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PREDICTING CUSTOMER RETENTION LIKELIHOOD IN THE CONTAINER SHIPPING INDUSTRY THROUGH THE DECISION TREE APPROACH

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Key words: customer retention, decision tree, customer relationship management, container shipping.

ABSTRACT

This study aimed to develop a practical method for predicting customer retention likelihood by employing analytical methods different from those used by previous studies. A decision tree (DT) methodology was applied to predict the likelihood of customers not switching to new service providers (NSPs). Because the benefits of using DTs are flexibility and comprehensibility, the DT technique was used to select the items for predicting customer retention likelihood. Empirical data were collected from container shipping customers to demonstrate that the DT technique could be used to develop a customer retention prediction model for the container industry. The results showed that the service attribute of "Container carriers have a very close relationship with shippers" was the covariate with the largest correlation with NSPs. This indicated a close relationship between container carriers and shippers had the greatest influence on a customer who decides not to switch to another NSP. Our results not only suggest a simple decision rule for predicting customer retention likelihood in the container shipping industry, but also provide evidence to support a marketing assertion that customer retention is a central topic in the management and marketing decisions of the industry. Finally, managerial implications are also discussed.

I. INTRODUCTION

From the industry life cycle perspective, the container shipping industry has been in the so-called advanced maturity stage since the 1980s. The strategic focuses of operators in this stage are: (1) high customer sophistication, (2) low product differentiation, and (3) continued shakeout and industry concentration (Chiu, 1996). In general, operators face tremendous pressure because of shakeout and price competition; the key success factors are cost efficiency through capital intensity, scale efficiency, and low input costs (Grant, 2008). Container carriers have fully applied the strategy of constructing ultralarge container vessels (ULCVs) with capacities of more than 18,000 or 21,000 TEUs. These ULCVs will ultimately contribute to containership oversupply (Drewry, 2015); in addition, slow growth in the global economy since 2009 has not alleviated the negative situation for container carriers who continue to suffer operating losses.

When confronted with the overcapacity of service providers, deskilling of producers, and deterioration of the market, container carriers must adopt novel strategies to retain customers instead of engaging in traditional price cutting to maintain profitability. Customer retention has a direct impact on profitability, which has been emphasized by various researchers. Reichheld and Sasser (1990) indicated that customer defections have a notably powerful impact on service companies because they can have more influence on a company profits than scale, market share, unit costs, and numerous other factors usually associated with competitive advantages. As a customer's relationship with the company lengthens, profits can rise considerably. Companies can improve profits anywhere from 25% to 85% by reducing customer defections by 5%. Heskett et al. (1994) indicated that the costs of attracting new customers were five times that of retaining current customers. In the customer equity management model, retention equity is a crucial component of relationship value (Grönroos, 2007).

Since 2013, a constant stream of vessel deliveries has added pressure to the supply side, and weak demand across nearly all global trade lanes has substantially lowered container ship demand. Customers are increasingly demanding greater reliability of container shipments at a lower total cost. Furthermore, infrastructure constraints as well as threats from new and more agile entrants challenge how industry players approach the market.

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In such a service environment, the most critical priority for container shipping companies should be to develop an effective marketing defensive strategy for retaining current customers to prevent them from switching to new service providers (NSPs). The success of marketing strategies created by container carriers depends on determining the most competitive service attributes (CSA) perceived by customers; otherwise, profits may decrease sharply.

Relevant research provides little information on predicting the purchase intentions of container shipping company customers. Chen et al. (2015) investigated the integrated opinions on the importance of service attributes of both container shipping company managers and their customers; they applied generalized cross entropy to estimate the relationships between attribute importance perceived by current customers and that of the prospective purchase intentions expected by the container shipping industry. However, their interpretation is difficult to assess because the multicollinearity of regression coefficient estimates will obscure the meaning of the results. Similarly, traditional algorithms and statistical methods such as structural equation modeling and logistical regression are also excessively difficult for managers seeking to analyze the results of such customer analyses (Hanssens et al., 2005).

In the past 10 years, many companies have perceived the retention of customers as a central topic in their management and marketing decisions (Van den Poel and Larivière, 2004). For investigating this subject, several data mining techniques are employed, and numerous commercial data systems are available (e.g., Larivière and Van den Poel, 2005). The decision tree (DT) was regarded as being among the most competitive random forest methods (Breiman, 2001) and as representing one of the simplest and most effective nonparametric supervised learning methods of classification. DT is a decision support tool that uses a tree-like graph or model of decisions to present possible consequences. The greatest benefits of DT are flexibility and understandability (Ledolter, 2013). The flexibility of this technique makes it particularly attractive, specifically because it presents the advantage of highly suggestive visualizations. Understandability can often yield a much simpler model to explain why observations are classified or predicted in a particular manner (e.g., when analyzing business problems, presenting a few simple if-then statements to management is easier than presenting elaborate equations).

Furthermore, customer opinion is a type of state preference (SP), and many previous studies have identified substantial measurement problems when only SP data are used to estimate attribute importance for forecasting behavioral intention (e.g., Ben-Akiva et al., 1994; Bemmaor, 1995; Mittal and Kamakura, 2001; Verhoef and Franses, 2003). DT can identify changes in consumer behavior from unstructured and ill-defined data sets because of the unsupervised learning feature of association rule mining (Breiman et al., 1984). Tinabo (2011) explored four potential data mining techniques for application to the problem of customer retention in the attribute importance sector, and proposed that a DT is the most effective technique.

Because of the aforementioned advantages of DT, this study applied the technique to identify a decision rule for determining why customers do not switch NSPs in the context of the importance of CSA, which can be understood easily by practitioners in the container shipping industry. By establishing a practical model for predicting NSPs, this paper can serve as a reference, particularly for container shipping companies and marketing practitioners in developing marketing strategies and programs targeting more specific groups of customers. This study also contributes to academic research in container shipping management by elucidating container shipping company customer behavior.

II. LITERATURE REVIEW

To maintain customer retention, managers require tools to assess the defection risk of each individual customer. Such tools traditionally identify customers that are the most likely to defect, enabling the allocation of resources across the customer base (Ganesh et al., 2000; Shaffer and Zhang, 2002). Hanssens et al. (2005) suggested a module-based approach; however, the estimated equations often vary somewhat between applications and over time. For example, predictor variables can be deleted from the relations according to initial empirical results.

The relationship between attributes and target variables such as service quality and repurchase intention is of great value to managers. SP data obtained from customers or experts are widely used to estimate attribute importance in the field of transportation and logistics research (Lijesen, 2006; Chen et al., 2009; de Jong et al., 2014; Zhu et al., 2015). A wide variety of methods for identifying attribute importance was proposed and examined (Van der Pligt et al., 2000). However, the convergent validity among these methods is low, and replications occasionally yield inconsistent results (Jaccard et al., 1986; Van Ittersum et al., 2007). Recently, several studies have combined different sets of data to jointly estimate the parameters of customer preferences for improving the efficiency of attribute importance estimations (e.g., Ben-Akiva et al., 1994), particularly the method of combining SP data and revealed preferences (RP) data, which refers to data describing actual behavior. Although the combination methodology appears to hold considerable promise for improving the efficiency of parameter estimation, consistency or convergence between RP and SP data remains unconfirmed (Azevedo et al., 2003; Urama and Hodge, 2006; Van Ittersum et al., 2007; Axsen et al., 2009; 2010).

To improve convergent validity, Chen et al. (2015) proposed a theoretical perspective of the NSP model involving the defensive strategies of current container providers and the offensive strategies of potential service providers, and demonstrated empirically how attributes could be derived from customer SPs and the judgments of container shipping managers. The purpose of the model proposed by Chen et al. (2015) was to determine maximum convergent validity, which refers to a final solution showing the smallest distance between the opinions stated by the customers and container shipping managers. However, the results of Chen et al. (2015) remain difficult for practitioners to interpret.

Customer retention can be defined as a customer's stated continuation of a business relationship with a firm (Keiningham et al., 2007). In a highly competitive environment such as the container shipping industry, successful customer retention is critical. NSPs are used as an indicator of customer retention (Chen et al., 2015); however, studies have also used distinct metrics to measure customer repurchase intention and actual repurchase behaviors, as summarized in a series of review papers such as those by Keiningham et al. (2007), Gupta and Zeithaml (2006), and Morgan and Rego (2006). Customer retention is an outcome resulting from several different antecedents such as customer satisfaction, customer switching costs, and customer relationship management. The service attributes in the current research are prices and discounts, service quality, customer relationship, personal selling, word of mouth (WOM), advertising, and switching costs. The detailed relationships between these attributes and customer retention are discussed in Section 3.2.

Currently, data mining techniques are employed in different areas, and numerous commercial data systems are available. Among them, DT can identify changes in consumer behavior from unstructured and ill-defined data sets through means such as handling missing data, robustness to outliers, and measurement errors. Furthermore, DTs are well-known methods of predictive modeling used for data mining because they provide interpretable rules and logic statements that enable more intelligent decision making. DT can be used to segment an original data set. The predictive segments derived from the DT accompany a description of the characteristics that define the predictive segment. Although the algorithms of DT may be complex, the results can be presented in an accessible manner that is highly useful to business users (Berson and Smith, 2008). Consequently, it is regarded as one of the most competitive data mining techniques (Breiman, 2001). Among the DT-based techniques, chi-squared automatic interaction detector (CHAID) and classification and regression trees (CARTs) have been widely applied in many fields (Savidas and Baker-Prewitt, 2000).

Many industries have employed DTs to examine problems. For example, Silverstein and Shieber (1996) predicted individual book use for off-site storage using DTs. Sherman et al. (2013) compared three probabilistic methods (scenario analysis, DTs, and simulation of estimating costs) for port security risk assessment. Cho et al. (2002) employed DT induction to minimize recommendation errors by making recommendations only for customers who were likely to purchase recommended products. Long and Wu (2012) constructed a model of student achievement by using DT algorithms.

Regarding data mining methods including DT for analyzing customer retention, Larivière and Van den Poel (2005) employed random forest techniques to predict customer retention and profitability for a large European financial services company; they discovered that random forests techniques provide a better fit for the estimation and validation of samples when compared with ordinary linear regression and logistic regression models. Baack (2012) examined the various aspects of customer retention in health care by using potential analysis, and concluded that health care providers should attempt to develop the following three pillars of customer retention for whenever a patient or a patient's family and friends perceive a service failure: loyalty, quality relationships, and service recovery techniques of promptness, courtesy, effort, and professionalism. By applying both qualitative and quantitative techniques, Khan (2013) determined the factors that play a crucial role in customer retention by comparing the Park Inn and the Grand Hotel, and discovered that customers of the Grand Hotel were retained on the basis of services offered, whereas customers of the Park Inn were retained on the basis of food quality. Thill and Venkitasubramanian (2015) developed a DT model of hinterland structure and overlap, which explained the nature of interport competition from three dimensions (space, commodity type, and shipment values) for assessing the competition posed by private ports on major public ports. They also reported that the data mining method can be utilized for conceptualizing the port hinterland as a dynamic spatial object and revealing multidimensional relationships.

DT analysis has rarely been used in the ocean transportation and logistics field. Durvasula et al. (2002) examined a sample of shipping managers in Singapore who evaluated the service dimensions of ocean freight shipping companies. By using DT calculus, they identified a combination of interfacing departments that maximize service satisfaction. Furthermore, Durvasula et al. (2007) used neural networks and DTs to identify a system of attributes for maximizing customer satisfaction by analyzing the same industry from their 2002 study.

III. METHODOLOGY

1. Decision Tree

The objective of decision analysis is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features. Some of the major advantages of DTs are as follows: (1) they are simple to understand and interpret, (2) the trees can be visualized, (3) they require little data preparation, and (4) they are able to manage numerical as well as categorical data (Pedregosa et al., 2011). In data mining, DTs can also be described as the combination of mathematical and computational techniques for discerning the attribute importance of the description, categorization, and generalization of a given set of data. DT learning is one of the most successful techniques for supervised classification learning. Data can be expressed as follows: $(\mathbf{x}, Y) = (x_1, x_2, \ldots, x_n, Y)$. The dependent variable, Y, is the target variable that is to be understood, classified, or generalized. The vector $\mathbf{x}$ is composed of the input variables (or attributes) x_1, x_2, x_3, etc., which are used for that task. The computational details involved in determining the most favorable split conditions for constructing a simple yet useful and informative tree are highly complex (Breiman et al., 1984). Numerous specific DT algorithms exist.

Notable algorithms include ID3 (Iterative Dichotomiser 3), C4.5 (successor of ID3), CART, CHAID, and multivariate adaptive regression splines (Hastie et al., 2001). Different algorithms apply distinct metrics to determine the most favorable decision result. C4.5 and CART are two recent classifications of tree algorithms. CART can be implemented using a tree or the rpart package in the programming language R-project, which we used for analyzing the surveyed data in the present research.

In the tree, DTs are formed by the following steps:

(1) A location in a covariate x_i is separated by the regression deviance that minimizes node impurity, which refers to the measurement of the homogeneity of the target variable within the subsets. The regression deviance of a node is defined as

$$D(I) = \sum_{j=1}^{I_k} (y_{I_j} - \overline{y}_I)^2 \quad (1)$$

where $y_{I_1}, y_{i_2}, \ldots, y_{I_k}$ are the values of the target variable that compose the node I, and $\overline{y}_I$ is their average. The deviance measures the node impurity and assesses the homogeneity of the values of the target variable within the node. The deviance of a DT is obtained by adding the deviance of all the nodes of the DT as follows: $D_T = \sum_I D(I)$.

The predictor variable x_i with maximum gain in deviance, which refers to the value obtained from D_T of the parent node (before splitting) minus D_T of the child nodes (after splitting) results in the variables used to split the data. When a predictor is selected and splits a node into two parts, the same process is applied to other predictor variables (i.e., it is a recursive procedure) until the tree building is stopped.

(2) The tree is pruned by removing splits from the bottom up. To achieve pruning, the objective function adds a penalty for the complexity of the tree. Instead of minimizing D_T, the pruning step minimizes the cost complexity of the tree, which is defined as

$$D_T(\alpha) = D_T + \alpha|T| \quad (2)$$

where $|T|$ is the number of terminal nodes and α is a penalty term, complexity parameter (CP), which ensures the greatest compromise between predictive accuracy and tree size. $D_T(\alpha)$ is used by the R-project command prune tree to trace the pruned trees for finding the most favorable DT, which can balance the deviance and complexity of the DT.

2. Aspects of Competitive Service Attributes

A container shipping company usually possesses two types of business customers: shippers and freight forwarders. Shippers are companies with cargo that must be transported from one place to another by truck, rail, or sea, in which container shipping companies are involved. Freight forwarders serve as intermediaries between the shippers and container shipping liners. Container shipping companies must provide attractive and valuable services to customers. Managing CSA implies an understanding of the factors that trigger customer defection. Many studies have identified factors (or service attributes) influencing customer retention or defection (e.g., Mittal and Kamakura, 2001; Verhoef and Franses, 2003; Gupta and Zeithaml, 2006). The service attributes are typically grouped as follows: customer relationships, prices and discounts, service quality, personal selling, advertising, WOM, and switching costs (Sen et al., 2001; Durvasula et al., 2002; Lu, 2003; Wuyts and Geyskens, 2005; Cramphorn and Meyer, 2009; Chen et al., 2015).

Valuable customer relationships between buyers and sellers are crucial for securing customer satisfaction and loyalty for firms. A valuable customer relationship between buyers and suppliers, which is defined as the intensity and valence of prior interaction, is a critical strategic choice for buyers when selecting a supplier for a new purchase agreement (Wuyts and Geyskens, 2005). A carrier's service attributes are crucial for developing shipper-carrier partnering relationships (Lu, 2003). Cannon and Homburg (2001) confirmed that customer firms tend to increase purchases from suppliers who provide beneficial buyer-seller relationships in terms of lowering commercial exchange costs. Boulding et al. (2006) argued that proven customer relationship management practices enhance firm performance. Verhoef (2003) determined that customer relationship management strategies can provide positive economic incentives, which can affect both customer retention and customer share development. Kumar et al. (2010) argued that executives not only believe that high customer relationship engagement is necessary for future growth, but that they also believe that low customer relationship engagement is detrimental to success because of lost sales or sales opportunities. Durvasula et al. (2007) discovered that mean satisfaction is highest when customers rate shipping firms favorably according to relationship and cooperation variables, among others. Jang et al. (2013) investigated shippers' future intentions to use the same carrier by exploring the role of logistics service quality in generating shipper loyalty and relationship quality in the context of container shipping; they suggested that container shipping lines should develop a high level of logistics service quality as well as relationship quality to attain higher levels of shipper loyalty, rather than only shipper satisfaction.

Prices and discounts are inevitably and crucially influential on buyer purchases. Sen et al. (2001) and He et al. (2008) reported that a price increase would lower sales and lead to customer boycotts. Price discounting is one of the most powerful and effective strategic tools in retailing (Van Heerde et al., 2001; Levy et al., 2004). Anderson and Simester (2004) investigated the effect of a current price discount and revealed that deep monetary price discounts in a current period increase future purchase prospects. Consumers in the container shipping industry are self-regarding and adopt an independent self-construal with container carriers worldwide, except in the United States; consumers prefer to obtain exclusive price discounts from carriers (Barone and Roy, 2010). Although U.S.-based companies or sole proprietors operating as ocean freight forwarders or non-vessel-operating common carriers (NVOCCs) are required to obtain a license from the U.S. Federal Maritime Commission, and despite all NVOCCs operating in U.S. trades being required to publish a tariff, Part 532 of the U.S. Commission's Regulations enable container shipping companies to enter into negotiated rate arrangements when exempt from certain tariff rate publication requirements (Chen et al., 2015). Durvasula et al. (2007) used neural networks and DTs to identify the system of attributes that maximizes customer satisfaction by analyzing the same industry from their 2002 study; they discovered that mean satisfaction is highest when customers rate shipping firms favorably according to relationship and cooperation, transit time, and freight rate.

Service quality has been defined as the discrepancy between customer expectation and perception of service (Parasuraman et al., 1988). From the perspective of current service providers, service quality is considered an antecedent of repurchase intention. Carrillat et al. (2009) argued that service quality is essential to customer perception of value and that support service quality leads to higher purchase intention according to empirical research metaanalysis. Chen et al. (2009) and Durvasula et al. (2002) reported the value of service quality in customer management in the shipping industry.

Personal selling is defined as face-to-face selling in which a seller attempts to persuade a buyer to make a purchase. This is a promotional activity that firms' sales representatives use to establish direct buyer-seller relationships. Hammann (1979) analyzed the strength of personal selling and its possible risks compared to advertising, and concluded that personal selling is of primary importance in the marketing of commodities that must be explained to the buyer through demonstration, particularly in industrial marketing and the marketing of services. Durvasula et al. (2002) examined a sample of shipping managers in Singapore who evaluated the service dimensions of ocean freight shipping companies; they concluded that the mean value of overall service satisfaction for firms with a favorable opinion of ocean freight shipping company sales representatives is higher than that of firms with an unfavorable opinion of sales representatives.

Advertising is concerned with changing behavior. It is an objective, outcome-oriented approach, and this is what should be measured. Lu (2000) addressed the fact that advertising in newspapers and magazines is the second most crucial strategic factor for Taiwanese maritime firms. Fornell (1992) as well as Weiss and Anderson (1992) have suggested that consumers consider switching barriers when contemplating switching service providers; these barriers tend to reduce the actual switching behavior of consumers. Although WOM is less controlled by firms, it may be more likely for success for various reasons (Grewal et al., 2003; Villanueva et al., 2008). Additionally, some scholars and practitioners have suggested that a company must possess something that reflects customer intention to recommend the firm to others (Reichheld, 2003). Bucklin and Sismeiro (2009) studied the effect of WOM on member growth on an Internet social networking site and determined that WOM elasticity is approximately 20 times higher than that of marketing events and 10 times higher than that of media appearances.

To establish a model for predicting the likelihood of an NSP, DT steps are applied to the data collected from a questionnaire. Specifically, by using the scores of an NSP as the target variable, an item among all attributes with maximum gain in deviance (i.e., Eq. (1)) is selected to split a sample into two nodes (groups) at each step. This iterative procedure is performed with the remaining items until the stop criterion is met, and an initial DT is obtained. By using the CP values calculated using the rpart algorithm, a certain rule is used to determine the number of nodes in the most favorable tree model that are selected to avoid the overfitting problem. This rule is employed to establish the most favorable tree model by pruning the DT generated in the preceding step. The retention likelihood of customers in each node is then calculated using the mean NSP scores divided by the sum of the maximum scale of items in the NSP construct.

IV. EMPIRICAL ANALYSIS

1. Data Collection and Measures

The data used in this study were from a survey of the 660 members of the International Ocean Freight Forwarders & Logistics Association in Taiwan in 2015. The measurement framework used in the questionnaire was adopted from studies reviewed in Section 3.2. Among the items adopted, 26 were service attributes (X1-X26) and three were used to measure a shipper's likelihood of switching to an NSP (Y1-Y3) (Table 1). The questionnaires were mailed on August 1, 2015. After a two-stage follow-up, 178 responses had been returned by September 21, 2015. Of the returned questionnaires, 127 provided complete and valid data, for a 20% effective response rate.

The 26 service attributes (Table 1) were classified into seven dimensions: X1-X3 belonged to the prices and discounts construct, X4-X8 belonged to the service quality construct, X9-X11 belonged to the customer relationship construct, X12-X15 belonged to the advertising construct, X16-X19 belonged to the personal selling construct, X20-X22 belonged to WOM, and X23-X26 belonged to switching costs. Respondents answered questions on a 9-point Likert-type scale: 1 (*very strongly disagree*), 2 (*strongly disagree*), 3 (*disagree*), 4 (*slightly disagree*), 5 (*as expected*), 6 (*slightly agree*), 7 (*agree*), 8 (*strongly agree*), and 9 (*very strongly agree*). The scoring format for Y1-Y3 was also a 9-point Likert-type scale, ranging from "*not at all*" to "*very certain.*"

An exploratory factor analysis was employed to identify the underlying dimensions of the scale and purify the construct scales. All Cronbach alphas of the eight constructs were above 0.64, and all factor loadings of the 29 items were between 0.54

Table 1. Measurement framework for container carrier services.

No.	Competitive Service Attributes (CSA)	Dimensions	Major References
X1	Good services priced appropriately to their quality	Price and discount	Sen et al., 2001; Van Heerde et al., 2001; Levy et al., 2004; He et al., 2008.
X2	Good services priced comparably with other shipping companies		
X3	Provide a deep price discount for shippers		
X4	Release delivery orders and bills of landing fast enough for shippers	Service quality	Durvasula et al., 2002; Chen et al., 2009.
X5	Allocate time to deliver shipper's cargoes		
X6	Create an environment of trust for shippers		
X7	Provide a reliable shipping schedule for shippers		
X8	Provide quick booking, and solving claims for shippers		
X9	Work very intensively with shippers	Customer relationship	Lu, 2003; Wuyts and Geyskens, 2005.
X10	Have a very close relationship with shippers		
X11	Have a very collaborative relationship with shippers		
X12	Advertisement informs shippers about the carrier's features	Advertising	Lu, 2000.
X13	Advertisement keeps shippers up-to-date		
X14	Advertisement is good		
X15	Advertisement provides valuable information		
X16	Sales staff are very knowledgeable	Personal selling	Hammann, 1979; Durvasula et al., 2002.
X17	Sales staff knows their service line very well		
X18	Sales staff are experts		
X19	Influenced by the recommendations of shipper's friends or other firms		
X20	Future carriers will have been influenced by your current carriers	Word of mouth	Reichheld, 2003; Bucklin and Sismeiro, 2009; Chen et al., 2009.
X21	Encourage your friends or other firms to employ your current carriers to deliver their container		
X22	Take a lot of time to switch from my current service provider to another container carrier		
X23	Feel uncertain about choosing a new container shipping carrier	Switch costs	Weiss and Anderson, 1992; Chen et al., 2009.
X24	Cost me a lot of money to switch from my current service provider to another carrier		
X25	Some new problems would arise to change from my current service provider to another carrier		
X26	Require a lot of effort to switch from my current service provider to another container carrier		
Y1	Not searching for new container carriers to handle shipment	Likelihood of NSP	Chen et al., 2009.
Y2	Not considering to purchase shipping service from your current container carriers as your first choice		
Y3	Purchase more services in the next few months from current container carriers		

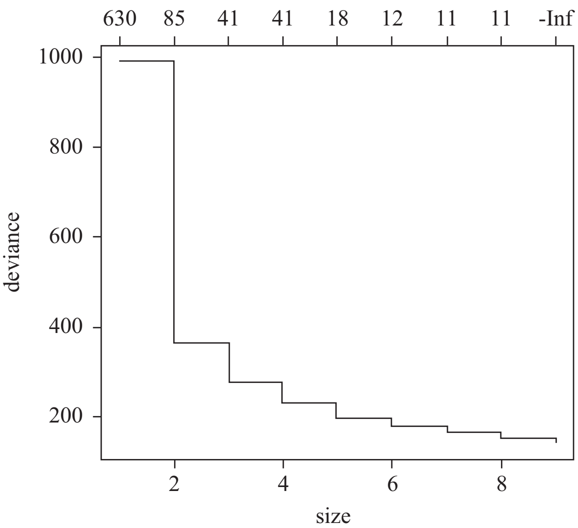
Sources: Compiled by the authors.

and 0.82, indicating satisfactory internal consistency and convergent validity. The discriminant validity of the measures was tested by calculating the composite reliability (CR) of the constructs and the average variance extracted (AVE). The criteria for discriminant validity were satisfied; AVE was above or close to 0.50 and CR was above or close to 0.70. The eight constructs measured using AVE and CR satisfied the criteria for discriminant validity. Finally, the criteria of X^2 were used for degrees of freedom less than 3; the evaluation demonstrated overall model fit with the root mean square error of approximation less than 0.1, and the goodness of fit index above or close to 0.9. Nearly all other fit indices were greater than their respective critical

Table 2. Relevant information for the most favorable DT.

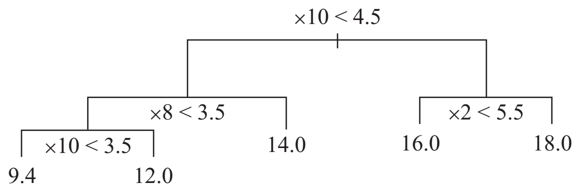
Node	CP	n	rel. error	x error	x std	y val
(1) root	0.636	127	1.000	1.023	0.103	14.53
(2) X10 < 4.5	0.086	67	0.363	0.380	0.047	12.42
(3) X10 > 4.5	0.041	60	0.277	0.306	0.034	16.88
(4) X8 < 3.5	0.041	33	0.235	0.313	0.039	11.27
(5) X8 > 3.5	0.011	34	0.194	0.236	0.033	13.53
(6) X2 < 5.5	0.010	40	0.183	0.275	0.036	16.30
(7) X2 > 5.5	0.010	20	0.172	0.284	0.038	18.05

Sources: Compiled by the authors.



Sources: Compiled by the authors

Fig. 1. Relationship between size and deviation of an unpruned tree.



Sources: Produced by authors

Fig. 2. Most favorable DT.

points, except for some degrees of freedom indicating that each construct was unidimensional (Hair et al., 2006).

2. Decision Tree Analysis Results

To analyze the data by using a DT, the CART model tree from R-project was employed. The goal was to predict the most valuable service attributes provided by container carriers regarding the 26 items shown in Table 1. A 9-point Likert-type scale was used for all items. The score of the NSP ranging from 3 to 27 was the sum of the scores of Y1-Y3. In the first step, on a seven-leaf tree (terminal), nodes were obtained using the tree. Table 2 summarizes the relevant information about the most favorable DT.

In Table 2, the rel. error of a node indicates a decrease in the proportion of the deviance of this node. For example, when starting at the top of the tree, service attribute X10 (very close relationship with shippers) is chosen to be split into two nodes: X10 < 4.5 (node 2) and X10 > 4.5 (node 3). The deviance of the tree with this attribute was 218.3 + 142.2 = 360.5; therefore, the relative error (360.5) to total error (991.7) was 0.363 (= 360.5/ 991.7). The CP values, which were calculated using rpart, are shown in the second column of Table 2. The default value of CP was 0.01 in the rpart; thus, only six splits and CP values greater than or equal to 0.01 are presented in Table 2. To avoid overfitting, R-project estimation uses an internal process of ten-fold cross-validation. In our case, we can observe that it would theoretically be better off with tree node 5, which had a lower estimated cross-validation error 0.236 ("x error" column). One selection rule for choosing the most favorable tree is the 1-SE rule (Ledolter, 2013). This rule involves examining the cross-validation error estimates and their standard deviations ("x std" column). In the current study, the 1-SE tree was the smallest tree with an error less than 0.269 (= 0.236 + 0.033), which was tree number 5. Additionally, the prune tree algorithm was used to evaluate the quality of prediction for the current tree. The tree deviance as a function of the penalty and the size of the tree obtained from the pruned tree are presented in Fig. 1. This figure shows that after node 5, the decrease of model deviance became relatively small, indicating that setting a CP value above 0.0105 or a node number equal to 5 would produce the most valuable model.

The structure of the final model was simple and is displayed in Fig. 2, which shows the nodes and how they were split. Only three service items (X10, X8, and X2) were involved in this model. The decision rules are described as follows:

1. The first split was on X10 ("Container carriers have a very close relationship with shippers"), with X10 > 4.5 (= 5-9); specifically, respondents did not disagree that the relationship between respondent companies and their current container carriers was very close. Otherwise, the customers' NSP of container shipping companies in this group was determined by service attribute X2 regarding the prices and discounts

that customers perceived. If respondent customers in this group perceived their container carriers as offering a service price superior to that of other container carriers, the mean NSP reached 18.0; this condition indicated that customer retention in this subgroup (Group 1) was approximately 67%. In the other subgroup (Group 2), the customers did not perceive their container carriers as offering service prices superior to other container carriers; the mean NSP was 16.0, meaning that the likelihood of customer retention in Group 2 was approximately 59%. The mean scores of customer retention in these two groups were greater than the mean retention rate of all respondents, which was equal to 14.53 (likelihood = 54%).

2. When X10 < 4.5, the NSP depended on the score of service attribute X8 ("Container carriers' employees provide quick booking and solve claims for shippers"). If the customer did not disagree this statement (X8 > 3.5), their mean NSP score was 14.0, smaller than the total NSP score of 14.53, indicating that the customer retention likelihood rate in this group (Group 3) was 52%.
3. Additionally, if customers disagreed that "Container carriers' employees provide quick booking and solve claims for shippers" (X8 < 3.5) and 3.5 < X10 < 4.5, then the mean NSP score of this group (Group 4) was 12.0, indicating a 44% customer retention rate. If customers disagreed that "Container carriers' employees provide quick booking and solve claims for shippers" (X8 < 3.5) and X10 < 3.5, the mean NSP score of this group (Group 5) was 9.4, indicating that the likelihood of customer retention rate of this group was only 35%-nearly half that of Group 1.
4. This research used the DT method to separate all respondents into five groups according to NSP score. ANOVA was used to test the hypothesis of the equality of all mean NSP scores; the resulting P value was 0.0043, indicating that the hypothesis was not supported by the evidence. Furthermore, all mean NSP scores were not equal to each other.

V. CONCLUSION AND DISCUSSION

1. Conclusion

This study identified 26 CSAs related to customer retention for container shipping companies and categorized them into seven dimensions: customer relationship, personal selling, prices and discounts, service quality, WOM, advertising, and switching costs. Additionally, customer retention was measured according to three attributes (Y1-Y3) regarding the likelihood that customers would not switch NSPs. A total of 127 complete questionnaires were collected and analyzed using the DT method. Furthermore, a customer retention prediction model was developed for the container industry.

The results of this study revealed that the CSA X10 ("Container carriers have a very close relationship with shippers"), which belonged to the customer relationship dimension, was the covariate with the largest correlation with NSP. If the scores that customers provided for the question were above "as expected," or even if the choice was "a few disagree," as long as the customers do not disagree with statement X8 ("Container carriers' employees provide quick booking and solve claims for shippers"), the likelihood of customers switching NSPs was greater than 50%. The likelihood of customers switching NSPs was less than 50% only when the customers provided answers to statement X10 ("Container carriers have a very close relationship with shippers") below "as expected," or they neither agreed with nor disagreed with statement X8 ("Container carriers' employees provide quick booking and solve claims for shippers"), which belonged to the service quality dimension.

According to the current results, only three items among the 26 CSAs separated the total respondents into five groups with different customer retention rates. Notably, the results did not absolutely ensure that no other items other than these three items influence customer retention for container shipping companies. Because one of the goals of a DT is to develop a simple tree structure for predicting data, relatively few variables may appear explicitly as splitters; thus, a variable in the variables table (Table 1) can be considered highly crucial even if it never appears as a node splitter. The phenomenon of one variable obscuring the significance of another (masking), is addressed in the rpart variable importance measure (Breiman et al., 1984). A variable can obtain an importance score of zero in rpart only if it never appears as either a primary or surrogate splitter. Because such a variable plays no role anywhere in the tree, eliminating it from the data set should make no difference to the results.

In our study, variables with importance scores that were nonzero to satisfaction were X10 ("Carriers have a very close relationship with shippers"), X8 ("Carriers' employees provide quick booking and solve claims for shippers"), X2 ("Carriers offer good service prices compared with other shipping companies"), X16 ("Carriers' sales staff are very knowledgeable"), X15 ("Carriers' advertising provides valuable information"), and X17 ("Carriers' sales staff know their service line very well"); X10 belonged to the customer relationship construct, X2 belonged to the prices and discounts construct, X8 belonged to the established service quality construct, X16 and X17 belonged to the personal selling construct, and X15 belonged to the advertising construct. In other words, this study actually demonstrated that customer relationship, prices and discounts construct, service quality, personal selling, and advertising relative advantages have an impact on customer satisfaction. These results are consistent with those reported by previous studies (e.g., Lu, 2000; Sen et al., 2001; Durvasula et al., 2002; Wuyts and Geyskens, 2005; Cramphorn and Meyer, 2009). Nevertheless, the unique contribution of this study is its provision of a simple rule in which only X10, X2, and X8 are involved in predicting the container shipping industry customer retention rate. Although X15, X16, and X17 are considered critical, they do not need to appear as predictors in the DT.

2. Managerial Implications

Our study offers several opportunities and implications for practitioners working in the container shipping industry. Although prices and discounts as well as service quality are included in the DT as predictors, customer relationship is clearly the most crucial predictor because when customer perceive that a relationship exists between themselves and their container carriers, their likelihood of switching to an NSP is greater than 50% regardless of the prices and discounts offered by their container carriers. However, service quality influences NSP only when the customers already respond with X10 < 4.5.

Our findings have valuable implications for the container carrier industry. Positive customer relationships between buyers and sellers are critical for securing customer satisfaction and loyalty for firms, and customer relationship management practices enhance firm performance (Boulding et al., 2006). In the past decade, numerous companies have perceived customer retention as a central topic in their management and marketing decisions (Van den Poel and Larivière, 2004). Currently, because of the Internet, customer relationship management is a customer-oriented feature with service response based on customer input, one-to-one solutions to customer requirements, direct online communications with the customer, and customer service centers that are intended to help customers solve their issues. Although an Internet customer relationship management system is a necessary tool for serving customers, service provided by container carrier salespeople is also crucial for stabilizing relationships with customers (Kohli and Jaworski, 1990).

The results of this study not only suggest a very simple decision rule for predicting customer retention likelihood in the container shipping industry, but also provide evidence to support the marketing assertion that customer retention is a central topic in management and marketing decisions. By using these techniques, an organization can manage customer relationships by identifying favorable customers and set optimal pricing policies.

3. Limitations and Future Research

Until now, customer retention prediction for container shipping companies has received little attention in the DT literature, except by Durvasula et al. (2002, 2007). This paper employs rpart algorithms of a DT to build if-then rules for predicting customer retention. Similar to most empirical studies, some limitations exist in the current study and warrant acknowledgment. These limitations lead to suggestions for future research. First, this study used NSPs to measure customer repurchase intention. This is based on the assumption that intention is a strong predictor of future behavior because customers who express a strong repurchase intention toward the container shipping companies they currently employed to handle cargo also had stronger corresponding behavior. Second, this paper exclusively used rpart algorithms to establish the prediction model. Investigating the same problem by using other DT algorithms or other methods such as the Bayesian network or artificial neural networks would be insightful (Shmueli et al., 2010). Consequently, the results of this study can be compared with those of studies that have employed different methodologies. The sample used is the third limitation; this study focused on shippers in Taiwan. If the same area could be explored in other countries with different cultural and societal environments, different business decision rules may be discovered. Such research could provide further insight into the different effects of facilitating conditions as well as social and cultural influences (Yang and Forney, 2013).

REFERENCES

Anderson, E. T. and D. I. Simester (2004). Long-run effects of promotion depth on new versus established customers: three field studies. Marketing Science 23(1), 4-20.

Azevedo, C., J. A. Herriges and C. I. Kling (2003). Combining revealed and stated preferences: consistency tests and their interpretations. American Journal of Agriculture Economics 85(3), 525-37.

Axsen, J., D. C. Mountain and M. Jaccard (2009). Combining stated and revealed choice research to simulate the neighbor effect: the case of hybridelectric vehicles. Resource & Energy Economics 31(3), 221-238.

Baack, D. (2012). Customer retention and the health care industry. Economics & Business Journal: Inquiries & Perspectives 4(1), 35-43.

Barone, M. J. and T. Roy (2010). Does exclusivity always pay off ? Exclusive price pro-motions and consumer response. Journal of Marketing 74, 121-132.

Bemmaor, A. C. (1995). Predicting behavior from intention-to-buy measures: the parametric case. Journal of Marketing Research 32(2), 176-191.

Ben-Akiva, M., M. Bradley, T. Morikawa, J. Benjamin, T. Novak, H. Oppewal and V. Rao (1994). Combining revealed and stated preferences data. Marketing Letters 5(4), 335-49.

Berson, A. and S. J. Smith (2008). Data Warehousing, Data Mining & OLAP. McGraw-Hill Inc., New York.

Boulding, W., R. Staelin, M. Ehret and W. J. Johnston (2006). A customer relationship management roadmap: what is known, potential pitfalls, and where to go. Journal of Marketing 69, 155-166.

Breiman, L. (2001). Random Forests. Machine Learning 45, 5-32.

Breiman, L., J. Friedman, R. Olshen and C. Stone (1984). Classification and Regression Trees, Wadsworth, Belmont, California.

Bucklin, R. E. and C. Sismeiro (2009). Click here for internet insight: advances in click stream data analysis in marketing. Journal of Interactive Marketing 23(1), 35-48.

Cannon, J. P. and C. Homburg (2001). Buyer-supplier relationships and customer firm costs. Journal of Marketing 65(1), 29-43.

Carrillat, F. A., F. Jaramillo and J. P. Mulki (2009). Examining the impact of service quality: a meta-analysis of empirical evidence. Journal of Marketing Theory and Practice 17(2), 95-110.

Chen, K. K., C.-T. Chang and C. S. Lai (2009). Service quality gaps of business customers in the shipping industry. Transportation Research Part E 45(1), 222-237.

Chen, K. K., C.-T. Chang and H. P. Ho (2015). Estimating attributes importance for container shipping industry by closing the listening gap with maximum convergent validity. Transportation Research Part E 79, 145-163.

Chiu, R. H. (1996). Logistics performance of liner shipping in Taiwan. Ph.D. Thesis, Department of Maritime Studies and International Transport, Cardiff University, Wales, UK, unpublished.

Cho, Y. H., J. K. Kim and S. H. Kim (2002). A personalized recommender system based on web usage mining and decision tree induction. Expert Systems with Applications 23(3), 329-342.

Cramphorn, M. F. and D. Meyer (2009). The gear model of advertising modeling human response to advertising stimuli. International Journal of Market Research 51(3), 319-39.

Drewry Shipping Consultants (2015). Oversupply will remain relentless. Port Technology (reported on 15 April 2015), <https://www.porttechnology.org/news/drewry_oversupply_will_remain_relentless>

Durvasula, S., S. Lysonski and S. C. Mehta (2002). Understanding the interfaces: how ocean freight shipping lines can maximize satisfaction. Industrial Marketing Management 31, 491-504.

Durvasula, S., S. Lysonski and S. C. Mehta (2007). Competitive positioning in international logistics: identifying a system of attributes through neural networks and decision trees. Journal of Global Marketing 20(1), 75-89.

de Jong, G., M. Kouwenhoven, J. Bates, P. Koster, E. Verhoef, L. Tavasszy and P. Warffemius (2014). New SP-values of time and reliability for freight transport in the Netherlands. Transportation Research Part E 64, 71-87.

Fornell, C. (1992). A national customer satisfaction barometer: the Swedish experience. Journal of Marketing 56 (1), 6-16.

Ganesh, J., M. J. Arnold and K. E. Reynolds (2000). Understanding the customer base of service providers: an examination of the differences between switchers and stayers. Journal of Marketing 64(3), 65-87.

Grönroos, C. (2007). Service Management and Marketing. John Wiley & Sons, Ltd. West Sussex, England.

Grant, R. M. (2008). Contemporary Strategy Analysis. Blackwell Publishing, Oxford, UK.

Grewal, R., T. W. Cline and A. Davies (2003). Early-entrant advantage, word-of-mouth communication, brand similarity, and the consumer decision-making process. Journal of Consumer Psychology 13(3), 187-197.

Gupta, S. and V. A. Zeithaml (2006). Customer metrics and their impact on financial performance. Marketing Science 25(6), 718-739.

Hair Jr., J. F., W. C. Black, B. J. Babin, R. E. Anderson and R. L. Tatham (2006). Multivariate Data Analysis. 6th ed., Prentice Hall, New Jersey.

Hammann, P. (1979). Personal selling. European Journal of Marketing 13(6), 141-176.

Hanssens, D. M., P. S. H. Leeflang and D. R. Wittink (2005). Market response models and marketing practice. Applied Stochastic Models Business and Industry 21, 423-434.

He, Y., L. K. Chan and S. K. Tse (2008). From consumer satisfaction to repurchase intention: the role of price tolerance in a competitive service market. Total Quality Management 19(9), 949-961.

Heskett, J. L., T. O. Jones, G. W. Loveman, W. E. Sasser Jr. and L. A. Schlesinger (1994). Putting the service-profit chain to work. Harvard Business Review 72(2), 164-175.

Jaccard, J., D. Brinberg and L. J. Ackerman (1986). Assessing attribute importance: a comparison of six methods. Journal of Consumer Research 12 (4), 463-468.

Jang, H. M., P. B. Marlow and K. Mitroussi (2013). The effect of logistics service quality on customer loyalty through relationship quality in the container shipping context. Transportation Journal 52(4), 493-521.

Keiningham, T. L., B. Cooil, L. Aksoy, T. W. Andreassen and J. Weiner (2007). The value of different customer satisfaction and loyalty metrics in predicting customer retention, recommendation, and share-of-wallet. Managing Service Quality: An International Journal 17(4), 361-384.

Khan, S. (2013). Determination of customer retention in hotel industry. Journal of Applied Economics and Business 1(3), 42-64.

Kohli, A. and B. Jaworski (1990). Market orientation: the construct, research proposition, and managerial implications. Journal of Marketing 54(2), 1-18.

Kumar, V., L. Aksoy, B. Donkers, R. Venkatesan, T. Wiesel and S. Tillmanns (2010). Undervalued or overvalued customers: capturing total customer engagement value. Journal of Service Research 13(3), 297-310.

Larivière, B. and D. Van den Poel (2005). Predicting customer retention and profitability by using random forests and regression forests techniques. Expert Systems with Applications 29(2), 472-484.

Ledolter, J. (2013). Data Mining and Business Analytics with R. John Wiley & Sons, Inc., Hoboken, New Jersy.

Levy, M., D. Grewal, P. Kopalle and J. Hess (2004). Emerging trends in retail pricing practice: implications for research. Journal of Retailing 80(3), 13-31.

Lijesen, M. G. (2006). A mixed logit based valuation of frequency in civil aviation from SP-data. Transportation Research Part E 42 (2), 82-94.

Long, X. and Y. Wu (2012). Application of decision tree in student achievement evaluation. Proceedings of International Conference on Computer Science and Electronics Engineering (ICCSEE) 2012, Volume 2, 243-247.

Lu, C.-S. (2000). Logistics services in Taiwanese maritime firms. Transportation Research Part E 36(2), 79-96.

Lu, C.-S. (2003). The impact of carrier service attributes on shipper-carrier partnering relationships: a shipper's perspective. Transportation Research Part E 39(5), 399-415.

Mittal, V. and W. A. Kamakura (2001). Satisfaction, repurchase intent, and repurchase behavior: investigating the moderating effect of customer characteristics. Journal of Marketing Research 38(1), 131-142.

Morgan, N. A. and L. L. Rego (2006). The value of different customer satisfaction and loyalty metrics in predicting business performance. Marketing Science 5, 426-439.

Parasuraman, A., V. A. Zeithaml and L. L. Berry (1988). SERVQUAL: a multiple item scale for measuring consumer perception of service quality. Journal of Retailing, 64 (1), 12-37.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot and E. Duchesnay (2011) Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research (JMLR) 12, 2825-2830.

Reichheld, F. F. (2003). The one number you need. Harvard Business Review 81(12), 46-54.

Reichheld, F. F. and W. E. Sasser Jr. (1990). Zero defections: quality comes to services. Harvard Business Review 68(5), 105-111.

Sen, S., Z. Gürhan-Canli and V. Morwitz (2001). With-holding consumption: a social dilemma perspective on consumer boycotts. Journal of Consumer Research 28, 399-417.

Shaffer, G. and J. Zhang (2002). Competitive one-to-one promotions. Management Science 48(9), 1143-1160.

Sherman, G., P.-O. Siebers, U. Aickelin and D. Menachof (2013). Scenario analysis, decision trees and simulation for cost benefit analysis of the cargo screening process. arXiv preprint arXiv:1306.5158, Retrieved from: https://arxiv.org/ftp/arxiv/papers/1306/1306.5158.pdf

Shmueli, G., N. R. Patel and P. C. Rruce (2010). Data mining for business intelligence. 2nd ed., John Wiley & Sons, Inc., Hoboken, New Jersy.

Silverstein, C. and S. M. Shieber (1996). Predicting individual book use for off-site storage using decision trees. The Library Quarterly 66(3), 266-293.

Savidas, E. and J. L. Baker-Prewitt (2000). An examination of the relationship between service quality, customer satisfaction, and store loyalty, International Journal of Retail & Distribution Management, 28(2), 73-82.

Thill, J.-C. and K. Venkitasubramanian (2015). Multi-layered hinterland classification of Indian ports of containerized cargoes using GIS visualization and decision tree analysis. Maritime Economics and Logistics 17, 265-291.

Tinabo, R. (2011). Decision tree technique for customer retention for retail section. In: Integrated Computing Technology, edited by Hursehka, Jr., E. R. et al., Springer-Verlag, Berlin, Heidelberg, 123-131.

Urama, K. C. and I. D. Hodge (2006). Are stated preferences convergent with revealed preferences? Empirical evidence from Nigeria. Ecological Economics 59(1), 24-37.

Van den Poel, D. and B. Larivière (2004). Customer attrition analysis for financial services using proportional hazard models. European Journal of Operational Research 157, 196-217.

Van der Pligt, J., N. K. de Vries, A. S. R. Manstead and F. van Harreveld (2000). The importance of being selective: weighing the role of attribute importance in attitudinal judgment. Advances in Experimental Social Psychology 32, 135-199.

Van Heerde, H. J., P. S. H. Leeflang and D. R. Wittink (2001). Semiparametric analysis to estimate the deal effect curve. Journal of Marketing Research 38(2), 197-215.

Van Ittersum, K., J. M. E. Pennings, W. Wansink and H. C. M. van Trijp (2007). The validity of attribute-importance measurement: a review. Journal of Business Research 60(11), 1177-1190.

Verhoef, P. C. (2003). Understanding the effect of customer relationship management efforts on customer retention and customer share development. Journal of Marketing 67, 30-45.

Verhoef, P. C. and P. H. Franses (2003). On combining revealed and stated preferences to forecast customer behavior: three case studies. International Journal of Market Research 45(4), 467-474.

Villanueva, J., S. Yoo and D. M. Hanssens (2008). The impact of marketing-induced versus word-of-mouth customer acquisition on customer equity growth. Journal of Marketing Research 45, 48-59.

Weiss, A. M. and E. Anderson (1992). Converting from independent to employee salesforces: the role of perceived switching costs. Journal of marketing Research 29(1), 101-115.

Wuyts, S. and I. Geyskens (2005). The formation of buyer-supplier relationships: detailed contract. Journal of Marketing 69, 103-117.
Yang, K. and J. C. Forney (2013). The moderating role of consumer technology anxiety in mobile shopping. Journal of Electronic Commerce Research 14(4), 334-347.
Zhu, Q., J. Sarkis and K.-H. Lai (2015). Supply chain-based barriers for truck-engine remanufacturing in China. Transportation Research Part E 68, 103-117.