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A mathematical programming model for estimating the importance levels of performance criteria and an application in e-commerce

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ABSTRACT

Similar to traditional brick-and-mortar shops, e-commerce websites also should perform well in terms of various performance criteria in order to win and retain customers. A number of e-commerce performance criteria have been identified in the literature. From the point of view of the manager of an e-commerce website, the relative importance levels customers attribute to these performance criteria are important. In this paper, we propose a new mathematical programming model for estimating the importance levels. The model is based on the Analytic Hierarchy Process and operationalised using goal programming. Application of the model highlights that the criterion "satisfaction with claims" is valued by customers as the most important criterion. This criterion requires coordination with multiple echelons of the supply chain – a clear description by the manufacturer of the product, introducing the correct description in the e-commerce website, processing customer orders accurately, and, picking and dispatching the right product from the warehouse.

1. Introduction

Mathematical programming models are being extensively used for understanding and improving many important problems in business and management. While it has been applied to many areas in management science (such as facility location, scheduling, etc.), it has received relatively little attention in understanding the drivers of customer loyalty in the marketing/operations literature. The contribution of customer loyalty towards success of an organization has been stressed in the literature (Dick & Basu, 1994). With the emergence of electronic commerce as an important component of overall commerce, this topic has gained increasing attention in the context of e-commerce in the recent literature (Burt & Sparks, 2003).

E-commerce has shown impressive growth in the last few years but the rate of growth is slowing down. For example, according the survey of the UK Office of National Statistics, internet sales by UK businesses rose to £130.4bn in 2006 which was 6.5 per cent of the total value of all sales by non-financial sector businesses and an increase of 29.1 per cent on the 2005 internet sales figure. This growth is much smaller compared to the growth of 62% of internet sales (excluding financial sectors) in 2001 compared to the year 2000. It is argued that, with the pricking of the internet bubble, many e-tailers are looking to develop sophisticated strategies to build customer loyalty and sales. Of related interest is the use of information from customers to assess the importance of product or service attributes that would stimulate customer loyalty and repeat purchase (Kwak, 2001). The literature on operations research and management science has a number of studies addressing this important issue, both in traditional and in e-commerce contexts.

There is a growing body of literature that deals with customer satisfaction and revenue management in the context of the electronic marketplace (e.g., Collier & Bienstock, 2006; Meziane & Kasiran, 2007; Netessine, Savin, & Xiao, 2006; Wang & Lin, 2009). Though e-commerce and the so called e-tailing are relatively recent phenomena, much has been written about the customer service criteria and quality measurement in e-tailing (Collier & Bienstock, 2006; Kaplan & Sawhney, 2000; Lee, Lee, & Park, 2007; Lee & Park, 2009). In general, customers use a variety of criteria to judge the quality of a website involved in e-commerce activity. For this paper, we group the criteria into four categories, (i) Criteria experienced before customers make their decisions to purchase (e.g., website design, and technical issues), (ii) Criteria experienced during purchase (e.g., privacy and security), (iii) Criteria experienced after the customer made the payment (e.g., delivery and the whole range of after-sales and support services), and (iv) Criteria based on both pre- and post-purchase experiences (e.g., receiving proper receipts for payment, documents, all the items ordered and not receiving anything not ordered).

There are studies that have specifically stressed the importance of these performance criteria in determining customer retention and loyalty and ultimately the success of firms (e.g., Collier & Bienstock,

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2006). Many of the empirical studies are based on the availability of significant amount of online customer ratings, customer feedback or customer reviews (e.g., Heim & Sinha, 2001; Meziane & Kasiran, 2007; Ramanathan, 2010). There are also studies that have used primary data collected through surveys (e.g., Balasubramanian, Konana, & Menon, 2003).

We focus in this paper on the use of online customer ratings. The last few years have seen many research studies that attempted to analyse online ratings empirically. Heim and Sinha (2001) have examined the relationship between customer loyalty and order procurement and fulfillment processes in the case of electronic retailers. They have used data from the online rating site, http://www.bizrate.com. They have identified three order procurement criteria (website navigation, product information and price) and three order fulfillment criteria (product availability, timeliness of delivery and ease of return) as significant in influencing customer loyalty. Thirumalai and Sinha (2005) have used online customer ratings from http://www.bizrate.com to identify the significance of order fulfillment criteria (on-time delivery, customer support, order tracking and product met expectations) on customer satisfaction among various product groups – convenience, shopping and specialty. Using factor analysis and ANOVA, they have found evidence that the importance of order fulfillment criteria were different for specialty goods than for convenience goods or shopping goods. Otim and Grover (2006) have studied online customer ratings from bizrate using ordinary least squares analysis to identify the effects of pre-purchase, transaction-related and post-purchase services on customer loyalty. They have found that post-purchase service criteria (order-tracking support, on-time delivery and customer support) influenced customer loyalty more significantly. Similar conclusions have been made by Jiang and Rosenbloom (2005) using Bizrate data by employing structural equation modeling. Heim and Field (2007) have provided a more in-depth study to understand the process drivers of specific e-commerce assessment criteria (payment process, on-time delivery, ease of returns and refunds, privacy experience and customer support). Deviating from earlier studies, they have chosen to use data from another online rating site, http://www.epubliceye.com. Interestingly, they have not considered customer loyalty in their analysis.

Most of these studies have used multivariate statistical approaches to draw their conclusions. As an alternative, we propose in this paper a new mathematical programming approach to estimate relative importance of e-commerce performance criteria. The need to develop methodologies that would help identify the relative importance of e-commerce criteria valued by customers has been stressed in the literature (Kwak, 2001).

2. Methodology – the mathematical programming model

For simplicity, we assume linear relationships. Our model has close relationships with hierarchical models used in the literature on analytic hierarchy process (AHP) (Forman & Gass, 2001). We first show the basic ideas of our approach using a simplified illustration in this section. For this illustration, let us consider four criteria and three alternative websites – A, B and C. The hierarchical model of the type typically used in analytic hierarchy process shown in Fig. 1.

When normal AHP is used to estimate final preference scores of websites, the importance levels of criteria are first estimated, websites are then rated in terms of each criterion, and they are combined to calculate the final preference scores of websites. Let c_j be the importance level of criterion j, and w_{ij} be the weight of website i when evaluated in terms of criterion j. When all the c_j and w_{ij} are known, the final preference scores of the website i, denoted here as f_i, is calculated as $\sum_j c_j w_{ij}$. In AHP, the c_j, w_{ij} and f_i are normalized such that $\sum c_j = 1, \sum w_{ij} = 1$ for each j, and $\sum f_i = 1$.

Our view of ratings follow the reverse of the usual logic employed in AHP – while a usual AHP analysis computes the final preference scores of websites from the importance levels of criteria and ratings of alternatives in terms of criteria, we tend to derive the importance levels of criteria from the final preference scores of websites. This procedure could be called the reverse AHP (R-AHP) model.

Criteria for our model are those available at http://www.epubliceye.com. We use customer loyalty rating as a proxy for final preference scores of websites. Suppose customer loyalty rating is available for the three websites. In line with AHP requirements, we normalize the customer loyalty ratings to get the final preference scores (f_i) such that the sum of normalized customer loyalty ratings for all three websites equals 1. We assume here that customer loyalty ratings represent the overall preference of customers and that these ratings are comparable across all the e-commerce websites listed in epubliceye.com. Similarly, w_{ij} are also obtained using normalization for each criterion. Since f_i and w_{ij} are known, c_j needs to be found. Ideally, c_j can be calculated by solving the set of simultaneous equations given by $f_i = \sum_j c_j w_{ij}$. However, it may not be possible to guarantee equality for all the simultaneous equations. We use a simple linear goal programming model (Stewart, 2005) that minimizes deviations (denoted as d_j^+ and d_j in the R-AHP model below) from the equalities. Specifically, we use the following model.

$$\begin{aligned}
&\text{Min} && d_j^+ + d_j^- \\
&\text{Subject to} && \sum_j c_j w_{ij} + d_j^+ - d_j^- = f_i \quad (R-AHPModel) \\
& && \sum_j c_j = 1 \\
& && c_j, d_j^+, d_j^- \geqslant 0
\end{aligned}$$

where the decision variables c_j denote the importance levels of criterion j, and d_j^+ and d_j^- respectively denote the under-achievements and overachievements since the equations given by $f_i = \sum_j c_j w_{ij}$ may not be entirely satisfied.

We propose that, when this R-AHP model is solved, resulting c_j can be interpreted as the implicit importance levels of criteria. This is true only when there is a unique solution for c_j. However, a goal programming model generally can give more than one optimal solution. Thus c_j from the above R-AHP model can be meaningfully

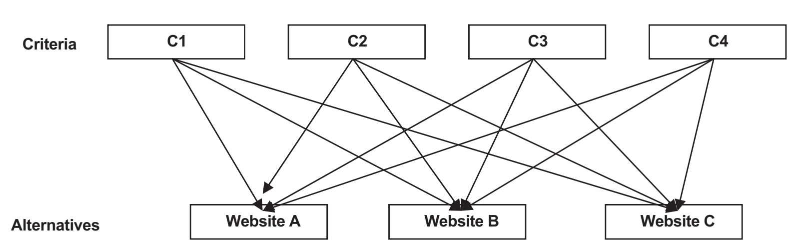

Fig. 1. A typical AHP hierarchy for rating three websites on the basis of four criteria.