An Advanced Analytical Framework for Customer Satisfaction with Impact Assessment: the Importance-Performance-Impact Analysis

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Abstract

Having an appropriate and advanced analytical framework is essential for transport service managers to optimize resource allocation to improve customer satisfaction. This study proposes a novel analytical framework, the "*Importance-Performance-Impact Analysis*" (IPIA), which aims to overcome several conceptual and methodological shortcomings associated with Importance–Performance Analysis (IPA). The IPIA framework further integrates advanced analytical techniques, such as Back Propagation Neural Network (BPNN), Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP). We illustrate the application the new, integrated framework in one of the 'Big Four' airlines in China. IPIA Table and IPIA Matrix help transportation managers to allocate resources better than IPA in order to improve customer satisfaction.

Keywords:

Importance-Performance-Impact Analysis; Importance-Performance Analysis; customer satisfaction; resources allocation; airlines; China

1. Introduction

Transport service operations managers need to constantly prioritize resource allocation in order to improve service quality and customer satisfaction (Celik et al., 2013; Gonçalves & Caetano, 2017; Kuo, 2011; Stelzer et al., 2016; Steven, Dong, & Dresner, 2012). One of the widely used analytical frameworks by managers 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 (Bacon, 2012; 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 customer satisfaction (Geng & Chu, 2012; Oh, 2001); (b) inadequate measures of attribute importance (Matzler et al., 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), neural network based IPA (Mikulić & Prebežac, 2012) among others. In the context of customer satisfaction with transport service, Celik et al. (2013) integrate fuzzy-MCDM (Multi-Criteria Decision Making) model to the IPA and Li et al. (2017) applied fuzzy analytic hierarchy process (AHP) for evaluation in-flight service quality.

These modifications have enhanced the usefulness of IPA for management practice. Nevertheless, there are at least three issues yet 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 (Hu et al. 2009). Third, prioritizing scarce resources in improving service delivery and enhancing customer satisfaction is a Multi-Criteria Decision Making (MCDM) task for managers (Aydin, 2017; Celik et al., 2013; Geng & Chu, 2012; Hu et al., 2009; Kuo, 2011).

This paper aims to provide an advanced analytical framework for improving customer satisfaction with transport service by addressing the above issues of IPA and introducing 'Importance- Performance-Impact Analysis' (IPIA), which is based on several advanced decision making techniques. The novel contribution of IPIA method is that 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. Moreover, IPIA uses systematically advanced and powerful analytical tools that have been tested conventional IPA analysis (Hu et al. 2009) but have not adopted widely. In so doing, IPIA arrives at reliable propositions overcoming data limitations. Further, the addition of impact dimension provides more insights to managers that help them in deciding how to allocate resources to achieve the desired level of 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, 2017b). The Chinese airline market 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, but soon it will surpass United States as the world's largest, as reported in a recent forecast by IATA (2017a).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, Zhang, & Lei, 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 (Lin & Filieri, 2015; Vlachos & Lin, 2014).

The next section reviews the conventional IPA in the context of airline service 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.

2. Importance-Performance Analysis

Importance-Performance Analysis (IPA) has been widely adopted in a variety of business sectors for understanding customer satisfaction, identifying areas for improvement, and prioritizing resource allocation (Arbore & Busacca, 2011; Geng & Chu, 2012; Kuo et al., 2012). 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 (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 by 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 (Oliver, 2014; Sever, 2015). 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 statistical inference methods to evaluate the relative importance of the attributes. For example, Matzler and Sauerwein (2002) used multiple 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. Customers are the best raters of how a company perform, yet they cannot estimate the impact of this performance on 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. 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 data mean values of observed importance and performance ratings as the cut-off points among quadrants and (ii) a scale-centred 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 favour 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), statistical techniques such as correlation analysis, multiple regression (Matzler & Sauerwein, 2002), and structural equation model have been used to acquire the implicitly derived importance of attributes (Hu et al., 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 over contextual factors. Most IPA studies ignore the need to control IPA results over contextual factors such as customer demographics, market or industry effects. 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 Performance and Importance. Over the years, the attribute linearity assumption, inherent in the conventional IPA, has been addressed in the literature (Matzler et al., 2004). 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 (Wang & Tzeng, 2012; Yang et al., 2008), researchers have employed a hybrid model combining Decision Making Trial and Evaluation Laboratory (DEMATEL) with Analytic Network Process (ANP) (Yang et al., 2008).

Subjective judgement of Performance. 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. However, psychology and consumer literature is based on the assumption that satisfaction is a mental condition of the customer, thus the performance evaluation of a provided product or service (or some of their characteristics) is quite subjective. According to expectancy disconfirmation model (Oliver, 1980), satisfaction may be defined as a pleasant past-purchasing experience from a product or service which disconfirms pro-purchase beliefs and perceived performance. In this way, conventional IPA uncovers subjective customer’s dissonance between cognition of a product or service and its post-purchase performance. Although expectancy disconfirmation analysis provides post-purchase performance measurement, a number of conceptual and methodological shortcomings limit its power to develop reliable performance standards which are required for resource allocation. To do so, an impact assessment analysis can reveal the direction and magnitude of the effect of these attributes on resource allocation. 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, and mismatch between customer's and provider's perceptions can result in a waste of resources, and possibly customer dissatisfaction and defection. Multi-source evaluation can enhance the firm's ability to self-monitor and correct the deficiencies that arise in areas for performance improvement.

3. Proposed analytical framework: Importance-Performance-Impact Analysis

3.1. 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 effect of customer attributes on resource allocation. Each task in an operation has a significant impact in meeting customer expectations. For example, safety in airlines is considered as an important attribute and key customer expectation. To achieve safety, airlines setup a number of tasks and processes according to international standards. These safety tasks and processes *impact* the resource allocation i.e. number of personnel, equipment and prioritization. Accordingly, organizations develop their operations based on customers' expectations. However, do customer expectations and impact on operations are aligned? If not, then organizations may spend too much on tasks to meet customer expectations that make little different to them or spend too little on tasks with huge impact on customer satisfaction.

Few studies have applied impact in customer satisfaction in transportation studies. Impact was assessed in a customer satisfaction measure of the Transportation Research Board Transit Cooperative Research Program (TCRP, 1999). Proposed by Morpace International Inc, The Impact Score assessed the relative impact of attributes on overall satisfaction, by measuring customers' relative decreases in overall satisfaction, when a recent problem with an attribute is reported. This approached distinguishes those users who have and have not experienced a service problem within the past 30 days and combines this with problem occurrence rate to produce an impact score for each service element. Therefore, the Impact Score is "Things Gone Wrong" approach which is based on customer input to assess service elements (Stradling, Anable, & Carreno, 2007).

IPA relies on consumer surveys and retail audit which cannot assess the impact of customer attributes on resource allocation. Further, the impact on attributes on resource allocation is far from being simple; rather there is a complex interdependence between attributes and tasks, value-added activities and operational processes. Resource allocation often requires multi-dimensional decision-making tools to allocate resources according to the importance and performance of customer attributes, yet traditional IPA do not apply MDDC although these tools are used in production planning and control.

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 experts in the industry.

3.2. Importance-Performance-Impact Analysis (IPIA)

To overcome the weaknesses of IPA, we propose the Importance-Performance-Impact Analysis (IPIA) to help managers prioritizing resources and control value-added activities 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.

There is a number of models depicting the hierarchical structure of satisfaction dimensions by classifying them into different categories such as the Kano model, data envelopment analysis, multidimensional scaling as well as customer loyalty analysis ((Arbore & Busacca, 2011; Kuo et al., 2012). 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 (Arbore & Busacca, 2011; Kuo et al., 2012). Kano model is used to identify critical factors associated with service performance that generate customer satisfaction (Chen, 2012). Following Matzler et al. (2004), the attributes are classified into three categories according to their relationship with overall customer satisfaction, i.e. basic factors, performance factors and excitement factors.

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 favour high importance scores in conventional IPA analysis, we measure Importance using back-propagation neural network (BPNN). This also allows to keep air traveller surveys short and increase response rate, thus statistical power of data analysis.

Artificial neural network models are a type of Artificial Intelligence or Computational Intelligence that uses computer to imitate the human pattern recognition function (Karlaftis & Vlahogianni, 2011; Ma et al., 2015). They were first introduced in the early 1960s, and have increasingly been used in various areas of research, including transportation and general business studies (Karlaftis & Vlahogianni, 2011; Leong et al., 2015; Ma et al., 2015; Tkáč & Verner, 2016). For example, Garrido, de Oña, and de Oña (2014) use artificial network to examine public transport service quality; Leong et al. (2015) combine the traditional structural equation modelling with artificial neural network to examine airline service quality, passenger satisfaction and loyalty; Goves et al. (2016) use artificial neural network for traffic prediction and Ma et al. (2015) use it for traffic speed prediction, and Hamad, Ali Khalil, and Shanableh (2017) use the method to model roadway traffic noise.

One of the advantages of artificial neural network models that they do not require any restrictive assumptions about the relationship between input and output variables, and are powerful in processing missing data and outliers (Karlaftis & Vlahogianni, 2011; Leong et al., 2015). 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 (Deng et al., 2008; Hu et al., 2009).

Back-propagation neural network (BPNN) is one of the most commonly used artificial neural network models that use optimization algorithms to minimizing the sum of squared errors (Ma et al., 2015). 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. The Importance of each attribute is based on their respective BPNN weightings. The structure of BPNN has three parts: one input 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).Step 1: Set attribute performance as the input variable at the input layer of BPNN and overall 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 analysing 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. We tested different normalisation functions and evaluated how well the data are depicted in the diagrams. 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 $arsinh = \ln(x + \sqrt{x^2 + 1})$ 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 et al., 2011; Tsai, Chou, & Lai, 2010)   The method has been widely applied in a range of studies usually in combination with other Multiple Criteria Decision Making (MCDM) methods, such as Analytic Network Process (ANP) method (e.g. Tsai 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 (AHP) which is a multidimensional ranking of decision alternatives originally developed by Saaty (1980). AHP relies on decision-makers' knowledge and expressed opinions in order to build a structure of hierarchically-organized objectives, criteria and decision alternatives. However, AHP is restrictive because of its a hierarchically structural nature, while ANP can take interdependent relationships into consideration (Saaty, 2004), thus addressing the invalid assumption of independence among attributes. 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. DEMATEL and ANP are described in detail in Supplement Material.

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. The hybrid model is particularly suitable for solving the issues of with different degrees of effects among attributes in a conventional IPA (Yang et al., 2008). 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.

4. Empirical application

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. 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.

4.1. 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), an initial list of 20 attributes was extracted from the extant literature, and presented to four airline experts for discussion. Experts were assumed knowledgeable of customers' expectations and provide a detail list of attributes to reflect their preferences. Alternatively, attribute identification could be conducted using customer panels, focus groups or other suitable methods. The advantage of this method of attribution selection is that experts can go back and discuss their choices in order to derive a shortlist of attributes that reflects customer preferences objectively. Experts 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.

4.2. IPIA Step 2

Passenger survey was conducted using a web-based questionnaire. The rationale of using web-based survey is the growing popularity among travellers in using online booking, e-ticketing 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 traveller community websites.

Their overall satisfaction of the airline was based on a 5-point scale by answering to the question '*Based on your overall travel experience, how would you rate this airline on the following aspects, from 1 to 5* (where 1 = extremely poor, and 5 = extremely good). The survey site went live for about 3 months and during this period, 2,640 invitations were sent, and 824 respondents completed the survey, corresponding to 31% response rate. Seven of the responses were incomplete and excluded from further analysis, thus the valid sample size is 817, which includes customers of all the major airlines in China. For IPIA illustration purpose, we selected only one airline to avoid bias between different companies, which resulted in 298 responses for data analysis. The sample demographics are representative of Chinese travellers. Specifically, 56% of them are business travellers; 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).

4.3. 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). 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 for 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.

4.4. 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.

5. Results

5.1. 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).

5.2. 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; 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 (0.10).

5.3. 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 analysed 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 of the online supplement to this paper.

5.4. 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.

5.5. Comparison of IPIA with a simplified IPA.

We compared IPIA with a simplified IPA to highlight the differences between the two methods.

The first important difference, and a major contribution of IPIA, is the inclusion of Impact dimension. Impact gives managers insights on the existing and future resource allocation to meet customer needs. Analysis of Impact dimension attributes was conducted with DEMATEL/ANP, which may seem time-consuming and resource intensive for some companies to run. We run this analysis in an MS Excel spreadsheet in an office PC. Therefore, with IPIA, airline managers can calculate the Impact of each attribute.

Another important difference is the IPIA Table and IPIA Matrix, which they contain more information to help insightful decision making. The IPIA Matrix maps airline attributes dimensions (performance, importance, impact) to the same illustration provide visual aids to make informed decisions. Knight et al. (2018) advocated the use of visual mechanisms to prompt meaning-making through the conversations they stimulate, thus creating strategic visibility. IPIA Matrix is a visual mechanism that integrates resources and customer satisfaction and can prompt strategic visibility, a characteristic that IPA is missing.

IPIA uses BPNN to calculate the values of Importance attributes. Previous studies advocated the use of BPNN to address methodological shortcomings of IPA (Hu et al. (2009). Further, we used BPNN method to overcome a shortcoming in airline questionnaire since the airline aimed to keep questionnaire short and didn't include importance attributes per se. Although it is recommended to use dedicated importance questions in air traveller survey, which can make survey a bit longer, without BPNN, airline managers cannot calculate the Importance dimension and produce IPA map. Unlike parametric models, BPNN models do not require any restrictive assumptions about the relationship between input and output variables. Therefore, BPNN method can help overcome methodological and conceptual shortcomings of IPA method.

6. Conclusion

The IPA as a management tool has been used as widely used in the service industries but it needs a more holistic perspective and updating with advanced analytical techniques. This study advances customer satisfaction and service operations management literature by proposing the addition of another dimension, Impact to create the Importance-Performance-Impact Analysis (IPIA). The framework was empirically applied in an airline company in China. IPIA addresses a number of conceptual and methodological shortcomings in IPA as well as advances the impact assessment of customer attributes on resource allocation. Table 2 compares IPIA with IPA shortcomings.

[Insert Table1 about here]

The main contribution of IPIA is the inclusion of the Impact dimension. Measuring Impact and relating it with Importance and Performance allows companies to assess the effects of customer satisfaction in resource allocation. The inclusion of the Impact dimension also addresses a number of shortcomings found in IPA. Specifically, to increase the validity of Importance construct, we used an advanced neural network method, BPNN that evaluates the relative importance of quality attributes, and uncovers any hidden layers of importance (Matzler and Sauerwein (2002). Then, to overcome the reliability of 'Performance' dimension, we took two steps. First, we incorporated the three-factor model in the analytical framework to create a structure among attributes (IPIA Step 1). We further used DEMATEL/ANP (IPIA Step 3) that takes into account the structure of attributes (Figure 2). Second, we expanded the IPA boundaries by including an Impact dimension into the analysis. Triangulating two sources of evidence, one from customers and one from managers thus increases the reliability of Performance and Impact attribute measurement.

The IPIA incorporates suggestions from previous studies to overcome inherent IPA shortcomings. To deal with the Construct validity of 'Importance' dimension, IPIA uses the three-Factor Kano Model to develop the list of attributes (Arbore & Busacca, 2011; Kuo, Chen, & Deng, 2012; Matzler and Sauerwein, 2002). It takes advantage of statistical power of Back Propagation Neural Network (BPNN), Decision Making Trial and Evaluation Laboratory (DEMATEL) and Analytic Network Process (ANP) in order to estimate the attribute values The reliability of 'Performance' dimension is increased by adopting a standardized scale means of observed ratings as well as Triangulating two sources of evidence one from customers and one from industry experts. In this way, it addresses the arbitrary selection of thresholds of IPA quadrants (Deng et al., 2008; Hu et al., 2009), which also addresses the control of contextual factors when IPIA is replicated across different customer segments, industries, and/or countries over time.

Compared to IPA table, IPIA offers two tools, the IPIA Table and the IPIA Matrix to present attribute values in ways that facilitate resource allocation. 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.

There is also a number of Practical contributions of IPIA compared to IPA method. IPIA is more information-reach than IPA. IPIA assists strategic resource allocation with two tools: IPIA Table and IPIA Matrix. Both tools include more information than conventional IPA that help manager to allocate resources for optimal level of customer satisfaction. The inclusion of Impact dimension helps managers to discriminate between high and low Impact attributes that are in the same IPIA quadrant. This is 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 than reducing ticket price. The IPIA Table and the IPIA Matrix are insightful for interpreting data results and creating strategic priorities regarding allocation of resources. Due to the importance of “Concentrate here” quadrant, managers may need to elaborate further the priority and resource allocated of the attributes in this quadrant by applying another tool i.e. a resource allocation model or cost-benefit analysis.

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 experts.

In measuring Performance, we utilised the mean values of the attributes as reported in the customer survey. Companies may use other tools than surveys to assess performance such as audits, benchmarks etc. Combining information from different sources (both objective and subjective measures) may derive in better estimation of the Performance values. In this study, Importance values were derived using BNPP in order to keep customer survey short; airline managers may include Importance attributes in the survey to measure them directly. Further, construct validity of the Importance dimension is usually influenced by cultural and demographic variables and this study focused on Chinese airline passengers with specific demographics. 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.

IPIA may seem more complex than traditional IPA, with the aid of analytical software, its application can be simple and straightforward. Statistical software such as SPSS and R can run BPNN analysis and DEMATEL can be applied in spreadsheet software like MS Excel. 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.

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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.

Table2. Comparison of IPA and IPIA

Shortcomings	IPA	IPIA	Literature Suggestions
Conceptual shortcomings			
Construct validity of 'Importance' dimension	proxy of customer expectations no agreement how to measure the perceived value or significance of a product or service attribute influenced by cultural and demographic variables	Use of Three-Factor Kano Model to develop the list of attributes. BPNN reveals the hidden importance value of each attribute	Statistical inference methods to reveal hidden importance (Matzler and Sauerwein (2002)
reliability of 'Performance' dimension	one source of evidence; Customers are the best raters of how a company perform, yet they cannot estimate the impact of this performance on resource allocation	scale means of observed ratings. Triangulating two sources of evidence one from customers and one from experts	(i) a data-centric and (ii) a scale-centred approach
Methodological shortcomings			
Discriminating the thresholds of IPA quadrants	The positioning of the thresholds that divide the plot into quadrants is based on subjective judgment	• Importance and Performance attributes normalized to allow comparisons and minimize subjective judgement. • Use of suitable techniques for different dimension: BPNN to reveal hidden importance; Scale means for performance; DEMATEL/ANP for Impact	Statistical techniques such as correlation analysis, multiple regression (Matzler & Sauerwein, 2002), structural equation modelling, Back-Propagation Neural Network (BPNN) to estimate attribute importance (Deng et al., 2008; Hu et al., 2009).
Measurement errors	Scales and measures of Importance and Performance are not developed in a systematic way.	• measure Importance using artificial neural networks and Back-propagation neural network • Measuring and analysing the IPA dimensions independently • Customer surveys	
Lack of control	No control IPA results over contextual factors.	• Standardization of Dimensions measurement and scales allow the replication, testing and control of the IPIA model in different contexts. • Replicating IPIA steps 2-4 in different contexts (customers, industry, countries) can control over contextual factors.	Receiver Operating Characteristic (ROC) analysis (Sever, 2015)
Non-linear relationships between attributes	Linearity is inherent in IPA analysis	• Attributes development is based on structure model (Three-Factor Theory) and data is	Three-Factor Theory (e.g. Arbore & Busacca, 2011; Kuo et al., 2012). To

Performance and Importance		analysed with hybrid model DEMATEL/ANP. • A 3-dimentional IPIA analysis is more reach in information about relationships about Importance and Performance thus addresses *Non-linear*ity problems	deal with the problems of interdependence among attributes (Wang & Tzeng, 2012; Yang et al., 2008), researchers have employed a hybrid model combining Decision Making Trial and Evaluation Laboratory (DEMATEL) with Analytic Network Process (ANP) (Yang et al., 2008)
No impact assessment on resource allocation	Not addressed	• Addition of Impact dimension in IPIA analysis. • Data collected from experts and analysed with multi-dimensional decision making tools	

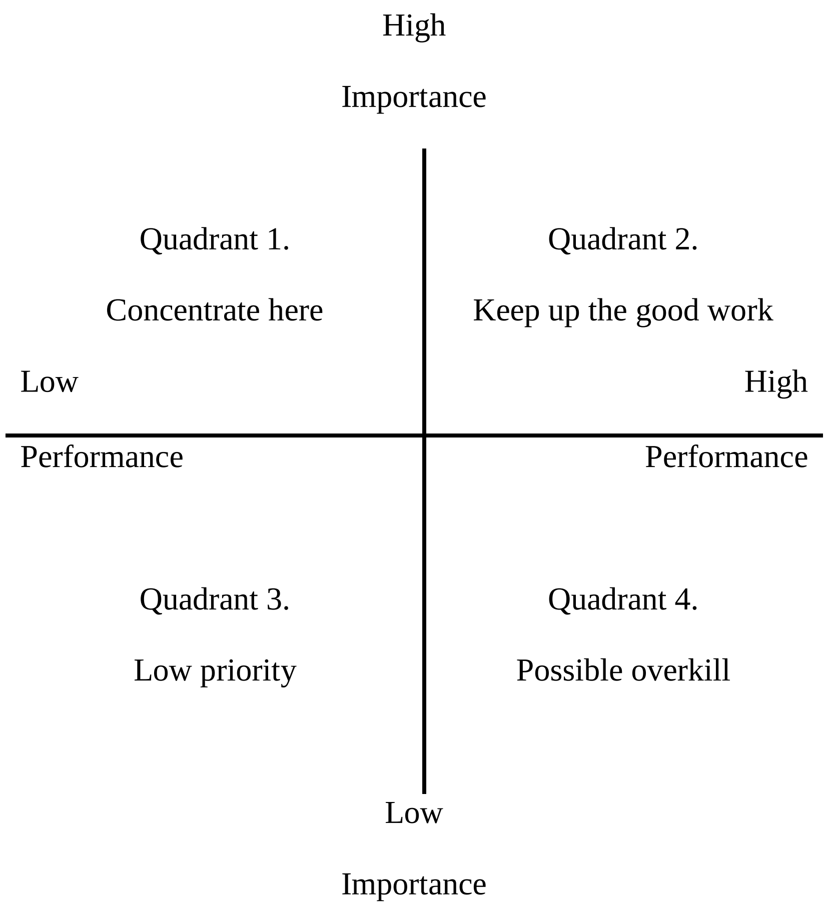


Figure 1. The Importance-Performance Analysis (IPA) Matrix (adapted from Martilla & James, 1977)

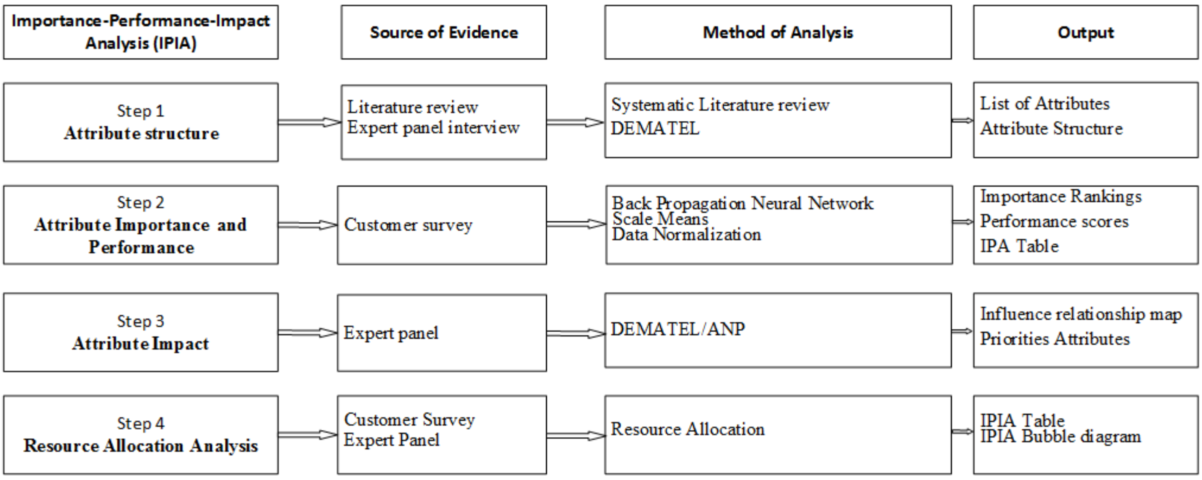


Figure 2. IPIA research design

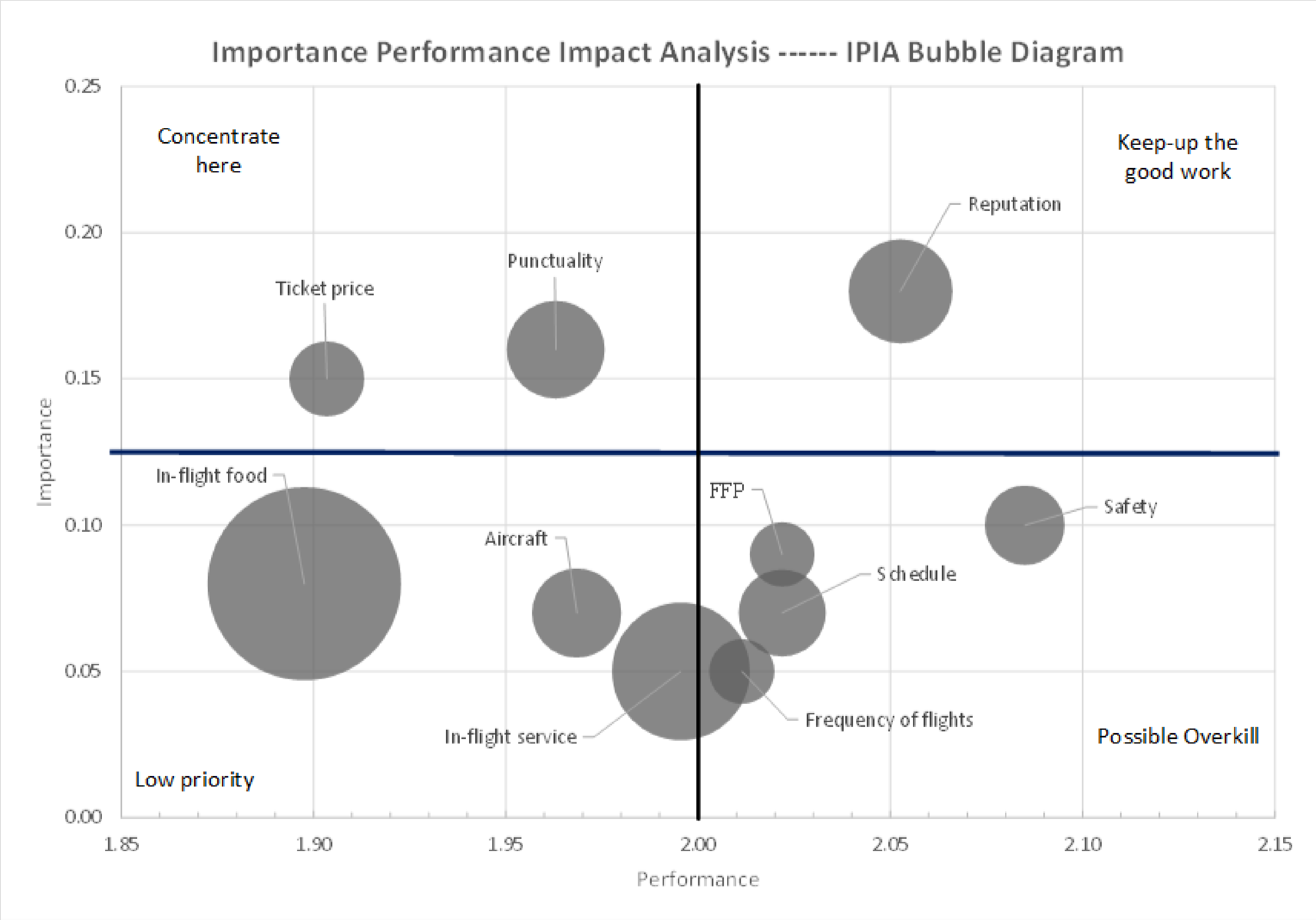


Figure 3. IPIA matrix

APPENDICES 1-7: The detailed results of the DEMATEL and ANP

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	

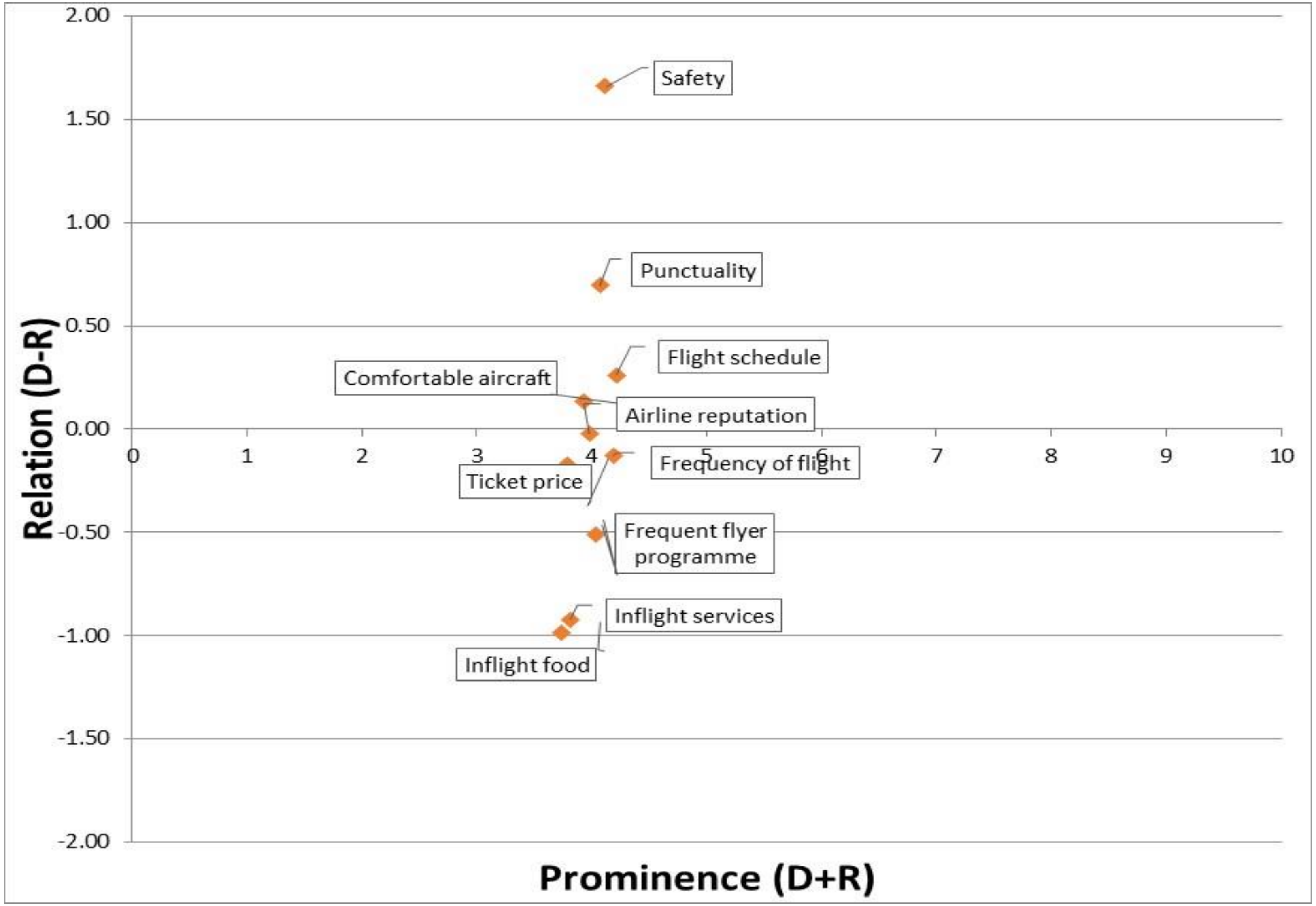
Appendix 2. The total-influence matrix T.

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

		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	0.171	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

Supplement Material – DEMATEL and ANP Calculations

DEMATEL Step 1: **Generating the direct-relation matrix**. The comparison scale among the criteria has ten levels from 0 (no influence) to 9 (very high influence). Experts are given pairs of factors and make pair-wise comparisons in terms of influence and direction between criteria. The expert evaluations are the initial data obtained as the direct-relation matrix that is a n×n matrix A, in which a_{ij} is denoted as the degree to which the criterion i affects the criterion j (equation 1).

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix} \quad (1)$$

DEMATEL Step 2: Normalizing the direct-relation matrix. The normalisation of the direct-relation *matrix* A produces the normalized direct-relation matrix X obtained through formulas (2), (3) and (4).

$$X = A/k \quad (2)$$

$$k = Max\left[\max_{1 \leq i \leq n} \sum_{i=1}^{n} a_{ij} \, , \max_{1 \leq j \leq n} \sum_{j=1}^{n} a_{ij}\right] \quad (3)$$

$$X = \begin{bmatrix} {a_{11}}/{k} & \cdots & {a_{1j}}/{k} & \cdots & {a_{1n}}/{k} \\ \vdots & & \vdots & & \vdots \\ {a_{i1}}/{k} & & {a_{ij}}/{k} & & {a_{in}}/{k} \\ \vdots & & \vdots & & \vdots \\ {a_{n1}}/{k} & & {a_{nj}}/{k} & & {a_{nn}}/{k} \end{bmatrix} \tag{4}$$

DEMATEL Step 3: Compute the **total-relation matrix**. Having calculated the normalized direct-relation matrix X, the total relation matrix T can be acquired by using formula (5), in which I denotes the identity matrix (6).

$$T = X + X^2 + X^3 + \cdots + X^p = X(I - X)^{-1}, p \to \infty \tag{5}$$

$$I = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{6}$$

The totals for each row and each column in formula (4) can be obtained as follows:

$$r_i = \sum_{i=1}^{n} t_{ij} \text{ , } i = 1,2, \dots, n \tag{7}$$

$$c_j = \sum_{j=1}^{n} t_{ij} \text{ , } j = 1,2, \dots, n \tag{8}$$

where r_i represents the direct influence value which is given by the factor a_i; c_j represents the indirect influence value which is given by the factor a_j. Vector D and vector R, respectively denote the sum of rows and the sum of columns from total- relation matrix **T** respectively.

DEMATEL Step 4: Set a threshold value and obtain the impact-relation map. The total relation matrix contains the values of impact between the factors. However, the structural relations in the matrix should not take into account unsuitable effects between the factors. Based on the matrix ***T***, each aspect *tij* of matrix ***T*** provides information about how aspect *i* influences aspect *j*. If all the information from matrix ***T*** converts to the network relation map (NRM) the map will be too complex to show the necessary information for decision-making. A threshold value (P) is necessary to remove those effects from consideration in matrix T. Only those aspects, whose influence level in matrix T is higher than the threshold value, can be chosen and converted into the impact-digraph-map. Typically, experts discuss how to decide each factor's threshold to make the rational decisions.

In this study, the frequency of t_{ij} was decided by the experts, yet the T value was also decided to cut off less than 30% of values. To do so, the frequencies of t_{ij} were calculated and the T threshold was found. If the threshold value is too low, the map will be too complex to reveal the necessary information for decision-making. If the threshold value is too high, many aspects will be presented as independent aspects without revealing the relationships with other aspects. Therefore, a number of trial-and-error attempts were pursued to justify the correct T value. Each time the threshold value increases, some aspects or relationships will be removed from the map. After the threshold value and relative impact-digraph-map are decided upon, the final influence result can be illustrated.

ANP Step 2: Calculate the unweighted supermatrix W. Since DEMATEL produced the total-influence matrix, the unweighted supermatrix W can be calculated by normalizing the sum of influence for each criterion in each hierarchy under the criteria of total-influence matrix. To normalize the total-influence matrix produced by DEMATEL, the criteria total-influence matrix T_c (9) yields T_c^a as shown in equation (10) where T_c^{a11} is obtained by equations (11) and (12). T_c^{aij} to T_c^{ann} are calculated with the same equations (11,12). In the normalized criteria total-influence matrix, the interdependence relationship among clustering is incorporated into the un-weighted supermatrix W as shown in equation (13). The equation (10) shows the calculation of W_{11} and the calculation of element W_{ij} to W_{nn} are based on the same way.

$$T_c = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & \cdots & D_n \\ c_{1_1} \cdots c_{1_{m1}} & c_{2_{m2}} \cdots c_{2_{m2}} & \cdots & c_{n_1} \cdots c_{n_{mn}} \end{array} \\ \begin{array}{cc} D_1 & \begin{array}{c} c_{1_1} \\ c_{1_{21}} \\ \vdots \\ c_{1_{m1}} \end{array} \\ \begin{array}{c} D_2 \\ \vdots \\ \vdots \end{array} & \begin{array}{c} c_{2_1} \\ c_{2_2} \\ \vdots \\ c_{2_{m2}} \\ \vdots \end{array} \\ D_n & \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} T_c^{11} & T_c^{12} & \cdots & T_c^{1n} \\ T_c^{21} & T_c^{22} & \cdots & T_c^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_c^{n1} & T_c^{n2} & \cdots & T_c^{nn} \end{bmatrix} \end{array} \qquad (9)$$

$$T_c^{\alpha} = \begin{array}{cc} & \begin{array}{ccccccccc} & D_1 & & & & D_2 & & \cdots & D_n \\ c_{1_1} & \cdots & c_{1_{m1}} & c_{2_{m2}} & \cdots & c_{2_{m2}} & \cdots & c_{n_1} \cdots & c_{n_{mn}} \end{array} \\ \begin{array}{cc} & c_{1_1} \\ D_1 & c_{1_{21}} \\ & \vdots \\ & c_{1_{m1}} \\ D_2 & c_{2_1} \\ \vdots & c_{2_2} \\ & \vdots \\ \vdots & c_{2_{m2}} \\ & \vdots \\ & c_{n1} \\ D_n & c_{n2} \\ & \vdots \\ & c_{nm_n} \end{array} & \begin{bmatrix} T_c^{a11} & T_c^{a12} & \cdots & T_c^{a1n} \\ T_c^{a21} & T_c^{a22} & \cdots & T_c^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_c^{an1} & T_c^{an2} & \cdots & T_c^{ann} \end{bmatrix} \end{array} \tag{10}$$

$$d_j = \sum_{j=1}^{n} t^{ij} \ , j = 1,2,\ldots,n \tag{11}$$

$$T_c^{a11} = \begin{bmatrix} t_{c^{11}}^{11} / d_1^{11} & \cdots & t_{c^{1j}}^{11} / d_1^{11} & \cdots & t_{c^{1n}}^{11} / d_1^{11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{i1}}^{11} / d_2^{11} & & t_{c^{ij}}^{11} / d_2^{11} & & t_{c^{in}}^{11} / d_2^{11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{n1}}^{11} / d_n^{11} & & t_{c^{nj}}^{11} / d_n^{11} & & t_{c^{nn}}^{11} / d_n^{11} \end{bmatrix} = \begin{bmatrix} t_{c^{11}}^{a11} & \cdots & t_{c^{1j}}^{a11} & \cdots & t_{c^{1n}}^{a11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{i1}}^{a11} & & t_{c^{ij}}^{a11} & & t_{c^{in}}^{a11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{n1}}^{a11} & & t_{c^{nj}}^{a11} & & t_{c^{nn}}^{a11} \end{bmatrix} \tag{12}$$

$$W = \begin{array}{cc} & \begin{array}{ccccccccc} & D_1 & & & D_2 & & & \cdots & D_n \\ c_{1_1} & \cdots & c_{1_{m1}} & c_{2_{m2}} & \cdots & c_{2_{m2}} & \cdots & c_{n_1} \cdots & c_{n_{mn}} \end{array} \\ \begin{array}{cc} & c_{1_1} \\ D_1 & c_{1_{21}} \\ & \vdots \\ & c_{1_{m1}} \\ D_2 & c_{2_1} \\ \vdots & c_{2_2} \\ & \vdots \\ \vdots & c_{2_{m2}} \\ & \vdots \\ & c_{n1} \\ D_n & c_{n2} \\ & \vdots \\ & c_{nm_n} \end{array} & \begin{bmatrix} W^{11} & W^{12} & \cdots & W^{1n} \\ W^{21} & W^{22} & \cdots & W^{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W^{n1} & W^{n2} & \cdots & W^{nn} \end{bmatrix} \end{array} \tag{13}$$

$$W_{11} = \begin{array}{cc} & \begin{array}{ccccc} c_{11} & & c_{12} & \cdots & c_{1m_1} \end{array} \\ \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} & \begin{bmatrix} t_{c^{11}}^{a11} & \cdots & t_{c^{21}}^{a11} & \cdots & t_{c^{m1}}^{a11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{12}}^{a11} & & t_{c^{22}}^{a11} & & t_{c^{m2}}^{a11} \\ \vdots & & \vdots & & \vdots \\ t_{c^{1m_1}}^{a11} & & t_{c^{2m_1}}^{a11} & & t_{c^{mm_1}}^{a11} \end{bmatrix} \end{array} \tag{14}$$

ANP Step 3: Obtain the weighted supermatrix by normalizing the sum of impact for each hierarchy and each dimension in the dimensions total-influence matrix as illustrated in equation (15). Normalizing the total influence matrix T_D yields T_D^a (16). The weighted supermatrix is obtained by incorporating the unweighted supermatrix into the normalized dimensions total-influence matrix (17).

$$T_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & & t_D^{ij} & & t_D^{in} \\ \vdots & & \vdots & & \vdots \\ t_D^{n1} & & t_D^{nj} & & t_D^{nn} \end{bmatrix} \tag{15}$$

$$T_D^a = \begin{bmatrix} t_D^{11}/d_1 & \cdots & t_D^{1j}/d_1 & \cdots & t_D^{1n}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_D^{i1}/d_2 & & t_D^{ij}/d_2 & & t_D^{in}/d_2 \\ \vdots & & \vdots & & \vdots \\ t_D^{n1}/d_n & & t_D^{nj}/d_n & & t_D^{nn}/d_n \end{bmatrix} = \begin{bmatrix} t_D^{a11} & \cdots & t_D^{a1j} & \cdots & t_D^{a1n} \\ \vdots & & \vdots & & \vdots \\ t_D^{ai1} & & t_D^{aij} & & t_D^{ain} \\ \vdots & & \vdots & & \vdots \\ t_D^{an1} & & t_D^{anj} & & t_D^{ann} \end{bmatrix} \tag{16}$$

$$W = \begin{bmatrix} t_D^{a11} \times W_{11} & t_D^{a21} \times W_{12} & \cdots & \cdots & t_D^{an1} \times W_{1n} \\ & & & & \vdots \\ t_D^{a12} \times W_{21} & t_D^{a22} \times W_{22} & & & \\ \vdots & \vdots & & & \vdots \\ \vdots & \cdots & t_D^{aij} \times W_{ij} & \cdots & t_D^{ani} \times W_{ni} \\ \vdots & \vdots & & & \vdots \\ t_D^{a1n} \times W_{n1} & t_D^{a2n} \times W_{n2} & & & t_D^{ann} \times W_{nn} \end{bmatrix} \tag{17}$$

ANP Step 4: Obtain the limited supermatrix, by multiple productions of the weighted supermatrix until the vector values in the limited supermatrix become stable (equation 18, with W being the limited supermatrix and z tending to infinity). The vectors of the limited supermatrix represent the relative weights of each factor in relation to the defined objective. Sorting the limited supermatrix W according to the relative weights of each factor gives insights on the significance and contribution of each factor as well as each cluster to the objective of network.

$$\lim_{z \to \infty} = W_w^z \tag{18}$$