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Competitive Positioning in International Logistics: Identifying a System of Attributes Through Neural Networks and Decision Trees

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Abstract: *Firms involved in international logistics must develop a system of service attributes that give them a way to be profitable and to satisfy customers' needs at the same time. How customers trade-off these various attributes in forming satisfaction with competing international logistics providers has not been explored well in the literature. This study explores the ocean freight shipping sector to identify the system of attributes that maximizes customers' satisfaction. Data were collected from shipping managers in Singapore using personal interviews to identify the chief concerns in choosing and evaluating ocean freight services. The data were then examined using neural networks and decision trees, among other approaches to identify the system of attributes that is connected with customer satisfaction. The results illustrate the power of these methods in understanding how industrial customers with global operations process attributes to derive satisfaction. Implications are discussed.*

Introduction

In the 1990's, the so called "Logistics Renaissance" (Council of Logistics Management 1995) reflected the new era of supply chain management. This "renaissance" compelled firms to examine their supply chain efficiencies to cut costs while simultaneously enhancing customer satisfaction. Indeed, Bowersox (1995) argues that "there have been more changes in the process of logistics during the past 10 years than in all the decades since the industrial revolution" while Fuller, O'Conor and Rawlinson (1993) envision logistics as the next governing element in shaping competitive business strategy. Globalization is also dramatically contributing to a renewal in thinking as to how the logistics part of the supply chain should be constructed and managed (Poirier 1999).

International logistics operations have become critical in recent years given that about one fifth of the output of U.S. firms is produced overseas and one-fourth of U.S. imports are between foreign affiliates and U.S. parent companies (Dornier et al. 1998). Moreover, costs associated with logistics operations now make up the most significant portion of international trade expenses (Rodrigues, Bowersox, & Calentone, 2005). Logistics, once ignored, has now

become a key driver of global firms' competitiveness.

Amidst this dramatic change, international logistics providers need to identify the most important attributes that determine the value of the services they offer to logistics users looking to improve their supply chain effectiveness (Dadzie Chelariu, & Winston, 2005; Lambert & Burduroglu, 2000). According to Mentzer et al. (2004), the way a service provider performs logistics operations significantly affects the service provider's competitive advantage in both efficiency (cost leadership) and effectiveness (customer service). Customer service in how the logistics activities are performed has become a key to customer satisfaction, loyalty and market share (Daugherty, Stank, & Ellinger, 1998; Innis & La Londe, 1994; Stank et al., 2003). Hence, the service provider must maintain its quality of service and ensure the value added by the service is worth the cost it charges its clients; otherwise, clients may switch to others or provide the service themselves (Fung and Wong 1998).

The business environment for logistics service providers is notably competitive especially as more firms outsource their logistics solutions to third party logistics providers. To operate in such an environment, logistics firms need a competitive strategy that is different than their rivals, need to perform different activities from rivals, or perform similar activities in different ways (Porter 1996). In essence, logistics service providers are compelled to combine various service attributes into the right package or system so as to achieve a sustainable competitive advantage. Pivotal to achieving such a goal is an accurate understanding of what service attributes are important to their (industrial) customers. Yet, how industrial customers (or supply chain participants) choose logistics service providers is not well understood. Which service attributes have the strongest impact on satisfaction? What combination of service attributes maximizes satisfaction?

The *purpose* of this paper is to explore this choice process by investigating firms which ship their goods using one type of logistics provider, the ocean freight shipping service. We use the techniques of neural networks and decision trees as our approach to understand this process. The literature reports no application of these techniques to probe the mindset of industrial customers. Our study is in response to the dearth of research on what system of service attributes affect customer choice of certain logistics companies over others.

In this paper, we use responses to unstructured (or open-ended) surveys to discover the reasons why customers patronize certain shipping companies while avoiding others. Via this approach, we identify the relevant service attributes that customers consider when they evaluate logistics firms. Subsequently, we use a neural network approach to determine the relative

importance of these service features that drive customer satisfaction and how customers mentally processes this system of attributes. We then apply decision tree analysis to identify what “system” or combination of service features maximizes customer satisfaction. Understanding this system via these two approaches sheds light on the calculus that global logistics firms may use when allocating their resources to build customer retention and loyalty.

The paper first begins with a discussion of Porter’s (1996) ideas on how to construct a profitable system of attributes and its strategic importance. Subsequently, we examine service satisfaction, its antecedents, and its consequences. Next, we offer a brief discussion of the features of neural networks and decision trees and their usefulness in our research. We then present our research method, including a description of the sample and survey measures consisting of structured and unstructured questions. After providing the results, we discuss the efficacy of such analytical techniques in understanding the formation of customer satisfaction in the logistics industry. The paper concludes with implications for firms that provide international logistics services and insight into developing their system of offerings. Our paper contributes to a better understanding of international logistics by investigating an important area that has received little attention.

Strategic Importance of Constructing a Profitable System of Service Attributes

Porter (1996) argues that firms must understand the tradeoffs that exist in establishing a competitive position in the marketplace. The essence of strategic positioning is to choose activities that are different from rivals; strategy rests on these unique activities to deliver a unique mix of value. It is, therefore, essential that international logistics companies identify what type of service attributes or offerings (e.g., price, reputation, delivery speed, claim handling) to focus on so that service satisfaction remains high–even if the company does not provide maximum service levels in every aspect of the service delivery. In sum, an international logistics company must be concerned with how to construct a “system” of attributes that will be attractive and satisfying to customers and will be profitable while recognizing that there are tradeoffs in this process.

Unfortunately, extant research in the logistics services area does not provide easy solutions to address these concerns. Porter (1996) illustrates an excellent mapping process to understand how services attributes and activities are linked to one another to form a system, yet he does not recommend a procedure in how to analyze or quantify these linkages. These activities, clearly, must be ones that customers value for this combination to be superior to

competing offerings. He warns firms that such strategic positioning is not obvious; finding them requires creativity and insight. Our research, therefore, is guided by Porter's exhortation and by Behara, Fisher and Lemmnik (2002) who advocate using neural network analysis to identify the optimal operation of service attributes.

Because of its connection to profitability, building customer loyalty has become a major preoccupation with firms. The question "What are the key drivers of customer loyalty?" is essentially about finding the right combination of activities at various levels that provide superior value and high levels of customer satisfaction as Porter (1996) advocates. Unfortunately, there is no easy answer to this question, perhaps due to the diversity of customers and industry situations. Because a service is intangible, it has properties regarding quality that make it much more difficult to identify and, therefore, to quantify drivers of loyalty. Nonetheless, *customer satisfaction* is regarded as a pivotal concept that is considered to be at the core of building this loyalty.

Heretofore, the preponderance of evidence in the service sector suggests that providing superior service is the way to increase customer satisfaction, which, in turn, sustains repeat purchases and enhances loyalty. Providing superior service, however, can be very expensive since it may involve infrastructure development and heavy costs involving human resources. Becoming the best service provider may seem initially like the surest route to success if the costs are not considered. For international logistics firms with limited resources, key decisions must be faced in terms of the tradeoffs involving giving maximum service versus focusing on optimal profitability. These tradeoffs in logistics costs are crucial in determining customer service levels in supply chain decisions. Given the need to develop a combination of logistics attributes, we now examine the role of customer satisfaction in building this combination.

The Importance of Customer Satisfaction

Customer satisfaction in the B2B sector with services (such as logistics operations) has become a key concern as the service sector continues to expand and competition among service providers intensifies. Customer evaluation of the service which ultimately determines satisfaction involves a plethora of service attributes including quality, service encounters, and value. Presently, it is believed that there is a causal sequence where service quality (as reflected in these attributes) drives satisfaction, which, in turn, affects attitudinal loyalty (favorable word of mouth) and behavioral loyalty (repurchase intentions). Hence, satisfaction is a crucial variable in this causal chain. Fung and Wong (1998) view maximizing customer satisfaction as an essential

part of a service strategy in logistics.

Customer satisfaction has been widely studied in consumer research (Yi, 1989), economic psychology (Johnson & Fornell, 1991), marketing (Fornell & Werneldt, 1987), and service management (Hallowell, 1996). In the marketing literature, satisfaction is argued to have impacts on customers' loyalty intentions (Bearden and Teel 1983; LaBarbera & Mazursky, 1983; Oliver, 1996; Yi, 1990), which in turn affects profitability (see for example, Heskett et al., 1994; Storbacka, Strandvik, & Gronroos, 1994). Empirical findings have also found supportive evidence that satisfaction is associated positively with customers' repurchase intentions (i.e., behavioral loyalty) (Anderson & Sullivan, 1993; Woodside, Frey, & Daley, 1989;) and propensity to recommend to others (i.e., attitudinal loyalty) (Hartline & Jones, 1996; Selnes, 1993; Zeithaml, Berry, & Parasuraman, 1996). Lovelock (2001) also argues that it can generate positive word of mouth, more agreeable customers, and customer retention.

Since understanding customer satisfaction is crucial, it is essential to identify the significant factors that form or drive customer satisfaction. Heretofore, the bulk of research investigating these factors has exclusively relied on standard 7-point rating scales to quantify satisfaction. A more powerful approach, however, may be to identify the factors customers use to evaluate the service and the concomitant satisfaction experienced. It is also crucial to identify the reasons customers give in deciding if they should continue their relationship with their preferred service provider. Knowing the relative importance of those factors and reasons can provide valuable insight for international logistics firms in designing a more satisfying "system" of service attributes or features. We discuss below the techniques to map out the attributes that drive satisfaction.

Techniques to Understand Satisfaction: Neural Networks and Decision Trees

One way to quantify the importance of various service attributes or features and reasons in driving satisfaction is via ordinary regression analysis or path analysis. These analytic techniques are constrained by assumptions regarding linearity of relationship between satisfaction and its determinants and the possibility of multi-collinearity among the determinants of service satisfaction. However, the relationship between service satisfaction and its determinants may not always be linear. Moreover, multi-collinearity causes instability among parameter estimates, thereby limiting the applicability of traditional analytic methods (Draper & Smith, 1981; Hair, Tatham, & Black 1998). In this scenario, other techniques such as neural networks or decision trees offer a better promise.

Neural networks can be used when there is a non-linearity in the relationship between customer satisfaction and its determinants. These networks, which mimic how the brain may work, are helpful in sorting the most important service features that drive customer satisfaction. Decision trees, on the other hand, are particularly useful in mapping out the combination of service satisfaction attributes that maximize satisfaction. Knowing this combination would allow a firm to develop a more profitable "system" of service features or attributes that would lead to higher levels of satisfaction among its customers. Neural networks and decision trees, therefore, offer an analytic power that regression analysis cannot provide. The discussion below gives greater details concerning the features and application areas of neural networks and decision trees.

Neural Networks

Neural networks complement, or even outperform techniques such as regression analysis, path analysis, and discriminant analysis by allowing for nonlinear relationships and complex interactions among predictors. Neural network analysis is mainly used for prediction purposes. In our study, we use this approach to assess the relative importance of various service features of ocean freight shippers in predicting satisfaction of their clients.

The literature reports many successful uses of neural networks in business settings. In particular, the field of financial services has used neural networks for credit card fraud determination (Rochester, 1990), bank failure prediction (Tam & Kiang, 1992), mortgage underwriting judgments (Collins, Ghosh, & Scofield, 1988), prediction of corporate bond ratings (Sukran & Singleton, 1990), among other uses. Application of the neural network methodology in other service areas is also growing. Bellandi, Dulmin and Mininnao (1998), for example, used neural networks to forecast failure rate of buses for an Italian bus manufacturing company while Xu et al. (1999) used the approach to examine the complexities of urban tax services in Hong Kong. Neural networks have also been used to forecast service problems of aircraft structural components (Nordmann & Luxhoj, 2000). Recently, Rodrigues, Bowersox and Calentone (2005) applied neural networks to predict global logistics expenditures.

Behara, Fisher and Lemmink (2002) point out that researchers are just beginning to model the qualitative and intangible aspects of services using this technique. One study by Mozer et al. (1999) developed neural models of customers who switch from one cellular communications provide to another. The model developed (using customer service variables) was able to predict customer churn rates better than the more traditional logit regression models. Most recently, Behara, Fisher and Lemmink (2002) used the neural network modeling approach

to evaluate service quality. Their model predicted overall service quality, as viewed by customers, with a 75 per cent accuracy level. This research demonstrated that neural networks can be a valuable method to understand customer evaluation of services so as to develop better service quality. Their research used the SERVQUAL dimensions, but it did not look specifically as satisfaction levels.

Given the wide range of applications of neural network analysis, it can also be used to examine how customer satisfaction is formed. The neural network in our paper represents mental processes of the industrial customers of logistics service providers. We employ this technique to understand the relative importance of various drivers of customer satisfaction. Appendix A provides a more in depth discussion of the mechanics of neural networks.

Decision Tree Analysis

Decision tree analysis is used for predicting the response to a target variable or for classifying consumers into mutually exclusive groups based on responses to several predictor variables. It does not attempt to model the brain, but instead, tries to identify how various attributes are linked to one another in combinations. This technique is particularly suitable over traditional regression analysis when the relationship between the target variable and its predictors is nonlinear or when there are interactions among the predictor variables. Decision tree analysis is a popular analytic tool because of the advantages it offers in terms of ease of use, interpretability of results, handling of missing data, robustness to outliers and measurement errors, and graphical display of results (cf. Morrison, 1998; Peacock, 1998; Vanecko & Russo 1999; Witten & Frank 2000). As compared to neural network analysis, results based on decision tree analysis are easier to interpret. Appendix A gives more discussion of the technical aspects of decision trees.

Method

Study Location and Sample

Our study focuses on the ocean freight shipping sector of the logistics industry. Data were collected from Singapore based companies that used services of ocean freight shipping lines. We chose the Port of Singapore since it is the world's busiest port in terms of shipping and cargo tonnage and the second busiest for container throughput. It handles about one-fifth of the world's total container transshipment throughput. In 2005, Singapore terminals handled 22.28 million twenty-foot equivalent units (TEUS) of containers through 4 container terminals and 2 multi-purpose terminals. The Port links shippers to an excellent network of 200 shipping lines

with connections to 600 ports in 123 countries. The Singapore Strait is one of the world's busiest waterways used by international shipping. Due to its location, Singapore has become a center of multinational operations and a shipping hub with huge transshipment cargo for onward movement to many countries in the region including Australasia, China, and the Indian subcontinent. Because of its well-managed port operations and excellent infrastructure, Singapore has developed into one of the world's leading ports. It was voted the "Best Container Terminal Operator (Asia) for the 16th time at the 2005 Asian Freight & Supply Chain Awards, and "Best Container Terminal" at the Lloyd's List Maritime Asia Awards, for the 5th time. Additional details on the importance of this port can be found at the Port of Singapore Authority website.

Two phases (as outlined below) were used to collect data from shipping managers and shipping line executives of various organizations in Singapore who regularly use the services of ocean freight shipping companies for their exporting requirements.

Phase 1

Names of 985 key accounts were obtained from a large shipping company in Singapore. Some of the shippers on the list were customers of that shipping company, while others were customers of competing shipping lines. From this list, 234 accounts were randomly selected; 222 of these agreed to participate in the study resulting in a 95% response rate. An important reason for the high response rate was the affiliation of one of the researchers with the National University of Singapore, an institute highly regarded by the respondents.

Personal interviews were conducted with these shipping managers. They were asked to provide five reasons why they selected a certain shipping line to take care of their logistics requirements and to list five reasons why they would avoid such a shipping line. Next, they were asked to list three major problems they encountered with shipping lines in general. The shipping managers in the sample also described the companies that they represented on several criteria. Included among those criteria were company size in terms of annual sales, annual freight expenses of these companies, and how often these companies reviewed the shipping lines' performance on a comprehensive basis.

Results of Data from Phase 1

Responses to the first phase survey measures were analyzed using SPSS. Results are described in Tables 1 and 2. As shown in Table 1, the sample of shipping companies that use ocean freight shipping services varies in size, with annual sales turnover ranging from under $10 million (45.3% of the sample) to over $100 million (9.4%). The annual freight expenses of these companies ranged from less than $10000 (7.6%) to over $100000 (31.8%). Responses to the

question “How frequently do these companies conduct a comprehensive review of their shipping lines’ performance” varied from rarely or never (12.4%) to continuously (56%).

Table 2 lists the reasons for choosing or avoiding certain shipping lines. It is clear one of the primary reasons behind the choice of a shipping line is competitive freight rates indicated by sixty nine percent of the sample. 46.2% of the customers would not select a shipping line if it does not offer competitive freight rates. Other important reasons for choosing are good service, having a regular service (or frequency of operation), maintaining good relationship, how short the transit time is, punctuality, reliability, and trustworthiness of the shipping line. At least 20% of the customers cited each of these reasons for their choice of a shipping line. Absence of these qualities in a shipping line would prevent the customer companies from patronizing that firm. Somewhat less significant reasons for selection, but noteworthy reasons nevertheless, are speedy documentation, good reputation, and prompt shipment. The significance of these key service features can also be gauged from the major problems that customer companies experienced with shipping lines. The results presented in Table 2 identify the features that shipping lines should focus on to enhance customer satisfaction.

To find out whether the reasons for choosing shipping lines varied on the basis of customer company characteristics, we performed a series of cross tabulations using the “multiple response set” feature of SPSS. Results indicate that the same set of key service features as identified above are cited by all customer companies, irrespective of their size, annual freight expenses, or how frequently they review shipping lines’ performance. In sum, the first phase of the survey identified competitive freight rates, good service, regular (or frequent) service, good relationship, short transit time, punctuality and reliability, and trustworthiness as key service features that customers of ocean freight shipping lines care about and that are likely to have an impact on customer satisfaction.

Phase 2

In the second phase of the survey, we measured customer evaluations of key service features as identified in the first phase along with overall customer satisfaction. Unlike most studies that adapt generic rating scales to measure the determinants of satisfaction (e.g., service quality), we developed specific scales based on customer input. Such customized measures are likely to be more powerful when evaluating logistics service providers since they capture the perceptions of shipping line customers. The list below outlines the themes of those service features, the number of scale items to measure them, and examples of scale items. Insights obtained during preliminary interviews with shipping line executives and a small sample of

customer companies facilitated the development of these measures. We verified the face validity of these scales by discussions with managers and experts in logistics. For all scale items, 7-point rating scales anchored by “poor” and “excellent,” were used. We summed the item responses for each dimension to derive a composite score. Parenthetically, factor analysis also supported uni-dimensionality of the following seven services features.

1. *Competitive freight rates* (3 items) (e.g., Competitive rates, Has lowest rates; scale reliability as measured by coefficient alpha is .73)
2. *Good Service* (3 items) (e.g., emphasize customer satisfaction, good after sales service; scale reliability is .80)
3. *Regular Service* (1 item) (good frequency of sailings)
4. *Good relationship/cooperation* (4 items) (e.g., listens to customers, values customers’ input, responsive to customers’ requests; scale reliability is .76)
5. *Short transit time* (2 items) (e.g., short transition time; scale reliability is .71)
6. *Punctual* (3 items) (e.g., punctuality of sailings, good on-time performance; scale reliability is .70)
7. *Reliable and Trustworthy* (4 items) (e.g., trustworthy, delivers on promises, gives correct/proper information; scale reliability is .76)

The questionnaire also measured subjects’ overall satisfaction with their most preferred shipping line’s service on a scale from 1 (Extremely Poor) to 7 (Excellent).

In phase 2, the same managers again provided responses to the 20 scale items measuring the 7 service features and overall service satisfaction as identified above. A total of 117 useful responses were available for analysis. To keep the survey length manageable, customers were asked to evaluate the service features of only their most preferred shipping lines. We used this data to perform neural network analysis and decision tree analysis.

Results of Neural Network Analysis

Responses to the second phase of the survey enabled us to examine the relationship between the key service features and overall service satisfaction. The seven service features that we measured in the second phase serve as the predictors of satisfaction. Correlations among the predictors varied from .53 to .82. In view of the potential for multi-collinearity among the predictors, possibility of interaction effects among predictors, and the likelihood of a non-linear relationship between those variables and satisfaction, traditional regression analysis

or path analysis is not appropriate. For this reason, we analyzed the data using neural network analysis and decision trees. Clementine 6.5, a data mining package marketed by SPSS, was used for this purpose.

We first performed a neural network analysis using the simple multi-layer Perceptron model. This model consists of one hidden layer besides one input layer and one output layer. There are seven input nodes (or neurons), one for each predictor variable, with customer responses serving as inputs. Customer satisfaction is the target variable that served as the output node. The number of hidden layer nodes is determined by the software program. In our case, the model used four hidden layer nodes to fit the data. The neural network detects the best relationship between the seven service features and satisfaction based on supervised learning. Considering our sample size (n = 117), we used 85% of the sample for training the network and the other 15% for validation purposes. Results of the analysis, presented in Table 3, are very encouraging; the prediction accuracy of the model is 83.5%. The difference between the mean customer satisfaction score for the original data and the predicted mean are fairly close, indicating that the performance of the neural network is satisfactory.

Table 3 also indicates the relative importance of the service features. Clearly, the key drivers of satisfaction are reliability and trustworthiness of the shipping line, quality of relationship the shipping line maintains with its customers, good service, and regular (or frequent) service. Relatively less important features are punctuality, competitive freight rates, and short transit time. These results offer important insights for shipping lines as to how to maximize satisfaction. It is likely that there were no differences in customer responses with respect to features such as punctuality because all shipping lines are adequate in these areas; hence, these attributes are not differentiating drivers of satisfaction in the minds of customers.

Results of Decision Tree Analysis

When unlimited resources are available, a shipping line would be able to significantly enhance its service offering in every aspect, whether it involves competing more aggressively on freight rates, offering superior quality service, or reducing the transit time. When faced with resource constraints, however, the shipping line would have to make trade-offs in terms of what service features to devote most of its resources. In this scenario, the question is what combination of service features either enhances or undermines customer satisfaction? To address this issue, we performed a decision tree analysis.

As with neural network analysis, the target variable for decision tree analysis is satisfaction, and the predictor variables are the seven service features. Prior to performing

decision tree analysis, we dichotomized responses to the predictor variables using the “mean split” criterion whereby those customers who rated the shipping lines above the mean on freight rates were recoded as 1 (i.e., “stronger” rating) and those below the mean were recoded as 0 (i.e., “weaker” rating). Next, we used the C&R (classification and regression) tree technique for generating the decision tree (cf. Breiman et al., 1980), as this technique is considered to be robust in the presence of problems of missing data and large numbers of predictor variables. Also, the tree that is developed using this technique is considered to be easier to understand. It is a binary tree growing algorithm.

As with any tree growing algorithm, C&RT technique splits the root node (or parent node) consisting of all data records into a number of branches and sub-branches (or child nodes) consisting of more homogeneous data records. C&RT tree starts by examining the input fields (i.e., the seven service features) to find an input field that offers the best split. The input field that provides the best split is one that gives the largest reduction in an impurity index. On the basis of this best input field, the root node is split into two child nodes or branches. For each child node, then, the program identifies the next input field that provides the best split. The child node is then split into two more nodes, and so on until one of the stopping criteria is reached. The stopping rule for C&RT depends on the minimum change in impurity. If splitting a node results in a change in impurity that is less than the minimum, the node is not split any further.

For any branch of a decision tree, the child nodes are “more” pure (or they have smaller within group variances) than their parent node. Here, purity refers to the values of the target variable (i.e., customer satisfaction). When a node is completely pure, then all of the data records in that node have the same value for satisfaction. This result indicates that within-group variance of that node is zero.

Decision tree analysis results are presented in Figure 1. As shown in the root node of the tree, overall mean satisfaction is 5.97. The first split of the tree is made on the variable “good relationship and cooperation.” This demonstrates that “good relationship” is the most determining feature (of the seven features we measured) of service satisfaction. This split gives a reduction in impurity of .11. For those customers that have a weaker perception of shipping lines on “good relationship,” the next determining feature is freight rates. Customers of this group who had a stronger rating of shipping lines on freight rates experienced a higher level of customer satisfaction (average value = 6.10) as compared to the entire sample. For this group, there is a gain in satisfaction of 102%. When we interpret the results this way, the largest gain (6.50 or 109%) in customer satisfaction occurs when customers provide strong ratings of shipping lines

on cooperation, transit time, and freight rates. Clearly, results of the decision tree show what steps a shipping line must take in order to enhance customer satisfaction.

Discussion

For all types of ocean freight shipping line customers, irrespective of their size, annual freight expenses, or how frequently they perform a comprehensive review of various shipping lines, “competitive freight rate” is the number one listed reason for choosing a certain shipping line, followed by “good service.” Other notable reasons are “regular service,” “good relationship,” “short transit time” and “reliability and trustworthiness.” These results suggest that ocean freight shipping firms cannot trade off price/wider network for service. Exclusively focusing on some service attributes may not be attractive to customers if the freight line operates a small fleet with fewer destination choices. Highly competitive rates coupled with poor service will also turn away customers. So, it is clear that logistics companies should either offer everything (e.g., best price & service) or offer a small network with great service, but integrate operations with partner lines so that customers see a seamless connection (as in Star Alliance for airlines). These results confirm the logic suggested by Porter (1996) in how to develop effective strategy.

When comparing the neural network and decision tree results, we find some similarities as well as some differences. For example, both techniques identify good relationship/cooperation and reliability/trustworthiness as important for customer satisfaction. In the case of neural networks, good relationship and reliability/trustworthiness are the most important predictors of satisfaction followed by quality of service and “regular service” (or service frequency). In decision tree analysis, customers’ perception of good relationship is the basis for segmenting them into two groups–those who rated service providers as low on good relationship and those who rated service providers as high on good relationship. For the first group, the overall satisfaction decreased, while it increased for the later group.

The primary objectives of the two techniques are different, however. For this reason, we find some differences in the results for these two techniques. The purpose of neural network analysis is to identify the relative importance of factors when the objective is to predict customer satisfaction. For logistics providers in the shipping industry, the factors that are the most important for predicting satisfaction are reliability/trustworthiness of the service provider and good relationship with the service provider. The purpose of decision tree analysis is to segment customers into several sub groups based on their perceptions of various service features and their overall satisfaction. This technique is applicable when the objective is to find out what

combination of service feature perceptions maximizes customer satisfaction. For example, customer satisfaction is the maximum when customers rate logistics providers highly on reliability/trustworthiness, transit time, and freight rates. For this group of customers, there is an increase in customer satisfaction of almost 9% (i.e., 6.5/5.96) when compared to the overall mean satisfaction for the entire sample. Customer satisfaction is the lowest for the segment of customers which rated the service providers low on reliability/trustworthiness, freight rates, and punctuality. For this segment, there is a decrease in satisfaction of about 9% (i.e., 5.43/5.96) as compared to the overall mean. The decision tree model provided an accurate prediction of service satisfaction given that the correlation of .77 between the original and predicted values of service satisfaction is high.

Since the two techniques provide different insights into the data, it is important for service providers to use results from both techniques when formulating a marketing strategy. Nonetheless, it is important to note that relationship quality surfaced as important in both types of analysis. Relationship quality is highly intangible and subject to marketing control. Ocean freight shippers firms could potentially use this quality as a way of differentiating themselves to enhance customer loyalty.

Analysis of customer complaints (or problems) with ocean freight shipping companies provides clues concerning the attributes that may enhance customer satisfaction. For example, customers frequently cited shipping delays, document delays, and communication breakdown as the major problems; suggested possible solutions that logistics firms could use were more knowledgeable staff and advance notification of shipping delays.

Implications and Conclusion

Our study provides ideas that contribute to understanding the dynamics of the service attributes in logistics that have not been explored well in the literature. We can offer several implications for logistics service providers in general and ocean freight shipping lines in particular based on our analysis. Neural networks and decision trees provide a powerful lens into the workings of these attributes. First, research on satisfaction can be deceptive depending on the method used. In particular, responses to open ended questions would suggest that freight rates as the most important factor. Yet, such a conclusion may hide what is happening under the surface (in the minds of users). Using neural network we can see that trust, cooperation, etc. are relatively more important. Why the difference? On a basic level, freight rates are clearly a key driver. Yet, a firm cannot easily differentiate itself as the low cost provider if others can offer

similar low prices as Porter (1996) would argue. Providing low cost rates is not likely to be a sustainable competitive advantage. If all customers provided the same ratings to shipping lines on freight rates then there is very small variation in freight rates vis a vis customer satisfaction. This understanding does not mean that freight rates can be ignored. Freight rates, in general, are not the differentiating factor in enhancing satisfaction when you look at the entire data. However, for subgroups of customers, freight rates are still very crucial in enhancing satisfaction. This understanding comes across clearly when we look at the decision tree results. Since we limited our data collection to customers' perceptions of their most preferred shipping lines, these results are useful because they could serve as the bench mark.

The results of this study clearly illustrate that neural networks used in tandem with decision trees offer a powerful procedure to identify elements that can maximize satisfaction and the sequence or combination in the way they may operate. Trying to understand how satisfaction develops through the conventional methods of surveys and descriptive statistical analysis does not penetrate the complexity involved in the way the human brain may function. Using simple frequencies for reasons for preferring or rejecting shipping lines only scratches the surface. Neural networks facilitate our understanding of how humans process information to derive an emotional response, namely satisfaction.

There is a clear implication of these findings in terms of Porter's (1996) framework of strategy. Firms that are highly successful learn how to develop attributes that other firms cannot imitate easily. Sustainable competitive advantage comes from developing a unique position in the market place. For example, Southwest Airlines in the USA has developed a unique position in the marketplace that emphasizes less service, frequent departures, and low fares (Porter 1996). Although such a combination of attributes may seem obvious or easily copied, Southwest continues to maintain its strategic position despite imitators. Porter (1996) says a firm needs to concentrate on deepening a strategic position rather than broadening and compromising it and to make the firm's activities more distinctive, strengthening fit and communicating the strategy better to those customers who should value it. Relationship quality is likely to be one of those characteristics that would allow for a deeper strategic position.

In the case of ocean freight shipping services, the results indicate that it is not enough to provide a good price, i.e., freight rates. Instead, firms must realize that there is a sequence or combination of service factors that maximizes service satisfaction. Discovering the best sequence depends in part on the segment that the firm is pursuing or the extent to which firms all seem alike. Differentiating the offering by providing specific levels of attributes is more likely to

lead to higher levels of satisfaction. Such satisfaction is likely to lead to higher levels of loyalty. Deepening this differentiated position is likely to give a firm a strong advantage in the marketplace. The key is to understand how to make the right tradeoffs in the way the system of attributes is combined. Indeed the goal is to pursue the right combination of attributes that gives a firm a unique position that cannot be easily copied.

In sum, our exploratory study finds important results related to developing a system of attributes that are of value to customers of logistics services. By using cross tabulations, decision trees and neural network analyses, we show how ocean freight shipping firms in the logistics sector should go about in identifying the sequence or combination of service factors that maximizes service satisfaction and, in turn, loyalty–this is exactly what Porter (1996) suggests firms should do to find a sustainable competitive advantage in the marketplace.

Notes

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Appendix

Neural Networks

The concept of a neural network is based on a mathematical abstraction of the way the human brain works (McMillen & Henley, 2001). In the human brain, information is processed by cells which are also called neurons. Each neuron collects information from other neurons that are attached to it, and it aggregates that information and passes it along to other neurons. In an artificial neural network, elements called nodes function similarly to the neurons in our brain. Each node sums information that it receives from nodes connected to it, and it passes the processed information to the nodes that it connects to. When several nodes are connected together, they process information in parallel, allowing the system to find complex relationships quickly. Information in a neural network is represented in the strengths (or weights) of the connections between nodes (Berry & Linoff, 2000).

Figure 2 shows a simple neural network, also known as the multi-layer perceptron or the back-propagation network. In this network, the “neurons” or “nodes” are organized into “layers.” There are typically three layers in a network: the input layer, the hidden layer, and the output layer. Each layer consists of several nodes or neurons. Further, each node is linked to every neuron in the preceding layer by connections that have strengths or **weights** attached to them. The first layer is called the **input layer** since it consists of nodes that uniquely represent each input or predictor variable. Input values for the predictor variables are presented to these input nodes. The information then flows through the network and is processed by nodes in the second layer, also known as the **hidden layer**. The hidden layer represents a sort of black box in that the nodes of this layer are hidden from the input and output. This layer is essential for mapping nonlinear relationships between the target output and the predictor inputs. It is important to point out that the hidden layer is an intervening layer and it facilitates the propagation of information from the input layer to the output layer. The third layer (called the **output layer**) consists of one or more output nodes. These output nodes combine information from the hidden nodes to generate predictions for the target variables.

Once a neural network is set up by defining a set of nodes and how they are connected, the network has to be trained. The network trains itself by looking at one record at a time. For each record, it makes a guess against the actual value for that case. It then adjusts the weights so that its next guess will be better. This implies that the network learns from its mistakes. Initially all weights are randomly set to small values and the predictions that come out of the network are likely to be nonsensical. However, as the network processes more and more data, it gets better and better at making predictions. Eventually, when the network learns all it can from the input data, it stops training. At this stage, it is ready to be tested on new data.

Since each node in any layer is connected to every node in the previous layer of the network, it is important to recognize that a single input predictor can influence the output through a variety of paths, which allows for greater model complexity. Another important feature of the

neural network is that the input for each hidden neuron is the weighted sum of data values from the input nodes that are transformed using a **nonlinear** function. Typically, such a function is the logistic function, though other transformation functions can also be applied. Thus, there is a nonlinear mapping of data values that occurs in the hidden layer before the next set of weights (relating the hidden layer to the output layer) is applied. This way, the neural network captures complex interactions among inputs and nonlinear relations between the inputs and the output. Further, increasingly complex relationships between the inputs and outputs can be captured by specifying a higher number of neurons for the hidden layer or by specifying more than one hidden layer during the model setup stage.

Decision Trees

In simple terms, a decision tree is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a classification or decision. The tree shows how the value of a target variable can be predicted by using the values of a set of predictor variables. The graphical representation of the tree shows a number of inter-connected "nodes." Each node represents a set of records (rows) from the original dataset. Nodes that have child nodes are called "interior" or "branch" nodes. Nodes that do not have child nodes are called "terminal" or "leaf" nodes. The topmost node is called the "root" node. While a real tree has its root at the bottom, decision trees are represented in such a way that the root node is always at the top. The root node in a decision tree represents all of the rows in the dataset.

A decision tree is constructed by a binary or non-binary split that divides the rows of the root node into two or more groups (child nodes) based on categories of the "best" predictor. The same procedure is then used to split the child groups based on other predictor variables. This process is called "recursive partitioning." The splitting process continues until no more statistically significant predictors can be found.

Decision trees can be applied to solve both regression type problems and classification type problems. Regression-type problems are those where the objective is to predict the values of a continuous variable from one or more continuous and/or categorical predictor variables. For example, one may be interested in predicting service satisfaction with a logistics service provider based on how the service provider is evaluated on several service variables. In this example, service satisfaction and its determinants are all measured using Likert-type scales. In contrast, classification-type problems are those where the objective is to predict values of a categorical dependent variable (class, group membership, etc.) from one or more continuous and/or categorical predictor variables. For example, one may be interested in predicting whether or not consumers patronize a logistics service provider depending on how they evaluate that firm on a number of service related factors. In this example, decision to patronize a service provider is categorical.

Among the decision tree based techniques, CHAID (chi-squared automatic interaction detector) (Biggs, de Ville, & Suen, 1991; Kass, 1980) and C&RT (classification and regression trees) (Brieman et al., 1980) have been widely applied in segmentation, stratification, and interaction identification studies in the areas of direct mail, credit scoring, human resources, market analysis, and health care (Sargeant & McKenzie, 1999, Sargeant & Msweli, 1999, Wyner, 1995). Recent studies have found that both techniques provide similar set of results, making them popular tools in marketing research applications (Berry & Linoff, 2000; Haughton & Oulabi, 1997).

In this study, our aim is to determine what combinations of features of service features enhance customer satisfaction with logistics firms. Because satisfaction is a continuous variable, we face a regression-type problem. We employed the C&RT technique to obtain the decision tree.

Table 1
Profile of Shipping Lines' Customers Annual Turnover in Singapore Dollars

	Frequency	Percent
Upto 10 million	101	45.3
10 to 25 million	54	24.2
26 to 50 million	25	11.2
51 to 100 million	16	7.2
over 100 million	21	9.4

Annual Freight Expenses in U.S. $

	Frequency	Percent
Less than 10000	17	7.6
Between 1000 and 24999	33	14.8
Between 25000 and 49999	55	24.7
Between 50000 and 99999	43	19.3
Above 100000	71	31.8

Frequency of Comprehensive Review of Shipping Lines' Performance

	Frequency	Percent
Never/Rarely	26	12.4
About once in 2 to 3 years	8	3.8
About once a year	25	12.0
Every 6 months	33	15.8
Continuously	117	56

Table 2
List Five Reasons Why You Chose a Particular Shipping Line? Responses Across the Five Reasons Are Summarized as Shown Below

	Percent of Cases
• Competitive freight rate→	69.0
• Good service→	50.0
• Regular service→	44.3
• Short transit time→	24.8
• Good relationship/cooperation→	24.3
• Customer's choice→	13.3
• Punctual→	12.4
• Reliable/trustworthy→	10.0
• Speedy document→	7.6
• Good reputation→	7.1
• Prompt shipment→	6.7
• Wide network→	4.3
• Efficient→	3.3
• Gives me priority→	3.3
• Ample vessel space→	2.4
• Special equipment→	1.4
• Other→	1.4

List Five Reasons Why You Don't Like Using A Certain Shipping Line? Responses Are Summarized As Shown Below

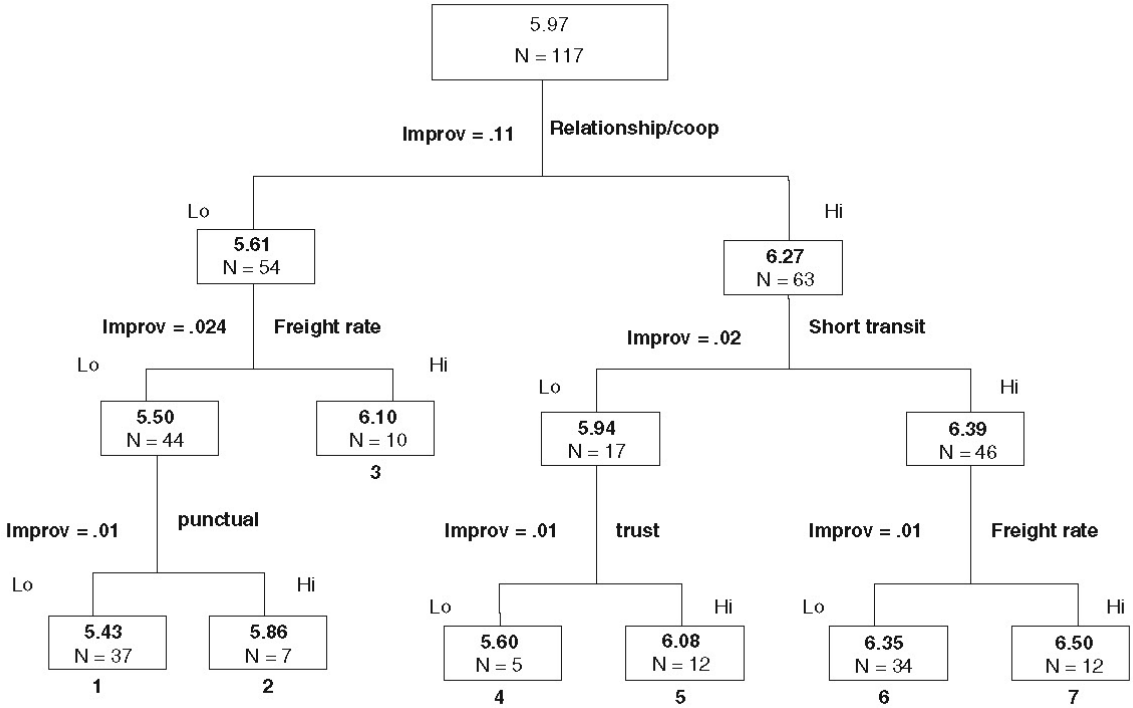
	Percent of Cases
• Uncompetitive freight rate→	46.2
• Poor service→	32.3
• Long transit time→	24.6
• Irregular service→	21.5
• Slow documentation→	13.8
• Not punctual→	13.8
• Uncooperative/inflexible→	13.8
• Small network area→	4.6
• Inefficient→	4.6
• Not reliable/trustworthy→	4.6
• Poor reputation→	3.1
• Shipment not prompt→	3.1
• No special equip→	3.1
• Office location inconvenient→	1.5
• Others	

Note: Service features identified by "→" are used as input to Neural Network and Decision Tree Analysis

Table 3
Importance Weights of Predictor Variables Based on Neural Network Analysis (Dependent Variable: Service Satisfaction)

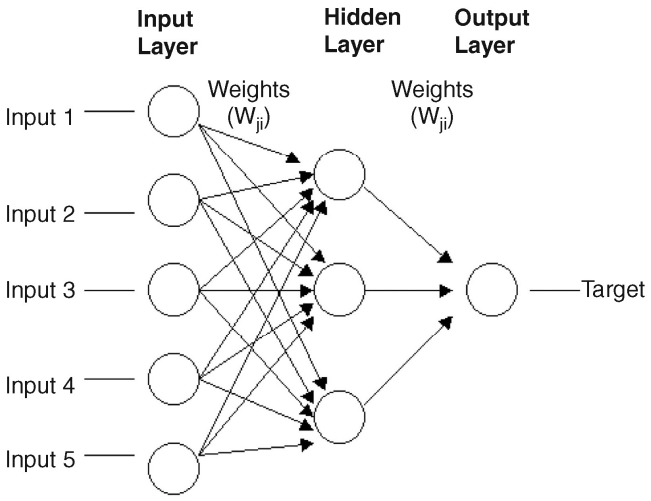
Service Variable	Importance Weight
Reliability–Trustworthiness	0.31
Good Relationship	0.16
Regular Service	0.06
Good Service	0.06
Short Transit Time	0.01
Competitive Freight Rates	0.00
Punctual	0.00
Prediction Accuracy of Model	**83.5%**
Mean Service Satisfaction	
Original data	5.97
Estimated by Model	5.86

Figure 1
Decision Tree Analysis



Note:
1. The figure shows mean service satisfaction score and sample size for various nodes of the tree. For example, the mean service satisfaction for the root node consisting of a sample of 117 customers is 5.97.
2. The improvement statistic shows the reduction in impurity when a parent node is split into child nodes.
3. As shown in the figure, there are 7 terminal nodes for this tree.
4. Mean satisfaction is the highest when customers have rated shipping firms favorably on relationship/cooperation, transit time, and freight rate.
5. Mean satisfaction scores for nodes 3, 5, 6, and 7 are higher than the mean satisfaction for the entire sample.

Figure 2
Simple Neural Network



Note: In this study, input nodes represent customer evaluations of ocean freight shipping lines' service features. The output node represents customer satisfaction. The hidden layer is responsible for a nonlinear mapping of the relationship between customer satisfaction and its predictor.