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Increasing the Transaction Success Rate in Online Shopping

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Abstract

Online retailer facing a group of strategic customers. Due to various website issues, there is a possibility of transaction failure in the process of customer online purchasing. Customer is going to purchase the online shopping through the internet. That time they are facing the various website issues like transaction failure. Transaction failure rate can be separated and transaction success rate can be separated. Transaction failure rate can be reduced using threshold policy method. Transaction success can be improved by using transaction success probability.

Keywords: *Online Retailing, Strategic Customers, Technology Adoption, Transaction Failure***.**

1. Introduction

As information technology has developed, more and more retailers have opened online channels for sales; thus, online sales has seen a dramatic increase in the past several years. For example, according to Spending Pulse, a MasterCard Advisors report, there was more than 15% increase in online sales in 2010 compared with 2009. An increasing number of consumers conduct their shopping through the Internet. Website issues often make consumers abandon transactions, leading to transaction failures. Moreover, website issues result in negative customer experiences. The customers may tell their friends about their bad experiences or write them down on some related forums. Other online shoppers can have easy access to the comments, which leads to word-of-mouth effects that damage the reputations of online retailers.

According to the consumer mercantile model in , consumer purchasing activity consists of three phases, namely, pre purchase interaction, purchase consummation, and purchase interaction. Consumers obtain various types of information on online retailers in the phase of pre purchase. It is documented that these kinds of information do affect consumers' attitudes toward a website (or an online retailer). The attitudes, in turn, lead to their intentions to use the website and the eventual acceptance of the website (or the online retailer). On type of information that affects the customers' final choice is the website's (the online retailer's) ability to complete transactions without any problem . Therefore, website issues can lead to transaction failure and customer defection, causing huge losses to online retailers. It is reported that retailers who operate through online channels may have lost more than $44 billion over the past year as a result of transaction problems on their website

We propose adjusting selling prices and upgrading web systems to reduce online retailers' profit losses from website issues. The network operation and maintenance engineers of Baidu, Inc. (China's largest search engine service provider) explain to the authors that website issues are mainly attributed to hardware and software problems of web systems. The hardware problems mainly include the lack of sufficient number of servers to support by internet service providers. On the other hand, the software problems are mainly caused by redundant processing logic that results in denial of access and unreasonable web design that causes inconvenience to online customers. Therefore, online retailers can upgrade the web systems by improving the hardware capacity (e.g., purchasing new servers) and optimizing the processing logic and the web design. Since these actions could be very costly, how to price and when to upgrade web systems are crucial problems for online retailers.

First, we characterize a threshold policy for strategic customer purchasing: There exists a unique threshold such that a customer will buy the product if his valuation isgreater than the threshold and will not buy the product otherwise. We further demonstrate that a customer will be more likely to conduct an online purchase if the website is technically more reliable (lower probability of website issues), the transaction cost of purchasing is lower, or the customer is less risk averse. Second, this paper provides guidelines for the online retailer on how to price and when to upgrade the web system. We propose a multi period model in which the online retailer has an opportunity to set price and upgrade its web system at the beginning of each period. The optimal price for each period is derived, and a threshold policy is proposed for upgrading: There exists a threshold for each period such that the online retailer may upgrade the web system to the highest available transaction success probability (TSP) if the current TSP is below the threshold and not upgrade otherwise. Sensitive analysis is conducted to investigate how the threshold and the optimal profits of the online retailer change with various model parameters.

Third, this paper discusses the online retailer's cost of ignoring customer strategic behavior. It is proved that the online retailer tends to price higher when ignoring customer strategic behavior. Numerical examples show that the profit loss is substantial (sometimes the profit-loss rate can be up to 65%).To alleviate the negative effect of ignoring customer strategic behavior, the online retailer should: 1) increase customer valuations for the product by better product design or more impressive advertising; and 2) decrease the customer transaction cost by providing better navigation aids. In addition, if the customers are less risk averse, the negative effect of ignoring customer strategic behavior is smaller

1.1 Existing system:

We consider a stylized dynamic pricing model in which a monopolist prices a product to a Sequence of customers, who independently make purchasing decisions based on the price off erred according to a log it choice model. The parameters of the log it model are unknown to the seller, whose objective is to determine a pricing policy that minimizes the regret, which is the expected difference between the seller's revenue and the revenue of a clairvoyant seller who knows the values of the parameters in advance. When there is a single unknown parameter, we show that the T-period regret is (log T), by establishing an (log T) lower bound on the regret under an arbitrary policy, and presenting a pricing policy based on maximum likelihood estimates that achieves a matching upper bound. For the case of two unknown parameters, we prove that the optimal regret is (p T). Numerical experiments show that our policies perform well against several competing strategies.

1.2. Proposed system:

Online retailer facing a group of strategic customers. Due to various website issues, there is a possibility of transaction failure in the process of customer online purchasing. Customer is going to purchase the online shopping through the internet. That time they are facing the various website issues like transaction failure. Transaction failure rate can be separated and transaction success rate can be separated. Transaction failure rate can be reduced using threshold policy method. Transaction success can be improved by using transaction success probability. To overcome the transaction failure using the Transaction Success Probability for optimal purchasing decision of customers. It is used reduce the time and more flexible to buy the product. It improve the service cost of the particular product using the customer purchase behavior.

2. Literature Review

2.1 Online Retailing:

Considered pricing and web system upgrading problems for an online retailer who faces a group of strategic customers. Due to various website issues, there is a possibility of transaction failure when a customer purchases a product through the Internet**.** Online retailing has attracted a great deal of attention, and numerous studies have emerged considering issues related to this field. In general, the studies in this field can be divided into two categories. The first focuses on the design of channel structure and the influences of online retailing entry over traditional retailing forms. Examples of this category include mixed channel, price competition, channel substitution, and so on. The second kind of study is devoted to designs and attributes of the online retailing website. Among the research studies in this category, some focus on the characteristics of the website, and others provide suggestions on how to design the website by exploring consumer characteristics such as consumer shopping orientations, demographic variables and psychological variables Chang *et al.* [10] provide a comprehensive review of this literature. This paper falls into the second category and contributes to this literature by considering transaction/service failure due to website issues. It consider as to transaction/service failure of online retailing. Comparing all these empirical research studies, this paper proposes a mathematical model to provide guidelines for online retailers on pricing decisions and technology upgrading policy.

2.2 Customer Behavior:

In traditional operations management (OM) literature, customer demand is often assumed to be exogenous, i.e., demand functions are usually set as specified functions of price product attributes However, in the real world, all customers, at some point, actively evaluate alternatives and make choices, e.g., how much to pay, which product to buy, and when to buy .That is, the customers will engage in decision-making processes and are not simply governed by the demand profile specified at the outset. It is shown that these customers' decision processes deserve attention, and for many practical problems. It contributes to this literature by considering strategic customers who anticipate the probability of online transaction failure and make purchasing decisions based on their beliefs over this probability.

2.3 .Risk Aversion:

In general, the characterization of risk averse consists of: 1) mean–variance framework concave utility functions according to expected utility theory and 3) other measurements such as downside-risk and value-at-risk. This paper employs the second one and assumes that the customers have an identical utility function that is increasing and concave.

3. Model and Customer Purchasing Behaviour

Consider a firm that sells a single product through the Inter- net to a fixed population of online shoppers. The firm produces the product at a unit cost of c and sells it at a price of $p(p > c)$. Production cost c is exogenous and normalized to 0 for simplicity. We consider a market of N customers. Market size N is deterministic and very large. Customers have unit demand and heterogeneous valuations for the product, which is a random valuation drawn from a common cumulative distribution function (CDF) $F(v)$. Let $f(v)$ be the corresponding probability density function (PDF) and $\bar{F}(v) = 1 - F(v)$ be the corresponding complementary CDF. Furthermore, we assume that $f(v)$ is continuous and $F(v)$ has increasing hazard rate (failure rate), i.e., the hazard rate function $r(v) := f(v)/\bar{F}(v)$ is a weakly increasing function. Many distribution functions have increasing hazard rate, including uniform, exponential, and normal distributions; Weibull distribution with shape parameter $\alpha > 1$; Gamma distribution with shape parameter $\alpha > 1$; etc. The customers are risk averse and have an identical utility function $u(\cdot)$, which is an increasing and concave function with $u(0) = 0$ and $u(+\infty) = +\infty$. The customers have a homogeneous transaction cost $h(h > 0)$ for the online purchase, including time costs of searching, bargaining, paying bill by personal Internet bank, etc.

The customers will make an unsuccessful purchase with a probability $1 - q$ due to various website issues (e.g., slow speed and web errors). We refer to q as TSP. We assume that the customers have correct anticipations (observations) on TSP. This assumption is made based on the following facts: Nowadays, more and more people have access to the Internet with computers or other communication instruments, which leads to more and more online shoppers writing down their past experiences of shopping on some websites. Customers can estimate TSP by examining the experiences of former online shoppers.

Next, we will characterize the purchasing behavior of a strategic customer with random realization v as valuation for a given selling price p. It is easy to know that the customer will buy the product if his valuation $v < p + h$. If $v \geq p + h$ the customer will decide by comparing the utility of buying the product with that of not buying. In particular, the strategic customer will (not) try to buy the product if

$$qu(v - p - h) + (1 - q)u(-h) \geq (<)u(0). \quad (1)$$

Note that "$\geq$" of inequality (1) is the condition that a customer will try to buy the product online but may not necessarily buy due to website issues. For simplicity, we omit the words "try to" if there is no confusion. The following proposition characterizes the optimal purchasing decisions for customers.

Proposition 3.1:

Suppose the selling price p is given. There exists a unique threshold $x(q, h) > h$ satisfying

$$(x(q, h) - h) + (1 - q)u(-h) = 0 \quad (2)$$

Such that the customer will buy the product if his valuation $v \geq p + x(q, h)$ and will not buy the product if $v < p + x(q, h)$.

Proposition 3.1 prescribes the optimal purchasing decisions for the customers in the presence of various website issue threshold x(q, h) is a function of q and h representing an invisible cost of online purchasing behavior, which is determined by transaction cost h and TSP q. A threshold policy is optimal for the customers: If the valuation for the product is abx(q, h) + p, the customer should buy the product and otherwise the customer should not buy.

Proposition 3.2:

$x(q, h)$ is decreasing with respect to q and increasing with respect to h.

Proposition 3.2 indicates that customers are more likely to buy the product if TSP q is higher or if transaction cost h is lower. The latter result is consistent with previous results of which find that customers are less price sensitive and more likely to purchase the product when information provided on the website is easier to navigate (i.e., lower transaction cost). Another question is: How does $x(q, h)$ change with the customers' degree of risk aversion? According to [33], an increase in the degree of risk aversion can be represented by an increasing concave transformation. Let $w(\cdot) = \phi(u(\cdot))$, where $\phi(\cdot)$ is an increasing concave function with $\phi(0) = 0$. Thus, $w(\cdot)$ represents a higher degree of risk aversion than $u(\cdot)$. Let $xu(q, h)$ and $xw(q, h)$ stand for the thresholds corresponding to $u(\cdot)$ and $w(\cdot)$, respectively. Hereafter, we assume that functions $u(\cdot)$ and $\phi(\cdot)$ are differentiable.

Proposition 3.3:

$$x^u(q, h) \leq x^w(q, h).$$

Proposition 3.3 indicates that customers are less likely to buy the product if they are more risk averse. For simplicity, hereafter, we say that y is increasing (decreasing) with respect to the customers' degree of risk aversion if $y^w \geq y^u$ ($y^w \leq y^u$), where y^w and y^u are two quantities corresponding to $u(\cdot)$ and $w(\cdot)$, respectively (note that $w(\cdot)$ represents a higher degree of risk aversion than $u(\cdot)$).Propositions 3.1–3.3 enable us to derive the firm's total m demand and to discuss how various model parameters, such as q, h, and customers' degree of risk aversion, affect the firm's total demand and profit.

4.Service Pricing

Adjusting selling price p and performing web upgrading to increase TSP q are effective solutions to solve the transaction failure problem caused by various website issues. Next, we study the firm's joint decisions of pricing and web upgrading. To this end, we consider an n-period model. We assume that in period $i (i = 1, 2, \ldots, n)$, TSP can not exceed q_i due to technology limitations and that $0 < \underline{q} = q_1 \leq q_2 \leq \ldots \leq q_n \leq 1$, which means that the highest technology available develops. In period $i (i = 1, 2, \ldots, n)$, the timing of events is as follows.

Observing current TSP q_i , the firm decides whether to upgrade its web system to increase TSP an d how much to increase it by (i.e., choose $q \in [q_i, q_i]$). The firm incurs a fixed cost K_i for the system upgrade. This means that the cost for the upgrade is $K_i\,\delta(q - q_i)$, where $\delta(x) = 1$ if $x > 0$ and $\delta(x) = 0$ if $x = 0$.

The firm decides the selling price p based on q. Customers make purchasing decisions according to p and q. Here, we assume that the purchasing behaviors of the customers in each period only depend on the price and TSP in the current period, irrelevant to those in other periods. In addition, we assume that customers can correctly expect the value of q. This rational expectation assumption is also adopted in other literature.

The state transition among periods follows

$$q_i = q^*_{i-1},\ i = 2, 3, \ldots, n$$

Where q_i stands for TSP at the beginning of period i (before upgrading decision), and q^*_{i-1} is optimal TSP chosen in period $i - 1$

4.1 Pricing Decisions:

we derive the optimal price in each period for any given TSP q. With selling price p, according to Proposition 3.1, only customers with valuation $v \geq p + x(q, h)$ will buy the product. According to the assumption in Section III that market size N is deterministic and very large, the demand with selling price p is $N(1 - F(p + x(q, h))) = N\bar{F}(p + x(q, h))$.

The transactions only succeed with a probability q. Then, the firm's expected profit in a single period with TSP q and selling price p is

$$\pi(p, q) = pqN\bar{F}(p + x(q, h)). \quad (3)$$

For any given $0 < q < 1$, $\pi(p, q)$ is uni modal with respect to p, and the optimal price $p^*(q)$ is the unique solution of

$$1 - p \cdot r(p + x(q, h)) = 1 - \frac{p\, f(p + x(q, h))}{\bar{F}(p + x(q, h))} = 0. \quad (4)$$

Proposition 4.1:

a) $p^*(q)$ is increasing with respect to q and decreasing with respect to h and the customers' degree of risk aversion.

b) $\pi^*(q) := \pi(p^*(q), q)$ is increasing with respect to q and decreasing with respect to h and the customers' degree risk aversion.

Proposition 4.1 shows that the online retailer should price higher and will get a higher profit if its website's ability to complete transactions without any problems is higher, customers' transaction cost is lower, or if customers are less risk averse.

We introduce the notion of hazard rate order for random variables. Given two nonnegative random variables X and Y with PDFs $f_X(x)$ and $f_Y(y)$, the corresponding CDFs are $F_X(x)$ and $F_Y(y)$.We define that X is no more than Y according to hazard rate order (denoted by $X \leq_{hr} Y$, or equivalently $F_X(\cdot) \leq_{hr} F_Y(\cdot)$) if

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$rX(v) := fX(v)/FX(v) \geq rY(v) := fY(v)/FY(v)$ for all $v \geq 0$, or equivalently, $FX(v)/FY(v)$ is decreasing in v over $[0,+\infty)$. Hazard rate order, which often appears in decision theory, is an effective way to compare two nonnegative variables. For example, if X follows a uniform distribution random over $[0, AX]$ and Y follows a uniform distribution $[0, AY]$, then $X \leq$hr Y is equivalent to $AX \leq AY$.

Proposition 4.2:

Suppose that $pFX\pi{*}F(p{*}FY$and $\pi{*}FY)$are respectively the optimal price and the single-period profit corresponding to CDF $FX(\cdot)$(CDF$FY(\cdot)$). If both $FX(\cdot)$ and$FY(\cdot)$ have increasing hazard rates and $FX(\cdot) \leq$hr $FY(\cdot)$, then $p{*}FY\geq p{*}FX$ and $\pi{*}FY\geq \pi{*}FX$

Proposition 4.2 indicates that both the optimal price and single-period profit are higher if customer valuations for the the customers). For simplicity, we say that y is increasing (decreasing) with respect to customer valuations if $FX(\cdot) \leq$hr $FY(\cdot)$ implies that $yX \leq yY$ ($yX \geq yY$), where yX and yY are two quantities corresponding to CDFs $FX(\cdot)$ and $FY(\cdot)$, respectively.

4.2 Upgrading thresholds change with model parameters:

It investigates how the firm's optimal total discounted profit and the upgrading thresholds change with model parameters.

TABLE I

THRESHOLDS VERSUS CUSTOMER VALUATIONS FOR THE PRODUCT

	T for Period 1	T for Period 2	T for Period 3	T for Period 4	T for Period 5
A=35	0.4401	0.5662	0.6918	0.8171	0.9423
A=40	0.4483	0.574	0.6994	0.8245	0.9496
A=45	0.4546	0.5799	0.7051	0.8303	0.9554
A=50	0.4593	0.5847	0.7098	0.8348	0.9599

The optimal threshold T changes with model parameters. To this end, we do some numerical examples in which $F(x)$ is the CDF of uniform distribution over$[0,A]$, $n = 5$, $N = 1000$, $u(x) = 1 - \exp(ax)$, $Ki = 500$, i =1, 2, . . . 5, $q1 = 0.5$, $q2 = 0.625$, $q3 = 0.75$, $q4 = 0.875$, $q5$ 1, and $\beta = 0.9$. First, we set $h = 4$ and $a = 0.01$ and investigate how threshold T changes with A. The results are listed in Table I. It demonstrates that T increases as A increases, which means that the firm is more likely to upgrade its web system when customer valuations for the product are higher. This is because it is more profitable to upgrade the web system when the product is more attractive to the customers.

TABLE II

THRESHOLDS VERSUS CUSTOMER TRANSACTION COST

	T for Period 1	T for Period 2	T for Period 3	T for Period 4	T for Period 5
h=2	0.4497	0.5748	0.6999	0.8249	0.9499
h=4	0.4483	0.574	0.6994	0.8245	0.9496
h=6	0.4458	0.5726	0.6984	0.8239	0.9492
h=8	0.4409	0.5703	0.6971	0.8229	0.9485

set $a = 0.01$ and $A = 40$ and investigate how T changes with h. The results are listed in Table II. We find that T becomes smaller when customer transaction cost becomes higher. This indicates that the firm is less likely to upgrade its web system when customer transaction cost is higher. It is also very natural because it is less profitable to upgrade the web system when customer transaction cost is higher, which results in smaller population of customers who try to buy the product.

TABLE III

THRESHOLDS VERSUS CUSTOMERS' DEGREE OF RISK AVERSION

	T for Period 1	T for Period 2	T for Period 3	T for Period 4	T for Period 5
a=0.01	0.4483	0.574	0.6994	0.8245	0.9496
a=0.03	0.4501	0.5751	0.7001	0.8251	0.95
a=0.05	0.4522	0.5764	0.7009	0.8256	0.9505
a=0.07	0.455	0.5778	0.7018	0.8262	0.9509

set $h = 4$ and $A = 40$ and investigate how T changes with customers' degree of risk aversion. The results are listed in Table III, in which larger a represents higher degree of risk aversion. The result demonstrates that the firm is more likely to upgrade the web system when facing more risk-averse customers. The explanation is as follows. When customers are more risk averse, they are more sensitive to the possibility of transaction failure. Thus, upgrading the web system, which increases TSP, attracts more customers to buy the product. This means that upgrading the web system is more profitable when customers are more risk averse; thus, T increases with customers' degree of risk aversion. further numerical analysis demonstrates that T has no explicit relationship with period number $i(i = 1, 2, \ldots, 5)$. The relationship between threshold T and period number i depends on the interactions of several parameters such as qi and $Ki(i = 1, 2, \ldots, 5)$.

5. Costs of Ignoring Customer Strategic Behavior

An interesting question is: What happens if the firm ignores customer strategic behavior and makes decisions based on the belief that customers think $q = 1$? In this section, we will answer this question. From Part (a) of Proposition 4.1, we have

$$p* (1) > p*(q), \text{ for any } 0 < q < 1$$

which shows that the online retailer will price higher if it ignores customer strategic behavior. Let $\tilde{\pi}(q) := \pi(p*(1), q)$ be the online retailer's single-period profit with TSP q when ignoring customer strategic behavior. Similarly as in Section IV, let $\tilde{V}n+1(q) = 0$ for any $q \in [q, qn]$and

$$\tilde{V}i(qi) = \max q\in [qi, \bar{q}i]\{-Ki\,\delta(q - qi) + \_\pi(q) + \beta\ \_Vi+1(q)\}$$

Then, $\tilde{V}i(qi)$ stands for the online retailer's total discounted profit from period i to period n with TSP qi when ignoring customer strategic behavior. Denote the online retailer's profit loss rate of ignoring customer strategic behavior by

$$r = \frac{V1(q) - \tilde{V}1(q)}{v1\ (q)}$$

It investigate how large r is and how r changes with model parameters. Let $F(x)$ be the CDF of uniform distribution over $[0,A]$, $u(x) = 1 - \exp(ax)$, $n = 3$, $N = 1000$, $Ki = 1000$, $i = 1, 2, 3$, $q0 = 0.5$, $q1 = 0.6$, $q2 = 0.7$, $q3 = 0.8$, and $\beta = 0.9$

6. Future Enhancement

Pricing and web system upgrading problems for an online retailer who faces a group of strategic customers. Due to various website issues, there is a possibility of transaction failure when a customer purchases a product through the Internet. The strategic customers can anticipate the probability of transaction failure and decide whether to purchase the product based on their belief in TSP. It have two types.

We characterize the optimal purchasing policy for customers: There exists a threshold such that a customer will buy the product if his valuation for the product is above the threshold and will not buy otherwise. Furthermore, the threshold is lower if the TSP is higher, the customer transaction cost is lower, or if customers are less risk averse.

The online retailer tends to price higher if it ignores customer strategic behavior. The cost of ignoring customer strategic behavior can be significantly high (sometimes, the profit-loss rate of ignoring customer strategic behavior can be up to 65%). To alleviate the negative effect of ignoring customer strategic behavior, the online retailer should: 1) increase customer valuations for the product by better product design or more impressive advertisement; or 2) lower customer transaction cost by providing better navigation aids. In addition, when facing less risk-averse customers, the negative effect of ignoring customer strategic behavior is lower.

These results are robust since they remain true for several extensions and variations of the model.

First, in this paper, we assume that the customers' valuation follow a distribution with increasing hazard rate, and for the situation where upgrade cost $Ci(q - qi)$ is a general concave function, our discussions are limited to the risk-neutral customers (i.e., $u(x) = x$) and the uniform valuation distribution. It will be worthwhile to relax these limitations to get the optimal upgrading policies. Second, this paper focuses on pricing and web system upgrading problems of a monopolist. It is more interesting to study similar problems when online retailers face competition from rivals. Third, this paper assumes that the TSP does not depend on the number of customers who purchase the product. It is more interesting to study similar problems when the TSP depends on the number of customers who try to purchase the product

7. Conclusion

Online retailer who faces a group of strategic customers. Due to various website issues, there is a possibility of transaction failure when a customer purchases a product through the Internet. This transaction failure rate will be reduced using threshold policy algorithm. To overcome the transaction failure using the Transaction Success Probability for optimal purchasing decision of customers. It is used reduce the time and more flexible to buy the product.

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