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# Developing similarity based IPA under intuitionistic fuzzy sets to assess leisure bikeways



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#### HIGHLIGHTS

- A new IPA approach is developed to solve the inconsistency in traditional IPA.
- A means of converting Likert scale into intuitionistic fuzzy sets is presented.
- A well-defined similarity measure is proposed and proved.

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#### ABSTRACT

Since its introduction in 1977, importance-performance analysis (IPA) has been used widely to assess marketing and operating strategies. In previous IPA studies, three methods have been used to position the crosshairs: the mean, median, and middle positions of scale. However, as several studies have pointed out, differently positioning the crosshairs may lead to dramatically different results. To resolve this inconsistency, this study proposes a similarity-based importance-performance analysis (SBIPA) under intuitionistic fuzzy sets. The basic idea of SBIPA is to classify service attributes into the most similar quadrant of a conventional IPA grid according to the proposed similarity measure. Using SBIPA to assess the Tamsui Golden Riverside Bikeway shows that the natural environment of the bikeway is attractive enough to support tourism, but authorities should pay greater attention to improving the facilities of the bikeway.

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#### 1. Introduction

In recent years, as the concepts of sustainability and leisure have gained more popular attention, many people have adopted the bicycle as a means of commuting, and of pursuing leisure activities, due to its human-orientation, green characteristics (low pollution, and energy consumption), low user-cost, and sporting nature.

In some cities, to fulfill the growing demands for cycling-friendly infrastructure and provide environmentally-friendly transportation facilities, relevant government bureaus have been tasked with constructing bikeways and improving the cycling environment (Pucher, Buehler, & Seinen, 2011). Chang and Chang (2009) investigate the relationship between environmental preferences and level of satisfaction with bicycling facilities and find that bikeway facilities and resources are the primary factor influencing the degree of satisfaction derived from cycling. Thus,

assessing service attributes is critical for the authorities intent on adopting operating strategies appropriate to improving riders' experiences cycling on the bikeways.

In the literature related to service attribute assessment, importance-performance analysis (IPA) is widely used in the areas of transportation (Chou, Kim, Kuo, & Ou, 2011; Chou, Tserng, Lin, & Yeh, 2012; Ding, 2012), leisure and tourism (Caber, Albayrak, & Matzler, 2012; Deng, 2008, 2007; Deng & Pei, 2009; Huan, Beaman, & Shelby, 2002; Vaske, Beaman, Stanley, & Grenier, 1996; Zhang & Chow, 2004), and other areas, including education (Chen & Chen, 2012; Lin & Chen, 2010; Wang, Tai, Chen, & Yang, 2010; Wang & Tseng, 2011), and environmental protection (Tseng, 2011; Tseng, Lan, Wang, Chiu, & Cheng, 2011).

The basic idea of IPA is to classify the attributes of services and products in order to help practitioners and decision makers craft marketing and operating strategies. Measuring the importance and performance of the attributes of products and services as perceived by customers, IPA classifies those attributes into four strategic quadrants ('Keep up the good work', 'Concentrate here', 'Low priority', and 'Possible overkill') (as shown in Fig. 1), and provides

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suggestions on the allocation of limited resources to improve the overall performance of organizations.

However, inconsistencies in the results may arise in traditional IPA processes. Most researchers use the mean values of observed importance and performance to set the crosshair point of the IPA grid, but, as Martilla and James (1977) argue, using the mean value as the crosshair point implies the use of an interval scale, which is not, in fact, the case in many situations. Actually, there are three means of positioning the crosshairs: mean, median, and middle position. The positioning of the vertical and horizontal axes on the grid are "a matter of judgment" (Martilla & James, 1977). Nevertheless, the different settings of the crosshair (i.e. the intersection of the vertical and horizontal axes) may produce different results and interpretations (Azzopardi & Nash, 2013; Martilla & James, 1977; Oh, 2001; Tonge & Moore, 2007). Thus, one of the sources of inconsistency is the selection of the crosshair position.

In addition, perception and attitude can be vague, uncertain and subjective. In a traditional IPA survey, the usual means of measuring respondents' perceived degree of importance and performance is the Likert scale. Respondents are asked to rate their perceptions ranging from 1 to H for the given linguistic assessments (for example, 1 = "very unimportant", 2 = "unimportant", 3 = fair, 4 = "important", 5 = "very important") by equally-spaced crisp (non-fuzzy) numbers. However, because the same words can indicate very different perceptions due to uncertainty and fuzziness (Deng, 2008), using crisp numbers is not an appropriate means of addressing perceptions.

For dealing with fuzziness, fuzzy set theorems (Zadeh, 1965) or, more generally, intuitionistic fuzzy sets (Atanassov, 1986), have been used to model linguistic assessments in some IPA research (Deng, 2008; Deng & Pei, 2009; Lin & Chen, 2010; Tseng, 2011; Tseng et al., 2011; Wang et al., 2010; Wang & Tseng, 2011). In most of these studies, the method of fuzzifying linguistic assessments is to assign differing vague values to linguistic variables, then aggregate these vague values across respondents in order to obtain integrated vague values, and then defuzzify the integrated vague values of importance and performance for the various attributes. Finally, assign the service attributes into quadrants according to a pre-determined crosshair. This method may take into account the fuzziness of respondents' perceptions; however, this still requires a pre-determined crosshair position for the IPA classification. Furthermore, different defuzzification methods may produce differing classification results.

IMPORTANCE	QUADRANT I	QUADRANT II
	Concentrate Here	Keep Up the Good Work
	High Importance	High Importance
	Low Performance	High Performance
	QUADRANT III	QUADRANT IV
	Low Priority	Possible Overkill
	Low Importance	Low Importance
	Low Performance	High Performance

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**Fig. 1.** Traditional IPA grid. Source: Zhang and Chow (2004).

Accordingly, this study aims to propose a methodology for dealing with the inconsistency incurred by the selection of the crosshair point and the vagueness of respondents' reported perceptions. This proposed methodology can also be applied in the fuzzy environment as it is a special case of an intuitionistic fuzzy set.

#### 2. Methodology

2.1. Intuitionistic fuzzy sets for importance-performance survey data

Since being proposed by Zadeh (1965), fuzzy set theory has been applied successfully in various fields. As such, it is regarded as a proper tool for describing the real world in which we live.

According to the theory, a fuzzy set, F, in the universe of discourse  $X = \{x_1, x_2, \dots, x_n\}$  is defined as follows:

$$F = \{(x, \mu_F(x)) | x \in X, \mu_F(x) \in [0, 1] \}$$
 (1)

where the function  $\mu_F(x)$ : $F \rightarrow [0,1]$  denotes the membership degree of x to F, and  $\nu_F(x) = 1 - \mu_F(x)$  represents the non-membership degree of x to F.

Atanassov (1986) further generalized fuzzy set theory and identified the extension as an intuitionistic fuzzy set (IFS). In the extension, Atanassov (1986) added a second degree (a degree of non-membership) to the fuzzy set to construct IFSs. Thus, according to Atanassov's theory, an intuitionistic fuzzy set (A), in the universe of discourse  $X = \{x_1, x_2, \dots, x_n\}$  is defined as follows:

$$A = \{(x, \mu_A(x), \nu_A(x)) | x \in X, \mu_A(x) \in [0, 1], \nu_A(x) \in [0, 1], 0$$

$$\leq \mu_A(x) + \nu_A(x) \leq 1\}$$
(2)

Let  $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ ,  $\pi_A(x)$  indicates a degree of hesitancy or vagueness of x to A. Obviously, when  $\mu_A(x) + \nu_A(x) = 1$ , for every  $x \in X$ , A will degenerate to a fuzzy set, implying a traditional fuzzy set is a special case of IFS. Thus, IFSs are more realistic than fuzzy sets as hesitancy is considered.

In order to introduce the IFS technique into traditional IPA, this section proposes a method to construct IFS for the IPA survey data. In an IPA survey, if respondents are asked to rate service attributes on their agreeableness, ranging from L (strongly disagree) to H (strongly agree) with a midpoint M (referring to ambivalence), direct comparisons of their ratings will be invalid due to variations in the values respondents ascribe to the ratings. To obtain a unit-free measurement that lies between L and H with a neutral agreeableness M, the rating value should be normalized. Suppose that the rating value of the description of jth service attribute evaluated on the kth criterion by ith respondent is  $x_{ij}^k$ ; in that case, the normalized rating value of  $x_{ij}^k$ , denoted by  $N_{ij}^k$  can be calculated by:

$$\begin{aligned} N_{ij}^{k} &= L + \left(H - L\right) \left(x_{ij}^{k} - \min\left\{x_{ij}^{k} \middle| \forall j, k\right\}\right) \middle/ \left(\max\left\{x_{ij}^{k} \middle| \forall j, k\right\}\right) \\ &- \min\left\{x_{ij}^{k} \middle| \forall j, k\right\}\right), \end{aligned} \tag{3}$$

where  $i=1,2,...,n, j=1,2,...,m, k=1,2,...,K, N_{ij}^k \in [L,H]$ , and  $x_{ij}^k$  is the rating value of the description of jth service attribute on kth criterion rated by ith respondent. The value of  $N_{ij}^k$  is from L to H. When  $N_{ij}^k = H$ , ith respondent strongly agrees with the description of jth attribute on kth criterion, whereas  $N_{ij}^k = L$  indicates a strong disagreement, and if  $N_{ij}^k = M$  then the respondent should be relatively ambivalent or hesitant to decide upon the degree of agreeableness. The obvious means of assessing the degree of agreement

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