Consumer Choice Modeling: Comparing and Contrasting the MAAM, AHP, TOPSIS and AHP-TOPSIS Methodologies

by

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ABSTRACT

While making decisions, consumers are often confronted with choosing between multiple product and brand alternatives that may be viewed as specific bundles of attributes/criteria. Researchers, attempting to understand this decision-making process, employ multi-criteria decision making (MCDM) models in numerous ways for predicting ultimate brand choice. This thesis compares and contrasts four types of MCDM models within a laptop brand choice context—specifically, the Multi Attribute Attitude Model (MAAM; Fishbein 1967), Analytical Hierarchy Process (AHP; Saaty, 1980), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS; Hwang & Yoon, 1981), and a mixed AHP-TOPSIS model (Ghosh, 2011; Bhutia & Phipon,2012). While Fishbein's MAAM model evaluates brand choice by multiplying attribute belief ratings with their importance weights, the AHP does a pair-wise comparison to elicit relative weights of brand attributes and alternatives. The TOPSIS method, on the other hand, proposes that consumers choose brands that are nearest to (i.e., the shortest distance from) their ideal brand solution as well as the farthest from (i.e., the greatest distance from) their worst solution. Advantages and disadvantages of each of these methods are reviewed, and a mixed AHP-TOPSIS method that addresses some of the drawbacks is proposed here. The results attained via TOPSIS and AHP-TOPSIS are the same. However, it is coincidental in the chosen laptop choice example. By applying the two models within an alternative hotel choice scenario, the rankings obtained are demonstrated as being different. Sensitivity analyses conducted also demonstrate these differences across models.

This thesis has both theoretical and practical implications. From a theoretical perspective,

it brings the knowledge of decision making methodologies from the supply chain management field to further the understanding of marketing related issues. Furthermore, this research is the first to apply a mixed AHP-TOPSIS model that demonstrates greater accuracy in predicting consumer brand choice. In terms of practical significance, it allows companies to improve the impression that customers hold about its performance on specific attribute types.

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Chapter One: Introduction

I Introduction

In a consumption context, people are often confronted with the problem of comparing and choosing amongst multiple products or brand alternatives (Bhatt, Bhatnagar, & Appadoo, 2012). Brands—that can be viewed as bundles of attributes—can be compared directly across standard attributes within a product category (Johnson, 1984). For instance, different brands of televisions (such as Sharp, Sony, Samsung, LG, and Phillips) can be compared on attributes such as price, screen quality, picture quality, and technical content; and different brands of laptop computers (such as, Epson, Canon, and Toshiba) can be compared on weight, price, processor speed, and battery life. Different brands may perform strongly on certain attributes but not as well on others. For example, amongst these television alternatives, Sony may be superior on picture quality and technical content, but inferior on screen type and price; and Sharp may be outstanding on technical content and screen type, but inferior on price and picture quality. Literature on consumer decision making suggests that consumers typically integrate attribute information and employ comparative techniques in order to arrive at a final brand choice (Bahmani & Blumberg, 1987; Beckwith & Lehmann, 1973; Brown, 1950; Gangurde & Akarte, 2013; Ramdhani, Alamanda, & Sudrajat, 2012).

Why consumers select a particular brand out of many possible alternatives is a question that has received much attention in decision-making research (e.g., by Baltas, 1997; Bettman, 1979; Brown, 1950; Hansen, 1972; Johnson, 1984; Verma, Plaschka, Hanlon, Livingston, & Kalcher, 2008)**.** Marketers and decision makers use multi-attribute decision making models for integrating information on sets of alternatives in order to identify one or more optimal solutions and predict choice (e.g., Saaty, 1980; Wind & Saaty, 1980). While there has been a strong research focus on lists of attributes that can influence consumer choice and ways to combine them, the manner of measurement of attribute importance weights remains under-investigated.

Consumers' brand choice can be regarded as a multi-criteria decision-making (MCDM) problem where they must take numerous factors into account. One such decision making model, Fishbein's Multi Attribute Attitude Model (MAAM; 1967), predicts brand choice by multiplying attribute belief ratings with their importance weights. This model is popular and widely used by marketers (Bhatt et al., 2012). In fact, a search using the Google Scholar search engine yielded approximately 83,700 hits for MAAM related marketing research. Moreover, the Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS) that has been used often in the field of decision sciences (e.g. Lai, Liu, & Hwang, 1994; Hwang, Lai, & Liu, 1993; Kim, Park, &Yoon, 1997), has not been widely adopted within marketing. To my knowledge, the technique has only been applied within three marketing papers—specifically, by Cheng, Gong and Zhang (2012) for the purpose of customer value assessment; Bhatt, Bhatnagar, and Appadoo (2012) for brand choice prediction; and Wu, Lin, and Lee (2010) within the context of marketing strategy selection. From a consumer decision-making perspective, the philosophy underlying the TOPSIS framework coincides with the way that people often make brand decisions—i.e., when they lean towards products and services regarded as ideal and avoid those they view in a negative light. Research on motivational direction shows that people are inclined to get close to positive goals/outcomes and get away from negative ones (Elliot, 1999; Elliot & Thrash, 2002; McClelland, 1987).

TOPSIS—wherein brands are assessed by finding the one with the shortest distance from the positive ideal solution and farthest distance from the negative ideal solution—is in line with an approach-avoidance situation where people want to approach a positive aspect related to an entity while also wanting to avoid negative aspects associated with it. Numerous advantages have been associated with TOPSIS: the calculation method is straightforward and easy to understand, attribute importance weights can be assigned easily by direct rating and point allocation techniques, and it is useful in brand situations that don't require a great deal of precision in outputs, or involve modest to low priced products (where the risk is not high even if the optimal choice is not accurately predicted). Despite the advantages inherent in TOPSIS, some drawbacks—especially with respect to importance weight elicitation—have also received considerable criticism from scholars (e.g., Shih, Shyur & Lee, 2007; Shih, Lin, & Lee, 2001; Tan, Lee, & Goh, 2010; Zhang, Shang & Li, 2011). Namely, with respect to the issue of lack of accurate importance weight evaluation through the direct rating, point allocation, and ranking methods employed here. Different weight elicitation ways can result in wide discrepancies in the final results arrived at, and adopting an effective procedure to calculate the relative importance weights of various attributes is imperative. The Analytical Hierarchy Process (AHP) technique from the field of operations research (Saaty, 1980) allows researchers to calculate importance weights more accurately via pairwise comparison processes and consistency check procedures.

This thesis explores a mixed AHP-TOPSIS mixed decision-making model that would not only allow for an incorporation of consumers' approach-avoidance tendencies, but would also have the capability to elicit attribute importance weights with precision. The AHP-TOPSIS mixed model attempts to combine the advantages of the two component models while overcoming their shortcomings. Such a technique has been used within a variety of areas such as customer-driven product design (Lin et al., 2008), recreational fishing simulation modeling (Gao & Hailu, 2013), supplier selection (Bhutia, & Phipon, 2012), tourist satisfaction evaluation (Abedi, Shafei, &Kalantari, 2012), and flexible manufacturing system assessments (Venkata Rao, 2008). However, this methodology is as yet unexplored and unapplied within the consumer decision making realm. Keyword searches via the Google Scholar search engine yielded zero results for the method within consumer research. The AHP-TOPSIS mixed model is most suitable for estimating choice within the bulk commodity or high priced product categories where accuracy of choice is of great importance (as tiny weight elicitation differences can lead to huge discrepancies in the final results).

The rest of the thesis is structured as follows. First, a theoretical overview of literature on consumer decision-making and brand choice is laid out. This is followed by descriptions of the MAAM, TOPSIS, and AHP models, their application within a laptop brand choice scenario (adapted from Hawkins, Best, & Coney, 1998), and their associated advantages and drawbacks. The mixed AHP-TOPSIS method that addresses drawbacks of the previous approaches—namely, the oversimplified calculation structure of Fishbein's MAAM, the drawbacks of weight elicitation associated with TOPSIS, and the complicated calculation processes associated with AHP—is then suggested as an alternative to the previous approaches. Finally, the results arrived at via the different methods are compared and discussed, and limitations and associated avenues for future research, and theoretical and managerial contributions are identified.

II Scope of Research

The research questions addressed within this thesis are as follows:

(1) To understand the manner in which people make decisions and choose amongst competing alternatives (*Chapter 2*).

(2) To draw upon decision making literature spanning the areas of marketing and supply chain management in order to understand and mathematically simulate consumer brand choice via competing approaches. The benefits, drawbacks, and application of each of these approaches will be presented. The thesis will specifically,

   a. Examine Fishbein's Multi Attribute Attitude Model (MAAM), its application within brand choice settings, and its benefits and drawbacks (*Chapter 3*).

   b. Draw upon the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) from the field of supply chain management to further understand consumer brand choice (*Chapter 4).*

   c. Investigate the Analytical Hierarchy Process (AHP) approach as an alternative to the Fishbein model for estimating consumer brand choice (*Chapter 5).*

d. Develop a mixed AHP-TOPSIS model for predicting consumer brand choice—in order to build upon the strengths of the previous methods and address some of their drawbacks (*Chapter 6*).

e. Apply the TOPSIS and AHP-TOPSIS mixed model within an alternative scenario—that of hotel choice—to demonstrate that the lack of discrimination in rankings obtained from the TOPSIS and AHP-TOPSIS mixed model in the previous laptop choice scenario was merely the result of the importance weights chosen in the example (*Chapter 7*)

(3) Consolidate the benefits and drawbacks of all four models, and the results estimated in a comprehensive fashion. Additionally, conduct sensitivity analysis to further assess predictions made via these techniques. Finally, discuss the limitations and areas for further research, and theoretical and impractical implications arising from this research (*Chapter 8*).

Chapter Two: Theoretical Background

I Decision Making and Brand Choice

Brand choice can be a complicated process wherein consumers that must choose amongst several brands, consider and compare the attributes of these alternatives, select one and reject the rest (Bettman & Park, 1980). Consumers faced with deciding between multiple product or brand alternatives frequently go through a series of stages prior to arriving upon their final choice (Solomon, Zaichkowsky, & Polegato, 2011, pp. 292). These stages typically comprise of the following sequence of steps: (1) problem recognition, (2) information search, (3) evaluation of alternatives, and (4) product choice. In the first *problem recognition* stage, consumers that see a significant difference between where they currently are (their current state of affairs) and where they would like to be (their ideal state of affairs) view this gap as a problem that requires resolution.

This need to approach their ideal state (i.e., problem resolution) fuels a search for information relevant to making a decision. *Information search* may therefore occur internally (e.g., via a scan of memory of past similar incidents) or externally (e.g., via a scan of sources such as ads or other consumers' experiences). The extent to which a person searches for information can be influenced by factors such as his or her prior expertise in the area or perceived risk associated with the decision. Past literature presents an inverted U-shaped relationship between customers' past expertise and the amount of external information that needs to be searched. Those consumers that possess moderate knowledge about the product tend to search the most. Novices with limited prior knowledge may not even know where to begin searching, and might therefore simply rely on the opinions of others and use "non-functional" attributes (such as brand names and prices) to select alternatives (Solomon, White, & Dahl, 2014, pp. 257). People with significant prior knowledge would already possess a thorough understanding of the product category and brands operating within it, and recall information from their memory as opposed to scanning external sources. Past literature also distinguishes between several types of risk perceptions. Products decisions, for instance, can be associated with monetary risk (where wrong decisions carry the possibility of significant monetary loss; Jacoby & Kaplan, 1972; Roselius,1971), performance risk (e.g., the possibility that the product chosen is limited in its usefulness or lifespan; Simpson & Lakner, 1993; Jacoby & Kaplan, 1972, or is unable to meet customer expectations; Simpson & Lakner, 1993), physical risk (where the product possibly proves harmful to health or life; Jacoby & Kaplan, 1972), social risk (e.g., concerns about other people's perceptions; Jacoby & Kaplan,1972, and the their lack of acceptance; Lim, 2003), and psychological risk (e.g., mental stress created due to an unsuccessful product choice; Jacoby & Kaplan, 1972). A variety of information search behaviors are suggested for dealing with situations that have different levels of perceived risk. Hugstad, Taylor and Bruce (1987) further demonstrate that people use many sources of information in high perceived risk as opposed to mid or low perceived risk situations. In addition, the source where this information originates from (e.g., relatives, friends, salespeople) is given greater importance in high versus low risk situations. Given that information is present in internal memory and/or the external environment, consumers need to somehow integrate this information to make a decision.

Two general approaches are widely used by consumers to combine information: (i) where they utilize an existing strategy that has been used previously for a similar brand choice decision, or (ii) where they construct a new strategy on the spot utilizing attributes that can be accessed to evaluate existing information (Bettman, Johnson, & Payne, 1991)

The information found is subsequently used for the *evaluation of alternatives*—a phase that itself consists of multiple stages: (a) alternative identification, (b) evaluative criteria identification, and (c) ultimate evaluation of alternatives. Sometimes, all possible alternatives within a decision category may be too many, forcing consumers to filter choices down to a manageable number for comparison purposes. The subset of alternatives that are actively considered within the evaluation process are often surprisingly few and are part of what is known as the consumer's consideration set or evoked set. The comparisons amongst alternatives contained within the consideration/evoked set are made on the basis of some key evaluative criteria (that can range from functional/utilitarian attributes such as price to experiential/hedonic ones such as prestige). While brand alternatives may be similar on some attributes and different on others, those that are ultimately used for distinguishing amongst alternatives and arriving at a brand choice are labelled as the determinant attributes.

A variety of decision rules for the use of decision criteria are proposed based on the degree of decision importance and complexity. These rules fall broadly within the categories of compensatory rules—where being good on a criterion can compensate for being bad on other criteria—and non-compensatory rules—where being good on a criterion does not compensate for poor performance on other criteria. The multiple criteria decision making (MCDM) refers to a problem solving approach that is applied to select the optimal choice amongst a number of alternatives. An MCDM method is a procedure that specifies how criteria information is to be processed in order to arrive at a choice. The methods of MCDM include, multi attribute attitude models (MAAM), weighted product methods (WPM), technique for order preference by similarity to ideal solution (TOPSIS), and analytic hierarchy process (AHP).

This thesis examines a number of decision alternatives and multi-attribute models designed to predict brand choice from a variety of alternatives in different ways. The Multi-Attribute Attitude Model proposed by Fishbein (1967) is first examined and applied within a laptop computer choice setting. The Fishbein's model is a compensatory decision model that is widely used within the area of marketing. Results of this model are then contrasted with the Analytical Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and mixed AHP-TOPSIS decision methodologies.

Chapter Three: The Fishbein's Multi Attribute Attitude Model (MAAM)

I Methodology

Attitudes play a vital role in decision making and influence consumers' purchase decisions. Ramdhani, Alamanda, and Sudrajat (2012) proposed that consumers' actions related to a product are influenced by their attitudes towards it. They further argue that consumer attitudes are powerful predictors of product demand and purchase behaviors, and are fundamental to formulating marketing campaigns. Consumers' attitudes toward products may vary due to the different attributes associated with diverse products. Multi-attribute attitude models research attributes that can affect consumer attitudes toward products. In marketing scenarios, these models suggest that consumers' attitudes towards brands depend on how brands perform on their component attributes.

The most influential Multi-Attribute Attitude Model was developed by Fishbein (1967), and is widely used within attitude measurement. This model enables alternatives to compensate for performing badly on some attributes by performing better on others. Generally speaking, multi-attribute models are composed of three important elements: (1) *attributes* that are characteristics of the attitude object; (2) *beliefs* that refer to consumers' cognitions about the object; and (3) *importance weights* that are the relative weightage that consumers assign to the object. Fishbein's model evaluates overall attitude toward alternatives by multiplying attribute belief scores with the relative importance of these attributes. Fishbein's model has become commonplace in estimating consumer brand choice and consumer behavior as it provides information about attitudinal structure and a simple equation for behavioral prediction (Calder, 1975).

Typically, this model provides the following compensatory equation for consumers to evaluate brands on a certain number (n) of attributes:

$$A_j = \sum_{n=1}^{n} a_i B_{ij}$$

Where:

i = attribute or product characteristic

j = brand

A_j = the consumer's attitude toward brand j;

B_{ij} = the consumer’s belief about the strength of attribute i for brand j,

a_i = the importance weight given to attribute i.

II Application of Fishbein’s Model in Brand Choice Modeling

Fishbein’s Model is applied within a laptop brand choice scenario used within past literature (see Hawkins, Best, & Coney 1998). In this scenario, consumers are asked to choose a laptop from six given brands of notebook computers (Epson, Canon, Compaq, Keynote, IBM, and Toshiba) based on six assessment attributes (price, weight, processor speed, battery life, after sales report, and display quality) and their corresponding importance weights. The attribute scores and importance weights are established by Hawkins et al. (1998) and are represented in Table 3.1.

Table 3. 1 Attitude scores of laptop criteria and the attitude results of Fishbein's Model

	Price	Weight	Processor	Battery Life	After Sale Report	Display Quality	Attitude (Fishbein)
Epson	5	3	5	1	3	3	58
Canon	3	4	5	3	3	3	58
Compaq	3	5	5	1	4	3	62
Keynote	4	4	2	3	3	5	58
IBM	2	3	5	1	5	3	53
Toshiba	1	4	5	5	3	3	54
Importance Weights	3	4	3	1	2	3	

Note: Attribute belief scores: 1= do not think alternative possess attribute, 5= strongly believe; Attribute importance weights: 1= least important attribute, 5= most important attribute; Hawkins et al., (1998).

Rankings of laptop alternatives via this method are shown in Table 3.2 below.

Table 3. 2 Rankings of laptop alternatives calculated by Fishbein's Model

	Ranking
Epson	2
Canon	2
Compaq	1
Keynote	2
IBM	6
Toshiba	5

These results suggest that the Compaq laptop would be the optimal choice here as it receives the maximum attitude score of 62. However, the Epson, Canon, and Keynote brands all tie for second place.

III Advantages and Disadvantages of Fishbein's Multi Attribute Attitude Model

Within the brand choice context, a significant advantage of Fishbein's Model lies in its ability to serve as an information producing device. It can generate a wide range of insights about brand strengths and weakness, and allows multiple criteria in making decisions that directly reflect the weight of each criterion (Stewart, 1992). The easy and simple structure and low cost methodology also saves time for decision makers in terms of acquiring data and ranking alternatives. However, researchers (e.g., Laroche, 1978) have found methodological problems in Fishbein's approach which has restricted the further and deeper application of Multi Attribute Attitude Models.

First, they do not take into account the interaction amongst different attributes, and researchers are unable to understand the relative importance of various attributes in consumers' minds. Potential halo effects are another serious methodological issue related to Fishbein's model—i.e., consumers are apt to assign higher scores to a brand based on their general and personal attitude toward the brand (Beckwith & Lehmann, 1975). Moreover, consumers' attitudes are dynamic and ever evolving in reflection of their new personal experiences and beliefs. Situational variations may activate diverse cognitive processes with different evaluative attributes—these exceed the calculation capacity of Fishbein's model. The oversimplified equation, whose attribute weights are assigned by respondents arbitrarily, also largely limit further application of Fishbein's model. Although the simple and straightforward calculation process makes Fishbein's model widely used in the decision making fields, in this brand choice scenario consumers cannot compare the strengths and weaknesses of the Epson, Canon and Keynote options which tie for second place. Therefore, other more accurate approaches are sought in order to address these issues.

Chapter Four: The Technique for Order Preference by Similarity to Ideal Solution Method (TOPSIS)

TOPSIS (technique for order preference by similarity to ideal solution), developed by Hwang and Yoon (1981), is another popular technique in the domain of multi-criteria decision making. It can help decision makers identify measurement attributes and rank alternatives. The basic idea of TOPSIS stems from the notion of a displaced ideal point from which a compromise solution has the shortest distance (Belenson & Kapur, 1973; Zeleny, 1974). Hwang and Yoon (1981) further argued that the ranking of alternatives are based on an overall consideration of the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS) .The positive ideal solution contains the most favorable values and the least adverse values for attributes, while the worst solution contains the most adverse values and least favorable values for the attributes (Tsaur, Chang, & Yen, 2002). According to this, the optimal alternative would be an alternative that not only has the shortest distance from the Positive Ideal Solution (PIS), but also the farthest distance of the Negative Ideal Solution (NIS; Ghosh, 2011).

The TOPSIS method typically runs through the following stages (Olson, 2004; Zalm, Sanal, Torlak, & Zam, 2009): (1) Assess performance data for chosen alternatives with respect to each criterion to get a decision matrix, and normalize decision matrix; (2) Develop relative importance weights associated for each criteria; (3) Calculate positive ideal solution; (4) Calculate negative ideal solution; (5) Count the distance for each alternative from both the positive and negative ideal solutions; (6) Develop relative distance metrics for each alternative, where the distance to the negative solution is divided by the sum of the distances from the negative and positive solutions, and (7) Compute the relative closeness (RC) and rank alternatives by maximizing the relative distance metric.

I Theoretical Background:

From a consumer decision making perspective, the principle underlying the TOPSIS framework is congruent with brand choice situations that people often find themselves in—specifically, those situations where they lean towards a brand's attributes that seem favorable, while at the same time recoiling from other brand attributes that appear adverse (Bhatt, Bhatnagar, & Appadoo, 2012). For example, while deciding between laptop computers, a customer may be attracted to Epson laptops because of their low price and fast processor speed, but also be hesitant about them based on their short battery life and heavy weight. Such approach-avoidance situations can be embedded within research on motivational direction which proposes that people are motivated to access positive goals or events and get out of negative ones (Elliot, 1999; Elliot & Thash, 2002). According to Elliot (2006), an approach motivation is "the energization of behavior, or the direction of behavior toward, positive stimuli (objects, events, possibilities)". On the other hand, an avoidance motivation is "the energization of behavior by, or the direction of behavior away from, negative stimuli (objects, events, possibilities)". Contained within these definitions are five aspects: namely, (i) approach-avoidance motivations contain both energization and direction of behavior, (ii) physical or psychological movements are inherent within the approach-avoidance motivation, (iii) these movements have two distinguishable forms—in terms of approaching or avoiding new positive or negative solutions, as well as maintaining and sustaining existing solutions, (iv) the positive or negative valence is a conceptualized dimension that can take on different meanings in different situations—such as, good/bad, beneficial/harm, wanted/unwanted, and (v) stimuli can represent both concrete as well as abstract objects, events and possibilities.

Elliott (2006) argues an evolutionary explanation for approach and avoidance motivations that have been passed along from generation to generation. These approach-avoidance motivations have long been a subject of research. The writings of the ancient Greek philosopher Democritus (460 –370 B.C.) and Aristippus (430-360 B.C.) first put forward the concept of ethical hedonism wherein the pursuit of pleasure and escape from pain were regarded as central guides for human actions. This concept was also used within scientific psychology from the very beginning. For example, Freud (1915) pointed out that the ultimate motivation of psychological activities is to approach pleasure and avoid pain (i.e., an "un-pleasure"). As time has passed, the approach-avoidance motivation framework has provided a fundamental and useful guide spanning various areas of psychology such as attitudes (Cacioppo & Berntson, 1994), decision making (Kahneman & Tversky, 1979), affect and behavior (Elliot &Thrash, 2002). Abundant empirical applications of exploring approach-avoidance conflicts also exist within the field of consumer research (e.g., Foxall & Greenley, 1999; Foxall & Yani-de-Soriano, 2005; Penz & Hogg, 2011). Elliot (2006) established a hierarchical model about approach-avoidance by including both goals and motivations. The core premise is that the approach-avoidance distinction is fundamental principal to motivations, while goals that stand for the final element of motivations are the conceptual centerpiece. The hierarchical combination of approach and avoidance–i.e., wanting to approach certain aspects while also avoiding other aspects–demonstrates situations where people move away from undesirable aspects and move toward desirable results in an adaptive manner (Elliot, 2006).

Lewin (1935) further posited that goal-objects can have positive attributes that attract people to them while also having negative attributes that repel people from attaining them—this illustrates the expression of "approach-avoidance conflicts". Approach-avoidance conflicts occur in situations where a goal or event possesses both positive and negative attributes/characteristics simultaneously (Miller, 1944; Miller, 1959). The negative attributes instigate decision makers to get away from the goal or event, while positive attributes attract the decision maker to approach or proceed toward the goal or event. In the laptop selection example considered within this thesis, each laptop alternative is shown to have both positive and negative attributes. For example, Epson is portrayed as outstanding on price and processor speed, but inferior on battery life and weight; while Compaq is shown as good on processor speed and display quality, but bad on battery life and price. The intertwining effects of positive and negative attributes may result in an approach- avoidance conflict if the decision maker leans toward the positive attributes or leans away from the negative ones. Within this example, a consumer might approach a laptop that possesses a low price and quick processor speed. On the other hand, he or she might avoid the same laptop on account of its negative aspects of short battery life and heavy weight. The framework of TOPSIS (Hwang &Yoon, 1981)—which predicts brand choice by finding the one with the shortest distance from a positive ideal solution (i.e., the best solution) and farthest distance from a negative ideal solution (i.e., the worst solution)—is in line with the approach-avoidance motivation framework. Within TOPSIS, a trade-off is made such that we approach the positive ideal attributes by assigning them higher importance weights while avoid the negative ideal attributes by assigning them lower importance weights. The TOPSIS framework and its application are discussed next.

II Methodology

Supposing that a choice problem has m alternatives, $A_1,\ldots, A_m$, and n decision criteria, $C_1,\ldots,C_n$. Each alternative is assessed with respect to the n criteria. Ratings are placed on alternatives in accordance with each criterion of a decision matrix denoted by $D = (x_{ij})_{n\,m}$. Further, $W = (w_1, w_2, \ldots\ldots, w_n)$ is the relative weight vector of the criteria, satisfying $\sum_{i=1}^{n} w_i = 1$ and $W_i > 0$. The procedures of TOPSIS are captured within the following steps:

(1) Create an evaluation matrix to assess performance data for the considered alternatives.

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix}$$

(2) Compute the normalized decision matrix by using the following equation:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$$ i=1,2,….m, where r_{ij} is the normalized rating of decision matrix

(3) Calculate the weighted normalized decision matrix

$v_{ij} = r_{ij} \times W_j$, , i=1, 2,…., m; j=1, 2,…., n, where W_j is the relative weight of j_{th} criterion or attribute

(4) Calculate the positive ideal solution and the negative ideal solution, respectively.

$$A^* = \{v_1^*, v_2^*, \ldots\ldots, v_n\}^* = \{(\max_j v_{ij}, i \in I'), (\min_j v_{ij}, i \in I'')\}$$

i=1, 2, 3,….., m; j=1,2,3,…n

$$A^- = \{v_1^-, v_2^-, \ldots\ldots, v_n^-\} = \{(\min_j v_{ij}, i \in I'), (\max_j v_{ij}, i \in I'')\}$$

i=1, 2, 3,….., m; j=1,2,3,….n.

Where I' is associated with benefit criteria, and I'' is associated with cost criteria.

(5) Calculate the Euclidean distance D_i^* and D_i^- from the target alternative to the positive or negative ideal solutions, respectively:

$$D_i^* = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^*)^2}$$ i=1, 2,…., m.

$$D_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2}$$ i=1, 2,….., m.

(6) Calculate the relative distance of each alternative to the worst condition (the distance to the negative solution is divided by the sum of the distances from the negative and positive solutions);

$$RC_i^* = \frac{D_i^-}{D_i^+ + D_i^-}$$ i=1, 2,…, m.

(7) Sort alternatives by maximizing the relative distance to the ideal solution.

The bigger the RC_i^* is, the better the alternative is.

III Current Applications of TOPSIS in the Marketing and Management Fields

The TOPSIS methodology has been used widely to solve multi-criteria decision making problems. Most of these applications focus on evaluation and selection. For example, Kwong and Tam (2002) proposed TOPSIS for identifying a suitable design solution given many similar alternatives; Tong, Wang, Chen, & Chen (2004) applied TOPSIS to construct an overall performance index for multiple responses and determine the optimal factor collection. Bhatt et al. (2013) adopted TOPSIS within the field of consumer choice and contrasted it with Fishbein's (1967) Multi-Attribute Attitude Model. This research used the TOPSIS model within consumer research and demonstrated the feasibility and suitability of using TOPSIS in this field. Zhang, Shang, and Li (2011) applied TOPSIS to assess tourism destination competitiveness of the Yangtze River Delta in China and came up with tactics and strategies for improving tourism competitiveness. Danaei and Haghighi (2012) used this method to rank 27 industries based on six financial metrics including earnings per share (EPS), total equities, return on assets (ROA), growth profit, operating profit, and net growth. The results indicated that the biggest firms were considered as the best investment options, followed by the Cement industry, and oil refinery units. Mehraparvar, Shahin, and Shirouyehzad (2012) used TOPSIS to prioritize service quality dimensions (i.e., service tangibles, reliability, responsiveness, assurance and empathy), and demonstrated that the tangibility and reliability dimensions held the highest and lowest priority respectively. Wu and Zhang (2009) employed TOPSIS to comprehensively evaluate regional economy investment environments where five zones were evaluated within a fast developing economic society. Wang and Hsu (2004) used TOPSIS to assess five financial ratios (Inventory Turnover, Net Income Ratio, Earnings per Share and Current Ratio) to evaluate business operation performance in the Taiwan Stock Market. The ranking results were offered to the investors to serve as references for selecting target stock shares and analyzing investment strategies. Chiang and Yu (2013) developed a TOPSIS-based evaluation method to help real estate brokers in ranking real estate properties. This approach addresses buyer's needs by evaluating criteria based on actual needs, and helps brokers choose between multiple candidates whose attributes closely suit those of their clients. Cheng and Li (2001) applied TOPSIS to prioritize various forms of information required for a construction project in order to better allocate resources. The results revealed that managerial information was as important as technical information, and that decision makers should combine both types of information to establish an overall information system. Abbasi, Hemmati, and Abdolshah (2008) applied this method to analyze bank account profitability on six criteria that helped banks establish new marketing strategies. Current accounts were found as the best option in terms of banks' marketing investment efforts.

IV Application of TOPSIS in Brand Choice Modeling

The same laptop choice problem is now solved by using the TOPSIS model, and the data is accessed from past literature (see Hawkins et al., 1998; Bhatt et al., 2013). The attribute scores and importance weights are first normalized, and the normalized decision matrix is showed in Table 4.1.

Table 4.1 Normalization of the decision matrix

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Epson	0.6250	0.3145	0.4402	0.1474	0.3419	0.3586
Canon	0.3750	0.4193	0.4402	0.4423	0.3419	0.3586
Compaq	0.3750	0.5241	0.4402	0.1474	0.4558	0.3586
Keynote	0.5000	0.4193	0.1761	0.4423	0.3419	0.5976
IBM	0.2500	0.3145	0.4402	0.1474	0.5698	0.3586
Toshiba	0.1250	0.4193	0.4402	0.7372	0.3419	0.3586
Imp. Wts.	0.1875	0.2500	0.1875	0.0625	0.1250	0.1875

The weighted normalized decision matrix is calculated next where normalized attributes scores are multiplied with corresponding importance weights. The results are shown in Table 4.2.

Table 4.2 Weighted Normalized Decision Matrix

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Epson	0.1172	0.0768	0.0825	0.0092	0.0427	0.0448
Canon	0.0703	0.1048	0.0825	0.0276	0.0427	0.0448
Compaq	0.0703	0.1310	0.0825	0.0092	0.0570	0.0448
Keynote	0.0938	0.1048	0.0330	0.0276	0.0427	0.0747
IBM	0.0469	0.0786	0.0825	0.0092	0.0712	0.0448
Toshiba	0.0234	0.1048	0.0825	0.0461	0.0427	0.0448

Subsequent calculations of the positive and negative ideal solutions for each attribute is shown in Table 4.3 next.

Table 4.3 Positive and Negative Ideal Solutions

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Positive solution	0.1172	0.1310	0.0825	0.0461	0.0712	0.0747
Negative solution	0.0234	0.0786	0.033	0.0092	0.0427	0.0448

The positive ideal solution (D_i*) and negative ideal solution (D_i^-) of each alternative from the positive and negative ideal solutions, respectively are calculated next. The last step is to compute the relative closeness (RC*) of each alternative to the ideal solution. The results are shown in Table 4.4.

Table 4.4 Positive Ideal Solution (D_i^*), Negative Ideal Solution (D_i^-), and Relative Closeness (RC^*) for Each Alternative

	D_i^*	D_i^-	RC^*
Epson	0.0762	0.1060	0.5818
Canon	0.0702	0.0753	0.5177
Compaq	0.0682	0.0872	0.5611
Keynote	0.0696	0.0828	0.5435
IBM	0.0997	0.0618	0.3825
Toshiba	0.1057	0.0671	0.3881

Finally, we rank these alternatives based on RC*.

Table 4.5 Ranking based on Relative Closeness (RC^*)

	RC^*	Rank
Epson	0.5818	1
Canon	0.5177	4
Compaq	0.5611	2
Keynote	0.5435	3
IBM	0.3825	6
Toshiba	0.3881	5

When both the positive (best) and negative (worst) options are considered simultaneously—wherein the optimal solution maximizes the distance from the best option and minimizes the distance from the worst option at the same time—the Epson brand ranks the highest in terms of relative closeness (RC*) and receives the highest score, followed by the Compaq (2^{nd} optimal choice) and Keynote (3^{rd} optimal choice).

V The Advantages and Disadvantages of TOPSIS

According to Kim, Park & Yoon (1997), TOPSIS enjoys four advantages over other decision making methods because it has: (1) a sound and understandable logic that follows the rationale of human choice; (2) a scalar value that considers both the best and worst choices at same time; (3) a simple and straightforward calculation process that can be engaged in by using excel; and (4) the performance measures of all alternatives on attributes can be visualized on a polyhedron. Olson (2004), Deng, Yeh, and Willis (2000) also spoke highly of a concept that represents the best choice for each evaluative criterion in a simple mathematical form, and incorporates importance weights within the comparison procedures. It also requires very little training for decision makers to rank the weightage of each criterion, thereby increasing its popularity.

TOPSIS also has its drawbacks. While the optimal alternative should have the shortest distance to the positive ideal solution and the greatest distance from the negative ideal solution, TOPSIS does not take the relative importance of these distances into account (Opercovic & Tzeng, 2003). Previous research also shows that TOPSIS performs less accurately than AHP on ranking alternatives with the same criterion weights (Hsieh, Chin and Wu, 2006) and selecting the top ranked alternative (Tsaur, 2011) .

Rank reversal problems are often used by researchers to challenge the applicability of TOPSIS. Rank reversal refers to the notion that the rank of alternatives resulting from TOPSIS changes when another alternative is added or deleted within the initial group of alternatives (Hartwich, 1999). Changes to the weight of alternatives can also result in rank reversal. As TOPSIS multiplies the normalized decision matrix with weights, if the weights of alternatives change, the resultant rankings also change.

Another critical drawback of TOPSIS is that it does not provide a unique methodology for assigning criteria importance weights (Zhang et al., 2011). Existing approaches used to calculate weights for TOPSIS are overly complicated and beyond the scope of this research. Weights are assumed in advance in traditional TOPSIS models via direct ratings or point allocations that are largely influenced by consumers' subjective assessments. Different weight elicitation methods can result in wide discrepancies within the final rankings and influence the accuracy of results obtained. Moreover, no unique techniques for normalization exist for TOPSIS.

The drawbacks of TOPSIS can be resolved by AHP to some extent. AHP allows decision makers to calculate more accurate relative importance weights via a pairwise comparison process that mitigates subjectivity by conducting consistency checks. AHP also avoids situations where criterion weights of evaluative alternative have the same value and cannot be appropriately ranked (Hsieh, Chi, &Wu, 2006).

Chapter Five: The Analytic Hierarchy Process (AHP) Model

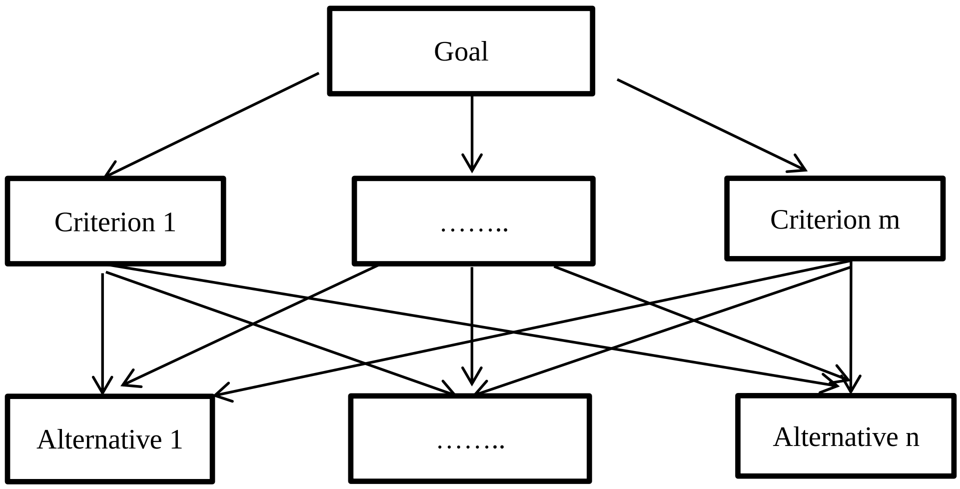
AHP is one of the most widely used multi criteria decision making (MCDM) approaches for solving complicated multi-criteria problems (Saaty, 1980). The processes of AHP include establishing a hierarchical model with multiple criteria, assessing the priority of these criteria, comparing alternatives for each criterion, and obtaining the final ranking of these alternatives (Douligeris & Pereira, 1994). Establishing the decision hierarchy is a salient feature of AHP. AHP can break down a multi-criteria problem into a hierarchy with at least three levels: objectives (overall goal), criteria that define the attribute or characteristics of alternatives, and the competing decision alternatives. Through establishing the hierarchical model, decision makers can identify all the decision elements accurately and recognize the interrelationship between alternatives (Albayrak & Erensal, 2004). Another distinguishing characteristic of the AHP is the transformation of decision makers' subjective and qualitative judgments into quantitative values. The pairwise comparison procedure allows decision makers to assign values according to the relative importance of elements. By doing this, AHP can help decision makers assess both subjective and objective evaluative judgments, check the consistency of the evaluative criteria and alternatives, and then reduce bias caused by subjectivity within decision making (Lai, Trueblood, & Wong, 1992).

I Methodology

The steps of AHP are illustrated below (Ghosh , 2011； Yu, Guo, Guo & Huang, 2011):

(1) Define the objective, determine the criteria/attributes that can be used to assess the objective, and choose the alternatives.

Figure 5.1 the Hierarchy of AHP (Saaty, 1980)



(2) Establish priority amongst alternatives via pair-wise comparisons with each other. Nine levels of the standardized comparison scale for comparing the importance of each element are used here.

Table 5.1 Standardized Pairwise Comparison of Nine-point Scales

Definition	Value
Equal importance	1
Weak importance	3
Essential importance	5
Demonstrated importance	7
Extreme importance	9
Intermediate values	2, 4, 6, 8

By using a_{ij} (i , j =1, 2,..., n) to represent the relative importance weight of each criterion, we can establish the valuation matrix:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix} \text{, where } a_{ij} = \frac{1}{a_{ji}}, a_{ii} = 1, a_{ij} > 0$$

(3) Calculate the priority (importance weights) of each criterion /alternative by normalizing the pair-wise comparison matrix, and average the sum of elements in each row to determine the priority of each criterion/alternative.

(4) Synthesize these judgments to create an overall priority for all alternatives.

(5) Calculate $\lambda_{\max}$.

Matrix consistency is necessary for AHP. Calculating $\lambda_{\max}$ by using the formula $AW = \lambda_{\max} W$ is the first step toward testing consistency.

Where:

A is the pairwise comparison matrix for the criteria;

W is the priority of each criterion (Eigen Vector);

$\lambda_{\max}$ is the average value of λ that need to be calculated.

(6) Calculate consistency.

$\lambda_{\max}$ can be used to calculate consistency.

Consistency index (CI) and consistency ratio (CR) are two parameters that assess consistency. The formulae are as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

$$CR = \frac{CI}{RI}$$

RI is a random index. Different counts of criteria correspond to different values. The relationship between the values of RI and the counts of criterion are presented in Table 5.2.

Table 5.2 Table of Random Index (Saaty, 1980)

N	1	2	3	4	5	6	7	8	9	10	11	12	13
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.58	1.56

If CR is < 0.10, the ranking result can be accepted, and matrix A is considered as having sufficient consistency. Otherwise, matrix A is not sufficiently consistent and the results cannot be accepted.

II Current Applications of AHP in the Marketing and Management Fields

AHP modeling is an emergent and rising solution for large, sophisticated, and dynamic multi-criteria decision-making problems within the fields of marketing and management. For instance, Armacost and Hosseini (1994) used AHP to identify the most discriminatory attributes amongst alternatives in order to rank them. The process also helps minimize ambiguities arising from dual questioning determinant attributes (DQDA; e.g., by considering all attributes simultaneously), and can identify determinants under multiple levels (e.g., via an AHP-DA or Determinant Attribute method). AHP is also widely used within the evaluation and assessment field. For example, Albayrak and Erensal (2004) employed AHP to develop a hierarchic structure representing factors that influence human performance, and demonstrated a relationship with management style. This enables the development of corporate performance evaluation metrics that do not rely on oversimplified measurements such as efficiency or effectiveness. Handfield, et.al (2001) used AHP to combine environmental dimensions with supplier selection decisions in order to resolve trade-offs and better evaluate supplier environmental performance. They demonstrated the usefulness of AHP for evaluating the relative importance of diverse environmental traits and performance of suppliers.

In the area of marketing, Wind and Saaty (1980) proposed the applicability of AHP in the areas of selecting target products and allocating resources amongst portfolio components, determining the direction of new product development and evaluation, and generating and evaluating marketing mix strategies under alternative environmental conditions and objectives. Further, Saaty (1980) recommended its application by designers for ranking the importance of consumer requirements, Schwartz and Oren (1988) adopted AHP to assess consumer preferences, and Yang and Shi (2002) used it to measure a firm’s overall performance under complex marketing conditions. Costa and Evangelista (2008) also employed AHP for evaluating intangible brand assets. The results illustrated the efficacy of AHP in measurements based on consumers’ role in generating brand value rather than adopting a mere accounting perspective. In processing consumer requirements, Saaty (1980) applied AHP for ranking value weights for consumer requirements. Erkarslan and Yilmaz (2011) optimized trough Quality Function Deployment (QFD) to blend design quality and consumer expectations. By using the AHP method, the most important consumer needs and technical characters were determined by considering the consumer’s perspective. The results indicated that companies should attach great importance to such attributes in order to satisfy consumer needs, and that the application of QFD at earlier periods can efficiently repair design defects. Bahmani and Blumberg (1987) adopted AHP model to assist in understanding the interaction of product safety dilemmas for over-the-counter medications involving price, product form, safety, reputation, and method in evaluating consumer reactions (product safety was found to be the most powerful factor in determining consumer OTC medication choice).

Selection is another key field where AHP has been employed. Chen (2006) used the AHP approach to predict convention site selection. The use of AHP helped decision makers in evaluating the relative importance of selection factors and point the way for destination managers to invest resource. Bhutta and Huq (2002) introduced AHP to weight suppliers' information for a construction project. Suppliers were evaluated on several criteria such as pricing structure, delivery (efficiency and cost), product quality, and service. Calantone, Benedetto and Schmidt (1999) used AHP as a decision support model to aid managers in selecting optimal new product ideas. Result showed that AHP can figure out each firm's challenges for supporting the screening decision and generating knowledge for a firm's expert support system.

AHP is also widely used in additional fields of management. For example, Sharma, Moon and Bae (2008) applied AHP for optimizing supply chain delivery networks in terms of cost and service, and illustrated that AHP can combine quantitative and qualitative factors to deal with various criteria and choose the optimal alternative. Millet and Wedley (2003) applied AHP in modelling risk and uncertainty. The authors show that traditional benefit/risk ratios might not be the appropriate measurement approach. Prototypical case studies verify that AHP can be used to deduce the relative importance of relative probabilities, risk criteria, and risk adjustment factors. Liang (2003) applied AHP to evaluate the choice of project termination or continuation according to factors such as top management support derived from benchmarking. Results showed that AHP provided a way to comprehensively assess the status of a project based on research and development case study in Taiwan.

III Application of AHP in brand choice modeling

The laptop choice problem used previously is now solved via the AHP technique.

Table 5.3 Rankings of Laptop Criteria

	Price	Weight	Processor	Battery Life	After Sale Report	Display quality
Epson	5	3	5	1	3	3
Canon	3	4	5	3	3	3
Compaq	3	5	5	1	4	3
Keynote	4	4	2	3	3	5
IBM	2	3	5	1	5	3
Toshiba	1	4	5	5	3	3
Importance Weight	3	4	3	1	2	3

Comprehensively analyze these judgments to garner overall rankings for the hierarchy. This would combine the customers' judgments about price, weight, processor, battery life etc. for notebook computers Epson, Canon, Compaq etc. into overall priorities for each property. The specific processes of applying the AHP in this brand choice scenario can be summarized as follows:

(1) Compare brands of laptop for each criterion in a pair-wise fashion (price, weight, processor, battery life, after sale report and display quality).

Table 5.4 Pairwise Comparison from Table 4.3 First Column (Price)

Price						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.6667	1.6667	1.2500	2.5000	5.0000
Canon	0.6000	1.0000	1.0000	0.7500	1.5000	3.0000
Compaq	0.6000	1.0000	1.0000	0.7500	1.5000	3.0000
Keynote	0.8000	1.3333	1.3333	1.0000	2.0000	4.0000
IBM	0.4000	0.6667	0.6667	0.5000	1.0000	2.0000
Toshiba	0.2000	0.3333	0.3333	0.2500	0.5000	1.0000

Table 5.5 Pairwise Comparison from Table 4.3 Second Column (Weight)

Weight						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	0.7500	0.6000	0.7500	1.0000	0.7500
Canon	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000
Compaq	1.6667	1.2500	1.0000	1.2500	1.6667	1.2500
Keynote	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000
IBM	1.0000	0.7500	0.6000	0.7500	1.0000	0.7500
Toshiba	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000

Table 5.6 Pairwise Comparison from Table 4.3 Third Column (Processor)

Processor						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Canon	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Compaq	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Keynote	0.4000	0.4000	0.4000	1.0000	0.4000	0.4000
IBM	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Toshiba	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000

Table 5.7 Pairwise Comparison from Table 4.3 Fourth Column (Battery Life)

Battery Life						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	0.3333	1.0000	0.3333	1.0000	0.2000
Canon	3.0000	1.0000	3.0000	1.0000	3.0000	0.6000
Compaq	1.0000	0.3333	1.0000	0.3333	1.0000	0.2000
Keynote	3.0000	1.0000	3.0000	1.0000	3.0000	0.6000
IBM	1.0000	0.3333	1.0000	0.3333	1.0000	0.2000
Toshiba	5.0000	1.6667	5.0000	1.6667	5.0000	1.0000

Table 5.8 Pairwise Comparison from Table 4.3 Fifth Column (After Sale Report)

After Sale Report						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
Canon	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
Compaq	1.3333	1.3333	1.0000	1.3333	0.8000	1.3333
Keynote	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
IBM	1.6667	1.6667	1.2500	1.6667	1.0000	1.6667
Toshiba	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000

Table 5.9 Pairwise Comparison from Table 4.3 Sixth Column (Display Quality)

	Display Quality					
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Canon	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Compaq	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Keynote	1.6667	1.6667	1.6667	1.0000	1.6667	1.6667
IBM	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Toshiba	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000

(3) Sum the values in each column of the pair-wise comparison matrix.

Table 5.10 Column Total for Each Brand in the Pair-wise Comparison Matrix of Price

Price						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.6667	1.6667	1.2500	2.5000	5.0000
Canon	0.6000	1.0000	1.0000	0.7500	1.5000	3.0000
Compaq	0.6000	1.0000	1.0000	0.7500	1.5000	3.0000
Keynote	0.8000	1.3333	1.3333	1.0000	2.0000	4.0000
IBM	0.4000	0.6667	0.6667	0.5000	1.0000	2.0000
Toshiba	0.2000	0.3333	0.3333	0.2500	0.5000	1.0000
Total	3.6000	6.0000	6.0000	4.5000	9.0000	18.0000

Table 5.11 Column Total for Each Brand in the Pair-wise Comparison Matrix of Weight

Weight						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	0.7500	0.6000	0.7500	1.0000	0.7500
Canon	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000
Compaq	1.6667	1.2500	1.0000	1.2500	1.6667	1.2500
Keynote	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000
IBM	1.0000	0.7500	0.6000	0.7500	1.0000	0.7500
Toshiba	1.3333	1.0000	0.8000	1.0000	1.3333	1.0000
Total	7.6667	5.7500	4.6000	5.7500	7.6667	5.7500

Table 5.12 Column Total for Each Brand in the Pair-wise Comparison Matrix of Processor

Processor						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Canon	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Compaq	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Keynote	0.4000	0.4000	0.4000	1.0000	0.4000	0.4000
IBM	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Toshiba	1.0000	1.0000	1.0000	2.5000	1.0000	1.0000
Total	5.4000	5.4000	5.4000	13.5000	5.4000	5.4000

Table 5.13 Column Total for Each Brand in the Pair-wise Comparison Matrix of After Sale Report

	After Sale Report					
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
Canon	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
Compaq	1.3333	1.3333	1.0000	1.3333	0.8000	1.3333
Keynote	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
IBM	1.6667	1.6667	1.2500	1.6667	1.0000	1.6667
Toshiba	1.0000	1.0000	0.7500	1.0000	0.6000	1.0000
Total	7.0000	7.0000	5.2500	7.0000	4.2000	7.0000

Table 5.14 Column Total for Each Brand in the Pair-wise Comparison Matrix of Display Quality

Display Quality						
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba
Epson	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Canon	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Compaq	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Keynote	1.6667	1.6667	1.6667	1.0000	1.6667	1.6667
IBM	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Toshiba	1.0000	1.0000	1.0000	0.6000	1.0000	1.0000
Total	6.6667	6.6667	6.6667	4.0000	6.6667	6.6667

(4) Divide each element of these matrices by its column total and average the sum of elements in each row to determine the priority of each criterion:

Table 5.15 Priority for Each Computer by Using Price Criterion

Price							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.2778	0.2778	0.2778	0.2778	0.2778	0.2778	0.2778
Canon	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
Compaq	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
Keynote	0.2222	0.2222	0.2222	0.2222	0.2222	0.2222	0.2222
IBM	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
Toshiba	0.0556	0.0556	0.0556	0.0556	0.0556	0.0556	0.0556

Table 5.16 Priority for Each Computer by Using Weight Criterion

Weight							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.1304	0.1304	0.1304	0.1304	0.1304	0.1304	0.1304
Canon	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739
Compaq	0.2174	0.2174	0.2174	0.2174	0.2174	0.2174	0.2174
Keynote	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739
IBM	0.1304	0.1304	0.1304	0.1304	0.1304	0.1304	0.1304
Toshiba	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739	0.1739

Table 5.17 Priority for Each Computer by Using Processor Criterion

Processor							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852
Canon	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852
Compaq	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852
Keynote	0.0741	0.0741	0.0741	0.0741	0.0741	0.0741	0.0741
IBM	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852
Toshiba	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852	0.1852

Table 5.18 Priority for Each Computer by Using Battery Life Criterion

Battery Life							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714
Canon	0.2143	0.2143	0.2143	0.2143	0.2143	0.2143	0.2143
Compaq	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714
Keynote	0.2143	0.2143	0.2143	0.2143	0.2143	0.2143	0.2143
IBM	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714
Toshiba	0.3571	0.3571	0.3571	0.3571	0.3571	0.3571	0.3571

Table 5.19 Priority for Each Computer by Using After Sale Report Criterion

After Sale Report							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Canon	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
Compaq	0.1905	0.1905	0.1905	0.1905	0.1905	0.1905	0.1905
Keynote	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429
IBM	0.2381	0.2381	0.2381	0.2381	0.2381	0.2381	0.2381
Toshiba	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429	0.1429

Table 5.20 Priority for Each Computer by Using Display Quality Criterion

Display Quality							
Brand	Epson	Canon	Compaq	Keynote	IBM	Toshiba	**Priority**
Epson	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
Canon	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
Compaq	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
Keynote	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
IBM	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
Toshiba	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500

(5) According to the ratings shown in Table 5.3, compare criteria in a pair-wise manner and obtain the following table.

Table 5.21 Pairwise Comparison from Table 4.3 Last Row (Weight)

Criterion	Price	Weight	Processor	Battery Life	After Sale Report	Display quality
Price	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Weight	1.3333	1.0000	1.3333	4.0000	2.0000	1.3333
Processor	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Battery Life	0.3333	0.2500	0.3333	1.0000	0.5000	0.3333
After Sale Report	0.6667	0.5000	0.6667	2.0000	1.0000	0.6667
Display quality	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000

Then, sum the values in each column of the pair-wise comparison matrix.

Table 5.22 Column Total of Each Criterion in the Pair-wise Comparison Matrix

Criterion	Price	Weight	Processor	Battery Life	After Sale Report	Display quality
Price	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Weight	1.3333	1.0000	1.3333	4.0000	2.0000	1.3333
Processor	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Battery Life	0.3333	0.2500	0.3333	1.0000	0.5000	0.3333
After Sale Report	0.6667	0.5000	0.6667	2.0000	1.0000	0.6667
Display Quality	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Total	5.3333	4.0000	5.3333	16.000	8.0000	5.3333

(6) Divide each element of the matrix by its column total and average elements in each row to determine the priority of each criterion:

Table 5.23 Priority for Each Computer by Using Criteria

Criterion	Price	Weight	Processor	Battery Life	After Sale Report	Display quality	**Priority**
Price	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875
Weight	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
Processor	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875
Battery Life	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
After Sale Report	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Display quality	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875

(7) Priority for each laptop brand by using each criterion:

Table 5.24 Priority for Each Laptop Brand by Using Each Criterion

	Price	Weight	Processor	Battery Life	After Sale Report	Display Quality
Epson	0.2778	0.1304	0.1852	0.0714	0.1429	0.1500
Canon	0.1667	0.1739	0.1852	0.2143	0.1429	0.1500
Compaq	0.1667	0.2174	0.1852	0.0714	0.1905	0.1500
Keynote	0.2222	0.1739	0.0741	0.2143	0.1429	0.2500
IBM	0.1111	0.1304	0.1852	0.0714	0.2381	0.1500
Toshiba	0.0556	0.1739	0.1852	0.3571	0.1429	0.1500

According to priorities for attributes obtained from Table 4.24: (i) for price, Epson is the best choice, and Keynote is the second one; (ii) for weight, Compaq is the best choice, followed by Canon, Keynote, and Toshiba, which are all the second choices; (iii) for processor speed, all rankings are same except for Keynote; (iv) for battery life, Toshiba is the best choice, and both Canon and Keynote are in second place; (v) for after sales support, IBM is the best choice, followed by Compaq; however, (vi) for display quality, Keynote becomes the best choice.

This begs the question: with rankings for different attributes being different, how can consumer arrive at an overall ranking that takes all attribute priorities into consideration? The following formula is thus used for calculate an overall ranking of alternatives:

$$\begin{array}{l} Epson \\ Canon \\ Compaq \\ Keynote \\ IBM \\ Toshiba \end{array} = \begin{bmatrix} 0.2778 & 0.1304 & 0.1852 & 0.0714 & 0.1429 & 0.1500 \\ 0.1667 & 0.1739 & 0.1852 & 0.2143 & 0.1429 & 0.1500 \\ 0.1667 & 0.2174 & 0.1852 & 0.0714 & 0.1905 & 0.1500 \\ 0.2222 & 0.1739 & 0.0741 & 0.2143 & 0.1429 & 0.2500 \\ 0.1111 & 0.1304 & 0.1852 & 0.0714 & 0.2381 & 0.1500 \\ 0.0556 & 0.1739 & 0.1852 & 0.3571 & 0.1429 & 0.1500 \end{bmatrix} \begin{bmatrix} 0.1875 \\ 0.2500 \\ 0.1875 \\ 0.0625 \\ 0.1250 \\ 0.1875 \end{bmatrix}$$

$$= \begin{bmatrix} 0.1699 \\ 0.1688 \\ 0.1767 \\ 0.1772 \\ 0.1505 \\ 0.1569 \end{bmatrix}$$

The first column of the leftmost matrix (0.2778, 0.1667,0.1667, 0.2222, 0.1111, 0.0556) comes from the priority for price (Table 4.16), the second column (0.1304, 0.1739, 0.2174, 0.1739, 0.1304, 0.1739) comes from the priority for weight (Table 4.17), the third column (0.1852, 0.1852, 0.1852, 0.0741, 0.1852, 0.1852) comes from the priority given to processor speed (Table 4.18), the fourth column (0.0714, 0.2143, 0.0714, 0.2143,0.0714, 0.3571) comes from the priority given to battery life (Table 4.19), the fifth column (0.1429, 0.1429, 0.1905,0.1429, 0.2381,0.1429) comes from the priority of after sales support (Table 4.20), and the last column of the leftmost matrix (0.1500, 0.1500, 0.1500,0.2500, 0.1500, 0.1500) comes from the priority of display quality (Table 4.21). The middle matrix comes from the priority for each computer by using each criterion. The rightmost matrix is the result of multiplying the leftmost matrix with the middle one.

(8) Check the consistency of judgments.

Based on the formula A*W= $\lambda_{\max}$ * W, where A is the pairwise comparison matrix for each criterion, W is the priority of each criterion, $\lambda_{\max}$ becomes the average value of λ that requires calculation.

So, for price,

$$\begin{bmatrix} 1.0000 & 1.6667 & 1.6667 & 1.2500 & 2.5000 & 5.0000 \\ 0.6000 & 1.0000 & 1.0000 & 0.7500 & 1.5000 & 3.0000 \\ 0.6000 & 1.0000 & 1.0000 & 0.7500 & 1.5000 & 3.0000 \\ 0.8000 & 1.3333 & 1.3333 & 1.0000 & 2.0000 & 4.0000 \\ 0.4000 & 0.6667 & 0.6667 & 0.5000 & 1.0000 & 2.0000 \\ 0.2000 & 0.3333 & 0.3333 & 0.2500 & 0.5000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.2778 \\ 0.1667 \\ 0.1667 \\ 0.2222 \\ 0.1111 \\ 0.0556 \end{bmatrix} = \begin{bmatrix} 1.6667 \\ 1.0000 \\ 1.0000 \\ 1.3333 \\ 0.6667 \\ 0.3333 \end{bmatrix}$$

So λ_{max} = 1/6 $(\frac{1.6667}{0.2778} + \frac{1.0000}{0.1667} + \frac{1.0000}{0.1667} + \frac{1.3333}{0.2222} + \frac{0.6667}{0.1111} + \frac{0.3333}{0.0556})$

= 6.0000

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

The degree of consistency is acceptable.

For weight,

$$\begin{bmatrix} 1.0000 & 0.7500 & 0.6000 & 0.7500 & 1.0000 & 0.7500 \\ 1.3333 & 1.0000 & 0.8000 & 1.0000 & 1.3333 & 1.0000 \\ 1.6667 & 1.2500 & 1.0000 & 1.2500 & 1.6667 & 1.2500 \\ 1.3333 & 1.0000 & 0.8000 & 1.0000 & 1.3333 & 1.0000 \\ 1.0000 & 0.7500 & 0.6000 & 0.7500 & 1.0000 & 0.7500 \\ 1.3333 & 1.0000 & 0.8000 & 1.0000 & 1.3333 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1304 \\ 0.1739 \\ 0.2174 \\ 0.1739 \\ 0.1304 \\ 0.1739 \end{bmatrix} = \begin{bmatrix} 0.7826 \\ 1.0435 \\ 1.3043 \\ 1.0435 \\ 0.7826 \\ 1.0435 \end{bmatrix}$$

So λ_{max} = 1/6$(\frac{0.7628}{0.1304} + \frac{1.0435}{0.1739} + \frac{1.3043}{0.2174} + \frac{1.0435}{0.1739} + \frac{0.7826}{0.1304} + \frac{1.0435}{0.1739})$

=6.0000

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

It is thus concluded that the degree of consistency is acceptable.

For processor speed,

$$\begin{bmatrix} 1.0000 & 1.0000 & 1.0000 & 2.5000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 2.5000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 2.5000 & 1.0000 & 1.0000 \\ 0.4000 & 0.4000 & 0.4000 & 1.0000 & 0.4000 & 0.4000 \\ 1.0000 & 1.0000 & 1.0000 & 2.5000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 2.5000 & 1.0000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1852 \\ 0.1852 \\ 0.1852 \\ 0.0741 \\ 0.1852 \\ 0.1852 \end{bmatrix} = \begin{bmatrix} 1.1111 \\ 1.1111 \\ 1.1111 \\ 0.4444 \\ 1.1111 \\ 1.1111 \end{bmatrix}$$

So $\lambda_{\max} = 1/6 \left(\frac{1.1111}{0.1852} + \frac{1.1111}{0.1852} + \frac{1.1111}{0.1852} + \frac{0.4444}{0.0741} + \frac{1.1111}{0.1852} + \frac{1.1111}{0.1852} \right)$

$=6.0000$

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

The degree of consistency is thus acceptable.

For battery life,

$$\begin{bmatrix} 1.0000 & 0.3333 & 1.0000 & 0.3333 & 1.0000 & 0.2000 \\ 3.0000 & 1.0000 & 3.0000 & 1.0000 & 3.0000 & 0.6000 \\ 1.0000 & 0.3333 & 1.0000 & 0.3333 & 1.0000 & 0.2000 \\ 3.0000 & 1.0000 & 3.0000 & 1.0000 & 3.0000 & 0.6000 \\ 1.0000 & 0.3333 & 1.0000 & 0.3333 & 1.0000 & 0.2000 \\ 5.0000 & 1.6667 & 5.0000 & 1.6667 & 5.0000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.0714 \\ 0.2143 \\ 0.0714 \\ 0.2143 \\ 0.0714 \\ 0.3571 \end{bmatrix} = \begin{bmatrix} 0.4286 \\ 1.2857 \\ 0.4286 \\ 1.2857 \\ 0.4286 \\ 2.1429 \end{bmatrix}$$

So $\lambda_{\max} = 1/6 \left(\frac{0.4286}{0.0714} + \frac{1.2857}{0.2143} + \frac{0.4286}{0.0714} + \frac{1.2857}{0.2143} + \frac{0.4286}{0.0714} + \frac{2.1429}{0.3571} \right)$

$=6.0000$

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

The degree of consistency can be accepted.

For after sales support,

$$\begin{bmatrix} 1.0000 & 1.0000 & 0.7500 & 1.0000 & 0.6000 & 1.0000 \\ 1.0000 & 1.0000 & 0.7500 & 1.0000 & 0.6000 & 1.0000 \\ 1.3333 & 1.3333 & 1.0000 & 1.3333 & 0.8000 & 1.3333 \\ 1.0000 & 1.0000 & 0.7500 & 1.0000 & 0.6000 & 1.0000 \\ 1.6667 & 1.6667 & 1.2500 & 1.6667 & 1.0000 & 1.6667 \\ 1.0000 & 1.0000 & 0.7500 & 1.0000 & 0.6000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1429 \\ 0.1429 \\ 0.1905 \\ 0.1429 \\ 0.2381 \\ 0.1429 \end{bmatrix} = \begin{bmatrix} 0.8571 \\ 0.8571 \\ 1.1429 \\ 0.8571 \\ 1.4286 \\ 0.8571 \end{bmatrix}$$

So $\lambda_{max} = 1/6\ (\frac{0.8571}{0.1429} + \frac{0.8571}{0.1429} + \frac{1.1429}{0.1905} + \frac{0.8571}{0.1429} + \frac{1.4286}{0.2381} + \frac{0.8571}{0.1429})$

$= 6.0000$

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

It is concluded that the degree of consistency can be accepted.

For the display quality,

$$\begin{bmatrix} 1.0000 & 1.0000 & 1.0000 & 0.6000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 0.6000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 0.6000 & 1.0000 & 1.0000 \\ 1.6667 & 1.6667 & 1.6667 & 1.0000 & 1.6667 & 1.6667 \\ 1.0000 & 1.0000 & 1.0000 & 0.6000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 0.6000 & 1.0000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1500 \\ 0.1500 \\ 0.1500 \\ 0.2500 \\ 0.1500 \\ 0.1500 \end{bmatrix} = \begin{bmatrix} 0.9000 \\ 0.9000 \\ 0.9000 \\ 1.5000 \\ 0.9000 \\ 0.9000 \end{bmatrix}$$

So $\lambda_{max} = 1/6\ (\frac{0.9000}{0.1500} + \frac{0.9000}{0.1500} + \frac{0.9000}{0.1500} + \frac{0.1500}{0.2500} + \frac{0.9000}{0.1500} + \frac{0.9000}{0.1500})$

$=6.0000$

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

The degree of consistency can be accepted.

For the criteria,

$$\begin{bmatrix} 1.0000 & 0.7500 & 1.0000 & 3.0000 & 1.5000 & 1.0000 \\ 1.3333 & 1.0000 & 1.3333 & 4.0000 & 2.0000 & 1.3333 \\ 1.0000 & 0.7500 & 1.0000 & 3.0000 & 1.5000 & 1.0000 \\ 0.3333 & 0.2500 & 0.3333 & 1.0000 & 0.5000 & 0.3333 \\ 0.6667 & 0.5000 & 0.6667 & 2.0000 & 1.0000 & 0.6667 \\ 1.0000 & 0.7500 & 1.0000 & 3.0000 & 1.5000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1875 \\ 0.2500 \\ 0.1875 \\ 0.0625 \\ 0.1250 \\ 0.1875 \end{bmatrix} = \begin{bmatrix} 1.1250 \\ 1.5000 \\ 1.1250 \\ 0.3750 \\ 0.7500 \\ 1.1250 \end{bmatrix}$$

So $\lambda_{\max} = 1/6\,(\frac{1.1250}{0.1875} + \frac{1.5000}{0.2500} + \frac{1.1250}{0.1875} + \frac{0.3750}{0.0625} + \frac{0.7500}{0.1250} + \frac{1.1250}{0.1875})$

$=6.0000$

CI=0, CR= $\frac{CI}{RI}$ =0<0.01

Thus the degree of consistency can be accepted.

(9) Finally, these alternatives are ranked based on the results of scores obtained

Table 5.25 the Ranking of Alternatives

Brand	Score	Rank
Epson	0.1699	3
Canon	0.1688	4
Compaq	0.1767	2
Keynote	0.1772	1
IBM	0.1505	6
Toshiba	0.1569	5

Results thus indicate that the best choice is Keynote which received the highest score. The second choice is Compaq, followed by Canon.

IV The Advantages and Disadvantages of AHP

AHP can be used in various types of decision making situations. It provides a framework for managers at different levels for seeking input about criteria and sub-criteria (Yang & Shi, 2002). Managerial decisions can easily be made by looking at the hierarchy model and ranking scores attributed to alternatives (Deshmukh & Millet, 2011).The pairwise comparison procedure associated with the AHP model allows decision makers to provide relative (rather than absolute) preference assessments. By introducing hierarchical settings and conducting consistency checks, AHP dramatically reduces biases and inconsistencies inherent in subjective decision making (Costa & Evangelista, 2008).

Additionally, AHP uses relative measurements of properties that cannot be measured by standard measurement scales and transforms qualitative information into quantitative data via normalization. This overcomes the difficulties due to the evaluation of decision factors. Prioritizing amongst alternatives is thus achieved in a structured setting even when sufficient quantitative data is lacking (Hartwich, 1999).

AHP, however, also suffers from some drawbacks. The time consuming procedure of pair-wise comparison is a distinct limitation of this model, and the number of pair-wise comparisons augments rapidly with increasing nodes in the hierarchy. Some decision makers may find the process somewhat tedious (Lockett et al, 1986). Extant literature (e.g., Millet & Harker, 1990) has put forth a software implementation of AHP that elicits assessments from decision makers, and saves time while retaining accuracy. Despite this, AHP still requires more time and effort investment compared to other approaches (Deshmukh & Millet, 2011).

The application of AHP has also been severely limited due to its capacity for information processing—it cannot deal with a mass of attributes and alternatives due to the tedious pairwise comparison process. The number seven plus or minus two is its threshold for comparisons (Saaty & Ozdemir, 2003). This weakness severely hinders the application of AHP where large numbers of alternatives and attributes exist. From this point of view, TOPSIS can alleviate the complicated paired comparison process. TOPSIS is also able to deal with many alternatives and attributes. Hence, TOPSIS would be more suitable for such complex situations, and is especially applicable for objective or quantitative data (Shih, Shyur, & Lee, 2007).

AHP and TOPSIS therefore possess inherent shortcomings that can be overcome via merging the two techniques. For the weight elicitation problem within TOPSIS, AHP can be used to calculate weights. For the information processing limitation and time consuming pair-wise comparison procedure for AHP, TOPSIS can compensate for this. A mixed AHP-TOPSIS model is therefore proposed here—where AHP techniques are used for calculating relative importance criteria weights, and TOPSIS procedures are used for calculating final rankings—in order to collate the advantages of AHP and TOPSIS while overcoming their individual shortcomings.

Chapter Six: The Proposed AHP-TOPSIS Mixed Model

To solve time consuming pairwise comparison procedures associated with AHP and problems with weight elicitation associated with TOPSIS, a blended AHP-TOPSIS mixed method is proposed here. By eliciting criteria weight via pairwise comparison of alternatives via AHP, weights for use within TOPSIS are obtained. The weights elicited by AHP are more accurate and objective than those obtained via traditional TOPSIS methodologies. What's more, the AHP-TOPSIS mixed model combines the advantages of AHP (which can compare alternative in pairs to elicit weights) with the advantages of TOPSIS (which doesn't suffer from capacity limits on numbers of attributes and alternatives). Thus, in situations where decision makers are unable to provide weightages for large numbers of alternatives or very precise weights are needed, this mixed approach can be utilized.

I Methodology

In the first step, AHP is used for calculating the weights of the criteria as well as overall weights of the alternatives. In the second step, these weights are used within TOPSIS to evaluate the problem. The basic procedures of the proposed AHP-TOPSIS mixed model are described below (Bhutia & Phipon, 2012; Ghosh, 2011):

Part A: Use the AHP technique to get the priority/weights for each criterion.

Step 1: Establish priority amongst the alternatives by pair-wise comparisons with the criteria by using 9 levels standardized comparison scales.

By using a_{ij} (i, j =1,2...n) to represent the relative weights of each criteria, we can obtain the valuation matrix:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nm} \end{pmatrix}, \text{ where } a_{ij} = \frac{1}{a_{ij}}, \quad a_{ii}=1,\ a_{ij}>0$$

Step 2: Calculate the weight of each criterion by normalizing the pair-wise comparison matrix, and average the elements in each row to determine the priority of each criterion.

Step 3: Compute the Eigen value and Eigen vector and conduct the Consistency Test.

Part B: Evaluate alternatives by using TOPSIS and determine the final rankings.

Step 4: Evaluate the performance of each alternative with respect to each criterion to obtain a decision matrix such as the one below:

$$X= \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}$$

Step 5: After establishing the decision matrix, normalize the decision matrix by using the formula below:

$$r_{ij} = \frac{x_{ij}}{\sqrt{x_{ij}^2}}$$, i=1,2,…, m, where r_{ij} is the normalized rating

Step 6: Calculate the weighted normalized decision matrix

$v_{ij} = r_{ij} \times W_j$, , i=1, 2,…., m; j=1, 2,…., n, where W_j is the relative weight of the j^{th}

criterion or attribute.

Step 7: Calculate the positive ideal solution and the negative ideal solution, respectively.

$$A^* = \{v_1^*, \mathrm{v}_2^*, ..., \mathrm{v}_n^*\} = \{(\max_j v_{ij}, i \in I^{'}), (\min_j v_{ij}, i \in I^{''})\}$$

i=1, 2, 3,….., m; j=1,2,3,…n

$$A^{-} = \{v_1^{-}, v_2^{-}, ..., v_n^{-}\} = \{(\min_j v_{ij}, i \in I^{'}), (\max_j v_{ij}, i \in I^{''})\}$$

i=1, 2, 3,….., m; j=1,2,3,….n.

Where $I^{'}$ is associated with benefit criteria, and $I^{''}$ is associated with cost criteria.

Step 8: Calculate the Euclidean distance D_i* and D_i^- from the target alternative to the positive or negative ideal solutions, respectively:

$$D_i^* = \sqrt{\sum_{j=1}^{m} (\mathrm{v}_{ij} - v_j^*)^2} \quad \text{i=1, 2,…., m.}$$

$$\mathrm{D}_i^- = \sqrt{\sum_{j=1}^{m} (\mathrm{v}_{ij} - v_j^-)^2} \quad \text{i=1, 2,….., m.}$$

Step 9: Calculate the relative distance of each alternative to the worst condition (the distance to the negative solution is divided by the sum of the distances from the negative and positive solutions);

$$RC_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \qquad \text{i=1, 2,…, m.}$$

Step 10: Rank the alternatives by maximizing the relative distance to the ideal solution. And the bigger the RC_i^*, the better the alternative is.

II Current Applications of the AHP-TOPSIS Mixed Model

In the literature, various applications of integrated AHP-TOPSIS are found. Such as, for identifying preferred management options (Gao & Hailu, 2013), selection of material in engineering design (Das, 2012), performance measurement for manufacturing companies (Yurdakul & Ic, 2005), supplier section (Bhutia & Phipon, 2012), customer-driven product design processes (Lin et al., 2008), mined land suitability analysis (Soltanmohammadi, Osanloo, & Aghajani, 2008), non-traditional matching processes (Chakladar &Chakraborty, 2008), assessment of flexible manufacturing systems (Venkata Rao, 2008), and transshipment site selection (Önüt &Soner, 2008). Nothing however has been done in terms of applying this technique within the area of consumer research.

III Application of the AHP-TOPSIS Mixed Model within Brand Choice Modelling

The same laptop choice problem with the data is from past literature (see Hawkins et al., 1998) was used.

Table 6.1 Weight of Each Attribute

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Weight	3	4	3	1	2	3

(1) Pair-wise comparison of evaluative criteria.

Table 6.2 Pairwise Comparison of Evaluative Criteria

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Price	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Weight	1.3333	1.0000	1.3333	4.0000	2.0000	1.3333
Processor	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Battery Life	0.3333	0.2500	0.3333	1.0000	0.5000	0.3333
After Sale Report	0.6667	0.5000	0.6667	2.0000	1.0000	0.6667
Display Quality	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000

(2) Sum the values in each column of the pair-wise comparison matrix.

Table 6.3 Column Total of Each criterion in the Pair-wise Comparison Matrix

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Price	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Weight	1.3333	1.0000	1.3333	4.0000	2.0000	1.3333
Processor	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Battery Life	0.3333	0.2500	0.3333	1.0000	0.5000	0.3333
After Sale Report	0.6667	0.5000	0.6667	2.0000	1.0000	0.6667
Display Quality	1.0000	0.7500	1.0000	3.0000	1.5000	1.0000
Sum	5.3333	4.0000	5.3333	16.0000	8.0000	5.3333

Divide each element of the matrix by its column total and average the elements in each row to determine the priority of each criterion：

Table 6.4 Priority for Each Criterion

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality	**Priority**
Price	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875
Weight	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500
Processor	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875
Battery Life	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
After Sale Report	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250
Display Quality	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875	0.1875

Check the consistency of the judgments.

As AX=λ_{max}*X,

$$\begin{bmatrix} 1.0000 & 1.6667 & 1.6667 & 1.2500 & 2.5000 & 5.0000 \\ 0.6000 & 1.0000 & 1.0000 & 0.7500 & 1.5000 & 3.0000 \\ 0.6000 & 1.0000 & 1.0000 & 0.7500 & 1.5000 & 3.0000 \\ 0.8000 & 1.3333 & 1.3333 & 1.0000 & 2.0000 & 4.0000 \\ 0.4000 & 0.6667 & 0.6667 & 0.5000 & 1.0000 & 2.0000 \\ 0.2000 & 0.3333 & 0.3333 & 0.2500 & 0.5000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1875 \\ 0.2500 \\ 0.1875 \\ 0.0625 \\ 0.1250 \\ 0.1875 \end{bmatrix} = \begin{bmatrix} 1.1250 \\ 1.5000 \\ 1.1250 \\ 0.3750 \\ 0.7500 \\ 1.1250 \end{bmatrix}$$

$$\text{So } \lambda_{max} = 1/6\left(\frac{1.1250}{0.1875} + \frac{1.5000}{0.2500} + \frac{1.1250}{0.1875} + \frac{0.3750}{0.0625} + \frac{0.7500}{0.1250} + \frac{1.1250}{0.1874}\right)$$

$$= 6.0000$$

$$CI=0,\ CR=\frac{CI}{RI}=0<0.01$$

This value of the CR is less than the allowable value of 0.10. Therefore, the consistency of the criteria matrix is found to be acceptable. However, if the consistency ratio is greater than 0.10, the criteria judgments require revision.

The attribute scores and importance weights are then normalized by using TOPSIS. The normalization of decision matrix is showed in Table 6.5.

Table 6.5 Normalization of Decision Matrix

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Epson	0.6250	0.3145	0.4402	0.1474	0.3419	0.3586
Canon	0.3750	0.4193	0.4402	0.4423	0.3419	0.3586
Compaq	0.3750	0.5241	0.4402	0.1474	0.4558	0.3586
Keynote	0.5000	0.4193	0.1761	0.4423	0.3419	0.5976
IBM	0.2500	0.3145	0.4402	0.1474	0.5698	0.3586
Toshiba	0.1250	0.4193	0.4402	0.7372	0.3419	0.3586
Imp. Wts.	0.1875	0.2500	0.1875	0.0625	0.1250	0.1875

The weighted normalized decision matrix is then calculated: where the normalized attributes scores are multiplied with corresponding importance weights. The results are in Table 6.6.

Table 6.6 Weighted Normalized Decision Matrix

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Epson	0.1172	0.0768	0.0825	0.0092	0.0427	0.0448
Canon	0.0703	0.1048	0.0825	0.0276	0.0427	0.0448
Compaq	0.0703	0.1310	0.0825	0.0092	0.0570	0.0448
Keynote	0.0938	0.1048	0.0330	0.0276	0.0427	0.0747
IBM	0.0469	0.0786	0.0825	0.0092	0.0712	0.0448
Toshiba	0.0234	0.1048	0.0825	0.0461	0.0427	0.0448

Calculate the positive and negative ideal solutions for each attribute. See Table 6.7.

Table 6.7: Positive and Negative Ideal Solutions

	Price	Weight	Processor	Battery Life	After Sale Support	Display Quality
Positive solution	0.1172	0.1310	0.0825	0.0461	0.0712	0.0747
Negative solution	0.0234	0.0786	0.033	0.0092	0.0427	0.0448

Calculate the positive ideal solution (Di^*) and negative ideal solution (Di^-) for each alternative from the positive and negative ideal solutions, respectively.

The last step is to compute the relative closeness (RC*) of each alternative to the ideal solution. The results are shown in Table 6.8.

Table 6.8: Positive Ideal Solution (D_i^*), Negative Ideal Solution (D_i^-) , and Relative Closeness(RC^*) for Each Alternative

	D_i^*	D_i^-	RC^*
Epson	0.0762	0.1060	0.5818
Canon	0.0702	0.0753	0.5177
Compaq	0.0682	0.0872	0.5611
Keynote	0.0696	0.0828	0.5435
IBM	0.0997	0.0618	0.3825
Toshiba	0.1057	0.0671	0.3881

Finally, alternatives are ranked based on the RC* to obtain the final estimates.

Table 6.9 Ranking Based on Relative Closeness (RC^*)

	RC^*	Rank
Epson	0.5818	1
Canon	0.5177	4
Compaq	0.5611	2
Keynote	0.5435	3
IBM	0.3825	6
Toshiba	0.3881	5

When both the positive (best) and negative (worst) options are considered simultaneously—wherein the optimal solution maximizes the distance from the best option and minimizes the distance from the worst option at the same time—the Epson brand ranks the highest in terms of relative closeness (RC*). This is followed by Compaq (2nd optimal choice) and Keynote (3rd optimal choice). The results computed via AHP-TOPSIS are the same as those obtained via TOPSIS alone.

IV The Advantages of the AHP-TOPSIS Mixed Model

AHP can efficiently deal with situations where the decision making process involves subjective judgments from different individuals. However, it is difficult to deal with too many pair-wise comparisons of attributes and alternatives (Venkata Rao, 2008). TOPSIS is more efficient at handling large numbers of alternatives (Hwang &Yoon, 1982; Chen & Hwang, 1992; Hwang, Lai & Liu, 1993; Yoon & Hwang, 1995; Bhangale et al., 2004, Yurdakul & Ic, 2005). However, the traditional TOPSIS method uses assumed importance weights and lacks an efficient procedure for assessing importance weights for different attributes. The shortcoming of weight elicitation existing within TOPSIS can be resolved by using the AHP model.

The AHP-TOPSIS Mixed Model combines the advantage of AHP (that allows pair-wise comparisons of alternatives while eliciting weights) with those of TOPSIS (that doesn't have capacity limitations on the numbers of f attributes and alternatives considered, and involves straightforward computations). Furthermore, the combination of AHP and TOPSIS enables us to discover the relative closeness values while solving another chief shortcoming of AHP–when weighted values are equivalent it is difficult to obtain a relatively higher ranking. Hsieh, Chin, and Wu (2006) pointed out that ranking the weighted value using AHP prior to applying TOPSIS can help avoid this predicament. For example: A_1 and A_2 are represented as the two alternatives, A^+ is the positive ideal solution, and A^- is the negative ideal solution in Figure 1.

In AHP, the line A^+A_2 is equal to A^+A_1, so we can say that $\overline{A^+A_2} = \overline{A^+A_1}$. When we only consider tested values' distance to the positive ideal solution, $\overline{A^{+}A_{2}} = \overline{A^{+}A_{1}}$, then $A_1 \approx A_2$. However, if we take the distance to the negative ideal solution into account, line $A^{-}A_1$ is larger than line $A^{-}A_2$. That is, $\overline{A^{-}A_{1}} > \overline{A^{-}A_{2}}$, A_1 is farther than A_2.Therefore, according to TOPSIS, we can judge $A_1 > A_2$, as shown in Figure 6.1.

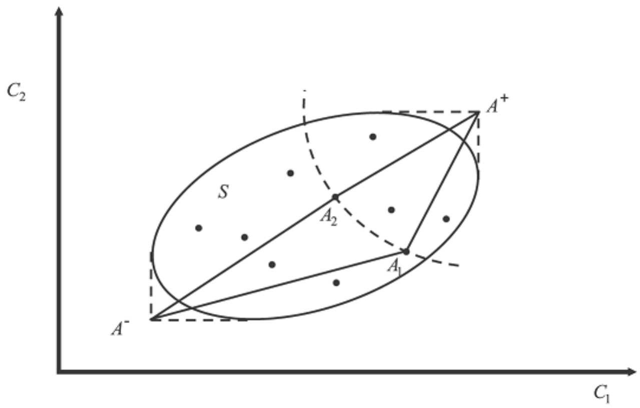


Fig. 6.1 TOPSIS Positive Ideal and Negative Ideal Chart (adapted from Hsieh et al., 2006)

Tavana and Hatami-Marbini (2011) proposed that the AHP-TOPSIS mixed model helps decision makers in: (i) breaking down complicated problems into manageable and hierarchical steps, (ii) reducing the subjectivity of decisions through checking consistency ratios within AHP, and (iii) attaining the final rankings through a bundle of rigorous logical techniques and structured steps rooted within TOPSIS. The mixed model also possesses features that address some of the limitations of current MCDM techniques:

(i) Analytical: The analytical procedures of the AHP-TOPSIS Mixed Model can help decisions makers to break down complex MADM problems to manageable steps, thus expanding the model's applicability to more decision making situations and simplified information input processes.

(ii) Comprehensive: The AHP-TOPSIS mixed model is an integrated model that does not have ceiling numbers on attributes and alternatives. It can process a wide range of importance weights, attributes, alternatives, and decision makers.

Chapter Seven: Hotel Choice Scenario

The rankings obtained from the TOPSIS and AHP-TOPSIS mixed model are the same in this research. The question as to whether this is coincidental, or the models have no discriminatory power, requires resolution. The thesis argument leans toward the former assessment—actual customers did not assign weights within the pairwise comparison matrix used in the AHP-TOPSIS application. Instead, data assumed from prior literature was drawn upon. In order to demonstrate that the similar rankings by both TOPSIS and AHP-TOPSIS in the laptop computer choice scenario due to the importance weights present within the example used, an alternative scenario is adopted.

In this alternative scenario, a customer must choose amongst four hotels (Cheraton, Milton, Harriott, and Starwood) based on four evaluative attributes (ambiance, location, cost, and service). In the TOPSIS model, assumed importance weights are used. However, in the AHP-TOPSIS mixed model, consumer themselves must engage in pairwise comparisons via the AHP technique to calculate importance weights. I therefore engaged in pairwise comparisons in order to generate data for this example. The attribute scores and importance weights (just used in the TOPSIS model) are represented in Table 7.1.

Table 7.1 Attributes Belief Score of Hotel Criteria and Corresponding Importance Weights

	Ambiance	Location	Cost	Service
Cheraton	5	2	5	5
Milton	2	3	3	3
Harriott	3	5	5	4
Starwood	5	4	2	5
Importance weights	3	4	5	2

Note: Attribute belief scores: 1= do not think alternative possess attribute, 5= strongly believe; Attribute importance weights: 1= least important attribute, 5= most important attribute.

I Use of the TOPSIS Model

1) The attribute scores and importance weights are first normalized according to the TOPSIS formula, and the normalized decision matrix is showed in Table 7.2

Table 7.2 Normalization of Decision Matrix

	Ambiance	Location	Cost	Service
Cheraton	0.6299	0.2722	0.6299	0.5774
Milton	0.2520	0.4082	0.3780	0.3464
Harriott	0.3780	0.6804	0.6299	0.4619
Starwood	0.6299	0.5443	0.2520	0.5774
Imp. Wts.	0.2143	0.2857	0.3571	0.1429

2) Then, the weighted normalized decision matrix is assessed: where normalized attributes scores are multiplied with corresponding importance weights. The results are shown in Table 7. 3.

Table 7.3 Weighted Normalized Decision Matrix

	Ambiance	Location	Cost	Service
Cheraton	0.1350	0.0778	0.2250	0.0825
Milton	0.0540	0.1166	0.1350	0.0495
Harriott	0.0810	0.1944	0.2250	0.0660
Starwood	0.1350	0.1555	0.0900	0.0825

3) Calculate the positive and negative ideal solutions for each attribute. See Table 7.4.

Table 7.4 Positive and Negative Ideal Solutions

	Ambiance	Location	Cost	Service
Positive Solution	0.1350	0.1944	0.2250	0.0825
Negative Solution	0.0540	0.0778	0.0900	0.0495

4) Calculate the positive ideal solution (Di*) and negative ideal solution (Di-) for each alternative from the positive and negative ideal solutions, respectively. Then, compute the relative closeness (RC*) of each alternative to the ideal solution. The results are showed in Table 7. 5.

Table 7.5 Positive Ideal Solution (D_i^*), Negative Ideal Solution (D_i^-), and Relative Closeness (RC^*) for Each Alternative

	D_i^*	D_i^-	RC^*
Cheraton	0.1166	0.1608	0.5796
Milton	0.1476	0.0595	0.2872
Harriott	0.0565	0.1812	0.7624
Starwood	0.1405	0.1170	0.4545

5) Finally, these alternatives are ranked based on the RC*.

Table 7.6 Ranking based on Relative Closeness (RC^*)

	RC^*	Rank
Cheraton	0.5796	2
Milton	0.2872	4
Harriott	0.7624	1
Starwood	0.4545	3

The result obtained via TOPSIS shows that Harriott is the best hotel choice, Cheraton is the second choice, and this is followed by Starwood and Milton. In order to compare the rankings from TOPSIS and the AHP-TOPSIS Mixed Model, the AHP-TOPSIS mixed model is now applied.

II Use the AHP-TOPSIS Mixed Model.

The attribute scores remain the same and are represented in Table 7.7. However, the weight calculations take place in accordance with the pairwise comparison matrices.

Table 7. 7 Attributes Belief Scores of Hotel Criteria

	Ambiance	Location	Cost	Service
Cheraton	5	2	5	5
Milton	2	3	3	3
Harriott	3	5	5	4
Starwood	5	4	2	5

1) Compare the evaluative criteria pairwise. The relative importance weights are weighted by consumers.

Table 7.8 Pairwise Comparison of Evaluative Criteria

Criterion	Ambiance	Location	Cost	Service
Ambiance	1.0000	0.2500	0.3333	2.0000
Location	4.0000	1.0000	2.0000	8.0000
Cost	3.0000	0.5000	1.0000	5.0000
Service	0.5000	0.1250	0.2000	1.0000

2) Summate the values in each column of the pairwise comparison matrix

Table 7.9 Column Total of Each Criterion in the Pairwise Comparison Matrix

Criterion	Ambiance	Location	Cost	Service
Ambiance	1.0000	0.2500	0.3333	2.0000
Location	4.0000	1.0000	2.0000	8.0000
Cost	3.0000	0.5000	1.0000	5.0000
Service	0.5000	0.1250	0.2000	1.0000
Total	8.5000	1.8750	3.5333	16.0000

3) Divide all elements of the matrix by their column totals and average the elements in each row to determine the priority of each criterion：

Table 7.10 Priority for Each Criterion

Criterion	Ambiance	Location	Cost	Service	**Priority**
Ambiance	0.1176	0.1333	0.0943	0.1250	0.1176
Location	0.4706	0.5333	0.5660	0.5000	0.5175
Cost	0.3529	0.2667	0.2830	0.3125	0.3038
Service	0.0588	0.0667	0.0566	0.0625	0.0611

According to the priority above, the importance weights and attributes belief scores are summarized in Table 7.11

Table 7.11 Attributes Belief Score for Each Criterion and its Corresponding Importance Weight

	Ambiance	Location	Cost	Service
Cheraton	5	2	5	5
Milton	2	3	3	3
Harriott	3	5	5	4
Starwood	5	4	2	5
Importance Weights	0.1176	0.5175	0.3038	0.0611

4) Check the consistency of the judgment.

$$\begin{bmatrix} 1.0000 & 0.2500 & 0.3333 & 2.0000 \\ 4.0000 & 1.0000 & 2.0000 & 8.0000 \\ 3.0000 & 0.5000 & 1.0000 & 5.0000 \\ 0.5000 & 0.1250 & 0.2000 & 1.0000 \end{bmatrix} \begin{bmatrix} 0.1176 \\ 0.5175 \\ 0.3038 \\ 0.0611 \end{bmatrix} = \begin{bmatrix} 0.4705 \\ 2.0846 \\ 1.2210 \\ 0.2454 \end{bmatrix}$$

So $\lambda_{\max} = 1/4(\frac{0.4705}{0.1176} + \frac{2.0846}{0.5175} + \frac{1.2210}{0.3038} + \frac{0.2454}{0.0611})$

$=4.0155$

CI=0.0052, CR=$\frac{CI}{RI} = \frac{0.0052}{0.90}$ =0.0056

This value of CR is less than the permissible level of 0.10.

Therefore, the consistency of the criteria matrix is found to be acceptable. However, if the consistency ratio is higher than 0.10, the criteria judgment must be revised.

5) The attribute scores and importance weights are then normalized by using TOPSIS. The normalization of the decision matrix is depicted in Table 7.12.

Table 7.12 Normalization of Decision Matrix

	Ambiance	Location	Cost	Service
Cheraton	0.6299	0.2722	0.6299	0.5774
Milton	0.2520	0.4082	0.3780	0.3464
Harriott	0.3780	0.6804	0.6299	0.4619
Starwood	0.6299	0.5443	0.2520	0.5774
Imp. Wts.	0.1176	0.5175	0.3038	0.0611

6) The weighted normalized decision matrix is calculated next: we multiply normalized attributes scores with corresponding importance weights. The results are shown in Table 7.13.

Table 7.13 Weighted Normalized Decision Matrix

	Ambiance	Location	Cost	Service
Cheraton	0.0741	0.1408	0.1914	0.0353
Milton	0.0296	0.2113	0.1148	0.0212
Harriott	0.0444	0.3521	0.1914	0.0282
Starwood	0.0741	0.2817	0.0766	0.0353

7) The positive and negative ideal solutions of the attributes are calculated. See Table 7.14.

Table 7.14 Positive and Negative Ideal Solutions

	Ambiance	Location	Cost	Service
Positive solution	0.0741	0.3521	0.1914	0.0353
Negative solution	0.0296	0.1408	0.0766	0.0212

8) Calculate the positive ideal solution (D_i^*) and negative ideal solution (D_i^-) of each alternative from the positive and negative ideal solutions, respectively. And the last step is to compute the relative closeness (RC^*) of each alternative to the ideal solution. The results are shown in Table 7.15.

Table 7.15 Positive Ideal Solution (D_i^*), Negative Ideal Solution (D_i^-), and Relative Closeness (RC^*) for the Various Alternative

	D_i^*	D_i^-	RC^*
Cheraton	0.2113	0.1239	0.3697
Milton	0.1669	0.0802	0.3244
Harriott	0.0305	0.2410	0.8878
Starwood	0.1347	0.1484	0.5241

9) Finally, the alternatives are ranked based on the RC*.

Table 7.16 Ranking based on Relative Closeness (RC^*)

	RC^*	Rank
Cheraton	0.3697	3
Milton	0.3244	4
Harriott	0.8878	1
Starwood	0.5241	2

The result received from the AHP-TOPSIS mixed model shows that Harriott is predicted as the best choice for the consumer, Starwood is the second choice, Cheraton is the third choice, followed by Milton. However, this ranking is different from that obtained via TOPSIS which predicts that Harriott is the best choice for the consumer, Cheraton is the second choice, and Starwood is the one chosen next. Milton is the worst choice of all.

This result demonstrates that the ranking obtained from TOPSIS and AHP-TOPSIS mixed model are varied, and results of the prior example was merely coincidental. When we let consumers do the pairwise comparisons within the AHP-TOPSIS mixed model, the ranking received can be different from those arrived at via the use of TOPSIS alone where importance weights are assumed.

Chapter Eight: Conclusions and Discussion

I General Discussion

This research examines consumption contexts where people are confronted with the problem of comparing and choosing amongst multiple products or brand alternatives. Brands here are viewed as bundles of attributes and are compared directly based on specific attributes within a product category (laptop computers). This is based on literature on consumer decision making that suggests that consumers typically integrate attributes of information and employ comparative techniques to make a final brand choice. While there has been a strong past research focus on lists of attributes that can influence consumer choice and ways to combine them, the manner of measurement of attribute importance weights remains under-investigated. Further complications to attribute importance weight assessments are introduced by the variable nature of brand attributes—while some attributes are quantitative (e.g., price and weight), others can be qualitative (e.g., service equality and brand image perceptions). Consumers' brand choice can be regarded as a multi-criteria decision-making (MCDM) problem, for which they need to take many attributes and alternatives into consideration while assessing and selecting the optimal marketing strategy or brand. This thesis aims to further the understanding of decision making methodologies that are as yet seldom seen in marketing. We use four multi-attribute decision making models – Fishbein's Multi Attribute Attitude Model (MAAM), AHP, TOPSIS, and an AHP-TOPSIS mixed model – and apply them within the same laptop brand choice scenario and compare results found.

MAAM is one of the most popular and widely used techniques in marketing. The easy and simple structure and low cost method of MAMM can save time for decision makers in terms of acquiring data and ranking alternatives. However, it does not take into account the interaction amongst different attributes, and researchers are unable to understand the relative importance of various attributes in consumers' minds. What's worse, the over simplified equation, where attribute weights are assigned by respondents arbitrarily, also largely influence the accuracy of results and limit further application of Fishbein's model. TOPSIS can help decision makers understand the inter-relationship between attributes and enhance accuracy of results. TOPSIS has been extensively used in multi-criteria decision making situations in the field of decision sciences, but hasn't been widely applied in marketing. Consumers many times are confronted with "approach-avoidance motivations". The framework of TOPSIS which assesses brands by finding the one with shortest distance from positive ideal solution and farthest distance from negative ideal solutions is in line with this approach-avoidance framework. The understandable logic, the straightforward calculations, the consideration of both best and worst choices at same time all make TOPSIS a good model for use in the field of decision making. However, TOPSIS doesn't have unique techniques to accurately evaluate importance weights. Different weight elicitation methods result in wide discrepancies within the final results, thereby making it important to more effectively elicit relative attribute importance weights. AHP that allows decision makers to calculate accurate importance weights via the pairwise comparison process and consistency checks is one way to make up for the drawbacks of TOPSIS. The pairwise comparison procedure of the AHP model allows managers only to provide relative (rather than absolute) preference assessment. However, AHP is still an imperfect model. The time consuming procedures are a distinct limitation, with some decision makers finding it too labor intensive and tedious. Furthermore, AHP is unable to deal with too many attributes and alternatives due to the complexity introduced into the pairwise comparison process (Saaty & Ozdemir, 2003). This weakness hinders the application of AHP in large alternatives and massive data solution. Due to the drawback and advantages of these models, an AHP-TOPSIS mixed model that can combine the advantage of these two models while overcome the drawbacks is examined here. The table 8.1 showed detailed comparisons of these four models on six different aspects. A '+' indicates that the model possesses that attribute, and a '-' indicates that the model does not possess that feature.

Table 8.1 The Comparison of Four Models:

	MAAM (Fishbein's)	AHP	TOPSIS	AHP-TOPSIS Mixed Model
Easy and simple structure	+	-	-	-
Reflects the inter-relationship between attributes	-	+	-	+
Transforms qualitative information into quantitative data	-	+	+	+
Information processing ability	+	-	+	+
Considers both best and worst choices at the same time	-	-	+	+
Attribute weights elicited within the model	-	+	-	+

We can find that AHP-TOPSIS mixed model is regarded as the best of the mix.

II Limitations and Future Research

In table 8.2, we conclude and contrast the results obtained from these four models.

Table 8.2 Summary of Results from the Four Models

	MAAM (Fishbein's)	AHP	TOPSIS	AHP-TOPSIS Mixed Model
Epson	2	3	1	1
Canon	2	4	4	4
Compaq	1	2	2	2
Keynote	2	1	3	3
IBM	6	6	6	6
Toshiba	5	5	5	5

Results via different choice models are not congruent given the variance in methodologies employed and weight elicitation techniques used. Only results attained via TOPSIS and AHP-TOPSIS are the same. However, it is a coincidence in this thesis and should be different. Because we used assumed importance weights in this thesis to do the pairwise comparison in the AHP-TOPSIS model, the rankings obtained from TOPSIS is same as that from AHP-TOPSIS mixed model. By applying these two models in an alternative hotel choice scenario, it was demonstrated that the rankings from these two models can be different. In the future research, a group solution strategy for the different pairwise comparisons within AHP warrants investigation (Appadoo, Bhatt, & Bector, 2012). Moreover, the example that forms the basis of analyses conducted here (from the research of Hawkins, Best, &Coney, 1998) is 16 years old now. The attributes and weights contained in the example are out of date, and don't contain contemporary attributes that consumers look for in the product category. The consideration of new attributes of laptops (such as heat dissipation, CPU, graphics card, etc.) can affect consumer choices. Future research can try to add some more up to date attributes that can reflect consumers' current needs.

In the summary table we find that the four models predict similar lowest and second lowest results. Is this a coincidence? In order to find the answer, we use sensitivity analysis. Sensitivity analysis is the study of how the changes in the coefficients of an optimization model influence the optimal solution (Anderson, Sweeney, Williams, Camm, & Martin, 2012). Pannell (1977) summarized the purposes of sensitivity analysis into four categories, including decision making, communication, increased understanding, and model development. Simanavicine and Ustinovichius (2010) proposed that the initial data of Multiple Criteria Decision Making (MCDM) problems might be imprecise and inaccurate, and performing sensitivity analysis is essential to check the accuracy of measurement data and final results. They further emphasized the importance of performing sensitivity analysis when using quantitative Multiple Criteria Decision Making Models (MCDM). Sensitivity analyses are widely used in checking the accuracy of values and weights of criteria in AHP (e.g., Chang, Wu, Lin, & Chen, 2007; Al-Harbi, 2001; Byun, 2001) and TOPSIS (e.g. Simanaviciene & Ustinovichius, 2010; Gumus, 2009).

1) Sensitivity Analysis Part 1

By using sensitivity analysis, we can examine how sensitive the alternatives rankings obtained from the four models are to changes within criteria importance weights. A number of sensitivity analyses are carried out next. The importance weights considered within the Hawkins et al. (1998) are listed in Table 8.3.

Table 8.3 Importance Weights of Attributes

	Price	Weight	Processor	Battery Life	After Sale Report	Display Quality
Importance weight	3	4	3	1	2	3

(a) Importance weights variation 1. When we increase each importance weight by 1, the weight for each of the attributes becomes (4, 5, 4, 2, 3, 4) respectively, and the subsequent ranking is shown in Table 8.4:

Table 8.4 Ranking for Importance Weights Variation 1

Ranking				
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	4	4	2	3
Canon	2	3	4	5
Compaq	1	2	3	4
Keynote	2	1	1	2
IBM	6	6	6	6
Toshiba	5	5	5	1

(b) Importance weights variation 2. When we deduct 1 from each importance weight, the weights for each of the attributes becomes (2, 3, 2, 1, 1, 2) respectively. Because the original importance weight of Battery Life is already 1 and it make no sense to reduce to 0, we keep it as 1. The subsequent ranking based on the new importance weights is shown in Table 8.5:

Table 8.5 Ranking for Importance Weights Variation 2

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	4	4	2	2
Canon	2	3	4	4
Compaq	1	2	3	3
Keynote	2	1	1	1
IBM	6	6	6	6
Toshiba	5	5	5	5

By analyzing Tables 8.4 and 8.5, we find that if the importance weight of each attribute changes by 1 in the same direction simultaneously (either all increase or decrease by 1), the rankings of the two tables are identical. What's more, IBM and Toshiba are still the last and second last choice (ranking 6 and 5, respectively). In order to further verify these results, we continue to change the importance weights to see whether the rankings are changed for IBM and Toshiba.

(c) Importance weights variation 3. When we keep the first, third and fifth importance weights constant while deducting 1 from the other three importance weights, the new importance weights for each of the attributes become (3, 5, 3, 2, 2, 4) respectively, and the subsequent ranking is listed in Table 8.6:

Table 8.6 Ranking for Importance Weights Variation 3

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	5	5	3	3
Canon	3	3	4	4
Compaq	1	2	2	2
Keynote	2	1	1	1
IBM	6	6	6	6
Toshiba	4	4	5	5

(d) Importance weights variation 4. When we keep the second, fourth and sixth importance weights constant, while deducting 1 from the other three importance weights, the new weight for each of the attributes becomes (2, 4, 2, 1, 1, 3) respectively, and the subsequent ranking is shown in Table 8.7.

Table 8.7 Ranking for Importance Weights Variation 4

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	4	5	3	3
Canon	3	3	4	4
Compaq	1	2	2	2
Keynote	2	1	1	1
IBM	6	6	6	6
Toshiba	4	4	5	5

The results obtained from sensitivity analyses show that when we change importance weights for each attribute in different directions, IBM and Toshiba are not always the sixth and fifth choice. When weights for each attributes is (3,5,3,2,2,4), shown in the importance weights variation 3 section, Toshiba can be the fourth or fifth choice (depending on results from different models). While weights when changed to (2,4,4,1,1,3), within the importance weights variation 4 section, Toshiba can end up as the third or fourth choice (depending on results from different models). However, no matter how the importance weights are changed, IBM is always the sixth (worst) choice. In other words, this is the ranking for IBM independent of changes to importance weights. This may be because the attributes belief scores for IBM are relatively low (2, 3, 5, 1, 5, 3).

2) Sensitivity Analysis Part 2

In order to verify this assumption, we further apply sensitivity analysis to change attributes belief scores for IBM. We keep attributes belief scores of other alternatives constant, but increase values of attributes belief scores of IBM by varying degrees. A number of sensitivity analyses are carried out next.

(a) Attributes belief scores of IBM variation 1: Change attributes belief scores of IBM to (6, 7, 10, 6, 10, 8). The standard attributes belief scores range from 1 to 5, however, we increase the attributes belief scores ranging from 6 to 10 to see whether the ranking of IBM can be changed significantly.

The rankings got from these four models are summarized in Table 8.8

Table 8.8 Ranking of Alternatives When Belief Scores of IBM Become (6, 7, 10, 6, 10, 8)

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	3	4	2	2
Canon	3	5	5	5
Compaq	2	2	3	3
Keynote	3	3	4	4
IBM	1	1	1	1
Toshiba	6	6	6	6

(b) Attributes Belief scores of IBM variation 2: Change attributes belief scores to (2, 4, 5, 1, 5, 4). The rankings obtained from these four models are summarized in Table 8.9

Table 8.9 Ranking of Alternatives When Belief Scores of IBM Become (2, 4, 5, 1, 5, 4)

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	3	4	1	1
Canon	3	5	4	4
Compaq	1	1	3	3
Keynote	3	2	2	2
IBM	2	3	5	5
Toshiba	6	6	6	6

(c) Belief scores of IBM variation 3: Change belief scores of IBM to (3, 4, 5, 2, 5, 3). The rankings obtained from these four models are summarized in Table 8.10

Table 8.10 Ranking of Alternatives When Belief Scores of IBM Become (3, 4, 5, 2, 5, 3)

	Ranking			
	Fishbein's Model	AHP	TOPSIS	AHP-TOPSIS Mixed
Epson	3	4	2	2
Canon	3	5	5	5
Compaq	1	2	3	3
Keynote	3	3	1	1
IBM	2	1	4	4
Toshiba	6	6	6	6

The results received from sensitivity analysis part 2 shows that when we increase the attributes belief scores of IBM by varying degrees, IBM is not always the sixth choice. When we drastically increase the attributes belief scores of IBM weight to (6, 7, 10, 6, 10, 8), whose results are shown in Table 8.8, IBM can be the optimal choice; However, those attributes belief scores are too extreme. Thus in variation 2 and 3, we slightly increase attributes belief scores of IBM to see how the rankings change. When we change attributes belief scores of IBM to (2, 4, 5, 1, 5, 4), where results are presented in Table 8.9, IBM can be the third, fourth, or fifth choice (depending on results from different models); And when the attribute scores of IBM were altered to (3, 4, 5, 2, 5, 3), where results are summarized in Table 8.10, IBM can be the first, second or fourth choice (depending on results from different models). These results reinforce the assumption that the previously unfavorable ranking received of IBM was due to its relatively low attributes belief scores (2, 3, 5, 1, 5, 3).

III Theoretical and Practical Implications

This thesis has both theory and practice implications. From a theoretical point of view, this thesis enhances the understanding of decision making methodologies that are seldom used in marketing. It applies multiple competing decision making approaches from supply chain management to understand and mathematically simulate consumer brand choices. This thesis successfully compares the results obtained from four mainstream models and discusses their pertinent application fields.

Results found here have practical implications for companies. Companies that have relatively low attributes belief scores (e.g., IBM) must improve consumers' impressions of their performance on various attributes (e.g., via improving technology, advertising, and promotions). Companies might also need to pay more attention to the attributes that are scored low on by consumers and try to improve consumers' impressions on these dimensions. In order to better evaluate differences in demand and save decision making time, companies can provide questionnaires on their website that list all the evaluative attributes. Pop-up dialog boxes can let consumers pick brand alternatives they are interested in and assign importance weights. Built-in AHP, TOPSIS, or AHP-TOPSIS Mixed Models can help consumers with the calculations. Finally, alternative ranking can be output in accordance with importance weights assigned and evaluative attributes picked by consumers.

This thesis also has practical significance for consumers dealing with different decision making scenarios. Consumers can choose decision making models according to their specific circumstances. When they simply desire rough rankings of alternatives and inaccurate decisions are acceptable, Fishbein’s model may be acceptable. When consumers have a strong “approach-avoidance” motivation, or when they don’t require accurate results (i.e., when the risk is not high even if the optimal choice is not predicted accurately), TOPSIS may be advisable. Consumers can choose the AHP model to make decisions with when they don’t have time constraints, or when precise importance weights are needed. When there is a time limit on decision making as well as accurate importance weights are imperative, the AHP-TOPSIS mixed model is the best choice.

References

Abedi, B, Shafei, A.D., & M Kalantari. (2012). Satisfaction Evaluation of Tourists About the Quality of Seaside Environment in Mahmoudabad City by Using AHP-TOPSIS Models. *Middle-East Journal of Scientific Research*, 12(3), 406-412.

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior Relations: A Theoretical Analysis and Review of Empirical Research. *Psychological Bulletin*, 84(5), 888.

Al-Harbi, K.M. (2001). Application of the AHP in Project Management. *International Journal of Project Management*, 19(1), 19-27.

Albayrak, E., & Erensal, Y.C. (2004). Using Analytic Hierarchy Process (AHP) to Improve Guman Performance: an Application of Multiple Criteria Decision Making Problem. *Journal of Intelligent Manufacturing*, 15(4), 491-503.

Anderson, D.R., Sweeney, D.J., Williams, T.A., Camm, J.D., & Martin, K. (2012). An Introduction to Management Science: Quantitative Approaches to Decision Making (13rd ed.). South-Western, Cengage Learning.

Appadoo, S.S., Bhatt,S.K., & Bector, C.R. (2012). A Mixed Solution Strategy for Group Multi-attribute TOPSIS Model with Application to Supplier Selection Problem[J]. *Journal of Information and Optimization Sciences*, 33(1),13-40.

Armacost, R.L., & Hosseini,J.C. (1994). Identification of Determinant Attributes Using the Analytic Hierarchy Process. *Journal of the Academy of Marketing Science*, 22(4), 383-392.

Bahmani, N., & Blumberg, H. (1987). Consumer Preference and Reactive Adaptation to a Corporate Solution of the over-the-counter Medication Dilemma—an Analytic Hierarchy Process Analysis. *Mathematical Modelling*, 9(3), 293-298.

Baltas, G. (1997). Determinants of Store Brand Choice: a Behavioral Analysis. *Journal of Product & Brand Management*, 6(5), 315-324.

Beckwith, N.E., & Lehmann, D.R. (1973).The Importance of Differential Weight in Multiple Attribute Models of Consumer Attitude. *Journal of Marketing Research*, 4 (5), 141-145.

Beckwith, N.E. & Lehmann, D.R. (1975). The Importance of Halo Effects in Multi-Attribute Attitude Models. *Journal of Marketing Research*, 12 (8), 265-275.

Belenson, S.M., & Kapur, K.C. (1973). An Algorithm for Solving Multicriterion Linear Programming Problems with Examples. *Journal of the Operational Research Society*, 24(1): 65-77.

Bettman, J. R. (1979). An Information Processing Theory of Consumer Choice, Reading, MA: Addison- Wesley.

Bettman, J.R., Johnson, E.J., & Payne, J. W. (1991). Consumer Decision Making. *Handbook of Consumer Behavior*, 50-84.

Bettman, J. R., & Park, C.W. (1980). Effects of Prior Knowledge and Experience and

Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis. *Journal of Consumer Research*, 234-248.

Bhangale, P.P., Agrawal, V.P. & Saha, S. K. (2004). Attribute Based Specification, Comparison and Selection of a Robot. Mech. Mach Theory, 39, 1345–1366.

Bhatt, S.K., Bhatnagar, N., & Appadoo, S. (2012). Approaching the Best while Avoiding the Worst Option: Consumer Choice Modelling via TOPSIS, *Journal of Information and Optimization Sciences*, 33, 259-272.

Bhutia, P.W., & Phipon, R. (2012). Application of AHP and TOPSIS Method for Supplier Selection Problem. *IOSR Journal of Engineering*, 2(10), 43-50.

Bhutta, K.S., & Huq, F. (2002). Supplier Selection Problem: a Comparison of the Total Cost of Ownership and Analytic Hierarchy Process Approaches. *Supply Chain Management: An International Journal*, 7(3), 126-135.

Billings, R. S. & Scherer, L. L. (1988). The Effects of Response Mode and Importance on Decision-Making Strategies: Judgment versus Choice, *Organizational Behavior and Human Decision Processes*, 41(1), 1-19.

Biehal, G., Stephens, D., & Curio, E. (1992). Attitude Toward the Ad and Brand Choice. *Journal of Advertising*, 21(3), 19-36.

Brown, W.F. (1950). The Determination of Factors Influencing Brand Choice. *The Journal of Marketing*, 14(5), 699-706.

Brown,W.F. (1950). The Determination of Factors Influencing Brand Choice. *The Journal of Marketing,* 14(5), 699-706.

Bucklin, R.E., & Lattin, J.M. (1991). A Two State Model of Purchase Incidence and Brand Choice. *Marketing Science,* 10 (Winter), 24–39.

Byun, D.H. (2001). The AHP Approach for Selecting an Automobile Purchase Model. *Information & Management,* 38(5), 289-297.

Cacioppo, J.T., Berntson, G.G. (1994). Relationship between Attitudes and Evaluative Space: A Critical Review, with Emphasis on the Separability of Positive and Negative Substrates. *Psychological bulletin*, 115(3), 401.

Calantone, R.J., Benedetto, C.A., & Schmidt, J.B. (1999). Using the Analytic Hierarchy Process in New Product Screening. *Journal of Product Innovation Management,* 16(1): 65-76.

Calder, B.J. (1975).The Cognitive Foundations of Attitudes: Some Implications for Multi-attribute Models. *Advances in Consumer Research*, 2, 241-248.

Chakladar, N.D., Chakraborty, S. (2008). A Combined TOPSIS-AHP-method-based Approach for non-traditional Machining Processes Selection. Proceedings of the Institution of Mechanical Engineers, Part B: *Journal of Engineering Manufacture,* 222(12), 1613-1623.

Chang, C.W., Wu, C.R., Lin, C.T., et al. (2007). An Application of AHP and Sensitivity

Analysis for Selecting the Best Slicing Machine. *Computers & Industrial Engineering*, 52(2), 296-307.

Chen, C.F. (2006). Applying the Analytical Hierarchy Process (AHP) Approach to Convention Site Selection. *Journal of Travel Research*, 45(2), 167-174.

Chen, S.J.& Hwang, C.L. (1992). Fuzzy Multiple Attribute Decision Making—Methods and Applications (Springer-Verlag: Berlin). (Lecture Notes in Economics and Mathematical Systems).

Cheng, E.W.L., & Li, H. (2001). Information Priority-setting for Better Resource Allocation Using Analytic Hierarchy Process (AHP). *Information Management & Computer Security*, 9(2), 61-70.

Cheng, X., Gong, B., & Zhang, H. (2012). Customer Value Assessment Using the Fuzzy AHP and TOPSIS Methods: Application in Bank. *Journal of Information and Computational Science* 9, 12, 3431–3438

Chiang, T.C., & Yu, F.J. (2009). Improving Real Estate Broker Service Using TOPSIS Method. *Journal of Information and Optimization Sciences*, 30(2), 231-243.

Costa, R., & Evangelista, S. (2008) An AHP Approach to Assess Brand Intangible Assets. *Measuring Business Excellence*, 12(2), 68-78.

Davies, M. (2001). Adaptive AHP: A Review of Marketing Applications with Extensions. *European Journal of Marketing*, 35(7/8), 872-894.

Danaei, A., & Haghighi, M. (2013). Measuring the Relative Performance of Stock Market using TOPSIS. *Management Science Letters*, 3(1).

Das, D. (2012). Selection of Materials in Engineering Design using Ashby's Chart and AHP-TOPSIS. Jadavpur University Kolkata.

Deng, H., Yeh, C. H., & Willis, R. J. (2000). Inter-company Comparison Using Modified TOPSIS with Objective Weights. *Computers and Operations Research*, 27, 963–973.

Devlin, J.F. (2002). Consumer Knowledge and Choice Criteria in Retail Banking. *Journal of Strategic Marketing*, 10(4), 273-290.

Deshmukh, A., Millet, I. (2011). An Analytic Hierarchy Process Approach to Assessing the Risk of Management Fraud. *Journal of Applied Business Research (JABR)*, 15(1), 87-102.

Dickson, P. R., & Sawyer, A. G. (1990). The Price Knowledge and Search of Supermarket Shoppers. *Journal of Marketing*, 54 (7), 42–53.

Douligeris, C., Pereira, I.J. (1994). A Telecommunications Quality Study Using the Analytic Hierarchy Process. *IEEE Journal on Selected Areas in Communications*, 12(2), 241-250.

Elliot, A.J. (1999). Approach and Avoidance Motivation and Achievement Goals. *Educational psychologist*, 34(3), 169-189.

Elliot, A.J. (2006). The Hierarchical Model of Approach-avoidance Motivation.

Motivation and Emotion, 30(2), 111-116.

Elliot, A.J., & Thrash, T.M. (2002). Approach-avoidance Motivation in Personality: Approach and Avoidance Temperaments and Goals. J*ournal of personality and social psychology*, 82(5), 804.

Erkarslan, O., & Yilmaz, H. (2011). Optimization of Product Design through Quality Function Deployment and Analytical Hierarchy Process: Case Study Of A Ceramic Washbasin Metu Jfa, 28(1), 1-22.

Ertuğrul, İ., & Karakaşoğlu, N. (2009). Performance Evaluation of Turkish Cement firms with Fuzzy Analytic Hierarchy Process and TOPSIS Methods. *Expert Systems with Applications*, 36(1), 702-715.

Fan, C.K., Lee, Y.H., Lee, L.T., et al. (2011). Using TOPSIS & CA Evaluating Intentions of Consumers' Cross-Buying Bancassurance. *Journal of Service Science and Management*, 4, 469-475.

Fishbein, M. A. (1967). Attitude and the Prediction of Behavior. *Readings in attitude theory and measurement*, 477-492.

Fishbein, M. (1967) A Behavior Theory Approach to the Relations Between Beliefs about an Object and the Attitude Toward the Object. In M. Fishbein (Ed.), *Readings in attitude theory and measurement*, New York: Wiley, 389–399.

Foxall, G.R., Greenley, G.E. (1999). Consumers' Emotional Responses to Service

Environments. *Journal of Business Research*, 46(2), 149-158.

Foxall, G.R., Yani-de-Soriano, M.M. (2005). Situational Influences on Consumers' Attitudes and Behavior. *Journal of Business Research*, 58(4), 518-525.

Freud, S. (1915). Repression. In the Standard Edition of Complete Psychological Works of Sigmund Freud, vol. XIV.

Gangurde, S.R., & Akarte, M. M. (2013). Consumer Preference Oriented Product Design Using AHP-Modified TOPSIS Approach. *Benchmarking: An International Journal*, 20(4), 6-6.

Gao, L., & Hailu, A. (2013). Identifying Preferred Management Options: an Integrated agent-based Recreational Fishing Simulation Model with an AHP-TOPSIS Evaluation Method. *Ecological Modeling*, 249, 75-83.

Ghosh, D.N. (2011). Analytic Hierarchy Process and TOPSIS Method to Evaluate Faculty Performance in Engineering Education. UNIASCIT, 1(2), 63-70.

Gumus, A.T. (2009). Evaluation of Hazardous Waste Transportation Firms by Using a two- step fuzzy-AHP and TOPSIS Methodology. *Expert Systems with Applications*, 36(2), 4067-4074.

Handfield, R, Walton,S.V., Sroufe,R., et al. (2002). Applying Environmental Criteria to Supplier Assessment: A Study in the Application of the Analytical Hierarchy Process. *European Journal of Operational Research*, 141(1), 70-87.

Hansen, F. (1972). Consumer Choice Behavior. New York: Free Press

Hawkins, D. I., Best, R. J., & Coney, K. A. (1998). Consumer behavior. Irwin. McGraw Hill, 7th Edition.

Hartwich, F.(1999). Weighting of Agricultural Research Results: Strength and Limitations of the Analytic Hierarchy Process (AHP).

Hoyer, W. D. (1984). An Examination of Consumer Decision Making for a Common Repeat Purchase Product. *Journal of Consumer Research,* 11 (11), 822–29.

Hsieh, L.F., Chin, J.B., & Wu, M.C. (2006). Performance Evaluation for University Electronic Libraries in Taiwan. *Electronic Library*, 24(2), 212-224.

Hugstad, P., Taylor, J.W., & Bruce, G.D. (1987). The Effects of Social Class and Perceived Risk on Consumer Information Search. *Journal of Services Marketing,* 1(1), 47-52.

Hutcheson, G.D., & Moutinho, L. (1998). Measuring Preferred Store Satisfaction Using Consumer Choice Criteria as a Mediating Factor. *Journal of Marketing Management,* 14(7), 705-720.

Hwang, C.L., Lai, Y.J., & Liu, T.Y. (1993). A New Approach for Multiple Objective Decision Making. *Comp. Opr. Res.*, 20, 889–899.

Hwang, C.L., & Yoon, K. (1981). Multiple attribute decision making: Methods and applications. Berlin: Springer.

Hwang, C.L. & Yoon, K. (1982). Multiple Attribute Decision Making—Methods and Applications—A State of Art Survey (Springer Verlag: Berlin).

Iqbal, Z., Verma, R., & Baran, R. (2003). Understanding Consumer Choices and Preferences in Transaction-based E-services. *Journal of Service Research*, 6(1), 51-65.

Jacoby, J., & Kaplan, L.B. (1972). The Components of Perceived Risk. *Advances in consumer research*, 3(3), 382-383.

Johnson, M.D. (1984). Consumer Choice Strategies for Comparing non-comparable Alternatives. *Journal of consumer Research*, 741-753.

Kahneman, D. and Tversky, A. (1979) Intuitive prediction: Biases and Corrective Procedures. *TIMS Studies in Management Science*,12, 313-327.

Katona, G., & Mueller, E. (1955). A Study of Purchase Decisions. Consumer Behavior: The Dynamics of Consumer Reaction. New York University Press.

Khodam, A.M., Hemmati, M., & Abdolshah, M. (2008). Analysis and Prioritizing Bank Account with TOPSIS Multiple-Criteria Decision-A Study of Refah Bank in Iran. *21st Australasian Finance and Banking Conference*.

Kim, G., Park, C.S., & Yoon, K.P. (1997). Identifying Investment Opportunities for Advanced Manufacturing Systems with Comparative-integrated Performance Measurement. *International Journal of Production Economics*, 50(1), 23-33.

Kwong, C.K., & Tam, S.M. (2002). Case-based Reasoning Approach to Concurrent Design of Low Transformers. *Journal of Materials Processing Technology*, 128, 136–141.

Lai, Y.J., Liu, T.Y., & Hwang, C.L. (1994). Topsis for MODM. *European Journal of Operational Research*, 76(3), 486-500.

Lai, V.S., Trueblood, R.P. & Wong, B.K. (1992). Software Selection: a Case Study of the Application of the Analytical Hierarchical Process to the Selection of a Multimedia Authoring system. *Information & Management*, 25(2).

Laroche, M. (1978). Four Methodological Problems in Multi-attribute Attitude Models. *Advances in Consumer Research*, 5,175-179.

Lewin, K. (1935). A Dynamic Theory of Personality, New York: McGraw-Hill

Liang, W.Y. (2003). The Analytic Hierarchy Process in Project Evaluation: an R&D Case Study in Taiwan. *Benchmarking: An International Journal*, 10(5), 445-456.

Lim, N. (2003). Consumers' Perceived Risk: Sources versus Consequences. *Electronic Commerce Research and Applications*, 2(3), 216-228.

Lin, M.C., Wang, C. C., Chen, M.S., et al. (2008). Using AHP and TOPSIS Approaches in consumer-driven Product Design Process. *Computers in Industry*, 59(1), 17-31.

Mehrparvar, E., Shahin, A., & Shirouyehzad, H. Prioritizing Internal Service Quality dimensions using TOPSIS Technique (With a case study in Isfahan Steel Mill Co.).

Laroche, M. (1978). Four Methodological Problems in multi-attribute Attitude Models. *Association for Consumer Research*, 5, 175-179.

McClelland, D.C.(1987). Human motivation. CUP Archive.

Mehrparvar, E., Shahin, A., Shirouyehzad, H. (2012). Prioritizing internal service quality dimensions using TOPSIS Technique (With a case study in Isfahan Steel Mill Co.). I*nternational Journal of Business and Social Science*, 3(2), 210-217.

Millet,I., & Harker,P.T.(1990). Globally Effective Questioning in the Analytic Hierarchy Process. *European Journal of Operational Research*, 48(1), 88-97.

Millet,I., & Wedley,W.C. (2002). Modelling Risk and Uncertainty with the Analytic Hierarchy Process. *Journal of Multi Criteria Decision Analysis*, 11(2), 97-107.

Miller, N.E. (1944). Experimental Studies of Conflict.

Miller, N. E. (1959). Liberalization of basic S-R concepts: Extension to Conflict Behavior, Motivation, and Social Learning. Psychology: A Study of Science, 2, New York: McGraw-Hill.

Murthi, B.P.S., & Srinivasan, K. (1999). Consumers' Extent of Evaluation in Brand Choice. *The Journal of Business*, 72(2), 229-256.

Nelson, P. (1970). Information and Consumer Behavior. *The Journal of Political Economy*, 78(2), 311-329.

Newman, J. W., & Staelin, R. (1972). Pre-purchase Information Seeking for New Cars and Major Household Appliances. *Journal of Marketing Research*, 9 (8), 249–57.

Olson, D.L. (2004). Comparison of Weights in TOPSIS Models. *Mathematical and Computer Modelling*, 40(7-8), 721–727

Olshavsky, D.H., & Granbois, R. W. (1979). Consumer Decision Making— Fact or Fction? *Journal of Consumer Research*, 6 (9), 93–100.

Önüt, S., & Soner, S. (2008). Transshipment Site Selection Using the AHP and TOPSIS Approaches under Fuzzy Environment. *Waste Management*, 28(9), 1552-1559.

Pannell, D.J. (1997). Sensitivity Analysis of Normative Economic Models: Theoretical Framework and Practical Strategies. *Agricultural economics*, 16(2), 139-152.

Park, C.W., Iyer, E. S., & Smith, D. C. (1989). The Effects of Situational Factors on in-store Grocery Shopping Behavior: The Role of Store Environment and Time Available for Shopping. *Journal of Consumer Research*, 15 (3), 422–33.

Penz, E., & Hogg, M.K. (2011).The Role of Mixed Emotions in Consumer Behavior: Investigating Ambivalence in Consumers' Experiences of approach-avoidance Conflicts in Online and Offline Settings. *European Journal of Marketing*, 45(1/2), 104-132.

Ramdhani, A., Alamanda,D.T., & Sudrajat,H. (2012). Analysis of Consumer Attitude Using Fishbein Multi-Attributes Approach. *International Journal of Basic and Applied Science*, 1(1), 33-39.

Roselius, T. (1971). Consumer Rankings of Risk Reduction Methods. *The Journal of Marketing*, 56-61.

Saaty, T.L. (1980). Analytic Hierarchy Process, McGraw-Hill, Newyork.

Saaty, T. L., & Ozdemir, M. S. (2003). Why the Magic Number Seven Plus or Minus Two, *Mathematical and Computer Modeling*, 38, 233–244

Schwartz, R.G., & Oren, S. S. (1988).Using Analytic Hierarchies for Consumer Research and Market Modeling. *Mathematical and Computer Modeling*, 11, 266-271.

Sharma, M.J., Moon, I., & Bae, H. (2008). Analytic Hierarchy Process to Assess and Optimize Distribution Network. *Applied Mathematics and Computation*, 202(1), 256-265.

Shih, H. S., Lin, W. Y., & Lee, E. S. (2001). Group Decision Making for TOPSIS//IFSA World Congress and 20th NAFIPS International Conference, 2001. 9th, 2712-2717.

Shih, H.S., Shyur, H. J., & Lee, E. S. (2007). An Extension of TOPSIS for Group Decision Making. *Mathematical and Computer Modelling*, 45(7), 801-813.

Simpson, L., & Lakner, H.B. (1993). Perceived Risk and Mail Order Shopping for Apparel. *Journal of Consumer Studies and Home Economics*, 17(4), 377-389.

Simanaviciene, R., & Ustinovichius, L. (2010). Sensitivity Analysis for Multiple Criteria Decision Making Methods: TOPSIS and SAW. *Procedia-Social and Behavioral Sciences*, 2(6), 7743-7744.

Soltanmohammadi, H., Osanloo, M., & Aghajani, A. (2008). Developing a Fifty-attribute Framework for Mined Land Suitability Analysis Using AHP-TOPSIS Approach. proceedings of post-mining Symposium, Nancy, France, 1-12.

Solomon, M., Zaichkowsky, J.L., & Polegato, R. (2011). *Consumer Behavior*, Toronto, ON: Pearson Canada Inc.

Stewart, T.J. (1992). A Critical Survey on the Status of Multiple Criteria Decision Making Theory and Practice. Omega, 20(5), 569-586.

Sumarwan (2004). Perilaku Konsumen; Teori Dan Penerapannya Dalam Pemasaran. Ghalia Indonesia, Jakarta

Tan, P.S., Lee, S.S.G., & Goh, A.E.S. (2010). An Evaluation Framework to Identify Suitable MCDM Techniques for B2B Collaboration. Service Operations and Logistics and Informatics (SOLI), 2010 IEEE International Conference, 446-451.

Tavana, M., & Hatami-Marbini, A. (2001). A Group AHP-TOPSIS Framework for Human Spaceflight Mission Planning at NASA. *Expert Systems with Applications*, 38(11), 13588-13603.

Tong, L. I., Wang, C. H., Chen, C. C., & Chen, C.T. (2004). Dynamic Multiple Responses by Ideal Solution Analysis, *European Journal of Operational Research*, 156, 433–444.

Tsaur, R.C. (2011). Decision Risk Analysis for an Interval TOPSIS Method. *Applied*

Mathematics and Computation, 218(8), 4295-4304.

Tsaur, S. H., Chang, T.Y., & Yen, C.H. (2002). The Evaluation of Airline Service Quality by fuzzy MCDM. *Tourism Management*, 23(2), 107-115.

Verma, R., Plaschka, G.R., Hanlon, B., et al. (2008). Predicting Consumer Choice in Services Using Discrete Choice Analysis. *IBM Systems Journal*, 47(1), 179-191.

Venkata Rao, R. (2008). Evaluating Flexible Manufacturing Systems Using a Combined Multiple Attribute Decision Making Method. *International Journal of Production Research*, 46(7), 1975-1989.

Wang, T. C., & Hsu, J. C. (2004). Evaluation of the Business Operation Performance of the Listing companies by applying TOPSIS method. Systems, Man and Cybernetics, 2004 IEEE International Conference on IEEE, 2, 1286-1291.

Wind, Y., & Saaty, T. L. (1980). Marketing Applications of the Analytic Hierarchy Process. *Management Science*, 26(7), 641-658.

Wright, P.L. (1975). Consumer Choice Strategies: Simplifying Versus B Optimizing. *Journal of Marketing Research*, 11 (2), 60-67.

Wu, C.S., Lin, C.T., & Lee, C. (2010). Optimal Marketing Strategy: A decision-making with ANP and TOPSIS. *International Journal of Production Economics*, 127(1), 190-196.

Wu, Y. T., & Z, L.T. (2009). Comprehensive Evaluation of Regional Economy Investment

Based on TOPSIS. *Management and Service Science*, International Conference.

Yang, J., & Shi, P. (2002) Applying Analytic Hierarchy Process in a Firm's Overall Performance Evaluation: a Case Study in China. *International Journal of Business*, 7(1), 29-46.

Yoon, Y.P., & Hwang, C.L. (1995). Multiple Attribute Decision Making (SAGE Publications: Beverly Hills, CA).

Yu, X., Guo, S., Guo, J., & Huang, X. (2011). Rank B2C e-commerce Websites in e-alliance Based on AHP and Fuzzy TOPSIS. *Expert Systems with Applications*, 38(4), 3550-3557.

Yurdakul, M., & Ic, Y.T. (2005). Development of a Performance Measurement Model for Manufacturing Companies Using the AHP and TOPSIS Approaches. *International Journal of Production Research*, 43(21), 4609-4641.

Zalm, H., Sanal, M.,Torlak, N. G., & Zam, S. (2009). Analyzing Business Competition by Using AHP-weighted TOPSIS Method: an Example of Turkish Domestic Aviation Industry. *International Symposium on Sustainable Development*, 6(9-10).

Zeleny, M. (1974). Linear Multiobjective Programming. Berlin: Springer-Verlag,.

Zhang, G., Shang, J., & Li, W. (2011). An Information Granulation entropy-based Model for third-party Logistics Providers Evaluation. *International Journal of Production Research*, 50(1), 177-190.