An Analysis of Consumers’ Propensity to Return in E-Retailing

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Abstract: The B2C market in Taiwan is obviously becoming a noticeable market. As the market grows and matures, “return” becomes one of the challenges for E-retailers. In the past, most of the literature on return issues focused on the wholesaler-retailer relationship. Recently, due to the advent of Internet-based retailing within the past decade, attention is shifting to the issue of returns in the retailer-consumer relationship. In this study, we use empirical data and conduct a Decision Tree model to analyze the critical variables revealing the customer return propensity. There are 3 dimensions of variables in our data set- customer demographic variables, merchandise variables and service variables. We find that three variables- category, price and delivery days could be used to distinguishing customer return propensity more effectively. In accordance with these variables, we propose some strategies for website managers to control returns in E-retailing.

Key Words: E-retailing, Return Propensity, Decision Tree

1. BACKGROUND

The E-retailing is obviously a growing and noticeable market in Taiwan (MIC , 2007). In 2008, the growth rate in B2C market is expected to reach 38% and the total amount of business volume will be NT $138.5 billion. While the E-retailing market developing continually and maturely. The number of retailer increases and the competition among retailers turn to be severe as well. The furious competition is not only in price of various merchandises but also in service of specific website. In the past, most of the literature on return issues focused on the wholesaler-retailer relationship (Kandel, 1996; Padmanabhan & Png, 1997). Attention is shifting to the issue of returns in the retailer-consumer relationship until recently. This change results from the advent of Internet-based retailing within the past decade (Mollenkopf et al., 2007).

In this empirical study, the B2C model is different from the original one. The business part is
separated to two participants. One is the website operator who plays a role as an intermediary. It will charge a fee for facilitating transactions between customers and retailers. The other one is namely the retailer solicited by the website operator. The website operator is responsible for soliciting from diverse merchandise suppliers and unifying the information flow and payment flow. On the other hand, the retailers are responsible for deciding the marketing strategies and inventory flow. Consumers search information, order items and pay the bill via the website platform. Finally, retailers pick up the items to be delivered according to the orders.

To better understand the crucial factors of returns and effectively reduce the return rate in E-retailing, this paper aims to use empirical data and data mining analysis to understand how the consumer characteristics, merchandise dimension and service affect returns in E-retailing market. We will (1) review the significant case of E-retailing in Taiwan and the return process of internet shopping. (2) Identify the critical factors that related to customers’ propensity to return by decision tree induction. (3) Apply return knowledge to propose suggestion on developing strategies.

2. LITERATURE REVIEW

2.1 Return Issues in E-retailing

Based on two classification schemes- Seller and Buyer, e-commerce can be placed into four categories: B2B, B2C, C2B, and C2C business model (Kricjnamurthy, 2003). E-retailing provides a 24 hrs shopping opportunity and in theory widens the “store” catchment area from the local to national or global level. Thus the traditional retail boundaries of “store reach” are changed both temporally and geographically. Buyers and suppliers that have previously had trouble reaching each other can connect in E-retailing. Suppliers can gain access to more buyers. Buyers can participate easily and view items from multiple suppliers. The electronic interface should lower transaction costs for both buyer and seller, and these transparencies will likely drive down prices as well (Burt and Sparks, 2003).

Wood (2001) investigated the effect of return policy leniency on remote purchase. He concluded two characteristics raise the risk level to consumers- precluded product examination and waiting time for delivery. Yalabik et al. (2005) focused on the system-design level of return management system. They identified three components of an integrated product returns system that can improve a company’s bottom line. First, a refund policy decreases a customer’s risk associated with making a purchase, and thereby increases the total demand for the product. In addition, an efficient logistics process could result in either or both of two effects: it could increase total demand by reducing the customer’s cost associated with making a purchase; or it could increase the average profit margin by reducing direct costs. Third, an effective marketing initiative to sharpen market segmentation could result in an increased average number of matches per sale. Mollenkopf et al. (2007) proved impact of the returns management system upon customer loyalty intentions. Their research demonstrated that “perceived value of the returns offering” and “return satisfaction” directly and positively influence customer loyalty intentions.

2.2 Data Mining in E-retailing

Data mining techniques are applied to solving recommendation problems in e-commerce in
most cases. Recommendation systems track past actions of a group of customers to make a recommendation to individual members of the group. Kim et al. (2002) focused on the recommendation problem of helping selective customers find which products they would like to purchase by suggesting a list of top-N recommended products for each of them at a specific time. The suggested procedure is based on Web usage mining, product taxonomy, association rule mining, and decision tree induction. This personalized recommendation procedure can get further recommendation effectiveness when applied to Internet shopping malls. Lee et al. (2007) identified some characteristics of services which encourage customers to buy online and to develop a prediction model for success based on customer recognitions of service offerings in e-commerce. A review of Decision Tree model reveals that purchasing frequency and price are key factors for online services by being selected as decision criteria at the first layer. E-customer behavior model was suggested from the findings and can be used for predicting customer behavior.

Lee and Tan (2003) identified various factors impacting customer choice on virtual store vis-à-vis physical one. They concluded that customers are less likely to shop on-line from lesser-known retailers who carry well-known brands than from reputable retailers, even if the latter carry lesser-known brands. Yu and Wang (2007) recognized factors which identify customers return rate by a hybrid mining approach. The result from simulated data implied that customer and product dimension could be key factors to identify the return ratio. Furthermore, the association rules provide some suggestions on the leniency of return policy. On-line shopping customers receive higher risk than in-store shopping. In this situation, return management will be relatively more significant to reduce the perceived risk of customers. Some literatures have verified that return management has positive effect on lowering cost and increasing sales of on-line retailing business. In E-retailing, most of the applications of data mining technology are used within marketing field. Few are applied in the return part in E-retailing. However, while the E-retailing market becomes more and more flourishing and competitive, return issue should be regard as important clue for sustained success.

3. METHODOLOGY

A classification technique (or classifier) is a systematic approach to building classification models from an input data set. Classification technique employs a learning algorithm to identify a model that best fits the relationship between the attribute set and class label of the input data. The model generated by a learning algorithm should both fit the input data well and correctly predict the class labels of records it has never seen before. Therefore, a key objective of the learning algorithm is to build models with good generalization capability; i.e., models that accurately predict the class labels of previously unknown records (Tan et al., 2005).

Usually, the given data set is divided into training and test set, with training set used to build the model and test set used to validate it. Given a collection of records (training set); while each record contains a set of attributes, one of the attributes is the “class” (also termed target variable in this study). A classifier is to find a model for class attribute as a function of the values of other attributes. Previously unseen records (test set) should be assigned a class as accurately as possible.

There are well-known decision tree induction algorithms such as CHAID (Kass, 1980), CART (Breiman, 1984), C4.5 (Quinlan, 1993), etc. In this paper, we choose to use C4.5 as
our decision tree induction algorithm. C4.5 is an algorithm improved from ID3 which was brought up by J. R. Quinlan in 1979. Not only is it a relatively new algorithm but a trendy post-pruning technique among other algorithms. There is a concept explanation of C4.5 in this section. C4.5 use “Entropy” based on ID3 to evaluate the degree of impurity,

$$Entropy(t) = - \sum_{i=0}^{c-1} p(i \mid t) \log_2 p(i \mid t)$$

while $p(i \mid t)$ is the relative frequency of class $i$ at node $t$.

To determine how well a test condition performs, we need to compare the degree of impurity of the parent node (before splitting) with the degree of impurity of the child nodes (after splitting). The information gain, $\Delta_{\text{Info}}$, is a criterion that can be used to determine the goodness of a split:

$$\Delta_{\text{Info}} = E(\text{parent}) - \sum_{j=1}^{k} \frac{N(v_j)}{N} E(v_j)$$

$E(\cdot)$ is the Entropy of a given node. 
$N$ is the total number of records at the parent node. 
$k$ is the number of attribute values. 
$E(v_j)$ is the number of records associated with the child node, $v_j$

Since $E(\text{parent})$ is the same for all test conditions, maximizing the gain is equivalent to minimizing the weighted average impurity measures of the child nodes. When Entropy is used as the impurity measure in Equation 3.2, the difference in entropy is known as the Information Gain, $\Delta_{\text{Info}}$.

The concept of Information Gain is used both in ID3 and C4.5. To maximize Information Gain, the algorithm tends to prefer splits that result in large number of partitions, each being small but pure. However, the large number of partitions may lead the number of record in each leaf node too small and the result unreliable. To overcome this problem, a splitting criterion known as Gain Ratio is used in C4.5 to adjust Information Gain by the Entropy of the partitioning. Namely, higher Entropy partitioning (large number of small partitions) is penalized.

$$\text{Gain Ratio} = \frac{\Delta_{\text{Info}}}{\text{Split Info}}$$

$$\text{Split Info} = - \sum_{i=1}^{m} P(v_i) \log_2 P(v_i)$$

$m$ is the total number of split. 
Gain Ratio suggests that if an attribute produces a large number of splits, its split information will also be large, which in turn reduced its gain ratio.
4. RESEARCH CASE AND EMPIRICAL DATA

There are six steps to complete the decision tree analysis procedure. First, we will start from case introduction to understand the return issue in real business and identify the subject of this research. We define the problem as a binary choice model and use decision tree to distinguish the return happened or not. Further, data collection and data preprocessing are applied to assure the data quality. To continue, we will check the collinearity and correlation between each predicted variable and target variable. Then, we input the selected variables and target variable and build decision tree model. Finally, By way of arborescence visualization, we will conclude the findings of return rules and provide suggestion for strategy developing.

Only physical merchandise will be discussed in this study while financial and digital merchandise will be excluded. Exchange service will be included in this study. However, it is transformed to return the undesirable items and purchase a new one.

4.1 Case Introduction

The online shopping website plays a role as an intermediary, which facilitates transactions between buyers and sellers and receives a fee for each transaction. It integrates the information and the payment flow thus gains the margin from every successful transaction. The retailers consistently own the specific brand and take responsible for the inventory flow and marketing strategies. With the relationship, the online shopping website and retailers cooperate to gain as much profits as possible.

There are more than 4,400 retailers in the website platform to sell more than 964,000 items (May, 2008) in this case of E-retailing intermediary. In addition, there are approximately 150 new retailers joining the online shopping website per month. The procedure of order and return in the on-line shopping market is illustrated in Figure1 and Figure2. Payment flow and information flow between customers and retailers are facilitated by the website operator. Inventory flow is expedited by post or logistics providers.

![Figure 1 Order Procedure of Online Shopping](image-url)
4.2 Data Collection and Variable Explanation

The data was collected by Pchome.com in Taiwan. The individual data in the selection were chosen on a basis that customers who had at least one return record. The observation data are collected by the customer ID as an index to involve his/her overall transaction records.

Transformation skill is used here to create new feature for better interpretable under our objective. For categorical data, data generalization is used to combine detailed data to more generalized form. In addition, statistics test and descriptive statistics analysis are used to review the continuous data to ensure a reasonable data quality. In the step of data preprocessing, we eliminate the outliers and noise in original data, and exclude the collinear variables as well. We finally conclude the predicted variables into 3 dimensions and a target variable. Finally, the target variable is measured by whether would be a return happened from each transaction records.

The original data is composed of four dimensions, covering customer demographic profile, merchandise characteristics, website/retailer services and transaction records. The customer demographic data includes gender, age, location, purchasing experience in online trading. The merchandise characteristics include price and category. The website/retailer services include payment, carriage, delivery approach, and evaluation function establish by the online shopping website. Finally, the target variable is measured by whether would be a return claim happened from transaction records. The overall number of data in this analysis data set is 56,904 including 51,949 non-return orders and 4,955 returns. We define the target variable as 0 (non-return) and 1 (return). The average return rate in this data set is 8.71% (4,955/56,904). The predicted variables and target variable are shown in Table 1.

In this paper, we use SAS Enterprise Miner vision 4.1 to conduct classification. The data analysis mentioned before indicated that this problem is a binary choice model with a skewed distribution. The number of “Return” is noticeably less than “Non-return”. Thus, we use the whole “Return” data and sample from the “Non-return” data to lead the ratio of each other equal 1:1.
Table 1 Description of Input Variables

<table>
<thead>
<tr>
<th>Data Dimension</th>
<th>Variables</th>
<th>Data Type</th>
<th>Data Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer</td>
<td>Age</td>
<td>Continuous</td>
<td>10 to 78</td>
</tr>
<tr>
<td></td>
<td>Gender</td>
<td>Binary</td>
<td>[0] Female [1] Male</td>
</tr>
<tr>
<td></td>
<td>Location</td>
<td>Nominal</td>
<td>24 counties</td>
</tr>
<tr>
<td>Merchandise</td>
<td>Price</td>
<td>Continuous</td>
<td>NT $1 to NT $180,000</td>
</tr>
<tr>
<td></td>
<td>Category</td>
<td>Nominal</td>
<td>32 kinds of merchandise</td>
</tr>
<tr>
<td></td>
<td>Payment</td>
<td>Nominal</td>
<td>[0] ATM: Pay by ATM Transfer</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[1] CRD: Pay by credit card</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[2] DIV: Pay by installments</td>
</tr>
<tr>
<td></td>
<td>Delivery Approach</td>
<td>Nominal</td>
<td>[0] TPS: Home Delivery</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[1] CVS: Retail Delivery</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0] Pay by retailers</td>
</tr>
<tr>
<td></td>
<td>Carriage</td>
<td>Nominal</td>
<td>[1] Pay by Consumers</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[2] Conditional Payment</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0] Deliver on the order day</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[1] Deliver in 1 day</td>
</tr>
<tr>
<td></td>
<td>Actual Delivery Days</td>
<td>Ordinal</td>
<td>[2] Deliver in 2 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[3] Deliver in 3 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[4] Deliver in 4 days</td>
</tr>
<tr>
<td></td>
<td>Average Delivery Days</td>
<td>Ordinal</td>
<td>[5] Deliver more than 5 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0] Deliver on the order day</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[1] Deliver in 1 day</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[2] Deliver in 2 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[3] Deliver in 3 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[4] Deliver in 4 days</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[5] Deliver more than 5 days</td>
</tr>
<tr>
<td></td>
<td>Accumulated Number of Buyers</td>
<td>Continuous</td>
<td>1 to 13,611</td>
</tr>
<tr>
<td></td>
<td>Accumulated Number of Browsers</td>
<td>Continuous</td>
<td>0 to 12,656,670</td>
</tr>
<tr>
<td></td>
<td>Total Number of Merchandise</td>
<td>Continuous</td>
<td>0 to 15,344</td>
</tr>
<tr>
<td></td>
<td>Target</td>
<td>Return</td>
<td>Binary [0] Non-return [1] Return</td>
</tr>
</tbody>
</table>

5. ANALYSIS RESULTS AND STRATEGY DEVELOPMENT

5.1 Analysis Results

Merchandise dimension variables are the most applicable variables for classification. Retailer evaluation function (service dimension) variables also show some directions for distinguishing return propensity. However, variables of customer dimension (Location) are short of consistence. Cross Tabulation showed average return rate is related to “Payment”, “Delivery Approach” and “Carriage” though, nevertheless, they are not selected to distinguish
return behavior of each order in classifiers. We try different kinds of trees according to customer feature; Table 2 summarizes the trees we conducted and reveals some important variables for different customers groups.

<table>
<thead>
<tr>
<th>Table 2 Summary Information of Decision Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT Types</td>
</tr>
<tr>
<td>Variables</td>
</tr>
<tr>
<td>Number of Samples</td>
</tr>
<tr>
<td>Accuracy of Training</td>
</tr>
<tr>
<td>Accuracy of Validation</td>
</tr>
<tr>
<td>Accuracy of Test</td>
</tr>
</tbody>
</table>

Customer Dimension
- "Age" and "Location" are chosen to be predicted variables, "Gender" is not a good one for distinguishing return propensity. Even so, "Age" only shows up in Male-DT while "Location" lack of consistence for directing return propensity.

Merchandise Dimension
- "Category" and "Price" play the major roles in identifying return propensity for different groups of customers by being selected as decision criteria at the 1st and 2nd layer.
- "Category", which dominate the first layer to separate the return propensity to high (more than 60%), medium (between 50% and 55%) and low (approximately 30%) in four customer-based DTs.
- If "Price" is less than approximately NT $400, then customers tend to not return. If "Price" becomes higher, then the return propensity will increase simultaneously. However, when "Price" is extremely high, return propensity may become lower contrarily.

Service Dimension
- Variables of service dimension- “Payment”, “Delivery Approach” and “Carriage”
are not selected in distinguishing return behavior of each order in the five models.

- Variables of service dimension- Service evaluation function (include “Average Delivery Days”, “Accumulated Number of Buyers”, “Accumulated Browsers”, “Number of Merchandise”) also represent some directions for return propensity.
- If “Average Delivery Days” is more than (include) 3 days, then customers tend to return.

5.2 Data Collection and Variable Explanation

We conclude four main points for developing strategy to improve the return management in E-retailing.

- Category: Since we have already known what kinds of merchandise were returned more frequently, coupled with the average sales volume, we can suggest which retailers should be emphasized to improve the high-frequent returns. No matter from the viewpoint of gender or transaction frequency, customer return propensity is especially high for “Female Clothing” and “Female Shoes”. Both of the merchandise categories are the main developing items in E-retailing thus they should be paid attention on even more.

- Price: If “Price” is less than approximately NT $400, then customers tend to not return. While “Price” becomes higher, the return propensity will increase simultaneously. This result could be inferred that return cost (such as the time and fee for return delivery) for customers bought low-price merchandise is relatively high. On the contrary, return cost is relatively low for customers bought high-price merchandise. Thus, low-price merchandise won’t be returned as often as higher ones.

- Remedy Service: To better understand the customer return behavior, we illustrate the frequency of transaction and average frequency of return in 2007. There are three reasons for us to contend that managers should put more attention on the low-transaction frequency customers. First, Customers whose transaction frequency is equal to or less than 12 are approximately 70% of total customers in the data set. However, they only contribute to 30% of orders per year. These customers might be new customers or defected customers. As we’ve known, the cost of attracting a new customer is 4 times than maintaining an old one. These potential customers are specifically important for expanding customer base and increasing profits. If the low-transaction frequency customers could not become higher ones, the company simply retains a smaller group of (somewhat more satisfied) customers, but often with reduced sales and profits as a result. Second, since new customers have not established their loyalty to this website yet, they might be easier to lose while they confronted a return (which is commonly an unsatisfying experience). Fig. 3 shows when the number of transaction increase, however, the number of return doesn’t increase with rapid growth. Therefore, the objective is obvious to encourage low-transaction frequency customers to higher one. To sum up, it’s clear that managers should provide remedy service to avoid customer defection, especially for the low-transaction frequency customers.
Delivery Days: Since we have found that especially for female and low-transaction frequency customers, “Average Delivery Days” could affect the decision of return. In particular, the return propensity will be increase rapidly while the delivery day is more than 3 days (see Fig. 4).

To solve delivery day’s problem, we develop strategies as below:

**Strategy 1:**

For high return propensity categories, we should control the delivery days in 2 days. Namely, picking and packing must be finished and send the merchandise to the logistics provider in 2 days. The speed of delivery is especially important for female customers and low -transaction frequency customers. Here, we assume the time of delivery from logistic provider to customer is one day. Namely, customers could receive the merchandise no more than 3 days. In this way, we could control return by efficient logistics flow. Fig. 5 illustrates this concept.
Strategy 2:

To accomplish the delivery on time, “safety stock” should be maintained to support the demand quantity. If the safety stock doesn’t work, there should be a backup plan—“order lead time” must be controlled to assure supplier could replenish the short of items. Retailers must check the inventories frequently to assure the punctuality of inbound and outbound logistics.

Strategy 3:

Orders on Friday and Saturday need to be handled exceptionally since there are day-off between ordering and receiving. If the retailers do not work on Weekend, then customer may receive the merchandise at least 5 days later from the order date (as shown in Fig. 6). Retailers could reduce the waiting time of customers by handling these orders on Saturdays (as shown in Fig. 7).
6. CONCLUSION

This paper is one of few empirical investigations that deal the customer behavior with respect to return issue in E-retailing market. Wer provides several meaningful insights of customers’ propensity to return in E-retailing. The results show that:

- Decision Tree Induction is suitable for high dimension data. In this study, all of the models conducted reveal more than 60% accuracy of classification. Hence, the models are available for distinguishing return propensity of customer behavior.

- In our data set, “Category”, “Price” and “Average Delivery Days” play the major roles in identifying return propensity by being selected as decision criteria at the 1st and 2nd layer.

- Since we concluded that Female Clothing and Shoes were returned more frequently, we could suggest website managers emphasize on retailers selling these merchandise to improve the high-frequent returns.

- If “Price” is less than NT $400, then customers tend to not return. If “Price” becomes higher, then the return propensity will increase simultaneously. This inferred that as the merchandise value going up and the return cost becomes relatively low for customers, hence return propensity will grows. For this situation, retailers selling high-value merchandise should provide more details to customers to make up for the precluded product examination.

- “Average Delivery Days” is especially important for female and low-transaction frequency customers. The return propensity will be increase rapidly while the delivery days are more than (include) 3 days. “Safety stock” and “Order lead time” should be controlled to support the demand quantity. Further, retailers handle the picking and packing on weekend to save the total delivery time before customers receiving items.
Variable could be involved more completely. There are three dimensions of variables in our paper to classifying the binary target variables. However, there are still some variables excluded might be useful for understanding this topic, such as income levels, education levels, merchandise size, and ease of operation. Customer may consider return policy: Who is responsible for paying return carriage? How long products may be returned after purchase? Refund is provided or not? Whether returns will be questioned or not? Whether sales items are acceptable? These services could also affect return critically. More factors could be involved for a better completeness.

Some strategies may cause higher sales volume coupled with higher returns; however, few studies had paid attention on the trade-off between sales and returns. Retailers may expect loose return policy could stimulate the sales volume by guaranteeing return acceptability; nevertheless, it may also lead to the abuse of return power. Retailers are afraid that customers buy a product with the intention of returning it. On the contrary, retailers would be unwilling to see that a strict return policy reduce the sales. Research on this dilemma could provide more information for management in E-retailing.

This paper has attempted to demonstrate a few simple prioritized questions to understand return propensity. However, further studies in researching customer return behaviors are needed to provide more details. There are the limitations and suggestions for future work. To give an example, some strategies may cause higher sales volume coupled with higher returns; however, few studies had paid attention on the trade-off between sales and returns. Retailers may expect loose return policy could stimulate the sales volume by guaranteeing return acceptability; nevertheless, it may also lead to the abuse of return power. Retailers are afraid that customers buy a product with the intention of returning it. On the contrary, retailers would be unwilling to see that a strict return policy reduce the sales. Research on this dilemma could provide more information for management in E-retailing.

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