614	0.0592	0.0607	0.0605	<u>0.0402</u>	0.0425	0.0410	0.0407
D ₄	0.0643	0.0683	0.0632	0.0675	<u>0.0534</u>	0.0593	0.0577	0.0538	0.0554
D ₅	0.0707	0.0702	0.0666	0.0703	0.0676	0.0645	0.0632	0.0607	<u>0.0599</u>
D ₆	0.0588	0.0577	0.0573	0.0576	0.0548	0.0496	0.0511	0.0452	<u>0.0445</u>
D ₇	0.0596	0.0589	0.0607	0.0588	0.0563	0.0584	0.0586	0.0520	<u>0.0503</u>
D ₈	0.0593	0.0570	0.0595	0.0573	0.0523	0.0539	0.0542	<u>0.0506</u>	0.0507
D ₉	0.0714	0.0707	0.0701	0.0707	0.0696	0.0639	0.0644	<u>0.0624</u>	0.0633
D ₁₀	0.0638	0.0596	0.0627	0.0598	0.0586	<u>0.0517</u>	0.0558	0.0607	0.0594
D ₁₁	0.0721	0.0701	0.0746	0.0701	0.0726	0.0708	0.0676	0.0683	<u>0.0670</u>
D ₁₂	0.0589	0.0565	0.0578	0.0566	0.0570	0.0524	0.0528	0.0489	<u>0.0452</u>
Overall	0.0647	0.0640	0.0641	0.0639	0.0615	0.0575	0.0575	0.0551	<u>0.0546</u>

Table 3. Shapley Values of Hotel Criteria for Different Travel Types and Regions

Travel Type	Region	Hotel Criteria					
		Value	Location	Sleep	Room	Cleanliness	Service
Business	Asia	0.192	0.125	0.108	<i>0.075</i>	0.142	0.358

	Europe	0.117	0.100	<i>0.083</i>	0.308	<i>0.075</i>	0.317
	North America	0.217	0.217	<i>0.017</i>	0.183	0.100	0.267
	Oceania	0.317	0.233	0.200	0.150	<i>0.033</i>	<i>0.067</i>
Couple	Asia	0.250	0.133	0.150	0.150	0.183	0.133
	Europe	0.208	0.125	0.192	0.200	0.133	0.142
	North America	0.208	<i>0.092</i>	0.117	0.258	0.133	0.192
	Oceania	0.133	0.108	<i>0.092</i>	0.283	0.158	0.225
Family	Asia	0.208	0.125	<i>0.083</i>	0.242	0.150	0.192
	Europe	0.139	<i>0.089</i>	0.103	0.231	0.228	0.211
	North America	0.125	0.192	0.100	0.150	0.208	0.225
	Oceania	0.100	0.100	0.217	0.250	<i>0.067</i>	0.267

Table 4. Interaction Indices for Business Travellers

Region	Interaction Index					
Asia		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	-0.212	-0.182	0.000	0.000
	Location		0.000	0.000	0.000	0.060
	Sleep			0.000	0.000	0.182
	Room				-0.091	-0.121
	Cleanliness					0.152
Europe		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	0.000	0.000	-0.429
	Location		0.053	-0.015	0.068	0.023
	Sleep			0.000	0.000	0.143
	Room				0.000	0.000
	Cleanliness					0.000
North America		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.300	0.000	0.000
	Location		0.000	0.000	0.100	0.000
	Sleep			0.000	0.000	0.000
	Room				0.000	0.500
	Cleanliness					0.000
Oceania		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-1.000	0.000	0.000
	Location		0.000	0.000	0.000	0.000
	Sleep			0.000	0.000	0.000
	Room				0.000	0.000
	Cleanliness					0.000

Table 5. Interaction Indices for Couple Travellers

Region	Interaction Index					
Asia		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	-0.014	-0.321	0.000	0.000
	Location		0.014	0.017	0.038	-0.027
	Sleep			-0.014	0.171	0.014
	Room				-0.055	-0.028
	Cleanliness					0.291
Europe		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.285	0.000	0.000
	Location		-0.028	-0.115	0.093	-0.093
	Sleep			0.000	0.018	0.161
	Room				-0.071	0.162
	Cleanliness					0.042
North America		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.375	0.000	0.000
	Location		0.000	-0.125	0.000	0.000
	Sleep			0.000	0.000	0.125
	Room				0.000	0.000
	Cleanliness					0.125
Oceania		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.333	0.000	0.000
	Location		0.000	-0.167	0.000	0.000
	Sleep			0.000	0.000	0.000
	Room				0.000	0.167
	Cleanliness					0.278

Table 6. Interaction Indices for Family Travellers

Region	Interaction Index					
Asia		Location	Sleep	Room	Cleanliness	Service
	Value	-0.006	0.000	-0.178	0.045	-0.149
	Location		0.006	-0.034	0.006	0.066
	Sleep			-0.164	0.000	0.086
	Room				0.028	0.058
	Cleanliness					0.124
Europe		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	0.000	0.000	-0.333
	Location		0.000	0.000	0.000	0.000
	Sleep			0.000	0.125	0.062
	Room				0.208	-0.042
	Cleanliness					0.104
North America		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.250	-0.125	0.000
	Location		0.042	0.000	0.042	0.000
	Sleep			0.000	0.042	0.097
	Room				0.083	0.000
	Cleanliness					-0.042
Oceania		Location	Sleep	Room	Cleanliness	Service
	Value	0.000	0.000	-0.167	0.000	0.000
	Location		0.000	0.000	0.167	0.000
	Sleep			0.000	0.000	0.000
	Room				0.000	-0.167
	Cleanliness					0.333