Proceedings Paper:
Lin, Z and Vlachos, I (2015) Introducing Importance-Performance-Impact Analysis (IPIA): A method to strategically prioritize resources allocation. In: Proceedings of EURAM 2015. EURAM 2015: 15th Annual Conference, 17-20 Jun 2015, Warsaw, Poland. EURAM. ISSN: 2466-7498.

Introducing Importance-Performance-Impact Analysis (IPIA): A method to strategically prioritize resources allocation

Abstract

The importance–performance analysis (IPA) model has been widely used as a strategic resource allocation tool for improving customer satisfaction. There are several shortcomings associated with IPA which could lead to incorrect decisions. In this paper, we propose a novel analytical framework, the “Importance-Performance-Impact Analysis” (IPIA) to overcome those shortcomings so as to provide managers with a powerful decision making tool. The IPIA takes advantage of several advanced analytical techniques, such as Back Propagation Neural Network (BPNN), Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP). We illustrate IPIA using the case of an airline company in China. Two primary data sources were used: A passenger survey to obtain the attribute importance and performance, and an expert panel survey to obtain attribute impact. Resources allocation recommendations for improving passenger satisfaction were then derived from the IPIA. We discuss limitations and provide recommendations for future research.

Keywords

Importance-Performance-Impact Analysis; Strategic resources allocation; Airlines transportation, Customer satisfaction; China

Introduction

Company managers need to strategically prioritize resource allocation to achieve optimal level of customer satisfaction, which has been well recognized as the key to the firm's competitive advantage (Arif, Gupta, & Williams, 2013). One of the widely used analytical frameworks by manager to make such decision is importance-performance analysis (IPA, Azzopardi & Nash, 2013; Caber, Albayrak, & Loiacono, 2013; Pan, 2015). First introduced by Martilla and James (1977), IPA is a simple and useful analytical tool based on a two-dimension matrix, which displays the results of customer evaluation of the importance and performance for the attributes of a product or service. In spite of its popularity, IPA suffers from a number of shortcomings that reduce its reliability and usefulness of resource allocation decisions (Deng, 2007; Oh, 2001). These shortcomings include conceptual ones, such as construct validity of 'Importance' dimension and reliability of 'Performance' dimension, and methodological ones, such as discriminating thresholds of IPA quadrants, measurement errors, lack of control, and the relationships between attributes Performance and Importance. Critics of IPA have highlighted: (a) erroneous assumptions of linear relationships between attribute performance and overall customer satisfaction (Caber et al., 2013; Deng, 2007; Geng & Chu, 2012; Oh, 2001); (b) inadequate measures of attribute importance (Matzler, Bailom, Hinterhuber, Renzl, & Pichler, 2004); and (c) assuming independence individual attributes whereas there is strong correlation among them (Geng & Chu, 2012; Matzler et al., 2004; Oh, 2001). Different modifications of IPA have been proposed in the literature, such as IPA with Kano's Model or Three-Factor Theory (e.g. Arbore & Busacca, 2011; Kuo, Chen, & Deng, 2012), Marginal Utility Analysis based IPA (Bacon, 2012), neural network based IPA (Mikulić & Prebežac, 2012) and the Asymmetric Impact-Performance Analysis (Caber et al., 2013).

These modifications have enhanced the usefulness of IPA for management practice. Nevertheless, there are at least three issues that need to be solved. First, there are still a number of conceptual and methodological shortcomings that need to be tackled. Second, there have been very few studies that have integrated advanced decision making techniques such as Back Propagation Neural Network (BPNN), Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) into IPA (e.g. Hughes, Bond, & Ballantyne, 2013; H.-S. Lee, 2015; O'Leary & Deegan, 2005; Sheng, Simpson, & Siguaw, 2014; Ziegler, Dearden, & Rollins, 2012). Third, prioritizing scarce resources in improving service delivery and enhancing customer satisfaction is a Multi-Criteria Decision Making (MCDM) task for managers (Geng & Chu, 2012; Hu, Lee, Yen, & Tsai, 2009). Researchers have adopted MCDM techniques to improve IPA, nevertheless, their analysis was not based on manager decision making data (eg. Hu et al., 2009). This is surprising, because ultimately it is the manager decisions on prioritizing investment on delivery of the service that impact on customer experience and satisfaction.

This paper aims to address the above issues of IPA by introducing a novel framework - 'Importance- Performance-Impact Analysis' (IPIA), which is based on several advanced decision making techniques. The contribution of IPIA method is threefold: (a) it overcomes a number of conceptual and methodological shortcomings by adding a new dimension (impact) to the existing two IPA attributes (performance, importance), thus increasing the reliability and validity of the proposed resource allocation. (b) IPIA takes advantage of several advanced and powerful analytical tools that was not available in conventional IPA analysis. In so doing, IPIA arrives at reliable propositions overcoming data limitations. (c) the addition of impact dimension provides more insights to tourist managers that helps them in decide how to allocate resources to achieve the desired customer satisfaction.

We selected one of the major airline companies in China for the empirical illustration of our framework, because of the growing importance of the Chinese market for the global airlines industry (IATA, 2013), and the intense competition within the Chinese domestic airline market (Shaw, Lu, Chen, & Zhou, 2009). The Chinese airline industry has experienced tremendous growth in the last 30 years, and it is now the world's second largest aviation market, only behind the United States (Fu, Zhang, & Lei, 2012). The market continues to grow at a very fast pace, thanks to a growing affluent middle class in the country, and it is expected that the number of civil airports will reach 244 in 2020 (Fu et al., 2012). Competition among industry rivals is particularly fierce due to the recent relaxation of market entry for private firms, and global airlines entering to the Chinese market through either direct flights or global alliance networks, such as Oneworld, SkyTeam and Star Alliance. Intense competition also come from the aggressive development of the country's high-speed rail service, which has the world's largest high-speed rail network linking virtually all major cities in the country (Fu et al., 2012). This provides an especially appropriate field context for the research.

The next section reviews the conventional IPA in the context of airline services literature and discusses the development of IPIA, providing solutions to the existing weaknesses of IPA in more detail. The subsequent section presents the four steps of IPIA method, the selection of airline service in China, and the application of IPIA in this airline. It follows findings section presenting the IPIA results, the IPIA table and IPIA bubble matrix. The paper concludes with a discussion of findings, research limitations and further research.

Importance-Performance Analysis

Importance-Performance Analysis (IPA) has been widely adopted in a variety of sectors for understanding customer satisfaction, identifying areas for improvement, and prioritizing resource allocation. In a conventional IPA (Martilla & James, 1977), data are collected from customer surveys that measure customer perceptions of the importance of a list of several product and/or service attributes, and their satisfaction with respect to each of the attributes. The data are then presented in a matrix, with the x-axis depicts attribute importance and the y-axis attribute satisfaction, i.e. performance, with four quadrants based on their rankings (see Figure 1). Attributes located in Quadrant 1 are “high importance and low performance”, which require managers to “concentrate” their efforts and resources; Quadrant 2 is for attributes that have both high importance and performance rankings, thus managers need to “keep up the good work”; attributes in Quadrant 3 are low in both importance and performance rankings, which are “low priority” for resource allocation, finally those fall into Quadrant 4 are low in importance but high in performance, thus possibly ‘overkill’, managers might direct their resources elsewhere, particularly to improve the performance of attributes in Quadrant 1.

[Figure 1 about here]

The main advantage of IPA method is its simplicity for supporting management decisions, yet there are several conceptual and methodological shortcomings which have been identified in the literature (Bacon, 2003; Lai & Hitchcock, 2015; Matzler & Sauerwein, 2002; Oh, 2001; Sever, 2015).

Conceptual shortcomings

Conceptual shortcomings of IPA include: construct validity of ‘Importance’ dimension and reliability of ‘Performance’ dimension.

Construct validity of 'Importance' dimension. Importance is often used as a proxy of customer expectations (Oh, 2001), yet there is no agreement how to measure the perceived value or significance of a product or service attribute to an individual. Construct validity of the Importance dimension is usually influenced by cultural and demographic variables, which makes the comparison of research results hard to interpret. Scholars also argue that customer self-expressed value of importance cannot adequately capture the relative importance of the attributes, which is another assumption of IPA method. To deal with this problem, some scholars have resorted to the statistic inference methods to evaluate the relative importance of the attributes. For example, Matzler and Sauerwein (2002) used multi-regression analysis to derive the relative importance of quality characteristics, termed as the hidden importance.

Reliability of 'Performance' dimension. Performance dimension is used to evaluate how well companies perform in allocating their resources based on the levels of customer satisfaction. However, relying on one source of evidence to evaluate performance can jeopardize resource allocation. Companies often use other sources of evidence such as mystery shopping, retail and brand audits and competitor benchmarking to evaluate how well they perform across a number of key performance indicators. Restricting Performance measurement across only the importance attributes would mislead resource allocation decisions.

Methodological shortcomings

Methodological shortcomings of IPA include: discriminating the thresholds of IPA quadrants, measurement errors, lack of control, and non-linear relationships between attributes' Performance and Importance.

Discriminating the thresholds of IPA quadrants. The positioning of the thresholds that divide the plot into quadrants is based on subjective judgment which could lead to inconsistencies in IPA result interpretation (Bacon, 2003). This shortcoming raises concerns over IPA validity in empirical applications. Two approaches have been commonly used to determine the thresholds, which could lead to opposing results: (i) a data-centric approach uses the actual the data mean values of observed importance and performance ratings as the cut-off points among quadrants and (ii) a scale-centered approach uses the actual scales e.g. Likert scales to divide IPA map. Results generated from using arbitrary scales could be biased and make IPA comparisons unreliable. Moreover, actual data mean values of observed importance and performance factors violates the conceptual assumption of IPA method that importance and performance are measured independently.

Measurement errors: scales and measures of Importance and Performance are not developed in a systematic way. Systematic bias towards attributes that favor high importance scores would result in scales that underestimate performance attributes. To overcome the inadequacy of direct measure of attribute importance (Matzler et al., 2004; Oh, 2001; Ryan & Huyton, 2002), statistical techniques such as correlation analysis (Deng, 2007), multiple regression (Matzler & Sauerwein, 2002), and structural equation model have been used to acquire the implicitly derived importance of attributes (Deng & Pei, 2009). Researchers have recently applied artificial neural network analysis such as Back-Propagation Neural Network (BPNN) to estimate attribute importance (Deng, Chen, & Pei, 2008; Hu et al., 2009).

Lack of control: Most IPA studies ignore the need to control IPA results over various factors. IPA studies do not use statistical methods to examine the validity and reliability of results. For example, Sever (2015) used Receiver Operating Characteristic (ROC) analysis to categorize IPA attributes, while testing its validity and reliability.

Non-linear relationships between attributes Performance and Importance: Over the years, the attribute linearity assumption, inherent in the conventional IPA, has been addressed in the literature (Azzopardi & Nash, 2013; Matzler et al., 2004; Mittal & Kamakura, 2001). In an attempt to deal with the non-linear relationships between attribute performance and overall customer satisfaction, researchers have incorporated Three-Factor Theory (e.g. Arbore & Busacca, 2011; Kuo et al., 2012). To deal with the problems of interdependence among attributes (Tsai & Chou, 2009; Wang & Tzeng, 2012; Wu, 2008; Yang, Shieh, Leu, & Tzeng, 2008), researchers have employed a hybrid model combining Decision Making Trial and Evaluation Laboratory (DEMATEL) with Analytic Network Process (ANP) (Yang et al., 2008).

Most of the improvements made to conventional IPA still focus on one perspective only, namely by comparing the differences between attribute importance and performance based on customer experience. But the intra-customer importance-performance analysis is not sufficient for management decision making (Brown & Swartz, 1989; Krepapa, Berthon, Webb, & Pitt, 2003). Although customer experience of services has impact on satisfaction and consequently retention, ultimately it is the service provider's perceptions that directly affect the design and delivery of the service (Krepapa et al., 2003), and mismatch between customer's and provider's perceptions can result in a waste of resources, and possibly customer dissatisfaction and defection (Brown & Swartz, 1989). Multi-source evaluation can enhance the firm's ability to self-monitor and correct the deficiencies that arise in areas for performance improvement (Krepapa et al., 2003).

Proposed analytical framework: Importance-Performance-Impact Analysis

Inclusion of Impact dimension

In order to overcome the shortcomings of IPA method, we included one more dimension, Impact, in the existing two dimensions of importance and performance. Impact refers to the direct impact of attributes on resource allocation. Consumer surveys and retail audit can only assess the indirect impact of attributes on resource allocation via performance, yet, decision makers need to take into account how attributes influence resource allocation. For example, putting too much emphasis on one attribute over the others can impact their availability, production processes. The relation between attributes and resource allocation are far from being linear and there is a complex interrelation between attributes and operation processes, requiring multi-dimensional decision making tools to assist resource allocation. Consumer surveys are not suitable for assessing attributes impact but experts and managers can provide invaluable insights on it. Therefore, we propose to include an Impact dimension in the existing IPA method. The data source for attribute impact is drawn from panel interview of experienced managers in the industry.

Importance-Performance-Impact Analysis (IPIA)

To overcome the weaknesses of IPA, we propose the Importance-Performance-Impact Analysis (IPIA) to help managers prioritizing resources, by adding Impact attribute dimension to the existing importance and performance dimensions in IPA. Specific, IPIA takes place the following steps (Figure 2):

Step 1. Determine attribute structure

Step 2. Measure and normalize the Importance and Performance of attributes

Step 3. Measure and normalize the Impact of each attributes,

Step 4. Determine resource allocation using the IPIA Table and the IPIA bubble Matrix.

[Figure 2 about here]

IPIA Step 1: Determine attributes Structure. The IPA model is considered as an expectation-disconfirmation model that models customer satisfaction as a function of importance and performance of different product or service attributes (Oh, 2001; Sever, 2015). Identifying the key attributes, it is the first step to prioritize and allocate resources that create customer satisfaction. However, there is no systematic way of generating a list of key attributes. Furthermore, the linearity and independence of attributes is an assumption in IPA studies.

A number of empirical studies have reported that integrating Kano model or the 'three-factor theory' with a revised IPA is superior to conventional models that have not considered the non-linear effects. For example, the study of mobile service in Taiwan by Kuo et al. (2012); the study of Taiwanese hot springs tourism by Deng (2007), the study of customer satisfaction of banking service in Italy by Arbore and Busacca (2011), and the study of European tourist satisfaction of their holiday destination, the Balearics, Spain by Alegre and Garau (2011).

IPIA Step 2: Measure and Normalize attributes Importance and Performance. IPIA is an extension of IPA method, therefore we suggest that the Importance and Performance of attributes need to be measured using the established IPA tools taking into account any conceptual and methodological shortcomings. For this reason, we use customer surveys as the data source for measuring Importance and Performance of attributes. However, to overcome the systematic bias towards attributes that favor high importance scores in conventional IPA analysis, we measure Importance using artificial neural networks and Back-propagation neural network.

Artificial neural network models were first introduced in the early 1960s, and have been widely used in different areas of research including travel and tourism (e.g. Kim, Wei,

& Ruys, 2003; Law, 2000; Tsaur, Chiu, & Huang, 2002; Uysal & El Roubi, 1999). Artificial neural network models are computer models that imitate the human pattern recognition function (Chiang, Zhang, & Zhou, 2006; Hu et al., 2009). They do not require any restrictive assumptions about the relationship between input and output variables. Moreover, they are adaptive and can respond to structural changes in the data generation process in ways that parametric models cannot and in most cases, they outperformed parametric models used in statistical techniques such as correlation, regression and structural equation modelling (Chiang et al., 2006; Deng et al., 2008; Garver, 2003; Hu et al., 2009).

Back-propagation neural network (BPNN) is one of the most commonly used artificial neural network models (Hu et al., 2009). In the context of tourism demand forecast study, Law (2000) show that BPNN outperforms regression models, time-series models, and feed-forward neural networks in terms of forecasting accuracy. Researchers have recently used BPNN in IPA studies, for example, Hu et al. (2009) employ BPNN to estimate attribute importance in their case study of the computer industry in Taiwan.

Therefore, the Importance of each attribute is based on their respective BPNN weightings. The structure of BPNN has three parts: one put layer, one or several hidden layers, and one output layer, and based on a BPNN model that is completely trained, importance of the input variable requested is used as the importance weights for the IPIA (Hu et al., 2009). BPNN run in three steps, as suggested by Hu et al. (2009): (a). Set attribute performance as the input variable at the input layer of BPNN and customer satisfaction as output variable at the output layer for BPNN; (b) Step 2: Train and test the BPNN model; and (c) Step 3: Obtain the impact of each attribute. The absolute weights of each attribute are the Importance values in the IPIA framework.

Since the importance of customer self-expression cannot authentically render the relative importance of quality features, BPNN reveals the hidden importance value of each attribute thus overcoming the systematic bias found in traditional IPA methods. Further, it reliably determines the quadrant thresholds providing meaningful interpretations of IPA observations.

Measurement of Performance follows the conventional IPA approach, i.e. by using scale means of observed ratings. This has the advantage of measuring and analyzing the IPA dimensions independently. There is no hidden layer in performance or hidden performance similar to hidden importance, therefore, the scale means of Performance attributes are considered reliable.

Importance and Performance needs to be normalized in order to produce meaningful comparisons. Data transformations to improve normality include square root transformation, log transformation, inverse transformation, arcsine transformation and box-cox transformation. The following formula was used to normalize numeric Importance values: $x_{i.normalised} = \frac{x_i - x_{min}}{x_{max} - x_{min}}$. Performance values were normalized with the inverse hyperbolic function in order to produce the IPIA diagram.

IPIA Step 3: Measure and Normalize attributes Impact. Instead of relying on customer surveys to allocate resources, we choose to have expert opinions on the impact of attributes on resource allocation. Since this is a complex, multidimensional, decision making problem that needs to produce a one-dimensional scale that prioritizes the inputted attribute set, we choose to adopt a combination of DEMATEL and ANP methods. Responses from managers were inputs of DEMATEL/ANP methods to produce an Impact ranking attributes taking into account the interdependencies between the attributes and any structure that may exist among the attributes.

Decision-making trial and evaluation laboratory (DEMATEL) method was originally developed by the Science and Human Affairs Program of the Battelle Memorial Institute of

Geneva between 1972 and 1976 (Fontela & Gabus, 1976). DEMATEL method takes into account the interrelations between attributes and divides the relevant attributes into cause and effect groups in a visual structural map (Hu, Chiu, Cheng, & Yen, 2011; Tsai, Chou, & Lai, 2010). The method has been widely applied in a range of studies, including travel and tourism, usually in combination with other Multiple Criteria Decision Making (MCDM) methods, such as Analytic Network Process (ANP) method (e.g. Horng, Chou, Liu, & Tsai, 2013; Tsai, Chou, et al., 2010), whereas combination with other methods have also been used, for example, Liu, Tzeng, and Lee (2012) employed the method in a different hybrid model for improving national tourism policy implementation.

ANP is an extension of the analytic hierarchy process and it addresses the invalid assumption of independence among attributes for prioritization decision making in analytic hierarchy process (Saaty, 1980). The ANP has the advantage of being able to handle dependence within a cluster of attributes (inner dependence) and among different clusters (outer dependence), in addition to its nonlinear structure (Yang et al., 2008). ANP has been a successful strategic decision support method, and has been used in a variety of industries from manufacturing (e.g. Van Horenbeek & Pintelon, 2014) to services, which includes travel and tourism (e.g. Tsai, Hsu, Chen, Lin, & Chen, 2010).

In a hybrid model of DEMATEL and ANP, the key interdependences of variable clusters are obtained via DEMATEL, and the ANP algorithm determines the interdependences between the clusters of variables (Yang et al., 2008). The hybrid model is particularly suitable for solving the issues of with different degrees of effects among attributes in a conventional IPA. The hybrid model has been widely used in a number of areas, specifically for travel and tourism, in studies such as performance of national park websites (Tsai, Chou, et al., 2010), hot spring hotels (Chen, Hsu, & Tzeng, 2011) and restaurant dining environment design (Horng et al., 2013). Data normalization was conducted in the same way the other two attributes were normalized.

IPIA Step 4: Resource allocation analysis: Develop the IPIA Table and IPIA Matrix. The Importance weights generated from BPNN, the Performance scale means of performance, and the Impact attribute weights of DEMATEL/ANP for each attribute are presented in IPIA Table, normalized, and depicted in the IPIA bubble Matrix to help resources allocation. The IPIA Table is similar to IPA Table having one more column, that of Impact dimension. The IPIA bubble Matrix is similar to IPA Matrix with Importance and Performance axes to determine the four quadrants. We incorporate the Impact dimension by using the size of the bubble for each observation.

Empirical application: The case of an airline company in China

The case company is one of the 'Big Four' airlines in China, namely Air China, China Eastern, China Southern and Hainan, which together accounted approximately 90% of the domestic market share by capacity. According to the International Air Transport Association (IATA, 2014), the case company was the world's third largest airline among the 240 IATA member airlines in 2013. The data used in this study include a survey of 298 customers of the firm and an expert panel that includes ten of the company's managers who are responsible for marketing or passenger services.

IPIA Step 1

IPIA starts with the identification of key airline service attributes. Following the process of service attribute selection as suggested by Oh (2001) and adopted in the prior studies (eg. G. Lee & Lee, 2009), an initial list of 20 attributes was extracted from the extant literature, and presented to four airline managers for discussion.

We select airline managers based on their experience and willingness to contribute to this study. All managers had over 10 years working expertise in airline companies. The managers were asked to select from the list of attributes that are essential for an airline to attract and retain customers for creating a competitive edge in the market, and then group them into the different categories, according to each attribute's respective impact. The managers were told that they could amend the attributes in the list or add new attributes as necessary. Since this is a quantitative study and managers filled in the questionnaires, there were no qualitative evidence collected or analysed.

IPIA Step 2

Passenger survey was conducted using a web-based questionnaire. The rationale of using web-based survey is the growing popularity among travelers in using online booking, eticketing and online check-in for airline services. Participants were invited to participate in the survey through an introduction message and a link posted in two large nation-wide air traveler community websites. Online travel community members are more willing to participate in web-based survey, as they often have a high level of interest in travel surveys because of their strong desire to improve their travel experience (Van Selm & Jankowski, 2006). The item wording and measurements in the questionnaire are similar to those commonly used in industry customer satisfaction surveys (Mittal & Kamakura, 2001).

Respondents were asked to rate their perception of their frequently traveled airline along the ten service attributes, anchored on a 5-point scale (where 0=very poor, and 5=excellent). Their overall satisfaction of the airline was based on an 11-point scale by answering to the question 'based on your overall travel experience, how would you rate your satisfaction with this airline?' (where 0 = extremely dissatisfied, and 10 = extremely satisfied). The survey site went live for about 3 months and during this period, the site received 2,640 visits, with 824 survey responses, generated a response rate of 31%. Seven of the responses were incomplete and excluded from further analysis, thus the valid sample size is 817, which include customers of all the major airlines in China. For IPIA illustration purpose, we selected the sample of the case company's customers only, which include 298 responses for data analysis. Within this sample, 56% of them are business travelers; 78% of them have one or more FFP cards; 83% of them male; 91% of them have a university degree or above; 54% of them were in the high income bracket (annual income over 10K Chinese Yuan).

IPIA Step 3

A panel survey of managers' perceptions is used to assess the impact of the attributes in decision making. In the manager panel survey, participants were asked to make pair-wise comparison of the ten attributes on a matrix table based on an 11 point rating scale (Hu et al., 2011; Hu et al., 2009; Huang, Wu, & Hsu, 2006). The four managers participating in the discussion of service attribute selection invited their colleagues in their own and other airlines to join the manager panel. The panel consisted of twenty-two managers responsible from their airlines' sales, passenger services or marketing tasks. All members in the sample had a bachelor's degree or above. Twenty-five participants in the manager survey represented four of the major airlines in the country: Air China, China Southern, Xiamen Airlines, and Hainan Airlines. We selected the data contributed by the 10 managers of the case company for analysis.

IPIA Step 4

The IPIA Matrix and IPIA Table were developed and are presented in the next section that illustrates IPIA method in airline passenger service in China.

Findings

IPIA Step 1: Attributes structure

Following a discussion with the airline managers, we produced a final list of 10 items which were organized along the three categories of factors: basic factors (safety, punctuality, comfortable aircraft, and frequent flyer program or FFP), performance factors (frequency of flights, schedule, and price) and excitement factors (in-flight food and drinks, and in-flight staff service).

Findings - IPIA Step 2: Measurement of Importance and Performance

We run BPNN to obtain the values of attribute importance using customer responses as the input to the BPNN model. The learning rate and momentum were both set at 0.7, and decreased as training proceeds; and the process was set to terminate at 100,000 cycles. The training sample used 151 cases (approx.50%) randomly selected from the dataset and validating sample used the remaining 147 cases. The results show that the mean absolute percentage error (MAPE) was 0.019 (with a maximum of 0.32 and minimum of 0.00), indicating a good model fit (Hu et al., 2009). The key important attributes are reputation (0.18), punctuality (0.16), price (0.15) and safety.

IPIA Step 3: Measurement of the Impact

The panel consisted of ten managers responsible from their airlines' sales, passenger services or marketing tasks. The sample's tenure in the management position ranged from 3 years to over 20 years, with a median of 7 years. Two of the respondents were in senior-level management, five were in middle-level, management, and the remaining three were in frontline supervisory positions. The median age of the participants was 35 years old, with a range from 25 to 55.

The interdependent relationships of ten airline attributes were analyzed by applying DEMATEL and ANP. Among the ten attributes, both Excitement factors are the most important ones: In-flight services (weight 0.54), and In-flight food (weight 0.46). The score of weights refer to the membership of the cluster but the limiting value does not change the rank of attributes. High in priority the following airline attributes were also ranked: Airline reputation (weight 0.36), safety (0.27), punctuality (0.26), flight schedule (0.26) and frequent flyer program (0.25). The lowest priority received the attributes: frequency of flights (0.18), ticket price (0.20), and conformable aircraft (0.22). The detailed results of the DEMATEL and ANP are presented in Appendix1-7.

IPIA Step 4: IPIA Table and IPIA Matrix

The weights of Performance, Importance and Impact were presented in Table 1, IPIA Table depicted in Figure 3, the IPIA Matrix. According to data included in IPIA Table, airline reputation had the highest valued in all three attributes, indicating a right balance of allocated resources and customer satisfaction. Punctuality and ticket price had high Importance values but Performance was relatively low, indicating a need to concentrate on these two attributes. The reported Impact was low for both punctuality and ticket price, yet punctuality had a higher Impact value than ticket price which indicates that airlines requires more resources to achieve punctuality in their flights while ticket price reflects the strategic orientation and business operations of the specific company. Therefore, the company needs to concentrate on both punctuality and ticket price with a higher priority on punctuality. Although managers' priority is right, given the punctuality is a 'basic' factor, managers are advised to improve its performance if resources are available.

[Table1 about here]

[Figure 3 about here]

In-flight service, safety, frequent flyer program, and frequency of flights were attributes with low importance but high performance, which may indicate that more resources have been allocated to them than customer satisfaction requires. Among these attributes, only in-flight service had a high Impact value which indicates that airline puts too much emphasis on it and needs to remove attention to other priorities. Attributes with low Impact and low Importance often are either overlooked by managers or get more resources allocated than needed. In-flight food and drink received a high Impact from managers, yet Importance and Performance were low, indicating that management might spend too much time on this attribute, overlooking other priorities. The rankings of aircraft comfort were low across all the three dimensions. Therefore, the company may maintain the current position and improve it when resources are available. However, due to the large capital investment in aircraft fleet, this attribute would be a less priority than other attributes.

Conclusion

Conventional IPA studies have received criticisms regarding methodological and conceptual shortcomings. A stream of research has developed improved IPA models and suggested a number of improvements over the original IPA method. This study proposes a novel analytical framework to strategically prioritize resources allocation to achieve optimal level of customer satisfaction: the Importance-Performance-Impact Analysis (IPIA). The framework was empirically applied in an airline company in China. In so doing, this study has the following three contributions:

Theoretical contributions: Scholars also argued that using Importance as a proxy of customer expectations (Oh, 2001) cannot authentically render the relative importance of quality features, particularly for the tourist sector that culture mediate expectations and experience. In this study, we used advanced neural network method (BPNN) to increase the validity of Importance construct to evaluate the relative importance of quality attributes. Another conceptual limitation of conventional IPA is the reliability of 'Performance' dimension. Restricting Performance measurement across only the Importance attributes would mislead resource allocation decisions. To overcome this shortcoming, we took two steps. First, we incorporated the 3-factor model with IPA to create a structure among attributes (IPIA Step 1). The relation between attributes and resource allocation are far from being linear and the often complex relation between attributes and operation processes requires multi-dimensional decision making tools to solve complex resource allocation problems. This study used DEMATEL/ANP (IPIA Step 3) that takes into account the structure of attributes (Figure 2). Secondly, we expand the IPA boundaries by including Impact into analysis. Triangulating two or more sources of evidence (customers, managers) increases the reliability of Performance and Impact attributes.

Methodological contributions: IPIA takes advantage of statistical power of techniques, such as Back Propagation Neural Network (BPNN), Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) in order to estimate attribute values. IPIA Table and IPIA Matrix present attribute values in ways that facilitate resource allocation. Further, scales were normalized so results are comparable across companies and the industry over time. The IPIA method inherits the strengths of conventional IPA: the results are simple to interpret and to easily applicable in strategic resource allocation decision making. In addition, as the values of attribute importance are derived from performance measures, eliminating the needs to set questions for measuring the importance of attributes, customer survey questionnaire is thus greatly simplified.

Practical contributions: IPIA presents resource allocation with two tools: IPIA Table and IPIA Matrix. Both tools include more information than conventional IPA that help manager to allocate resources to achieve optimal level of customer satisfaction. The inclusion of Impact values help manager to discriminate between high and low Impact attributes that are in the same IPIA quadrant. This is easily depicted in the IPIA bubble Matrix that visualizes the impact as the size of each attribute.

The empirical application of IPIA in examining the service of an airline company in China confirms that IPIA outperforms conventional IPA. For example, Punctuality had a higher Impact value than Ticket price which indicates that the airline would require more resources to achieve Punctuality in their flights. The IPIA Table as well as the IPIA Matrix are useful tools to interpret results and create operational priorities regarding allocation of resources based on their impact on customer satisfaction.

Limitations and further research

There are several limitations associated with this study, which introduce further research opportunities. Although IPIA triangulates data from different sources of customers and managers thus improves the validity of the study compared to traditional IPA method, our customer data were collected from a cross-sectional survey and the expert panel consisted of a limited number of managers. We suggest future IPIA studies to maintain the current research design and take advantage of more data sources such as retail audits and wider expert panels. We also recommend future studies to apply IPIA method in other industries and countries which would generate a basis for cross-validation of the model. Customer satisfaction was used as an outcome variable in BPNN model as in conventional IPA, and future research may explore other variables such as customer perceived value, and word of mouth referral intention, and customer repurchase intention instead of customer satisfaction, as these variables incorporates customers' consideration of competitive offers and costs (Kumar, 2002).

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Table1. The IPIA Table

Attributes	Importance (BPNN)		Performance (Scale means)		Impact (DEMATEL+ANP)		Management recommendations
Reputation	0.18	High	3.83	High	0.36	High	Right balance, maintain resources
Punctuality	0.16	High	3.49	Low	0.26	Low	Concentrate here
Ticket price	0.15	High	3.28	Low	0.20	Low	Concentrate here
In-flight service	0.05	Low	3.61	High	0.54	High	Re-locate resources to other customer needs to address impact
Safety	0.10	Low	3.96	High	0.27	Low	recover resources to other priorities
Frequent flyer plan	0.09	Low	3.71	High	0.25	Low	recover resources to other priorities
Schedule	0.07	Low	3.71	High	0.26	Low	recover resources to other priorities
Frequency of flights	0.05	Low	3.67	High	0.18	Low	recover resources to other priorities
In-flight food	0.08	Low	3.26	Low	0.46	High	Divert attention to other priorities
Aircraft comfort	0.07	Low	3.51	Low	0.22	Low	Right balance, could be improved
Min & Max, Average	0.05-0.18; 0.10		3.26-3.96; 3.60		0.18-0.54; 0.30		Overall, reputation is high, yet company needs to focus on punctuality and ticket price rather than in-flight service.

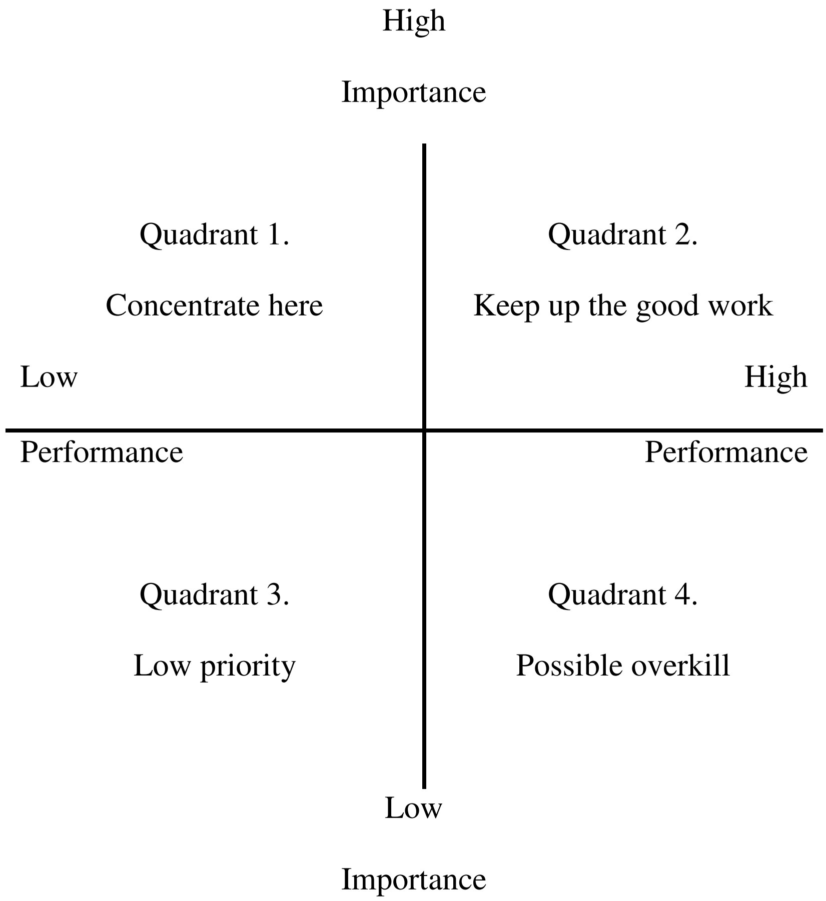


Figure 1. The Importance-Performance Analysis (IPA) Matrix (adapted from Martilla & James, 1977)

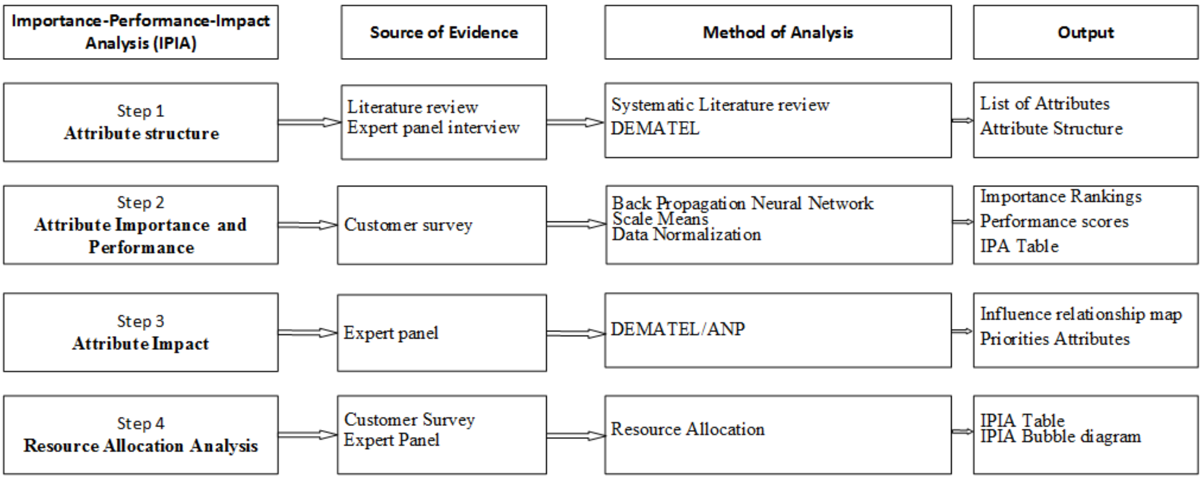


Figure 2. IPIA research design

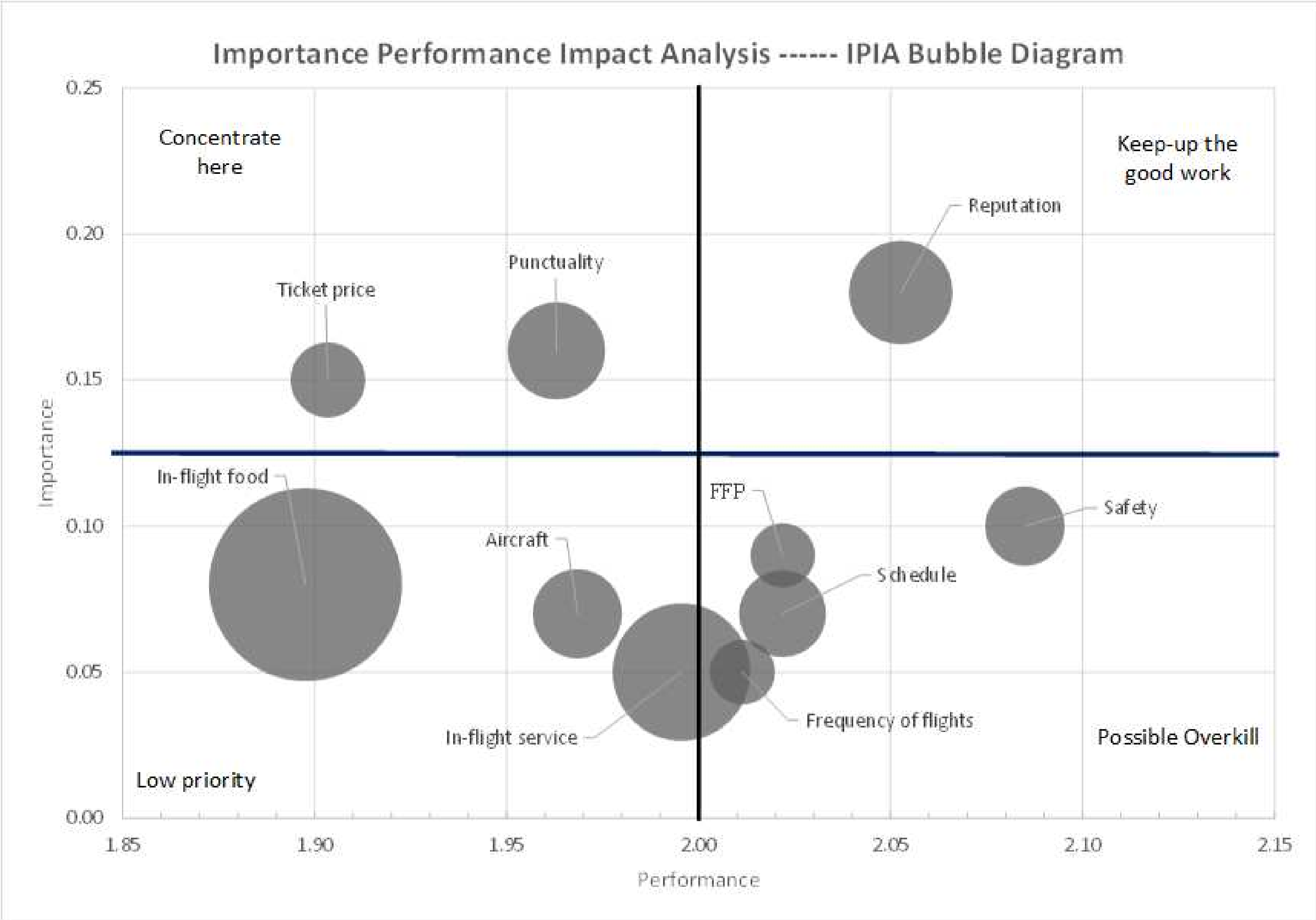


Figure 3. IPIA matrix

APPENDICES

Appendix 1. The direct-influence matrix A.

	Ticket price	Flight schedule	Frequency of flight	Inflight services	FFP	Punctuality	Comfortable aircraft	Safety	Airline reputation	Inflight food &drinks	Zi
Ticket price	NA	5	5	6	5	5	4	4	4	6	43
Flight schedule	6	NA	7	7	6	5	5	4	6	7	55
Frequency of flight	6	6	NA	6	6	5	5	4	5	6	49
Inflight services	4	4	4	NA	4	3	4	2	4	6	35
FFP	4	5	6	5	NA	5	5	2	4	6	42
Punctuality	6	7	7	8	8	NA	7	4	6	7	59
Comfortable aircraft	6	5	6	7	6	4	NA	3	6	7	50
Safety	8	8	8	8	8	8	8	NA	7	8	71
Airline reputation	5	5	6	6	7	5	5	4	NA	6	48
Inflight food &drinks	3	4	4	4	6	3	4	2	4	NA	33
Zj	48	48	53	58	55	41	46	29	49	58	

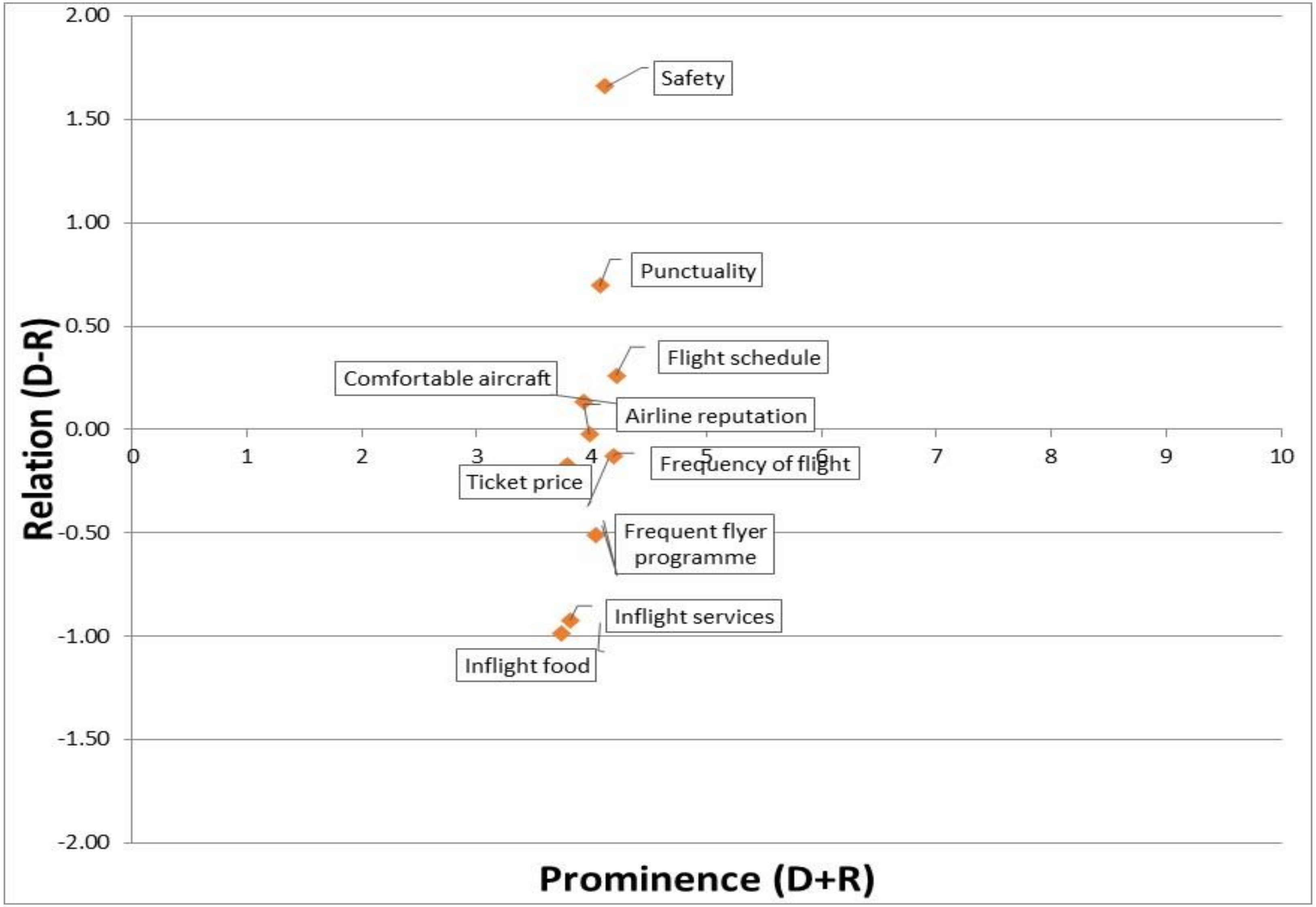
Appendix 2. The total-influence matrix T.

Factors	Ticket price	Flight schedule	Frequency of flight	Inflight services	Frequent flyer	Punctuality	Comfortable aircraft	Safety	Airline reputation	Inflight food &drinks
Ticket price	0.1228	0.1933	0.1998	0.2201	0.2104	0.1640	0.1687	0.1245	0.1814	0.2227
Flight schedule	0.2308	0.1514	0.2542	0.2765	0.2557	0.1982	0.2147	0.1464	0.2363	0.2741
Frequency of flight	0.2185	0.2157	0.1507	0.2469	0.2363	0.1772	0.1955	0.1391	0.2103	0.2420
Inflight services	0.1462	0.1509	0.1637	0.1172	0.1648	0.1214	0.1434	0.0939	0.1550	0.1905
Frequent flyer	0.1779	0.1812	0.2105	0.2124	0.1371	0.1606	0.1775	0.1076	0.1782	0.2186
Punctuality	0.2421	0.2477	0.2654	0.2910	0.2816	0.1374	0.2389	0.1514	0.2466	0.2825
Comfortable aircraft	0.2141	0.1993	0.2254	0.2523	0.2372	0.1726	0.1316	0.1288	0.2208	0.2525
Safety	0.2956	0.2962	0.3193	0.3424	0.3290	0.2674	0.2897	0.1225	0.2906	0.3373
Airline reputation	0.1966	0.2012	0.2213	0.2440	0.2396	0.1777	0.1984	0.1331	0.1362	0.2330
Inflight food &drinks	0.1386	0.1408	0.1512	0.1670	0.1798	0.1134	0.1422	0.0818	0.1485	0.1114

Appendix 3. The sum of influences of factors

Category	Attributes	D	R	D+R *Prominence*	D-R *Relation*
Performance factor	Ticket price	1.81	1.98	3.79	-0.18
Performance factor	Flight schedule	2.24	1.98	4.22	0.26
Performance factor	Frequency of flight	2.03	2.16	4.19	-0.13
Performance factor	Airline reputation	1.45	2.37	3.82	-0.92
Basic factor	Frequent flyer program	1.76	2.27	4.03	-0.51
Basic factor	Punctuality	2.38	1.69	4.07	0.69
Basic factor	Comfortable aircraft	2.03	1.90	3.94	0.13
Basic factor	Safety	2.89	1.23	4.12	1.66
Excitement factor	Inflight food	1.98	2.00	3.99	-0.02
Excitement factor	Inflight services	1.37	2.36	3.74	-0.99

Appendix 4. Influence relationship map



Appendix 5. Un-weighted Supermatrix

Groups	Factors	1. Basic factors: Safety	Punctuality	Comfortable aircraft	FFP	2. Performance factors: Frequency of flight	Flight schedule	Ticket price	Airline reputation	3. Excitement factors: Inflight food & drinks	Inflight services
1. Basic factors	Safety	0.171	0.272	0.260	0.256	0.243	0.248	0.234	0.247	0.232	0.240
	Punctuality	0.321	0.213	0.331	0.321	0.295	0.300	0.297	0.291	0.302	0.295
	Comfortable aircraft	0.304	0.303	0.196	0.287	0.272	0.268	0.271	0.276	0.269	0.260
	FFP	0.204	0.212	0.213	0.136	0.190	0.184	0.199	0.186	0.198	0.205
2. Performance factors	Frequency of flight	0.191	0.196	0.206	0.193	0.139	0.218	0.212	0.211	0.190	0.200
	Flight schedule	0.260	0.268	0.260	0.265	0.286	0.186	0.285	0.297	0.263	0.259
	Ticket price	0.230	0.216	0.221	0.230	0.241	0.234	0.157	0.252	0.236	0.231
	Airline reputation	0.318	0.320	0.313	0.312	0.334	0.362	0.346	0.240	0.310	0.309
3. Excitement factors	Inflight food & drinks	0.587	0.588	0.594	0.594	0.571	0.610	0.583	0.619	0.478	0.677
	Inflight services	0.413	0.412	0.406	0.406	0.429	0.390	0.417	0.381	0.522	0.323

Appendix 6. Weighted Supermatrix

		1. Basic factors				2. Performance factors				3. Excitement factors	
Groups	Factors	Safety	Punctuality	Comfortable aircraft	FFP	Frequency of flight	Flight schedule	Ticket price	Airline reputation	Inflight food & drinks	Inflight services
1. Basic factors	Safety	0.057	0.091	0.087	0.085	0.081	0.083	0.078	0.082	0.077	0.080
	Punctuality	0.107	0.071	0.110	0.107	0.098	0.100	0.099	0.097	0.101	0.098
	Comfortable aircraft	0.101	0.101	0.065	0.096	0.091	0.089	0.090	0.092	0.090	0.087
	FFP	0.068	0.071	0.071	0.045	0.063	0.061	0.066	0.062	0.066	0.068
2. Performance factors	Frequency of flight	0.064	0.065	0.069	0.064	0.046	0.073	0.071	0.070	0.063	0.067
	Flight schedule	0.087	0.089	0.087	0.088	0.095	0.062	0.095	0.099	0.088	0.086
	Ticket price	0.077	0.072	0.074	0.077	0.080	0.078	0.052	0.084	0.079	0.077
	Airline reputation	0.106	0.107	0.104	0.104	0.111	0.121	0.115	0.080	0.103	0.103
3. Excitement factors	Inflight food & drinks	0.196	0.196	0.198	0.198	0.190	0.203	0.194	0.206	0.159	0.226
	Inflight services	0.138	0.137	0.135	0.135	0.143	0.130	0.139	0.127	0.174	0.108

Appendix 7. Limit Supermatrix

		1. Basic factors				2. Performance factors				3. Excitement factors	
Groups	Factors	Safety	Punctuality	Comfortable aircraft	FFP	Frequency of flight	Flight schedule	Ticket price	Airline reputation	Inflight food & drinks	Inflight services
1. Basic factors	Safety	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080
	Punctuality	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
	Comfortable aircraft	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090	0.090
	FFP	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065	0.065
2. Performance factors	Frequency of flight	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066	0.066
	Flight schedule	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088	0.088
	Ticket price	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
	Airline reputation	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105	0.105
3. Excitement factors	Inflight food & drinks	0.195	0.195	0.195	0.195	0.195	0.195	0.195	0.195	0.195	0.195
	Inflight services	0.139	0.139	0.139	0.139	0.139	0.139	0.139	0.139	0.139	0.139