



CSWIM 2010

PROCEEDINGS

The Fourth China Summer Workshop on Information Management

**June 19-20, 2010
Wuhan, China**

Edited by

**Han Zhang, Georgia Institute of Technology, USA
Yaobin Lu, Huazhong University of Science & Technology,
China**



FOREWORD

Welcome to the Fourth China Summer Workshop on Information Management (CSWIM 2010), held in Wuhan, China on June 19-20, 2010. The purpose of the CSWIM is to create a bridge to promote lively exchanges in the area of information systems and management between scholars in China and other countries. In particular, CSWIM focuses on creating a unique experience for information systems (IS) researchers around the world who would like to communicate and collaborate with China-based scholars and study how information systems and technologies affect individuals, businesses, organizations, and societies. In the past three workshops (Shanghai, 2007; Kunming, 2008; Guangzhou, 2009), approximately 100 participants attended each workshop, representing most of the top IS programs in North America, China, and Asia.

The call-for-papers solicited original research papers addressing issues concerning the theory, design, development, evaluation, and application of information systems and management. As a research workshop, CSWIM encouraged submissions of research-in-progress that were innovative and thought-provoking. Research articles driven by business problems and validated with proper research methodologies were in high demand.

In total, 37 papers were presented at CSWIM 2010. This workshop was an internationally representative conference with approximately 2/5 of the papers coming from the US, 2/5 from China, and 1/5 from other parts of the world.

CSWIM 2010 Featured (1) one keynote speech: “Social Effects in Electronic Commerce” (Dr. Ting-Peng Liang, National Chair Professor of Information Management, The National Sun Yat-sen University, Fellow of the Association for Information Systems) and (2) two panels: “Cracking the Hard Nuts: Strategies and Tactics for Publishing in Top-Tier Journals in Information Systems” (Panelists: J. Leon Zhao (Chair), Paulo Goes, Vijay S. Mookerjee, Sumit Sarkar, Kwok-Kee Wei and Ping Zhang) and “The Future Directions of Information Systems Discipline in China” (Panelists: Yaobin Lu (Chair), Lihua Huang, Gang Li, Guihua Nie, and Qiang Ye).

We thank the members of the Advisory Committee (Guoqing Chen, Paulo Goes, Alan Hevner, Robert Kauffman, Ramayya Krishnan, T.P. Liang, Vijay Mookerjee, Vallabh Sambamurthy, Michael Shaw, Olivia R. Liu Sheng, Detmar Straub, Bernard Tan, Kwok-kee Wei and Andrew B. Whinston), who gave us advice and encouragement throughout the preparation stages of the workshop. We are grateful to the PC members for their diligent work during the short review cycle. The importance of the Best Paper Award Committee (Yong Tan (Chair), Paulo Goes and Zhangxi Lin) cannot be overemphasized; its members’ collective insight, experience, and fairness enabled CSWIM 2010 to nominate the best candidates and final winner of the Best Paper Award.

Special thanks are owed to the sponsors of CSWIM 2010, including the School of Management, Huazhong University of Science & Technology; the College of Management, Georgia Institute of Technology; the Alfred Lerner College of Business & Economics, University of Delaware; and the Information Systems Society.

Furthermore, we would like to thank our Publication Chair and Webmaster Harry Jiannan Wang, currently an assistant professor at University of Delaware, for his diligent work in customizing and maintaining the conference system. We also want to acknowledge the superb service of the Local Arrangement Co-Chairs, Dr. Xuefeng Zhao and Dr. Qihong Wang, of Huazhong University of Science & Technology, China, whose tireless work made it possible to have a successful workshop in Wuhan.

Finally, we would like to acknowledge the contribution and support of the Honorary Chair Dr. Jinlong Zhang, Dean of the School of Management, Huazhong University of Science & Technology. Dr. Zhang and his school provided tremendous financial support for CSWIM 2010. Without him, CSWIM 2010 would not have been a success!

We hope that you enjoyed CSWIM 2010, and that you will remain involved in future CSWIM conferences. Information about CSWIM 2010 is at <http://process.lerner.udel.edu/cswim2010>.

Han Zhang, Georgia Institute of Technology, USA
Yaobin Lu, Huazhong University of Science & Technology, China
Co-Chairs of CSWIM 2010

Table of Content

Session 1A: Online Pricing	7
Payment Schemes for Internet Advertising: A Tale of Two-sided Information Asymmetry (Nominated for Best Paper Award)	7
Pricing Tied Digital Contents and Devices	13
Oligopoly Pricing under Ordered Search (Nominated for Best Paper Award)	17
Session 1B: Technology Adoption and Technology Use	23
E-Commerce Adoption in Chinese Martial Arts Schools	23
What Make Them Happy and Curious Using the Internet? ——An Exploratory Study on High School Students’ Internet Use from a Self-Determination Theory Perspective	28
Explaining the Role of User Commitment in Innovative Use of Information Systems.....	33
Session 1C: Data mining and Applications.....	39
Mining User Opinions in Social Network Webs.....	39
The Dynamic Detection of Influenza Epidemics Using Google Search Data	45
Exploiting Item Heterogeneity for Collaborative Filtering Recommendation.....	52
Session 2A: IT productivity	58
How Does Information Technology Affect Inventory? The Role of Moderators and Mediators	58
Does IT Matter? The Evidence	63
Session 2B: Economics of IT	70
Offer Sets, User Profiles, and Firm Payoffs (Nominated for Best Paper Award)	70
Co-development of Software and Community Formation	75

Session 2C: Success of Products, Services and Systems	80
A Pilot Study of Top-Down Compulsory eGovernment Systems Success Model:	
Organizational Users Perspective.....	80
Are You Doing It in the Right Way? The Effects of Regulatory Fit in IT Product Trial	85
Session 3A: Risk, Trust and Privacy	91
An Empirical Study on the Sources of C2C Sellers' Perceived Risk and Their Corresponding	
Relationship with Perceived Risk Types.....	91
Disclosure or Disclosure Avoidance? Internet Users' Information Privacy and Emotions	
Experienced on a B2C Web Site	96
Analysis of Online P2P Lending Market Risk Based on Signaling Game	103
Session 3B: Online Consumer-to-Consumer (C2C) Markets	108
Learning from Other Buyers: the Effect of Purchase History Record in Online	
Marketplaces	108
Inflated Reputation Detection in C2C E-market.....	114
Age Effect on Firm Exit in the Online C2C Market	119
Session 3C: IT Services	124
The Effect of Information-Sharing Services on Enterprise Customer Loyalty Intention	124
Research on the Impact Factors of Using Mobile Enterprise Services in Hubei	130
Comparing Service Quality in 3D Virtual Worlds to Web-based Service.....	137
Session 4A: Online Business-to-Consumer (B2C) Markets	143
Advertising Effects of Online Social Capital on E-tailer Performance: A Theoretical	
Framework	143

Research on Dual-channel Coordination of Reservation Tourism Supply Chain in the E-commerce Environment	149
Session 4B: Electronic Markets	154
An Empirical Analysis of Participant Contribution and Duration of Participation in Electronic Brainstorming Communities	154
Predictive Power of Internet Search Data for Stock Market: A Theoretical Analysis and Empirical Test	159
Session 4C: Technical Issues in Electronic Markets.....	165
XBRL and Interoperability of Financial Statements in the U.S.	165
Inter-organization Collaboration Management in Dynamic Virtual Alliances	171
Session 5A: User Attitude, Web 2.0 and Online Communities.....	178
Crowding In or Crowding Out? Informational and Normative Social Influence in Online Communities (Best Paper Award Winner)	178
User Attitude toward Adaptive Interfaces of Mobile Web Services.....	184
A Value Based Analysis of Web 2.0 Usage.....	189
Session 5B: Media Selection Preferences and Online Reviews.....	194
Media Selection Preferences of US College Students: Empirical Evidence and A Proposed Research Model.....	194
A Model Based Measurement of "Helpfulness" of Online User Review	199
Online User Reviews and Expert Opinions: A Bayesian Hierarchical Approach to Model the Mediating Role and Time-Variant Impact	205
Web 2.0 Online Reputation Systems.....	211

Payment Schemes for Internet Advertising: A Tale of Two-sided Information Asymmetry¹

De Liu
University of Kentucky
de.liu@uky.edu

Siva Viswanathan
University of Maryland
sviswana@rhsmith.umd.edu

Abstract

This study examines how the uncertainties facing advertisers about the quality of a publisher and the uncertainties facing publishers about the quality of advertisers affect the optimal choice of payment schemes (such as pay-per-impression, pay-per-click, and pay-per-sale) in keyword auctions.

Keywords: Analytical Modeling, Internet Advertising, Payment Scheme, Auction

1. Motivation

The growth of digitization has led to the emergence of new business models and pricing mechanisms in a wide range of sectors including financial services, consumer retailing, and advertising among others. The advertising sector, in particular, has undergone significant changes in terms of both the technologies used, as well as the payment mechanisms. Digital technologies have improved the targetability (the ability to target individual consumers) as well as the measurability (the ability to measure the outcomes) of advertising giving rise to a number of new payment schemes that try to cater to the differing needs of publishers as well as advertisers. The three most commonly used payment schemes are (i) Pay-per-impression (PPI), wherein advertisers are charged for each impression or exposure, (ii) Pay-per-Click (PPC), wherein the advertiser pays only when a user clicks on the link, and (iii) Pay-per-Sale (PPS), where in the advertisers pay only when a sale, originating from the advertisement, is consummated. As we move from PPI to PPS, the payments (i.e., the advertising expenses) are more closely tied to the outcomes (i.e., the advertisers' sales and revenue). It is not surprising then that, PPS is often considered the holy grail of advertising. However, the predictions that these new payment mechanisms (PPC and PPS, in particular) would supplant the more common PPI mechanism have not materialized. On the contrary, these different payment mechanisms coexist, with some publishers still choosing PPI over PPC and PPS. Given the choice of these three payment schemes, this paper examines the optimal choice of payment scheme for a publisher.

2. Modeling Primitives

We formulate the problem setting as one in which the advertiser's valuation of advertising resources (impressions) are determined by (hidden) characteristics of both the publisher and the advertiser. The model assumes that the transaction occurs between a single publisher (drawn from a pool of publishers) and n advertisers. The publisher has a single advertising slot to offer and decides which advertiser will get the slot via an auction. Consumers' respond to the advertisement in three successive steps: impressions (I), clicks (C), and sales (S). We focus on

¹Research in progress.

the transition from I to C (stage 1) and from C to S (stage 2). The rates of successful transition in each stage, denoted by CPI (the click-through rate) and SPC (the conversion rate), are determined by both advertiser factors and publisher factors. Specifically, we model the CPI as $A_1 B_1$ and SPC as $A_2 B_2$, where $A_1 \in \{A_{1l}, A_{1h}\}$ and $A_2 \in \{A_{2l}, A_{2h}\}$ represent advertisers' CPI and SPC rates and $B_1 \in \{B_{1l}, B_{1h}\}$ and $B_2 \in \{B_{2l}, B_{2h}\}$ represent the publisher's CPI and SPC rates respectively. Therefore the rate of transitioning from I to S can be decomposed as:

$$\underbrace{A_1 A_2 B_1 B_2}_{\text{Sales Per Impression}} = \underbrace{A_1 B_1}_{\text{Click Per Impression}} \times \underbrace{A_2 B_2}_{\text{Sales Per Click}}$$

The rates of the publisher and advertisers (A_1 , A_2 , B_1 and B_2) are independently drawn from their respective pools. We denote a_1 and a_2 as the proportions of stage-1 and stage-2 h-type advertisers respectively, and b_1 and b_2 as the proportions of stage-1 and stage-2 h-type publishers (in the publisher pool) respectively. An advertiser's valuation for a sale is $v \in [\underline{v}, \bar{v}]$. v is advertiser's private information and is distributed according to $F(v)$ with density $f(v)$.

The misclassification and the perceived types: The publisher and the advertisers can learn each other's rate types with some imperfection. We model this imperfection through the notion of misclassification. Specifically, a publisher misclassifies an advertiser's rate type (from l to h or from h to l) with probability α . She correctly classifies the advertiser with probability $1-\alpha$. Similarly, the advertiser misclassifies a publisher with probability β . We also assume all advertisers agree on the classification of a publisher. Because of misclassification, the proportions of *perceived* rate types at each stage are different from those of the true types. We denote \hat{a}_1 and \hat{a}_2 as the proportion of *perceived* h-type advertisers at two stages. Correspondingly, we use denote $A_1 \in \{\hat{A}_{1h}, \hat{A}_{1l}\}$ and $\hat{A}_2 \in \{\hat{A}_{2l}, \hat{A}_{2h}\}$ as the expected rates of *perceived* advertiser types at two stages. Naturally, $A_{sl} \leq \hat{A}_{sl} \leq \hat{A}_{sh} \leq A_{sh}$, $s=1, \dots, 2$.

Auction formats: Each publisher chooses one of the three payment schemes, PPI, PPC, and PPS. Under PPI, advertisers are ranked by willingness-to-pay (WTP) per impression. The winner pays the second highest price. Under PPC or PPS, the publisher considers advertisers' expected rates of clicks or sales when ranking their bids. Specifically, under PPC, advertisers are ranked by WTP per click times perceived rate of clicks \hat{A}_1 . The winner pays the lowest per-click price that makes him stay ahead of the next highest advertiser (we call such auction a "second-score auction"). Under PPS, advertisers are ranked by WTP per sale times perceived rate of sales (per impression) $\hat{A}_1 \hat{A}_2$. Once again, a second-score payment rule applies.

A publisher's choice is a mapping from the publisher's type $\{ll, lh, hl, hh\}$ to payment schemes. Denote $g_{t_1 t_2}^m$ as the probability for a publisher with stage-1 type $t_1 \in \{l, h\}$ and stage-2 type $t_2 \in \{l, h\}$ to choose a payment scheme $m \in \{I, C, S\}$.

3. Publisher's Revenues under Different Payment Schemes

Lemma 1: *In the second-score PPI (PPC, PPS) auctions with one slot, the advertisers will bid their true unit-valuation.²*

As a result of Lemma 1, we can characterize the equilibrium winning probabilities under each payment scheme ($t_1, t_2 \in \{l, h\}$ represent the perceived type of a random bidder at stage 1 and stage 2 respectively).

$$\begin{aligned}\phi^I(vA_1A_2) &= \left[\sum_{t_1, t_2} \Pr(A_{1t_1}A_{2t_2}) F(vA_1A_2 / (A_{1t_1}A_{2t_2})) \right]^{n-1} \\ \phi^C(v\hat{A}_1A_2) &= \left[\sum_{t_1, t_2} \Pr(\hat{A}_{1t_1}A_{2t_2}) F(v\hat{A}_1A_2 / (\hat{A}_{1t_1}A_{2t_2})) \right]^{n-1} \\ \phi^S(v\hat{A}_1\hat{A}_2) &= \left[\sum_{t_1, t_2} \Pr(\hat{A}_{1t_1}\hat{A}_{2t_2}) F(v\hat{A}_1\hat{A}_2 / (\hat{A}_{1t_1}\hat{A}_{2t_2})) \right]^{n-1}\end{aligned}$$

We denote (note that in PPI, $\hat{A}_{1t_1} = A_{1t_1}, \hat{A}_{2t_2} = A_{2t_2}$ and in PPC, $\hat{A}_{2t_2} = A_{2t_2}$)

$$\pi_{base}^m = \sum_{t_1, t_2} \Pr(\hat{A}_{1t_1}\hat{A}_{2t_2}) \hat{A}_{1t_1}\hat{A}_{2t_2} \int_{\underline{v}}^{\bar{v}} \phi^m(v\hat{A}_{1t_1}\hat{A}_{2t_2}) J(v) dv, m \in \{I, C, S\}, J(v) = vf(v) - [1 - F(v)]$$

Lemma 2: A publisher's total expected revenue is given by

$$\begin{aligned}\pi^I(B_1, B_2) &= \sum_{t_1, t_2} \Pr(\hat{B}_{1t_1}^I, \hat{B}_{2t_2}^I | B_1, B_2) \hat{B}_{1t_1}^I \hat{B}_{2t_2}^I \pi_{base}^I \\ \pi^C(B_1, B_2) &= \sum_{t_2} \Pr(\hat{B}_{2t_2}^C | B_2) B_1 \hat{B}_{2t_2}^C \pi_{base}^C \\ \pi^S(B_1, B_2) &= B_1 B_2 \pi_{base}^S\end{aligned}$$

As can be observed from the above expressions, the revenues can be separated in B -part (B and \hat{B} 's) and the *base revenue* part. The B -part captures the effect of being misclassified by the advertisers and the base revenue captures the impact of misclassifying advertisers. When there is no error in classifying advertisers, the base revenue part is equal among three payment schemes. With errors in classifying advertisers, the base revenues can be generally ranked as $\pi_{base}^I > \pi_{base}^C > \pi_{base}^S$, reflecting the increasing inaccuracy in selecting the best advertiser. The efficiency loss under PPC and PPS becomes more prominent as 'n' increases because the error of selecting a l-type of advertiser is especially severe when there are many other more qualified advertisers. On the other hand, an h-type publisher prefers to being viewed as having a rate of B than \hat{B} (the latter is generally smaller than the former). While the publisher might prefer a particular payment scheme for its signaling properties, she has to balance this against the potential risk of greater misallocation associated with the payment scheme. Based on the revenue formulas, we have the following results about the equilibrium choices of payment schemes.

Proposition 1:

- (1) When there is no error in classifying publishers, all publisher types adopt PPI.
- (2) When there is no error in classifying advertisers, ll→PPI, lh→PPS, hl→PPC, and hh→PPS.
- (3) ll-type and hl-type publishers will never choose PPS.
- (4) hh-type and lh-type publishers must rank PPS and PPC the same way.

² Due to space limitation, all proofs and derivations are omitted and available upon request.

We next discuss the implications of Lemma 2 and Proposition 1. The figures (see Fig. 1, Fig. 2, and Fig. 3) illustrate the optimal choice of payment schemes by the publisher as a function of the misclassification (error) rates of the advertisers (in the X-axis) as well as the publisher's (Y-axis). The optimal choices of payment schemes for lh-type, hl-type, and hh-type publishers are illustrated in Fig. 1, Fig. 2, and Fig. 3 respectively. The ll-type's optimal choice is always PPI and thus omitted.

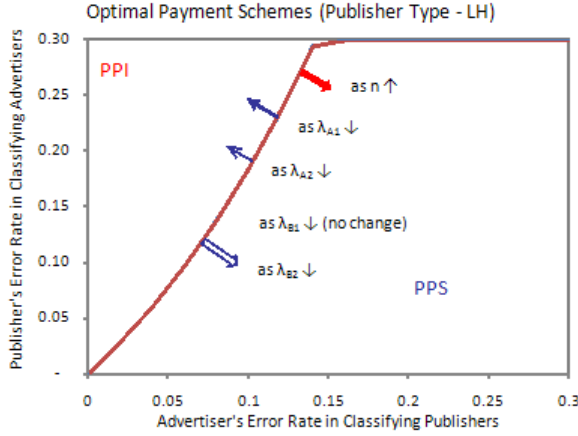


Figure 1

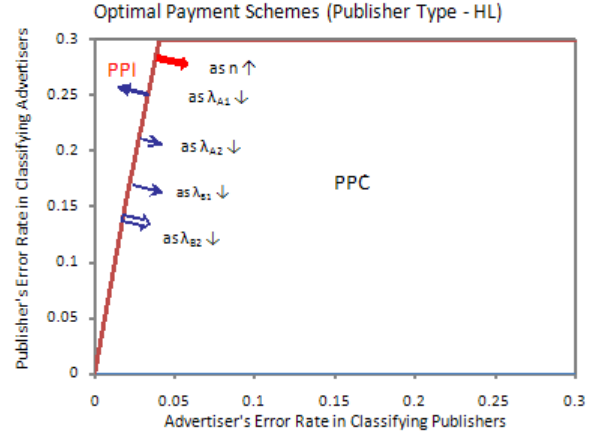


Figure 2

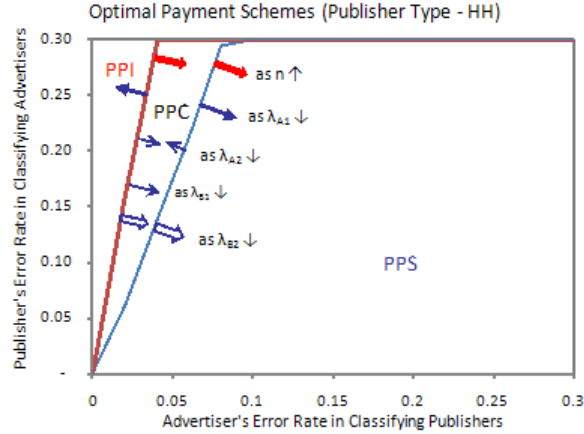


Figure 3

Recall that a higher-order payment scheme (in the order of $PPI \rightarrow PPC \rightarrow PPS$) allows an h-type publisher to avoid being misclassified as an l-type but also requires the publisher to estimate advertisers' rates which may result in efficiency loss when misclassification occurs. As a result, a publisher will "advance" to a higher-order payment scheme only if the benefit from "separation", which is enjoyed only by h-type, overcomes the loss of efficiency from misclassifying advertisers. An lh-type publisher never chooses PPC (Fig. 1) because it provides her no benefit of separating from other types. For a similar reason, an hl-type publisher never chooses PPS (Fig. 2). An hh-type publisher may choose either payment scheme (Fig. 3).

When advertiser's error rate (in classifying publishers) increases, an h-type publisher is worse off under payment schemes where she may be misclassified as an l-type (such as PPI and PPC). This explains why when advertisers' error rates increase, the lh-type publisher moves from PPI to PPS,

the hl-type moves from PPI to PPC, and the hh-type moves from PPI to PPC and to PPS. When the publisher's error rate in classifying advertisers increases, a publisher is worse off under payment schemes where she must classify advertisers. This explains why when the publisher's own error rate increases, the lh-type publisher moves from PPS to PPI, the hl-type moves from PPC to PPI, and the hh-type moves from PPS to PPC and to PPI.

As we indicate earlier, as the number of advertisers 'n' increases, the revenue loss from misclassifying advertisers under PPC and PPS is relatively more pronounced. As a result, lh-type, hl-type, and hh-type publishers move away from PPC and PPS as 'n' increases.

When the conversion rates of advertisers become more homogeneous (λ_{A2} decreases), lh-type and hh-type publishers prefer PPS more because as the advertisers become more homogeneous, the loss from misclassifying those decreases. But we also see hl and hh type publishers are marginally more likely to offer PPI. This is because similar to the case of increasing 'n', the increase of homogeneity among advertisers intensifies competition and makes the misclassification error more pronounced, which is in favor of PPI. Similarly, when the click-through rates of advertisers become more homogeneous (λ_{A1} decreases), lh-type, hl-type, and hh-type's preference for PPC and PPS increases relative to PPI because the loss from misclassifying advertisers' click-through rates decreases.

When the click-through rates of publishers become more homogeneous (λ_{B1} decreases), hl-type and hh-type publishers prefer PPI more because as the publisher pool becomes more homogeneous in click-through rates, the need for high click-through-rate publisher to separate decreases. When the conversion rates in the pool of publishers become more homogeneous (λ_{B2} decreases), lh and hh type publishers prefer PPS less due to their reduced need for separating.

4. Concluding Remarks

The above findings have interesting implications for publishers as well as advertisers. As the technologies that enable publishers to predict the performance of advertisers improve, advanced payment schemes become more popular. High quality publishers are more likely to benefit from such technologies as they enable these high quality publishers to separate themselves from the pack without much adverse impacts. However, as the demand increases significantly (i.e., as the competition among advertisers increases), publishers are more likely to resort to PPI, and have little incentive to adopt the more advanced payment schemes (PPC and PPS). For publishers who are good at attracting clicks, but not very good at converting these click to sales (search engines, for instance), PPC is still the dominant choice, and is unlikely to disappear. Further, in markets where conversion rates among advertisers are more homogeneous, PPS is more likely and PPC is less likely, while in markets where click-through-rates among advertisers are more homogeneous, PPI is less likely and PPC is more likely. On the other hand, in markets where conversion rates among publishers are more homogeneous, PPI is more likely and PPS is less likely, while in markets where click-through rates among publishers are more homogeneous, PPI is more likely and PPC is less likely.

A natural extension of our current analysis is to allow the publisher to offer multiple payment

schemes so that advertisers can self-select themselves into different payment schemes. Our ongoing work includes an investigation of whether or not the publisher should offer multiple payment schemes at the same time and if yes, how the publisher should choose between advertisers using different payment schemes.

Pricing of Tied Digital Contents and Devices

Deb Dey

Ming Fan

Lin Hao

University of Washington

Seattle, WA 98195

{ddey, mfan, linhao}@uw.edu

Abstract

Media companies are increasingly offering digital content online. In this study, we aim to study the following questions: How do consumers value tied products such as digital contents that they are likely to buy repeatedly? How do Companies price digital device and contents? We have studied pricing strategies for a monopoly provider of digital device and contents. Our results suggest the provider would price the contents at marginal price and device higher than marginal price when consumers are homogeneous. When there are two types of consumers, the provider can develop two pricing plans, still charging marginal price of digital contents for high-demand customers, but a higher price for contents for low-demand customers.

Keywords: digital media, pricing, tying

1. Introduction

Media companies are increasingly offering digital content online. Apple Computer is one of the pioneers in selling digital music at its iTunes store. Consumers can buy digital songs and videos starting at just 99 cents a piece (Taylor, 2003). With the high speed Internet, Apple, Netflix, TiVo and some other companies are providing videos directly to televisions at home. As “the last bastion of analog”, according to Amazon.com’s founder Jeff Bezos, books will be digitized as well (Levy 2007). Amazon.com introduced its popular e-book reader Kindle in 2007 and sells digital versions of New York Time best sellers and new releases for just \$9.99.

In this study, we aim to study the following questions: How do consumers value tied products such as digital contents that they are likely to buy repeatedly? How do Companies price digital device and contents?

2. Monopoly Market

In the monopoly case, a firm sells both the digital device and the digital contents. The contents and the digital device are tied, which means that the firm makes the sale of the digital contents, e.g. e-books, conditional upon the purchasers also buying the device, e.g. Kindle, from the same firm. The contents can only be played at the tied digital device and the major function of the digital device is to play the digital contents.

We let the unit price of digital contents to be p_e . Following Laffont et.al (1998), we assume the demand function for digital contents has a constant elasticity:

$$q_e = \theta \cdot p_e^{-\eta},$$

where η is the elasticity of demand and $\eta > 1$ and $\theta > 0$. Thus, the price function is:

$$p_e = \left(\frac{q_e}{\theta} \right)^{-\frac{1}{\eta}}.$$

A consumer's net surplus from purchasing digital contents is:

$$v(p_e) = \int_0^{q_e} p_e dq_e - p_e q_e = \frac{\theta \cdot p_e^{-\eta+1}}{\eta-1}.$$

Consumers have heterogeneous preferences, α , for the digital device. The α is uniformly distributed in $[0,1]$. Let the digital device's price be p_k . The utility of the tied digital contents and device is:

$$\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - p_k - \frac{\alpha}{\sigma}$$

where the $\sigma > 0$ is a scaling constant.

A consumer will make a purchase if her utility is greater than 0, i.e.

$$\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - \frac{\alpha}{\sigma} - p_k > 0.$$

We find the point α_0 when a consumer is indifferent between purchasing or not purchasing:

$$\alpha_0 = \sigma \cdot \left(\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - p_k \right).$$

All consumers with $\alpha < \alpha_0$ will choose to purchase. Thus, the demand function for the tied contents and device is

$$D = \sigma \cdot \left(\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - p_k \right).$$

Let the unit cost of digital contents be c_e and the cost of the digital device be c_k . The total profit for the firm is:

$$\pi = \left((p_e - c_e) \cdot \theta \cdot p_e^{-\eta} + (p_k - c_k) \right) \cdot \sigma \cdot \left(\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - p_k \right).$$

Solving the above problem leads to the following result:

Proposition 1. When $c_k < \frac{\theta \cdot c_e^{(-\eta+1)}}{\eta-1}$, the optimal prices for the tied contents and device are:

$$p_e^* = c_e, \text{ and } p_k^* = \frac{1}{2} \left(\frac{\theta \cdot c_e^{(-\eta+1)}}{\eta-1} + c_k \right),$$

This proposition implies that the firm should gain the profit from the sales of the digital device rather than the digital content. Also, $c_k < \frac{\theta \cdot c_e^{(-\eta+1)}}{\eta-1}$ is a reasonable assumption. When the firm sets both the device and contents prices at their marginal costs, we expect the demand for the bundle will be great than zero, i.e. $\sigma \cdot \left(\frac{\theta \cdot p_e^{-\eta+1}}{\eta-1} - c_k \right) > 0$, which is exactly the condition for Proposition 1. Otherwise, no consumers will ever purchase the device and digital contents.

From Proposition 1, we know that the monopoly provider sets the price for digital contents equal to the marginal cost.

3. Heterogeneous Customers and Differentiated Pricing

In the previous section, we assume that consumers are homogeneous regarding their demand on digital contents. A more realistic situation is that consumers may consumer different amount of contents given the same price. In this section, we assume there are two types of consumers. The monopoly firm may use differentiated pricing in order to maximize its profits. We analyze a sequential game. In the first stage, the monopoly firm sets two different pricing plans. In the second stage, each consumer segment selects the plan that maximizes its own utilities. Consumers also have the option of not consuming the bundle.

The two types of consumers differ in their demand for digital contents. The high-demand consumers consume more digital contents than the low-demand ones. The demand function for the high-demand consumers is $q_{eH} = \theta_H \cdot p_{eH}^{-\eta}$, while the low-demand consumers' demand function is: $q_{eL} = \theta_L \cdot p_{eL}^{-\eta}$ where $\theta_H > \theta_L > 0$, and p_{eH} and p_{eL} are the content prices for set for high-demand and low-demand consumers, respectively.

The optimization problem has to satisfy the following two incentive compatible (IC) constraints:

$$\begin{aligned} \frac{\theta_H \cdot p_{eH}^{-\eta+1}}{\eta-1} - p_{kH} - \frac{\alpha}{\sigma} &\geq \frac{\theta_H \cdot p_{eL}^{-\eta+1}}{\eta-1} - p_{kL} - \frac{\alpha}{\sigma}, \\ \frac{\theta_L \cdot p_{eL}^{-\eta+1}}{\eta-1} - p_{kL} - \frac{\alpha}{\sigma} &\geq \frac{\theta_L \cdot p_{eH}^{-\eta+1}}{\eta-1} - p_{kH} - \frac{\alpha}{\sigma}. \end{aligned}$$

In addition, it also has to satisfy the following two individual rational (IR) constraints,

$$\begin{aligned} \frac{\theta_L \cdot p_{eL}^{-\eta+1}}{\eta-1} - p_{kL} &\geq 0 \\ \frac{\theta_H \cdot p_{eH}^{-\eta+1}}{\eta-1} - p_{kH} &\geq 0 \end{aligned}$$

Lemma 1. The equilibrium content prices have to satisfy: $p_{eH}^* \leq p_{eL}^*$.

Lemma 2. Only the first IC condition needs to be binding, which can be simplified as:

$$\frac{\theta_H \cdot (p_{eH}^{-\eta+1} - p_{eL}^{-\eta+1})}{\eta-1} \geq p_{kH} - p_{kL}$$

Thus, the firm's problem as follows:

$$\begin{aligned} \max \pi &= \pi_L + \pi_H \\ \text{s.t.} \quad &\frac{\theta_H \cdot (p_{eH}^{-\eta+1} - p_{eL}^{-\eta+1})}{\eta-1} \geq p_{kH} - p_{kL} \end{aligned}$$

Solving the firm's problem, we can derive the following result:

Proposition 2. When $c_k < (1-a) \cdot \frac{\theta_H \cdot c_e^{-\eta+1}}{\eta-1}$, there exists a unique equilibrium, in which the firm offers two sets of pricing plans: (p_{eH}^*, p_{kH}^*) and (p_{eL}^*, p_{kL}^*) . The high-demand consumers choose (p_{eH}^*, p_{kH}^*) and low-demand consumers choose (p_{eL}^*, p_{kL}^*) .

Proposition 3 suggests that a separating equilibrium exists. The monopoly firm can design two pricing plans and consumers will self-select the plan that works best for their type.

4. Conclusions

We have studied pricing strategies for a monopoly provider of digital device and contents. Our results suggest the provider would price the contents at marginal price and device higher than marginal price when consumers are homogeneous. When there are two types of consumers, the provider can develop two pricing plans, still charging marginal price of digital contents for high-demand customers, but a higher price for contents for low-demand customers. Future studies will examine pricing policies when there are multiple players in the marketplace.

5. References

1. Laffont, J., Rey P., Tirole, J. "Network Competition: I. Overview and Nondiscriminatory pricing," *RAND Journal of Economics* (29:1), 1998, pp. 1-37.
2. Levy, S. "The Future of Reading," *Newsweek*, Nov 17, 2007.
3. Taylor, C. "The 99 Cents Solution," *Time*, November 17, 2003.

Oligopoly Pricing under Ordered Search

Lizhen Xu
University of Texas at Austin
xulizhen@gmail.com

Jianqing Chen
University of Calgary
jiachen@ucalgary.ca

Andrew Whinston
University of Texas at Austin
abw@uts.cc.utexas.edu

Abstract

We set up a game-theoretic model to examine the oligopolistic price competition, given the two unique features of online search, namely, the existence of a common search ordering and shoppers who have non-positive search cost. We show that in absence of further heterogeneity, the unique online search behaviors alone can drive significant level of price dispersion. Specifically, we derive two-dimensional price dispersion, with both temporal fluctuation and spatial variation. We show that equilibrium price expectation monotonically decreases in line with consumers' search ordering. We also uncover a unique format of equilibrium pricing with stair-like sequence of price supports and localized price competition.

Keywords: Pricing, Online Search

1. Introduction

Researchers have been devoting to exploring the driving forces of the well observed online price dispersion. Various theories emphasize the differentiation among products, from the actual differentiation in product quality or firms' competitive advantage to the virtual differentiation such as brand recognition. We take a different perspective and try to explain online price dispersion in absence of the heterogeneity among products and firms.

One classic view attributes price dispersion to the heterogeneity in consumers' search behavior. Compared to traditional off-line search, the Internet has revolutionized the way people search, largely owing to the powerful online search engines. In addition to providing relevant information to users' search queries, search engines are also able to gather numerous merchant sites competing in the same product market under the revolutionary advertising model---search advertising. In search advertising, by listing advertising links (or sponsored links) alongside search results for specific keywords according to advertisers' bids, search engines respond to potential consumers' queries by providing a list of merchant sites selling similar products which consumers are interested in.

Motivated by the unique features of consumers' online search behavior in association with search advertising, we study how these features affect the resulting price dispersion. Compared to traditional off-line search, there are at least two distinctive features in consumers' online search behaviors: (i) There exists a commonly observed ordering; (ii) Consumers search costs are highly diversified, in particular, there exist “shoppers” who have non-positive search cost.

The first feature of online search behavior originates from the organization of advertisements in search engine result pages. The common format is that the sponsored links are listed on the right column alongside the organic search results, one after another from the top downward. Due to

the reading habit and eye-movement pattern of most human beings, consumers usually process the information following the order of the list, from the top downward. Therefore, consumers generally first pay attention to the top advertising slot of the sponsored list, and then the next, and so on, while some of them stop searching in between. The arrangement of advertisements and the resulting ordering of the search create a huge prominence difference among advertising slots with different ranks.

The second feature owes to the advance of information technology, which greatly facilitates informational searches by significantly reducing the physical search cost. The physical cost to sample a product and quote the price from a store, which would otherwise be a non-negligible expense with necessary travel to the store, is now only several mouse clicks. In addition, some consumers do derive hedonic utility from shopping online (Childers et al., 2001): They enjoy the process of searching different places, comparing prices, and finding the best deal, evidenced by those who spend hours and hours surfing the web to shop. Altogether, with the flourishing of the Internet and online search engines, there arises a certain portion of consumers who have a non-positive (zero or even negative) net search cost. We call them *shoppers*. On the other hand, however, not everybody purchasing online has such luxury. The convenience of e-commerce brings many people with stringent time constraints, whose only goal is to find the product with a minimum of time spend. In addition, the information overload with the Internet and the extra skills needed to accomplish computer-based searches add to the cost for some online consumers. Therefore, there also exists a certain number of consumers who have a positive search cost, whom we may refer to as *non-shoppers*.

2. Model

There are n (≥ 2) firms selling homogeneous products and competing for consumers in a product market. These firms have a same marginal production cost, which is normalized to zero. There is a continuum of consumers with unit mass. Each consumer has a unit demand of the product and realizes a unit utility by consuming the product. Therefore, consumers will buy the product only if its price does not exceed 1. Essentially, firms are identical except for their ranks in the search ordering, and consumers are identical except for their search behavior.

Consumers obtain product information through an online search engine, which lists hyperlinks directed to firms' websites where purchase can be conducted directly. Firms are placed at different positions in the list, which can be viewed as an outcome of pre-game competition such as bidding competition. Because all firms are identical ex ante, the location competition outcome is irrelevant for analyzing the price competition. Therefore, we do not include the location competition in the model but start from after firms get placed at different positions. Different positions have different prominence levels which can be strictly ordered. Without loss of generality, we call the most prominent position the first position, the second most prominent position the second one, and so on. For convenience, we call the firm at the i th position firm i ($i = 1, \dots, n$). Consumers' search behavior is modeled in a way reflecting the two unique features of online search pattern: First, there exists a commonly observed search ordering so that all consumers start searching from the first position and may continue to the second, then the third, and so forth. Second, consumers' search costs are highly diversified so that they may stop the

searching process at different stages. Especially, there exists a certain portion of shoppers, who have non-positive search cost, sampling all positions before making the purchase decision.

We start with the case in which consumers' sequential search decision is treated as exogenously given. Assume that after sampling the i th position, a portion of α_i ($0 < \alpha_i < 1$) stops searching, while the other $1 - \alpha_i$ continue to sample the next position, such that the portion who visit the i th ($i \geq 2$) position is $\prod_{j=1}^{i-1} (1 - \alpha_j)$. To rule out violent fluctuation in the attention declining rates α_i 's, we make the smoothness assumption that $\alpha_i \geq \alpha_{i+1}(1 - \alpha_i)$ ($1 \leq i < n$). This condition requires that the attention declining rates do not increase dramatically from one to the next, which can be easily satisfied (e.g., a same declining rate across positions ($\alpha_i = \alpha_{i+1}$) satisfies this condition). We can also endogenize consumers' search decision to show that similar results continue to hold to some degree.

The timing of the game is as follows. Firms first get placed at different positions in the search list. Based on their own positions, they price the product simultaneously. Consumers sample the position(s), learn the price(s), and make the purchase decision. For those who sample at least two positions, they purchase from the firm with the lowest price. When there is a tie in the lowest price, they randomly pick one firm with equal probability.

3. Analysis and Results

We first derive firms' equilibrium pricing strategies and then analyze the pattern of equilibrium price dispersion. In deriving the equilibrium pricing, first notice that due to the existence of shoppers, any static pricing is unstable.

Lemma 1: There is no pure-strategy equilibrium in the price competition.

Since there exists a certain portion ($\prod_{j=1}^{n-1} (1 - \alpha_j)$) of consumers who sample all positions to look for the lowest price, a slight cut in price to become the lowest can lead to a significant increase in market share by capturing this portion of consumers. As a result, competing firms keep lowering their prices relative to the rivals. However, once the price is pushed to the lowest possible level (i.e., the competitive price), firms end in zero profitability. In this case, the firm at a better position in terms of the search ordering may deviate to achieve positive profit by charging a higher price and exploiting those consumers who stop searching right there. Therefore, any pricing strategy in which firms statically stay with one price cannot be stable. In other words, due to the presence of shoppers and the locational asymmetry created by the search ordering, it is not surprising that no pure-strategy equilibrium exists in the price competition.

Naturally, we next examine the mixed-strategy equilibrium pricing. We use $F_i(p)$, $i = 1, \dots, n$, to describe firm i 's mixed strategy of pricing. Like regular cumulative distribution functions, $F_i(p)$ measures the probability that firm i charges a price less than or equal to p .

Proposition 1: The equilibrium mixed strategy of pricing from position i is as follows.

$$\begin{aligned}
F_i(p) &= \begin{cases} 1 - \frac{\bar{p}_{i+1}}{p} & p \in [\bar{p}_{i+1}, \bar{p}_i) \\ 1 - \frac{\alpha_{i+1}(\bar{p}_{i+1} - p)}{\alpha_i(1 - \alpha_{i+1})p} & p \in [\bar{p}_i, \bar{p}_{i-1}] \end{cases} \quad (1 \leq i \leq n-1) \\
F_n(p) &= 1 - \frac{\alpha_{n+1}(\bar{p}_{n+1} - p)}{(1 - \alpha_{n+1})p} \quad p \in [\bar{p}_n, \bar{p}_{n-1}]
\end{aligned} \tag{1}$$

where \bar{p}_i 's are recursively defined as

$$\begin{aligned}
\bar{p}_0 &= \bar{p}_1 = 1 \\
\bar{p}_i &= k_{i-1} \bar{p}_{i-1} \quad (i = 2, \dots, n)
\end{aligned} \tag{2}$$

The coefficients k_i 's are recursively defined as

$$\begin{aligned}
k_{n-1} &= \alpha_{n-1} \\
k_i &= \frac{\alpha_i}{\alpha_i + \alpha_{i+1}(1 - \alpha_i)k_{i+1}} \quad (i = n-2, \dots, 1)
\end{aligned} \tag{3}$$

We use an example to illustrate the pattern of the equilibrium mixed-strategy pricing.

Example 1: Take a case of four positions with a same declining rate as an example. Specifically, let $n = 4$ and $\alpha_1 = \alpha_2 = \alpha_3 = 1/2$. According to the above recursive definition in Eq.(3), $k_3 = \alpha_3 = 1/2$, and it can then be derived $k_2 = 4/5$ and further $k_1 = 5/7$. Thus, according to Eq.(2), $\bar{p}_1 = 1$, $\bar{p}_2 = k_1 \bar{p}_1 = 5/7$, $\bar{p}_3 = k_2 \bar{p}_2 = 4/7$, and $\bar{p}_4 = k_3 \bar{p}_3 = 2/7$. Notice that by definition, the sequence of price support bounds $\{\bar{p}_i\}_{i=1}^n$ is monotonically decreasing, so that $\bar{p}_1 > \bar{p}_2 > \bar{p}_3 > \bar{p}_4$. The pricing strategies of the four firms are as follows.

$$\begin{aligned}
F_1(p) &= \begin{cases} 1 - \frac{5}{7p} & p \in [\frac{5}{7}, 1) \\ 1 & p = 1 \end{cases} \\
F_2(p) &= \begin{cases} 1 - \frac{4}{7p} & p \in [\frac{4}{7}, \frac{5}{7}) \\ 1 - \frac{2(1-p)}{p} & p \in [\frac{5}{7}, 1] \end{cases} \\
F_3(p) &= \begin{cases} 1 - \frac{2}{7p} & p \in [\frac{2}{7}, \frac{4}{7}) \\ 1 - \frac{2(5-7p)}{7p} & p \in [\frac{4}{7}, \frac{5}{7}] \end{cases} \\
F_4(p) &= 1 - \frac{4-7p}{7p} \quad p \in [\frac{2}{7}, \frac{4}{7}]
\end{aligned} \tag{4}$$

Figure 1 illustrates the supports and distributions for the pricing strategies in these four positions.

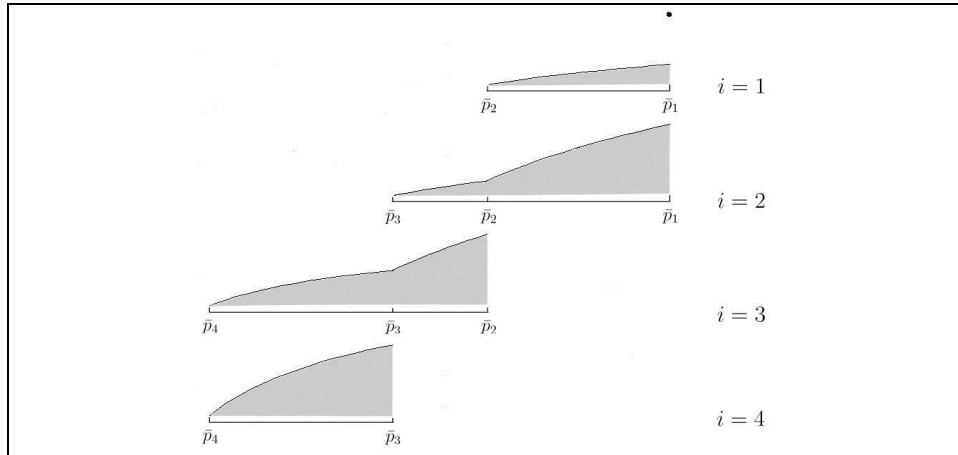


Figure 1. Price Support and Cumulative Distribution for Different Positions

It is worth noting several features of the equilibrium pricing. First notice that except for the first firm, all firms' equilibrium pricing strategies are atomless within their entire support, including the upper and lower bound. The only mass point arises at the upper bound of the first firm's price support. This is because a mass point in one firm's price distribution would result in a downward jump of another firm's expected demand at that point and consequently lower profit levels in a contiguous region right to that point. For this reason, the only possible place where a mass point may occur is \bar{p}_1 : Although the mass point in $F_1(\cdot)$ causes a downward jump in firm 2's expected profit at $p = \bar{p}_1$, since $F_2(\cdot)$ places non-positive probability measure on that particular point, firm 2's actual expected profit is not affected, which hence complies with the equilibrium requirement.

More interestingly, the sequence of the price supports here exhibits a stair-like shape. This is because firms have to take into account competition from both the firms ranked above and those ranked below. In fact, each firm only competes with its direct neighbors. They do not overcharge or undercut to compete with more distant opponents, because entering those territories only entangles itself into a more fierce competition which results in a less profit. This kind of stay-in-your-own-territory pattern keeps the price competition localized and sustainable, as can be observed in reality.

The mixed-strategy pricing means that, instead of statically charging one price, firms may charge any price within some possible price range according to certain probability distributions. If we imagine that consumers visit a particular position at different times, then the mixed pricing helps explain the existence of temporal price dispersion (i.e., the price varies over time, with occasional sales and frequent price fluctuations).

In addition to the temporal dispersion, noticing that firms at different positions adopt different pricing strategies, we are also interested to investigate the pattern of spatial price dispersion (i.e., (expected) prices vary across different locations). Intuitively, the firm at the first position will take advantage of the best location and charge the highest price. The next finding coincides with such expectation.

Proposition 2: The expected price decreases monotonically from the first position towards the last one, i.e., $E(p_i) > E(p_{i+1})$, $i = 1, \dots, n-1$.

Proposition 2 reveals an interesting pattern of spatial price dispersion, that is, the equilibrium price expectation decreases monotonically along the direction of consumers' search ordering. As a result, search is rewarding in the sense that those who keep searching are more likely to find a lower price. On the other hand, locational advantage is also rewarding in the sense that the firm at advantageous location may charge a price premium even with the same product.

Despite the fact that we have eliminated all potentially distractive differentiation among firms and consumers, we are able to derive two-dimensional price dispersion in equilibrium. It is thus clear that the unique features of consumers' online search behavior are among the fundamental

driving forces of the pervasive and persistent price dispersion observed in the ecommerce environment. As we can see, due to the existence of shoppers with non-positive search cost, which is a direct result of the advance of information technology, firms price probabilistically rather than statically, which leads to the emergence of the temporal price dispersion. Meanwhile, due to the existence of a commonly observed search ordering, which is a prevalent phenomenon in online search advertising, firms with different ranks exploit their different levels of locational advantage and differ in the price expectation, which results in the appearance of spatial price dispersion.

E-Commerce Adoption in Chinese Martial Arts Schools

Duanning Zhou
Eastern Washington University, USA
dzhou@ewu.edu

Abstract

This in-progress study explores the determinants of e-commerce adoption in Chinese martial arts schools (and studios). Based on the upper echelon theory and the technology-organization-environment framework, this paper hypothesizes that the age of top management, education of top management, perceived benefits, perceived cost, competitive pressure, customer pressure, and third party support will positively or negatively affect the intent to adopt e-commerce in Chinese martial arts schools.

Keywords: E-commerce adoption, Chinese martial arts schools, small to medium-sized enterprises, upper echelon theory, technology-organization-environment framework

1. Introduction

Chinese martial arts is quite popular in China. There are about 35,000 Chinese martial arts boarding schools as well as Chinese martial arts studios with more than 2 million students in the boarding schools and 20 million students in the studios (Chinese Martial Arts, 2002). In addition, there are 40 million Chinese martial arts practitioners who are not affiliated with any Chinese martial arts school or studio (Chinese Martial Arts, 2002). While more and more Chinese martial arts schools (studios) have some web presence displaying school basic information, the majority of them have no functional e-commerce websites which promote the schools, support on-line selling and teaching. Most Chinese martial arts schools belong to small to medium-sized enterprises (SMEs), which have limited resources financially and technologically.

IT (e-commerce included) adoption in SMEs has been a traditional research stream in the field of information systems (e.g., Caldeira and Ward, 2003; Chuang et al., 2009; Harrison *et al.*, 1997; Riemenschneider *et al.*, 2003; Thong, 1999). It is interesting to examine what factors facilitate or inhibit the e-commerce adoption in Chinese martial arts schools. To our best knowledge, there is no documented empirical study about e-commerce adoption in Chinese martial arts schools.

2. Literature Review

The topic of IT adoption in SMEs has broadly attracted many researchers' interests. Many studies have been conducted to investigate factors affecting the decision of IT adoption. Those studies differ with regard to underlying theories and technologies under investigation. Popular theories adopted by existing research include the innovation theory (e.g., Thong, 1999), the technology-organization-environment framework (e.g., Zhu et al., 2003), the theory of planned behavior (TPB) (e.g., Harrison *et al.*, 1997), the technology acceptance model (TAM) (e.g., Riemenschneider *et al.*, 2003), the resource-based theory (e.g., Caldeira and Ward, 2003), and the upper echelon theory (Chuang *et al.*, 2009).

By synthesizing prior research that is based on Rogers's innovation theory (Rogers, 1983), Thong (1999) identified four contextual elements that were related to the adoption of technological innovation: (1) characteristics of the CEO; (2) characteristics of the technological innovation; (3) characteristics of the organization; and (4) characteristics of the environment. He examined the impact of these four contextual factors in the likelihood of and the extent of IT adoption. Thong found that the likelihood of IT adoption was significantly associated with CEO characteristics, IS characteristics, and organizational characteristics.

The Theory of Planned Behavior (TPB) (Ajzen, 1991) and Technology Acceptance Model (TAM) (Davis et al., 1989) have been widely employed to examine the issue of the IT adoption. Employing the TPB as the theoretical foundation, Harrison *et al.* (1997) investigated executive decision processes of IT adoption in a multiphase field study. Their findings indicate that attitude, subjective norms, and perceived control are sufficiently explaining the IT adoption decision. Furthermore, they found that the firm size moderated the effect of the three social-psychological factors. Riemenschneider *et al.* (2003) argued that TPB and TAM possessed complementary advantages and disadvantage in predicting the adoption of IT. Consequently, they asserted that combining these two theories would offer a better explanation of IT adoption.

Early research and advocates of the Internet adoption prescribe that the adoption of the Internet follows a stages model, progressively moving from web presence, information access, transacting businesses, supply chain integration, to leveraging know-how (e.g., Willcocks and Sauer, 2000). However, such propositions of linear progressive models are not well supported by research. As a result, Levy and Powell (2003) proposed a contingency model, named "transporter" model, of the Internet adoption based on the evidence of multiple case studies. The model indicates that the major factors of the Internet adoption are the SME owner's perception of business value of the Internet and attitude towards business growth. The combinations of these two dimensions generate four segments of the Internet adoption: brochureware (low value and unplanned growth), business support (low value and planned growth), business opportunity (high value and unplanned growth), and business development (high value and planned growth). Their research suggests that the adoption of the Internet unlikely follows the stages model and instead, it is dependent on the owners' strategic intention for business growth.

Brown and Lockett (2004) investigated the adoption of e-business in SMEs from a provider perspective. They found that, given the context of a particular category of e-applications, perceived application complexity was crucial for SMEs to be engaged in an e-application aggregation and that the substantial support from trusted third parties had a great impact on the adoption of e-business applications of high-level complexity by SMEs.

The effect of organizational demographical factors, such as gender, age, and education of top management team, on the adoption of IT has recently become the interest of research in this area (Chuang *et al.*, 2009). Basing their research on the upper echelon theory (Hambrick and Mason, 1984), Chuang *et al.* (2009) found that the age and education of top management team were significant predictors of the extent of IT adoption.

3. Theoretical Foundation

3.1 The Upper Echelon Theory

The upper echelon theory (Hambrick and Mason, 1984) suggests that organizational strategic outcomes and processes are a function of managerial characteristics of top managers. The main notion of the upper echelon theory is that strategic choices, unlike operational decisions, are more of the outcome of behavioral factors than that of mechanic calculation for economic optimization. As a result, strategic choices generally own a great deal of behavioral components and somehow reflect decision makers' idiosyncrasies. Top managers' idiosyncrasies include their cognitive base (knowledge/assumption about future events, knowledge of alternatives, and knowledge of consequences of alternatives) and values (principles for ordering consequences or alternatives). These idiosyncrasies filter and frame the decision situation that executives face and eventually create their perceptions of the situation.

The upper echelon theory suggests that because cognitive base, values and perception are unobservable, measurable managerial characteristics could be adequate surrogates for and provide reasonable indicators of those latent constructs (Carpenter *et al.*, 2004). Hambrick and Mason (1984) suggested an unexhausted list of observable managerial characteristics, including age, functional tracks, career experiences, education, socioeconomic roots, financial position and group characteristics. Furthermore, they proposed 21 propositions relating those characteristics to strategic choices and the performance of organizational outcomes.

3.2 Technology-Organization-Environment Framework

The technology-organization-environment (TOE) framework (Tornatzky and Fleischer, 1990) has widely applied in studies of SMEs (e.g., Kuan and Chau, 2001; Ramdani et al., 2009; Zhu et al., 2003). Consistent with Rogers' (1983) theory of innovation diffusion, TOE framework identifies three aspects of a firm's context that affect the adoption of innovations: technological context, organizational context, and environmental context.

4. Research Model and Hypotheses

In the application of the upper echelon theory to the present study, taking into consideration the structure and characteristics of top management in Chinese martial arts schools, we are interested in examining how the age composition, and education composition of top management team affect the adoption of e-commerce. Also based on the TOE framework, we added the technological, organizational, and environmental factors into our research model which is illustrated in Figure 1.

Here, the c-commerce adoption is defined as the use of web to promote the schools, provide on-line equipment and materials selling, and on-line teaching and learning.

Due to the page limitation, we give our hypotheses as below without further explanation.

H1: The age average of top management team is negatively associated with the intent to adopt c-commerce.

H2: The average amount of formal education of top management team received is positively related to the intent to adopt c-commerce.

H3: The perceived benefit of e-commerce website is positively related to the intent to adopt c-commerce.

H4: The perceived cost of e-commerce website is negatively related to the intent to adopt c-commerce.

H5: The perceived competitive pressure is positively related to the intent to adopt c-commerce.

H6: The perceived customer demand of adopting website is positively related to the intent to adopt c-commerce.

H7: The perceived support from third parties is positively related to the intent to adopt c-commerce.

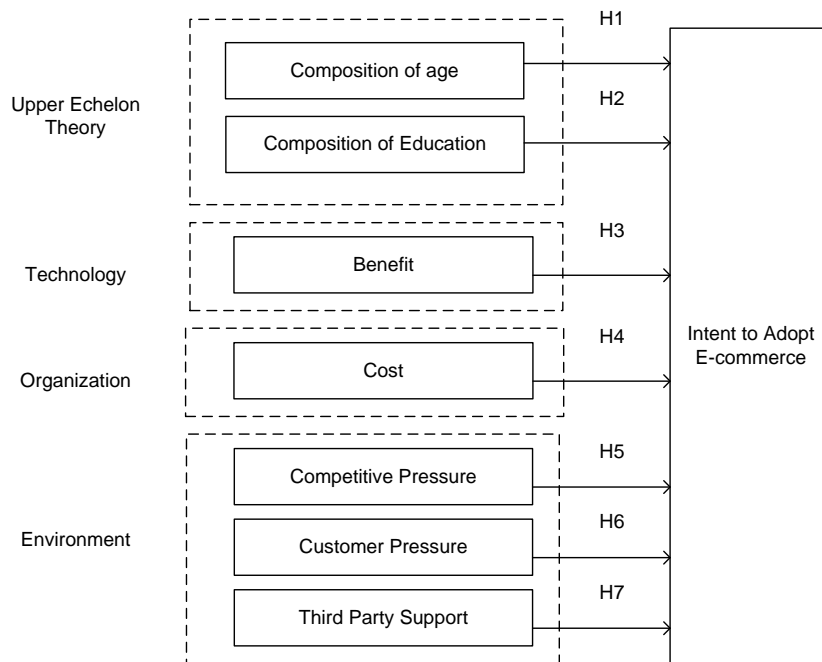


Figure 1. Research Model

5. Conclusion

This in-progress study will explore the determinants of c-commerce adoption in Chinese martial arts schools. The research model which explicitly combines the upper echelon theory and the technology-organization-environment framework, and the empirical test in the context of Chinese martial arts schools will be the main contributions of this study. We plan to adopt the measurements of the constructs from the literature and then develop the questionnaires and

translate them into Chinese. The survey will be mailed to a random sample of about 300 Chinese martial arts schools in China.

References

1. Ajzen, I. "The theory of planned behavior," *Organizational Behavior and Human Decision Processes* (50), 1991, pp. 179 – 211.
2. Brown, D. H., and Lockett, N. "Potential of Critical E-applications for Engaging SMEs in E-business: a Provider Perspective," *European Journal of Information Systems* (13:1), 2004, pp. 21–34.
3. Caldeira, M. M., and Ward, J. M. "Using Resource-based Theory to Interpret the Successful Adoption and Use of Information Systems and Technology in Manufacturing Small and Medium-sized Enterprise," *European Journal of Information Systems* (12:2), 2003, pp. 127-141.
4. *Chinese Martial Art*, No. 7, 2002.
5. Carpenter, M. A., Geletkanycz, M. A., and Sanders, W. G. "Upper Echelon Research Revisited: Antecedents, Elements, and Consequences of Top Management Team Composition," *Journal of Management* (30:6), 2004, pp. 749-778.
6. Chuang, T.-T., Nakatani, K., and Zhou, D. "An Exploratory Study of the Extent of Information Technology Adoption in SMEs: an Application of Upper Echelon Theory," *Journal of Enterprise Information Management* (22:1/2), 2009, pp. 183-196.
7. Davis, F., Bagozzi, R., and Warshaw, P. "User Acceptance of Computer Technology: A Comparison of two Theoretical Models," *Management Sciences* (35:8), 1989, pp. 982–1003.
8. Hambrick, D. C. and Mason, P. A. "Upper Echelons: The Organization as a Reflection of Its Top Managers," *Academy of Management Review* (9:2), 1984, pp. 193-206.
9. Harrison, D. A., Mykytyn, P. P. Jr., and Riemenschneider, C. K. "Executive Decisions about Adoption of Information Technology in Small Business: Theory and Empirical Tests," *Information Systems Research* (8:2), 1997, pp. 171-195.
10. Kuan, K. K. Y., and Chau, P. Y. K. "A Perception-based Model for EDI Adoption in Small Businesses Using a Technology-Organization-Environment Framework," *Information and Management* (38:8), 2003, pp. 507-521.
11. Levy, M., and Powell, P. "Exploring SME Internet Adoption: Towards a Contingent Model," *Electronic Markets* (13:2), 2003, pp. 173 – 181.
12. Ramdani, B., Kawalek, P., and Lorenzo, O. "Predicting SME's Adoption of Enterprise Systems," *Journal of Enterprise Information Management* (22:1/2), 2009, pp. 10-24.
13. Riemenschneider, C. K., Harrison, D. A., and Mykytyn, P. P. Jr. "Understanding IT Adoption Decisions in Small Business: Integrating Current Theories," *Information and Management* (40:4), 2003, pp. 269 – 285.
14. Rogers, E. M. *Diffusion of Innovations*, 3rd ed., NY: Free Press, 1983, New York.
15. Thong, J. Y. L. "An Integrated Model of Information Adoption in Small Business," *Journal of Management Information Systems* (15:4), 1999, pp. 187 – 214.
16. Tornatzky, L. G., and Fleischer, M. *The Processes of Technological Innovation*. Lexington Books, 1990, Lexington, MA.
17. Willcocks, L., and Sauer, C. *Moving to E-Business*. Random House, 2000, London.
18. Zhu, K., Kraemer, K. L., and Xu, S. "Electronic Business Adoption by European Firms: a Cross-County Assessment of the Facilitators and Inhibitors," *European Journal of Information Systems* (12:4), 2003, pp. 251-268.

What Make Them Happy and Curious Using the Internet? ——An Exploratory Study on High School Students' Internet Use from a Self-Determination Theory Perspective

Ling Zhao	Yaobin Lu	Bin Wang	Wayne Huang
Huazhong University of Sci. & Tech.		University of Texas-Pan American	Ohio University
lingzhao@smail.hust.edu.cn	luyb@mail.hust.edu.cn	binwang@utpa.edu	huangw@ohio.edu

Abstract

From a self-determination theory perspective, we investigate how perceived autonomy support, perceived relatedness and competence affect high school students' intrinsic motivations (enjoyment and curiosity) to use the Internet, and the related outcomes of the motivations. Based upon the analysis on data collected from high and middle schools in China, we get following results. For the perceived autonomy dimension, teacher support only significantly affects curiosity while parental support doesn't have any significant effects on the two intrinsic motivations. As to the perceived relatedness dimension, peer influence is found to exert the greatest influence on both motivations and Internet self-efficacy, which belongs to the perceived competence dimension, also positively relates to enjoyment and curiosity. As to the outcomes of intrinsic motivations, both enjoyment and curiosity lead to flow state. However, curiosity but not enjoyment positively related to online exploratory behavior, and flow experience also predicts exploratory behaviors.

Keywords: Self-Determination Theory, Internet self-efficacy, Intrinsic Motivations, High school students, Internet use

1. Introduction

It is estimated that, among all adolescent student Web users in China, 21.11 million (36.4%) are high school students and 15.41 million (26.6%) are middle school students (26.6%) in the whole adolescent students web users. For those students, Internet access and skills are critical because the Internet is widely used in education, research, and distance education. Thus, understanding why and how young Web users use the Internet are important. Though previous researches revealed that intrinsic motivation important role in information technology acceptance (Teo et al. 1999), what environmental factors facilitate the intrinsic motivation deserves more attention. In addition to examining effects of the intrinsic motivation on individual behavior, we also investigate the effects of different facilitating conditions in the environments on the intrinsic motivation in this study.

2. Literature Review

Self-determination theory (SDT) “views human beings as proactive organisms whose natural or intrinsic functioning can be either facilitated or impeded by the social context” (Deci et al. 1994). SDT identifies three natural or inherent psychological needs—autonomy, competence, and relatedness—as the basis for self-motivation. The need for autonomy refers to one's desire to feel that her action is volitional and freely chosen. The need for competence is the desire to be

effective and skillful in performing an activity or interaction with the environment. The need for relatedness is the need to feel connected with and cared by others that one considers to be important. According to the SDT, the extent of intrinsic motivation depends on the satisfaction of these three basic psychological needs. Thus, the better a condition satisfies these basic needs, the more intrinsically motivated an individual will be.

Intrinsic motivation refers to “doing an activity for the inherent satisfaction of the activity itself” (Ryan et al. 2000), and it encourages a person to perform an activity for its own sake, such as curiosity and enjoyment. Among many types of intrinsic motivation, enjoyment and curiosity are two vital ones for adolescents. Perceived enjoyment is defined as the extent to which using a specific system is perceived to be enjoyable in its own right, ignoring the consequences resulted from the use. Curiosity is the desire to acquire and investigate new knowledge and new sensory experience. Flow, a state closely related to the intrinsic motivation, is “the holistic sensation that people feel when they act with total involvement” (Csikszentmihalyi 1975). The state of flow occurs when a person feels that her skills match the challenges that are brought on by the tasks at hand. If the balance between skills and challenges is broken, one will feel bored or anxious. In a flow state, one usually gets absorbed in her activities, which could be characterized by loss of self-consciousness and a high concentration on the tasks.

3. Research Model and Hypotheses

Base upon the above theories, we propose our research model in Figure 1. We assume support from teachers and parents, peer influence from friends, and Internet self-efficacy will affect high school students’ intrinsic motivation due to enjoyment and curiosity. Further, enjoyment, curiosity, and online flow experience will influence online exploratory behaviors.

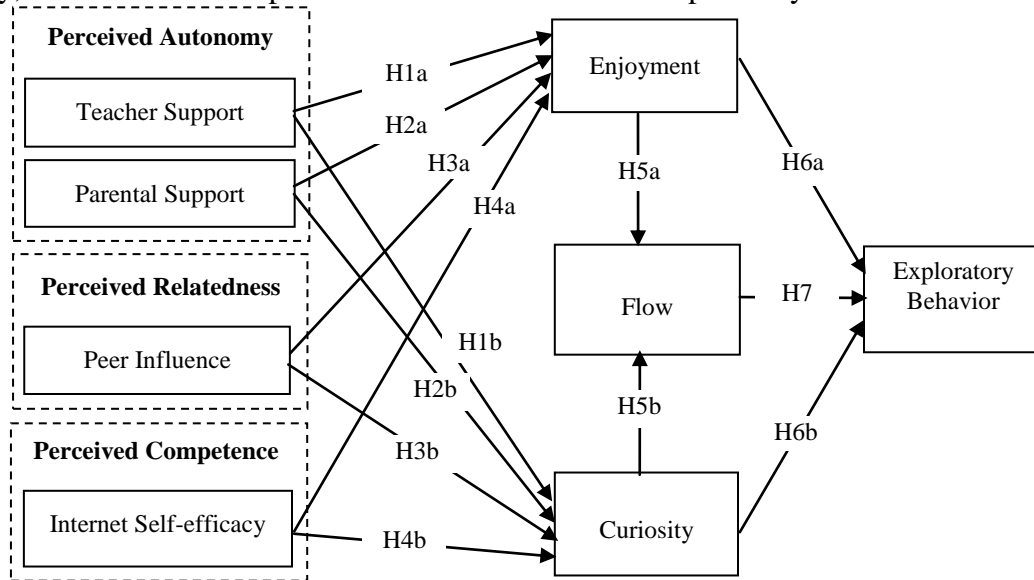


Figure 1. The Research Model

3.1 Perceived Autonomy

Autonomy is an important need for human beings that is usually associated with positive outcomes. In school settings, autonomy-supportive teaching results in higher levels of enjoyment and achievement in students (Connell et al. 1990). Individuals are more likely to be intrinsically

motivated when people important to them act in an autonomy-supportive way. When students are supported by their parents or teachers, they will consider their actions as permitted and encouraged. Thus we have:

H1a: Perceived support from teachers is positively related to high school students' enjoyment in using the Internet.

H1b: Perceived support from teachers is positively related to high school students' curiosity in using the Internet.

H2a: Perceived support from parents is positively related to high school students' enjoyment in using the Internet.

H2b: Perceived support from parents is positively related to high school students' curiosity in using the Internet.

3.2 Perceived Relatedness

Roca and Gagné (2008) propose that perceived relatedness represents a form of social influence, which is defined as "one's assessment of whether or not people important to him or her feel the behavior should be performed" (Ajzen 1991). In previous studies, social influence has been proved to be an important factor affecting people's attitude or behavior intention. For those high school students, their friends or classmates is an important source of personal influence. Teenagers would get more fun when they use the Internet together, such as playing online games or chatting. Moreover, as high school students spend great time staying with classmates and friends at school, they should also exchange interesting online experiences with each other frequently, which would facilitate the curiosity of students to try the same thing. Thus we have:

H3a: Perceived peer influence is positively related to high school students' enjoyment in using the Internet.

H3b: Perceived peer influence is positively related to high school students' curiosity in using the Internet.

3.3 Perceived Competence

Perceived competence is similar to "self-efficacy," which is "people's judgment of their capabilities to organize and execute courses of action required to attain designated types of performances" (Bandura 1986). Internet self-efficacy (ISE) describes an individual's judgment of her capability to use the Internet. A positive perception of ability will induce intrinsic motivation more than a negative perception of ability. Self-efficacy reduces the anxiety of technology use, and individuals will feel more comfortable to use the Internet. Thus we have:

H4a: Perceived Internet self-efficacy is positively related to high school students' enjoyment in using the Internet.

H4b: Perceived Internet self-efficacy is positively related to high school students' curiosity in using the Internet.

3.4 Motivation and Outcomes

Hoffman and Novak (1996) propose that intrinsic motivation enhances self-relevance, making an individual feel more involved in an activity. Thus we propose that intrinsic motivation influences the flow state. Woszczynski et al. (2002) contend that there is a circular reinforcement relationship between the flow state and playful behaviors. Curiosity will also lead high school students to high involvement in the activity, which is a reflection of the flow state. We have:

H5a: High school students' enjoyment in using the Internet is positively related to their flow state.

H5b: High school students' curiosity in using the Internet is positively related to their flow state. The intrinsic motivation and flow state both predict exploratory behaviors. We believe that, when an individual gets more fun from the activity he is engaged in, he will try more behaviors, including exploratory behaviors, to enhance this happy feeling. In addition, previous research on curiosity also reveals that the more curious an individual becomes when using the Internet, the more exploration he may try online. Finally, exploratory behavior is always regarded as one outcome of the flow experience (Novak et al. 2000). Thus, we have:

H6a: High school students' enjoyment in using the Internet is positively related to their exploratory behavior when using the Internet.

H6b: High school students' curiosity in using the Internet is positively related to their exploratory behavior when using the Internet.

H7: High school students' flow state in using the Internet is positively related to their exploratory behavior when using the Internet.

4. Methodology

To assure the reliability and validity of the instrument, we selected most items from existing research. Questionnaires were distributed to ten high schools and seven middle schools in Xiangfan, which is a prefectural-level city in central China. 4304 questionnaires were collected through the survey, and 3475 were valid with a valid rate of 80.7%. We used structural equation modeling (SEM) to test both the measure model and the structural model. Items that led to low reliability and validity of the scale were deleted. AMOS was used to test the structural model. We tested our research model and summarized the results with AMOS coefficients in Figure 2. Most hypotheses were supported except H1a, H2a, H2b and H6a. The proportions of variances explained were 30.3% for enjoyment, 23.7% for curiosity, 50.4% for flow, and 24.1% for exploratory behavior. All fit indices were within acceptable ranges except χ^2/df , indicating a good fit between the theoretical model and the data.

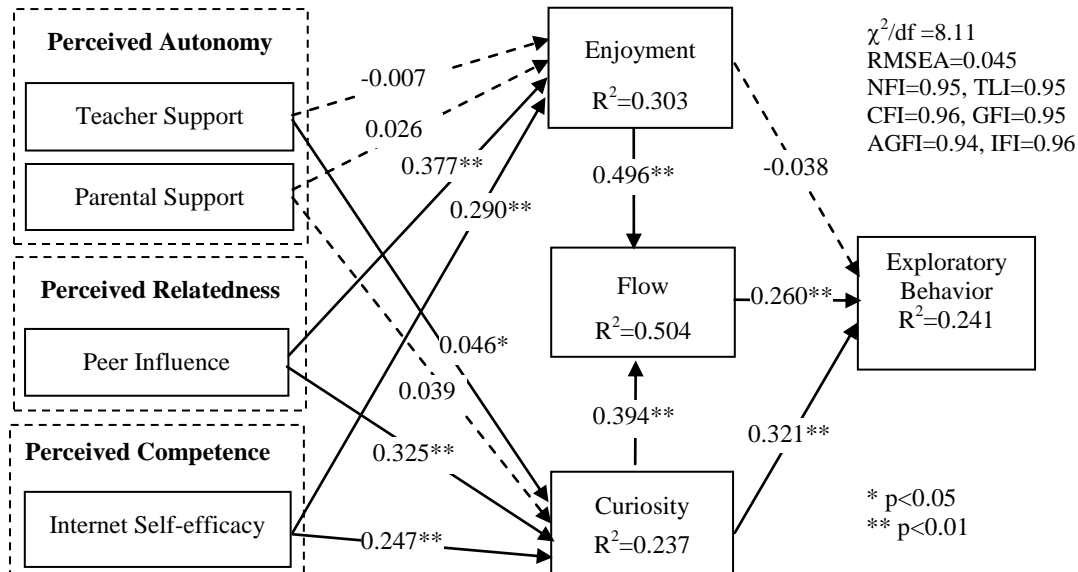


Figure. 2 Results of the Model Test

5. Conclusion

In present study, from a self-determination theory perspective, we investigate how perceived autonomy support, perceived relatedness and competence affect high school students' intrinsic motivations (enjoyment and curiosity) to use the Internet, and the related outcomes of the motivations. As to the autonomy support, we find that only teacher support significantly influences high school students' curiosity, and parental support doesn't have positive influence on the intrinsic motivations. The probable explanation for this might be that for high school students in China, teachers or parents may not support students using the Internet and even consider it harmful to their schoolwork because of the pressure from intensive competition for high school students to enter senior schools or universities. For the outcomes of intrinsic motivations, both enjoyment and curiosity lead to flow experience which further predicts exploration behavior. However, curiosity but not enjoyment has significant effects on the exploration behavior in Internet use. Compared to curiosity, the insignificant relationship between enjoyment and exploratory behavior might imply that curiosity is a more important intrinsic motivation that facilitates exploration.

References

- Ajzen, I. "The Theory of Planned Behavior," *Organizational Behavior & Human Decision Processes* (50) 1991, 179-211.
- Bandura, A. *Social foundations of thought and action* Prentice Hall, Englewood Cliffs, NJ, 1986.
- Connell, J.P., and Wellborn, J.G. "Competence, autonomy, and relatedness: A motivational analysis of self-system processes," in: *The Minnesota Symposium on Child Psychology: Vol.22. Self-processes in development*, M.R. Gunnar and L.A. Sroufe (eds.), Lawrence Erlbaum, Hillsdale, NJ, 1990, 43-77.
- Csikszentmihalyi, M. *Beyond Boredom and Anxiety* Jossey-Bass, San Francisco, 1975.
- Deci, E.L., Eghrari, H., Patrick, B.C., and Leone, D.R. "Facilitating internalization: The self-determination theory perspective," *Journal of Personality* (62) 1994, 119-142.
- Hoffman, D.L., and Novak, T.P. "Marketing in hypermedia computer-mediated environments conceptual foundations: Conceptual foundations," *Journal of Marketing* (60:3) 1996, 50-68.
- Novak, T.P., Hoffman, D.L., and Yung, Y.-F. "Measuring the customer experience in online environments: a structural modeling approach," *Marketing Science* (19:1) 2000, pp 22-42.
- Roca, J.C., and Gagné, M. "Understanding e-learning continuance intention in the workplace: A self-determination theory perspective," *Computers in Human Behavior* (24:4) 2008, 1585-1604.
- Ryan, R.M., and Deci, E.L. "Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being," *American Psychologist* (55:1) 2000, 68-78.
- Teo, T.S.H., Lim, V.K.G., and Lai, R.Y.C. "Intrinsic and extrinsic motivation in Internet usage," *Omega, International Journal of Management Science* (27:25-37) 1999.
- Woszczynski, A.B., Roth, P.L., and Segars, A.H. "Exploring the theoretical foundations of playfulness in computer interactions," *Computers in Human Behavior* (18) 2002, 369-388.

Explaining the Role of User Commitment in Innovative Use of Information Systems

Wei Wang
Business School Shantou University
wangw@stu.edu.cn

Yong Liao
Business School Shantou University
09yliao@stu.edu.cn

Abstract

In the information systems (IS) field, research interest in post-adoptive usage has fluctuated over the past decades given its importance for a firm to improve performance and sustain competitive advantage. As a form of post-adoptive usage, innovative use is a conscious behavior beyond routine that requires the strong involvement of users' time and efforts. Drawing upon the insights from the IS continuance model and organizational commitment model, this study develops a research model to investigate the role of user commitment in the innovative use of IS. The research hypotheses are proposed and the research methodology used to test the hypotheses is discussed. The contributions of the study are also presented.

Keywords: Affective Commitment, Continuous Commitment, Normative Commitment, Innovative Use, Post-adoptive Usage

1. Introduction

In the information systems (IS) field, research interest in post-adoptive usage has fluctuated over the past decades given its importance for a firm to improve performance and sustain competitive advantage. Post-adoptive usage behaviors are referred to the usage behaviors at the post-adoption stages, including continuance, routine use, extended use, innovative use, and so on. IS continuance model was widely used in explaining the post-adoptive usage behaviors. Bhattacharjee (2001) proposed user satisfaction as the key to understand IS continuance, and two affective factors, i.e. perceived usefulness and confirmation of expectation from prior use, are the important determinants to user satisfaction. However, there is an obvious limitation in its ability to accommodate the impact of non-affective elements on post-adoptive behavior.

In recent years, the investments in new information systems increase very rapidly. However, the firms that implement the systems are more and more difficult to realize the promised return on investment. Under this circumstance, firms that can stimulate employees to apply the IS creatively are more likely to successfully respond the ever-changing market situations (Wang et al 2008). Some researchers argue that IS use gradually becomes spontaneous as the frequency of use increases. However, innovative use is a conscious behavior beyond routine which requires the strong involvement of the time and efforts of users. Distinguishing innovative use from continuance has significant implications for both research and practice. For research, there are a large number of studies on continuous use issue; however, whether the findings can be applied into other post-adoptive usage context need further exploration. For practice, continuous use is an important step to innovative use. If users stop using an IS, innovative use will be impossible. Given that innovative use is a conscious behavior, without technology commitment, individual users may not attain that state. Although many studies (e.g., Li et al. 2006; Malhotra & Galletta 2005) have verified the importance of commitment in explaining the technology adoption/acceptance; however, the effect of users' commitment on their innovative use remains unaddressed.

This study attempts to investigate the technology commitment and its antecedents as determinants to the IS innovative use. The study uses the theory of user commitment to understand how an individual's IS innovative use is influenced by his or her commitment toward the IS.

2. Theoretical Foundations and Research Hypotheses

2.1 IS Continuanace Model

Continuance is defined as a form of post-adoption behaviors which follow initial acceptance. The IS continuance model (Bhattacharjee 2001) posits that a users' intention to continue use is determined primarily by his or her satisfaction with previous usage and perceived usefulness (PU), and satisfaction is the stronger predictor. In addition, user satisfaction is positively influenced by PU, which is positively associated with confirmation of expectation (COE). IS continuance model has been widely used to explain the usage behaviors in the post-adoption context, such as continuance, extended use and innovative use (Bhattacharjee et al. 2008; Hsieh & Wang 2007; Wang et al. 2008).

2.2 Organizational Commitment Model

Commitment refers to a "force that binds an individual to a course of action" (Meyer & Herscovitch 2001, p. 301). It can be viewed as the psychological attachment felt by an individual in an organization and reflects the degree to which the individual internalizes or adopts characteristics or perspectives of the organization. Commitment can be conceptualized in terms of three dimensions: affective, continuous, and normative. According to Allen & Meyer (1990), affective commitment (AC) is the identification with, involvement in, and emotional attachment to a relationship such as an employee-organization relationship; continuous commitment (CC), also termed as calculative commitment, reflects the fact that a person recognizes the costs associated with leaving a relationship and is thus concerned with a purely cognitive cost/benefit analysis of maintaining a relationship; normative commitment (NC) explains moral obligations, social norms, and one's responsibility to the other party in a relationship. In short, AC is a mindset of desire, CC is a mindset of cost-avoidance, and NC is a mindset of obligation.

2.3 Research Hypotheses

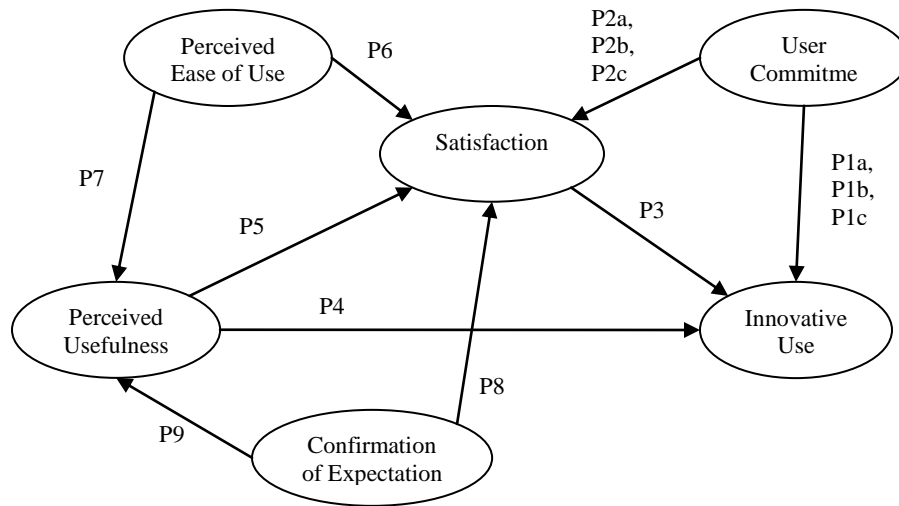


Figure 1 Research Model

Innovative use is defined as a higher level usage behavior that is innovative in nature and can potentially lead to better results and returns (Wang et al. 2008). Innovative use occurs in the post-acceptance stage after initial adoption, more exactly, the stage beyond routine. Thus, innovative use is a voluntary behavior. IS continuance model can serve as a basis to further investigate the phenomenon of innovative use. Commitment is related to a variety of attitudinal and behavioral consequences among employees in an organization (Meyer & Allen, 1997). Moreover, commitment can influence behavior independent of motivation and attitudes (Allen & Meyer 1990; Meyer & Herscovitch 2001). From this line, it is reasonable to link the commitment and innovative use. In this vein, this study incorporated the IS continuance model and organizational commitment model (Meyer & Herscovitch 2001) to develop a research model (Figure 1) to examine the effects of user commitment on IS innovative use.

As a higher level use usually takes place after users' initial usage, innovative use can be viewed as post-acceptance behavior that involves creative use of an information system to support one's tasks. In the present study, we define user commitment as the users' psychological attachment to IS use (Malhotra & Galletta 2005). Here, *affective commitment* (AC) is defined as a situation in which an individual demonstrates an affective and emotional attachment to the relationship with system use (Li et al. 2006). Given their psychological attachment, system users feel and believe that the use of the new system is the right thing. Therefore, these users are more likely to satisfy with the system use and throw themselves to find novel ways of using the system to support their work performance. Hence,

P1a: Affective commitment is positively associated with innovative use.

P2a: Affective commitment is positively associated with user satisfaction.

Continuous commitment (CC) is defined as a situation in which an individual recognizes the rewards and benefits associated with continuing to use an adopted IS and maintaining a relationship with the system (Li et al. 2006). CC when a user recognizes that the costs associated with stopping his/her use of the system are higher than rewards. These costs involve financial and non-financial elements such as opportunity costs, learning curves, sunk costs, and so on. Since enterprise information systems such as enterprise resource planning (ERP) or customer relationship management (CRM) are normally complex, employee users have to invest much time and effort to learn. Such investments will be lost if employee users stop using the adopted system. As a result, a user's investment will serve as a powerful psychological inducement to maintain a relationship with the system. From this perspective, it is reasonable to believe that these users are more likely to innovate with the system use to support their work performance in order to increase their rewards from the adopted system. Moreover, given that the discontinued costs are too high, these users are most likely to accept the system, and form the positive affect with their prior system use. Hence,

P1b: Continuous commitment is positively associated with innovative use.

P2b: Continuous commitment is positively associated with user satisfaction.

Normative commitment (NC) is defined as a situation in which an individual is attached to an IS due to internalized obligations to compliance (Allen & Meyer 1990; Wang & Datta 2006). Unlikely with AC and CC, NC reflects the external motivation for an individual to remain attached to an IS. That is, NC occurs only when the external pressure exists; otherwise, such commitment will diminish or disappear. NC can be experienced either as a moral duty or a sense of indebtedness to influence IS usage behavior (Meyer and Parfyonova 2009). Moral

involvement can bind individuals to an IS with a sense of duty and has a strong influence on individual behavior such as innovative use. Therefore, when an individual has the pressure of the internalization obligation, they are most likely to accept the adopted system, try to find good things of the system and form the positive affect with the system use. Similarly, these users are most likely to find the novel ways to use the system for their performance enhancement. Hence,

P1c: *Normative commitment is positively associated with innovative use.*

P2c: *Normative commitment is positively associated with user satisfaction.*

Satisfaction is an experience-based affect reflecting users' overall feeling about their interaction with an IS. For employee users to innovate with an enterprise system, their satisfaction can serve as an affective precondition of their innovative behaviors. If employees are satisfied with their direct use of the system, they are more likely to embrace it, accept it, and even use it creatively.

P3: *Satisfaction is positively associated with innovative use.*

Perceived usefulness (PU) motivates individual usage behavior because of its instrumental consideration. PU at the post-acceptance stage is formed mostly through users' own first-hand experience and is, therefore, more reliable. For employee users to find new ways of using an enterprise system to support their task performance, their evaluation of the utility of the system use represents the logical and rationale assessment, i.e. whether their time and effort is paying off. In this vein, the higher the perception of usefulness of the system, the more likely they will innovate with the IS.

P4: *Perceived Usefulness is positively associated with Innovative Use.*

Previous studies have also revealed that PU impacts individuals' affects substantively across innovation stages. Satisfaction can be conceived as an individual affect in the post-acceptance stage. As PU influences attitude affect during the acceptance stage, PU is expected to be the salient ex post expectation that influences satisfaction affect in the post acceptance stage.

P5: *Perceived Usefulness is positively associated with User Satisfaction.*

In the adoption stage, there is important links among PEOU, PU and Affect (Davis 1989). Many scholars believe that the effect of PEOU diminish after users are gradually familiar with the adopted IS. However, other scholars empirically found the important role of PEOU in the post-acceptance stage, i.e. continuance and extended use (Hong et al. 2006; Hsieh & Wang 2007). With the same line of reasoning applied to the relationship among COE, satisfaction and PU, we propose the following hypotheses:

P6: *Perceived Ease of Use is positively associated with Satisfaction.*

P7: *Perceived Ease of Use is positively associated with Perceived Usefulness.*

Confirmation of Expectation (COE) is defined as the extent to which expectation is confirmed (Bhattacharjee 2001). It provides the baseline level against which users can assess the confirmation of their expectation to determine their satisfaction. In contrast, disconfirmation occurs when actual performance is lower than expected performance. COE implies realization of the expected benefits of an IS use, thus confirmation is positively related to satisfaction with the system use.

P8: *Confirmation of Expectation is positively associated with Satisfaction.*

At first, users often have their expectation from IS use, and gradually adjust it after direct interaction with the system. Such perceptions may be adjusted higher as they know more about the system and accumulate experience about the system use. Nevertheless, user may experience

cognitive dissonance if their actual usage is inconsistent with their expectation. Users often possess the tendency to adjust their perceptions to be consistent with reality. Hence,
P9: Confirmation of Expectation is positively associated with Perceived Usefulness.

3. Research Methodology

The research will be conducted as a cross-sectional field study in a large manufacturing firm using ERP systems via survey questionnaires. Since an ERP system can help organizations incorporate their complete range of business activities into a single information technology infrastructure, various departments within an organization can share information and communicate with each other. Therefore, its successful deployment and effective use are critical to organizational performance.

Given that a large number of the firms have adopted ERP systems in the Chinese manufacturing industry, how to receive the benefits from the ERP system is the common interest of the adopted firms. This study will choose a large firm, one of Top 500 firms in China, as our research site.

AMOS will be used to conduct data analysis. It is a multivariate technique that combines aspects of multiple regression and factor analysis to estimate a series of interrelated dependence relationships simultaneously (Hair et al. 1998). That is, two-step data analysis will be done to first assess the measurement model and then test the hypotheses by fitting the structural model.

4. Contributions and Conclusions

Innovative use is a higher level volitional usage behavior which is beyond routine. Such usage behavior is innovative in nature and can potentially lead to better results and returns. Both research and practice have recognized the importance of realization of user commitment to volitional system use. Therefore, drawing upon the IS continuance model and organizational commitment model, this study develops a research model to examine how user commitment affects innovative use. The present study is a good direction for the extension of IS continuance model. The study has offered the theory development part, and theory testing part will be conducted further in the future study.

Acknowledgements

The work described in this paper was fully supported by a grant from the Natural Science Foundation of China (No. 70971081/G011201) and a grant from the Natural Science Foundation of Guangdong Province (No. 9451503101003590).

References³

1. Allen, N. J., and Meyer, J. P. "The Measurement and Antecedents of Affective, Continuance and Normative Commitment to the Organization," *Journal of Occupational Psychology* (63:1), 1990, pp.1-18.
2. Bhattacharjee, A. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), 2001, pp. 351-370.
3. Bhattacharjee, A., Perols, J., and Sanford, C. "Information Technology Continuance: A Theoretic Extension and Empirical Test," *The Journal of Computer Information Systems* (49:1), 2008, pp. 17-26.

³ Full references are available through the authors upon request.

4. Hsieh, J. P.-A., and Wang, W. "Explaining Employees' Extended Use of Complex Information Systems," *European Journal of Information Systems* (16), 2007, pp. 216-227.
5. Wang, W., Hsieh, J. P.-A., Butler, J., and Hsu, S.-H. "Innovate with Complex Information Technologies: A Theoretical Model and Empirical Examination," *Journal of Computer Information Systems* (49:1), 2008, pp. 27-36.

Mining User Opinions in Social Network Webs

Kaiquan Xu

Department of Information Systems,
City University of Hong Kong
kaiquan.xu@student.cityu.edu.hk

Yuxia Song

Department of Information Systems,
City University of Hong Kong
yuxisong@cityu.edu.hk

Stephen Shaoyi Liao

Department of Information Systems,
City University of Hong Kong
issliao@cityu.edu.hk

Long Liu

Department of Information Systems,
City University of Hong Kong
liulong85212@gmail.com

Abstract

With the emergence of Social Network Services (SNS) technologies, many websites for expressing user opinions begin to support SNS functions with permitting users to build various relationships. The user opinions in these SNS sites will bring greater impacts on customers' decisions than traditional user opinion websites. Mining the user opinions in SNS sites not only can help producers discover their products' strengths and weaknesses, but also identify customer communities with different concerns. The findings will be very useful for analyzing customers and targeting marketing. In this study, some initial ideas are presented on mining user opinions in SNS, and an initial study is executed.

Keywords: Business Intelligence, Opinion Mining, Social Network Mining

1. Introduction

In web 2.0, users are permitted to express their opinions on products and services through many channels, such as online forums, shopping websites, blogs, and wikis. These opinions have lots of business values, and mining these data can bring many benefits: from the producers' perspective, they could better understand the relative strength or weakness of their products, and hence developing better products to meet the consumers' requirements; from the consumers' perspective, they could exercise more informed purchasing decisions by comparing the various features of certain kind of products. A lot of studies have done on mining these user opinion data, but these work only focus on mining user opinion data.

Recently, the emerging Social Network Services (SNS) sites (such as facebook.com, twitter.com, epinions.com) permit users to build various relationships in online communities for communications and sharing. So some user opinion sites (epinions.com and amazon.com etc.) also integrate some functions of SNS. For example, one user can build trust relationship with another by adding him/her into the trust list, or block him/her with the block list. With supplementing SNS functions, the opinions of one person will have more effective impacts on others than in original user opinion sites, because people more easily believe the opinions of the persons with trust relationships. The influence of opinions in SNS sites can propagate more distantly.

Although there exist lot of studies in opinion mining and social network mining, few of work was done on mining user opinions with considering social network factors. Mining the user opinions in SNS sites usually can bring more benefits for producers than in user opinion sites: it not only can help producers discover their products' strengths and weaknesses, but also identify customer communities with different concerns, for example, discover the user communities with negative sentiments on your products, even on which attributes. This will be very useful for analyzing customers' segments and targeting marketing. In this paper, the initial idea is presented on this issue.

The paper is organized as: Section 2 introduces the related work; some ideas are presented in Section 3; Section 4 is the conclusion and future work.

2. Related Work

2.1 Opinion Mining

Much research exists on sentiment analysis of user opinion data (Chau and Xu, 2007; Chen, 2006; Liu, 2006; Pang and Lee, 2008; Raghu and Chen, 2007), which mainly judges the polarities of user reviews. In these studies, sentiment analysis is often conducted at one of three levels: the document level, sentence level, or attribute level. Sentiment analysis at the document level classifies reviews into the types of polarities—positive, negative, or neutral—based on the overall sentiments in the reviews. A number of machine learning techniques have been adopted to classify the reviews (Pang and Lee, 2002). Abbasi and Chen et al. propose the sentiment analysis methodologies for classification of Web forum opinions in multiple languages (Abbasi et. 2008). Sentiment analysis at the sentence level mainly focuses on identifying subjective sentences and judging their polarities. Most of these studies adopted the machine learning methods (Wiebe, 1999; Yu and Hatzivassiloglou 2003). Sentiment analysis at both the document level and sentence level has been too coarse to determine precisely what users like or dislike. In order to address this problem, sentiment analysis at the attribute level is aimed at extracting opinions on products' specific attributes from reviews.

2.2 Social Network Mining

As we know, some studies have been done on trust relationship in social network. In (Guha et. 2004), a framework of trust propagation schemes is developed and evaluated on a large trust network. Many trust prediction methods are proposed, for example in (Leskovec, 2010), the proposed models can make prediction with high accuracy across the diverse range of sites. The bidirectional effects of trust and rating on social networks is explored in (Matsuo et. 2009). Some machine learning based methods are used for trust prediction in (Liu, 2008; Kim, 2008). Some work tries to discover user communities in online social networks. In (Zhang et. 2008), some characters of "Web of Trust" are discovered, and a corresponding algorithm is proposed to detect small target marketing groups. Some antagonistic communities are discovered for analyzing some users' interesting behaviors.

3. Mining User Opinions in SNS Sites: a Proposed Approach & an Initial Study

The objective of this study in mining user opinions in SNS sites is: identify the user communities with different opinions. These communities always represent the groups of customers with different preferences, and they can be used for producers to know customer segments, in order to do targeting marketing or design adaptive products for them. The following steps are proposed to achieve this:

- 1) Analyzing user opinions: some text mining technologies are used to extract attributes of product and sentiment polarities of users from user opinions data.
- 2) Discovering social communities: the social communities are discovered, based on the similarities of the users' opinions.
- 3) Analyzing the results: some characters of social communities are summarized, such as the main sentimental polarities of communities.

Also, this approach can be used to support competition analysis, by comparing the social communities of competitive products.

In this initial study, we only consider the product ratings given by users as the users' opinions, without analyzing users' text opinions. The groups with similar product ratings are discovered, and the groups are divided into three categories: the group with positive opinions, negative ones and no opinions. This should be very useful in helping producers to customers' segments and opinions.

3.1 Data Collection

The dataset for the experiments is obtained from a famous opinion site, Epinions (www.epinions.com), which allows users to write text reviews and to express trust of other users based on his/her previous experience. Here, the data in mobile phone domain is collected. Since the number of users' opinions on one product is low, the brand is the analyzing unit, by averaging the product rating given by users.

3.2 Analysis Results

Here, the simple partition analysis is done by partition users into three subsets: negative one, positive one and on opinion. The following figures show the analysis results on several brands (green/red vertexes are users with positive/negative opinions, green/red arcs are the TrustBy relationships of users with positive/negative opinions):

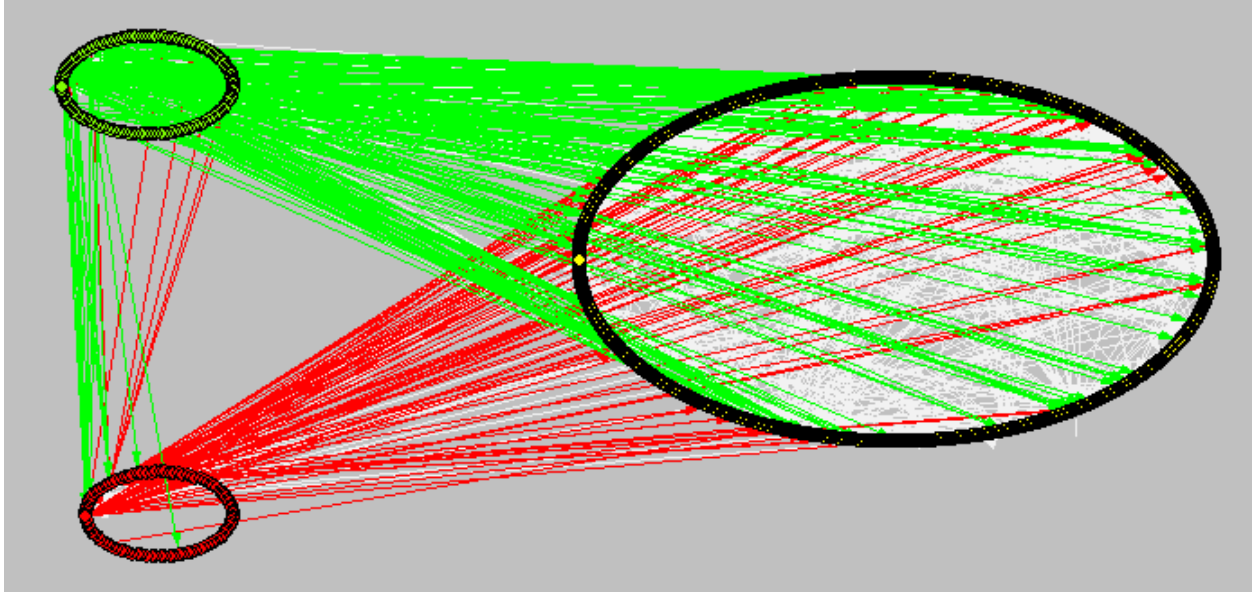


Fig 1: Social Network Partition on motorola.

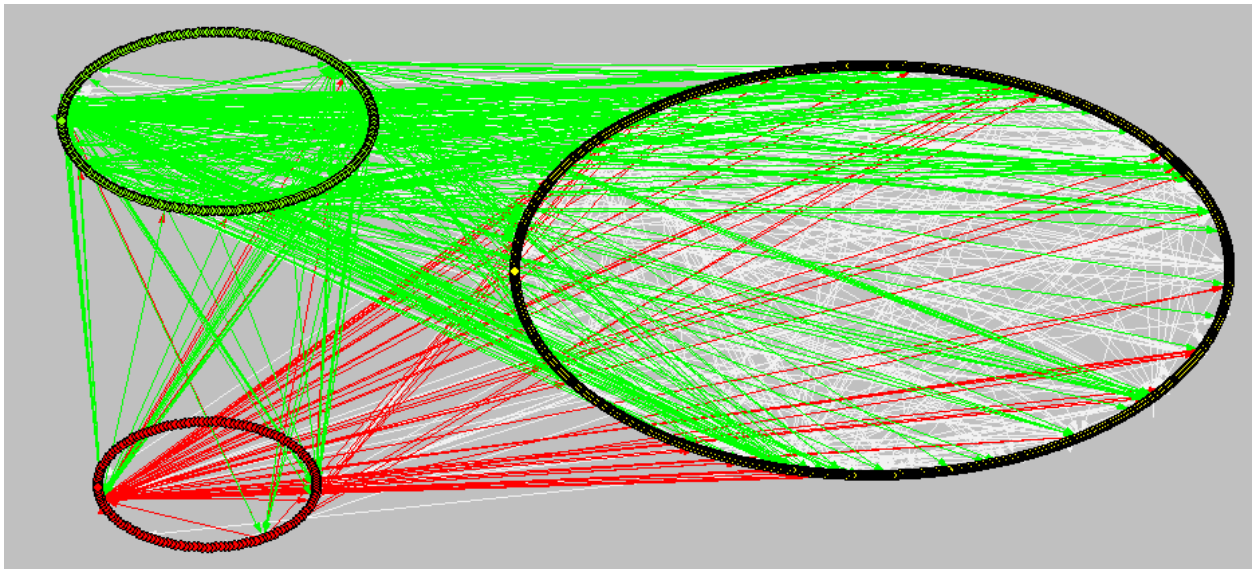


Fig 2: Social Network Partition on rim blackberry.

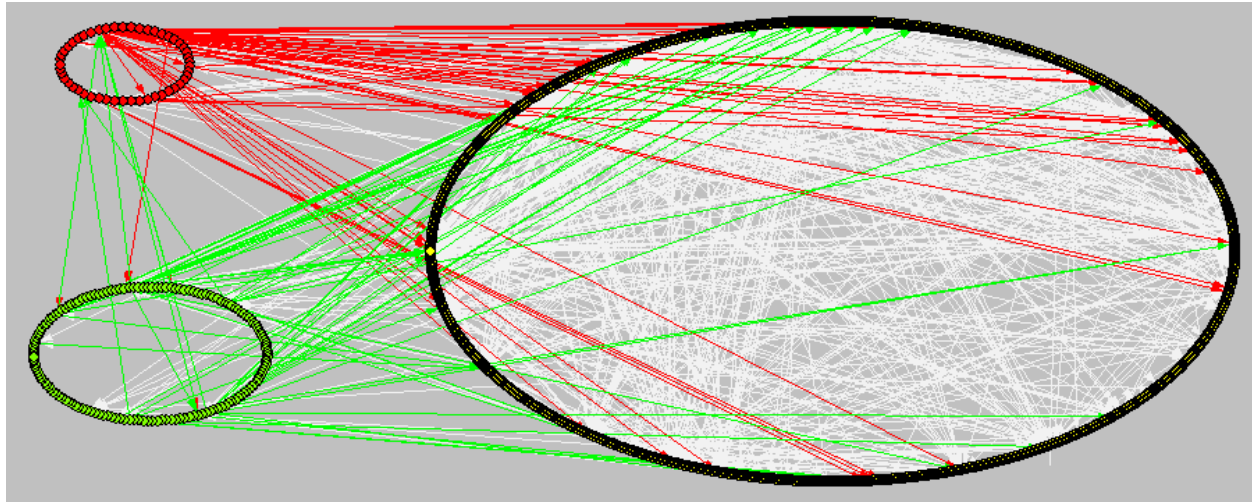


Fig 3: Social Network Partition on nokia.

4. Conclusion & Future Work

The emerging SNS functions in user opinions sites brings many new challenges for mining business intelligence, and mining these data will be very useful for producers in analyzing customers and targeting marketing. In this study, an initial study is presented on mining user opinions in SNS. In the future, an innovative community discovery algorithm will be developed for discovering core user communities; users' text opinions will be analyzed with considering detail users' opinions; also the large scale experiment will be executed for evaluating the proposed method.

References

1. Abbasi A., Chen H., Salem A., *Sentiment Analysis in Multiple Languages: Feature Selection for Opinion Classification in Web Forums*. ACM Transactions on Information Systems 26(3) (2008).
2. Chau M., Xu J., *Mining communities and their relationships in blogs: A study of online hate groups*. International Journal of Human-Computer Studies, 65(1) (2007).
3. Chen H., *Intelligence and security informatics: information systems perspective*. Decision Support Systems 41(3) (2006)
4. Guha R., Kumar R., Raghavan P., A. Tomkins. *Propagation of Trust and Distrust*. Proceedings of the 13th international conference on World Wide Web. 2004.
5. Kim Y.A., Le M.T., Lauw H.W., Lim E., Liu H., and Srivastava J., *Building a Web of Trust without Explicit Trust Ratings*. ICDE 2008 Workshop on Data Engineering for Blogs, Social Media, and Web 2.0. 2008.
6. Leskovec J., Huttenlocher D., Kleinberg J., *Predicting Positive and Negative Links in Online Social Networks*. Proceedings of the international conference on World Wide Web. 2010.
7. Liu B., *Web Data Mining- Exploring Hyperlinks, Contents and Usage Data*. (Springer, 2006).

8. Liu H., Lim E., Lauw H.W., Le M.T., Sun A., Srivastava J., Kim Y.A., *Predicting Trusts among Users of Online Communities – an Epinions Case Study*. Proceedings of the 9th ACM conference on Electronic commerce. 2008.
9. Matsuo Y., Yamamoto H., *Community gravity: measuring bidirectional effects by trust and rating on online social networks*. Proceedings of the 18th international conference on World wide web. 2009.
10. Pang B., Lee L., *Opinion mining and sentiment analysis*. in: J. Callan, F. Sebastiani (Ed.) Foundations and Trends in Information Retrieval 2(1-2), (Now Publishers; 2008).
11. Pang B., Lee L., Vaithyanathan S., *Thumbs up? Sentiment Classification using Machine Learning Techniques*. in: D. Yarowsky, D. Radev, Proceedings of the Conference on Empirical Methods in Natural Language Processing, Philadelphia, PA, USA (2002) 79-86.
12. Raghu T.S., Chen H., *Cyberinfrastructure for homeland security: Advances in information sharing, data mining, and collaboration systems*, Decision Support Systems 43 (4) (2007)
13. Wiebe J.M., Bruce R.F., O'Hara T.P., *Development and use of a gold-standard data set for subjectivity classifications*. in: R. Dale, K. Church (Ed.), Proceedings of the 37th annual meeting of the Association for Computational Linguistics on Computational Linguistics, College Park, Maryland, USA (1999) 246 – 253
14. Yu H., Hatzivassiloglou V., *Towards answering opinion questions: separating facts from opinions and identifying the polarity of opinion sentences*, in: M. Collins, M. Steedman (Ed.), Proceedings of the 2003 conference on Empirical methods in natural language processing, Sapporo, Japan (2003) 129-136
15. Zhang Y., Wu Z., Chen H., Sheng H., Ma J., *Mining Target Marketing Groups from Users' Web of Trust on Epinions*. The 2008 AAAI Spring Symposium. 2008.

The Dynamic Detection of Influenza Epidemics Using Google Search Data

Fan Liu

School of Management, Graduate University of Chinese Academy of Sciences

E-mail: jeffery.van@gmail.com

Geng Peng

School of Management, Graduate University of Chinese Academy of Sciences

E-mail: penggeng@gucas.ac.cn

Benfu Lv

School of Management, Graduate University of Chinese Academy of Sciences

E-mail: lubf@gucas.ac.cn

Abstract

Some new researches demonstrated that the search data can be used to detect public health trends and short-term syndromic surveillance. In this paper, we study the problem of influenza epidemics surveillance using Google search data. A hybrid model with dynamic search query set is developed, which was more accurate in influenza forecast than Google flu trends, especially for the irregular new influenza strain forecasts. This research is valuable for improving the timeliness of syndromic surveillance.

Keywords: Influenza surveillance, hybrid model, Google flu trends, search engine data

1. Introduction

The Internet search engine has become an important channel for people to seek life information. Meanwhile, the Internet search data record what the searchers are concerned about, and reflect peoples' activity trends in a certain extent. Some new studies present that the search data can help to detect public health trends and syndromic surveillance (Hulth, Rydevik and Linde 2009; Polgreen, 2008; Eysenbach, 2006; Doornik, 2009). A recent fundamental study is Ginsberg et al (2009) using Google search data to detect influenza epidemics, and their new method can improve the timeliness compared to the traditional surveillance method. The model was also used to Google Flu Trend. Following this work, Jurgen A. Doornik (2009) extended it to an auto-regression model with calendar effects, and improved the prediction accuracy. However, both models are powerless in predicting the turning point when a new flu outbreak in April 2009.

In this paper, we do some work about the irregular new strain prediction. Section 2 of this paper reviews the two typical models in former literature. Following Section 3 discusses the flu data, search query data, and why integrating the two types of data. The hybrid model with fixed query set is presented in Section 4. It can detect the seasonal fluctuations of influenza, but doesn't do well in capturing the turning point in May 2009. Then we build a dynamic model in Section 5, which detect the new influenza strain successfully by adding new queries into the former fixed query set.

2. The Current Models and Query Selection Method

Ginsberg et al (2009) built a simple linear regression model to predict influenza-like illness (ILI) in United States based on Google search engine query data, and it can be two weeks in advance of the release of CDC's flu report. The model selects 45 best fitting ones from 50 million of most common search queries, and reached a mean correlation of 0.97. This indicates that the Google search query data indeed has predictability of influenza epidemics. But the Google Flu Trends model has a serious deficiency. The model shows severe insensitiveness to the non-seasonal influenza outbreaks, because the selected 45 can't be amended with characteristic queries of new influenza symptoms. As a consequence, it is helpless in the new influenza forecast. An example is that at the end of April 2009 when a new swine flu began to outbreak, the model made a long period of forecast failure, and completely omitted the trend of this influenza peak.

In order to robustify the Google Flu Trends model, Jurgen A. Doornik (2009) extended it to an auto-regression model with calendar effects. In his model, the lagged dependent variables were used to capture the long-term cycle, and the calendar dummy variables were used to capture the seasonal and asymmetric effects. The new model not only improved the prediction accuracy, but also has self-correct capability that it needs two periods or more to revise when the swine flu suddenly arose in 2009-04-26 (week 17). However, we find that the robustified model still couldn't capture the turning point when the sudden and unprecedented fluctuation occurred. So the new model yet does not solve the key issue of turning point detection.

3. The Integration of Time Series Data and Search Query Data

Influenza is a seasonal infectious disease. In United States, Centers for Disease Control and Prevention (CDC) defines the flu season as the duration between the 40th week each year and the 20th week next year (about early October to mid May next year). In flu season, CDC releases weekly influenza surveillance report. The main indicator of influenza surveillance is the percentage of visits for influenza-like illness (ILI%) in hospital outpatients. We can draw out the trends of historic influenza activity with the CDC reported ILI% weekly data. In Figure 1, the curves of ILI% 2006-07 and ILI% 2007-08 are only in the flu season. By comparing the three curves, the influenza activity is highly seasonal. In October of each year, the flu season began, and between January and February the peak appeared, and then gradually fell. Importantly, the trend of each year is extremely similar. Based on this characteristic, using time series modeling for influenza surveillance would be an appropriate method (Reis and Mandl, 2003; Batal, 2001).

In history, the influenza activity had dropped to very low level after April, and even down to the level of non-flu season after May, while Figure 1 shows that in April and May 2009 there is a significant peak of ILI% compared with the same time of past years, which is due to the outbreak of the H1N1 flu. The time series methods are unable to detect the abnormal fluctuation, which can only be adjusted after the outbreak (Doornik, 2009). In 2009, by massively calculating the correlation between the time series of 50 million queries and the influenza (ILI% series), Ginsberg et al finally selected 45 best fitting ones to monitor influenza activity. The 45 queries are all related to influenza. They got fairly good results using simple linear regression. However, their model also can't capture the above-mentioned volatility.

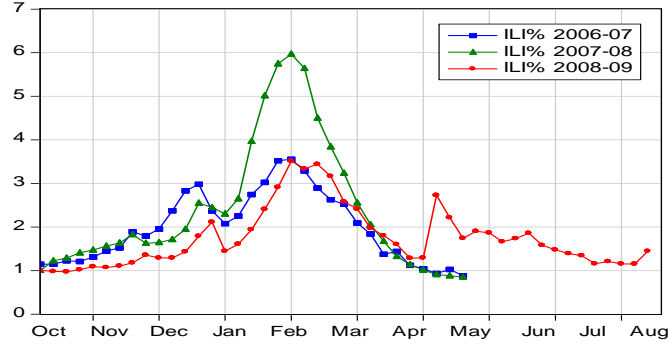


Figure 1 The percentage of visits for influenza-like illness (ILI%) released by CDC.

4. Hybrid Model with Fixed Query Set

We use the above-mentioned 45 queries' search volume and weekly ILI% data from CDC to build a static model. The data collection duration is the flu season from 2003 to 2009 (week 40 in 2003 to week 29 in 2009). Here we split the data into two segments: Segment 1 is from Week 40 in 2003 to Week 20 in 2007, and segment 2 is from Week 40 in 2007 to Week 29 in 2009. We use the segment 1 data to estimate our static model, while the segment 2 is for forecasting.

In order to reduce the data variation and instability, we use the logit transformation to preprocess the variable ILI%:

$$\text{logit}(ILI\%) = \log\left(\frac{ILI\%}{100 - ILI\%}\right)$$

The log-transformation is used to convert Q , the sum of the 45 queries' weekly search volume, to $\ln Q$. The dependent variable is $\text{logit}(ILI\%)_t$, and explanatory variables are the lagged 1-order dependent variable $\text{logit}(ILI\%)_{t-1}$ and current search volume $\ln Q_t$. As the query set is fixed, we call it static model:

$$\text{logit}(ILI\%)_t = -4.525 + 0.649 \text{logit}(ILI\%)_{t-1} + 0.695 \ln Q_t$$

(0.371)
(0.030)
(0.059)

$$\bar{R}^2 = 0.942, \sigma = 12\%$$

The estimated coefficients are all highly significant, and their standard errors are in parentheses. The standard error of this static model regression is 12%, Doornik' auto-regression model with up to the 53rd lag is also about 12%, while the Google Flu Trends model is up to 65%.

In forecasting, since the Google Flu Trends model used real-time search data, it could detect influenza activity about two weeks in advance of CDC, but don't have predictability to the future trends of influenza. Therefore, in practice, the Google Flu Trends model can be used for influenza surveillance two weeks ahead. In Figure 4, the static model forecasts have been transformed by the anti-logit transformation. Before Week 16 in 2009 (April 26), the forecasts from static model is mainly consistent with the actual value, but after that the prediction was significantly underestimated. Obviously, the static model did not detect the influenza abnormal fluctuation in May 2009.

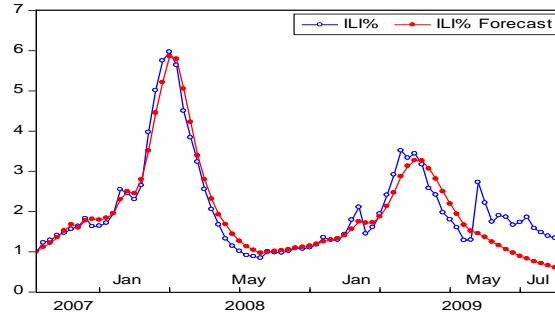


Figure 4 The forecasts from static model and the actual ILI%

Since in May 2009 the H1N1 flu outbreak appeared in United States, it led to the higher level of flu activity than the same period of history. The 45 queries used in the static model are all concerning ordinary flu which were build in 2008, so they didn't reflect the new influenza such as H1N1 and swine flu. In order to monitor the unusual volatility, we must add queries about new influenza into our model.

5. Hybrid Model with Dynamic Query Set

For the influenza outbreak in May 2009, pure time series model couldn't predict it, but only adjusted to a reasonable level in a few weeks after the abnormality occurred (Doornik et al, 2009). To detect similar influenza outbreak, we try to use Google Trends (<http://www.google.com/trends>) to supplement our query set with queries about H1N1 and swine flu. With Google Trends, people can inquiry the terms' search volume in any topics, based on a subset of Google's search database.

According to the characteristics of new influenza and the actual situation of Google Trends data, we mainly consider the H1N1 and swine flu related queries weekly search volume after Week 13 in 2009 (April 4). All the added queries are listed in Table 2. The search volumes of all queries are very small before April 2009, but there is a sudden surge in the end of April, and then dropped to a lower level quickly after May. These features are consistent with the development of new influenza.

Table 2 The added queries about H1N1 and swine flu

H1N1 related queries	Swine related queries
H1N1	Swine Flu
H1N1 Flu	Swine Flu Symptoms
Symptoms H1N1	Swine Flu Vaccine
H1N1 Virus	Swine Flu Cases
H1N1 Flu Symptoms	Swine Flu H1N1
H1N1 CDC	Swine Flu CDC

The dynamic model added new queries is estimated as follows

$$\log it(ILI\%)_t = -6.072 + 0.554 \log it(ILI\%)_{t-1} + 0.95 \ln Q_t$$

(0.393)
(0.030)
(0.063)

$$\bar{R}^2 = 0.965, \sigma = 10.6\%$$

The dynamic model is estimated better than the static model in various indicators. The standard error of regression is only 10.6%, and the residual also meets the requirements. Similarly, we split the data into the same two segments for predictive test.

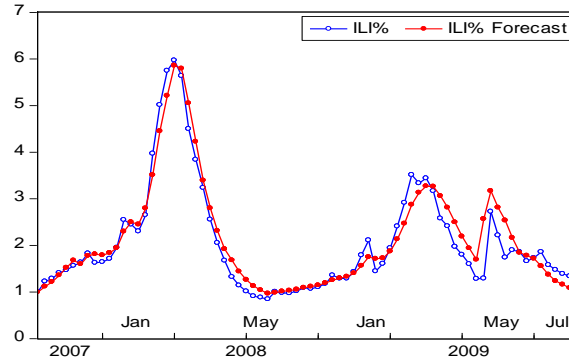


Figure 5 The forecasts from dynamic model and the actual ILI%

Table 3 Forecast statistics for ILI% of two hybrid models, Google Flu Trends model and autoregressive with calendar effects

	The Static Model	The Dynamic Model	Google Flu Trends	autoregressive with calendar effects
ROME	0.29	0.15	0.29	0.41
MAPE	4.78	2.87	12	12

In table 3, the forecast statistics of dynamic model is very satisfactory. The root mean squared error (RMSE) is 0.15, the mean absolute percentage error (MAPE) is 2.87, and the covariance proportion is up to 0.93. Our hybrid models are superior to the models of Google Flu Trends and the autoregressive with calendar effects (Doornik, 2009), and the dynamic hybrid model is far better than the static.

As shown in Figure 5, by adding new influenza-related queries, the dynamic model monitored the outbreak of influenza in May 2009, and the forecasts are highly in line with the actual in the subsequent phases. This demonstrates that the adding queries basically reflect the influence of new flu in 2009.

6. A Mechanism of Selecting New Flu-related Queries

Due to frequent variation of flu virus, new symptoms and mutations emerge constantly. This often causes the volatility of influenza activity different from previous years. Therefore, it's difficult to reflect the new features of influenza with the fixed query set. Though the dynamic model which includes new influenza-related queries can detect the abnormalities, it is just the ex-post analysis. The linchpin of successful prediction and real-time surveillance is how to select the new queries prior to the anomalies. It is also pretty significant to recognize and prevent the disease.

There is a period of spreading time from the emergence of new influenza to the outbreak. The on-line querying before outbreak is critical for selecting new queries. Some phenomenon, such as influenza activity, has the season and trend cycle factors in time series, and also has certain irregular variability under the influence of random factors. For this phenomenon, we propose a selection mechanism called the basic query plus hot query.

In our dynamic model, the lagged 1-order dependent variable showed the performance of the historical information, and the inertia of influenza activity. So-called basic queries are which indicate the seasonal and cyclic variation of the incidents. Its amount is fixed. In influenza monitoring, Google Flu Trends has identified it as 45, which has been validated to be suitable by the ILI% data before 2009. And the hot queries are to reflect the abnormal changes, the influence of instantaneous factors and more than a certain search volume. The quantity of hot query is variable with the people's concern about the incidents.

The selection of hot queries can use the top searches and rising searches provided by Google Insight for Search (google.com/insights/search/). Top searches can inquiry the most popular queries in relationship with an event, while the rising searches provide queries which volumes visibly increase in a certain time. The rising searches about an event-related query reflect the changes of people's concern. Top searches and rising searches can work together to identify the range of new queries.

7. Summary and Concluding Remarks

In order to detect influenza activity, the static hybrid model utilizes the 45 queries of the Google Flu Trends. It accurately predicted the influenza activity before 2009. Although its results were better than Google Flu Trends and time series model, it can't detect the outbreak in May 2009. The main reason is that the fixed query set doesn't include the new influenza-related queries. Furthermore, we built the hybrid model with dynamic set, which was added the H1N1 and swine flu related queries. This model forecast the abnormal fluctuation successfully.

References

1. Ginsberg, J. et al. "Detecting influenza epidemics using search engine query data," *Nature* Vol 457, 2009, PP.1012-1014.
2. Hulth, A., Rydevik, G., and Linde, A. "Web Queries as a Source for Syndromic Surveillance," *PLoS ONE*, Volume 4, Issue 2, 2009, e4378.
3. Polgreen, P. M., et al. "Using Internet Searches for Influenza Surveillance," *Healthcare Epidemiology*, 2008, PP.1443-8.
4. Eysenbach, G. "Infodemiology: tracking flu-related searches on the web for syndromic surveillance," *AMIA Annu. Symp. Proc*, 2006, PP.244-248.
5. Doornik, J. A. "Improving the Timeliness of Data on Influenza-like Illnesses using Google Search Data," 2009, [http://www.doornik.com/flu/Doornik\(2009\)_Flu.pdf](http://www.doornik.com/flu/Doornik(2009)_Flu.pdf).
6. Askitas, N., and Zimmermann, K. F. "Google Econometrics and Unemployment Forecasting," *Applied Economics Quarterly*, Vol. 55, (2009) 2, PP.107-120.
7. Choi, H., and Varian, H. "Predicting the Present with Google Trends," 2009, http://ec.europa.eu/dgs/policy_advisers/experts_groups/alexis_jacquemin/docs/google_predicting_the_present.pdf.

8. Sano, Y., and Takayasu, M. "Macroscopic and microscopic statistical properties observed in blog entries," 2009, <http://arxiv.org/abs/0906.1744>.
9. Centers of Disease Control and Prevention. "Flu Activity & Surveillance. Reports & Surveillance Methods in the United States," <http://www.cdc.gov/flu/weekly/Fluactivity.htm>.
10. Reis, B. Y., and Mandl, K. D., "Time series modeling for syndromic surveillance," *BMC Medical Informatics and Decision Making* (2003) 3.
11. Batal, H. "Predicting patient visits to an urgent care clinic using calendar variables," *Acad Emerg Med* 8(1), 2001, PP.48-53

Exploiting Item Heterogeneity for Collaborative Filtering Recommendation

Hung-Chen Chen
Dept. of Info. Management
National Taiwan University
Taipei, Taiwan, R.O.C.
JesseHCChen@gmail.com

Ying-Siou Dai
Inst. of Tech. Management
National Tsing Hua University
Hsinchu, Taiwan, R.O.C.
ransondai@gmail.com

Chih-Ping Wei
Dept. of Info. Management
National Taiwan University
Taipei, Taiwan, R.O.C.
cpwei@im.ntu.edu.tw

Yu-Kai Lin
Inst. of Service Science
National Tsing Hua University
Hsinchu, Taiwan, R.O.C.
yklin@mx.nthu.edu.tw

Abstract

Among various recommendation approaches, collaborative filtering (CF) is the most successful and widely adopted one. However, measuring user similarity and predicting user preference without considering item heterogeneities renders traditional collaborative filtering approach to be less effective. In this study, we propose the content-weighted collaborative filtering (CWCF) technique that extends the traditional CF approach by considering the content similarities of items. Our empirical evaluation results show that our proposed CWCF technique substantially improves the prediction accuracy in comparison with the CF approach.

Keywords: Item Heterogeneity, Content Similarity, Collaborative Filtering

1. Introduction

Internet facilitates the creation, distribution, and access of information so that online users can search for products that better match their personal preferences or requirements. However, the well-known information overload problem makes the search activity rather difficult and inefficient. In response, recommendation systems, also called recommendation agents, have emerged to address the challenge of information overload by suggesting items that users may like or be interested in. Although prior studies have proposed and developed several different recommendation approaches (Wei et al., 2002), the collaborative filtering approach (Resnick et al., 1994; Konstan, et al., 1997) is the most successful and widely adopted one. Specifically, the collaborative filtering approach relies on users' preferences as its inputs and identifies users whose tastes are similar to those of a target user (or called an active user) and recommends to the active user items they have liked.

However, the traditional collaborative filtering approach ignores item heterogeneities and thus may not be effective when applying to an environment in which content heterogeneities of items are commonly observed. For example, movies can be classified into such categories as romance, war, suspense, horror, drama, comedy, and so on. If we want to predict an active user's preference on a particular suspense movie, user preferences on movies of the suspense category or similar categories (e.g., horror) would be more relevant to the target prediction task than user

preferences on dissimilar categories (e.g., comedy). Likewise, suppose we have a collection of books with topics such as data mining, data warehousing, decision support systems, cognitive psychology, sociology, technology management, etc. To predict a user's preference on a data mining book, user preferences on those books pertaining to data mining, data warehousing, and decision support systems appear to be more relevant than those on other dissimilar topics such as cognitive psychology, sociology, and technology management. Unfortunately, existing collaborative filtering techniques do not exploit item heterogeneities and simply consider user preferences (i.e., rating scores) of items identically important by giving users' preferences an equal weight when computing similarities among users. To improve recommendation effectiveness, the collaborative filtering approach needs to be extended by giving higher weights to user preferences on those items that have greater content similarity with the target item when estimating user similarities.

In this study, we propose a content-weighted collaborative filtering technique that extends the traditional collaborative filtering approach by considering content similarities of items. Specifically, the content similarity between items is first measured. Subsequently, to predict an active user's preference on a particular item, only the user preferences on items similar to the target item are considered when determining the similarity between the active user and each of the other users. We use the MovieLens Dataset collected by the GroupLens Research Project (Resnick et al., 1994) and conduct a series of experiments using the traditional collaborative filtering approach as the performance benchmark. According to our empirical evaluation results, our proposed content-weighted collaborative filtering technique improves the prediction accuracy, compared with its benchmark.

The remainder of this paper is organized as follows: The design of our proposed technique is detailed in Section 2. We then depict our evaluation design and discuss important evaluation results in Section 3. We conclude in Section 4 with a summary and some future directions.

2. Content-Weighted Collaborative Filtering (CWCF) Technique

Error! Reference source not found. shows the overall process of our proposed CWCF technique. To exploit item heterogeneities for greater recommendation effectiveness, the first phase is to estimate the content similarity between items based on the cosine similarity measure. To predict the preference score of an active user u_a on a target item i_t , the neighborhood formation phase determines, among all users that have expressed their preferences on i_t , the top- N users whose preferences are most similar to those of u_a as his/her neighbors. We develop a content-weighted correlation coefficient measure that considers content similarities when estimating the similarity between the active user and each of other users who have rated i_t . Finally, the known preferences of the neighbors on i_t are used to predict the preference of u_a on i_t .

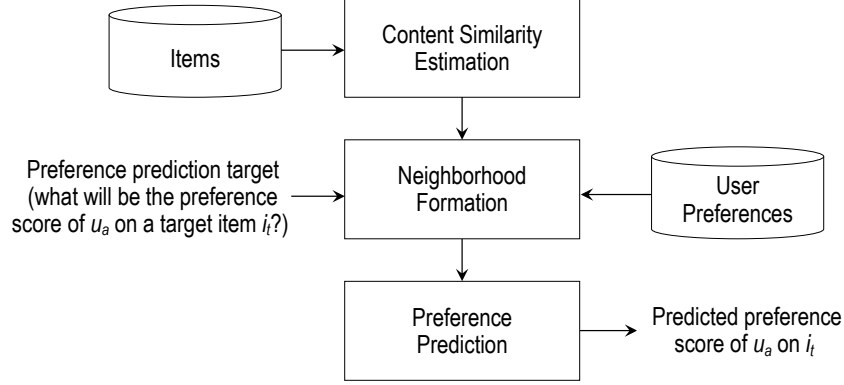


Figure 1. Overall process of content-weighted collaborative filtering (CWCF) technique

2.1 Content Similarity Estimation

Because most of items to be recommended (e.g., movies, songs, or electronics) possess text descriptions, the text-processing tasks, i.e., keyword extraction, keyword selection, and item representation, can be performed in advance for estimating content similarities. In this study, we assume that each item has been represented as a feature (i.e., keyword) vector. To assess the content similarity between two items, the cosine similarity measure is adopted, as follows:

$$sim_{content}(i_x, i_y) = \frac{\vec{i}_x \cdot \vec{i}_y}{\|\vec{i}_x\|_2 \|\vec{i}_y\|_2}, \text{ where } \vec{i}_x \text{ (or } \vec{i}_y) \text{ is the corresponding feature vector of } i_x \text{ (or } i_y) \text{ and “} \cdot \text{”}$$

denotes the dot-product of the two vectors.

2.2 Neighborhood Formation

The Pearson correlation coefficient measure is widely adopted in traditional collaborative filtering approaches to compute the similarity between two users. However, all the preferences on the co-rated items of two users contribute equally to the similarity of the users and may lead to find inappropriate users as the neighbors for the active user. To address this limitation, we take into account content similarities when estimating the similarity between the active user and each of other users who have rated the target item and propose the content-weighted correlation coefficient measure that gives higher weights to the preferences on the co-rated items that have higher content similarity with the target item. Consequently, the content-weighted correlation coefficient measure between u_a and u_b from the perspective of the target item i_t is defined as:

$$sim(u_a, u_b, i_t) = \frac{\sum_{x=1}^m (sim_{content}(i_t, i_x) p(u_a, i_x)) (sim_{content}(i_t, i_x) p(u_b, i_x))}{\sqrt{\sum_{x=1}^m (sim_{content}(i_t, i_x) p(u_a, i_x))^2} \sqrt{\sum_{x=1}^m (sim_{content}(i_t, i_x) p(u_b, i_x))^2}}, \text{ where } p(u_a, i_x)$$

(or $p(u_b, i_x)$) denotes the preference score of the user u_a (or u_b) on item i_x , and m is the number of items co-rated by u_a and u_b .

Furthermore, to increase the number of items co-rated by u_a and u_b , we design a fill-in strategy using the constrained k -nearest item method. Specifically, if u_a (or u_b) has rated item i_x but the

other user has not, the preference score of u_b (or u_a) on i_x is temporally filled-in with the weighted average preference score of the items rated by u_b (or u_a). That is, among all items rated by u_b (or u_a), we select only the top- k items whose similarities to the item to be filled-in (i.e., i_x) are highest and are greater than a prespecified threshold δ to compute the weighted average preference score i_x for u_b , where the similarity between a selected item i_f and the item to be filled-in (i.e., i_x) is employed as the weight. Afterwards, the top N users with the highest user similarities estimated by the content-weighted correlation coefficient measure are selected as the neighbors for the active user.

2.3 Preference Prediction

After identifying the N nearest neighbors and forming the neighborhood for the active user u_a , the known preferences of the neighbors on the target item i_t are aggregated to arrive at a preference prediction for u_a on i_t . We extend the prevalent deviation-from-mean method (Resnick et al., 1994; Konstan, et al., 1997) by modifying how the average preference score of the active user or each of his/her neighbors selected previously is calculated, as follows:

$$p(u_a, i_t) = \bar{p}(u_a) + \frac{\sum_{b=1}^N (p(u_b, i_t) - \bar{p}(u_b)) \text{sim}(u_a, u_b, i_t)}{\sum_{b=1}^N \text{sim}(u_a, u_b, i_t)}, \text{ where } \bar{p}(u_a) \text{ (or } \bar{p}(u_b) \text{) is the}$$

weighted average preference score of u_a (or u_b), determined by the constrained k -nearest item method (employed by the fill-in strategy of the previous phase).

3. Empirical Evaluation

We conduct the empirical evaluation of the proposed CWCF technique and use the traditional collaborative filtering (namely CF) approach as the performance benchmark. The evaluation dataset and the evaluation metrics are first depicted in Section 3.1. Subsequently, important evaluation results are discussed in Section 3.2.

3.1 Evaluation Dataset and Evaluation Metrics

We use the MovieLens dataset collected by the GroupLens Research Project at the University of Minnesota to conduct a series of experiments. There are 100,000 ratings (with a scale from 1 to 5) from 943 users on 1,682 movies. All of the users in the original dataset have rated at less 20 movies. Because, in the MovieLens dataset, many users gave identical or highly similar preference scores on all movies that they rated, the preference prediction for these users is considered uninteresting. Thus, we remove those users with low variance on their preference scores (i.e., variance ≤ 1.3) from the original database. As a result, we retain 6,392 ratings from 225 users on 1,637 movies as our evaluation dataset. Furthermore, because the MovieLens dataset does not contain the description of each movie, we obtain these descriptions from the Internet Movie Database (IMDB) and accordingly represent each movie as a feature vector.

Two evaluation metrics are employed, including prediction accuracy and coverage. For prediction accuracy, we adopt the mean absolute error (MAE) measure (Shardanand and Maes, 1995), which is defined as: $MAE = (\sum_{i=1}^T |p_i - q_i|) / T$, where p_i is a predicted preference score, q_i

is its actual rating for the same preference prediction task, and T is the number of preference prediction tasks. The second evaluation metric is coverage (Herlocker et al., 1999), which is defined as the percentage of the preference prediction tasks that can be predicted by a recommendation technique investigated.

3.2 Performance Comparison

Our proposed CWCF technique involves two important parameters: δ and k in the constrained k -nearest item method (in the fill-in strategy and the modified deviation-from-mean method). In this study, we increase the threshold δ from 0.1 to 0.2 and set k 11 for our proposed technique and compare its effectiveness with that of CF. As we show in Figure 2, as δ increases from 0.1 to 0.2, the MAE achieved by the proposed CWCF technique substantially reduces at any number of neighbors examined (from 1 to 7). CWCF noticeably outperforms CF when δ is greater than 0.1. The result demonstrates that considering item heterogeneities can help improve the prediction accuracy. However, while improving the prediction accuracy, CWCF inevitably sacrifices its coverage. As Figure 3 shows, the coverage attained by CWCF decreases considerably as δ increases. To balance the tradeoff between prediction accuracy and coverage, we can combine CWCF with CF. Specifically, CF is activated when CWCF cannot make a prediction for an active user. As a result, the hybrid approach (for $\delta=0.2$) can achieve the same coverage as CF does and its average prediction accuracy is still better than that of CF.

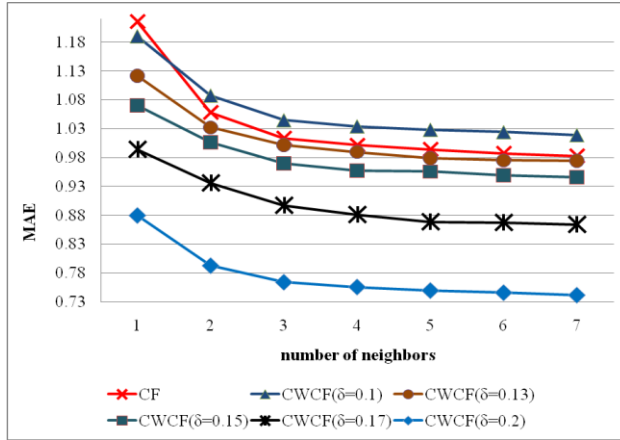


Figure 2. Comparative evaluation on MAE

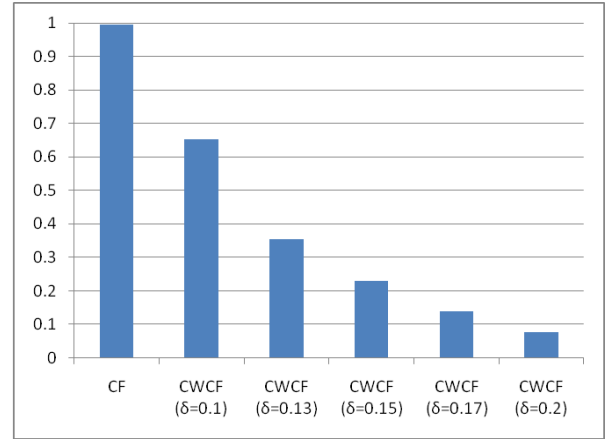


Figure 3. Comparative evaluation on coverage

4. Conclusion

In this study, we propose a content-weighted collaborative filtering (CWCF) technique that takes into account content heterogeneities when making preference prediction. Our empirical evaluation results suggest that our proposed CWCF technique substantially outperforms the traditional CF approach in prediction accuracy (i.e., MAE). To address the low coverage of CWCF, we also suggest a hybrid approach that combines CWCF and CF. In the future, to improve the generalizability of the evaluation results reported in this study, we should conduct additional evaluations that involve different contexts (i.e., book, music recommendations). Moreover, the extension and improvement of CWCF that can achieve higher coverage while maintaining similar accuracy level represents an essential direction for future research.

Acknowledgement

This work was supported by the National Science Council of the Republic of China under grant NSC NSC 98-2410-H-002-232-MY2.

References

1. Herlocker, J., Konstan, J., Borchers, A. and Riedl, J., "An Algorithmic Framework for Performing Collaborative Filtering," *Proceedings of 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, 1999, pp.230-237.
2. Konstan, J. A., Miller, B. N., Maltz, D., Herlocker, J. L., Gordon, L. R. and Riedl, J., "GroupLens: Applying Collaborative Filtering to Usenet News," *Communications of the ACM*, Vol. 40, No. 3, 1997, pp.77-87.
3. Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P. and Riedl, J., "GroupLens: An Open Architecture for Collaborative Filtering of Netnews," *Proceedings of the Conference on Computer Supported Cooperative Work (CSCW)*, Chapel Hill, NC, 1994, pp.175-186.
4. Shardanand, U. and Maes, P., "Social Information Filtering: Algorithms for Automating Word of Mouth," *Proceedings of ACM CHI'95 Conference on Human Factors in Computing Systems*, 1995, pp.210-217.
5. Wei, C., Shaw, M. J., and Easley, R. F., "A Survey of Recommendation Systems in Electronic Commerce," Chapter 8 in *E-Service: New Directions in Theory and Practice*, R. T. Rust and P. K. Kannan (Eds), M. E. Sharpe Publisher, 2002.

How Does Information Technology Affect Inventory? The Role of Moderators and Mediators

Richard Lai
University of Pennsylvania
lairk@wharton.upenn.edu

Sean Xin Xu
Tsinghua University
xuxin@sem.tsinghua.edu.cn

Kevin Zhu
University of California, San
Diego
kxzhu@ucsd.edu

Abstract

Prior research shows some evidence that IT reduces inventory, but also raises important estimation issues—possible endogeneity, omitted complementarity, and omitted variables. We address these issues using data of 1,052 firms over 6 years. Surprisingly, we see no evidence of IT impact on inventory for the average firm. We next probe deeper beyond just the average firm, by examining moderators and mediators of the IT-inventory relationship. We then find that the aggregate IT effect on inventory masks two contrasting roles that IT plays. First, the further up a supply chain where distortion is the greatest, the more IT reduces inventory. Second, IT facilitates firm growth, which increases inventory. Together our analyses open up new directions, both empirically and theoretically, to relate IT to inventory.

Keywords: Inventory, Information Technology, Supply Chain, Distortion, Firm Growth

1. Motivation

In this paper, we focus on a specific mechanism through which IT could enhance productivity at the firm level, that is, by reducing a critical form of working capital: inventory. Inventory is a central subject of study in operations management and it arises as working capital because of mismatches in supply and demand. Its importance is evident: it comprises 20% of total assets for the average listed firm. So we ask: does IT really reduce inventory at the firm level?

2. Baseline Result: A Direct Relationship between IT and Inventory

Our analyses, at the first step, find no evidence to support a direction relationship between IT and inventory. This is somewhat surprising in light of both substantial investment in IT in industries and widely recognized theories in academia that IT improves information flows along supply chains, which in turn increase efficiencies in inventory management (e.g., Milgrom and Roberts 1988). Further, there is some empirical evidence in the literature suggesting that IT reduces inventory (e.g., Mukhopadhyay, et al. 1995, Barua, et al. 1995, among others). We extend this literature by taking into account of three important estimation issues:

- We employ novel instrumental variables (e.g., executives' college majors and age, and the number of transistors on microchips) to address possible endogeneity that IT could be endogenously determined due to decreased inventory and thus increased productivity. The idea is that firms whose executives are younger and have more IT-related majors are more likely to have higher IT. They are unlikely to be correlated with factors that jointly determine inventory and IT or mechanisms that go from inventory to IT (such as firm profitability).
- We address complementarities of IT components in a firm's IT infrastructure, by examining not only specific IT measure like ERP usage but also board measures like IT stock.
- We try to avoid omitted variable biases by adding controls for inventory, which are just reported in recent operations studies (Gaur, et al. 2005, Rumyantsev and Netessine 2007).

With these three econometrics issues addressed, our regression model is as follows:

$$l_{it} = \sum_{y=t-l}^t \tau_{iy} + \Delta_{it} + \phi_i + \phi_t + \varepsilon_{it} \quad (1)$$

where l_{it} is a measure of inventory (log days of inventory) for firm i in year t . τ is IT, the variable of interest, with up to l lags. Δ is a vector of control variables that can affect inventory (Gaur, et al. 2005, Rummyantsev and Netessine 2007)). ε is assumed to be white noise. ϕ captures firm-fixed effects and ψ , year effects.

We use data from several sources. From the *Computer Intelligence* (CI) database, we obtain proprietary information on firms' IT infrastructure (based on which we compute IT stock) and ERP applications (based on which we compute scores to indicate the extent of firm-level usage of supply chain ERP and general ERP systems). From *Information Week*, we obtain rankings of firms' use of IT, as an additional measure of IT. We use *Compustat* for accounting data such as inventory. We use GVKEY to establish concordance among these datasets. Our final dataset consists of 1,052 unique firms during 2001-2006. In the subsequent analysis (Tables 1-3), we try both IT stock and IT rank and obtain highly consistent results. For example, Table 3 presents results for IT rank; using IT stock gives qualitatively similar results.

Table 1 shows our baseline results. In columns (A), (B), and (C), we show that our IT measures can replicate results in previous studies that IT reduces inventory; these prior studies tend to use narrow measures for specific IT (like ERP). To address complementarities of IT applications, we use broader measures of IT as well. In (D) and (E), we use two example broad measures: the log of IT stock and *Information Week*'s IT rank indicating IT leaders. While we are still able to obtain a negatively signed estimate in (D), we could not in (E), where the IT rank arguably better captures overall complementarity than that of IT stock. In columns (F) and (G), we address omitted variables bias by introducing control variables for inventory. As examples, we report estimates using the narrow "supply chain ERP score" in (F) and the broad IT stock measure in (G); both columns use the Gaur, et al. (2005) control variables as an example. In (F), we see that the IT measure has now lost its minor statistical significance in (A). We obtain qualitatively similar results using other IT measures and the control variables from Rummyantsev and Netessine (2007) instead. In columns (H) and (I), we address endogeneity by introducing instrumental variables. Now, all IT measures are statistically indistinguishable from zero.

In sum, addressing the three estimation issues—possible endogeneity, omitted complementarity bias, and omitted variables bias, we see ***absence of evidence*** that IT reduces inventory for the average firm, which suggests the need to revisit the current evidence in the empirical literature.

3. Moderating Effect on the IT-Inventory Relationship

Next we propose a moderator hypothesis that we are more likely to observe more negative IT effects for upstream firms (manufacturers versus retailers) because they face higher information distortion than firms at the downstream—according to the "bullwhip" effect—and because IT helps to mitigate impacts of distortion. Table 2 presents the results. To reiterate, we conduct IV estimation, use both specific and broad measures for IT, and employ controls for inventory (similar analyses performed in section 4). In columns (A), (B), and (C), we run seemingly unrelated regressions in a system of equations for manufacturers, wholesalers, and retailers. When we measure IT with a narrow measure—such as supply chain ERP as shown in Table 2—

we see mostly no IT effect; the best is a weakly significant and positive estimate of the IT effect for retailers. A possible interpretation is that IT may facilitate firm growth (Mitra 2005). When we measure IT with a broad measure—such as the log of IT stock—we see that the IT effect is significantly negative for manufacturers, not significant for wholesalers, and significantly positive for retailers. Here, we are concerned about the **differences** in the IT effect, e.g., differences across columns (A)-(C), rather than the absolute level of the effect. The last row of Table 2 shows results from a generalized Hausman cross-equation test. The differences are mostly significant, consistent with a theory in which IT works through the mechanism of mitigating information distortion to *reduce* inventory.

4. Mediating Effect on the IT-Inventory Relationship

From another theoretical perspective, we hypothesize that IT affects inventory via mediators like firm growth. The underpinning theory is that IT facilitates growth (Mitra 2005), which tends to increase inventory (Porteus 2002). We use three measures for firm growth, growth in sales, assets, and costs of goods sold (COGS). In Table 3, column (A) uses supply chain ERP as an example of narrow measures for IT, and sales growth as the measure for firm growth. It has two parts, the mediator regression and the structural equation (see Table 3 for explanations). In the mediator regression, IT is positively signed. The estimate for IT in the structural equation becomes statistically insignificant (i.e., 0.000 in the “Struct” column). In column (B), we show another example estimation, this time using a broad measure of IT and a different measure of firm growth. The result is similar. Indeed here, once we include the growth mediator, the IT effect turns even negative, to -0.003. Growth in COGS gives consistent results. In sum, the results are consistent with the view that IT may *reduce* inventory (perhaps by reducing information distortion in product market uncertainty), but this reduction can be more than compensated by IT’s *increasing* inventory via firm growth.

5. Concluding Remarks

To sum up, our analyses extend the literature by specifying a model that deals with the three econometrics issues when relating IT to inventory. We estimate the model using a recent, large-scale dataset; and a striking result is the absence of evidence for IT affecting inventory for the average firm. The result is robust to alternative model specifications, various measures of IT and inventory, alternative instrumental variables, and correction for potential selection bias (untabulated). These analyses emphasize that our result is achieved with rigorous econometrics, thus suggesting the need to revisit the commonly recognized role of IT in reducing inventory. We advance the theoretical development along this line by showing how the role of IT in inventory management may be shaped by moderators related to information distortion, as well as by mediators pertaining to the strategic role of IT in enabling firm growth. Overall, these results help us better understand, both empirically and theoretically, the role of IT in inventory management in modern firms.

Acknowledgement

Richard Lai is grateful for financial support from the Wharton Global Research Initiatives Program, the University of Pennsylvania Provost Office’s International Research Grant, and the Penn Lauder Center for International Business Education and Research. Sean Xu acknowledges financial support from the National Natural Science Foundation of China (70831003, 70890080) and the Program for New Century Excellent Talents in University (NCET-10-0508). Kevin Zhu

acknowledges the financial support of the CAREER Award from the U.S. National Science Foundation (NSF#0654400), and the financial support by the National Natural Science Foundation of China (Grant #: 70728002).

References

1. Barua, A., Kriebel, C.H. and Mukhopadhyay, T. "Information Technologies and Business Value: An Analytic and Empirical Investigation," *Information Systems Research* (6:1), 1995, pp. 3-23.
2. Gaur, V., Fisher, M.L. and Raman, A. "An Econometric Analysis of Inventory Turnover Performance in Retail Services," *Management Science* (51:2), 2005, pp. 181-194.
3. Milgrom, P. and Roberts, J. "Complementarities and Fit Strategy, Structure, and Organizational Change in Manufacturing," *Journal of Accounting and Economics* (19:2/3), 1995, pp. 179-208.
4. Mitra, S. "Information Technology as an Enabler of Growth in Firms: An Empirical Assessment," *Journal of Management Information Systems* (22:2), 2005, pp. 279-300.
5. Porteus, E.L. *Foundations of Stochastic Inventory Theory*, Stanford University Press: Palo Alto, CA, 2002.
6. Rumyantsev, S. and Netessine, S. "What can be Learned from Classical Inventory Models? A Cross-Industry Exploratory Investigation," *Manufacturing & Service Operations Management* (9:4), 2007, pp. 409-429.

Table 1. A Direct Relationship between IT and Inventory

The dependent variable is log days of inventory, and the regression model is equation (1) in the text. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

	REPLICATION			OUR APPROACH					
	(A)	(B)	(C)	(D) +Broad measure	(E) +Broad measure	(F) + Control vars	(G) + Control vars	(H) +IV	(I) +IV
IT MEASURE									
Supply chain ERP score	-.034* (.023)					-.003 (.024)		-1.43 (17.4)	
General ERP score		-.049** (.024)	-.070*** (.026)						
- 1 lag			-.024 (.021)						
- 2 lags			-.002 (.021)						
Log IT stock				-.027*** (.006)			-.029*** (.007)		.031 (.149)
IT rank					.000 (.000)				
CONTROLS^{\$}									
Gaur, et al. (2005)						Yes	Yes	Yes	Yes
N	5306	5306	5306	4871	4871	4269	3937	1204	1204
P	.000	.000	.000	.000	.000	.000	.000	.000	.000

*, **, *** means significance at the 10%, 5%, 1% levels.

^{\$} These controls are from Gaur, et al. (2005). Using controls in Netessine and Rudi (2006) yields consistent results.

Table 2. Moderation

The dependent variable is log days of inventory. The specification is in the baseline model, equation (1) in the text. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

(Manufacturers: NAICS 31-33; wholesalers: NAICS 42; retailers NAICS 44-45)						
	(A) Manuf	(B) Wholesale	(C) Retail	(D) Manuf	(E) Wholesale	(F) Retail
IT MEASURE						
<i>Narrow measure:</i>						
Supply chain ERP score	0.057 (.308)	0.22 (.273)	.378* (.219)			
<i>Broad measure:</i>						
Log IT stock				-.196*** (.055)	0.259 (.196)	.344*** (.063)
CONTROLS [§]						
Gaur, et al. (2005)	Yes	Yes	Yes	Yes	Yes	Yes
<i>F</i>	386	161	2038	386	161	2038
<i>p</i>	.000	.000	.000	.000	.000	.000
GENEALIZED HAUSMAN CROSS-EQUATION TEST						
	(A) vs. (B)		(B) vs (C)	(D) vs. (E)		(E) vs. (F)
χ^2	3.29		103.0	20.35		34.05
<i>p</i>	.772		.000	.002		.000

*, **, *** means significance at the 10%, 5%, 1% levels.

[§] These controls are from Gaur, et al. (2005). Using controls in Netessine and Rudi (2006) yields consistent results.

Table 3. Mediation

The dependent variables are shown in the column heading, where “Med” means a regression of the mediator on IT and other controls for firm growth and “Struct” means a structural equation that regresses log days of inventory on IT as in equation (1), but including the mediator as an additional covariate. All estimations are done with Huber-White robust standard errors. We also cluster at the firm level to minimize serial correlations of the error term. Numbers in brackets are standard errors.

	(A) Med	Struct	(B) Med	Struct
IT MEASURE				
<i>Narrow measure:</i>				
Supply chain ERP score	12.89*** (2.28)	.000 (.000)		
<i>Broad measure:</i>				
IT rank			.116*** (.040)	-.003*** (.001)
MEDIATOR				
Sales growth		.120*** (.030)		
Assets growth				.120*** (.032)
CONTROLS [§]				
Gaur, et al. (2005)	Yes	Yes	Yes	Yes
<i>F</i>	21.67	30.56	17.22	3.56
<i>P</i>	.000	.000	.000	.000

*, **, *** means significance at the 10%, 5%, 1% levels.

[§] These controls are from Gaur, et al. (2005). Using controls in Netessine and Rudi (2006) yields consistent results.

Note. The “Med” regressions include controls for firm growth identified from prior research, including COGS, gross margin, gross PPE, debt leverage, cash flow on assets, and book-to-market ratio.

Does IT Matter? The Evidence

BRIAN L. DOS SANTOS
University of Louisville
Louisville, KY40292, USA
brian@louisville.edu

ZHIQIANG (ERIC) ZHENG
University of Texas at Dallas
Richardson, TX 75080, USA
ericz@utdallas.edu

VIJAY S. MOOKERJEE
University of Texas at Dallas
Richardson, TX 75080
vijaym@utdallas.edu

HONGYU CHEN
University of Texas at Dallas
Richardson, TX 75080, USA
hxc051200@utdallas.edu

Abstract

This paper determines whether the opportunities for firms to use IT to improve their performance have been decreasing over time, by examining how IT industry firms' stock prices react to changes in economic conditions. We develop a novel event-study approach and explain the logic behind our empirical analysis. Our analysis of the IT industry as a whole indicates that the opportunities for firms to use IT to improve their performance are not vanishing. However, there are sectors within the IT industry that no longer provide value-enhancing opportunities for firms.

Keywords: business value of IT, event study, stock price volatility

1. Introduction

The article titled "IT Doesn't Matter," published in the May 2003 issue of the *Harvard Business Review* (HBR) created quite a stir. Carr's claims suggest that firms should not invest in new IT applications (Carr 2003). If firms stop funding new IT applications, IT academics and IT practitioners, and many firms in the IT industry will be in serious trouble. Such actions by firms would lead to the demise of many firms in the IT industry, a smaller role for IT practitioners in non-IT industry firms, and a reduction in jobs in IT-related disciplines.

The absence of strong evidence to indicate that firms benefit from their IT investments, together with the controversy created by Carr's article makes it increasingly important to provide evidence of the business value of IT. In this paper we describe an event study that does so in an unconventional way. We assert that if IT no longer provides opportunities for firms to improve their performance, firms would *stop* investing in *new IT applications*. As a result, financial market data can be used to determine whether firms' investments in new IT applications are decreasing. We argue that the volatility in market value of an industry to economic news indicates whether the industry provides an undifferentiated input (e.g., electricity) or one that could potentially be the key to improving firm performance. So if IT has become (or is becoming) an undifferentiated input, its volatility to economic news should be low, comparable, for example, to the volatility in the electric power industry. We lay out the bases for our assertions in the next section.

We study firms in the IT industry and the Utilities, and Transportation & Freight industries from 1980 to 2007. Our analysis clearly indicates that overall, the IT-engendered opportunities for firms to improve their performance have not decreased over time. Firms continue to invest in new IT applications and the investments in new IT applications are not decreasing. We conclude that IT spending on new IT applications is not an endangered species.

2. Theory and Hypotheses

2.1 Categorization of IT Investments made by Firms

We lump all investments made by firms into two categories: investments necessary to maintain a firm's current business (ICB) and investments in new initiatives (INI). ICB investments are necessary to sustain a firm's current operation in order to sustain a firm's current business model. INI investments fund new initiatives that will enable a firm to perform better in the future. INI investments may enable a firm to expand operations, change the way it will perform some operation in the future, or even completely change the firm's direction.

In an IT investment context, ICB are investments that are necessary to sustain the IT applications currently in use. These IT investments are necessities if a firm is to exploit its current capabilities. For example, if a firm discovers a new IT security threat, it may have to make IT investments to fend off this threat. INI are discretionary investments in new IT applications that a firm plans to deploy in the future. For example, a firm may consider launching a Knowledge Portal that facilitates sharing of ideas among employees and community building.

The IT investments made by firms are contingent upon whether or not new IT applications provide opportunities for firms to improve their performance, i.e., whether IT matters? Firms will only make INI investments if new IT applications enable firms to improve future performance. Firms have to make ICB investments whether IT matters or IT does not matter. We describe later how the IT investments made by firms affect demand for the products and services provided by IT industry firms. The literature suggests that firms favor ICB investments at the expense of INI investments, because ICB investments are less risky and offer more immediate benefits. We assert that firms make ICB investments before they make INI investments.

2.2 Economic Conditions, IT Investments and their Impact on the IT industry

In an economy, economic conditions improve, stay the same, or worsen over time. The demand for products in the economy is affected by these conditions. In general, when economic conditions improve, product demand increases, and vice versa. However, the changes in demand emanating from changes in economic conditions differ across products. For example, economic conditions affect demand for medicines less than demand for furniture or vacations. Medicines are more of a necessity for most consumers than is furniture or a vacation. The products of some industries are necessities for their customers, while others are discretionary. From our earlier discussion we can conclude that ICB investments are more of a necessity than are INI investments. Since ICB investments are a higher priority than INI investments, economic conditions have a greater impact on INI investments than ICB investments.

2.3 Market Assessment of IT Investments

It is a well-established paradigm in finance that asset prices in financial markets are affected by the arrival of new information. For example, studies have investigated the "new information" effect on stocks, bonds, futures contracts, foreign-exchange rates, interest rates and currency options, etc. (Nofsinger and Prucyk 2003). However, in all earlier IT business value-related event studies (BVES), the "new information" events were specific, IT-related decisions made by individual firms and their effects on the stock price of the firm making the IT-related decision. In this study, the "new information" events are news releases of macroeconomic information that may indicate to financial markets that economic conditions have changed, and the effects of such changes on the stock prices of groups of firms (e.g., IT industry firms). The stock price of firms

whose product demand is relatively invariant to economic conditions will not be greatly affected by new information indicating a change in economic conditions, and vice versa.

If IT does not provide performance-enhancing opportunities, firms will make fewer INI investments (in the extreme case, no INI investments). Therefore, if the opportunities to use new IT applications to increase firm value are decreasing, the volatility of stock prices of IT industry firms (as a whole) to changes in economic conditions should be decreasing and approaching the stock price reaction of firms in industries that produce widely-used inputs that no longer are the impetus for performance enhancing investments (i.e., they are ICB investments). This leads us to our primary hypothesis.

H1: The volatility of stock prices of firms in the IT industry to changes in economic conditions has decreased over time and is approaching the volatility of stock prices of firms in industries that produce widely-used inputs that primarily are ICB investments for their customers.

We refer to non-IT industries that produce widely-used inputs that primarily are ICB investments for their customers as WUICB industries. WUICB industries supply inputs that do not provide the impetus for firms to improve their performance.

Consider a firm in the IT industry that produces a single product. If the product is an INI investment for its customers, the demand for its product will likely be greatly affected by changes in economic conditions. However, if the product is an ICB investment for its customers (e.g., the firm provides security protection), economic conditions will have relatively little effect on the demand for its product. Hence, the stock prices of IT industry firms whose products are INI investments for their customers will be greatly affected by economic conditions, while the stock prices of IT industry firms whose products are ICB investments for their customers will not be greatly affected by economic conditions. This leads us to state the following hypotheses:

H2a: The volatility of stock prices (to changes in economic conditions) of IT industry firms whose products primarily are ICB investments for their customers, will be lower than the volatility of stock prices of the IT industry as a whole.

H2b: The volatility of stock prices (to changes in economic conditions) of IT industry firms whose products are ICB investments for their customers will be similar to the volatility of firms in WUICB industries.

H3: The volatility of stock prices (to changes in economic conditions) of IT industry firms whose products primarily are INI investments for their customers will be higher than the volatility of stock prices of the IT industry as a whole.

Hypotheses 2 and 3, in effect determine whether our key assumption, that firms make ICB investment before they make INI investments, is merited. In our empirical study, we do not directly observe individual firms' investment decisions. By observing the effects of changing economic conditions on the stock prices of relevant firms in the IT and WUICB industries, we can determine the extent to which firms are making INI investments.

3. Empirical Study - The Data

In this study, it was necessary to: (1) identify public firms in the IT industry and those in WUICB industries, (2) identify news sources signaling a change in economic conditions, (3) determine the price reaction for groups of firms to economic news, and (4) analyze the price reaction for groups of firms to changes in economic conditions to test our hypotheses.

We chose two industries to represent WUICB industries: (1) Utilities, and (2) Transportation & Freight (TF). We chose these industries for the following reasons: (1) The products of both these industries are widely-used inputs by firms, just as most firms use IT industry products to run their business today, and (2) Utilities and TF are infrastructure-providing industries, similar to IT. Moreover, this choice mimics the development of electricity and railroads in Carr (2003). At the six-digit NAICS level, eight utility sectors, eleven TF sectors and twenty-five IT sectors appeared in our data.

The US government and independent agencies release a variety of monetary and non-monetary information (e.g., the unemployment rate, personal income, consumer price index, durable goods orders, producer price index, construction spending, gross national product, etc.) that is indicative of economic conditions. Following the literature, we chose a relatively comprehensive set of 16 different types of events. For each announcement, we computed a market-weighted price change for the announcement for each group (industry or sector, as needed for each hypothesis) on the announcement day. We computed the price volatility for group j on day t (R_{jt}) as follows,

$$R_{jt} = \frac{\sum_i (|P_{ijt} - P_{ij,t-1}| \times N_{ij,t-1})}{\sum_i (P_{ij,t-1} \times N_{ij,t-1})} \quad (1)$$

where the price of the stock of company i in group j at the end of trading day t is denoted by P_{ijt} , $N_{ij,t}$ is the number of shares outstanding for firm i , in group j , at the end of trading day t . R_{jt} is the market-weighted price change for the firms in group j on day t . We compute the absolute value of the change in price because we are interested in the magnitude of the change, not the direction.

4. Analysis & Results

4.1 Hypothesis 1

Our initial analysis focuses on whether there is a significant difference between the volatility of IT industry and WUICB industry firms; and whether IT volatility is decreasing and approaching that of WUICB over time. The three industries of interest include 44 sectors at the six-digit NAICS level. We test the first hypothesis by estimating the following model:

$$Volatility_{ijt} = \beta_0 + \beta_1 \times UT + \beta_2 \times TF + \beta_3 \times Event_j + \beta_4 \times Year_t + \beta_5 \times UT \times Year_t + \beta_6 \times TF \times Year_t + \varepsilon_{ijt} \quad (2)$$

where $Volatility_{ijt}$ is the volatility of sector i , to event j in year t . We coded the IT industry as 0 and created two dummy variables UT and TF for the Utility and Transportation & Freight industries, respectively. Equation (2) specifies a simple fixed-effects model with interactions. We treated $year$ as a continuous variable, coding the year as follows: 0 for 1980, 1 for 1981, 2 for 1982, etc. The interaction terms between each WUICB industry (utility and TF) and year tests whether the difference between IT and the relevant WUICB industry changes over time. Estimation results for this model are reported in Table 1, under the “Model 1.1” heading. Due to space, we do not display the fixed-effects coefficients for the variable $Event$ (15 coefficients) in the table. First notice that the two main effects, the UT coefficient (-0.015) and the TF coefficient (-0.008) are negative and highly significant ($p < 0.001$). This suggests that over the entire period from 1980 to 2007, the IT industry was very different than both WUICB industries. The interaction term between UT and $Year$ is not significant ($p = 0.41$), indicating that the trend over time is the same for both IT and utility industries. However, the interaction between TF and $Year$

is negative and significant (-0.0002), indicating that the difference is amplified over time. This is not a surprise since the TF industry had very high volatility prior to 1985. The net effect shows that on average, IT industry volatility is 1.5 percent higher than the utility industry and 0.82 percent higher than the TF industry.

4.2 Hypotheses 2a and 2b

To test hypothesis 2a and 2b, we sought a group of IT industry firms that provide products that are primarily ICB investments for firms. Consider firms that manage the computing facilities (MCF) of other firms (e.g., Electronic Data Systems, OAO Technology Solutions, Inc.). Demand for the services of these firms is primarily driven by their customers' need to keep the IT applications they currently use running smoothly. The demand for the services of these firms are ICB investments for their customers. Investments in new IT applications (INI) are likely to have little effect on MCF firms' demand, until these new applications are put to use (i.e., production). IT firms that manage computing facilities are included in two NAICS codes, 541513 and 518210. The data indicates that the volatility of MCF firms has been consistently lower than that of other IT firms' over time and is very close to the volatility of UT and TF firms. To test hypothesis 2a, we estimated the following model:

$$Volatility_{ijt} = \beta_0 + \beta_1 \times MCF + \beta_2 \times Event_j + \beta_3 \times Year_t + \beta_4 \times MCF \times Year_t + \varepsilon_{ijt} \quad (3)$$

We created a dummy variable *MCF* (1 for IT firms in the MCF sectors and 0 otherwise). We also added an interaction term *MCF*×*Year* to examine the volatility of *MCF* firms over time. Note that only IT industry firms are included in the estimation to test hypothesis 2a. The results are reported in the column "Model 2.1" in Table 1. Firms in the *MCF* sector have a significantly lower volatility (coefficient -0.009 and p-value less than 0.001), than the other IT sectors. The *MCF*×*Year*_{*t*} term is also significant and negative, suggesting that over time the volatility of MCF firms has decreased relative to firms in the other IT sectors. Thus, hypothesis 2a is supported.

Hypothesis 2b states that the volatility of *MCF* firms is similar to that of firms in the WUICB industries. To test this hypothesis we use the model specified in equation (2). However, in this case the IT data only includes MCF firms, which were coded as 0, while UT and TF firms were coded as 1. The estimation results are reported under "Model 2.2" in Table 1. These results indicate that MCF firms' volatility is significantly higher than that of UT (main effect of UT is -0.007), but the gap is shrinking (the interaction with year is positive with a coefficient of 0.0003). Thus, MCF firms are becoming more utility-like. The comparison with the TF industry tells a more interesting story. The volatility of MCF firms is not significantly different than that of TF, both for the main effect (p = 0.81) and the interaction effect with year (p = 0.14). Together, these results indicate that the products offered by MCF sector firms are very similar to products offered by WUICB industry firms. The services offered by firms in these sectors are ICB investments for their customers.

4.3 Hypotheses 3

To test hypothesis 3, we sought a group of IT industry firms that provide products that are primarily INI investments for firms and their products provide most of the firms' revenues. Over the past few years there has been an increased awareness that RFID-based applications may have become commercially viable (Lee and Ozalp 2007). We identified 12 public firms from the Hoover's company information database that produce RFID-based products and meet one additional condition; these firms' main line of business is in RFID-related products. The results

in the column titled “Model 3.1” indicate that the volatility of stock prices for this group of firms is greater than the IT industry as a whole (excluding firms in the RFID group). The results in the columns titled “Model 3.2” and “Model 3.2” indicate that the volatility of stock prices for this group of firms is also much greater than the WUICB industry firms and the S&P500 firms respectively. These results provide additional support for the logic upon which our study is based. IT industry firms that provide products that are necessary for the new IT applications being deployed by firms are much more sensitive to changes in economic conditions than firms whose products keep existing IT applications running smoothly.

5. Summary & Conclusions

This study provides evidence as to the validity of Carr’s claims. Our results indicate that firms’ impetus to invest on new IT applications has not vanished, as would be expected if IT does not provide firms with opportunities to create value. Our results show that managers still believe that IT provides opportunities to improve firm performance, even though some studies have found that firms do not retain any of the value generated by IT investments (Hitt and Brynjolfsson 1996). Our results should be good news for IT-related professions: they are not in the process of becoming an endangered species. Besides, this study provides evidence that many firms continue to find new ways to use IT to improve performance. It should cause managers who were swayed by Carr’s arguments to re-visit their decisions regarding investments in new IT applications. Moreover, continued investments in new IT applications by firms should also be good news for the economy as a whole (Brynjolfsson and Saunders 2010).

Table 1: Hypothesis testing results

	Hypothesis 1	Hypothesis2a	Hypothesis2b	Hypothesis 3		
Variables	Model 1.1	Model 2.1 (vs. IT)	Model 2.2 (vs. UT&TF)	Model 3.1 (vs. other IT)	Model 3.2 (vs WUICB)	Model 3.3 (vs SP500)
Intercept	0.024 ***	0.025 ***	0.015 ***	0.027 ***	0.012 ***	0.010 ***
UT_Dummy	-0.015 ***	-	-0.007 ***	-	-	-
TF_Dummy	-0.008 ***	-	-0.0001	-	-	-
Year	0.0002 ***	0.002 ***	-0.000	0.0001 ***	0.0001 ***	0.00004
UT_Dummy × Year	0.00003	-	0.0003 ***	-	-	-
TF_Dummy × Year	-0.0002 ***	-	0.000	-	-	-
MCF	-	-0.009 ***	-	-	-	-
MCF × Year	-	-0.0002***	-	-	-	-
RFID	-	-	-	0.008 ***	0.022 ***	0.027 ***
RFID × Year	-	-	-	-0.00008	-0.0004	0.0000
Event	Included	Included	Included	Included	Included	included
<i>R-square</i>	0.058	0.02	0.018	0.01	0.082	0.094
<i>F-Value</i>	308.35 ***	62.02 ***	45.15 ***	35.75 ***	245.24 ***	52.46
<i>df</i>	20	18	20	18	18	18
<i>N</i>	99448	55730	49107	99557	48792	9103

*** significant at 0.001

References

Brynjolfsson, E. and A. Saunders, *Wired for Innovation: How Information Technology is Reshaping the Economy*, The MIT Press, Cambridge, MA, 2010.

Carr, N.G., "IT Doesn't Matter," *Harvard Business Review*, 81, 5, (2003), 41-49.

Hitt, L. and E. Brynjolfsson, "Productivity, Business Profitability, and Consumer Surplus: Three Different Measures of Information Technology Value," *MIS Quarterly*, 20, (1996), 121-142.

Lee, H. and O. Ozalp, "Unlocking the Value of RFID," *Production & Operations Management*, 16, (2007), 40-64.

Nofsinger, J.R. and B. Prucyk, "Option volume and volatility response to scheduled economic news releases," *Journal of Futures Markets*, 23, 4, (2003), 315-345.

Offer Sets, User Profiles, and Firm Payoffs

Pelin Atahan
Özyeğin University

pelin.atahan@ozyegin.edu.tr

Monica Johar
University of North Carolina
at Charlotte

msjohar@uncc.edu

Sumit Sarkar
University of Texas at Dallas

sumit@utdallas.edu

Abstract

Personalization and recommendation systems are being increasingly utilized by ecommerce firms to provide personalized product offerings to visitors at the firms' web sites. These systems often recommend multiple items (referred to as an offer set) that might be of interest to a visitor. When making recommendations firms typically attempt to maximize their expected payoffs from the offer set. This paper examines how a firm can maximize its expected payoffs by leveraging the knowledge of the profiles of visitors to their site. We provide a methodology that accounts for the interactions among items in an offer set in order to determine the expected payoff. Identifying the optimal offer set is a difficult problem when the number of candidate items to recommend is large. We develop an efficient heuristic for this problem, and show that it performs well.

Keywords: Personalization, recommendation, e-commerce, probability theory

1. Introduction

Effective personalization can help firms reduce their customers' search costs and enhance customer loyalty. This, in turn, translates into increased cash inflows and enhanced profitability (Ansari and Mela 2003). Extant research has shown that in electronic shopping environments, personalized product recommendation enable customers to identify superior products with less effort (Häubl and Trifts 2000). These works have demonstrated that personalization can be an effective tool for firms.

The personalization process consists of two important activities, *learning* and *matching*. Learning involves collecting data from a customer's interactions with the firm and then making inferences from the data about the customer's profile. For instance, the relevant profile for a customer may be her membership in one of several possible demographic or psychographic segments, which could be based on age, gender, zip code, income, political beliefs, etc. (Montgomery et al. 2001, Wall Street Journal October 17 2007). Matching is the process of identifying products to recommend based on what is known about the customer's profile. Naturally, the quality of a customer's profile should impact the ability of the firm to provide high quality recommendations targeted towards sales (viz., the matching ability).

In this research, we examine how a firm can maximize its expected payoffs when making recommendations to users by leveraging the knowledge of the profiles of visitors to the site. In order to identify the best set of items to offer (e.g., links on a page to a set of recommended items that we call the *offer set*), a firm would first need a methodology to evaluate the expected payoff given an offer set. Then, the optimal offer set can be determined by selecting the set of items that maximizes the expected payoff for each page requested by the visitor based on what the firm

knows about the visitor's item history (denoted by IH) and the profile. To evaluate the expected payoffs from an offer set the firm would need to evaluate the likelihood of each offered item being viewed and eventually purchased. The probability that an item will be viewed when provided in an offer set depends not only on the probability parameters associated with the item itself, but also on the other items in the offer set. Therefore, the interaction among items in an offer set should be accounted for when evaluating the expected payoffs from that offer set.

Extant literature has not formally analyzed the impact of the composition of an offer set on the resultant expected payoffs. Existing approaches that consider multiple recommendations typically sort the items identified for recommendation by some criteria and simply take the top n items to recommend (Huang et al. 2004, Zaïane 2002). A novelty of the proposed approach is that it explicitly studies the impact of an item in the offer set on the probability of other items in the offer set being viewed and ultimately purchased when calculating the expected payoffs from that offer set.

In the next section, we present the framework to evaluate the expected payoffs from an offer set. A firm can evaluate all feasible offer sets using this framework and select the optimal one. We present in Section 3 an efficient heuristic approach to determine the offer sets quickly when the number of sets to evaluate is large. Section 4 discusses experiments to evaluate the performance of the proposed approach. Concluding remarks are provided in Section 5.

2. Evaluating the Expected Payoff from an Offer Set

The interactions between a visitor and the site are iterative in nature, with the firm providing a new offer set at each interaction (i.e., each time the visitor makes a page request). Given an offer set, the visitor may either view detailed information on one of the offered items or ignore the offer set. When the visitor views information on one of the items (say i_j) by clicking on the appropriate link, the site provides detailed product information for item i_j , along with a new offer set (i.e., a new set of recommendations) in case the visitor does not like the product. If, on viewing the information on item i_j , the visitor decides to purchase that item, it results in a payoff to the firm. If the visitor does not purchase that item, then the visitor has the option of selecting an item from the new offer set for further evaluation, and the process repeats.

A visitor's decisions are driven by the visitor's profile and the items previously viewed by the visitor. A visitor's profile is represented by the set of possible classes (a_i) the visitor may be a member of, accompanied by the probability associated with each class. At any point in time, the visitor's item history is known to the site; the site can derive a probability distribution of the visitor's profile information given the visitor's item history, i.e., the probability $P(a_i|IH)$ for each a_i (details of the belief revision process are suppressed for lack of space). To estimate the probability that a given visitor purchases an offered item i_j , the site needs to estimate the joint probability distribution of the visitor viewing the item (v_j), purchasing the item (s_j) and the visitor's profile, i.e., the site needs the joint probability $P(s_j, v_j, a_i|IH)$ for each a_i . This probability can be expressed as:

$$P(s_j, v_j, a_i|IH) = P(s_j|IH, v_j, a_i)P(v_j|IH, a_i)P(a_i|IH).$$

Given an offer set (O) and the knowledge about the visitor's profile, the firm can calculate the expected payoff from that offer set ($EP(O)$) in the following manner:

$$EP(O) = \sum_{a_i} \sum_{i_j \in O} P(s_j | IH, a_i, v_j, O) P(v_j | IH, a_i, O) P(a_i | IH) \omega_j,$$

where ω_j is the profit realized from sales of item i_j .

To operationalize this framework, the firm would need to estimate the following probability parameters associated with the choices made by the visitor.

- The probability that a visitor associated with a given profile and item history will view item i_j when presented with an offer set $O = \{i_1, \dots, i_n\}$, i.e., $P(v_j | IH, a_i, O)$.
- The probability that such a visitor will purchase item i_j after viewing information on that item, i.e., $P(s_j | IH, v_j, a_i, O)$.

It would be difficult to directly estimate these parameters from historical data because the number of feasible combinations of item histories and offer sets would be typically very large. On the other hand, the site may relatively easily estimate the probabilities $P(v_j | IH, a_i)$ and $P(s_j | IH, v_j, a_i)$ using techniques such as association rule mining (Agrawal and Srikant 1994) or other probabilistic approaches (Breese et al. 1998). To estimate the probability that an offered item will be viewed, $P(v_j | IH, a_i, O)$, the firm can first normalize the probabilities associated with the visitor viewing each of the items $P(v_j | IH, a_i)$ in the offer set to 1. This assumes that the visitor will view at least one of the offered items. The unconditional probability that the visitor will view an offered item (i.e., without assuming the visitor must view an offered item) can be calculated by multiplying the normalized probability of the visitor viewing an item with the probability that the visitor will view at least one of the offered items. To estimate the probability that the visitor will view at least one of the items, the firm can first estimate the probability of the visitor not viewing any of the offered items (thus allowing for the situation where a visitor leaves the site without making any purchases), which is one minus the probability that the visitor will view at least one of the offered items.

We assume the probability that a user will purchase an item after viewing information on that item is independent of the other offered items given the user's class, user's item history, and the fact that the user has viewed that item among the offered items, i.e., we assume $P(s_j | IH, v_j, a_i, O) = P(s_j | IH, v_j, a_i)$.

3. Determining the Offer Set

We consider the firm's objective to be one where it wishes to select the offer set (including a predetermined number of items n) that maximizes its expected payoff in each interaction with a visitor. An obvious way to identify the offer set that maximizes the firm's expected payoffs in an interaction would be to evaluate all feasible offer sets and then provide the offer set that leads to the highest expected payoff. However, when the number of items for consideration is large it may not be feasible to evaluate all possible offer sets in real time. We develop an efficient heuristic approach to determine the offer set in such situations.

Our approach selects items to include in the offer set in a greedy manner. In the first iteration, the algorithm identifies the optimal offer set of size 1 (based on expected payoffs). In subsequent iterations, each remaining item is evaluated for inclusion in the offer set. The algorithm calculates and compares the expected payoffs from offer sets obtained by adding an item to the

current offer set and includes in the offer set the item that leads to the highest expected payoff. The complexity of our algorithm is $O(n*K)$, where n is the cardinality of the offer set and K is the total number of items the site considers. The complexity for the optimal approach through exhaustive search is $O(K^n)$.

4. Experiments

To validate our approach we have performed simulated experiments. We use expected payoffs from the identified offer sets as a measure of performance. We compare the performance of the proposed approach with that of the optimal offer set for many problem instances.

In our experiments, we used a binary class attribute for a visitor's profile. We generated the probabilities associated with viewing an item $P(v_j/IH, a_i)$ based on a uniform distribution, $U[0.1, 0.7]$. We expect the probabilities associated with an item being viewed by members of a class and the item being purchased by members of that class to be correlated. Therefore, the probabilities associated with members of a class purchasing an item $P(s_j/IH, v_j, a_i)$ were generated based on a uniform distribution that is correlated with the distributions associated with members of that class viewing the items (correlation level of 0.2 was used in the reported experiments), and normalized to be between 0 and 0.4. The profit from each item is assumed to be the same and equal to 1.

Table 1. Comparison with Optimal		
Profile Probability for one Class	Rank	Difference in Expected Payoff
0	1	0%
0.1	2	-0.24%
0.2	1	0%
0.3	2	-0.15%
0.4	1	0%
0.5	1	0%
0.6	2	-0.79%
0.7	1	0%
0.8	1	0%
0.9	1	0%
1	1	0%

To determine the optimal solution, we evaluated the expected payoffs from all possible offer sets and selected the one that provides the highest expected payoff. In these experiments, the cardinality of the offer set is 8 and there are 40 candidate items. This leads to 76,904,685 possible offer sets to evaluate. For a given profile distribution, the proposed approach was implemented first to determine the optimal offer set. The expected payoff from the offer set identified by the proposed approach was compared with the expected payoff from every feasible offer set. We recorded the rank of the expected payoff from this offer set compared to all other offer sets and the percentage difference of the expected payoff from this offer set from that of the optimal offer set. We repeated the experiments on the same dataset for 11 different user profile distributions (profile probability for one class ranging from 0 to 1 in increments of 0.1). The results of these experiments are presented in Table 1.

The results of these preliminary experiments are very promising, and the proposed approach performs extremely well in all the experiments. It is able to identify the best or second best offer sets in all the experiments (even when there are in excess of 76 million alternative solutions!).

5. Conclusion and Discussions

Firms typically make multiple recommendations to visitors traversing their sites. However, extant research has not addressed how the multiple items in an offer set impact each item's viewing and purchasing probabilities and hence a firm's expected payoffs from an offer set. We study how a firm should compose the offer set to maximize its payoffs from the recommendations. We propose an efficient heuristic algorithm to determine the offer sets quickly when there are a large number of items that are considered for inclusion in the offer set. Preliminary experiments demonstrate that the heuristic performs very well compared to the optimal approach. We are conducting additional experiments to determine how robust our approach is for different problem parameters. Future research will also consider a firm's objective where it wishes to maximize its expected payoff over the entire duration of a session.

References

1. Agrawal, R. and Srikant, R. "Fast Algorithms for Mining Association Rules in Large Databases," *Proceedings of the 20th International Conference on Very Large Data Bases*, 1994, pp. 487-499.
2. Ansari, A., and Mela, C. F. "E-Customization," *Journal of Marketing Research* (40:2), 2003, pp. 131-145.
3. Breese, J. S., Heckerman, D., and Kadie, C. "Empirical Analysis of Predictive Algorithms for Collaborative Filtering," *Proceedings of the 14th Annual Conference on Uncertainty in Artificial Intelligence (UAI98)*, 1998, pp. 43-52.
4. Häubl, G., and Trifts, V. "Consumer Decision Making in Online Shopping Environments: The Effects of Interactive Decision Aids," *Marketing Science* (19: 1), 2000, pp 4-21.
5. Huang, Z., Chung, W., and Chen, H. "A Graph Model for E-Commerce Recommender Systems", *Journal of the American Society for Information Science and Technology*, 55(3) 2004, pp. 259-274.
6. Montgomery, A.L. "Applying Quantitative Marketing Techniques to the Internet," *Interface* (30:2), 2001, pp. 90-108.
7. The Wall Street Journal. "Firm Mines Offline Data to Target Online Ads," October 17, 2007.
8. Zaïane, O.R. "Building a recommender Agent for e-Learning Systems", *Proceedings of the International Conference on Computers in Education (ICCE '02)*, 2002.

Co-development of Software and Community Formation

Juan Feng WeiThoo Yue Leon Zhao
City University of Hong Kong
juafeng, weityue, jlzhao@cityu.edu.hk

Abstract

Community source has been touted to be a new software development model in the Internet era, in which a group of firms co-develop the community software. This approach may reduce the software development costs as well as the risk of software failures. We study firm decision on whether to join the community to develop the software initially or wait to adopt the software until it is successfully developed. We find that whether a firm chooses to be a community developer is largely determined by the tradeoff between the control on the software features, the cost savings and the licensing fee. Further, the community organizer could control the size of the community by setting an appropriate licensing fee.

Keywords: Community-based, software development co-development, community formation

1. Introduction

Complex and specific business requirements nowadays often require firms to create proprietary software that is tightly coupled with their business processes. However, this approach often requires significant commitment in software development effort (costs) and the ability to control software project failure risks. In recent years, we have seen a great deal of emphasis on extending beyond a firm's boundaries to co-create business values with other firms (Feller, et al. 2008). Community source is one novel software development model that has garnered increasing attention from the industry to be an alternative form of software development model. Essentially, the model involves firms participating in interorganizational collaboration and communication to co-develop software (Wheeler 2007). The community source approach is essentially a hybrid model of proprietary development and open source in the sense that a group of firms join the community to develop the software and retain intellectual rights of the software developed in the community.

Open source has emerged in recent years to be one of the innovative models to create software. However, open source approach has its limitation. First, feature sets that are developed in open source are typically standard or common feature sets (Kogut and Metiu 2001). Second, the design of open source software is typically controlled by a few people, and thus not all participants have direct influence over the final software product (Raymond 2001). Lastly, from a firm perspective, there is still the question about the incentives for firm to create a "public good" in the open source community (Dam 1995). In fact, there has been debate about how firms should utilize open source. Community source model represents an alternative to collective development effort that allows firms to harness the overall efforts from a group of firms.

Co-development of software introduces the benefits of cost reduction and risk sharing. The cost aspect is simply the "economics of scale" effect, in which more firms shoulder the development costs together, thus achieving a cost-sharing effect. Software development also involves complex and extensive risks, and many projects often ends up in failure. The risks are especially severe if IT is not the core business capability of the firm. However, participating early in the software development process allows firms to exert more influence on the software

design. Furthermore, firms that participate in software development could enjoy the benefits of acquiring licensing fees from other firms should the software project turns out to be successful.

In this study, we consider a problem in which firms have the options to co-develop the software in a community of firms or wait till the software is produced by the community and then adopt the software by paying a licensing fee. We are interested in studying the firm's decision about the timing of adopting the software. That is, should a firm join the community initially to develop the software or wait until the software product is more mature? Under what circumstances will a larger community in software development be beneficial, for the software developers and/or for all the potential users of the software? How to optimally set up a licensing fee? How are the decisions different from those in an open source community (when the licensing fee is zero)?

In this project, we developed a theoretical model to examine the formation of a community to co-develop software. We found that the individual firm's decision in joining the community is largely determined by a tradeoff between (a) joining the community earlier by incurring a software development cost and asserting control on the software features with the potential of receiving licensing fees in the future if the software is successfully developed and (b) joining the community later by paying a licensing fee once the software is complete, with less control on the software features. We also found that a social organizer who aims to maximize the social welfare may discourage a large crowd in developing the software in the first period when the cost of developing software is relatively high.

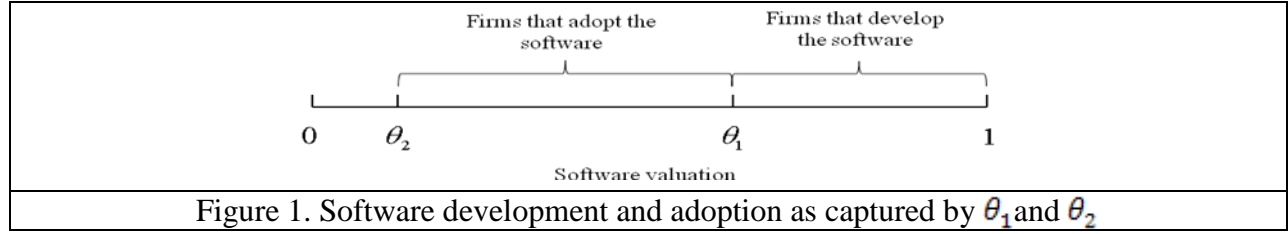
2. Model

We assume there are n firms in the market. Each firm makes the decision on either co-developing the software with other firms in period 1 ($T = 1$) or adopting the completed software in period 2 ($T = 2$). Co-development in period 1 allows a firm to participate in the design and implementation of the software and therefore ultimately enjoys the advantage of creating a software product that matches well with its requirements. On the other hand, participating in software development involves risk of certain project failure. If a firm waits until the second period to adopt the software, it can avoid unsuccessful projects. However, it could miss the opportunity to exert influence on successful projects. In that case, the firm can only adopt software that may not completely meet its requirements.

A successful project generates value $v = 1$, with each firm having its own private software valuation of $\theta \cdot 1$. We use α to capture the effect of lack of control in software design for firms that adopt the software in period 2., i.e., a firm with software valuation of $\theta \cdot 1$ in period 1 will have a valuation of $\alpha\theta \cdot 1$ if the firm chooses to adopt the software in period 2 rather than develops the software in period 1. We assume θ is distributed in the firm population with a distribution function of $F(\theta)$. The function is differentiable with density function $F'(\theta) = f(\theta)$. In period 1, the total development cost is equally shared amongst the collaborating firms. Let $C(\theta_1)$ be the average development cost; $1 - \theta_1$ is the number firms participating in software development. Ex-ante firms are aware that the project has a probability of success γ . When the project failed, the project value is 0.

Let the private valuation of software $\theta > \theta_1$ for firms participating in the software development. In the second period, the completed software is licensed to the remaining firms with a licensing fee l . Denote $(\theta_1 - \theta_2)$ to be the number of firms choose to pay the licensing fee and adopt the software, the average licensing income for the developing firms is $L(\theta_1, \theta_2, l)$.

Figure 1 shows the segments of population firms participating in the software development and software adoption, respectively.



We assume payoff is realized in period 1 for a firm that participates in software development in the first period, and payoff is realized in period 2 if the firm chooses to adopt the software. Thus, we can write a firm's payoff when it adopts the software in period 2 as

$$\gamma(\alpha\theta_2 - l)$$

whereas a firm's payoff if it joins the community to develop the software in period 1 is:

$$\gamma\theta_1 - C(\theta_1) + \gamma L(\theta_1, \theta_2, l)$$

We assume all firms that participate in developing the software share the development cost equally. The average development cost is

$$C(\theta_1) = \frac{c}{1 + \text{number of firms develop the software}} = \frac{c}{1 + (1 - \theta_1)}$$

where c is the total development cost. Similarly, firms that develop software enjoy the licensing fee payment from the firms that adopt the software in period 2. The average licensing fee paid is

$$L(\theta_1, \theta_2, l) = \frac{l \cdot \text{number of firms adopt the software}}{1 + \text{number of firms develop the software}} = \frac{l(\theta_1 - \theta_2)}{1 + (1 - \theta_1)}$$

A firm will choose to co-develop the software in period 1 if period 1's payoff is higher than period 2's payoff

$$\gamma\theta_1 - \frac{c}{(2 - \theta_1)} + \frac{\gamma l(\theta_1 - \theta_2^*)}{(2 - \theta_1)} \geq \gamma(\alpha\theta_1 - l) \quad (1)$$

Firms will adopt the software in the second period if the payoff is non-negative

$$\gamma(\alpha\theta_2 - l) \geq 0$$

Consequently, the optimal number of firms that develop and adopt the software is

$$\theta_1^* = 1 \pm \sqrt{1 - A}, \quad \theta_2^* = \frac{l}{\alpha} \quad (2)$$

where $A = \frac{1}{(1-\alpha)} \left(\frac{c}{\gamma} - l \left(2 - \frac{l}{\alpha} \right) \right)$. We thus can observe the results stated in Lemma 1.

Lemma 1: *The equilibrium size of developers (in period one) is decreasing in α and c , and increasing in γ and l . That is,*

$\frac{\partial \theta_1^*}{\partial \alpha}$	$\frac{\partial \theta_1^*}{\partial \gamma}$	$\frac{\partial \theta_1^{**}}{\partial l}$	$\frac{\partial \theta_1^*}{\partial c}$
+	-	-	+

Due to space limitation, all proofs are omitted and are available upon request.

Lemma 1 is intuitive: if firms expect the software design is likely to misaligned with their requirements ($\alpha < 1$), firms have a natural tendency of joining the community in the first period to develop the software. The more valuable the software is in the second period, or the higher the development cost, the less likely firms will join the community to develop the software in the first period. On the contrary, when it is more likely that the project will be successful, or the higher the licensing fee in the second period, then more firms will participate in the first period.

2.1 Optimal Licensing Fee (l)

We consider two ways to set the optimal licensing fee. One is from the social planner's perspective, and the other is from the software developer perspective.

Maximize the Welfare of the Software Developer

For firms that participate in software development in Period 1, the payoff function is

$$V = \int_{\theta_1^*}^1 \left(\theta - \frac{c}{\gamma(2 - \theta_1^*)} + \frac{l(\theta_1^* - \theta_2^*)}{(2 - \theta_1^*)} \right) d\theta \quad (3)$$

Proposition 1: *The optimal licensing fee l^* that maximizes the payoff of software developers is determined by the following condition:*

$$\frac{dV}{dl} = -\frac{1 - \alpha}{2} A' - \sqrt{1 - A} - (\alpha - l) \frac{A'}{2\sqrt{1 - A}} = 0 \quad (4)$$

Corollary 1: *The optimal licensing fee is increasing in both α and c and decreasing in γ .*

As discussed previously, the licensing fee of the software is a design variable that can be used to manage/control the community formation. From Corollary 1, we can see that, when the value of the software is high or when the software development cost is high, assuming that firms have a natural tendency to avoid participation in the first period, the community organizer should raise the licensing fee to discourage the “waiting” strategy, and when the software project is more likely to succeed, firms may have more confidence in joining the community in the first period. In this case, the organizer could set a lower licensing fee to encourage adoption of software in the second period.

Maximize the Social Welfare

Based on the optimal θ_1 and θ_2 , the social planner function can be written as

$$SW = \int_{\theta_2^*}^{\theta_1^*} \gamma(\alpha\theta - l) d\theta + \int_{\theta_1^*}^1 \left(\theta - \frac{c}{\gamma(2 - \theta_1^*)} + \frac{l(\theta_1^* - \theta_2^*)}{(2 - \theta_1^*)} \right) d\theta \quad (5)$$

Proposition 2: *The optimal licensing fee l_s^* that maximizes the payoffs of the software developers is determined by the following condition:*

$$\frac{dV}{dl} = -\frac{1-\alpha(1-\gamma)}{2}A' - \sqrt{1-A} - (\alpha-l)\frac{A'}{2\sqrt{1-A}} - \gamma\left(1-\frac{l}{\alpha}\right)$$

Proposition 3: *A social planner sets a higher licensing fee and invite less firm participate in the software development when the cost of developing the software is relatively high, that is, when $c > \gamma\left(2-\frac{l}{\alpha}\right)$*

Proposition 3 is intuitive. When the cost of developing the software is high, the community organizer has stronger incentive than a social planner to have more firms joining in the first period to share the development cost.

4. Conclusion

In this paper, we studied a firm's decision to join a community to co-develop a software or wait till later to adopt the software when it is fully developed. We found that the formation of a community to co-develop a software is largely determined by the tradeoff of control on the software features, cost saving and licensing fees. Understanding the characteristics of the software being developed, the organizer or initiator of the software may manage the size of the community by setting an appropriate licensing fee.

Many extensions remain to be done. For example, it is worthwhile to study a more realistic environment in which more firms joining the community may increase the coordination cost among the developing firms so that the final development cost may not always decrease. It is interesting to incorporate the risk-sharing features of software co-development so that more firms joining the community may reduce the software failure risks. Finally, it is interesting to study a dynamic game in which the quality of the software may improve over time, which may give some firm less/more incentive to wait to adopt the software when it is more mature.

References

- Dam, Kenneth W. "Some Economic Considerations in the Intellectual Property Protection of Software." *Journal of Legal Studies* 24, no. 2 (1995): 321-377.
- Feller, Joseph, Patrick Finnegan, Brian Fitzgerald, and Jeremy Hayes. "From Peer Production to Productization: A Study of Socially Enabled Business Exchanges in Open Source Service Networks." *Information Systems Research* 19, no. 4 (December 2008): 475-493.
- Kogut, Bruce, and Anca Metiu. "Open-Source Software Development and Distributed Innovation." *Oxford Review of Economic Policy* 17, no. 2 (2001): 248-264.
- Raymond, Eric Steven. *The Cathedral and the Bazaar: Musings on Linux and Open Source by an Accidental Revolutionary*. Sebastopol, CA: O'Reilly, 2001.
- Wheeler, Bradley C. "Open Source 2010: Reflections on 2007." *EDUCAUSE Review* 42, no. 1 (Jan/Feb 2007): 68-69.

A Pilot Study of Top-Down Compulsory eGovernment Systems Success Model: Organizational Users Perspective

Yong Zhang
Donghua University
zhangyong@mail.dhu.edu.cn

Xianfeng Zhang
Xi'an Jiaotong University
zxf@xjtu.edu.cn

Bingyong Tang
Donghua University
tangby@dhu.edu.cn

Qi Li
Xi'an Jiaotong University
liq@xjtu.edu.cn

Abstract

When the complexity of the IS evaluation met with the top-down compulsory e-Government systems, new ways of thinking should be reminded. This study takes the perspective of both managers and individual users among the organization, and proposes a success model based on DeLone and McLean's model and the ERG needs theory. The pilot study reveals organizations significantly stress on the relatedness fulfillment, while the individuals feel efficient work performance.

Keywords: e-Government, eGovernment systems, IS Success Model, Organization

1. Introduction

It is widely recognized that the IS evaluation is complex, since a large number of stakeholders are involved and each bears different objectives and values. However, usable evaluation frameworks are still needed, and usually only some key elements can be incorporated in. That is to say, only when the appropriate approach is applied to the appropriate context, may IS evaluation contribute to the IS success (Farbey et al. 1993).

The evaluation of e-Government systems has proven to be more perplexing, but essentially even vital in developing countries when over 60%-80% e-Government projects turned to be failure in those places (UNPAN, 2003). During the past decades, various groups or research centers constructed evaluation matrixes, and conducted surveys to evaluate the e-Government portals (Brown University 2004, UNPAN, 2003-2008). Many researchers focused on the individual citizen's perspective, and discussed their adoption and satisfaction (Carter and Bélanger 2005, Hung et al. 2006, Horst, et al. 2007). Still, a few scholars put their efforts in the organizational level. Chu et al (2004) explored the success factors for government electronic tendering system through investigating the public administrators in government agencies and large enterprises. Tung and Rieck (2005) directly discussed the organizational adoption of e-Government services through surveys among companies in the 'Singapore 1000' listing. However, in the organizational level, there are still many government-driven top-down systems, which directly overtake the traditional means of connection between organizations and government agencies, and leave organizations only have the choice to take compulsive usage instead of voluntary adoption. The evaluation of those e-Government systems, though left to be less noticed, are potentially essential, since the net benefits those organizational staff users perceived may be totally different from what the administrators of the organizations think. In addition, the

resistance from the organizations will also influence the overall satisfaction of the e-Government systems.

This paper is to discuss the top-down compulsory e-Government systems success from the organizational aspect. Based on the DeLone and McLean IS success model and the needs theory, the paper tests the success model through considering the perception of both individual staff users as well as that of the upper administrators. The paper is organized as the following: a research model is proposed in section two, and the research design and data collection are reported in section three. In section four and five, the data analyses results and corresponding discussions are respectively displayed.

2. Research Model and Hypothesis

2.1 DeLone and McLean Model

Since DeLone and McLean first proposed their six-variable IS success model in 1992 and later updated to seven variables in 2003, the IS success model and its elements have been tested numerously in the field as well as in the related area (DeLone and McLean 1992 2003). Generally speaking, the categories of taxonomy the D&M model synthesized are information quality, system quality, service quality, IS use/use intention, user satisfaction, benefits. They are constructed into three levels, qualities of IS will influence the use and user satisfaction, and the use or satisfaction then further engender benefits to both individuals and organizations.

2.2 Needs Theory

The needs theory is primarily based on the work of Maslow (1943), McClelland (1965), and Alderfer (1969). All those theories share the commonalities that there are diversified needs among human beings, and people are motivated to fulfill those needs. Based on the prior theories, Alderfer (1969) proposed the ERG theory through identifying three core human needs – existence, relatedness, and development. The ERG theory has been reconsidered in the IS field, and the three core elements are endowed with new meanings (Alter 1999, Rosenberg 2004, Au et al. 2008). The existence needs are connected with the work performance fulfillment, referring to the fulfillment the user experienced from using the IS in finishing their assigned job. Relatedness fulfillment refers to the satisfaction of the users' all social needs from using the IS systems, such as social relatedness, power and control. The self-development fulfillment is the highest needs, including current security and competitiveness, and future growth and advancement.

Most IS literatures only cover the work performance fulfillment, for instance, the TAM model measures how useful IS are in meeting the end user's job performance related needs, while the TTF model discusses how the technology fits the task to raise the total work performance (Davis 1989, Goodhue and Thompson 1995). Only a few scholars, if any, consider the other two needs, though it has been found evidence that the social and self-development needs may potentially cause user resistance (Wang 1997). Au et al (2008) well extended the understanding of IS satisfaction through bringing in the antecedents of equitable needs fulfillments. From this viewpoint, the fulfillment of needs can also be expanded to the consequences of benefits received, since the difficulties of quantifying benefits hinder IS evaluation (Symons and Walsham 1988).

2.3 Research Model

Therefore, the research model is proposed as the table 1. On the one hand, the variable of use intention or actual use behavior is not considered in the model, since the top-down e-Government systems are usually compulsively implemented, and organizational users must use the system to contact the government agencies for related services. On the other hand,

organizational users involve not only individual staff users who represent their own, and use the e-Government systems to finish the related jobs. In addition, the top-administrative users who stand on behalf of the organizations are another indispensable portion. Those top managers normally hold a comprehensive perception of the value e-Government systems brought to their organizations. Accordingly, the satisfaction and benefits of both individual users and organizations will be discussed in the model. The elements of EGD needs theory are adopted with the introduction of the fulfillment of job-performance, relatedness and self-development so as to well evaluate the benefits.

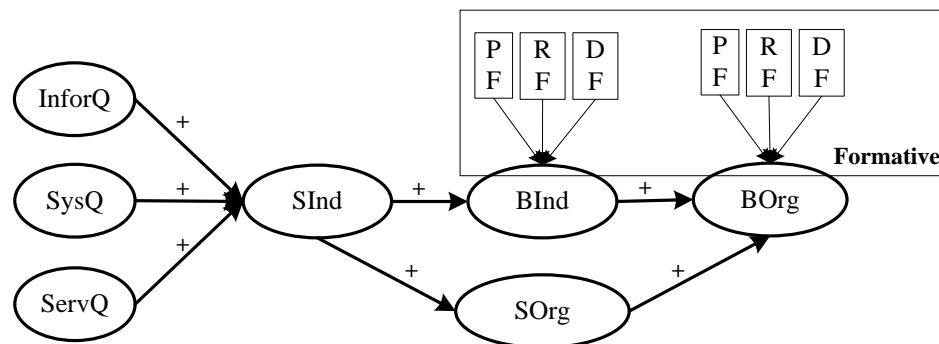


Figure 1 the Research Model

Thus seven hypotheses are proposed. First of all, the information quality (InforQ), the system quality (SysQ), and the service quality (ServQ) of the e-Government systems have a respective positive relationship with the satisfaction of the individual users within an organization. Following the DeLond and McLean model, the satisfaction will then positively correlates to the benefits e-Government systems brought to individuals and organizations. In view that most administrators donot use the system for daily routine work, and their aircscape are mainly from a comprehensive balance and partially from the individual users' feedbacks, the organizational satisfaction is set to only play a mediation role from individual satisfaction to organizational benefits. The performance fulfillment (PF), relatedness fulfillment (RF), and self-development fulfillment (DF) are constructed as formative factors to measure the benefits, because the direction of causality is from three indicators to the constructs, and no interchangeability and covariation necessities exist among those indicators (Jarvis et al. 2003).

3. Research Design and Data Collection

In order to ensure the content validity of the scales used to measure the variables, measurements of the prior studies are referred, and each item is adapted to the top-down compulsive e-Government systems environment. The items to measures the information quality and system quality is from DeLone and McLean(1992), Goodhue and Thompson(1995). Service quality is measured by a six-item scale from Bailey and Pearson (1983), Kettinger and Lee (1994). Satisfaction measurement is adapted from Rai et al (2002) and Wang et al. (2001). The scale of Benefits is formative, and comes from Laudon and Laudon (2000), Alter(1999), Rosenberg (2004) and Eason (1988). Likert scales 1-7, ranging from strongly agree to strongly disagree, is used for all questions. Pretest is conducted through collecting suggestions from the faculty members and students in the IS area, and due adjustments are made afterwards.

The drivers' training system deployed in one province is chosen for the pilot study. In China, the drivers' training system is the long needs of the transportation sectors, as the governing process is difficult to handle. For instance, many training schools intentionally shorten the training hours,

or the trainees personally donot like to take practices in school, and accordingly numbers of new drivers donot have the needed competencies to drive safe, which is rather dangerous. Pushed by the newly released National Guideline for Drivers' Training Process, many provinces compulsively deployed the training systems to better monitor the procedure, though during which process, strong resistance is from the training schools. Two types of Questionnaires are designed, one for individual staff users, and another for the managers or the top administrators of the school. Questionnaires were distributed to a population of the 101 training schools in that province, and each school is dismissed two types of questionnaires, one for the manager and another for the individual staff who is usually responsible for the system related work like typing-in the trainee's information, helping the coaches to automatically update the training records, and eventually submitting the information to transportation sectors. Of the 117 training schools, 67 usable questionnaires of individual users were returned, representing a response rate of 57%, whereas, only 37.6% of the whole managers gave feedbacks, resulting in 44 valid samples. Thus, 44 sets of corresponding pair samples are used in the analysis.

4. Results

PLS is adopted in the research for two reasons. For one thing, PLS employs a component-based approach, and can handle formative factors better than Lisrel. Second, PLS places minimal restrictions on sample size, and comparatively works the best to our pilot study with only 44 sets of samples.

4.1 Measurement Model Results

Principle components analysis with varimax rotation is used to detect the usable indicators. Following guidelines regarding an acceptable observation-to-item ratio of approximately 5 to 1, two sets of analyses are adopted due to the limit of the valid samples (Stevens 1996). The final number of items is reported in Table 1. In order to validate the measurement model, the reliability, convergent and discriminant validity are checked. As showed in Table 1, all the internal consistency scores calculated by the composite reliability are above the recommendation level 0.7 (Fornell and Larcker 1981). To access the convergent validity, the 0.7 cross loading criterion is used. All the indicators load high in their construct, and well above 0.7. The discriminant validity is judged through two tests: First, items should load more strongly on their constructs than on other constructs. This is met in the cross-loading table derived from the PLS analysis. Second, all constructs should share more variance with their indicators than with other constructs, simply requiring the square root of the average variance extracted to be larger than the inter-construct correlations. As it is in the Table 1, the constructs also exhibit adequate discriminant validity.

Table 1 Composite Reliability, Correlation Matrix and AVEs of the Constructs

	Items	CR	BInd	BOrg	InforQ	SysQ	ServQ	SInd.	SOrg.
BInd	2	0.0000	0.0000						
BOrg	5	0.0000	0.4919	0.0000					
InforQ	3	0.9013	0.6405	0.6845	0.8679				
SysQ	3	0.8853	0.6022	0.3964	0.6559	0.8491			
ServQ	4	0.9645	0.6600	0.4451	0.6041	0.5168	0.9336		
SInd.	2	0.9831	0.8612	0.5505	0.7013	0.6260	0.7412	0.9833	
SOrg.	2	0.9834	0.6855	0.8498	0.7062	0.4665	0.5469	0.6907	0.9756

Note: CR refers to composite reliability, and the diagonal elements are the square root of the AVE.

4.2 Structural Model Results

The results of the PLS structural model analysis are shown in Figure 2. According to Chin (1998), to judge the overall model fit, the factor loadings should be preferably greater than 0.7, while the path coefficients be at least 0.2. For the variance one construct is explained by the other antecedent constructs, the higher, the better.

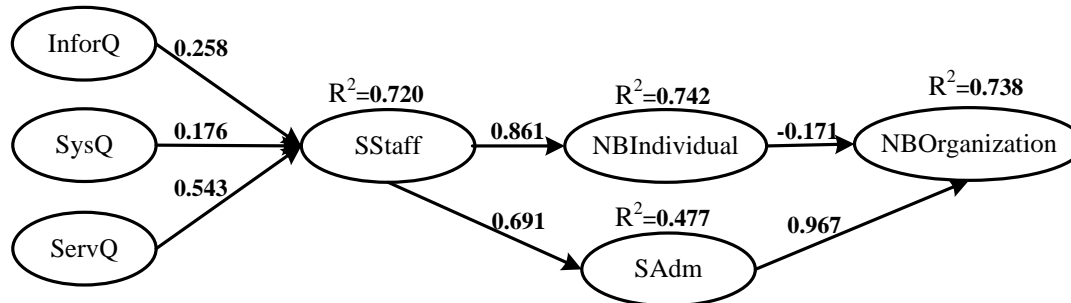


Figure 2 the Research Result

The research model performs tolerably fair. All relationship is as significantly predicted, with the only exception that the benefits between individual users and organizational managers are negatively correlated with the path coefficient of 0.171. Among the three qualities of e-Government system, the service quality is the strongest, with a 0.543 coefficient, followed by the information quality and system quality. The results also indicate that the three types of qualities explain 72 percent of the variance in individual's satisfaction. Similarly, 74.2% of the variance in the individual users' benefits is explained by their satisfaction, and the individual benefits then explain 73.8% share of the variance in organizational benefits. The variance in the organizational satisfaction is marginally half explained by the individual's satisfaction.

5. Discussion

Two rough conclusions can be drawn from the pilot study. First, service quality acts as the core player to engender user satisfaction. Second and the most important, individual staff users' perceptions are different from that of the organizations, and among the formative indicators of organizational benefits, only relatedness fulfillment shows significant. Simply expanding, it is nearly true that the e-Government system might appear successful through raising the individual users' job performance, however, from the social level, the organizational stakeholders are still less satisfied with few needs fulfilled and low benefits experienced. Several works need to do in the future large-scale survey. The questionnaires will be further amended to raise the convergent and discriminant validity, because some indicators are not obvious in its constructs, and the cross loadings of a few items like satisfaction and work performance are still high. Two or more e-Government systems are to be included to raise the external validity. Second-order constructs will be necessarily adopted to well measure the three fulfillments indicators.

Acknowledgement

This research was supported by "the Fundamental Research Funds for the Central Universities"

References

1. Alderfer, C. An Empirical Test of a New Theory of Human Needs. *Organizational Behavior and Human Performance*, vol. 4, 1996, pp. 142 - 175.

Other References Omitted for the Space Limit.

Are You Doing It in the Right Way?

The Effects of Regulatory Fit in IT Product Trial

Xue Yang

Department of Electronic Business
Nanjing University
yangxue@nju.edu.cn

Shu Schiller

Department of Information Systems
& Operations Management
Wright State University
shu.schiller@wright.edu

Hock-Hai Teo

Department of Information Systems
National University of Singapore
teohh@comp.nus.edu.sg

Quansheng Wang

Department of Electronic Business
Nanjing University
wangqs@nju.edu.cn

Abstract

Recent research has directed attention to investigate how the way in which an individual achieves certain goal could influence his/her ultimate decision making besides the well recognized motivational factors (e.g., product satisfaction), which has been continuously neglected in previous IT adoption studies. Inspired by this stream of focus, in this study, we attempt to explore the relationship between a user's information search strategy during IT product trial and his/her propensity of continuous usage after the trial. In particular, lying on the theoretical insights of cognitive stopping rules (CSRs) and the regulatory fit theory (RFT), we propose a preliminary research framework arguing that the regulatory fit between a user's information search strategy and the current IT product trial task will influence his/her post-trial decision confidence, and in turn influence the continuous usage decision. . Proposed research methodology and expected contribution are discussed.

Keywords: IT Product Trial, Cognitive Stopping Rules (CSRs), Regulatory Fit Theory (RFT), Decision Confidence

1. Introduction

Conducting trial with information technology (IT) product (e.g., software, website, instant messenger, enterprise systems, etc) prior to long-term commitment has become a common practice of most IT users. The trial experience can provide users with firsthand information for prudent decision making. Various factors directly related to the IT product per se (e.g., usefulness, ease of use, satisfaction, perceived benefits, etc) have been identified to be influential to continuous usage decision. Besides those well-established factors directly related to IT products, however, little is known about the role of the process through which IT product trial task is conducted and its impact on individual decision.

Following this view, we paid special attention to some recent research studying the way which leads to a decision and its influence on the monetary value which an individual would like to

assign to the same product (e.g., Avnet and Higgins 2006). One typical manifestation of this focus is reflected by the fit between an individual's goal orientation and the manner of the individual's engagement with the target product, which is known as the **regulatory fit effect** (Higgins 2000, 2002). When there is a fit, people feel right about their reactions to the object and become more confident in their judgment and the decision to be made (e.g, Chernev 2004; Dhar 1997; Duan et al. 2009). Such decision confidence may exist in a biased way (e.g., exaggerated) or even surpass the direct effects of product-related factors (Joseph and Hutchinson 2000; Russo et al. 2006). To this end, the way a user tests an IT product and its match with the objective of trial will substantially influence the user's decision confidence and in turn the propensity of making a solid decision.

In specific, we treat IT product trial as a well-structured/decomposable information search task which has clear objectives and decomposable steps to achieve these objectives (Browne et al. 2007). According to the cognitive stopping rules (CSRs) theory, some cognitive information search strategies are especially suitable for well-structured tasks (as opposed to poorly-structured/holistic tasks), and some are not (Browne et al. 2007). Thus, we argue that besides the common factor of IT product satisfaction, when there is regulatory fit between the trial task and the information search strategy (as identified by the CSRs), the user will generally have more decision confidence and in turn the higher propensity to make a continuous usage decision. To answer this research question, we build up a research framework in this study and propose future endeavors to test it. Brief expected contribution to theoretical, methodological and practical advances will be discussed. Since the factor of satisfaction has been extensively explored in prior studies, we will focus on the regulatory fit effect between CSRs and IT product trial task in the following sections.

2. Theoretical Review and Theoretical Background

2.1 Information Search and Cognitive Stopping Rules (CSRs)

Information search is defined as a task in which a person seeks data or knowledge about a problem, situation or artifact such as IT products (Browne et al. 2007). Consistent with the task characteristics approach (Fleishman and Quaintance 1984; Hackman 1969; Wood 1986), it is assumed that certain task elements should elicit particular types of behaviors from individuals (e.g., task processing strategy) (Browne et al. 2007). In prior decision making or problem solving studies, two task elements, task structure and cognitive strategy, are especially emphasized (e.g., Davies 2003; Morera and Budescu 1998; Porter 2004; Sirvastava and Raghurir 2002). First, **task structure** refers to the degree to which the necessary inputs, operations on those inputs, and outputs are known and recognizable to the decision maker (Byström and Järvelin 1995; Rowley 2000; Vakkari 1999). The task structure can be defined as either *well-structured* (e.g., search for a pre-specified product or a job) or *poorly structured* (e.g., search for a rare map) (e.g., Browne et al. 2007; Sinnott 1989).

Second, the **cognitive strategy** used to deal with the task can be distinguished between *decomposable and holistic* (Morera and Budescu 1998; Smith 1998; Srivastava and Raghurir 2002). When a decomposition strategy is applied, various task elements, criteria, or attributes can be separately identified and the constituent elements in the resulting mental representation can be individually recognized (Browne et al. 2007). In contrast, holistic strategy is organic and

integrative that individuals can only depend on a whole representation of the current situation rather than individual elements of the task.

Further, people usually use different **cognitive stopping rules** to terminate information search in a variety of tasks (e.g., Browne and Pitts 2004; Nickles et al. 1995; Saad and Russo 1996). Consistent with previous research (Browne et al. 2005; Nickles et al. 1995), five rules have been proposed as the most common strategies for people to gauge information sufficiency and to terminate search behavior. They are termed as the mental list rule, the representational stability rule, the difference threshold rule, the magnitude threshold rule and the single criterion rule (see Table 1). The five rules are cognitive oriented because they all involve reasoning and/or judgment regarding the decision maker's information search (Nickles et al. 2005).

Table1. Cognitive Stopping Rules (adapted from Browne et al. 2007)

Rule	Description
Mental List	Person has a mental list of items that must be fulfilled before he will stop collecting information.
Representational Stability	Person searches for information until his mental model or representation, stops shifting and stabilizes. The focus is on the stability of the representation.
Difference Threshold	Person sets an a priori difference level to gauge when he is not learning anything new. When he stops learning new information, he stops his information search.
Magnitude Threshold	Person has a cumulative amount of information that he needs before he will stop searching. The focus is on having "enough" information.
Single Criterion	Person decides to search for information related to a single criterion and stops when he has enough information about that criterion.

In the present research, following Browne et al (2007)'s classification on information search tasks, we define IT product trial as an information search task that is well-structured because the functions of a particular IT product (e.g., software) are predefined and presented with a clear structure. Thereby, IT product trial tasks should be dealt with by decomposable cognitive strategy (as opposed to holistic cognitive strategy for tasks with poorly-structured nature). Further, well-structured and decomposable tasks are supposed to work better with certain CSRs (e.g., mental list or single criterion) than others (e.g., representational stability, difference threshold and magnitude threshold). In this sense, depending on its match or fit with the specific task, each cognitive stopping rule has different impact on a user's continuous use decision. In particular, the regulatory fit theory (RFT) will be applied to examine this phenomenon.

2.2 Regulatory Fit Theory (RFT)

The pragmatic and situated nature of human cognition determines that cognition needs to be responsive to people's goals (Schwarz 2006). The underlying theme of RFT is that people can experience different utility or value from the same product depending on the relationship between their current goal orientations and the manner they achieve the goals (Avnet and Higgins 2006). It emphasizes the importance of how an individual achieves a process goal, which functions in background and might operate outside people's awareness (Kruglanski 2006). Thus, regulatory fit reflects a metacognitive assessment of how well the person's current strategy (e.g., a particular CSR) matches the requirements of his/her goal pursuit (e.g., IT product trial).

In turn, the fit perception can enhance the sense of self-assurance or self-worth (Kruglanski 2006). The possible outcomes include such as heightened confidence in decision making, increased importance of the reactions or more polarized or intensified attitude toward the decision (Aaker and Lee 2006; Avnet and Higgins 2006). Regarding the product evaluation task, for example, people are willing to offer more money for the same chosen product when the choice strategy fits their process goal orientation than it does not fit (Avnet and Higgins 2003; Higgins et al. 2003). To this extent, fit serves as an important additional source that affects the decision value but not the focal need or concern itself (i.e., relevance).

In this study, the cognitive stopping rules (CSRs) are incorporated as a set of typical information search strategies that users usually employ in IT product trial. The effects of regulatory fit between different CSRs and a user's IT product trial task which are reflected in varying degree of decision confidence will be examined. The overall objective is to investigate factors influencing the regulatory fit in IT product trial and how the fit influence a user's IT product continuous use decision.

3. Proposed Research Framework, Research Methodology and Contribution

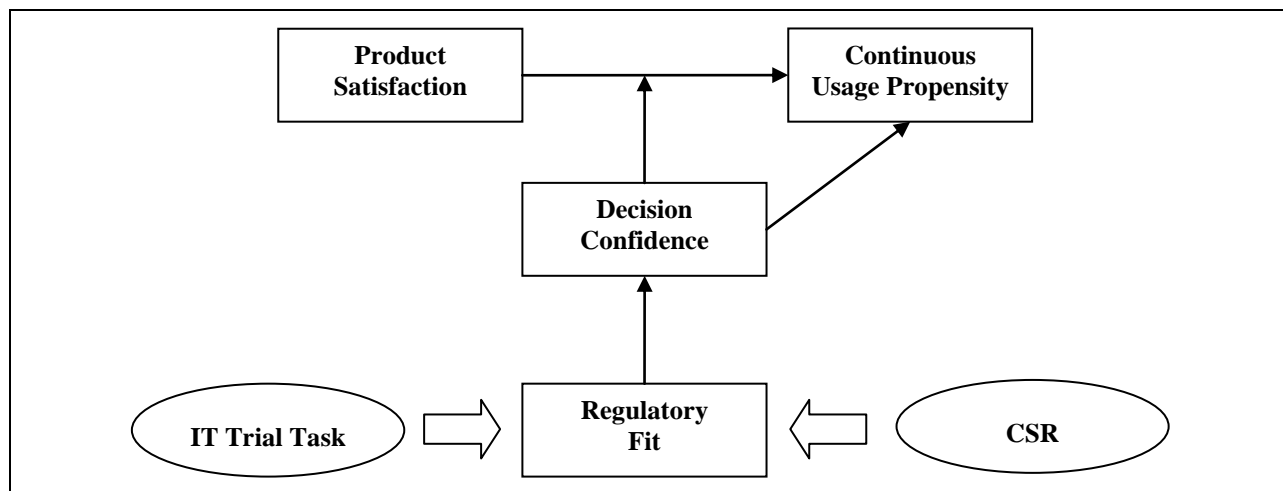


Figure 1. Research Framework

Figure 1 shows the proposed research framework in the current study. Typically, we propose that regulatory fit between IT product trial task and the CSR applied by a user can influence the user's decision confidence in continuous use decision. In turn, the decision confidence will moderate the relationship between the user's satisfaction with the IT product and his/her continuous use propensity. Degree of satisfaction can be manipulated by directly relating to IT product characteristics, such as usefulness or ease of use. Decision confidence may also have direct relationship with the continuous use propensity as confidence may make a user feel right about the product regardless of its real value.

We will attempt to conduct a controlled lab experiment to test the more specified hypotheses of this research framework. In particular, an existing software title will be chosen for experiment participants to evaluate (suppose none of them has past experience with the software) and their true responses and decisions will be captured. Different trial instructions will be provided to each participant to direct them to apply an information search strategy that is either with good fit or

bad fit. Through this manipulation, we expect to see the different effects of information search strategy on final decision making.

We believe this study can contribute to existing literature by emphasizing the importance of the situation in which a decision is made. Through the theoretical development, this study can fill the literature gap that other than the IT product characteristics (e.g., usefulness), certain less visible factors (i.e., regulatory fit) are no less significant for trial outcomes. It raises the often neglected issue in the IS field that the process is as important as the product and develops a formal theoretical model to advance the knowledge. As an early attempt of conducting this empirical study, the results can be used to verify the validity of the regulatory fit theory in the IT product trial context. It will shed light on the understanding on the antecedents and consequences of regulatory fit in special situations (e.g., IT product trial) and advance the methodology development to systematically assess the effects of regulatory fit (Aaker and Lee 2006).

Practically, the results of this study can illustrate to the practitioners such as IT companies how to enhance the effects of IT product trial in facilitating decision making. By understanding users' CSRs and their relationship with trial goals, practitioners can provide customized guidance and support to facilitate the trial process and generate higher revenue.

4. References

1. Avnet, T., and Higgins, E. T. "How Regulatory Fit Affects Value in Consumer Choices and Opinions," *Journal of Marketing Research* (43:1), February 2006, pp. 1-10.
2. Higgins, E. T. "Making a Good Decision: Value from Fit," *American Psychologist* (55:11), Nov2000, pp. 1217-1230.
3. Higgins, E. T. "Regulatory Fit: An Experience that Creates Value," *Journal of Evolutionary Psychology* (2:1), August 2004, pp. 9-22.
4. Chernev, A. "Goal Orientation and Consumer Preference for the Status Quo," *Journal of Consumer Research* (31:3), Dec2004, pp. 557-565.
5. Duan, W. J., Gu, B., and Whinston, A. B. "Informational Cascades And Software Adoption On The Internet: An Empirical Investigation," *MIS Quarterly* (33:1), Mar2009, pp. 23-48.
6. Russo, J. E., Carlson, K. A., Meloy, M. G. "Choosing an Inferior Alternative," *Psychological Science* 17(10), 2006, pp. 899-904.
7. Joseph, A. W., and Hutchinson, J. W. "Knowledge Calibration: What Consumers Know and What They Think They Know," *Journal of Consumer Research* (27:2), Sep2000, pp. 123-156.
8. Browne, G. J., Pitts, M. G., and Wetherbe, J. C. "Cognitive Stopping Rules For Terminating Information Search In Online Tasks," *MIS Quarterly* (31:1), Mar2007, pp. 89-104.
9. Browne, G. J., and Pitts, M. G. "Stopping rule use during information search in design problems," *Organizational Behavior & Human Decision Processes* (95:2), Nov2004, pp. 208-224.
10. Browne, G. J., Pitts, M. G., and Wetherbe, J. C. "Stopping Rule Use During Web-Based Search," *Proceedings of the 38th Hawaii International Conference on System Sciences*, 2005.
11. Davies, S. P. "Initial and Concurrent Planning in Solutions to Well-Structured Problems," *Quarterly Journal of Experimental Psychology, Section A* (56:7), 2003, pp. 1147-1164.
12. Morera, O. F., and Budescu, D. V. "A Psychometric Analysis of the 'Divide and Conquer' Principle in Multicriteria Decision Making," *Organizational Behavior and Human Decision Processes* (75:3), 1998, pp. 187-206.

13. Porter, A. M. "The Case for Holistic Strategies," *Purchasing* (133:5), 2004, pp. 55-59.
14. Srivastava, J., and Raghubir, P. "Debiasing Using Decomposition: The Case of Memory-Based Credit Card Expense Estimates," *Journal of Consumer Psychology* (12:3), 2002, pp. 253-264.
15. Byström, K., and Järvelin, K. "Task Complexity Affects Information Seeking and Use," *Information Processing and Management* (31:2), 1995, pp. 191-213.
16. Rowley, J. "Product Search in E-Shopping: A Review and Research Propositions," *Journal of Consumer Marketing* (17:1), 2000, pp. 20-35.
17. Vakkari, P. "Task Complexity, Problem Structure and Information Actions: Integrating Studies on Information Seeking and Retrieval," *Information Processing and Management* (35:6), 1999, pp. 819-837.
18. Sinnott, J. D. "A Model for Solution of Ill-Structured Problems: Implications for Everyday and Abstract Problem Solving," in *Everyday Problem Solving: Theory and Applications*, J. D. Sinnott (ed.), Praeger Publishers, New York, 1989, pp. 72-99.
19. Smith, G. F. *Quality Problem Solving*, ASQ Quality Press, Milwaukee, WI, 1998.
20. Shanteau, J. "Competence in Experts: The Role of Task Characteristics," *Organizational Behavior and Human Decision Processes* (53:2), 1992, pp. 262-266.
21. Schwarz, Norbert (2006), "Attitude Research: Between Occam's Razor and the Fundamental Attribution Error," *Journal of Consumer Research* (33:1), Jun2006, pp. 19-21.
22. Kruglanski, A. W. "The Nature of Fit and the Origins of "Feeling Right": A Goal-Systemic Perspective," *Journal of Marketing Research* (43:1), February 2006, pp. 11-14.
23. Aaker, J. L., and Lee, A. Y. "Understanding Regulatory Fit," *Journal of Marketing Research* (43:1), February 2006, pp. 15-19.
24. Avnet, T. T., and Higgins, E. "Locomotion, assessment, and regulatory fit: Value transfer from "how" to "what"," *Journal of Experimental Social Psychology* (39:5), Sep2003, pp. 525- 530.
25. Higgins, E. T., Idson, L. C., Freitas, A. L. Spiegel, S., and Molden, D. C. "Transfer of Value from Fit," *Journal of Personality and Social Psychology* (84), June 2003, pp. 1140–1153.

An Empirical Study on the Sources of C2C Sellers' Perceived Risk and Their Corresponding Relationship with Perceived Risk Type

LIU Xinyan

Zhongnan University of Economics and Law
Email: yanzido@163.com

LI Li, WAN Jingjing

Zhongnan University of Economics and Law
Email: lily_001426@163.com

Abstract

The C2C market is now occupying the dominant position of online retail market. The problem of its perceived risk is becoming increasingly conspicuous and shows different characters from that of B2C market, of which the existence of sellers' perceived risk is a typical example. In order to find practical measures to reduce the C2C sellers' perceived risk, this study analyzed the sources of which, employing the methodology of content analysis and using the posts of the Answer Center of EBay as the sample. The results suggest that there are 7 kinds of sources of C2C sellers' perceived risk: the sellers' unusual behavior; the buyers' violation of the transactional rules; the instability of transaction system; the buyers' incredibility; the unfair policies in transaction; the instability of the third party payment and the buyers' delayed response.

Keywords: C2C platform, Sellers, Perceived risk sources, Perceived risk types, Factor structure of risk sources

1. Introduction

There are 3 main characters of the existing researches of perceived risks in online retail market. First, the majority of them are related to B2C market; second, perceived risk is conceptualized as "buyer's perceived risk"; third, they often focus on the discussion of types of perceived risks. However, what is going on in the real world is another matter. First, the data from CNNIC shows that until 2008, the annual transactions of C2C market of China have exceeded 1,220 billion yuan, accounting for 93.3 percent of the total value of online retail market. This means the C2C market should be paid more attention to. Second, there are a lot of sellers competing with each other in one C2C platform and there are series of policies have been made to protect buyers' rights. From this point of view, the sellers of C2C market stand relatively equal position to buyers and their perceived risks become interesting to be explored. Third, in order to find effective solutions, practitioners not only need to know the results of perceived risks, but also have to know the reasons of them, which asks researchers to study the types and sources of perceived risks together. So, this study attempts to empirically analyze the sources of C2C sellers' perceived risk and their corresponding relationship with perceived risk type.

2. Literature Review

2.1 Definition of Perceived Risk

In the theory of consumers' behavior, perceived risk was considered as the uncertainty and the possibility of adverse consequences that consumers perceived in purchasing goods and services. Therefore, in this study, C2C sellers' perceived risk is defined as the adverse consequence that C2Csellers' expect in their participation of C2C transactions.

2.2 Types of Perceived Risk

Stone and Gronhaug tried to measure the perceived risk with six dimensions—financial, performance, physiological, psychological, social and time. This model interpreted 88.8% of total perceived risk, so it is widely accepted by scholars. Most scholars made some relevant researches based on their work. The typical conclusions were Jarvenpaa&Tidd's five-dimension model, Sophie Case's eight-dimension model, Jing miao&Zhou yin's eight-dimension model and so on.

2.3 Sources of Perceived Risk

The researches on perceived risk types focused on distinguishing the types of adverse consequences that consumers concerned with. However, the research on perceived risk sources is to identify what uncertain factors that consumers' expected adverse consequences come from.

Garbarino and Strahilevitz considered that perceived risk sources included the loss of credit card, the error of website, the leak of privacy, the problem of distribution and the mistake of products. Apparently, these sources are related to the new shopping mode-online transaction. Anne Sophie found the perceived risk online mainly resulted from the electronic shopping environment, including product, remote transaction, shopping in the internet and the website. Yu dan and Dong Dahai had similar conclusions in their later study. Nena Lin pointed out consumers' perceived risk not only came from online vendors, but also from Internet technology, consumers themselves and products. Chinese scholars SunXiang and Zhang Shuoyang thought the sources of perceived risk included information searching, transaction process, delivery and the risk after goods' arrival.

3. Research Design

3.1 Methodology

Questionnaire and group interviews are the main methods of existing researches, and there are many limitations: first, the backgrounds of respondents are similar and easily lead to systematic bias; second, respondents were separated from real situation and easily lead to memory bias; third, relatively closed questionnaire is unfavorable to find new risk types and to clarify the micro-level factors; forth, the sample size of group interviews is small and the data were not coded seriously. The study will employ Netnography as research method, which is based on internet and proposed by Kozinets (2002). Researchers can get information by observing and coding consumers' posts. It has two advantages compared to other methods: first, Netnography is completely "no-interference"; second, Netnography can save research resources significantly.

3.2 Sample

In accordance with the steps of Netnography, several famous C2C sites were compared by researchers, and Ebay community was the best choice. Next, several forums of Ebay were compared according to the standard proposed by Kozinets (2002): (1) the forum is easy to get data; (2) the contents of posts are related to the research; (3) descriptive rich data; (4) traffic of posting is heavy; (5) members of forum are interactive. Moreover, by calculating the average words of each post, the proportion of joking posts, and integrity of description and so on, answer center was taken as the best sample.

3.3 Data Coding

The category of “risk type” was designed draw on existing literature, and the result of having read the posts. Economic risk, time risk, privacy risk, image risk, estimated risk and qualification risk were incorporated into the coding framework.

The category of “risk sources” was designed by the method of Grounded Theory, which was proposed by Strauss & Corbin (1990). This method was divided into 3 stages. (1) In the stage of open coding, one coder accomplished initial coding alone, taking core contents of posts as the name of coding categories. Next, another coder involved in the coding, selecting a few posts of each category and coding with the first coder. (2) In the stage of associated coding, two coders compared their coding results at first, finding out and discussing all the inconsistencies. Second, Streamlining and consolidating of similar, repeated categories. Third, discussing and reclassifying those controversial posts. (3) Core coding is to select a core category based on the results of associated coding. Finally, the perceived risk sources of seller were divided into several categories: instability of third party payment, instability of transaction system, sellers’ unusual behavior, some buyers’ behavior and state.

The Cohen Kappa coefficient is 0.9, indicating that the consistency of the coders is good.

4. Data Analysis and Discussion

4.1 C2C Sellers’ Perceived Risk Sources and Factors

The coding result of sellers’ perceived risk sources was shown in table1. It suggests that, there are 7 kinds of sources of C2C sellers’ perceived risk, and these sources can be divided into 3 classifications by different subjects:(1) The sources due to the buyers: the buyers’ violation of the transactional rules, the buyers’ incredibility, buyers’ delayed response. (2) The sources due to the sellers: the sellers’ unusual behavior, which is resulted from the seller who is against general trading rules or trading habits. (3) The sources due to the C2C platform: the instability of transaction system, unfair policies in transaction and instability of third party payment.

Table 1. Perceived Risk Sources

Sources	n	%	Sources	n	%
buyers’ violation of the transactional rules	60	19.80	instability of transaction system	60	19.80
buyers’ incredibility	50	16.50	unfair policies in transaction	46	15.18
Buyers’ delayed response	6	1.98	instability of the third party payment	19	6.27
sellers’ unusual behavior	62	20.46			
Total (%)	303	100.00			

4.2 Corresponding Relationship between Perceived Risk Sources and Types of C2C Sellers

In the process of coding, some new risks were found, and some traditional risks disappeared: the new risks include estimated risk and qualification risk; the disappeared risks include privacy risk, functional risk, psychological risk and physiological risk. Based on the facts above, this study grouped C2C sellers’ perceived risk into 5 types: economic risk, estimated risk, time risk, image risk and qualification risk. The coding result was shown in table 2:

Table 2. Corresponding Relationship between Types and Sources

Risk types	Instability of third party payment	Buyers' incredibility	Sellers' violation of transactional rules	Buyers' delayed response	Sellers' unusual behavior	Instability of transaction system	Unfair policies in transaction	Total (%)
Economic risk	3.30	*15.18	5.28	0.66	4.95	4.62	*7.59	41.58
Estimated risk	1.32	0.33	*8.25		*9.24	1.65	*7.26	28.05
Time risk	0.99	0.99	*4.62	1.32	1.32	*13.53	0.33	23.10
Image risk			0.66		*1.65			2.31
Qualification risk	0.66		0.99		*3.30			4.95
Total (%)	6.27	16.50	19.80	1.98	20.46	19.80	15.18	100.00

4.2.1 Sources of sellers' perceived economic risk

Sources due to the buyers. Buyers' incredibility is the first source of economic risk. Sellers are sensitive to buyers' identities, and easy to perceive economic risk when buyers' accounts suspicious, or buyers asking for unconventional payment approach. Second, sellers will perceive economic risk for buyers' violation of transactional rules when buyers request unreasonable refund or do not pay money promptly. **Sources due to C2C platform.** The unfair policies in transaction are the second source of economic risk. First, sellers reacted strongly to the policies of "seller can not give negative comment" and "neutral comment can not be reckoned in the rate of praise". Second, the instability of transaction system was mainly due to the double counting listing fee, and showing wrong price of the products. Third, third party payment system leads to economic risk in such cases: system cannot accomplish the operation of cashing promptly, or cannot implement the operations of receiving and refunding accurately. **Sources due to the sellers.** Sellers' misoperation and sellers want blackout of transaction before receiving the payments are the main reasons.

4.2.2 Sources of sellers' perceived estimated risk

Sources due to the sellers. The unusual behavior is the first source of estimated risk. Particularly, sellers concerned about the neutral/negative comments caused by "complaining buyers" and "blackout of transaction". Besides, sellers would worry about losing the positive comments when register new accounts. Finally, sellers would worry about getting neutral/negative comments when they breach of agreements or cannot provide shipping certificate. **Sources due to the buyers.** Buyers' violation of transactional rules is the second source of estimated risk, and the core factor is buyers abusing safeguard mechanism. The most common case is buyers threaten sellers to give refund or free shipping by giving neutral/negative comments. **Sources due to C2C platform.** The unfair policies in transaction is the third source of estimated risk. As mentioned above, the policies of "seller cannot give negative comments" and "neutral comments cannot be reckoned in the rate of praise" made sellers worry about losing positive comments for buyers can give neutral/negative comments without scruple.

4.2.3 Sources of sellers' perceived time risk

Sources due to C2C platform. The instability of transaction system is the first source of time risk, and key service of transaction platform failure is the very factor which enable sellers to

worry the products cannot be sold. **Sources due to the buyers.** Buyers' violation of transactional rules is the second source of time risk, which is due to the buyers do not give payments timely.

4.2.4 Sources of Sellers' perceived qualification risk and image risk

Qualification risk and image risk are both mainly due to sellers' unusual behavior. Such as listing sensitive products information, worrying about trade qualification being restricted when blackout of transaction, and worrying about image lost when urging buyers.

5. Innovations of the Theory

The innovation of this study embodies in the following five aspects.

First, this study took C2Csellers as a new study perspective, and proved the sellers' perceived risk really occurred. Second, this study employed Netnography and used consumers' real data to carry on a strict qualitative analysis without interference, making up for the limitation of existing researches' openness and normative. Third, besides proved the importance of economic risk and time risk, this study firstly found two new exclusive C2C users' perceived risk types. Fourth, this study differentiated and classified the factors of perceived risk sources, establishing a C2Csellers' perceived risk source system with complete categories and rich factors. Fifth, this study matched perceived risk sources along with perceived risk types, proving each risk type has the mainly corresponding perceived risk sources.

References

1. Nina Koiso-Kanttila, *Time, Attention, authenticity and consumer benefits of the web*, Business Horizons, Vol. 48, Issue 1, pp.63-70, January-February 2005.
2. Rosenbloom, A., *How the virtual inspires the real*, Communications of the ACM, Vol.45, pp.29-30, 2002.

DISCLOSURE OR DISCLOSURE AVOIDANCE? INTERNET USERS' INFORMATION PRIVACY AND EMOTIONS EXPERIENCED ON B2C WEB SITE

Sarah P.W. Shek, Kai-Lung Hui

Department of Information Systems, Business Statistics, and Operations Management

Hong Kong University of Science and Technology

pwshek@ust.hk, klhui@ust.hk

Abstract

Previous research has suggested that consumers are concerned about online privacy, and they would often refuse to provide their personal data to Internet Web sites. The existing empirical studies, however, have been relatively silent about the underlying basis of the consumer concerns. In this study, we evaluate how consumer emotions arising from information disclosure affect their online behavior. We conducted a laboratory experiment in which we manipulated the extent to which consumer information would be viewed by different agents in an organization. We found that consumers are more likely to disclose their information and purchase from a Web site when the information is read only by a computer but not by the staff of the organization. Further, the mere effect of feeling embarrassed could significantly affect their choices, and the impact of consumer emotions varies systematically with the nature of the Web sites. These results suggest that in addition to fear of future information misuse, consumers may have innate concerns about information disclosure.

Keywords: Privacy as secrecy, embarrassment, emotions, information disclosure

1. INTRODUCTION

In the age of the Internet, marketers have developed an insatiable appetite for consumer information in an attempt to deepen relationships with whom they do business, provide personalized features and recommendations, and explore opportunities for new product or service introductions. To gain consumer information to enhance their services, marketers need consumers to respond willingly to requests for personal information with honest and accurate answers. However, the existing evidence has indicated that many consumers deliberately falsify or conceal information in Web site exchanges (Fox 2005). It is vitally important to understand how consumers perceive and respond to personal data requests, particularly how they counterbalance the firms' desire for individual-specific information with their own desire for swift services and privacy in the relationship (Hui et al. 2007; Charters 2002).

In this study, we seek to examine consumer emotions under different scenarios of secrecy involving specific information processing-related prescriptions, and the outcomes due to the consumer emotions. In particular, we propose that consumer emotions are conditional on online shopping episodes – whether the consumer information is subject to human or computing processing, and the type of products being sold on the Web site. We explore consumer emotions that arise from information disclosure along two dimensions: (1) different information handling environment (human vis-à-vis computer processing), and (2) different contextual sensitivity (a B2C Web site selling condom vis-à-vis USB flash memory devices). We further propose that the

aroused consumer emotions would affect consumer behavior (e.g., decision to register an account and intention to perform online shopping on the B2C Web site).

We conducted a laboratory experiment to manipulate the online shopping contexts. Subjects were randomly assigned to different treatments in the experiment. They were asked to browse a fictitious Web site and provide their personal information to register as a member of the Web site and fill out an exit survey which asks for their impressions of the Web site and the related emotions during the shopping episode. The results of a pilot study reveal that consumers are more likely to disclose their information and purchase from the Web site when the information is read only by a computer but not by the staff of the organization. Further, the mere effect of feeling embarrassed could significantly affect their decision to register an account and intention to perform online shopping. These results suggest that in addition to fear of future information misuse, consumers may have innate concerns about information disclosure.

This paper is organized as follows. The next section presents the theory and the research hypotheses. Then, we present the research methodology and findings. Finally, we conclude the paper with a discussion of theoretical and managerial implications.

2. THEORY AND PROPOSITIONS

Most privacy and consumer behavior research to date has focused on understanding the potential antecedents of individuals' willingness to divulge personal information to online firms. The majority of studies in this literature have used utilitarian-based analysis in understanding what affects consumers to conceal or divulge personal information (Smith et al. 1996; Stewart and Segars 2002; Malhotra et al. 2004). A key assumption underlying this line of research is that consumers make rational decisions on the basis of subjective views of fairness within the context of information privacy (Campbell 1997; Culnan and Armstrong 1999). For instance, the empirical evidence has indicated that consumers are enticed to divulge their personal information because of immediate monetary rewards (Hann et al. 2007; Hui et al. 2007). Further, sophisticated consumers may care about the economic contexts and indirect economic consequences associated with dissemination of personal information (Wathieu and Friedman 2007). Hence, consumers may make a risk-benefit tradeoff when deliberating whether to disclose personal information. Emotional elements *per se* may not be their primary focus.

However, apart from rational judgments, it is possible that consumers rely on both rational and emotional elements in their decision processes. Emotions and feelings have long been recognized as an important factor in understanding consumption and decision making in traditional shopping contexts (e.g., Holbrook et al. 1984; Richins et al. 1992). According to Richins (1997), emotion is "a valenced affective reaction to perception of situations". Emotions in online shopping may include those that are directly experienced from the consumption processes. They can occur at all stages of the consumption process: before, during, and after the purchase act. Eisenberg (2001) has shown that consumers make online purchase decisions based on emotions.

This research is a first attempt to examine the relationships between information privacy, consumer emotions, and online behavior. We expect that privacy concerns would be most significant at the beginning stage before trust and relation between consumers and online firms are established. In this regard, we focus our study on the commitment stage of the consumption process. For measurement of consumer emotions, we used embarrassment and a second-order factor that encompasses anger, worry and fear, and adopted the measurements from Hui and Bateson (1991) and Richins (1997).

When consumers first visit a B2C Web site, their decisions to register an account are greatly affected by the online shopping contexts. Communication theory suggests that anonymity from other people in online interactions increases information disclosure because it offers a safe channel for people to act without accountability, conformance pressure, or evaluation apprehension (Connolly et al. 1990; Nissenbaum 1999). In other words, being unknown during online shopping may make people feel less socially anxious and less emotionally unsafe, and hence, relieve consumers' privacy concerns. In computer-driven information processing, consumer information is mostly collected via online forms, surveys, or email links. The provided information would be recorded in a server and so usually no one is able to read any individual-specific information. This makes consumers more willing to share personal information online. However, the information practice of some Web sites would involve both human and computer (allowing some staff to access and analyze individual-specific data for marketing and/or personalization purposes). In these cases, apart from the same information processing by computer system, some employees of the organization may see the personal information of consumers in due business processes. Consumers may feel emotionally unsafe because of privacy concerns or sense of insecurity when, in addition to a computer, the information is exposed to the employees (Joinson 2001). This may inhibit them to reveal their information to the Web sites. Hence, our first proposition is:

Proposition 1: A setting with only computer processing will lead to higher consumer intention to register in a Web site than a setting with both computer and human processing.

Next, to assess the relationships between online shopping contexts and consumer emotions, we considered embarrassment and other negative emotions as recommended by Hui and Bateson (1991) and Richins (1997). Embarrassment is a socially occurring phenomenon driven by a concern for what others are thinking about us (Miller 1995). Embarrassment may occur when unwanted events intervene and/or unwanted evaluations were performed by real or imagined audiences (e.g., one may feel embarrassed when purchasing a "sensitive" product like condom). Dahl et al. (2001) cite embarrassment as a significant factor influencing many facets of human behavior. To be embarrassed, one must be aware of someone watching and potentially evaluating their actions (Schlenker and Leary 1982). Consequently, we propose that if consumer information is read by the staff of an online firm, and, if the purchase or the events happened during the purchase communicate undesirable information about a consumer, then purchasing a product may lead consumers to feel awkward and embarrassed because of the potential for evaluation by the some people (e.g., the staff of the company).

Besides feeling embarrassed, consumers may experience other negative emotions when individual-specific information is read. Richins (1997) has identified a list of emotions that characterize specific discrete emotions in the purchasing context. Anger, worry, fear and shame (embarrassed) are the most significant negative emotions involved in information disclosure, and these emotions have been shown to significantly affect consumer purchase decisions. This leads to the following proposition:

Proposition 2: A setting that involves human processing will lead to a higher level of embarrassment than a setting with only computer processing. Such an embarrassment is negatively related to information disclosure (register on/intention to visit a Web site).

Proposition 3: A setting that involves human processing will lead to a higher level of negative emotions than a setting with only computer processing. Such negative emotions are negatively related to information disclosure (register on/intention to visit a Web site).

Further, the type of products carried on a Web site may affect consumer emotions and consumer behavior. Unfavorable repercussions may arise in different product/service domains (Culnan and Armstrong 1999), and therefore, lead to differing privacy concerns. In other words, in addition to information privacy, the context/domain of exchange may also influence consumer behavior. Our last two propositions are:

Proposition 4: Consumers will experience a higher level of embarrassment during a sensitive product purchase and, in turn, a lower information disclosure intention (to register on/visit the Web site).

Proposition 5: Consumers will experience a higher level of negative emotions during a sensitive product purchase and, in turn, a lower information disclosure intention (to register on/visit the Web site).

3. EXPERIMENTAL DESIGN

We designed a laboratory experiment for this pilot study. Specifically, we created three treatments for information processing and recorded how subjects responded to each: (1) a *baseline control*: a general privacy policy is provided (this served as a control because the same privacy policy was also used in the other two treatments); (2) a treatment group with *high secrecy*: the subjects were told (prominently) that the provided information would be recorded in a server which does not go through any human processing. No one would gain access to the individual-specific data in the server, and only aggregated data/statistical estimation results will be used for marketing/personalization purposes; (3) a treatment group with *low secrecy*: the same computer operations was told, but after the computer has processed and stored the information, related staff of the company may access and randomly check some of the individual-specific data to verify the operations of the system, and some other staff may use the data for marketing and/or personalization. All other aspects of the experiment were identical across the three treatments. Hence, the only difference lied in whether some unknown people (staff of the firm) would have a chance to see the individual-specific information of consumers. Further, we manipulated the contextual sensitivity by varying the type of products sold on the Web sites.

Products. We conducted a focus group with three student subjects to select the types of products for sale on our fictitious Web site to manipulate contextual sensitivity. A pool of sensitive/embarrassing and non-sensitive/non-embarrassing products were listed by the focus group, from which condoms and USB flash memory devices were selected as the product categories for our investigation.

Subjects. 99 undergraduate students at a large university participated in the experiment. We randomly assigned the subjects to the different experimental conditions. Each subject received a token monetary payment for his/her participation.

Procedure. First, we explained the experimental task and procedures to the subjects. We informed the subjects that the aim of this study was to collect user feedback on a newly established Web site selling condom/USB flash memory devices. The subjects were also invited

to register as a member of the Web site with their *name, gender, age group, 3 digits of HKID/Passport ID for the non-local subjects, email, address*, etc. to earn a welcome gift (extra \$50 cash reward). The subjects were told that the Internet firm will send them offers and promotions, as well as the HK\$50 cash coupon welcome gift via email. We contacted the subjects who had filled in the online registration form by email and paid them the HK\$50 cash coupon 10 days after the experiment.

Control. We collected additional data, such as consumer's trust on the experimental Web site, perceived relationship with the Web site (short-term vs. long-term), familiarity, and general privacy concerns in an exit survey, and used them as control variables in the subsequently analysis.

4. FINDINGS

Table 1 presents the responses in each experimental condition (the number of subjects who registered for a membership and hence disclosed their personal information during the experiment). Providing some preliminary support to Proposition 1, 60% of the subjects registered in the "control" and "high secrecy" groups, compared with only 40% in the "low secrecy" groups.

Table 1: Number of subjects registered

<i>Registered</i>	Control (1)	Higher secrecy (2)	Lower secrecy (3)	Total
Yes	21	22	13	56
No	13	12	18	43
Total	34	34	31	99

We tested the proposed theoretical model using two statistical tools, SPSS and PLS. For the measurement model, the results from the data suggest good construct reliability (Cronback's alphas above 0.84), convergent validity (factor loadings greater than 0.8) and discriminant validity (the square root of AVE of each latent variable exceeded all shared correlations with other latent variables).

The structural model assessment consists of two parts: (1) to evaluate the structure of the second-order factor – negative consumption-related emotions as recommended by Richins (1997), and (2) to test hypotheses based on the path coefficients and R^2 .

Table 2: Correlation coefficients of consumption-related emotions

2nd-order Factor	1st-order Factor	Weights	t-statistics	Significant
Negative consumption-related emotions	Anger	0.877	29.07	Yes (at 0.01 level)
	Worry	0.942	57.53	Yes (at 0.01 level)
	Fear	0.923	53.02	Yes (at 0.01 level)

Table 2 shows that the correlation coefficients were significant at the 0.01 level for all the first-order constructs about negative consumer emotions. This means that anger, worry and fear are good representatives of negative consumer emotions in the presented online shopping context.

The R^2 for "intention to shop" was 0.28 and that for "decision to register" was 0.19. Table 3 shows that consumers experienced a higher level of embarrassment during a sensitive product (condom) purchase which, in turn, led to a lower intention to register on a Web site and lower intention of future visit. Hence, Proposition 4 is supported. However, the effect of the secrecy treatment (presenting subjects with a situation where their personal information may be

read by humans) on embarrassment is insignificant, and hence Proposition 2 is not supported. This suggests that the potential antecedent of embarrassment is related to types of products being sold on a B2C Web site, but not the information practices of the Web site *per se*. This implies that information disclosure would lead consumers to feel awkward and embarrassed only when the purchase or the events happened during the purchase communicate undesirable information about the consumers.

Further, the results reveal that with humans involved in information processing, the subjects exhibited more negative emotions such as anger (e.g., they may feel angry about the company letting its employees see their sensitive information), worry and fear (e.g., they may worry about how other people might judge them based on their personal information). However, these negative emotions did not have any association with their decision to register an account and intention to conduct online shopping at the Web site. Hence, Proposition 3 is partially supported.

Since we could not find any association between the nature of product purchase and consumers' negative emotions, Proposition 5 is not supported.

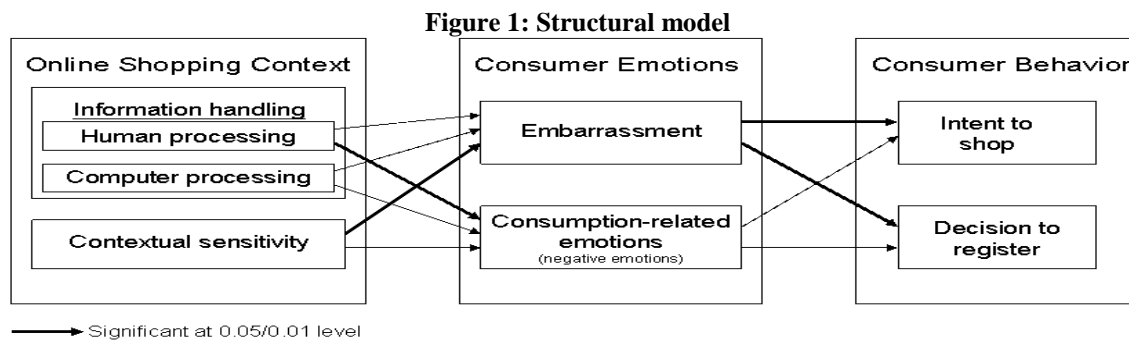


Table 3: Assessment of structural model

Path	Coefficient	t-statistics	Significant
Computing processes -> Embarrassment	-0.046	0.41	No
Human processes -> Embarrassment	0.151	1.43	No
Product -> Embarrassment	0.255	2.64	Yes (at 0.01 level)
Embarrassment -> Intention	-0.208	2.27	Yes (at 0.01 level)
Embarrassment -> Registered	-0.188	1.75	Yes (at 0.10 level)
Computing processes -> Consumption-related emotions	-0.091	0.78	No
Human processes -> Consumption-related emotions	0.202	2.02	Yes (at 0.05 level)
Product -> Consumption-related emotions	0.020	0.21	No
Consumption-related emotions -> Intention	0.100	0.74	No
Consumption-related emotions -> Registered	0.029	0.23	No

5. CONCLUDING REMARKS

This study shows that in addition to utilitarian-based analysis and general privacy fears such as future information misuses, consumer may have innate concerns or emotions about information disclosure. The practical implication is straightforward – consumer emotions are often predictable. Online firms may want to know how consumers would feel when collecting consumers' personal information, since emotions serve as a useful source of indicator for predicting how consumers will behave.

The use of student subjects is one major limitation of this study. The high level of disclosure that we observed (60% for the “control” and “high secrecy” groups and 40% for the “low secrecy” group) may not be generalizable to other populations. We urge future research to replicate and extend this study using a more varied pool of subjects and experimental contexts.

REFERENCES

1. Connolly, T., Jessup, L.M., and Valacich J.S. “Effects of Anonymity and Evaluation Tone on Idea Generation in Computer-Mediated Groups,” *Management Science* (36:6), 1990, pp.689-703.
2. Culnan, M.J., and Armstrong, P.K. “Information Privacy Concerns, Procedural Fairness, and Impersonal Trust: An Empirical Investigation,” *Organization Science* (10:1), January-February 1999, pp.104-115.
3. Dahl, D. W., Manchanda, R.V., Argo, J.J. “Embarrassment in consumer Purchase: The Roles of Social Presence and Purchase Familiarity,” *Journal of Consumer Research* (28), December 2001, pp. 473-481.
4. Hann, I.H., K.L. Hui, T.S.Y. Lee and I.P.L. Png “Overcoming Online Information Privacy Concerns: An Information Processing Theory Approach,” *Journal of Management Information Systems* (42:2), Fall 2007, pp. 13-42.
5. Holbrook, M. B., Chestnut, R.W., Oliva, T.A., and Greenleaf, E.A. “Play as a Consumption Experience: The Roles of Emotions, Performance, and Personality in the Enjoyment of Games,” *Journal of Consumer Research* (11), September 1984, pp.728-739.
6. Hui, M.K., and Bateson, J.E.G. “Perceived Control and the Effects of Crowding and Consumer Choice on the Service Experience,” *Journal of Consumer Research* (18), September 1991, pp. 174-184.
7. Hui, K.L., Teo, H.H., and Lee, S.Y. T. “The Value of Privacy Assurance: An Exploratory Field Experiment,” *MIS Quarterly* (31:1), March 2007, pp.19-33.
8. Joinson, A.N. “Self-Disclosure in Computer-Mediated Communication: The Role of Self-Awareness and Visual Anonymity,” *European Journal of Social Psychology* (31), 2001, pp.177-192.
9. Malhotra, N., Kim, S., and Agarwal, J. “Internet Users’ Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model,” *Information Systems Research* (15:4), 2004, pp. 336-355.
10. Nissenbaum, H. “The Meaning of Anonymity in an Information Age,” *The Information Society* (15), 1999, pp. 141-144.
11. Richins, M. L. “Measuring Emotions in the Consumption Experience,” *Journal of Consumer Research* (24), September 1997, pp. 127-146.
12. Richins, M. L., McKeage, K.K.R., and Najjar, D. “An Exploration of Materialism and Consumption-Related Affect,” in *Advances in Consumer Research* (19) 1992, pp.229-236.
13. Schlenker, B. R., and Leary, M.R. “Social Anxiety and Self-Presentation: A Conceptualization Model,” *Psychological Bulletin* (92), November 1982, pp. 641-669.
14. Stewart, K.A., and Segars, A.H. “An Empirical Examination of the Concern for Information Privacy Instrument,” *Information Systems Research* (13:1), 2002, pp.36-49.
15. Wathieu, L. and Friedman, A. “An Empirical Approach to Understanding Privacy Valuation,” Harvard Business School Working Paper, 2007, No. 07-075.

Analysis of Online P2P Lending Market Risk Based on Signaling Game

Dongyu Chen

School of Economic Information
Engineering, Southwestern University
of Finance and Economics Chengdu,
Sichuan, P.R.China, 611130
dychen1981@gmail.com

Jun Tan

School of Economic Information
Engineering, Southwestern University
of Finance and Economics Chengdu,
Sichuan, P.R.China, 611130
jtan@yahoo.cn

Abstract

The online P2P lending market make it convenient and fast to transact between borrowers and lenders, but the risk in transaction has been haunting the lenders, due to information asymmetry. This paper proposes a signaling game model to study the factors influencing the equilibrium, and proposes the strategies in setting the lending rate to control the risk in the online P2P lending market.

Key words: online P2P lending, signaling, risk, lending rate

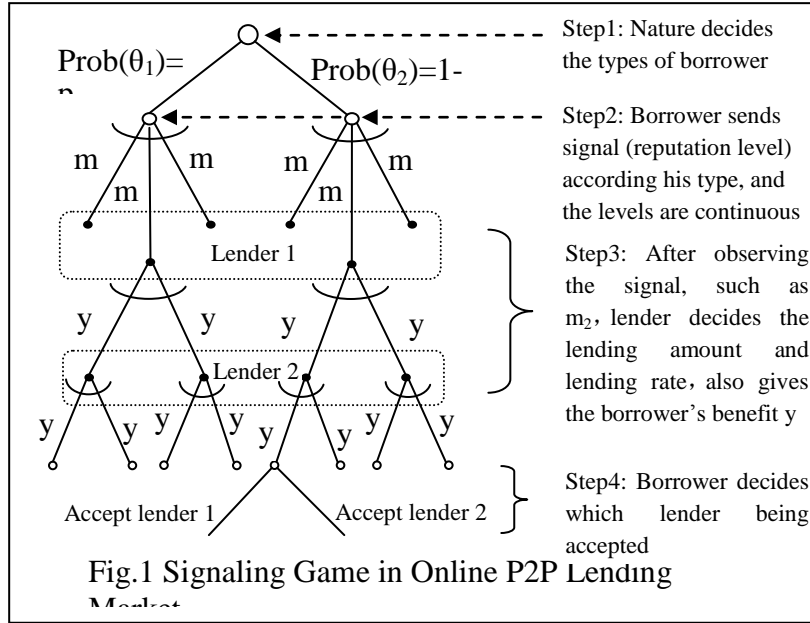
1. Introduction

Empowered by the innovative ideas in electronic commerce, online P2P (peer-to-peer) lending is getting popular worldwide. Prosper, Zopa UK, Lending Club, Kiva, MicroPlace, ZimpleMoney, PPdai.com, CreditEasy, and Qifang are the most active P2P lending market providers in different countries. However, all of them are challenged by the low lending success rate because of the high potential risk in the transactions. On a P2P lending platform, borrowers provide basic background information, and lenders can bid on listings that are attractive to them. Because of the information asymmetry, cheating and fraudulent transactions are inevitable. The risk hampers the development of online P2P lending markets.

So far, researches on information asymmetry problem in online P2P lending market are mainly about management and behavior. For example, Everett(2008) and Mingfeng Lin(2009) discussed the information asymmetry problem in online P2P market by social network. Greiner(2009) using data from Prosper.com suggested that social capital does not provide equal benefits to all members and the mechanisms to promote social capital should be carefully designed.

In this paper, we present a signaling game model to study the possible Nash Equilibriums between borrowers and lenders under different situation in an online P2P lending market. We identify the factors influencing the equilibrium, which lead to the suggestions in reducing information asymmetry in online P2P lending market.

2. Signaling Game in P2P Lending Market



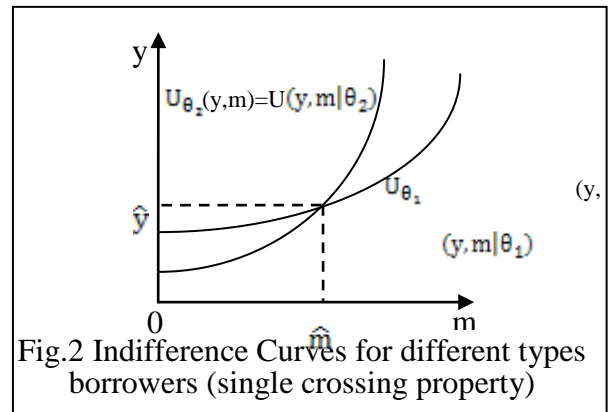
Consider a signaling game with two players--lenders and borrowers involved in a transaction in the online P2P lending market (Fig.1). The borrower is one of the borrowers in a pool, which can be classified in two types θ_1 (honest) and θ_2 (opportunistic), $\theta_1, \theta_2 \in \Theta$, the probability which borrower is honest is p , and the borrower is opportunistic with probability $1-p$. The borrower knows his/her own type and the lender does not have the information of borrower's type but can perceive the reputation information signal sent by a

borrower in a transaction. In a specific transaction, a borrower of any type can choose a reputation information signal $m, m \geq 0$, m is continuous. The reputation information signal can be the reputation record or other documents which can prove the borrower's reputation. By choosing $m=0$, it is meant that the borrower is cheating or has no reputation verification. Because the information asymmetry problem exists in online market, the opportunistic borrower can send information to misguide lenders lending money. Default usually happen in that case. The lenders are willing to lend money with the lending rate r and $0 \leq r \leq 1$.

A borrower's payoff can be expressed as $U_\theta(y, m) = y(\theta, m) - C(m, \theta)$, $C(m, \theta)$ is the cost of sending signal m , $C(0, \theta) = 0$, $C_m(m, \theta) > 0$, $C_{mm}(m, \theta) > 0$. Thus both the cost and the marginal cost of performance level are assumed to be lower for honest borrower. Meanwhile, $y(\theta, m) = Q - (1+r)L + R(m, \theta)$, where Q is the revenue of the project, L is the total amount of loan, and $R(m, \theta)$ is the expected gain from default. On the other hands, a lender's payoff is $Y = rL - R(m, \theta)$, r is determined by the lender after observing the signal.

Denote the lender's belief that a borrower is type θ_1 after observing the reputation information signal m as $\mu(m) \in [0, 1]$ and $\mu(m)$ are consistent with the strategies in sense of Bayesian Law. Hence the expected benefit is $y = \mu(m)y(\theta_1, m) + (1-\mu(m))y(\theta_2, m)$ (1)

In this game, to be a perfect Bayesian equilibrium, the benefit $y(m^*)$ is equal to the borrower's expected benefit. Meanwhile, given $y(m)$, the borrower chooses a reputation information signal to maximize his/her utility. So the borrower's decision function is:



$$\max U_\theta(y, m) \quad (2)$$

$$\text{s.t } y(m^*) = \mu(m^*)y(\theta_1, m) + (1 - \mu(m^*))y(\theta_2, m) \quad (3)$$
 In the online P2P lending market, we assume that

$$\partial U / \partial y > 0, \partial^2 U / \partial y^2 \leq 0, \partial U / \partial m < 0, \partial^2 U / \partial m^2 < 0,$$
 then the indifference curves are in single crossing property and shown in Fig2.

3. Analysis of Signaling Model in Online P2P Lending Market

A set of strategies and a belief function $\mu(m)$ is a perfect Bayesian equilibrium if:

(i) The borrower's strategy is optimal, when given the lender's belief and willing-to-lending.

(ii) The lender's belief $\mu(m)$ is derived from the borrower's strategy using Bayesian rule wherever possible.

(iii) The lender's willingness-to-lending following each m constitute a Nash equilibrium in which the probability that the borrower is of θ_1 type is $\mu(m)$.

3.1 Separating Perfect Bayesian Equilibrium

Lemma 1: In any separating perfect Bayesian equilibrium, $y^*(m^*(\theta_1)) = y(\theta_1, m)$ and $y^*(m^*(\theta_2)) = y(\theta_2, m)$, namely, every type borrower gets benefit respectively.

Lemma 2: In any separating perfect Bayesian equilibrium, $m^*(\theta_2) = 0$, namely, the opportunistic borrower will send signal $m = 0$. The so-called separating perfect Bayesian equilibrium means that the two types of borrowers choose different reputation information signals.

According to lemma 1 and 2, we can derive a separating equilibrium shown in Fig.3: let $m^*(\theta_1) = \tilde{m}$, $m^*(\theta_2) = 0$. Given the benefit $y^*(m)$, an opportunistic borrower will choose $m = 0$ and the honest borrower will choose $m = \tilde{m}$ to maximize their utility, meanwhile, lender's

belief is $\mu^*(m) = (y^*(m) - y(\theta_2, m)) / (y(\theta_1, m) - y(\theta_2, m))$. When $m \neq \tilde{m}$ and $m \neq 0$, the lender has any belief and $\mu(0) = 0$, $\mu(\tilde{m}) = 1$.

However, separating perfect Bayesian equilibrium is not the unique equilibrium. Other separating equilibriums can be derived as follows: (i) The lender believes that the borrower is of

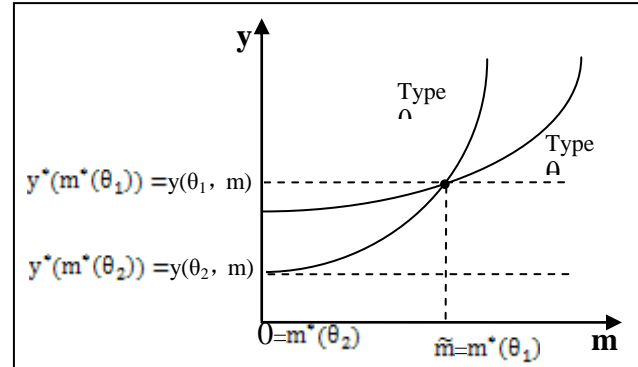


Fig.3 Separating Equilibrium 1 (borrower's type derives from reputation information signal)

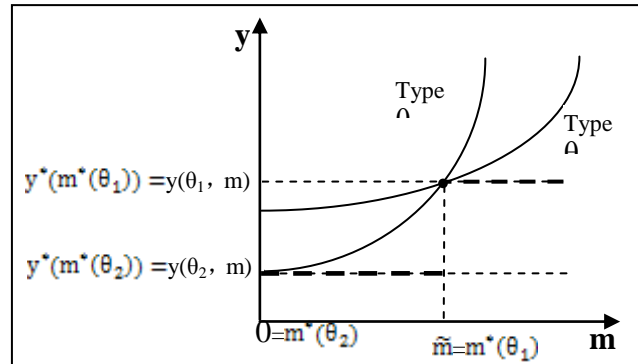


Fig.4 Separating Equilibrium 2 (the same reputation information signal as Fig.5 and different belief on unequilibrium path)

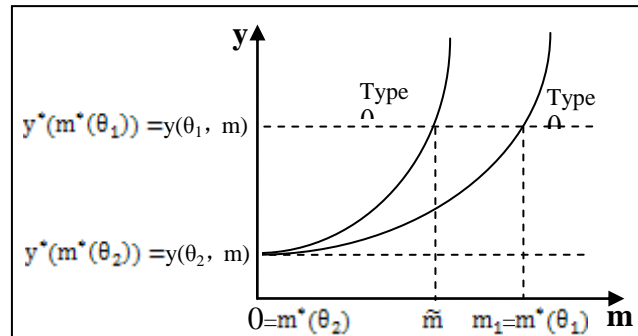
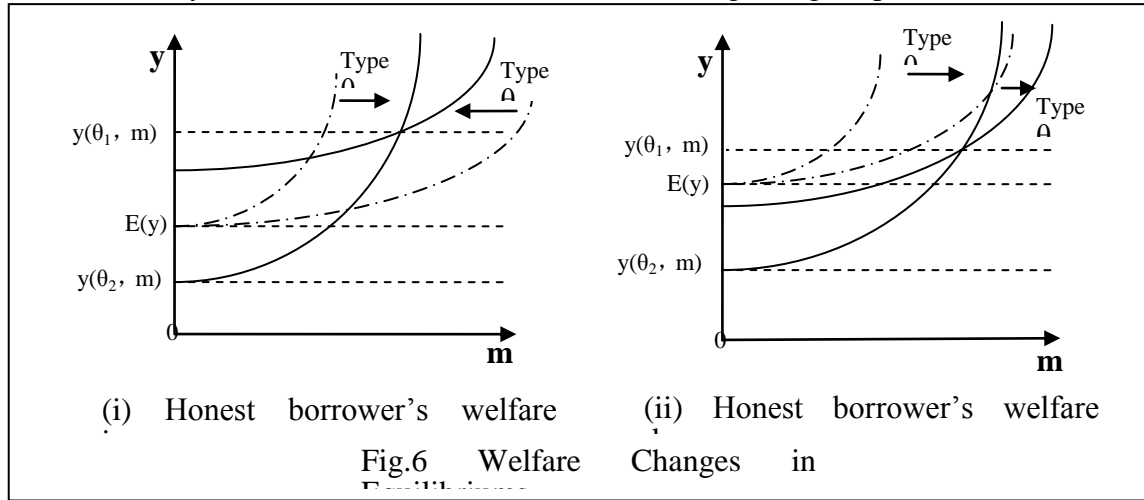


Fig.5 Separating Equilibrium 3 (reputation information signal $m^*(\theta_1) > \tilde{m}$)

θ_1 if and only if $m \geq \tilde{m}$. Accordingly, the benefit $y^*(m) = y(\theta_1, m)$ if $m \geq \tilde{m}$, otherwise $y^*(m) = y(\theta_2, m)$ in Fig.4. (ii) Consistently, the honest borrower offers $m \geq m^*$ and the opportunistic borrower also offers $m=0$. This type of equilibrium is possible when $m^* \in [\tilde{m}, m_1]$ (Fig.5). Different separating equilibria can be Pareto ranked. The Pareto optimal separating equilibrium is the one with $m^*(\theta_1) = \tilde{m}$. Other separating equilibria can be Pareto dominated by the no-signaling outcome. Indeed, the opportunistic borrowers are strictly worse off, while the honest borrowers may be either better or worse off when signaling is possible, as shown in Fig.6.



From the figure, at separating equilibrium the welfare changes with $E(y)$ and $E(y) = py(\theta_1, m) + (1-p)y(\theta_2, m)$. Although the set of separating equilibrium is completely unaffected by the parameter p , the welfare is influenced by p . When p is changing toward zero, namely the proportion of honest borrowers is small, sending signal makes honest borrowers better off, and vice versa.

3.2 Pooling Perfect Bayesian Equilibrium

The so-called pooling perfect Bayesian equilibrium means that the borrowers of different types choose the same reputation level $m^*(\theta_1) = m^*(\theta_2) = m^*$. After observing signal m^* , the probability, in which the lender believes that borrower is honest, is p . So in any pooling equilibrium, it is certain that $y^*(m^*) = py(\theta_1, m) + (1-p)y(\theta_2, m) = E(y)$.

In Fig.7 a pooling equilibrium may like the following: each borrower chooses a signal m' to maximize their utility, and the lender gives lending rate and $E(y)$. But the case with $m > m'$ is not an equilibrium, because the signal cost is too high to reduce the borrower's utility. Even if the opportunistic borrower realizes that the benefit is $y(\theta_2, m)$ when they do not send a signal, they always choose $m=0$. Therefore, pooling equilibrium only exists when $m \in [0, m']$.

The Pareto optimal pooling equilibrium entails both types of borrowers offer no signal. This particular equilibrium generates the same outcomes as the equilibrium when signaling is impossible. So pooling equilibrium is (weakly) Pareto dominated by the no-signaling outcome.

4. Conclusions

In online P2P lending market, borrower's default is one of the main risks. From welfare analysis, we can conclude that when the proportion of the opportunistic borrower is large, sending signal is necessary which increases the welfare of an honest borrower.

In separating equilibrium, opportunistic borrowers can be screened beforehand. Since $U_\theta(y, m) = y(\theta, m) - C(m, \theta)$, $y(\theta, m) = Q - (1+r)L + R(m, \theta)$, the lending rate and the cost of signal is key factors. As lenders, restricting the maximum lending rate r is practical. A high lending rate usually implies high risk. In other words, restricting lending rate is helpful to prevent opportunistic borrowers from misleading lenders. However, too low lending rate is not attractive for lenders. In this way, lenders could opt for between a better benefit and a lower risk. Secondly, as platforms, increasing borrowers' cost of sending the same signal is also a feasible measure. Last but not the least, building history reputation records in long-run is effective to reduce the default intentions in the online P2P lending market.

While previous studies have discussed information asymmetry problem in online P2P lending market by management methods, this paper addressed a signaling game model to that problem. The limitation of this paper is that risk aversion is not considered.

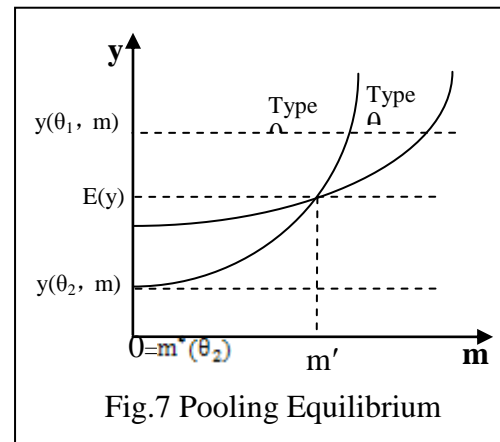


Fig.7 Pooling Equilibrium

Reference

1. Craig R. Everett. "Group membership, relationship banking and loan default risk: the case of online social lending". The Krannert School, Purdue University, 2008
2. De Janvry, A., et al. "The supply-and demand-side impacts of credit market information", *Journal of Development Economics*(09), 2009, pp. 8-24
3. Jain Sanjay. Symbiosis vs. "Crowding-out: The Interaction of Formal and Informal Credit Markets in Developing Countries", *Journal of Development Economics*(53), 1999, pp. 419–444
4. Martina E. Greiner, Hui Wang. "The Role of Social Capital in People-to-people Lending Marketplaces", *Thirtieth International Conference on Information Systems*, Phoenix 2009
5. Shao Peng. Analysis on Investment Decision-making in Uncertain Cases——Based on Personal Characteristic. Fudan University, 2007

Learning from Other Buyers: the Effect of Purchase History Record in Online Marketplaces

Qiang Ye School of Management, Harbin Institute of Technology yeqiang@hit.edu.cn	Zhuo (June) Cheng School of Accounting and Finance, Hong Kong Polytechnic University zhuo.cheng@inet.poly u.edu.hk	Bin Fang School of Management, Harbin Institute of Technology binfang@hit.edu.cn	Kevin Zhu Rady School of Management, University of California, San Diego kxzhu@ucsd.edu
---	--	---	--

Abstract

In this paper, we investigate a new element of information – purchase history record – in affecting the buyer's behavior in the online marketplaces. Purchase history record, provided on the item description page and instituted by the online transaction platform, is more pertinent to the item on hand than the overall feedback score/rating of the seller, which may be accumulated by selling many other items. The purchase history record of a seller on a certain item will directly affect potential buyer's perception on the quality of the item. Buyers are more likely to buy from the seller whose item has purchase history record. We collect purchase data from eBay and Taobao.com and find that across a variety of products we sample and control for price and a number of seller characteristics such as feedback score/rating, higher history sales in a period of 30 days are consistently associated with a higher sale in the following seven days, indicating that the buyers are learning from others.

Keywords: E-Commerce; historical selling record; C2C Market; eBay.com, Taobao.com

1. Introduction

Customers often face the choice between different products, different sellers, and different brands. When they only have limited information regarding to the different value of the alternatives, they often choose to follow other buyers. People observe other buyers' choice by, for example, bestseller list, length of queue in front of a seller, or the fraction of seats occupied in a restaurant. Information about other buyers' choices can be noisy and very hard to obtain in the offline world. With the emergence of online marketplaces, it becomes much easier to observe other buyers' choice. EBay, the world's largest online marketplace, provides a link to the purchase history record for each item listed. Taobao.com, the leading online platform for C2C trading in China, lists the historical purchases in the last 30 days on each item description page. In this paper, we examine the effect of a seller's purchase history record on its current sales performance in C2C online market, with an attempt to answer the question: to what extent do customers learn from other buyers?

Our argument is that, for the buyers, the purchase history of a seller signals the quality of the product and the credibility of the seller. In the online marketplaces, where buyers and sellers are physically separated and product cannot be experienced right away, buyers face a considerable amount of uncertainty on both the quality of the product and the credibility of the seller. Online marketplaces such as eBay and Taobao.com provide feedback mechanism, which helps to reduce

the uncertainty. There has been a lot of research looking at the feedback scores/ratings and the detailed feedback text comments. However, the feedback score/rating is an overall rating of the seller. A lot of sellers sell more than one products in eBay or Taobao.com. The feedback score may not be directly related to the item that a customer is looking for. Purchase history, on the other hand, might affect the buyer's perception of the quality of the product. We argue that customers are more likely to purchase from the seller whose item has historical purchase record.

We collect "buy it now" purchase data from eBay and Taobao.com. Auction purchases are excluded, since only bidding history record for the particular auction on hand is available on eBay. In Taobao.com, the majority of transaction is completed by "buy it now" (Ye, Li, Kiang, and Wu, 2009). We control for price and a number of seller characteristics such as feedback score/rating and eBay/Taobao.com backed institutional guarantees. We find that across a variety of products we sample, higher historical sales in a period of 30 days are consistently associated with higher sales in the following seven days.

2. Literature review

Our research draws on the literature of online reputation and information cascade.

Online reputation literature: There has been a lot of research investigating the online feedback mechanism in building trust in the online marketplaces (Ba and Pavlou, Paul 2002; Houser and Wooder 2006; Lucking-Reiley et al, 2007). Dellarocas (2003) provided an excellent review of the studies on eBay. This line of research looks at the effect of positive and negative feedback on price and probability of sale. The results are mixing. Among the components of the eBay's feedback profile, the overall number of positive and negative ratings matters most in influencing buyers' decision, followed by the number of recently posted negative comments. Pavlou and Dimoka (2006) went a step further and examined the role of detailed feedback text comments, as opposed to merely numerical ratings, in building a buyer's trust in a seller. Trust was analyzed along two dimensions: benevolence (goodwill trust) and credibility (competence and reliability). Their results showed the evidence of price premium associated with extraordinary past seller behavior contained in the detailed feedback text comments. Their assumption is that buyers have the time and the patience to explore details of the text comments.

Information cascade literature: In the seminal paper by Bikhchandani, Hirschleifer and Welch (1992, 1998), information cascade is the situation in which "it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information." The rationale is that individuals have imperfect information about the true value of alternatives. Obtaining information and evaluating the alternatives are costly and time-consuming. Individuals choose to imitate others to take advantage of others' hard-won information, hoping that others know better than themselves. Duan, Gu and Whinston (2009), hereafter DGW, applied the information cascade theory to the online world and studied the effect of download ranking on the adoption of software.

3. Methodologies

3.1 Empirical Data

The data in this study were collected from TaoBao.com and global.eBay.com. They both provide information of purchase history of a seller for each of his/her bidding items. The total number of sales in recent 30 day is indicated on the web page of this item on taobao.com. More historical sales record can also be checked for this seller by click a button on below.

We develop a Java based crawler program to download HTML web pages of seller information and the transaction information from TaoBao. Another Java program was developed to parse HTML web pages into a database. The data on global.eBay.com were collected manually. Three products were selected as targets for analysis from Taobao.com. They are “Kingston DDRII 800 2G Memory”, “CK Perfume 10 ml”, “Prepaid Mobile Refill Card RMB 100”. “Kingston DDRII 800 2G Memory” was selected as target product from globale.Bay.com. The data collection was conducted in May 2009. First of all, we retrieved information of all the sellers for each selected product. Their transaction information of the targeted products between February 2009 and May 2009 was retrieved. Table 1 summarizes the data we collected from TaoBao and eBay. Totally, we have 9400 transactions of 3549 sellers on TaoBao and eBay.

Table 1. Summary of the Dataset

Web Site	Taobao.com			eBay.com
Products	Kingston Memory	CK Perfume	Mobile Refill Card	Kingston Memory
Number of Sellers	1148	405	1920	76
Number of Transactions	1346	1122	6704	228

We choose transactions of a seller in recent seven days as its present selling performance. The number of transactions in the 30 days’ before those seven days is taken as the volume of historical sales. For Taobao data, we consider whether a seller joint one the four types of Customer Protection Program as four dummy variables.

3.2 Research Model

To identify the influence of historical sales, we developed the following log-linear regression model for an online seller i .

$$\ln(sales_i) = \mu + \beta_1 \ln(Historical_Sales_i) + \beta_2 Price_i + \beta_{31} \ln(Rating)_j + \beta_{32} Rp_j + \beta_4 \mathbf{D}_i + \varepsilon_i$$

In this model, $Sales_i$ presents the number of sales in recent seven days, $Historical_Sales_i$ presents the Number of transaction during the 30 days prior that seven days, $Price_i$ represents the price that seller listed for his/her product. $Rating_i$ represents the feedback score/rating that the web site labeled based on the evaluation by previous buyers of this seller. We use both seller feedback score/rating ($Rating$) and the ratio of positive ratings (Rp) among all buyers’ ratings to a seller to capture the seller’s credit. \mathbf{D}_i represent other observable features of the seller i that may have impact on its performance of sales, such as the customer protection programs on taobao.com. There are four types of customer protection programs in our data. To avoid the problem of taking the log of 0, we add “1” to both the current sales and the historical sales in the above models.

4. Results

The statistical results for each product are listed respectively in the tables from table 2 to table 5. Table 2 is the result for CK perfume on Taobao.com. Table 3 is the result for Prepaid Mobile

Refill Card on Taobao.com. Table 4 is the result for Kingston Memory on Taobao.com. Table 5 is the result for Kingston Memory on global.eBay.com. Dependent Variables are all $\ln(\text{Sales}+1)$ in these tables. The result reveals that purchase history record of a seller have significant positive impact on the performance of the seller's current sales. The proposed hypothesis gets supported by all the selected products on taobao.com and global.ebay.com in this study.

Table 2. CK Perfume on Taobao.com

Model		B	Std. Error	t	Sig.
1	(Constant)	0.370	0.123	3.014	0.003
	$\ln(\text{Historical_Sales}+1)$	0.169	0.028	6.088	0.000
	<i>D1</i>	0.026	0.043	0.591	0.555
	$\ln(\text{Rating}+1)$	0.031	0.010	3.158	0.002
	<i>Rp</i>	-0.005	0.001	-3.724	0.000
	<i>Price</i>	0.000	0.001	-0.667	0.505
	R	0.446			

Table 3. Prepaid Mobile Refill Card on Taobao.com

Model		B	Std. Error	t	Sig.
1	(Constant)	6.626	2.434	2.723	0.007
	$\ln(\text{Historical_Sales}+1)$	0.334	0.014	24.656	0.000
	<i>D1</i>	0.002	0.039	0.058	0.953
	<i>D4</i>	-0.036	0.143	-0.250	0.803
	$\ln(\text{Rating}+1)$	-0.022	0.009	-2.572	0.010
	<i>Rp</i>	0.001	0.001	0.766	0.444
	<i>Price</i>	-0.066	0.024	-2.689	0.007
	R	0.493			

Table 4. Kingston Memory on Taobao.com

Model		B	Std. Error	t	Sig.
1	(Constant)	-0.001	0.027	-0.020	0.984
	$\ln(\text{Historical_Sales}+1)$	0.150	0.012	12.150	0.000
	<i>D1</i>	-0.002	0.018	-0.105	0.916
	<i>D2</i>	0.056	0.020	2.826	0.005
	<i>D3</i>	-0.069	0.027	-2.506	0.012
	$\ln(\text{Rating}+1)$	0.003	0.004	0.686	0.493
	<i>Rp</i>	0.000	0.000	-0.153	0.879
	<i>Price</i>	0.000	0.000	-0.006	0.995
	R	0.391			

Table5. Kingston Memory on global.eBay.com

Model		B	Std. Error	t	Sig.
1	(Constant)	-1.458	6.733	-0.217	0.829
	$\ln(\text{Historical_Sales}+1)$	0.237	0.047	5.047	0.000
	$\ln(\text{Rating}+1)$	-0.006	0.015	-0.425	0.672
	<i>Rp</i>	0.016	0.067	0.230	0.819
	<i>Price</i>	0.000	0.000	-0.347	0.729
	R	0.541			

5 .Discuss and Conclusion

Our result indicates that buyers do take into account of purchase history record when they are making the decision of which seller to buy from. Historical sales are consistently significant across a variety of items we sample. In contrast, feedback scores/ratings are not significant for some items, for example, the Kingston memory on Taobao.com and eBay. Our explanation for that is that feedback scores/ratings, which is an overall rating of the seller, may not be directly related to the item that the buyer is buying. Purchase history, on the other hand, is pertinent to the item and it affects the buyer's perception of the quality of the item. Our result helps to explain the mixed findings of the relationship between feedback score/rating and the probability of sale, and it indicates that beyond feedback score/rating, customers put more weights on the information that is more relevant to the item on hand.

Our result has a number of implications. First, it establishes a new element in the online marketplace reputation mechanism – purchase history record. Purchase history record, to the buyer, signals the quality of the item, and it is sometimes a more important piece of information than the overall feedback score/rating of the seller. Second, we realize that the purchase history record is subject to the seller's manipulation, as the seller can easily create fictitious accounts, or ask his friends, to make the purchases and inflate the purchase history record. Online marketplaces have to take measures to restrict this kind of behavior in order to protect the buyers and maintain a healthy growth of the market. A game theoretical modeling of the seller's opportunistic behavior, the buyer's rational expectation, and the online marketplace's regulation is an interesting and fruitful topic for future research.

As a research in progress, this cross sectional analysis is still in its early stage to gain more general conclusions. We will download time series data on various products for further analysis to get better understanding on the impact of purchase history record in the near future.

References

1. Ba, S. and Pavlou, P. "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly*, (26:3), 2002, pp.243-268.
2. Bikhchandani S., Hirshleifer, D. and Welch, I. "A theory of fads, fashion, custom, and cultural change as informational cascades", *Journal of Political Economy*, (100:5), 1992, pp. 992-1026
3. Bikhchandani S., Hirshleifer, D. and Welch, I. "Learning from the behavior of others: conformity, fads, and informational cascades," *Journal of Economic Perspectives*(12:3), 1998, pp. 151-170
4. Dellarocas C. "The digitization of word of mouth: promise and challenges of online feedback mechanism," *Management Science*, (49:10), 2003, pp. 1407-1424
5. Duan, W., Gu B., and Whinston A. "Informational Cascades and software adoption on the Internet: An empirical investigation," *MIS Quarterly*, (33: 1), 2009, pp. 23-48
6. Houser, D. and Wooders, J. (2006). "Reputation in Auctions: Theory, and evidence from eBay." *Journal of Economics and Management Strategy*, (15:2), pp.353-369.
7. Lucking-Reiley, D., Bryan, D., Prasa, N. and Reeves, D. "Pennies from eBay: The Determinants of Price in Online Auctions." *Journal of Industrial Economics*, (55:2), 2007 pp.223-233.

8. Pavlou P. and Dimoka, A. "The nature and role of feedback text comments in online marketplaces: implications for trust building, price premiums, and seller differentiation," *Information System Research*, (17: 4), 2006, pp. 392-414
9. Ye Q., Li Y., Kiang M. and Wu W. "The Impact of Seller Reputation on the Performance of Online Sales: Evidence from TaoBao Buy-It-Now (BIN) data". *Database for Advances in Information Systems*, (40:1), 2009, pp. 12-19.

Inflated-reputation Detection in C2C E-Market⁴

Weijia You

School of Economics and Management
Beihang University
weijiawx@gmail.com

Mu Xia

Leavey School of Business Information
Santa Clara University
mxia@scu.edu

Zhaohui Chen

Business Intelligence
Taobao.com
zhchen@alibaba-inc.com

Lu Liu

School of Economics & Management
Beihang University
liulu@buaa.edu.cn

Abstract

This paper proposed a mechanism to identify sellers who employed accounts to “inflate” his reputation in a C2C market. Using the theory of the economics of crime, a Cost-benefit Analysis of the collusive sellers is presented and five features of collusive behaviors for inflating reputation are hypothesized and tested by a dataset of inflated accounts from Taobao, the largest C2C market of China. A detection model which combined above features is shown to be effective in distinguishing the collusive sellers from non-collusive ones.

Keywords: C2C Market, Collusive Behavior, Cost-benefit Analysis

1. Introduction

Reputation system, composed of the feedbacks, induces a substantial improvement in transaction efficiency compared to the market without it, and also exhibits a kind of public goods. (Bolton et al. 2004). Therefore, the most popular online shopping websites, such as eBay, Amazon, Yahoo Auction, and Taobao, are utilizing the reputation systems, though by different rules, to recommend trusted sellers and buyers. By the empirical studies, the reputation system is demonstrated to be effective for predicting future performance and on-line auction fraud (Resnick & Zeckhauser 2002, Macinnes et al. 2005, Gregg & Scott 2006).

However, the manipulation of reputation, usually in the form of inflated reputation by collusive behavior can defeat proper scoring rules and frustrate the electronic commerce to be success (Dellarocas 2003, Zhang et al 2008). Some scholars have proposed some methods for detecting this specific type of deceptive behaviors. Wang and Chiu (2008) adopted the measurements from social network analysis and found that k-core value is positively correlated to the bad comments by Kruskal-Wallis test. Nevertheless, A group of buyers buying from a set of sellers simultaneously is a common phenomenon in ever-popular “group purchasing” for that buyers in the group would benefit from the extra discount provided by the seller. The “group purchase phenomenon” makes the single k-core value far from enough for distinguishing the inflated-reputation accounts from legal ones.

⁴ Acknowledgment: This research was supported by Natural Science Foundation of China under Grant No. 90924020 and the PhD Program Foundation of Education Ministry of China under Contract No. 200800060005

This paper tried to answer the following research question: From the view of economics of crime, how to extract the features of the sellers who had inflated his/her reputation? The collusion which we are trying to figure out is not the supportive transactions between friends but the business which some illegal organizations did to make money.

2. Theoretical Background

Before Becker's theory about crime (1968), conventional thoughts attribute the crime to mental illness and social oppression. However, acknowledging that many people operate under a high moral and ethical constraint, Becker proposed that criminals made rational decisions. Criminals rationally see that the benefits of their crime outweigh the cost such as the probability of apprehension, conviction, and punishment, as well as their current set of opportunities. This shed new light to the criminology by noting that potential criminals will be deterred from offending by the increase in the probability of being caught and punished, and by the increase in the amount of punishment if caught. Based on above work, viewing the criminology from economic aspect inspired a lot of researches towards different areas of laws. Ehrlich (1973) developed a theory of participation in illegitimate activities and tested against data on variations in index crimes. He argued that a simple model of choice between legal and illegal activity can be formulated within the framework of the usual economic theory of choice under uncertainty.

3. Hypotheses Development

In this study, the collusion to inflate reputation which makes the reputation system invalid was viewed as a specific "crime" in the context of electronic business. Different from the electronic crime which will be related with financial loss, court and jail, the crime here is just a violation of public order and good morals. Then based on the idea behind the economics of crime which treat all the behaviors rational decisions, we try to find out the features of collusive sellers from the cost and benefit analysis.

3.1 Cost of inflated reputation

Cost before the "crime": The registration for being a buyer on Taobao is really simple. Unique username and a valid email address are what you need to provide to obtain an identity in Taobao. After activating the link which is sent to your registered email box, an identity is set up. The economical cost in registration to become a buyer is close to zero due to the free mailbox service provided by a large number of websites. However, it takes time and efforts to own different email boxes, and to keep the user name and password of both the mailbox and Taobao community identity in mind. It's easy to see that as the number of transactions involved increase, average registration cost decreases, so we raise first hypothesis:

H1: Transaction frequency of collusive accounts is higher than non-collusive accounts.

Cost during the "crime": two parts of the cost should be considered. First part is the time value of money held by Alipay. Usually, Alipay, the third party guarantee of the transactions on Taobao, will hold the money for about 2~5 days or even longer. So if it's a large amount of money, the time value of money would come to a considerable amount. Second part is the value of the money paid to each inflated reputation. In order to gain as many positive ratings as possible by certain amount of money, low value transaction is the best choice. Since the collusion is illegal and the rights of the seller who paid first is not protected by the oral contract

for inflating the reputation, the less the seller paid, less potential loss he will suffer. So the second hypothesis could be raised as follows. Meanwhile, applying k-core to figure out the collusion has been demonstrated to be effective by Wang and Chiu (2005). So we utilize the indicator they employed in this study.

H2: Average value of the goods in collusive transactions is lower than that of non-collusive transactions.

Cost after the “crime”: it could be more accurately described as the risk of being figured out as collusion by the detection efforts made by Taobao. Actually, to prevent the sellers from the intention of inflating reputation, Taobao has set the punishment for inflating reputation, including deleting the inflating part of the reputation, or subtracting the reputation score twice the score he/she inflated, or even closing the collusive accounts. As the detection process of Taobao usually starts from the report from other users, one of the effective ways to avoid the detection is to “buy” anonymously. So the hypothesis is proposed as follows:

H3: Percentage of anonymous transactions of collusive accounts is higher than that of non-collusive accounts.

3.2 Benefit of inflated reputation

Content of comments: Besides the benefit, like price premium and large amount the sales, of score accumulated by positive, neutral, and negative ratings (Ba & Pavlou 2002, Livingston 2005), content of the comments also contributes to the sellers’ reputations. For the potential buyer who wants to make purchase from a specific seller, the detailed comments for this seller are more valuable than the simple “positive”. We assume that when a buyer is willing to take time to praise the seller, the seller must be good enough to be trusted. So we infer that five types of comments contribute differently to the seller’s reputation in this order: $E \ll D < A < B < C$.

Table 1 Types of comments

Type of rating	Content of comment	Class
Positive	“No comment is good comment”	A
	Click the “good” button	B
	Specific comments for the transaction	C
Neutral	Whatever	D
Negative	Whatever	E

There are three types of ratings on Taobao, which are “positive”, “neutral”, and “negative”. Besides the rating you place on a seller, you can also provide detailed text comments for the seller. The text box is open to whatever you want to say about this transaction or this seller. For the convenience of buyers, if no rating was given by buyer during the 15 days since seller evaluated the buyer (it indicated that the transaction is closed), there will be a “positive” rating with the comment of “no comment is good comment” appearing in seller’s evaluation history. If the buyer doesn’t have specific praise for the seller, he could simply click the button of “good” for comments and we would see the “good” in seller’s evaluation history. According to the options provided by Taobao, we classified the comments into five groups in this study (shown in Table 1), and we propose the fourth hypothesis:

H4: Percentage of type A comments for collusive accounts is lower than that of non-collusive accounts.

4. Detection Model

4.1 Data collection

The empirical data of this paper were collected from the leading online C2C website in China, Taobao. We obtained the confirmed fraudulent accounts (specific for reputation inflation) and its related transaction and evaluation history from Taobao under the Non-Disclosure Agreement. After a total of 100 collusive sellers' information were provided by Taobao, we proceeded with collecting non-collusive accounts by a self-developed parsing program which parsed the web pages of related buyers to extract the transaction and evaluation records which include comments to the sellers, time of transaction, value of goods, rating to the counterparty and so on. There're a total of 37,885 records collected from May 1st 2009 to June 30th 2009. To avoid the defects in imbalanced data mining (He & Garcia 2009), this study randomly selected 100 non-collusive accounts from the large amount of non-collusive sellers we obtained to construct a balanced dataset. There might be some "collusive accounts" in the non-collusive group as they have "survived" in the Taobao's investigation. This kind of limitation is shared across studies of all forms of deviant behavior and is commonly accepted by criminological research (Grazioli and Jarvenpaa 2003).

4.2 Regression model

Logistic regression is suitable for building a fraud detection model because the dependent variable is dichotomous (Gregg & Scott 2006). In this study the dependent variable is whether the seller was inflating his/her reputation, where "1" stands for collusion and "0" stands for non-collusion. The detection model is (Logit-linear):

$$Collusion_i = Frequency\ of\ transaction_i + k_core\ value_i + Average\ price_i + Anonymous\ percentage_i + Comments\ of\ type\ A_i$$

The result of the regression, summarized in Table 2, demonstrated that the indicators inferred from the cost and benefit analysis are effective in distinguishing the collusive accounts from non-collusive ones. The Hosmer-Lemeshow goodness-of-fit test (Hosmer & Lemeshow 2000) showed that Hosmer-Lemeshow $\chi^2(8) = 8.02$ and Prob > $\chi^2 = 0.4314$, which means that the model is acceptable. The result of cross validation presented that the AUC (area under ROC curve) approaches 0.9774 and it is an effective model for collusion detection.

Table 2 Estimation of the coefficients

fraud	Coef.	Std. Err.	z	P>z
Frequency of transaction	1.135***	0.258	4.40	0.000
k_core value	0.767***	0.183	4.18	0.000
Average price	-0.008*	0.004	-2.17	0.030
Anonymous percentage	5.853*	3.206	1.83	0.068
Comments of type A	-3.312*	1.726	-1.92	0.055

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.1$

5. Conclusion

Contrast to the data-driven methods for fraud detection, this paper proposed the hypotheses of possible characteristics of the collusive transactions from the view of economics of crime for we assumed that nobody intends to break the rule unless considerable profit lures him/her. The collusion is just the result of trading off the benefit against cost. From this point of view, cost and benefit before, during, and after the transaction were analyzed. Inflated-reputation detection model is also proposed and demonstrated to be effective in collusion detection.

References

1. Ba, S., Pavlou, P. "Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior." *MIS Quarterly*. 2002, pp. 243-268.
2. Becker, G., "Crime and punishment: An economic approach." *Journal of Political economy*, 1968; 76(2) , pp.169-217.
3. Bolton, G.E., Katok, E. Ockenfels, A. "How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation." *Management Science*, 2004.50(11), pp.1587-1602.
4. Dellarocas, C. "The digitization of word of mouth: Promise and challenges of online feedback mechanisms", *Management Science*, 2003: 49(10), pp. 1407-1424.
5. Ehrlich, I. "Participation in illegitimate activities: A theoretical and empirical investigation," *Journal of political Economy*. 1973; 81(3): pp.521-565.
6. Garson, G.D. Logistic regression. In PA 765 Statnotes: An Online Textbook, www2.chass.ncsu.edu/garson/pa765/logistic.htm
7. Grazioli S, Jarvenpaa S. Consumer and business deception on the internet: content analysis of documentary. *International Journal of Electronic Commerce*. 2003; 7(4):93-118.
8. Gregg, D.G., Scott, J.E. "The role of reputation systems in reducing on-line auction fraud," *International Journal of Electronic Commerce*. 2006; 10(3): pp. 95-120.
9. He, H., Garcia, E. A. "Learning from Imbalanced Data," *IEEE Transactions on Knowledge and Data Engineering*, 2009; 21(9), pp.1263-1284.
10. Hosmer, D.W., Lemeshow, S. (eds.). *Applied logistic regression*. New York; Chichester, Wiley, 2000
11. Livingston, J. "How valuable is a good reputation? A sample selection model of internet auctions," *Review of Economics and Statistics* 2005.87(3), pp : 453-465
12. Macinnes, I., Li, Y., Yurcik, W. "Reputation and dispute in eBay transactions," *International Journal of Electronic Commerce*. 2005; 10(1), pp.27-54.
13. Resnick, P., Zeckhauser, R. "Trust among strangers in Internet transactions: Empirical analysis of eBay's reputation system," *Advances in Applied Microeconomics*. 2002; 11, pp.127-157.
14. Wang, J., Chiu, C. "Recommending trusted online auction sellers using social network analysis," *Expert Systems with Applications*. 2008; 34(3), pp.1666-1679.
15. Zhang B., Zhou, Y., Faloutsos, C. "Toward a comprehensive model in Internet auction fraud detection," *Proceedings of the 41st Annual Hawaii International Conference on System Sciences (HICSS 2008)*. 2008; 3, pp.79-87.

Age Effect on Firm Exit in the Online C2C Market

BINJIE LUO

Sichuan Key Lab of Financial
Intelligence and Financial
Engineering, Southwestern University
of Finance and Economics, Chengdu,
Sichuan 610074, China
luobinjie@gmail.com

ZHANGXI LIN

Center for Advanced Analytics and
Business Intelligence, Texas Tech
University, Lubbock, TX 79409-2101,
USA
zhangxi.lin@ttu.edu

Abstract

The firm exit problem has been well studied in the real economy, but little research has been done regarding firm exit in the online C2C market. This paper is intended to fill this gap with explorative studies. We collected time series data of 2,000 firms randomly sampled from eBay.com. Our findings about age effects on firm's exit are exciting. First, compared with previous studies in firms' average lifetime in the real economy, firms in the eBay market experience a much shorter life span. Second, the age effect on firm exit rate varies in accordance with different grouping methods. We believe that firm age has a positive effect on the exit. Third, the distribution of firm exit age is normal. These findings can be regarded as stylized facts, based which pave the way for our future studies.

Keywords: online C2C market, life-cycle, effect of age, firm exit, firm survival

1. Introduction

The exponential growth in E-commerce in recent years inspires the research interests in two aspects of market structure area with new dimensions. The first aspect mainly focused on the impact of E-commerce on classical market structure theories. As Barkos (1997) stressed, one of the most salient features induced by information systems, which serve as intermediaries between the buyers and sellers in E-commerce, is the reduced search cost for buyers, which have significant impact on the competition among sellers. Therefore, many studies in E-commerce are devoted to the market variations triggered by reduced search cost. The second strand puts the emphasis on the inner characteristics of electronic marketplaces. Ennew et al. (2005) found that if using customer visits to measure the concentration of Internet retail market, it would be highly concentrated. Lin et al. (2006) applied the Gibrat Law in the study of E-commerce market and revealed the lognormal distribution of online reputation scores. Lin et al. also claimed that the entry and exit of firms is one of causes resulting in this distribution. Luis and Ali (2004), based on the data from eBay, found that one unit increase in percentage of negative feedback will leads to a 9% decline in sale price, and sellers with worse records are more likely to exit.

A firm's life cycle can be roughly divided into five stages, entry, growth, maturity, decline and exit. Age, as an indicator of accumulated time effect, should affect each stage of firm's life cycle. Pertaining to the age effect on firm's exit, researchers have conducted in-depth studies and conceived various theories. However, little discussion about firm's age effect on exit in E-commerce marketplaces can be found. This paper is intended to fill this gap in the E-commerce research. With data collected from eBay market and explorative studies, we identified a number of stylized facts on which to base our theoretical and empirical work. First, comparing with the

work by Saridakis et al. (2008) and Baldwin and Gorecki (1991) in firm's average lifetime in the real economy, we found that firms in the eBay C2C market experience a much shorter life span. Second, we found the age effect on the exit rate varies across with different grouping strategies. Third, we revealed the distribution of exit age is normal. The remaining sections are organized as below. In section 2, we describe data collection process. In section 3, we present our findings. In the last section, we conclude our work and present the future research tasks for more rigorous outcomes.

2. Data Collection

In a C2C market place, anyone could play as a seller or a buyer. Follow the approach of Lin et al. (2006), we define a firm as a seller who was selling products when he/she is sampled, regardless whether he/she was a buyer or not in other transactions. To bridge the research conventions of E-commerce and market structure, we will use term seller and firm interchangeable in this paper. Although most of the census data from the real economy are measured by years, we measure seller ages based on the elapsed days in the market since the sellers registered, because of their faster grow-up pace.

The samples of online firms analyzed in this study were drawn randomly from eBay. Firstly, we randomly selected 2,000 sellers' ID from the eBay market on 20/Mar/2003. Secondly, we retrieved these sellers' transactional and individual information every month from 20/Mar/2003 to 20/Dec/2007/. The gathered datasets contains seller's registration date, and their positive, negative and neutral scores in 1 month, and 6 month. Thirdly, we treated a seller's state as "exit" if the seller's reputation scores are no longer retrieval from eBay' website.

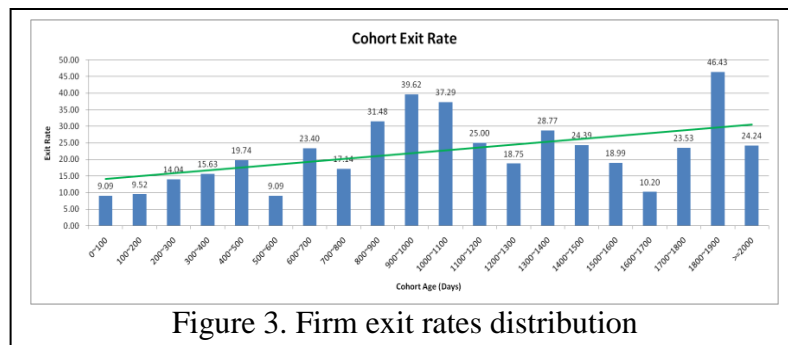


Figure 3. Firm exit rates distribution

3. Data Analysis

3.1 Age effect on Exit Rate

Researches revealed that new firms tend to have a high failure rate. Stinchcombe (1965) named it as "liability of newness". Carroll and Delacroix (1982), using historical data about the Argentinian and Irish press, found

newspapers suffer from high mortalities in their early years. Taylor (1999) claimed that less than 50% of self-employment start-ups since 1991 in UK have survived in their first two years. Saridakis et al. (2008) also demonstrated that firms are less likely to survive during their first years. Based on these findings, we divided sellers into different cohorts according to their ages at the first sample time point (in the following part, we will call it *entry age*) during our observation period, and calculate every cohort's exit rate, where exit rate is defined as aggregated exit sellers during our observation period divided by original sellers in each cohort (Figure 3). Based on the trend line, we can expect a positive relationship between cohort's age and exit rate. The OLS regression turns out that the exit rate is significantly correlated to the mean age of cohort with T-stat = 2.157, P-value = 0.045, and R-square = 20.5%. Therefore, we can infer that there exists a significant positive effect of age on exit rate, which signify older firms have higher exit rate.

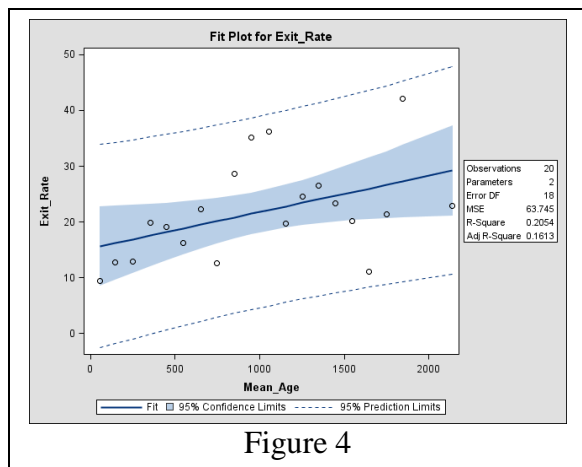


Figure 4

Figure 3 does not demonstrate there is the “liability of newness” in our dataset. While regarding to the age effect on firms exit or survival, there is a frequently referred proposition in real economy that is Jovanovic’s “learning” theory (Jovanovic 1982). Based on it, Dunne et al. (1989) deduced that failure rates should be a decreasing function of age. More works (Dunne et al. 1989) provided the empirical evidences for it. But with the fitted line in Figure 4, the exit rate for older sellers appears higher than younger ones. This is not consistent with “learning” theory. We investigated these inconsistencies for the possible

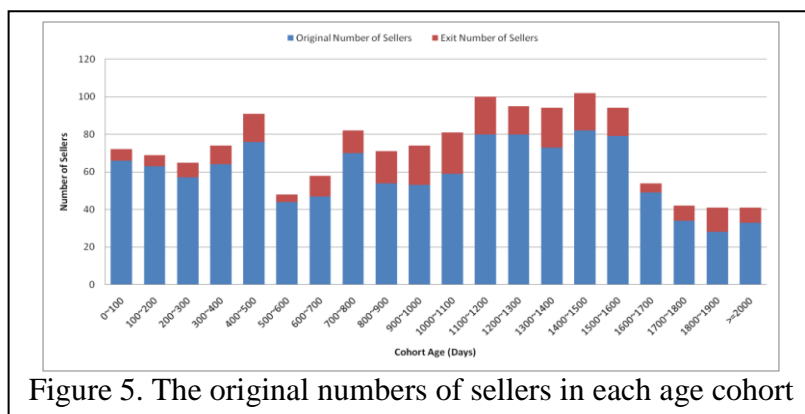


Figure 5. The original numbers of sellers in each age cohort

causes. Firstly, the distribution of sellers in each cohort (Figure 5) may not reflect the true distribution for each age cohort, and thus our sample is probably biased. It is possible that there are more sellers in cohort 0~100, and then we can observe more exit in that cohort during our observation period. Second possible reason is that we did not choose the right number of

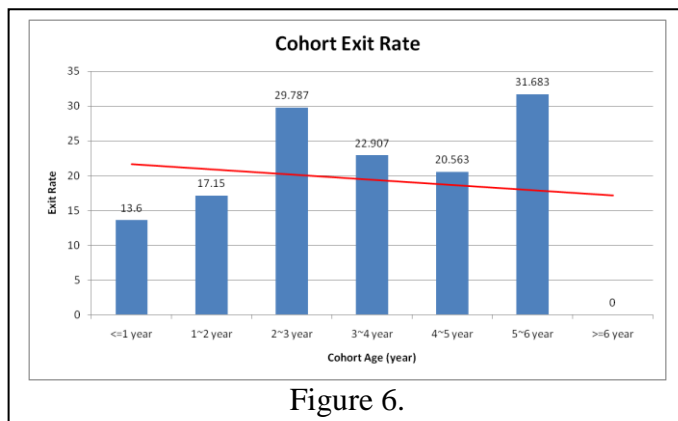


Figure 6.

cohorts. Therefore, we followed the traditional way to divide sellers into different cohort by years and measure exit rate as Figure 6 shows.

In Figure 6, we can see the exit rate for sellers whose entry age is more than 6 years at our first sample time point equals to zero. However, there are only 6 sellers in the cohort, it seems not very persuasive to get any conclusion. The general trend in Figure 6 seems in accordance with previous empirical studies, such as (Dunne

et al. 1989). Although we can get a consistent result with “learning” theory, we know that the small sample size provides us less power to infer a plausible verdict in statistic. In summary, we found that different grouping methods do give us different results about the relationship between firm age and exit rate. An OLS regression did not provide a significant outcome to support the trend in Figure 6.

Based on the above findings, we infer that age tends to have a positive effect on exit and older firms have higher probability to exit. This inference is the same as Figure 3 shows. This is a

different result from some researches (Dunne et al. 1989), but still having some supporting cases in the real economy. Agarwal found that, in high and non-high technical product industries, the age effect on exit rate may be different (Agarwal and Gort 1996). One of the explanations is that innovations yield superior knowledge to entrants than to many incumbents in high tech product industries. Can eBay market be viewed as a high tech arena in which innovations are required for sellers to survive better? We need more evidence to prove it is reasonable or not. Another possible explanation proposed by us is that, as the knowledge is wildly spread across the Internet, open sources and innovative ideas are available to everyone, new entrants to the eBay market can learn successful experiences easily and fast. Thus, they may not exhibit a higher exit rate than older firms. This will be investigated as the effect of knowledge spreading on market structure by us.

3.2 distribution of exit age

If we regard sellers' exit age as a random variable, then we can depict the histogram of 529 sellers' exit ages in Figure 7.

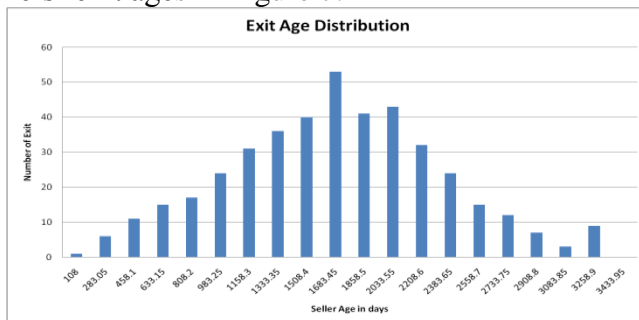


Figure 7

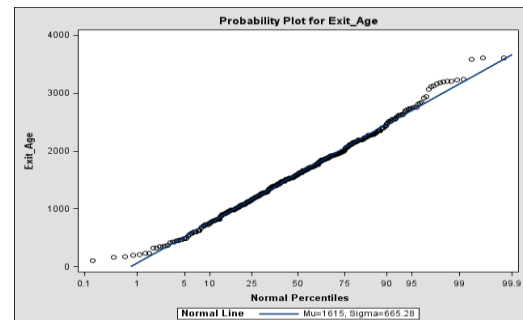


Figure 8

In general, the histogram demonstrates a “unimodal” appearance. The average death age is 1,615 days (about 4 to 5 years). Saridakis (2008) reported that the duration time for small firms in England is about 7 years. Baldwin and Gorecki (1991) also estimated the average length of life of a greenfield entrant was about 13 years. Comparing this with firms' survival time in the real economy, firms in the eBay market obviously have a much shorter life span. We gave the q-q plot and a reference line of estimated normal distribution in Figure 8. From the q-q plot, we find that except for several points in the left and right tails, which can be considered as outliers, most of the points fall on a straight line (the reference line of estimated normal distribution). This means the sample distribution did not violate the normal distribution assumption heavily. Shapiro-Wilk and Kolmogorov-Smirnov tests turn out p-value 0.0538 and >0.15 respectively. At 95% confidence level, all normality tests failed to reject the null hypothesis. Thus, we accept that it is normally distributed.

4. Conclusions

This study is distinguished from previous work by focusing on the firm exit problem in online C2C market. This study is still in the explorative stage and many promising research points are being tackled.

5. References

1. Rajshree Agarwal and Michael Gort, "The Evolution Of Markets And Entry, Exit And Survival Of Firms," *The Review of Economics and Statistics*, Vol. 78, No. 3 (Aug., 1996), pp. 489-498.
2. J. Yannis Bakos. "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science*, Vol. 43, No. 12, *Frontier Research on Information Systems and Economics* (Dec., 1997), pp. 1676-1692.
3. John R. Baldwin and Paul K. Gorecki, "Firm Entry and Exit in the Canadian Manufacturing Sector, 1970-1982," *The Canadian Journal of Economics / Revue canadienne d'Economie*, Vol. 24, No. 2 (May, 1991), pp. 300-323.
4. Glenn R. Carroll and Jacques Delacroix, "Organizational Mortality in the Newspaper Industries of Argentina and Ireland: An Ecological Approach," *Administrative Science Quarterly*, Vol. 27, No. 2 (Jun., 1982), pp. 169-198.
5. Timothy Dunne; Mark J. Roberts; Larry Samuelson, "The Growth and Failure of U. S. Manufacturing Plants," *The Quarterly Journal of Economics*, Vol. 104, No. 4. (Nov., 1989), pp. 671-698.
6. Christine Ennew, Andy Lockett, Ian Blackman and Christopher P. Holland, "Competition in Internet Retail Markets: The Impact of Links on Web Site Traffic," *Long Range Planning* 38 (2005) pp. 359-372.
7. Boyan Jovanovic, "Selection and Evolution of Industry." *Econometrica* 50 (May 1982), pp. 649-70.
8. Cabral, Luis M. B. and Hortacsu, Ali, "The Dynamics of Seller Reputation: Theory and Evidence from eBay," 2004, NBER Working Paper No. W10363. Available at SSRN: <http://ssrn.com/abstract=516704>.
9. Zhangxi Lin, Dahui Li, Balaji. Janamanchi, and Wayne Huang, "Reputation distribution and consumer-to-consumer online auction market structure," *Decision Support Systems* 41(2) (2006) pp.435-448.
10. George Saridakis, Kevin Mole, David J. Storey, "New small firm survival in England," *Empirica* (2008) 35, pp. 25–39.
11. Arthur L. Stinchcombe, "Organizations and social structure," In James G. March (ed.), *Handbook of Organizations*: 153-193. Chicago: Rand Mc-Nally.1965.
12. Mark P. Taylor, "Survival of the Fittest? An Analysis of Self-Employment Duration in Britain", *The Economic Journal*, Vol. 109, No. 454, *Conference Papers* (Mar., 1999), pp. C140-C155.

The Effect of Information-Sharing Services on Enterprise Customer Loyalty Intention

Yi-Ming Tai
National Pingtung Institute of Commerce
ymtai@npic.edu.tw

Yi-Cheng Ku
Providence University
ycku@pu.edu.tw

Abstract

Delivering quality service to enterprise customers is imperative for a firm to retain its profitable customers. To understand the factors influencing enterprise customer loyalty and to explore the effect of the information-sharing service, this study develops an integrated model from the perspective of relationship marketing to investigate the associations among enterprise customers' perceived value of information-sharing services, and enterprise customers' trust, commitment, and loyalty intention. An empirical survey was conducted to test the integrated model proposed in this study. Based on the PLS analysis with a sample comprising 61 Taiwan manufacturing firms, the results show that enterprise customers' perceived value of information-sharing services has a significant impact on trust. Moreover, trust not only has direct effects on enterprise customers' loyalty intention, but also has indirect effects on loyalty intention via commitment. The findings of this study provide implications for suppliers and the value of inter-organizational information systems.

Keywords: Information-sharing service, Trust, Commitment, Loyalty intention

1. Introduction

How to enhance enterprise customer value has been an important issue for business-to-business (B to B) relationship marketing studies (Eiriz and Wilson, 2006; Ulaga and Eggert, 2006). To develop an effective strategy to enhance enterprise customer perceived value is crucial for building, establishing and maintaining relationships with enterprise customers and could be achieved by information sharing. This is due to the fact that information sharing enhances collaboration activities among firms in a supply chain via inter-organization data access, such as sales, production, and logistics. Information sharing is the basic prerequisite for providing quick responses that lead to competitive advantages because through such responses, firms are able to reduce the level of uncertainty associated with transaction information (Yue and Liu, 2006; Patnayakuni et al., 2006). Although the value of information sharing in the business context has been investigated in previous studies (Yue and Liu, 2006; Chiang and Feng, 2007), rarely have studies investigated the effect of information sharing on loyalty intention.

Loyalty is a concept that describes the strength of the relationship between a customer's relative attitude towards an organization and repeating patronage (Zeithaml et al., 1996; Ahluwalia et al., 2000). As loyalty is formed through long-term interaction, both trust and commitment have been found to be two critical factors that will influence customers' loyalty (Ruyter et al., 2001; Gounaris, 2005). Since information sharing plays an important role during transaction processes and significantly enhances enterprise customer value, we argue that enterprise customers' perceived value of information sharing is another factor that will indirectly influence their loyalty intention. Hence, the purpose of this study is to explore the relationships among

information-sharing service, trust, commitment, and loyalty, from the perspective of relationship marketing.

2. Theoretical Background

As information sharing is of crucial importance to successful supply chains, many previous studies have investigated the impact of information sharing on supply chain performance (Chiang and Feng, 2007; Zhou and Benton, 2007). Since the inter-organizational information technology (IT) infrastructures enhance information transparency and information sharing among the firms in a supply chain, inter-organizational IT not only changes the interaction mode in a supply chain, but also affects the formation of relationships between suppliers and buyers. In light of this, the argument put forward in the present study is that if a supplier uses IT to provide an information-sharing service to the customers of his enterprise, the relationship between the supplier and customer will be enhanced.

As a form of marketing strategy, the objective of relationship marketing in an industrial context is to establish, develop, and maintain successful relational exchanges between supplier and buyer (Morgan and Hunt, 1994). In order to explore the effects of the information-sharing service on enterprise customer loyalty intention, this section reviews the factors influencing customer loyalty from the perspective of relationship marketing and proposes five hypotheses.

Enterprise customers' trust and commitment lead directly to cooperative behaviors that enhance relationship marketing (Morgan and Hunt, 1994). When an enterprise customer has a high level of trust in, or commitment to a firm, the customer is dedicated to building a long-term relationship. Previous studies have also found that trust and commitment are two antecedent variables of customer loyalty (Jap and Ganesan, 2000; Baloglu, 2002). In view of this, Hypothesis 1 (H1) and Hypothesis 2 (H2) are proposed as follows:

H1: An enterprise customer's loyalty intention toward a firm is positively influenced by the customer's trust in the firm.

H2: An enterprise customer's loyalty intention toward a firm is positively influenced by the customer's commitment to the firm.

On the other hand, trust has been recognized as the foundation for commitment generation (Morgan and Hunt, 1994; Sirdeshmukh et al., 2002). An enterprise customer who has engaged in building trust through repeat transactions is willing to commit to a firm. Thus, Hypothesis 3 (H3) is proposed:

H3: An enterprise customer's commitment to a firm is positively influenced by the customer's trust in the firm.

The service value perceived by an enterprise customer has significant influence on the customer's level of trust and commitment (Bloemer et al., 1998; Sirdeshmukh et al. 2002). Information sharing is a form of service that improves coordination among supply chain participants and increases the participants' identification with the supply chain. In addition, previous studies propose that the association between information sharing and partnership is positive in the context of the supply chain (Yu et al., 2001; Zhou and Benton, 2007). In light of

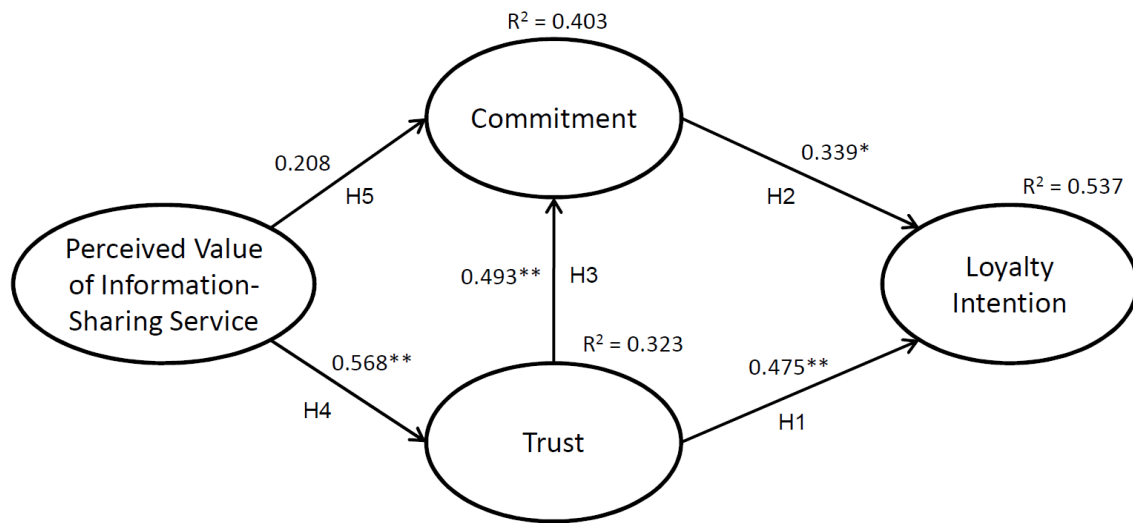
this, we infer that an enterprise customer's perceived value of an information sharing service will positively influence their degree of trust and commitment. Hence, Hypothesis 4 (H4) and Hypothesis 5 (H5) are proposed as follows:

H4: An enterprise customer's trust in a firm is positively influenced by the customer's perceived value of the information-sharing service provided by the firm.

H5: An enterprise customer's commitment to a firm is positively influenced by the customer's perceived value of the information-sharing service provided by the firm.

3. Methodology and Analysis Results

A survey was conducted in this study to collect empirical data and test hypotheses. The sampling unit was a manufacturer who had established a robust IT infrastructure for inter-organizational data exchange. In order to make contact with appropriate study subjects, the researcher collected company data from published government documents on electronic business (e-business) projects in Taiwan. In recent years, the Taiwanese government has subsidized the electronic integration of the supply chains of many leading domestic manufacturers. Focusing on supply chain integration, this series of e-business projects aimed to promote the domestic development of industrial information technology and applications for streamlining inter-organizational processes. Therefore, the robustness of the IT infrastructure of a company can be regarded as guaranteed if the company has participated in the e-business projects mentioned above. The questionnaire was mailed to 200 chief executives of Taiwanese manufacturing companies, out of which a total of 61 valid questionnaires were returned. This represents a valid response rate of 30.5%. Partial Least Squares (PLS) with the bootstrap procedure was adopted to analyze our research model. The research model and the results of PLS analysis are illustrated in Figure 1.



Note: * $p < 0.05$; ** $p < 0.01$

Figure 1 Research Model and the Results of Path Analysis

3.1 Results of assessment of the measurement model properties

The internal consistency reliability of the construct was assessed by Cronbach's alpha and the composite reliability (CR). The results of Cronbach's alpha (ranging from 0.759 to 0.846) and CR values of the constructs (ranging from 0.865 to 0.904) are higher than the recommended level of 0.70, indicating adequate internal consistency.

Convergent validity is demonstrated as the average variance extracted (AVE) values for all constructs. The results of AVE are higher than the suggested threshold value of 0.50. Comparing the square root of the AVE with the correlations among the constructs, each construct is more closely related to its own measures than to those of other constructs. Therefore, the discriminant validity is supported.

3.2 Results of structural model testing

A structure equation model was used to test the effects of trust and commitment on loyalty and the associations among perceived value of information-sharing service, trust, and commitment. Figure 1 presents a graphic depiction of the PLS results, which shows the standardized path coefficients among the constructs and the R^2 values for three constructs (i.e., trust, commitment and loyalty intention). All hypotheses are significant except H5. The results demonstrate that an enterprise customer's perceived value of the information-sharing service has no direct impact on commitment. In contrast, an enterprise customer's perceived value of the information-sharing service has indirect impact on commitment and loyalty via trust.

The explained variance- R^2 value is an indicator of the prediction. As Figure 1 shows, the R^2 of loyalty intention is 0.537, which implies that an enterprise customer's loyalty intention can be well explained by the degree of trust and commitment. On the other hand, the R^2 of trust and commitment are 0.323 and 0.403, respectively. The results reveal that an enterprise customer's perceived value of an information-sharing service is one of the significant factors affecting customer trust. Furthermore, an enterprise customer's loyalty intention will be influenced by his trust and commitment. Moreover, commitment will be enhanced by trust.

4. Conclusion

Based on the empirical survey of 61 manufacturers in Taiwan, this study provides perceptual measures of enterprise customer attitudes towards suppliers' information-sharing services. These measures of information-sharing services can be used to predict likely changes in an enterprise customer's relationship with a firm. The results of this study indicate that a firm's information-sharing service is an essential prerequisite for an enterprise customer's trust, and that trust will directly influence the customer's loyalty intention as well as indirectly influence the their loyalty intention via commitment.

Exploring the factors that enhance lasting and stable inter-organizational relationships is an important issue in relationship marketing in an industrial context (Leek et al., 2003; Gulati and Sytch; 2007). The primary contributions of this study are two-fold: first, while previous studies have found that an enterprise customer's loyalty will be influenced by trust and commitment, rarely have studies investigated the effects of an enterprise's information-sharing service on trust and commitment. This study proposes an integrated model to explore the associations among an

enterprise customer's perceived value of an information-sharing service, and customer trust, commitment and loyalty. It is argued that this integrated model reveals the value of an information-sharing service in B-to-B relationship marketing. Second, this study not only verifies that trust and commitment are two significant factors influencing an enterprise customer's loyalty, but also finds that the customer's perceived value of the enterprise's information-sharing service has a significant impact on trust only. Suppliers who implement inter-organizational information systems in order to share information and reduce uncertainty in a supply chain will enhance their customers' trust rather than their commitment. These results indicate that inter-organizational information systems not only enhance operation efficiency, but also improve inter-organizational relationships.

Acknowledgement

This work was supported by the National Science Council of the Republic of China under the grant NSC 98-2410-H-251-006.

References

1. Ahluwalia, R., Burnkrant, R. E. and Unnava, H. R. "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research* (37:2), 2000, pp. 203-214.
2. Baloglu, S. "Dimensions of Customer Loyalty," *Cornell Hotel and Restaurant Administration Quarterly* (43:1), 2002, pp. 47-50.
3. Bloemer, J., Ruyter, K. D. and Peeters, P. "Investigating Drivers of Bank Loyalty: The Complex Relationship between Image, Service Quality and Satisfaction," *International Journal of Bank Marketing* (16:7), 1998, pp. 276-286.
4. Chiang, W. K. and Feng, Y. "The Value of Information Sharing in The Presence of Supply Uncertainty and Demand Volatility," *International Journal of Production Research* (45:6), 2007, pp. 1429-1447.
5. Eiriz, V. and Wilson, D. "Research in Relationship Marketing: Antecedents, Traditions and Integration," *European Journal of Marketing* (40:3/4), 2006, pp. 275-291.
6. Gounaris, S.P. "Trust and Commitment Influences on Customer Retention: Insights from Business-to-Business Services," *Journal of Business Research* (58:2), 2005, pp. 126-140.
7. Gulati R., and Sytch M. "Dependence Asymmetry and Joint Dependence in Interorganizational Relationships: Effects of Embeddedness on A Manufacturer's Performance in Procurement Relationships," *Administrative Science Quarterly* (52:3), 2007, pp. 32-69.
8. Jap, S.D. and Ganesan, S. "Control Mechanisms and The Relationship Life Cycle: Implications for Safeguarding Specific Investments and Developing Commitment," *Journal of Marketing Research* (37:2), 2000, pp. 227-245.
9. Leek, S., Turnbull, P.W. and Naudé, P. "How is Information Technology Affecting Business Relationships? Results from A UK Survey," *Industrial Marketing Management* (32:2), 2003, pp. 119-126.
10. Morgan, R. M. and Hunt, S. D. "The Commitment-Trust Theory of Relationship Management," *Journal of marketing* (58:3), 1994, pp. 20-38.
11. Patnayakuni, R., Rai, A. and Seth, N. "Relational Antecedents of Information Flow Integration for Supply Chain Coordination," *Journal of Management Information Systems* (23:1), 2006, pp. 13-42.

12. Ruyter, K., Moorman, L. and Lemmink, J. "Antecedents of Commitment and Trust in Customer-Supplier Relationships in High Technology Markets," *Industrial Marketing Management* (30:3), 2001, pp. 271-286.

(Note: Other references are available by contacting the authors)

Research on the Impact Factors of Using Mobile Enterprise Services in Hubei

Yuqing Liu
Huazhong University of Science and
Technology

Jinlong Zhang
Huazhong University of Science and
Technology
jlzhang@mail.hust.edu.cn

Abstract

Mobile enterprise service develops quickly in recent years. This paper explored 25 main factors influencing acceptance of mobile enterprise service. Based on the valid data of questionnaires collected from the companies in Hubei, this study gives a list of influence factors using the logistic regression analysis. The result shows that the most three influential factors of the acceptance of mobile enterprise service are the purpose of enhancing the corporate image, the time of processing e-commerce and the purpose of reduce operating costs and etc. It can be concluded that those corporate with good development strategies and high degree of information are more likely to adopt mobile services.

Keywords: Mobile business; Mobile enterprise service; Logistic Regression Analysis

1. Introduction

As a central province, Hubei is not only a key agricultural province but also an old industrial base. Grasping the opportunity to develop mobile information technology is a feasible way to achieve national economic and great-leap-forward development of social informational, and it will nurture and build up a new industry full of opportunities, challenges and vast space for development. Through enforcing the efforts of construct mobile informationisation, it will promote the development of informationisation industry so as to effectively promote the economic development of Hubei province.

Mobile commerce technologies and services are new information system, and attract the interests of both practitioners and researchers.. Analyzing the technology and services of mobile commerce and constructing adoption models will help to raise the degree of the acceptance of new technology and services,

Generally, mobile services are divided into individual mobile service and mobile enterprise service. The development of individual mobile service has matured, while the application of mobile enterprise service still stayed in the primary stage. Studying the factors of using mobile enterprise services will prepare us well for the further research on mobile enterprise service.

2. Classification of Mobile enterprise services

According to the customer groups, we usually divided mobile services into individual mobile service and mobile enterprise service. Individual mobile service includes mobile QQ, mobile phone WAP internet etc. Mobile enterprise services consist mainly that enterprise's customers

utilize mobile termination to supply their enterprise management with supports that are called group's business. Most mobile service providers in China have already promoted their own group's business and have treated it as one of the mainly resources of main businesses' profits, for example, group's E net of China Mobile, group's mobile coloring ring back tone and so on. Presently many group's businesses stayed in the introduction stage as the development of 3G technology, new kind of business will be probably in the hot topic of research or soon turned out, and the diversification of group's business should not be completed in a harsh. Thus this paper examines the application of enterprise value-added service through using the comparatively common eight group's businesses.

Mobile OA is an important content of mobile office and it transfers the existing documents, address book, agenda, file management, memos etc to the mobile phone to let users do the office work anytime anywhere, for emergency events, with extremely efficiency and outstanding supports.

Mobile CRM (Mobile Customer Relationship Management) involves customer relationship management, speech communication management and business operation management. The detailed functions consist: enterprise communications catalog, outbound customer, conferencing, customer care, complaint handling, customer service, scheduling, business handling, business management, sales management, sales funnel analysis etc.

Mobile ERP is an integrated mobile phone office system based on internet and mobile telecommunication, using mobile phones visiting the enterprise operation management information through WAP to satisfy the needs of enterprise information management. The advantages of using mobile ERP are as follows: closely combined with ERP, we could synchronize with the company's information, does the business management conveniently, check cash flow, short message service costumed and query nevertheless away from company.

Mobile marketing's definition is: crossed multimedia marketing through the wireless communication media. The purpose of mobile marketing is very simple to increase brand awareness, collecting database of customer information, enhance the chances for clients to take part in the activities or visiting the retailing shops to improve customer confidence and increase revenue.

Mobile financial system mainly provides group key clients with a business application plan based on mobile wireless network visiting internal finance system and realizes the existing financial system's common business processes on the wireless network ensuring people equipped with PDA, mobile phones to access to the internal finance system for financial process management, collection, payment, reconciliation, query and other related business processes to improve efficiency, reduce costs, while fulfilling enterprises and institutions' mobile needs of financial management.

Mobile human resources management achieves all the staff to communicate with strategic HR information system wirelessly just using cell phone through wireless terminated value-added services , as a result, it achieves the synergy of human resources business applications. Its business contents cover: early warning of key issues, workflow service announcements, getting

dynamic HR system login password by short messages, self-written text messages management, SMS voting, SMS questionnaires and SMS memo function

The logistic geographical information system of mobile logistic management could be applied in GPS and other aspects, for circumstance, the drivers use cell phones to get the geographical information from wireless network. The satellite-based positioning system, GIS, can do vehicle management, track, search, and also help drivers to find the shortest feasible path by satellite positioning and laptop to connect with control center.

Mobile supply chain management is the combination of mobile commerce and supply chain management. By the use of mobile supply chain management, we can receive, store, deal with key information from all the processes of supply chain anytime anywhere to achieve cross-enterprise information exchange and sharing.

In this paper, data from scientific and technological research funded projects in Hubei Province: mobile commerce structure model and questionnaire on its application research (No.2007AA402A47). Base on the results of questionnaire, the application of eight group's businesses is described in table 1st.

3. Summary of impact factors of using Mobile enterprise services

This section aimed to find the impact factors of using mobile enterprise services and rank them according to the levels. Firstly, it assumed the possible impact factors to make questionnaire and do research. This paper examines that the impact factors of using mobile enterprise services come from four aspects: basic conditions of enterprises (by sector, corporate nature, the number of employees, sales, staff travel frequency, breadth of geographic distribution, senior managers' understanding), enterprise information situation (the number of information centers, informationisation construction time, time to carry out e-commerce, the number of departments to carry out information technology, IT investment, system operational status), the adaptability of mobile commerce (competitor situation, partners, the system's compatibility, technology maturity, staff easy usability, technical security) and mobile commerce's purpose of (strengthening customer communication, providing personalized service, obtaining first-mover advantage, improving company's image, improving enterprise operational efficiency, reducing operating costs) showed as figure 1nd.

Table 1. Acceptance statistics of mobile services

Business	User know		User don't know
	Ever used (from high to low)	Never use	
Mobile marketing	28%	62%	10%
Mobile OA	18%	75%	07%
Mobile human resources management	12%	53%	35%
Mobile CRM	09%	62%	29%
Mobile financial management	04%	58%	38%
Mobile ERP	04%	57%	39%
Mobile logistic management	03%	53%	44%
Mobile supply chain management	02%	52%	46%

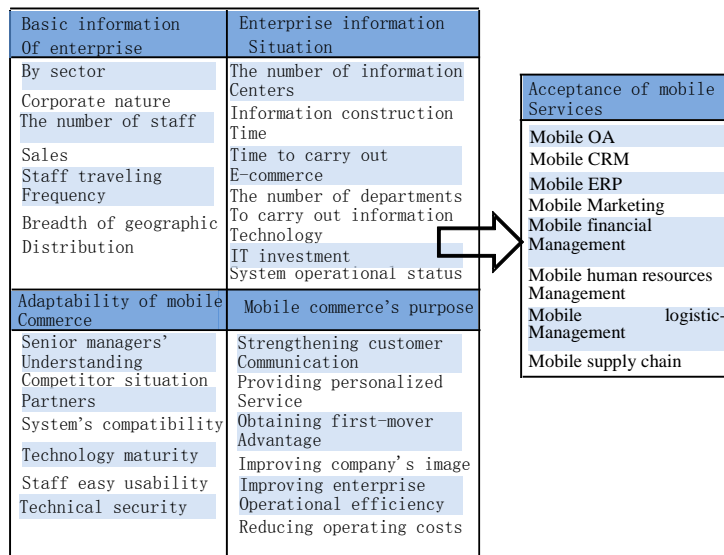


Figure 1. Classification of the Impact Factors

We developed a questionnaire based on figure1, In the questionnaire we listed the impact factors of using mobile enterprise services, and then conducted investigations in the companies that uses mobile services in Hubei to collected data. We had a total of 334 respondents finally, of which 188 were valid data, thus, the respond rate was 56%.

4. Logistic Regression Analyses

In real life, due to the relationship between variables and independent variables is usually not a linear relationship, take the content of this study for an example, when the enterprise's size is very small, as a small workshop with only a few employees, expanding the size has little effect on the increase the desire to use mobile OA; when the enterprise's size reaches a certain threshold value, the desire of using mobile OA will increase significantly; After enterprise scale reaches a certain level, the speed of increasing the desire to use mobile OA will become slow again [3]

Logistic regression model compared with the linear regression model doesn't require a linear relationship between the independent variables and variables, and is particularly suitable for

forecasting the probability of two categorical variables [3]. In this study as an example, taking the actual use of mobile OA as the dependent variable, due to the use of situation is either "used" or "Unused", so this is a two categorical variable, noting the used mobile OA, the value of variable Y is 1, otherwise is 0. Note the probability of user to use a mobile OA as P (Y = 1), clearly $0 \leq P \leq 1$. Generally take 0.5 as the boundary, when P is greater than 0.5, take the value of the dependent variable Y 1, or take Y 0. Logistic model's thinking aims to make the P function Logit (P) as the linear expression of independent variables, as follows:

$$\text{Logit}(P) = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p \quad (1)$$

Converse formulation:

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_{25} x_{25} \quad (2)$$

Taking mobile OA research for example is to find such a structure allowing the probability P of enterprises using mobile OA and every impact factor (25) to satisfy:

$$\text{Logit}(P) = \ln\left(\frac{P}{1-P}\right) \quad (3)$$

Using the statistical analysis software SPSS13.0, we carry out logistic regression analysis to determine the value of every parameter in table 2. Table 2 demonstrates that among 188 cases 159 studies sound judgment and the total accuracy rate is 84.6%.

Table2. Forecast accuracy of the acceptance of mobile OA

observed value	Predictive value			Overall accuracy
	Used	Unused	Accuracy	
Used	18	15	54.5%	84.6%
Unused	14	141	91.0%	

According to more detailed SPSS analysis, we could sort many factors affecting the use of mobile OA, and the result is shown in Table 3.

Table3. Sort of the Impact Factors of using mobile OA

impact factors of using mobile OA	B	Exp (B)	95. 0% C. I. for EXP(B)	
			Lower	Upper
Partners	1. 841	0. 159	0. 007	3. 707
corporate nature	1. 791	0. 167	0. 038	0. 722
improving company's image	1. 754	5. 779	0. 321	103. 979
reducing operating costs	1. 603	4. 970	0. 331	74. 719
breadth of geographic distribution	1. 412	4. 106	0. 525	32. 127
obtaining first-mover advantage	1. 313	3. 719	0. 199	69. 363
the number of employees	1. 242	3. 461	0. 281	42. 560
senior managers' understanding	1. 200	3. 321	0. 499	22. 093
technology maturity	1. 152	0. 316	0. 030	3. 290

competitor situation	1.091	0.336	0.030	3.727
IT investment	1.068	2.910	0.466	18.148
providing personalized service	0.977	0.376	0.021	6.627
time to carry out e-commerce	0.843	0.430	0.064	2.893
technical security	0.550	1.732	0.082	36.456
the system' s compatibility	0.422	1.525	0.125	18.663
staff travel frequency	0.401	0.670	0.070	6.450
informationisation construction time	0.400	1.492	0.189	11.784
Sales	0.397	0.672	0.088	5.107
system operational status	0.373	1.452	0.698	3.020
improving enterprise operational efficiency	0.363	0.696	0.027	17.958
the number of departments to carry out information technology	0.257	0.773	0.542	1.103
by sector	0.195	1.215	0.305	4.837
staff easy usability	0.111	0.895	0.087	9.190
the number of information centers	0.060	0.942	0.100	8.897
strengthening customer communication	0.007	1.007	0.070	14.600

Using the same analytical method, we can sort out inspected factors affecting adoption of eight group's businesses, summarize and sort results of those factors affecting mobile enterprise services, as shown in Figure2.

Integrated eight kinds of mobile enterprise services, placing at the top places of the most important impact factors are improving the company's image, time to carry out e-commerce, reducing operational costs, providing personalized service, technology maturity, partners and informationisation construction time and so on. This illustrates companies who informationised and carried out e-commerce earlier will adopt mobile enterprise business earlier, while large enterprises have significantly higher demands for mobile services. To provide customers and staff with personalized services and enhance the company's image are main purpose of the enterprises to adopt mobile services.

5. Conclusion

This paper conducted a combination and classification on impact factors affecting companies' adoption of enterprises businesses, and then empirically studied various impact factors based on a logistic regression. The results showed that for mobile OA and other common mobile enterprise services, the top important impact factors include the provision of corporate image, time to carry out e-commerce, reducing operational costs, providing personalized service, technology maturity, partners and informationisation construction time. Thus, in order to attract more enterprise users, mobile service providers should pay more attention to these facets when they develop or promote mobile enterprise services.

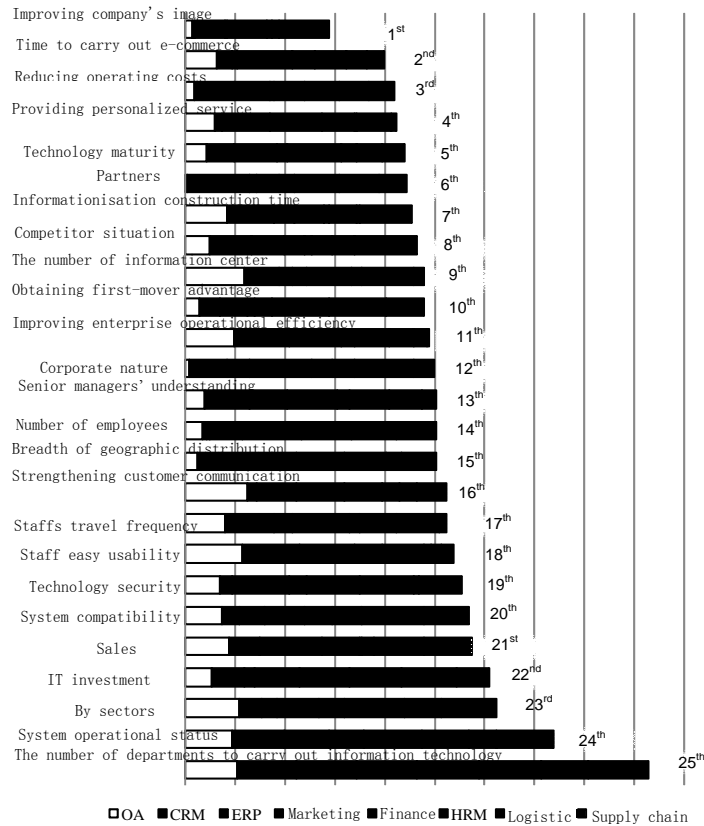


Figure2. Integrated sort of the Impact Factors

Acknowledgement.

This paper is supported by the Chinese National Science Foundation Important Program (No. 70731001).

References

1. Leem, C. S., Suh, H. S., Kim, D. S. A classification of mobile business models and its applications. Industrial Management & Data Systems. 2004, 104(1/2): pp78-87
2. Chen Zhiyu, Zhaohua Deng, Yaobin Lu, Classification of mobile services and the analysis of adoption model [J], Statistics and Decision, 2007,21, pp57-60 (Ch).
3. Chen Chih-Yu, Deng Chaohua, Lu Yaobin. The classification of mobile services and adoption of model analysis. Statistics and Decision. 2007,21, pp57-60
4. Wentong Zhang. An advanced tutorial of SPSS statistical analysis [M] Beijing, Higher Education Press, 2004. Zhang WT. SPSS statistical analysis of high-level tutorial [M]. Beijing: Higher Education Press, 2004.

Comparing Service Quality in 3D Virtual Worlds to Web-based Service

Sulin Ba Dan Ke Jan Stallaert John Zhang
University of Connecticut
sulin.ba, dan.ke, jan.stallaert, john.zhang@business.uconn.edu

Abstract

In the Internet era, web-based services have become a convenient alternative to physical customer service interactions. However, lack of face-to-face interaction makes web service communication inefficient. The immersive 3D virtual worlds provide a platform that offers customer service, where users can communicate “face to face” via their representative avatars. This paper is an exploratory study of proposing a potential channel of service in 3D immersive virtual worlds. We propose a conceptual model of service quality to compare the service quality and users’ satisfaction in 3D virtual worlds to that of web-based services. Theories of computer display technology, communication, and psychology, such as social presence theory, media richness theory, and social identity model of deindividuation effects, are applied to address how an immersive environment impacts users’ sense of presence, and their perception of customer service quality. We design an experiment in Second Life to test our model.

Keywords: Virtual Worlds, Service Quality, Immersion, Presence

1. Background

Customer service is important in customer relationship management and perceived service quality is regarded as the value of a company. In the Internet era, the web-based service becomes an alternative of physical customer center. However, lack of face-to-face interaction makes web service communication inefficient. Thus a new channel of online service is called for to satisfy customers. The immersive 3D virtual worlds provide a new platform that offers customer service, where users communicate “face to face” via their representative avatars.

In this paper, we examine whether 3D virtual worlds would be a preferred channel to 2D websites for offering online customer service. We propose a conceptual model of service quality in 3D virtual worlds, and compare the service quality in 3D virtual worlds to web service.

2. Model Development

We examine the influence of level of immersion on users’ psychology in computer-mediated environments. We contribute to the literature on users’ satisfaction on online service by conceptualizing service quality and comparing the quality in 2D and 3D online environments.

2.1 Immersion and Presence

Immersion in a virtual environment is “a quantifiable aspect of display technology, primarily determined by the extent to which displays are inclusive, extensive, surrounding and vivid” (Slater and Wilbur 1995). In a 3D virtual world where users are “in world” in the shape of their “avatars”, the objects and stimuli are modeled closer to the real world counterparts than those in a 2D environment; users’ avatars can “see” or even “touch” the avatars of their partners in the simulated environment, which is not realized with a 2D website (Biocca and Levy 1995); users’ avatars can navigate through the 3D environment from multiple perspectives, thus creating a more panoramic and vivid view of surroundings of the virtual objects. When he navigates in

the background environments and interacts with the virtual objects, the 3D design can provide him with more vivid feeling of being surrounded by real world objects than that in a 2D design.

Presence is a psychological consciousness, sense of being in the virtual environment (Slater and Wilbur 1995; Steuer 1992). Presence consists of two interrelated concepts: telepresence (spatial presence or physical presence) and social presence (Heeter 1992, Biocca 1997). Telepresence is defined as the phenomenal sense of “being there” including automatic responses to spatial cues and the mental models of mediated spaces that create the illusion of place. Social presence is defined as the sense of “being together with another” in a virtual environment, including primitive responses to social cues, simulations of “other minds,” and automatically-generated models of the intentionality of others (people, animals, agents, etc.).

Immersion and presence are two important constructs in research on computer-simulated virtual reality. In Slater’s model, they indicate that the higher level of immersion, the higher level of presence (Slater and Wilbur 1995, Slater et al. 1996). Other researchers’ work also demonstrates that the immersive computer environment leads to the sense of presence in the context of spatial fidelity (Barfield and Hendrix 1995, Barfield et al 1997). Thus, we propose that ***Hypothesis 1a: The higher level of immersion in a 3D virtual world leads to users’ higher sense of telepresence than that in a 2D virtual world.***

Hypothesis 1b: The higher level of immersion in a 3D virtual world leads to users’ higher sense of social presence than that in a 2D virtual world.

2.2 Measuring Service Quality in Virtual Worlds

The importance of service quality has been demonstrated that it contributes to market share and return on investment. The dimensions of service quality have been considered important by customers, companies, and researchers. Parasuraman et al. (1988) has developed a scale of five core factors named SERVQUAL: reliability, tangibles, responsiveness, assurance, and empathy. Their scale has become the most widely used scale for measuring service quality.

We propose our scale for measuring service quality originating from the five core dimensions of SERVQUAL. We apply the framework of SERVQUAL and derive the sub-dimensions of each of the five dimensions in the context of 2D and 3D virtual worlds.

Tangibles originally refer to physical facilities, equipment, and appearance of personnel. In the context of website service, some of these factors no longer apply and tangibles have been operationlized as, e.g., aesthetic design (Yoo and Donthu 2001) and visual appeal (Loiacono et al. 2002). In addition, playfulness (Liu and Arnett 2000) is an important factor to measure the visual characters of avatars, objects, and the environment. Thus, we measure tangibles with by *aesthetics* (design aesthetics of the virtual object and the environment), and *playfulness* (charming features of the service environment to attract customers and promote excitement).

Reliability is originally defined as the ability to perform the promised service dependably and accurately. We measure reliability with *information accuracy*, defined as to present information of a product or service in a clear and concise manner, including product information and the full disclosure of policies, procedures and charges (Collier and Bienstock 2006).

Responsiveness is the willingness to help and provide prompt service (Parasuraman et al. 1988). It is found that a responsive service directly leads to customer satisfaction in the end (Yoo and Donthu 2001; Long and McMellon 2004; Parasuraman et al. 2005).

Assurance is the knowledge and courtesy of employees and their ability to inspire trust and confidence (Parasuraman et al. 1988). The sub-dimensions we apply to measure assurance

are competence, communication, and courtesy, that are commonly adopted in existing literature of online service quality scale development (Loiacono et al. 2002; Parasuraman et al. 2005).

Empathy is the service person's ability to understand and care individualized attention provided to the customers. We rename it as *personalization* (Swaid and Wigand 2009).

2.3 Presence and Service Quality

Prior research has divided the sense of presence into telepresence and social presence. By definition, telepresence describes users' perception of spatial or physical cues in the environment (Steuer 1995), whereas social presence emphasizes their social cues that come from being with another in a virtual environment (Biocca 2003). In other words, telepresence focuses on users' sensory fidelity in the mediated place and social presence depends on the existence of others and communication with them in the environment.

Accordingly, the dimensions of service quality emphasize on physical features and human interaction respectively. We investigate the relationship between the sense of presence and virtual service quality by subdividing them into measurable constructs. Since tangibles are the physical features, we only explore the impact of telepresence on them. Reliability contains information both from the physical display and via human communication, thus we explore the impact of both telepresence and social presence on it. As for responsiveness, assurance and empathy, these are the users' perceptions based on their interaction with the customer service person. Thus we explore the impact of social presence on them as they are human-related factors and result from users' psychological response in the online environment.

2.3.1 Impact of Telepresence on service quality

The higher sense of telepresence the user has, the closer he/she feels being in the virtual world and closer to the virtual objects in world. This means the user feels within closer cognitive distance to the virtual objects and environmental display. The sense of telepresence enables the user to feel closer cognitive distance in the 3D virtual world so as to observe and experience the tangibles cues, (aesthetics and playfulness).

The sense of telepresence in a virtual world implies the property of representational richness of its virtual display and interaction with the environment. It enhances users' psychological state of being involved in an activity (Novak et al. 2000), so that enables the users to play with the virtual environments (including the background landscape, virtual objects, etc.) and get absorbed in the virtual world.

Hypothesis 2a: *A user's sense of telepresence has a positive effect on his/her perception of visual aesthetics of the customer service in an online environment.*

Hypothesis 2b: *A user's sense of telepresence has a positive effect on his/her perception of playfulness of the customer service in an online environment.*

The reliability of the service requires clear and concise information about a product or service. The closer cognitive distance enables the server to explain clearer related policy and terms of service. Cognitive distance plays a significant role in information spillover, when the user is closer to both the environment and the objects within it (D'Agata 2003). Thus, the sense of telepresence increases users' evaluation on the accuracy of the information in that the virtual environment delivers clearer information of the product and service visually to the users. Having the sense of telepresence, the user is able to and clearly get concrete and complete information of real-world product and service, which in turn improves his decision quality (Novak et al. 2000).

Hypothesis 3: *A user's sense of telepresence in has a positive effect on his/her perception of the information accuracy of the customer service in an online environment.*

2.3.2 Impact of Social Presence on service quality

Short et al. (1976) found the social presence theory about the social effects of communication technology. Social presence is a communicator's sense of awareness of the presence of an interaction partner, and the degree of social presence is equated to the degree of awareness of the other person during the course of a communication interaction (Sallnas 2000). Thus, we can argue the more social the interaction is, the more effective the communication is. The sense of social presence in the environment let the user feel about the server's responsiveness, courtesy, considerateness, and such constructs of people's communication properties and key elements to evaluate the service itself. To be specific, the more social the user feels in the environment, and the more possible the service person convey information of the product and service in a concrete manner.

Hypothesis 4: *A user's sense of social presence has a positive effect on his/her perception of the information accuracy of the customer service in an online environment.*

Hypothesis 5: *A user's sense of social presence has a positive effect on his/her perception of the responsiveness of the customer service in an online environment.*

Media richness theory (Daft and Lengel 1986) shares some common views with social presence theory. It addresses that the amount of information delivered through communication differs with respect to a medium's richness. It assumes that the main goals of communication are to resolve ambiguity and reduce uncertainty, and the more restricted the medium's capacity, the less uncertainty and equivocality it is able to manage.

Social presence decreases psychological distance among communication partners via interacting with each other and is predicted to increase trust via online communication (Gefen and Straub 2004). 3D virtual worlds are more social media than 2D websites, are richer communication media than 2D websites. Both of these communication theories support that 3D virtual worlds, as a richer and more social format of media, provide more efficient platforms for communication partners. The efficient communication in a more social environment makes it easy for the service person to provide responsive and competent service. Meanwhile, with the sense of being with each other, the users are more likely to feel the server's politeness and friendly manner during their interaction, i.e., the courtesy of the customer service.

Hypothesis 6a: *A user's sense of social presence has a positive effect on his/her perceptions of competence of the customer service in an online environment.*

Hypothesis 6b: *A user's sense of social presence has a positive effect on his/her perceptions of communication efficiency of the customer service in an online environment.*

Hypothesis 6c: *A user's sense of social presence has a positive effect on his/her perceptions of courtesy of the customer service in an online environment.*

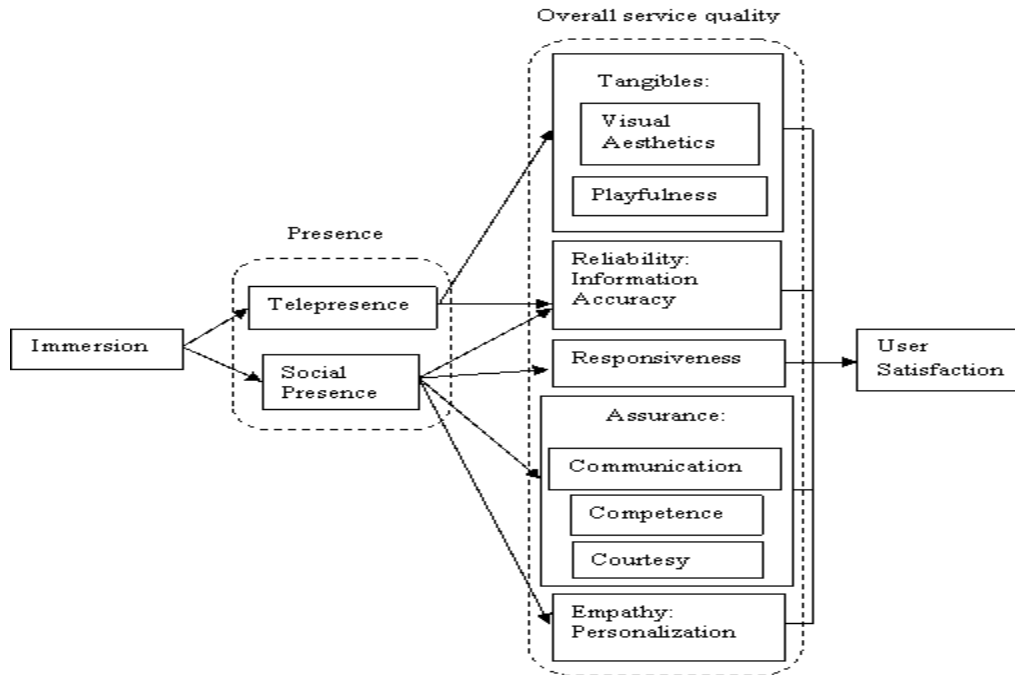
The social identity model of deindividuation effects (Postmes et al. 1998; Reicher et al. 1995; Spears and Lea, 1994) was developed as a response to the idea that anonymity and reduced presence made communication technology socially impoverished. It provides an alternative explanation for the "deindividuation effects" based on theories of social identity (Turner et al., 1987). In SIDE model, cognitive effects occur when communication technologies make "salient" particular aspects of personal or social identity. The social effect of the media realized in the computer mediated environment leads to personalization between communication partners.

Hypothesis 7: *A user's sense of social presence has a positive effect on his/her perception of the personalization of the customer service in an online environment.*

2.4 Overall Service Quality and User Satisfaction

Prior research has exploring the relationship between service quality and users' satisfaction, behavioral intention (Gupta and Zeithaml 2006, Zeithaml et al. 1996). It is accepted that the perceived overall service quality leads to users' satisfaction (Parasuraman et al. 1988).

Hypothesis 8: *A user's perception of each dimension for measuring service quality (tangibles, reliability, responsiveness, assurance, empathy) has a positive effect on his/her satisfaction on customer service offered in online environments.*



3. Methodology

An online experiment will be conducted to test the model. We choose Second Life as the platform for establishing a 3D virtual customer center. We create a virtual cruise with well furnished rooms and recreational facility inside the cruise. The subject can navigate from the land to the cruise and enter rooms in the cruise. There is a service person within the subject's sight and the subject can talk with him instantly. We design a mock-up website of cruise service with introductive texts on the WebPages and uploaded pictures and movies as well. We embed a pop-up chat window that allows the subject to enquire any information about the cruise service.

We use a within-subject design, as it will take less subjects and returns better statistical power (Pollatsek and Well 1995). To mediate the possible practice effects and carryover effects, we let some subjects experience 2D version first and then 3D version, and others in opposite order. We invite students at University of Connecticut to participate in the experiment. The subjects will participate in the experiment individually. They are assigned to accomplish a service task of figuring out the information of the cruise tour. The information includes the cruise route, term of service, room distribution, price, based on which they could make a decision to reserve a desirable cruise trip of equivalent condition in the real world. They are asked to fill in an administered survey for both versions.

4. Conclusions and Potential Contribution

Our research contributes to the literature in the following aspects. We explore a potential channel of customer service in 3D virtual worlds. Secondly, we compare the 2D and 3D virtual worlds and investigate the advantages and disadvantages in each from the perspective of user behavior, based on the theories of communication, psychology, and information technology. In addition, we propose a scale of measuring service quality in 3D virtual worlds. Finally, if our hypotheses are supported in the experiments, 3D virtual worlds will be a practical substitute for web-based customer service to market product and service for a company. The results will provide us some insights how to improve the customer service through the Internet.

Preference (*available upon request*)

Advertising Effects of Online Social Capital on E-tailer Performance: A Theoretical Framework

Youwei Wang
School of Management, Fudan
University, China

ywwang@fudan.edu.cn

Fuchun Zhao
The Institute of Information Science,
Shanghai Academy of Social Science,
China

nclzhaofc@sina.com

Shan Wang
School of Business, Renmin
University, China
shanwang@ruc.edu.cn

Hong Ling
School of Management, Fudan
University, China
hling@fudan.edu.cn

Abstract

E-tailers refer to small and medium size business managers and entrepreneurs primarily doing retailing businesses online based on a unified shopping platform. Currently, the number of E-tailers has grown to a scale of millions in China. However, few theoretical studies explaining the business performance of e-tailers exist. This study proposes a theoretical framework, in which advertising effects are proposed to be key drivers of e-tailers' business performance. In addition, online social capital (resources accrued through online social network) is proposed to be the antecedents of advertising effects. This framework contributes to the literature by furthering our understanding of how online social capital affects business performance, while paving the way for future empirical studies that potentially shed lights on the uniqueness of pure virtual business environments and how to excel in it.

Keywords: Internet Entrepreneurship, e-Tailers, Social Network, Social Capital, Institution-based Trust

1. Introduction

As network becomes more pervasive, logistic services are widely available and online payment mechanism is put into place, online shopping is growing increasingly popular. A recent survey shows that sales in web shopping market in China have witnessed an average annual growth rate of 102 per cent since 2004 (Alibaba.com 2009). In 2008, trade revenues reached 128.18 billion RMB (about \$20 billion), which accounted for 1.5 percent of the total retail sales of consumer goods in China. This figure is expected to reach a new height of 713 billion RMB (about USD107 billion) in 2012 (analysys.com.cn 2009). In particular, sales volume on Taobao.com in 2008 has surpassed the sum of the three big retailers in China, Lianhua, Walmart, and Carrefour. In the mean time, according to a report issued by Taobao recently, there are more than two million active stores listed on Taobao.com at the end of 2009.

E-Tailers, the major players which do business regularly on internet and rely upon online shopping platform, are mainly small and medium size enterprises and individual entrepreneurs (Alibaba.com 2009). In comparison with retailing in the physical world, transactions in virtual environment display several unique features. First, online trading platform is characterized by sociality. Sellers and buyers not only exchange commodities with one another online, but also

spend much time on such things as chatting, making friends, communicating information to strengthen their relationship and trust, and thereby forming a virtual social network (Stephen and Toubia 2009). Consequently, an e-tailor with more social ties enjoys higher opportunity to be found and patronized by buyers. Although the economic rents of social network in physical world have been well explored in the literature (Dyer and Singh 1998), the focuses of prior literature were on the networks of business partners, suppliers and downstream enterprises, or government offices, which are different from ours wherein online sellers interact *directly* with their peers as well as potential buyers. Second, it becomes of paramount importance for the success of both sellers and buyers to build mutual trust since they typically interact with each other virtually during the entire process of online shopping (Ba and Pavlou 2002). According to previous literature, inter-organizational trust can be based on calculation, knowledge, or institution (Gefen et al. 2003), and be arranged by either self enforcement or the third-party enforcement (Dyer and Singh 1998). Thus, understanding the mechanisms of how trust advances online sellers' performance is very important in online commerce contexts (Gefen et al. 2003). Third, the scales of e-tailers are typically small or medium, and therefore they don't have enough financial resources to advertise and promote their products. Considering the vast number of sellers for almost every product lines, it is undoubtedly important to raise consumers' awareness and recognition by economical means.

Despite the importance of the questions above, the prior ecommerce literature didn't offer prescriptions or guidelines for e-tailers beyond trust/reputation building. Most prior studies examine online transaction from consumer perspective (e.g., Gefen et al. 2003), or price premium and sales possibility from sellers' perspective (e.g., Ba and Pavlou 2002), they seldom investigate the mechanisms under which trust and other social capital affect e-tailers' performance. On the other hand, the social capital literature typically focuses on the knowledge and information acquisition effects of social network, and is primarily conducted in the offline context. Furthermore, although understanding the interaction between offline and online/digital social network has been underlined in the literature, such works are very rare to date (Agarwal et al. 2008).

The objective of the current research is thus to enhance our understanding of online social network and its effectiveness as a marketing tactic on e-tailers' performance. More specifically, we attempt to address the following question: *how can social capital in online shopping environment advance e-Tailers' business performance?*

2. Advertising Effect and E-Tailer' Performance

Internet provides unprecedented opportunities for consumers, and particularly engenders a plethora of commodity information for their preference. For the same kind of goods, it offers millions of options. For example, we are able to obtain over 623 thousands results when searching for "coat for men" on Taobao.com, over 191 thousands results for "basketball shoes, male 25 cm" (accessed on Jan 21st, 2010). In order to promote their products successfully, online sellers spare no efforts to attract customer attention through advertising activities which are likely to distinguish them from others and hence exert influences on purchasing decisions of consumers.

According to Clark et al. (2007), there are two types of advertising effects, namely the awareness (informative) effect and persuasive effect. *Awareness effect* is typically considered as informing consumers about the characteristics of the brand, thereby enabling consumers to learn about the brand's quality (Erdem and Keane 1996). In particular, for purpose of the current study, awareness mainly refers to the coverage of consumers who know about an online store (in comparison to consumer learning facilitation). *Persuasive effect*, in contrast, is concerned with positive signals of e-tailers and their stores that in effects convince consumers to patronize.

We expect the positive influence of these two advertising effects on organizational performance due to the following reasons. On the one hand, the chances of being found of their stores by consumers are of great importance to e-tailers. Although not every visitor can eventually been converted to customers, owning large number of store visitors always implies competitive advantages in the sense of having more potential buyers. On the other hand, if an online store exerts persuasive effect to store visitors by means of good image, high product quality, and positive word-of-mouth, it would have higher sales volume than those don't have such quality signals. As a result, we propose:

P1a: The more buyers being aware of the storefront of an e-tailer, the higher its business performance

P1b: The more buyers think an e-tailer's products are worthy of purchasing, the higher the e-tailer's business performance

Clearly, awareness and persuasiveness are not independent. When more people access the storefront and goods of an e-tailer, he/she will have more opportunity to show the merit of its products, and thus persuade potential customers to buy from them. Consequently, we propose:

P2: The more buyers being aware of the storefront of an e-tailer, the more buyers think this e-tailer's products are worthy of purchasing.

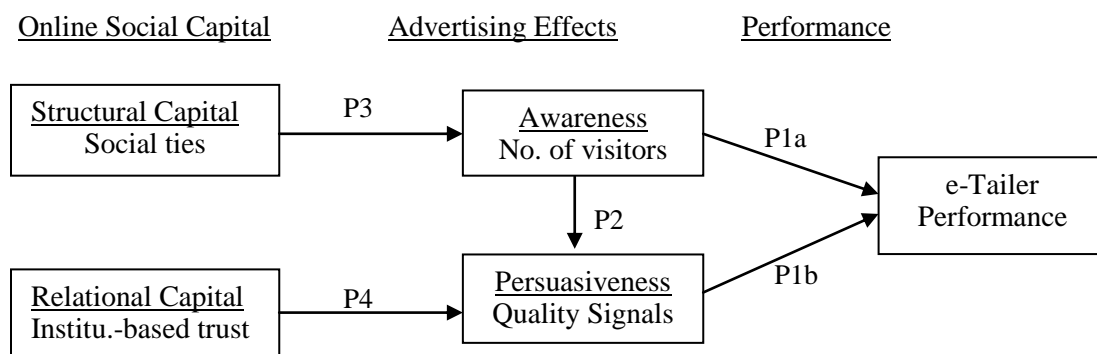


Figure 1. Theoretical Model

3. Online Social Capital and Advertising Effect

Nahapiet and Ghoshal (1998, p.243) defined social capital as “the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit”. Social capital thus comprises both the network and the assets that can be mobilized through that network (Burt 1992). Organization theorists have manifested empirically that social capital is a productive resource, facilitating outcomes that range from an individual's higher job satisfaction to a firm's performance (e.g., Tsai and Ghoshal 1998). In this study, we define online social capital as social resources embedded in the relationship generated by online socializing efforts.

A widely recognized classification of social capital is proposed by Nahapiet and Ghoshal (1998), who suggest that there exist three types, i.e., structural, relational, and cognitive social capital. While *structural capital* refers to the impersonal configuration of linkages between different nodes (i.e., actors in the social network), *relational capital* is concerned with the variety of personal relationships people have developed with each other through a history of interactions. In contrast, *cognitive capital* is termed to identify those resources providing shared representations, interpretations, and systems of meaning among parties.

While cognitive capital is also a critical dimension of social capital, it is not discussed in this paper because we assume all e-tailers sell under the umbrella of one unified shopping platform, which to a large extent supports identical norm and code for e-Tailers defined and enforced by the shopping platform.

3.1 Structural social capital

In the context of online network, despite of the fact that social capital has effects on business performance of all sellers, different sellers' social capital varies depending on their online socializing efforts. Friedkin (1982) claimed that rich connections in the network community are conducive to mutual understanding, behavioral norm and trust, which in turn facilitates members' collaboration and collective action. Putnam (2000) suggested that members tend to cooperate with each other when there are more good-will in social network environment, which subsequently enhances the survival and success rate of start-up enterprises.

Sellers can establish their social network among themselves by building friend linkage with each other or listing each other as friend shops, which can augment their chances of being found by consumers substantially. Furthermore, sellers are also able to establish social network with buyers by publishing articles or comments on the discussion forum or providing professional recommendations to potential buyers, and these activities of e-tailers signal their reliability and professionalism to buyers, which may expose themselves to more visitors and potential shoppers. Consequently, we propose:

P3: The more online social ties an e-tailer has, the more buyers will be aware of its storefront.

3.2 Relational social capital

According to Nahapiet and Ghoshal (1998), trust is the most important aspect of relational social capital. Gefen et al. (2003) posited that there are various types of trusts in e-commerce, that is,

knowledge-based, institution-based, and calculative-based trust. As far as this paper is concerned with sellers (rather than buyers), the most relevant one in our research context is institution-based trust, rather than knowledge-based trust or calculative-based trust. *Institution-based trust* refers to an individual's perceptions of the institutional environment such as Internet. McKnight et al. (2002) proposes two dimensions of institution-based trust, structural assurance and situational normality, which are particularly salient in the context of e-commerce. *Structural assurance* refers to structures such as guarantees, regulations, legal recourse, or other policies being put in place to promote the online exchange. *Situational normality*, on the other hand, refers to the sense that the environment is in proper order and success is likely because the situation is normal or favorable (Lewis and Weigert 1985).

In our research context, sellers can build up institution-based trust by following the business ethics procedures issued by the shopping platform. Institutional-based trust may encompass real-name registration authorization, consumer rights safeguarding plans, 3rd party payment systems, penalty on "bad" e-Tailers, etc. Taking consumer rights safeguarding plan as an example, in some shopping platform such as Taobao, a certain amount of money is collected in advance by the shopping platform to compensate unsatisfied consumers. Also, contract e-tailers need to illustrate that they would not sacrifice the commercial interests of consumers during the transaction processes. Correspondingly, a graphic icon will be put at conspicuous positions of the storefronts of e-tailers by the platform, signaling trustworthiness of this seller.

Therefore, buyers' level of trust on e-Tailer will increase indirectly because of the trustworthiness of a shopping platform. Since whether or not an e-Tailer joins in any platform authorization plan can be readily noticed on the storefront by buyers, we propose:

P4: In comparison to e-Tailers who don't join in any consumer rights protection plan issued by the shopping platform, those e-tailers who join in the plan will make more buyers think their products are worthy of purchasing.

4. Conclusion

Based on social network and e-business trust theory, the paper explores the effects of online social network on e-tailor performance and setup a testable theoretical model. We reason that online social capital of an e-tailor would produce two kinds of advertising effects, which in turn lead to business performance. In the meantime, we materialized online social capital into two types, i.e., structural and relational social capital, and advertising effects into awareness and persuasive effects.

The paper is in a prior stage of an empirical study. We have secured a panel data set (objective in nature) to test the proposed model. The proposed framework can reinforce our understandings on online entrepreneurship, internet marketing, and virtual community (augmenting transaction purposes), and has significant business implications for the management of internet shopping platforms and e-tailers.

Acknowledgement

This study was supported by National Nature Science Foundation of China (70931001, 70572027, 70828003), Social Sciences and Humanities Research Grant, Ministry of Education,

China (08JC630017), Scientific Research Foundation for Returned Scholars, Ministry of Education, China, and Shanghai Pujiang Project.

References

1. Agarwal, R., Gupta, A.K., and Kraut, R. "Editorial Overview: The Interplay Between Digital and Social Networks," *Information Systems Research* (19:3) 2008, pp 243-252.
2. Alibaba.com "Emergence of a new business paradigm: research report on the development of entrepreneurs in 2009," Research Center of Alibaba Group.
3. analysys.com.cn "Projection of China online retailing market trend: 2009-2012," Analysys International Industry Database.
4. Ba, S.L., and Pavlou, P.A. "Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior," *MIS Quarterly* (26:3), Sep 2002, pp 243-268.
5. Burt, R.S. *Structural Holes: The Social Structure of Competition* Harvard University Press, Cambridge, MA., 1992.
6. Clark, C.R., Doraszelski, U., and Draganska, M. "Information or Persuasion? An Empirical Investigation of the Effect of Advertising on Brand Awareness and Perceived Quality Using Panel Data," in: *SSRN eLibrary*, 2007.
7. Dyer, J.H., and Singh, H. "The relational view: Cooperative strategy and sources of interorganizational competitive advantage," *Academy of Management Review* (23:4), Oct 1998, pp 660-679.
8. Erdem, T., and Keane, M. "Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets," *Marketing Science* (15:1) 1996, pp 1-20.
9. Friedkin, N. "Information Flow through Strong and Weak Ties in Intraorganizational Social Networks," *Social Networks* (3) 1982, pp 273-285.
10. Gefen, D., Karahanna, E., and Straub, D.W. "Trust and TAM in online shopping: An integrated model," *Mis Quarterly* (27:1), Mar 2003, pp 51-90.
11. Lewis, J.D., and Weigert, A.J. "Trust as a social reality," *Social Forces* (63:4) 1985, pp 967-985.
12. McKnight, D.H., Choudhury, V., and Kacmar, C. "Developing and validating trust measures for e-commerce: An integrative typology," *Information Systems Research* (13:3), Sep 2002, pp 334-359.
13. Nahapiet, J., and Ghoshal, S. "Social capital, intellectual capital, and the organizational advantage," *Academy of Management Review* (23:2), Apr 1998, pp 242-266.
14. Putnam, R.D. *Bowling Alone* Simon & Schuster Press, New York, 2000.
15. Stephen, A.T., and Toubia, O. "Deriving Value from Social Commerce Networks," in: *SSRN eLibrary*, <http://ssrn.com/paper=1150995>, 2009.
16. Tsai, W.P., and Ghoshal, S. "Social capital and value creation: The role of intrafirm networks," *Academy of Management Journal* (41:4), Aug 1998, pp 464-476.

Research on dual-channel coordination of reservation tourism supply chain in the e-commerce environment

Lifang Peng
Management School of Xiamen
University, 361005, China
lfpeng@xmu.edu.cn

Qing Cai
Management School of Xiamen
University, 361005, China
niaohezhizhong@126.com

Abstract

In the industry of reservation tourism, increasing number of traditional travel/ticket agencies are entering an online direct channel which may cause conflict with the traditional channel. This phenomenon is investigated in this study by use of a Stackelberg game model. Characteristics of reservation tourism supply chain, which are different from the common assumptions of most previous studies, are taken into account. The result shows that the dual-channel can not be well coordinated in the decentralized decision-making process. Interiorization of the downstream agents therefore might be a viable alternative from the perspective of ticket agencies.

Keywords: Channel conflict, Channel coordination, Stackelberg game, E-commerce, Reservation tourism

1. Introduction

It is shown with ample evidence that reservation tourism, as an industry type, is of great potential, and on the cutting-edge in development of modern services. In recent years, new forms of company featured by online-only services exhibit a steep curve of popularization. Besides, a lot of traditional ticket agencies are also engaged in an online direct channel. The latter kind of companies as a result will have a distribution system with presence of both online direct channel and traditional indirect channel. Reservation tourism mainly serves ticket reservation, car rental, itinerary arrangement etc. This paper focuses on the typical civil aviation agency supply chain. In a dual-channel distribution system, the ticket agencies' products or services can reach the customers directly through the online channel, while put ticket agencies themselves in a new type of competition and cooperation with their downstream agents.^[1] This paper attempts to study on the issues involved in conflict and coordination of dual-channel, and end in some helpful propositions for the ticket agency and its downstream agent involved.

2. Literature review

Channel conflict is defined as the situation in which one channel member perceives another channel member(s) to be engaged in behavior that prevents or impedes it from achieving its goals^[2], which comes to cause conflict and dispute. The operational strategy and coordination mechanism in dual-channel distribution system receives increasing attention^[3]. Based on the findings of previous studies, to relief the conflict in dual-channel supply chain, there're two typical policies: (1) Single channel policy. According to Tsay and Agrawal (2004)^[3], schemes can be used to adjust the dual-channel relationship include paying the reseller a commission for diverting customers towards the direct channel, or conceding the demand fulfillment function entirely to the reseller. However, compared with other industries, the characteristics of supply chain in reservation tourism include: a. e-ticket is free of inventory and logistics cost here; b.

customers tend to accept multiple channels to satisfy their needs; c. the industry competition is severe and customers seldom have any switching cost to turn to another seller. So single channel policy therefore seems not to be the best feasible solution here. (2) Competitive pricing policy. The conclusions of typical relevant literatures are all based on the fact that the online channel is significantly less convenient than the conventional channel. However, in our certain background, because of the dematerialisation feature of the products or services (e-ticket), the premises are no longer supported.

3. Price equilibrium under Stackelberg competition

In the supply chain of reservation industry (Fig.1), airline companies are manufacturers, China Travelsky holding company implements unified information management. As a tier-one ticket agent, the ticket agency has the right to negotiate with Travelsky and the airline companies, and then sells tickets to its downstream agents. Though ticket agencies are not the manufacturers in fact, they have considerable advantages of information and resources. Thus we put it, denoted as m , in the core place, and study on its relationship with its downstream agent, denoted as n .

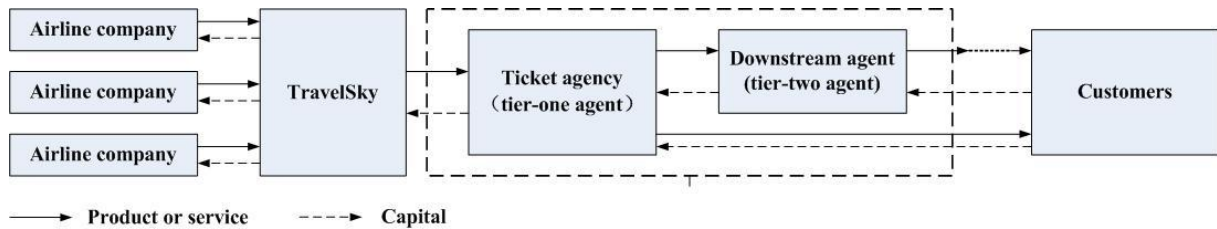


Fig.1. Supply chain of typical civil aviation agent operation

3.1 Assumptions

As broadly adopted in literature, customers are, in assumption, both price and service sensitive. Apart from the demand-to-price elasticity, customers may shift their preference according to price difference between sales channels (cross price elasticity). Channel interest or preference hereby depicts the service sensitivity, which is associated with a lot of factors, such as service expectation, risk perception, attitude of confidence, time cost as well as the extent of convenience etc.^[4] Assuming that the online channel and the traditional channel are of different basic demand on market, denoted as a_e and a_t , and the service quality in a certain channel remains relatively stable. In addition, the form of e-ticket is free of logistic circulation and inventory storage concerns, let alone the additional cost such as those on communication, personnel, etc. Assumption is also made that, in cases of no market withdraw, both parties, sales and purchasers, are rational decision makers and always seek to maximize the profit of their own.

3.2 The model

On the basis of above analysis, we choose linear demand function to express the demand. b is the price elasticity of demand, θ is the cross price elasticity,. According to the common knowledge that cross price elasticity only plays second fiddle, we have $0 < \theta < b$. A and α represent the total basic demand and the market ratio of online channel respectively. We have

$A = a_e + a_t$, $\alpha = \frac{a_e}{a_e + a_t}$, $\beta = b + \theta$ and $a_e = \alpha A$, $a_t = (1 - \alpha)A$ when $A > 0$, $0 < \alpha < 1$, $0 < \theta < b < \beta$. In centralized decision making process, the derivation is listed in table 1.

Table 1. Equilibrium in centralized decision making process

	Online channel	Traditional channel	Total
Demand	$\alpha A + \beta r_e - \theta r_t$	$(1 - \alpha)A + \beta r_t - \theta r_e$	-
Profit	$p(r_1 - r_e)(\alpha A + \beta r_e - \theta r_t)$	$p(r_1 - r_t)[(1 - \alpha)A + \beta r_t - \theta r_e]$	$p(r_1 - r_e)(\alpha A + \beta r_e - \theta r_t) + p(r_1 - r_t)[(1 - \alpha)A + \beta r_t - \theta r_e]$
Sales rebate*	$\frac{(\beta^2 - \theta^2)r_1 - (\theta + \alpha\beta - \alpha\theta)A}{2(\beta^2 - \theta^2)}$	$\frac{(\beta^2 - \theta^2)r_1 - (\beta - \alpha\beta + \alpha\theta)A}{2(\beta^2 - \theta^2)}$	-
Profit*	$p(r_1 - r_e^{I^*})(\alpha A + \beta r_e^{I^*} - \theta r_t^{I^*})$	$p(r_1 - r_t^{I^*})[(1 - \alpha)A + \beta r_t^{I^*} - \theta r_e^{I^*}]$	$p(r_1 - r_e^{I^*})(\alpha A + \beta r_e^{I^*} - \theta r_t^{I^*}) + p(r_1 - r_t^{I^*})[(1 - \alpha)A + \beta r_t^{I^*} - \theta r_e^{I^*}]$

r_1 = sales rebate offered by Travelsky or airline companies to the ticket agency

r_e = sales rebate offered by the ticket agency to customers

r_t = sales rebate offered by the downstream agent to customers

$r_e^{I^*}$ = optimal sales rebate of online channel in a integrated decision making situation.

In addition, r_2 is sales rebate offered by the ticket agency to its downstream agent. Sales rebate means the reward of one ticket offered by a seller to a purchaser in proportion to the par value of the ticket. These parameters always satisfy $0 \leq r_e < r_1$ and $0 \leq r_t < r_2 < r_1$. Adding the condition

$0 < \theta < \beta$, when $0 < \alpha < 1/2$, we have $r_e^{I^*} > r_t^{I^*}$; when $\alpha > 1/2$, we have $r_e^{I^*} < r_t^{I^*}$; when $\alpha = 1/2$, we have $r_e^{I^*} = r_t^{I^*}$. In practice, it's easy to see that the party having advantage in demand can probably raise the price.

However, practically the ticket agency has the priority to decide the sales rebate delivered to the downstream agent, then the downstream agent decides the sales rebate delivered to the customers at the second step. Factors like profit expectations are taken into consideration in this process. This is a pricing competition process under decentralized decision making, in which the ticket agency is the leader and the downstream agent follows. Thus the competition becomes a leader-follower game^[1]. The derivation is listed in table 2.

Table 2. Equilibrium in decentralized decision making process

	Online channel	Traditional channel	Total
Sales rebate*	$\frac{(\beta^2 - \theta^2)r_1 - (\theta + \alpha\beta - \alpha\theta)A}{2(\beta^2 - \theta^2)}$	$\frac{(\beta + \theta)(\beta^2 - \theta^2)r_1}{4\beta(\beta^2 - \theta^2)} - \frac{(3\beta^2 - \theta^2 - 3\alpha\beta^2 + \alpha\theta^2 + 2\alpha\beta\theta)A}{4\beta(\beta^2 - \theta^2)}$	-
Profit*	$p(r_1 - r_e^{S^*})(\alpha A + \beta r_e^{S^*} - \theta r_t^{S^*})$	$p(r_1^{S^*} - r_t^{S^*})[(1 - \alpha)A + \beta r_t^{S^*} - \theta r_e^{S^*}]$	$p(r_1 - r_e^{S^*})(\alpha A + \beta r_e^{S^*} - \theta r_t^{S^*}) + p(r_1 - r_t^{S^*})[(1 - \alpha)A + \beta r_t^{S^*} - \theta r_e^{S^*}]$

The optimal sales rebate offered by the ticket agency to its downstream agent in decentralized decision making process is:

$$r_2^{S^*} = \frac{(\beta^2 - \theta^2)r_1 - (\beta - \alpha\beta + \alpha\theta)A}{2(\beta^2 - \theta^2)}$$

3.3 Coordination of dual-channel

In a dual-channel supply chain, according to basic mathematical principle, it's obvious that the optimal total profit under centralized decision making is no less than profit under decentralized decision making. If the former value equals the latter value, the dual-channel can be considered to be well coordinated. In this case, we should have equivalent pricing as $r_e^{S^*} = r_e^{I^*}$, $r_t^{S^*} = r_t^{I^*}$.

We can find that, under the assumption that r_1 and A are normally of fixed value, the parameters always satisfy $r_e^{S^*} = r_e^{I^*}$, $r_t^{S^*} < r_t^{I^*}$. That means as long as there exists cross price elasticity, the price of online channel under decentralized decision making equals to that price under centralized decision making, while the price of traditional channel under decentralized decision making will surely be higher. Thus it can be seen, the total sales profit decreases under decentralized decision making, the downstream agent has to set a higher price so the consumer utility is decreased to some extent.

3.4 Existence conditions of dual-channel

In order to study the effect exerted on the downstream agent after entering the online channel, we have to compute the Stackelberg equilibrium sales rebate to be compared with. In a similar way, when there's only traditional channel in the supply chain, channel demand and profits of ticket agency and downstream agent are:

$$D_{t0} = a_t + br_{t0}, \pi_{m0} = p(r_1 - r_{t0})D_{t0} = p(r_1 - r_{t0})(a_t + br_{t0}), \pi_{n0} = p(r_{t0} - r_{t0})D_{t0} = p(r_{t0} - r_{t0})(a_t + br_{t0})$$

Thus the Stackelberg equilibrium sales rebates are (in a leader-follower game):

$$r_{t0}^* = \frac{br_1 - a_t}{2b}, \quad r_{t0}^* = \frac{br_1 - 3a_t}{4b}, \quad \pi_{m0}^* = \frac{p(br_1 + a_t)^2}{8b}, \quad \pi_{n0}^* = \frac{p(br_1 + a_t)^2}{16b}.$$

From above equations, in this case, profit of ticket agency will be twice of profit of downstream agent. In a dual-channel distribution supply chain, to drive the ticket agency to open up online channel and prevent the downstream agent from exiting traditional channel, we must have $\pi_m^{S^*} \geq \pi_{m0}^*$, $\pi_n^{S^*} \geq \pi_{n0}^*$. However, in practice, the ticket agency may not drop one channel due to customer satisfaction and expansion strategy etc.

4. Conclusions and future research

In this paper, we first discussed the limitations of the single channel policy and competitive pricing policy presented in previous studies. Then, we attained the equilibrium price (sales rebate) of the ticket agency and its downstream agent in Stackelberg game model, both under centralized and decentralized decision making process. At last, we focused on the coordination and existence condition of the dual-channel. The result shows, compared with centralized decision making, the optimal total profit and customer utility will decrease under decentralized decision making. In

this case, the dual-channel supply chain cannot be coordinated. We give some propositions for entities involved in the conflict: the ticket agency can interiorize the downstream agent or develop its own traditional channel agent; the downstream agent itself can open up an online channel. Through these policies, a decentralized decision making process can be turned into a centralized decision making process. There're also limitations in this paper. First, the model in this paper needs more consideration of effect on supply chain efficiency exerted by direct sales of airline companies (except brief explanation). Second, the values of some parameters cannot easily be attained in practice. This is also a common limitation of most related literatures. Third, we haven't covered all the characteristics of reservation tourism such as high fixed cost, low marginal cost, seasonal periodicity of demand, high requirement on timeliness of information etc. Future studies are expected to give more attention to these factors, to make the model closer to the real world as well as to solve the practical problems even better.

5. Acknowledgments

This research was supported by the National Social Science Foundation of China under Grant 08BJY115, the Social Science Key Foundation of Fujian Province of China under Grant 2007A006, NCET Foundation of Fujian Province of China 2007 and Tempus group of China.

References

1. Xiaoyuan Huang, Supply chain operations: coordination, optimization and control. Peking: Science press, 2007, pp.85-86, 104-110.
2. Kevin L. Webb, Managing channels of distribution in the age of electronic commerce. *Industrial Marketing Management*, Vol 31, pp. 95-102, 2002.
3. Swaminathan, J M, and S R Tayur, Models for supply chains in e-business. *Management Science*, Vol 49, pp. 1387-1406, October 2003.
4. Tsay, A, and Agrawal, N, Channel conflict and coordination in the e-commerce age. *Production and Operations Management*, Vol 13, pp.93-110, January 2004.
5. Chenhua Li, A pricing-game model for direct-retail dual channel based on channel-demand functions. *Journal of Zhongnan University of Economics and Law*, vol 54, pp.114-120, April 2009.
6. Tsay, A, and Agrawal, N, Channel conflict and coordination: an investigation of supply chain design. Working paper, Leavey School of Business, Santa Clara University, Santa Clara, CA, 1999.
7. Chunrong Guo, Gongyu Chen, and Zuchang Zhong, Review of research on supply chain with hybrid distribution Channels. *Foreign Economics and Management*, Vol 30, pp.22-27, September 2008.
8. Chiang, W. K. D. Chhajed and Hess J. D., Direct marketing, indirect profits: a strategic ananalysis of dual-channel supply-chain design. *Management Science*, vol 49, pp.1-20, January 2003.
9. Dongqing Yao and John J. Liu, Competitive pricing of mixed retail and e-tail distribution channels. *Omega*, vol 33, pp.235-247, 2005.
10. Kyle Cattani, Wendell Gilland, Hans Sebastian Heese, and Jayashankar Swaminathan, Boiling frogs: pricing strategies for a manufacturer adding a direct channel that competes with the traditional channel. *Production and Operations Management*, vol 15, pp.40-56, January 2006.

An Empirical Analysis of Participant Contribution and Duration of Participation in Electronic Brainstorming Communities

Li Chen • James Marsden • Zhongju Zhang

University of Connecticut

2100 Hillside Road, Unit 1041

Storrs, CT 06269

Email: {li.chen, jmarsden, john.zhang}@business.uconn.edu

Abstract

In today's dynamic business environment, companies are under tremendous pressure to become more innovative and maintain a steady stream of ideas that can lead to new and/or improved products/services. Many companies have devoted resources to exploring the possibility of capturing consumers' "collective intelligence" by providing electronic brainstorming communities (EBC) where individuals can share their ideas. The value of these open and voluntary EBCs depends largely on member's contribution level, the quality of the contributions, and their sustained participation. In this paper, we develop a theory that can help provide an understanding of: (1) what factors influence member idea submission level and quality, and (2) what factors influence the duration of a member's active participation. We provide preliminary findings of empirical data collected over two and a half years from the initiation of a pioneering brainstorming community. Our analyses demonstrate that the level of peer feedback and the responsiveness (speed) of sponsor company feedback have significant influences on member's contribution in an EBC. The sponsoring company's feedback, however, does not seem to influence member's contribution level.

Keywords: Brainstorming Communities, Idea Generation, Participant Contribution, Participation Duration

1. Introduction

Globalization has intensified business competition among firms. As a result, many firms are under pressure to maintain a continuing stream of new ideas and innovations (Björk and Magnusson 2009). Recently, many firms began pursuing consumers' "collective intelligence" by providing online platforms for people (typically current and potential consumers) to share ideas. Examples include Salesforce (IdeaExchange), Dell (Dell IdeaStorm), and Starbucks (My Starbucks Ideas). We define this approach of idea generation as "Electronic Brainstorming Communities (EBC)". In an EBC, the company can seek ideas on new technologies and products as well as on how to improve products and services in the future. The EBC community members participate by posting ideas, commenting on the ideas of others, offering idea ratings, etc.

EBCs integrate the sharing and commenting aspects of the GDSS (Group decision support systems), while taking advantage of Web 2.0 technology-based platform that enable interaction of very large numbers of participants without time and location limits. As a new tool of idea generation, EBCs can help move the sponsoring firms to a favorable position (Jeppesen and

Frederiksen 2006) by harnessing people's knowledge of innovation. However, the value of these open and voluntary EBCs depends largely on member's contribution level, the quality of the contributions, and their sustained participation. In this paper, we begin by developing a first theory that can help provide an understanding of: (1) what factors influence member idea submission level and quality, and (2) what factors influence the duration of a member's active participation. Through an empirical analysis using data collected over two and a half years from the initiation of a pioneering brainstorming community, we show that the level of peer feedback and the responsiveness (speed) of sponsor company feedback have significant influences on member's contribution in an EBC. The sponsoring company's feedback, however, does not seem to influence member's contribution level.

2. Theoretical Background

Electronic brainstorming communities (EBC) are a new form of group brainstorming facilitated by Web 2.0. Traditional brainstorming research has a long history. Osborn (1957) suggested that by using brainstorming, group members are able to generate more ideas and to increase the quality of ideas generated. Subsequent research on brainstorming focused on identifying various factors that influence the performance of brainstorming, including procedure, group size, and gender (Bouchard et al. 1974) and factors that inhibited the success of brainstorming such as free-riding and production blocking (Diehl and Stroebe 1987).

Traditional research in group brainstorming had the implicit or explicit assumption that participants are willing participants and contributors. However, this may not be the case in an EBC in which the sponsoring company has no direct link to participants. Although the literature of brainstorming has not extensively studied the issue of motivating and keeping participants, there are some previous studies on related application settings, including open source development (Lerner and Tirole 2002), online professional communities (Wasko and Faraj 2005), firm-hosted forums (Jeppesen and Frederiksen 2006) and "Internet-based voluntary technical support groups" for software problems (Moon and Sproull 2008). Our research contributes to the literature by specifically examining the effects of user interactions, peer feedbacks and the sponsoring firm feedback by using data collected over two and a half years from the initiation of a pioneering brainstorming community.

3. Theory and Hypotheses Development

Drawing from previous literature and from our initial understanding of the EBCs, we propose a research framework (Figure 1) detailing key relationships between various factors and the success and sustainability of an EBC - participant contribution and participant duration.

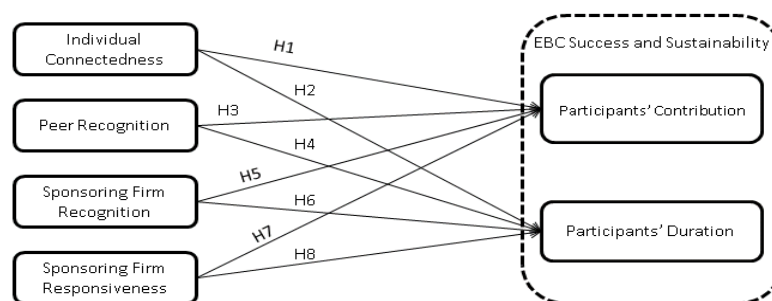


Figure 1: Research Framework on EBC Success and Sustainability

Individual connectedness EBCs usually involve hundreds of people, even thousands, resulting that participants may be more “densely connected” than other participants. Previous research shows that individuals with high level of connectedness in terms of centrality have higher commitment to a community and are more easily exposed to various forms of information useful for further contributions (Grewal et al. 2006). In addition, members may drop out of a community when they find it too difficult to be involved in the type of interaction they seek (Butler 2001). This leads to our first two hypotheses:

Hypothesis 1: Individual connectedness positively influences participants’ contribution in EBC.

Hypothesis 2: Individual connectedness positively influences participants’ duration in EBC.

Peer recognition Lerner and Tirole (2002) argued that “reputation gains and signaling” may help explain individuals’ contribution behavior where monetary rewards are absent. Therefore, we draw a positive link between peer recognition and a participant’s enhanced contribution. Meanwhile, we expect that participants who have a higher level of peer recognition will stay longer in an EBC. Thus, we set forth the following hypotheses:

Hypothesis 3: Peer recognition positively influences participants’ contribution in EBC.

Hypothesis 4: Peer recognition positively influences participants’ duration in EBC.

Sponsoring firm recognition EBC participants can also receive recognition from the sponsoring firm. Again, reputation and signaling theory suggest the likelihood of a positive link between sponsoring firm recognition and enhanced participant contribution (Jeppesen and Frederiksen 2006). In addition, Moon and Sproull (2008) suggests that positive feedback enhances the duration of participation while negative feedback shortens such duration. This results in the following hypotheses:

Hypothesis 5: Sponsoring firm recognition positively influences participants’ contribution in EBC.

Hypothesis 6: Sponsoring firm recognition positively influences participants’ duration in EBC.

Sponsoring firm’s responsiveness We also note that the speed of this recognition/feedback can also be an important factor influencing participant future behavior. Prior research has suggested that timely feedback can be an important factor in group decision making (Xanthopoulos et al. 2000) and in group goal-setting (Fried and Slowik 2004). On the other hand, slow responsiveness can build a negative image to make people leave early. Thus, we posit the relevance and importance of the following two hypotheses:

Hypothesis 7: Sponsoring firm responsiveness positively influences participants’ contribution in EBC.

Hypothesis 8: Sponsoring firm responsiveness positively influences participants’ duration in EBC.

4. Research Context and Data

In this paper, we use Dell IdeaStorm for our empirical analysis. Formally initiated on February 16th, 2007, Dell IdeaStorm was one of the first pioneering EBCs. The platform of Dell IdeaStorm was developed from Salesforce.com which allows online community members to submit, discuss and promote and demote ideas, in this case, related to Dell’s current and future products and services.

To test the hypothesis mentioned above, we collected data from Dell IdeaStorm using an automated agent and parsing of the HTML pages for each individual idea submitted from the system's initiation on February 16, 2007 through August 13, 2009. This yielded a total of 11894 ideas from 6143 different individuals (community ID's) were submitted to Dell IdeaStorm. For each idea, data collection included the community ID of the submitter, the time the idea was submitted, the content textual of the idea, the number of comments submitted on the idea, the number of commenters, and status tag (if any) assigned to the idea by Dell and the date each status tag was assigned. We define Dell's status tags into three categories: positive tags such as "Implemented" and "Partially Implemented" tags, negative tags such as "Not Now" and "Not Likely" tags, and review tags such as "Reviewed" and "Under Review".

5. Results

To test H1, H3, H5 and H7, we separate our dataset into multiple time periods (eight weeks), which allows us to explore the dynamic interaction. We choose eight weeks so that the time period is neither too long nor too short. We also try other lengths such as four weeks and 12 weeks. We use the number of new ideas submitted in the current period as the dependent variable. Negative binomial regression model rather than Poisson regression model is used because the later is limited by its implicit assumption of the same variance and mean (Greene 2003, p. 744). Our model is formulated as follows:

$$E(Y_{i,t} = y_{i,t} | X_{i,t} = x_{i,t}) = \exp(X_{i,t}'\beta_{i,t}) \quad (1)$$

where $X_{i,t}$ refers to the set of independent variables. In our paper, we measure individual connectedness by the normalized degree centrality, peer recognition by number of comments and comments from dell members per idea per period, sponsoring firm recognition by number of positive, negative and review tags per idea per period, and sponsoring firm responsiveness by log of average responsiveness, etc. Note that we compute the variables related to peer and sponsor recognition in the format of per idea and per unit of time to control the variation due to the scale of ideas submitted by and duration of a participant. Correlation analysis on explanatory variables does not show a strong multi-collinearity among them.

We use PROC GENMOD in SAS to run the negative binomial regression. Table 1 summarizes the statistical results. In Model 1, we only use peer's recognition and in Model 2 we only use sponsoring firms' recognition. We include all variables in Model 3.

Table 1: Results of Negative Binomial Regression Model

	Model 1	Model 2	Model 3
Intercept	-4.8377 (1.1339)**	-1.1149 (1.1679)	1.8204 (1.2634)
Avg_Norm_Centrality	88.8516 (70.5470)	135.6127 (62.6344)*	11.5366 (64.9393)
Comments_perIdea_perPeriod	0.2083 (0.0473)**		0.2071 (0.0434)**
Comments_Dell_perIdea_perPeriod	4.1957 (1.8376)*		3.4998 (1.5673)*
PosTags_perIdea_perPeriod		36.6184 (15.4457)*	8.4770 (14.2421)
NegTags_perIdea_perPeriod		12.4217 (13.0748)	4.7611 (12.3169)
RevTags_perIdea_perPeriod		-12.4044 (9.0161)	-15.5662 (9.0259)
Log_Avg_Response		-1.7656 (0.1758)**	-1.7895 (0.1753)**
Stay	0.0315 (0.0034)**	0.0585 (0.0042)**	0.0572 (0.0041)**
Log_Size	0.2896 (0.1533)	0.7968 (0.1315)**	0.3684 (0.1499)*
LogLikelihood	541.9678	581.4348	601.228

Note: ** Significance at 1%, * Significance at 5%

From the results, we have several major findings. First, the coefficient of participants' normalized centrality has the expected sign but it is not significant in both model 1 and model 3. Thus, H1 is not supported. This suggests that being "central" in the EBC-based network does not necessarily motivate members to contribute ideas. Second, we observe that the both coefficients of peers' recognition and sponsoring firm recognition (positive status tags) are positive and significant. Thus, H3 and H5 are supported. This finding is consistent with the reputation theory, which implies that receiving more recognition from the peers and sponsoring firm do motivate members to continually contribute. However, the coefficients of negative and review tags per idea per period are both insignificant. Finally, we notice that the average waiting time has a significant and negative influence in both Model 2 and 3. This confirms the importance of quick response from sponsoring firm on participant contribution of ideas. Thus, H4 is supported.

The analyses on H2, H4, H6 and H8 are in progress and will be reported later.

6. Conclusion

Web 2.0 platforms enable firms to use EBC's to engage large numbers of participants in collectively enhancing the innovation process. In this paper, we studied individual contributions and participation duration by developing a theory relating them to user interactions, peer feedback and the sponsoring firm feedback. Our empirical results supported the hypothesized positive influence of the responsiveness of sponsoring firm feedback as well as the peer feedback. There are several important managerial insights. First, companies need to develop an enhanced feedback processes to facilitate peer feedback. Second, the sponsoring companies need to discover a more efficient way to review ideas submitted to EBC in a timely manner.

Selected References

1. Björk, J., and Magnusson, M. "Where do Good Innovation Ideas Come From? Exploring the Influence of Network Connectivity on Innovation Idea Quality?" *Journal of Production Innovation Management* (26:6), 2009, pp. 662-670.
2. Butler, S. "The Role Membership Size, Communication Activity, and Sustainability: A Resource-based Model of Online Social Structures," *Information Systems Research* (12:4), 2001, pp. 346-362.
3. Greene, W. (eds.) *Econometric Analysis*, Prentice Hall, 2002.
4. Jeppesen, B., and Frederiksen, L. "Why do Users Contribute to Firm-hosted User Communities? The case of computer-controlled music instruments," *Organization Science* (17:1), 2006, pp. 45-64.
5. Moon, J., and Sproull, S. "The Role of Feedback in Managing the Internet-based Volunteer Work Force," *Information Systems Research* (19:4), 2008, pp. 494-515.
6. Osborn, A. F. (eds.). *Applied imagination: Principles and procedures of creative problem solving*, Charles Scribner's Sons, New York, NY, 1957.
7. Wasko, M., and Faraj, S. "Why should I share? Examining social capital and knowledge contribution in electronic networks of practice," *MIS Quarterly* (29:1), 2005, pp. 35-57.

Predictive Power of Internet Search Data for Stock Market: A Theoretical Analysis and Empirical Test

Liu Ying, Lv benfu, Peng Geng, Zhang Chong and Li Tianqi
Management School, Graduate University of Chinese Academy of Sciences
liuy218@126.com

Abstract

The Internet search data, recording hundreds of millions searchers' concerns and intends, can provide necessary data basis for the study of market transaction behaviors. In this paper, taking the stock market as a research object, we firstly establish a theoretical framework to reveal a lead-lag relationship between search data and stock market based on micro-perspective of investors' behaviors. Then according the meanings of search keywords and cross-correlation analysis, we develop three types of composite search index: investor action index, market condition index, and macroeconomic index. The empirical test indicates cointegration relationship between search index and the annualized yield of Shanghai composite index. In the long-term trend, each additional one percentage point increase in the three types search indices separately, the annualized yield will increase 0.22, 0.56, 0.83 percentage points in the next month. Furthermore, Granger causality test shows that the search indices have significant predictive power for the annualized yield of Shanghai composite index.

Keywords: Internet Search Data, Stock Market, cross-correlation, cointegration analysis, Granger causality

1. Introduction

Investors' attention represents the interest and expectation in an asset. Traditional studies use the proxy variables to measure the investors' attention, such as the number of news, advertising cost, etc. While the development of Internet provide a direct metric for investors' attention, that is Internet search volume data. Search engine, as the most general tools to get information from internet, connects information resources and user needs, helps users to get information. While at the same time, it also records their searching behavior. Based on hundreds of millions of searchers' records, the Internet search data can reflect the users' concerns and needs, mapping the user behavior in real life trends and patterns. Therefore, this data resources are gradually much accounted, some newly research indicate that: there are high correlation between internet search data and many societal or economical behaviors. For example, the flu monitoring model based on search data can not only better survey the trend of influenza epidemic, but also the timeliness can also be two weeks ahead of traditional investigation methods(Ginsberg, 2009); In economical area, search data can forecast the current sales of typical industry(Choi, Varian, 2009) and survey the rate of unemployment(Askatas, 2009).

However, these studies mostly focus on testing the statistical indicators with a substantial lag, and there are few studies on testing instantaneity market predicting and sufficiently revealing the predicting mechanization. Stock market is a typical instantaneity market, and the percentage of online transaction in total amount of market transactions has come up to 80%(Ma Guangti, 2009), so it has a certain universality of the stock transaction behavior reflected by search data. In this paper, we firstly setting up a theoretical frame to systematically carding the relationship between

Internet search data and stock market; Secondly, we introduce how to identify leading keywords ahead of stock market and how to combine keywords to search index with economical meanings; lastly we empirically test the predictive power of Internet search index for Stock Market.

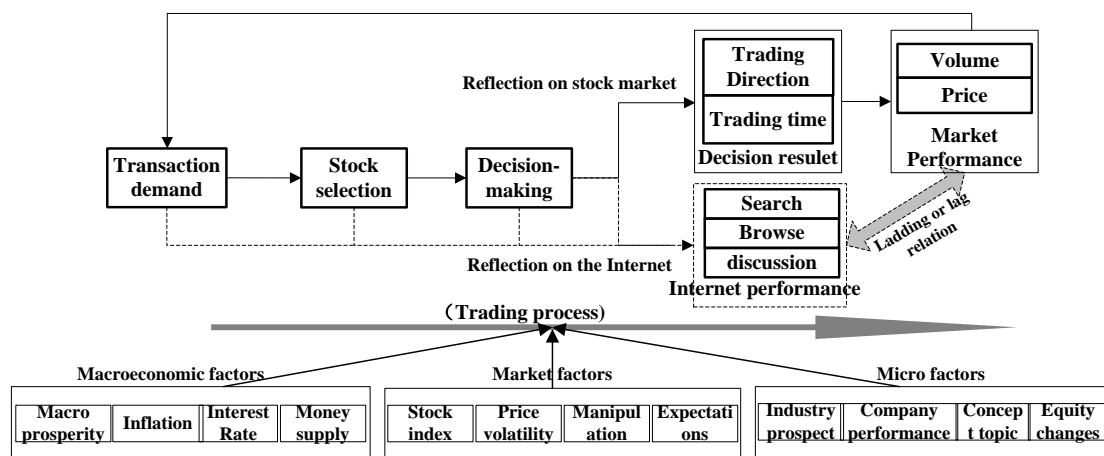
2. Literature Review

From the perspective of research object, there are two aspects: the first one is about epidemic symptomatic prediction. A good instance is Ginsberg, Mohebbi, Patel, Brammer, Smolinski and Brilliant (2009) using Internet search data to detect influenza epidemics, and their new forecast method can improve the timeliness compared to the traditional surveillance method. The model was also used to Google Flu Trend (google.org/flu trends), a new product by Google Inc. for flu activity estimation. Following this work, Jurgen A. Doornik (2009) extended it to autoregression model with calendar effects, and improved the prediction accuracy. However, both models are powerless in predicting the turning point when a new flu outbreak in April 2009.

Another one is prediction in economical area. Hyunyoung Choi and Hal Varian(2009) did an empirical test on American industry of retail trade, cars, buildings and travelling, adding keywords searches as new factor to traditional autoregression model, finding that the predicting precision of four industries have been obviously improved, and the predicting precision of the industry of automobile & components had most improved 18%.

3. Theoretical Analysis and Conceptual Framework

We create a conceptual framework from the aspect of investors' behavior as diagram 1 shows, theoretically analyzing the relationship between Internet data and stock market.



Note: The full line reflects investors' behavior in stock market, dotted line reflects investors' behavior in internet

Figure 1 the conceptual framework of the relationship between stock market and Internet

The basic idea of the conceptual framework is that investors' behavior can be reflected by stock market and Internet, and the reflection is incarnated as variations of transactions and price in stock market and variations of index such as searching and browsing in Internet. Because time delays reflected in the two markets are different, so there is a lead-lag relationship between search data and stock market. Identifying and using the leading index in Internet can help us to predict the stock market trend.

4. Empirical Analysis and Test

4.1 Comparison between Internet search data and stock yield

Search data origin from Google insights (www.google.com/insights/search). The stock data origin from Wind consulting financial database, research sample is closing price in Shanghai composite index (code: 000001) from January, 2004 to November, 2009.

Stock annual yield: $y_t = 100 \cdot \ln(P_t/P_{t-12})$, y_t is yield in Time t , P_t is closing price in Time t ;

Search annual rate of change: $x_t = 100 \cdot \ln(S_t/S_{t-12})$, S_t is search attention in Time t ;

4.2 Keyword choosing and judging

We choose 131 relevant keywords according to influence factors of stock transaction process. In order to appraise the relationship between search attention variation and stock yield, we attach 2 parameters to every keyword: leading order and relativity. If leading order >0 , then it represents leading relationship; if leading order $=0$, then it represents synchronous relationship; if leading order <0 , then it reflects hysteretic relationship. Relativity represents the similarity between rate of change curve of search attention and stock yield curve, and the relativity is higher, they are more similar. We use time difference relevance to compute leading order and relativity. The formula to compute cross correlation coefficient is as follows:

$$r_l = \frac{\sum_{t=1}^n (x_{t-l} - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^n (x_{t-l} - \bar{x})^2 \sum_{t=1}^n (y_t - \bar{y})^2}}, l = 0, \pm 1, \pm 2, \dots, \pm L$$

In this formula, r_l : the relativity whose time delay is l ; y : Shanghai composite index annual yield, \bar{y} is the mean; x : annual rate of change of keywords search, \bar{x} is the mean; l is the order x leads. The time order whose relativity is highest is leading order, which is the relativity between them.

4.3 Synthesis of keyword index

There are 2 methods to set weight in Academia, one is method of system assessment, the other is empowering according to the relativity. In this paper, we combine the two methods together, then divide antecedents into 3 categories, composing 3 type of index: investor behavior index, market quotation index and macro situation index.

4.4 Cointegration Analysis of keywords index and Shanghai composite index yield

In this paper choosing Shanghai composite index annual yield(y) as dependent variable, investor behavior index(x_1), market quotation index(x_2) and macro situation index(x_3) as independent variable. Firstly, use ADF Test to inspect the stationarity of every index.

Next use Co-integration Test to test whether there was long-time stable relationship between dependent variable and independent variable: firstly, erect regression equation of independent and dependent variables. $y_t = c + \beta_1 x_{1,t-1} + \beta_2 x_{2,t-1} + \beta_3 x_{3,t-1} + \varepsilon$ ①

Secondly, take residual error of the equation for ADF Test. The results are showed in Table 3:

Table 1: Regression Results and Co-integration Test

		independent variable t-2	independent variable t-1	independent variable t	independent variable t+1
c		-4.78	-5.94**	-6.64**	-6.03*
β_1		0.27**	0.22**	0.20*	0.15
β_2		0.46***	0.56***	0.59***	0.64***
β_3		1.19***	0.83***	0.64**	0.08
Adj-R ²		0.89	0.92	0.90	0.84
F-stat		158.10	232.21	183.11	99.33
AIC		8.88	8.53	8.76	9.29
Residual Stationarity	ADF	-2.94	-5.29	-3.80	-2.06
	1%	-2.62	-2.61	-2.61	-2.61
	5%	-1.95	-1.95	-1.95	-1.95
	10%	-1.61	-1.61	-1.61	-1.61
	results	Stationary	Stationary	Stationary	Stationary
Results		Cointegration	Cointegration	Cointegration	Cointegration

Note: *p<.1, **p<.05, ***p<.01.

From the aspect of degree of fitting, F value, criterion AIC, equation 1 is the best, and Co-integration equation is $y_t = -5.94 + 0.22x_{1,t-1} + 0.56x_{2,t-1} + 0.83x_{3,t-1}$ ②

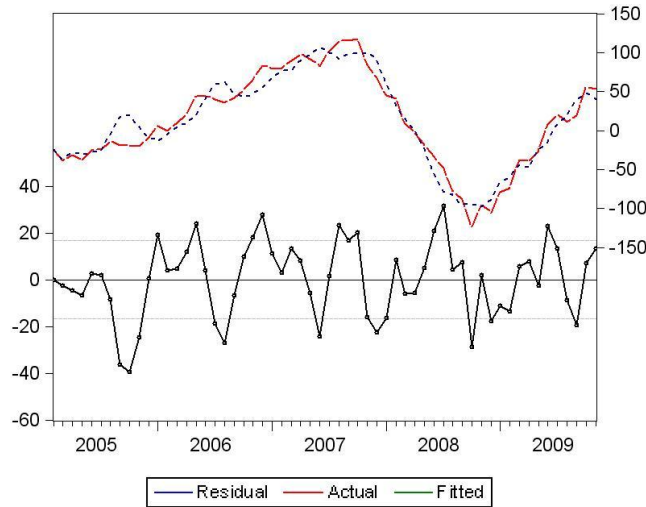


Figure 2: the long run relationship between search index and Shanghai composite index annual yield.

We erect ECM(Error Correction Model) including short-term factor, as shown in equation ③. The coefficient of ECM_{t-1} is -0.50, indicating that when independent variable drifts long-time equalization, it can be pulled to balanced state back.

$$\Delta y_t = 0.60 - 0.50ECM_{t-1} + 0.34\Delta x_{1,t-1} + 0.19\Delta x_{2,t-1} + 0.45\Delta x_{3,t-1} \quad (0.74) \quad (0.00) \quad (0.06) \quad (0.21) \quad (0.33) \quad ③$$

$$adj-R^2: 0.31 \quad F-stat: 7.15 \quad (prob. 0.00)$$

$$ECM_{t-1} = y_{t-1} - 0.22x_{1,t-2} - 0.56x_{2,t-2} - 0.83x_{3,t-2} + 5.94$$

5. Granger causality Test of keywords index and Shanghai composite index yield

When there are Co-integration between dependent variable and independent variable, there is Granger causality between them. Granger causality test could reveal whether one variable could predict another. We use ECM as followed:

$$\Delta y_t = \varphi + \lambda ECM_{t-1} + \sum_{i=1}^p \alpha_i \Delta y_{t-i} + \sum_{j=1}^q (\gamma_{1j} \Delta x_{1,t-j} + \gamma_{2j} \Delta x_{2,t-j} + \gamma_{3j} \Delta x_{3,t-j}) + \mu_t \quad (4)$$

In the equation, ECM_{t-1} is the same to equation (3), λ is coefficient; α_i 、 γ_{1j} 、 γ_{2j} 、 γ_{3j} is coefficient of every variable; p 、 q is lag order; μ_t is stochastic disturbance term.

In the test, we erect VEC(Vector Error Correction) to test Granger causality between variables, and ascertain lag order according to Criterion AIC and FPE suggested by Hsiao(1981).As a result, x_1 、 x_2 、 x_3 is the Granger causality of y separately to 5%、1%、10% significant level, their joint survey is notable; y is the Granger cause of x_1 , x_2 at 0.1 significant level, but can't cause x_3 .

6. Economic Explanation

6.1 Long run relationship between search index and Shanghai composite index annual yield

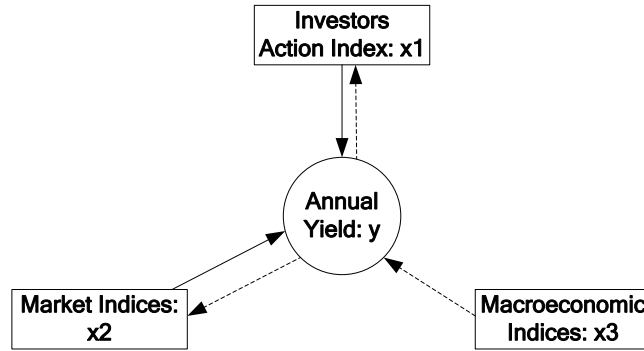
Intercept: maturity of the stock market. In equation (2), intercept is -5.94, which means when annual rate of change of search index is 0, Shanghai composite index annual yield is -5.94%, that is Shanghai composite index closing price will fall 5.94 percentage relative to last year. It can be concluded that our stock market is nonzero sum, and it takes short-time and speculative transactions as principal.

Coefficient: contribution margin of search index. Coefficients in the equation are all positive, which means there is positive correlativity between search index and Shanghai composite index yield. Macron situation index $x_3(0.83) >$ market quotation index $x_2(0.56) >$ investor behavior index $x_1(0.22)$, indicating that the prospects for macron situation most affects stock market, the second is investors' prospects for market quotation, and new private investors' prospects and behaviors less affects stock market.

Shortage term fluctuation: equation (3) describes the shortage term fluctuation, and the coefficient of ECM term is -0.50($p < .1$) that means when Shanghai composite index annual yield deviates from long-term trends, it will be pulled to stable situation by opposite power.

6.2 Predictive Power of Internet Search Data for Shanghai composite index annual yield

Granger causality test indicates that the causal relation between search index and Shanghai composite index annual yield have different characteristics in different keywords, the causal relation between Shanghai composite annual yield and investor behavior index, market quotation index is bidirectional, and the significance of search index is better, while macron situation index only uniaxially lead to Shanghai composite index annual yield, whose significance is worse($p < .1$)(Diagram 4)



Note: Granger causation leads to Granger results; full line $p < .05$, and broken line $p < .1$
 Figure 3: The causal relation between search index and Shanghai composite index

7. Conclusions, Limitations, and Future Work

This paper theoretically and empirically analyze the correlativity and predictive ability between search data and stock market. However, there are shortage in this paper, although net search has universality, it isn't the only channel to get information, it may leave out some valuable information. If the initial keywords sample is not comprehensive, it may affect the reliability and effect. The method to get initial keywords, combining net search with other indices in Internet, Internet index with traditional index are the future research.

8. Acknowledgment

This research was supported by the National Natural Science Foundation of China under Grant 70972104, the National Natural Science Foundation of China under Grant 70772103, Beijing Natural Science Foundation of China under Grant 9073020, and Chinese Academy of Sciences president of the Fund under Grant O65001J.

References

- [1] Ginsberg, Mohebbi, Patel, Brammer, Smolinski and Brilliant, 2009, *Detecting influenza epidemics using search engine query data* [J], Nature 457, 1012~1014.
- [2] Jurgen A. Doornik, 2009, *Improving the Timeliness of Data on Influenza-like Illnesses using Google Search Data* [J], Working paper, [http://www.doornik.com/flu/Doornik\(2009\)_Flu.pdf](http://www.doornik.com/flu/Doornik(2009)_Flu.pdf).
- [3] H Choi, H Varian, 2009, *Predicting the Present with Google Trends* [C], Technical Report, Google Inc.
- [4] N Askitas, and KF Zimmermann, 2009, *Google Econometrics and Unemployment Forecasting* [J]. Applied Economics Quarterly, 55(2), 107~120.
- [5] Lynn Wu, and Erik Brynjolfsson, 2009, *The Future of Prediction: How Google Searches Foreshadow Housing Prices and Sales* [J], Working paper.
- [6] Liu Fan, Liu Ying, and Lv Benfu, 2010, *The General Model of Influenza Epidemics Surveillance Using Search Engine Data* [J]. Working paper.
- [7] Fisher I., 1930, *The Theory of Interest* [M], Mcmillan, New York.
- [8] Tobin, J, 1969, *A General Equilibrium Approach To Monetary Theory* [J], Journal of Money, 1, 15~29.
- [9] Spyrou, S.I., 2004, *Are Stocks a Good Hedge against Inflation? Evidence from Emerging Markets* [J]. Applied Economics, 36, 41~48.
- [10] Westerlund, J., 2005a, *A Panel CUSUM Test of the Null of Vointegration* [J]. Oxford bulletin of Economics and Statistics, 67, 231~363.

XBRL and Interoperability of Financial Statements in the U.S.

Hongwei Zhu

College of Business and Public Administration
Old Dominion University
hzhu@odu.edu

Harris Wu

College of Business and Public Administration
Old Dominion University
hwu@odu.edu

Abstract

In the wake of global financial crisis, there is a pressing need for improving transparency and interoperability of the financials of public companies. XBRL and XBRL taxonomies have the potential of helping us accomplish this objective. In the U.S., the SEC has mandated that all publicly listed companies must file their financial statements using XBRL and the US GAAP taxonomy beginning mid 2009 to late 2014 according to a phased-in schedule. Are the XBRL-based financial statements interoperable? We address this question by analyzing all the annual XBRL financial statements filed to SEC as of this February. We find that the statements still lack interoperability, which is partly caused by issues related to the GAAP taxonomy and misuse of the taxonomy by companies. On average, only 37% data elements are directly comparable between a pair of statements. Our timely findings have practical implications that will ultimately help improve the quality of financial data.

Keywords: XBRL, GAAP, interoperability, data quality, long tail

1. Introduction

Publicly traded companies must disclose their financials quarterly and annually to regulators and investors. In United States, companies file their financial statements to the Securities and Exchange Commission (SEC). In recent years, financial statements are usually filed in digital format as PDF or HTML files. Although the digital filings are much better than the traditional paper filings, they are not easy to use due to substantial challenges in processing unstructured data. For example, it is often desirable to compare several companies on a set of metrics such as assets and net income. No tools are available to accurately and reliably automate such comparisons. In other words, the financial statements are not interoperable and cannot be conveniently analyzed using automated tools. To alleviate this problem, the filings are often semi-manually processed to have the data elements extracted and stored into structured databases. This process is inefficient and error-prone.

Extensible Business Reporting Language (XBRL) has the potential to address the interoperability problem (XBRL International 2006). Financial statements in XBRL format can be easily parsed using software tools because of the syntactic uniformity of XBRL. Furthermore, XBRL can be used to define a taxonomy that specifies a set of data elements commonly used in financial statements. If all companies report using common elements specified in a standard taxonomy, it would be easy to compare different companies' financial data.

In U.S. the SEC has adopted the US GAAP Taxonomy, developed by a national consortium, as the base taxonomy for financial reporting. In addition to the data elements specified in the taxonomy, companies are allowed to introduce their own custom elements to produce their financial statements. This gives companies more flexibility, which can lead to financial statements that more accurately reflect company financials. For example, a company may possess various types of assets that are not captured in the standard taxonomy. If only standard

elements are allowed, all these types of assets will have to be aggregated as “other assets”, losing detailed information useful to investors. To avoid this problem, companies are allowed to introduce custom elements by extending the standard taxonomy. With custom elements, all the special types of assets can be properly represented in financial statements. However, it has been recognized that extensibility can have adverse effects on interoperability of financial statements from different companies (Debreceeny et al. 2005).

Starting June 15, 2009, all companies with a public common equity float greater than \$5B must submit XBRL filings to the SEC. XBRL will be used by all public company filings in the U.S. by October 31, 2014. Has the use of XBRL and GAAP taxonomy made the filings interoperable? Motivated by this question, we analyzed all the official XBRL filings received by SEC up to February 26, 2010, when this paper is written. We identify issues in how companies use or misuse the standard taxonomy as well as issues related to the taxonomy itself.

2. Research Method

2.1 Data Acquisition, Processing, and Analysis

We have developed a set of methods and computer tools to support data acquisition, processing, and analysis of this research. A data acquisition agent monitors the RSS (Really Simple Syndication) Feed at SEC and other sites to obtain company filings submitted to the SEC. The acquisition agent downloads the financial statements and the accompanying taxonomy extensions into a local filing repository. The ETL (Extract, Transform and Load) program parses the files downloaded and loads the extracted data into a relational database. Stored SQL procedures and other programs are used to analyze the data stored in the relational database. While we are continuously downloading new filings as they come in, the results reported here include all XBRL filings to the SEC as of February 26, 2010. The dataset includes 1,231 filings submitted by 483 companies. The GAAP taxonomy is also processed to load the specified elements into the relational database. In this paper, we limit our study to the annual statements (i.e., 10-K). For companies with revised 10-K, we analyze their latest revised filings. This limited dataset includes 261 statements, each from a different company.

In XML and XBRL, a data element is identified by its name and name space. When a company extends the standard GAAP taxonomy by introducing new data elements, the elements have a name space unique to the company, typically labeled by the company’s stock symbol. Thus even if two companies use the same name for their data elements, the elements are different because they have different name spaces. Their statements may contain elements from namespaces other than GAAP or the company’s custom namespace. However, most such elements are not essential financial information (such as comments or addresses). Therefore we focus on the elements from GAAP and the custom namespaces in this paper.

2.2 Metric Definition

We introduce a number of metrics as interoperability indicator and factors. Before defining the metrics, let us first introduce several notations. Let $D=\{d_i \mid d_i \text{ is a financial statement, } i=1 \text{ to } n\}$ be a set of financial statements. Let $|d_i^g|$ be the number of GAAP elements used in d_i , $|d_i^c|$ be the number of custom elements introduced by a company that submitted d_i , and let $|d_i|$ be $|d_i^g|+|d_i^c|$.

The *interoperability* between a pair of statements is based on the common data elements used. This measures the amount of information that can be compared or exchanged (Daclin et al. 2006). Given two statements d_i and d_j , their interoperability ($I_{i,j}$) can be defined as:

$$I_{i,j} = \frac{|d_i \cap d_j|}{\sqrt{|d_i| |d_j|}}$$

The pair-wise interoperability for D is defined as the mean of pair-wise interoperability among all pairs. The pair-wise interoperability is important when investors and analysts compare two companies' financial statements against each other. When analyzing k companies' statements at the same time, the k -interoperability can be defined as:

$$I_{i_1, \dots, i_k} = \frac{|d_{i_1} \cap \dots \cap d_{i_k}|}{\sqrt[k]{|d_{i_1}| \dots |d_{i_k}|}}$$

The k -interoperability of D can be defined as the mean of the k -interoperability among all k -tuples. In this paper we will limit our discussion to pair-wise interoperability.

Several factors affect interoperability. One factor is *standard conformity*. For a given statement d_i , its *standard conformity* can be defined as $C_i = |d_i^s| / |d_i|$. We notice that custom elements are sometimes introduced unnecessarily when equivalent elements already exist in the GAAP taxonomy. As a first-order approximation, we count a custom element as a duplicate if the element name is identical to or a permutation (such as CashDividends and DividendsCash) of an existing element in the GAAP taxonomy. The *duplication score* for statement d_i is $DUP_i = |d_i^d| / |d_i^c|$, where d_i^d is the number of duplicate custom elements. In our ongoing research, we will refine the identification of duplicate elements by analyzing the textual and contextual similarity between custom elements and standard elements. Another factor is the usage of deprecated elements. The GAAP taxonomy includes 346 deprecated elements, which are not recommended to use. We can use d_i^o to denote the set of deprecated elements used in d_i . The *deprecation score* for d_i is $DEP_i = |d_i^o| / |d_i^s|$.

3. Empirical Findings

3.1 Element Usage

The GAAP taxonomy specifies a total of 13,452 data elements, among which 2,653 are abstract and 346 are deprecated on January 31, 2009. The number of concrete elements can be used in financial statements is 10,799, of which 10,537 are active (not deprecated).

All the 261 10-K statements used the GAAP taxonomy as the base taxonomy. For each statement, we identify data elements specified in the GAAP taxonomy and those introduced by the filing company. Overall, the statements utilized 2083 GAAP elements and 4403 custom elements, among which 1357 GAAP elements and 351 same-named custom elements were utilized in more than one statement. Generally, more taxonomy elements were used than custom elements in each statement. On average, a statement used 129 elements from the GAAP taxonomy and 20 custom elements. The distributions of number elements used are shown in a box plot in Figure 1.

It is useful to look at the usage frequencies of the GAAP elements and custom elements. An element can appear in a company statement more than once. For the purpose of interoperability analysis, we use binary counting method so that the usage frequency of an element is the # of companies that have used the element. In Figure 2, the Y-axis is the usage frequency of an element, and X-axis is the frequency rank. For company-introduced elements, we treat the same-named elements used by different companies as the same, disregarding the name space. Both GAAP and custom elements have a long-tail distribution in usage. Some elements are used

frequently, but most of the elements are only used in a small number of company statements. Only one element, “Assets” from the GAAP taxonomy, was used by all companies.

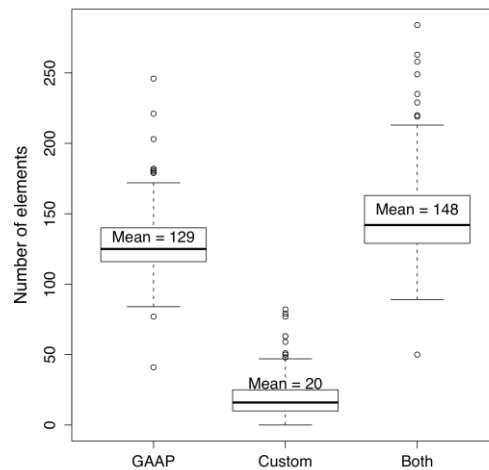


Figure 1. Number of elements used in 10-K statements

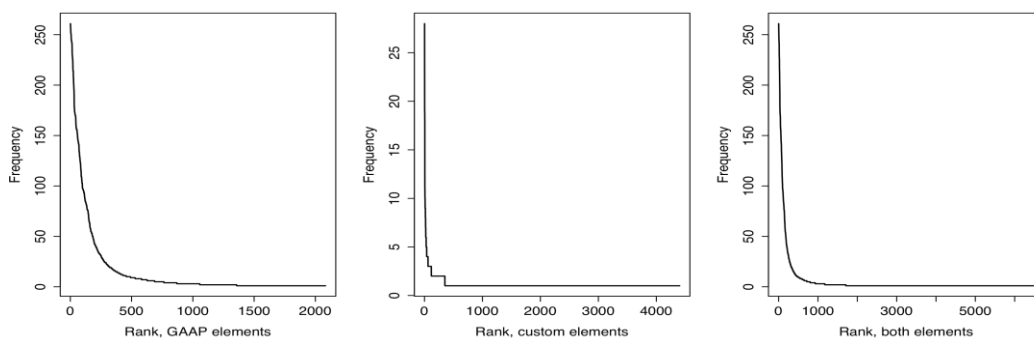


Figure 2. Use frequencies of GAAP taxonomy elements and custom elements

3.2 Interoperability

Out of the 261 statements, we computed pair-wise interoperability for 33390 ($261 \times 260 / 2$) pairs of statements. The first column of Table 1 shows a summary of the pair-wise interoperability. The highest interoperability score is 0.7646. On average, the interoperability score is only about 0.372. That is, investors can conveniently compare only about 37.2% of the financial information from two companies’ statements in XBRL.

	Interoperability	Interoperability if all elements are standardized	Interoperability if only GAAP elements are used
Min	0.1033	0.1033	0.1266
Max	0.7646	0.8261	0.8655
Mean	0.3724	0.3732	0.4250
Median	0.3798	0.3809	0.4340
Stand deviation	0.0837	0.0839	0.0859

Table 1. Statistics of interoperability among 10-K statements

The usage of duplicate or deprecated elements has a negative impact on interoperability. If all elements are standardized, i.e. all element with identical or permuted names are considered equivalent, the interoperability can be improved. The second column of Table 1 shows the results in this scenario. The interoperability score for the whole dataset can be improved to 37.3%. While the improvement is relatively minor, keep in mind that our preliminary approach of identifying equivalent elements cannot identify all potential equivalent elements in the statements.

While allowing flexibility, the usage of non-standard elements certainly affects interoperability. Many custom elements extend GAAP elements to allow for more detailed, company-specific reporting. If investors are not going to consider company-specific elements when comparing companies' financial statements, the interoperability can be computed based on GAAP elements only. The results for this scenario are reported on the 3rd column of Table 1. The interoperability score for the whole dataset is about 43%, when custom elements are excluded.

4. Conclusion

Prior research has attempted to identify various quality issues in XBRL financial statements (Boritz et al. 2008a; Boritz et al. 2008b; Chou 2006; Zhu et al. 2009). However, they all examined statements in an earlier experimental program. In addition to using most recent official XBRL statements, we have defined a metric to systematically measure interoperability of these statements. If an investor looks at two companies' statements, on average only 37% of the reported data can be compared head-to-head. The interoperability can be improved if companies adopt and extend the GAAP taxonomy more carefully, avoiding duplicate or deprecated elements. The interoperability can also be improved if common custom elements are incorporated into the GAAP taxonomy. If an investor looks at two companies using the criteria from the GAAP taxonomy only, the interoperability among company-reported data is around 43%. Companies seem to have a lot of freedom in choosing GAAP elements in their annual financial statements. Furthermore, the large portion of GAAP taxonomy unused may have contributed to low interoperability among company statements.

We are doing data analysis based on industry, and will report industry-based results in the future. We will also report k-interoperability results, which are useful for situations where investors would like to compare more than two companies at the same time. In our ongoing research, we are closely examining the financial statements trying to gain deeper insights on why companies adopt different sets of elements from the GAAP taxonomy. We plan to conduct interviews with the reporting companies and accounting firms to further understand how interoperability and readability of XBRL statements can be improved. We are also exploring how companies can collaborate in filings (Wu and Gordon 2004) to improve interoperability.

References

1. Boritz, E.J., and No, W.G. "Auditing an XBRL Instance Document: The Case of United Technologies Corporation," University of Waterloo, 2008a.
2. Boritz, E.J., and No, W.G. "SEC's XBRL Voluntary Program on Edgar: The Case for Quality Assurance " in: SSRN: <http://ssrn.com/abstract=1163254>, 2008b.
3. Chou, K.H. "How Valid Are They? An Examination of XBRL Voluntary Filing Documents with the SEC EDGAR System," in: The 14th International XBRL Conference, Philadelphia, USA, 2006.

4. Daclin, N., Chen, D., Vallespir, B.: Enterprise interoperability measurement – Basic concepts, Enterprise Modeling and Ontologies for Interoperability, Luxemburg, 2006.
5. Debreceeny, R.S., Chandra, A., Cheh, J.J., Guithues-Amrhein, D., Hannon, N.J., Hutchison, P.D., Janvrin, D., Jones, R.A., Lamberton, B., Lymer, A., Mascha, M., Nehmer, R., Roohani, S., Srivastava, R.P., Trabelsi, S., Tribunella, T., Trites, G., and Vasarhelyi, M.A. "Financial Reporting in XBRL on the SEC's EDGAR System: A Critique and Evaluation," Journal of Information Systems (29:2) 2005, pp 191-210.
6. XBRL International "Extensible Business Reporting Language (XBRL) 2.1," XBRL International, 2006.
7. Wu, H. and Gordon, M. "Collaborative Filing in a Document Repository," Proceedings of the ACM SIGIR 2004, Sheffield, UK, pages 518-519.
8. Zhu, H., and Fu, L. "Towards Quality of Data Standards: Empirical Findings from XBRL," in: The 30th International Conference on Information Systems (ICIS'09), Phoenix, AZ, USA, 2009.

Inter-organization Collaboration Management in Dynamic Virtual Alliances

Wang Yuchen, ZHANG Jinlong, Chong Xiaoli, Man Qingshan
School of Management, Huazhong University of Science and Technology
Wuhan, China
wangyuc@gmail.com

Abstract

The agility to collaborate in business networks has become essential for the success of both individual organizations and business value networks. The dynamic nature of alliances environment, the complexity of collaboration supporting in heterogeneous systems, and the autonomy of organizations all create new challenges for the operational computing environment. This paper describes a form of virtual alliance and proposes an integrated collaboration framework solution for inter-organization coordination management, including the using of ontologies-context pairing to support semantic level interoperability, and intelligent agent infrastructure to provide alliance life-cycle organizational autonomy

Keywords: Collaboration, Agility, Virtual Alliance, Contextual Ontology, Agent

1. Introduction

In today's businesses, as globalization of the economy accelerates and competition intensifies, the collaboration of companies has been regarded as one of the efficient methods to catch a transient opportunity in the fast changing market by sharing core competitiveness of each enterprise, which might includes knowledge and resources. Recent researches have been focusing on Virtual enterprise (VE) – a temporary consortium of enterprises that get together to respond to specific market opportunities (FungChen et al. 2008; WadhwaMishra et al. 2009; Ye and Li 2009), and may dissolve after the finish of objectives (GrefenMehandjiev et al. 2009; Ye and Li 2009).

Some common characteristics of VE are: they are self-organized by participants based on mutual interests; VE partners may have a large scope spanning over multiple functional domains; high dynamicity of partnership that participants might join and leave VE network at any time; and resources are shared in a controlled and accountable manner.

However, most actual situation about collaborative organizations in industry fields is that the major partners in a value chain keep remaining, while the relationship with some other secondary partners or suppliers varies along. In order to stay competitive in modern markets, the core part of VEs, or called VE leader, has to keep a certain degree of stabilization to maintain their business power in industry, for example the main manufacture in a supply chain won't change frequently. In the meanwhile, those VEs provide an open environment that allows organizations, suppliers, and even other VEs to join this community to pool their resources, take advantages of emerging market opportunities and exploit fast-changing market trends. To realize this, a special form of VE is presented, which called Dynamic Virtual Alliance (DVA). Especially, a DVA is an ad-hoc and automated coalition between organizations based on VE concept but with a relatively stable VE leader. Its collaboration is based on computer networks and utilizing

innovative technologies. The concept of DVA has already been applied to many cooperative business forms, for example, supply chains, e-business network and mobile business services.

Normally a virtual enterprise's operational environment can be categorized into two classes: closed and open environment. For instance, a VE of retail sale marketing value network where major supplier relationships are comparatively stable can be classified into closed environment, because product quantity and quality are specific according to contracts and orders which can be easily predicted. In contrast, a VE of mobile business value chain providing mobile applications and services to both individual and company customers would be operated in an open environment, since the demand is dynamic in terms of contents, quality, and hard to predict, while partnership is usually not stable in Hi-Tech industries. In our research, we claim that DVA locates between closed and open environment according to its features: highly dynamic partnerships and comparatively stable dominant VE leaders in the value network.

In this paper, we first analyze challenges of collaboration management in DVA context in section 2. Section 3 introduces an integrated collaboration solution for DVA environment. We elaborate on the contextual ontology method and intelligent agent as the basis of solution framework. Section 4 concludes related work and future development issues.

2. Challenges of Collaboration in DVA Environment

In dynamic business collaboration alliance, the construction and maintenance of a flexible and agile interoperability support mechanism are critical for business successes (WangTai et al. 2006). Such environment, characterized by large distributed, autonomous, diverse and dynamic information sources, is becoming increasingly complex for collaborating. This complexity mainly comes from two aspects: partner organizational autonomy requirement and system heterogeneity.

2.1 Enterprise Application Integration Analysis

Traditional inter-organizational interoperability solutions, such as EDI, SOAP and portals, are typically based on tightly paired application-level integration, or based on certain meta-data model (e.g. XML) to support interoperable business collaborations. Although normally correct operation of inter-organizational communication can be guaranteed via using these integrated or unified collaboration methods, since all required interoperability information is pre-defined explicitly in the resulting inter-organizational applications. This ability of coordination is achieved at the expense of enterprise autonomy, reusability and flexibility of business services and alliance networks, thus traditional methods are not suitable for DVA environment.

2.2 System Heterogeneity Analysis

System heterogeneity can be defined on several levels (Ouksel and Naiman 1994) and in a variety of ways (Zhao 2007), Table 1 elaborates our classification of system heterogeneity.

TABLE1. System heterogeneity classification

Classification	Examples
Platform Heterogeneity	<ul style="list-style-type: none"> ▪ Operation systems ▪ Hardware systems
Information System Heterogeneity	<ul style="list-style-type: none"> ▪ DBMSs

	<ul style="list-style-type: none"> ▪ Data models ▪ Application programming languages
Information Heterogeneity	<ul style="list-style-type: none"> ▪ Structural formats ▪ Syntactic formats ▪ Data semantics

Various heterogeneities will degrade the interoperability between enterprise information systems of DVA partners, which will fundamentally compromise organizational collaboration and producing efficiency in DVA. According to aforementioned classification of heterogeneity, there would be corresponding three levels of interoperability: Systematic, syntactic, and semantic interoperability. Till now, a lot of efforts have already been put on technologies that help to bridge the systematic and syntactic gaps across heterogeneous enterprise systems, such as ODBC, JDBC and XML. Typically the XML has been widely adopted in most enterprise application integration standards to support immediate communication among partners(Nurmilaakso 2008). It standardizes the syntax of information exchange by defining markups and structures of documents using tags, but still fails to capture the semantics of the data (Ray and Jones 2006). These technologies are inadequate in DVA environment for supporting dynamic interoperability of autonomous and heterogeneous information systems with possibly evolving and incompatible internal semantics.

3. The Integrated DVA Collaboration Framework

DVA takes advantage of existing and emerging technologies that are used to link and enable the entire alliance network to build a barrier-free moderate-open environment for business allied partners. The foundation is cross-enterprise interoperability solution to facilitate joint management of collaborations in the DVA context. Inter-organizational collaborations are modeled as an integrated framework that comprise of independently developed business services with the ability of automatic systems to process information from and to another at syntactic and semantic level without requiring either system to make changes to accommodate the other.

Fig.1 illustrates the integrated DVA collaboration framework for modeling business applications, developing and delivering enterprise solutions. It consists of business applications realized by business processes and workflow, contextual ontology components for intra- and inter-organizational semantic operability, and DVA organizational agent components for initiation, configuring and reorganizing partnerships. The integrated DVA framework provides a base for the effective encapsulation of agile business collaboration with flexibility.

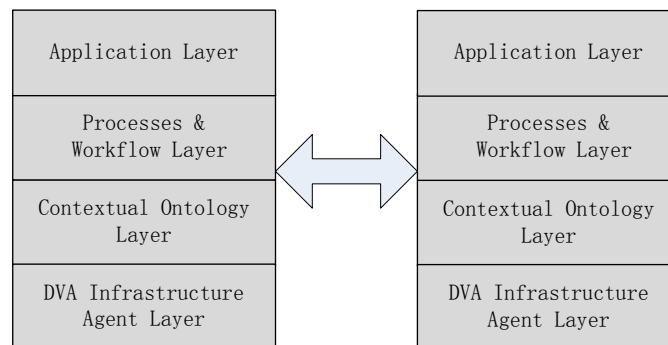


Figure 1. Integrated DVA collaboration framework

The highest two layers in the DVA collaboration framework provide the core business applications, processes and workflows that can be easily combined together and extended to offer a complete cross-organizational business solution. Specifically, the application layer allows disparate business applications to interoperate over DVA value-chain-wide networks and deliver consistent processes and workflow functionality. For instance, production process operational management, products or parts query and track for anti-counterfeiting and theft prevention, statistical and trace history analysis for logistic channel optimization, supply chain level demand forecasting, visibility of inventory, and analysis of pedigree and genealogy, etc. Attention is needed that the collaboration of business processes and workflows should be modeled without unnecessary revealing of local processing steps, only the collaborative external views should be exposed for collaboration purpose.

The third layer provides the infrastructure that is required in semantic mapping across heterogeneous data sources to build ontology level interoperability. In DVA collaboration architecture, ontology is adopted for the identification and association of semantically corresponding information concepts.

Known as shared representational vocabularies, ontologies have been proved to effectively help in resolving the problem of semantic heterogeneity and establish interoperable processes (StrangLinnhoff-Popien et al. 2003; YeYang et al. 2008). Ontology is an explicit, formal specification of a shared conceptualization of a domain of interest (StuderBenjamins et al. 1998). The term comes from philosophy in researching the existence of beings in the world. Then in recent years it has been introduced to and been widely active in various research areas, such as artificial intelligence, knowledge management, and information system integration (Pinto and Martins 2004). Typically, ontology includes a vocabulary of terms and specification of their meaning. By defining the specification and conceptualization, it is used to model application domain and to specify requirements. By providing shared understanding of a domain which used in communication between people and heterogeneous applications, it facilitates semantic interoperability and reuse of knowledge among systems (Pinto and Martins 2004).

There is an evolutionary process of using ontology to establish correspondence and sharing semantics in supporting intra- and inter- organizational semantic interoperation. The first level is “single ontology approach”, which use a global ontology to provide a shared vocabulary and specification of the semantics. The global ontology assures consensus among organizations by global views, however, at the cost of updating complexity, enterprise autonomy, and efforts for adding new ontology. The second level is called “Multiple ontology approach”, in which each information systems or organizations define their own local ontologies. These ontologies don’t necessarily share the same semantics. This approach remains system autonomy of each enterprise, makes it simple to add or remove local ontology from collaboration architecture without affecting the others, thus improves virtual enterprise flexibility. However it is necessary to build additional inter-ontology mapping for cross-organizational interpretation each time two partners need to work together.

We propose an advanced approach – contextual ontology – in DVA architecture establishment as a method of supporting ontology level interoperability. As shown in Fig.2.

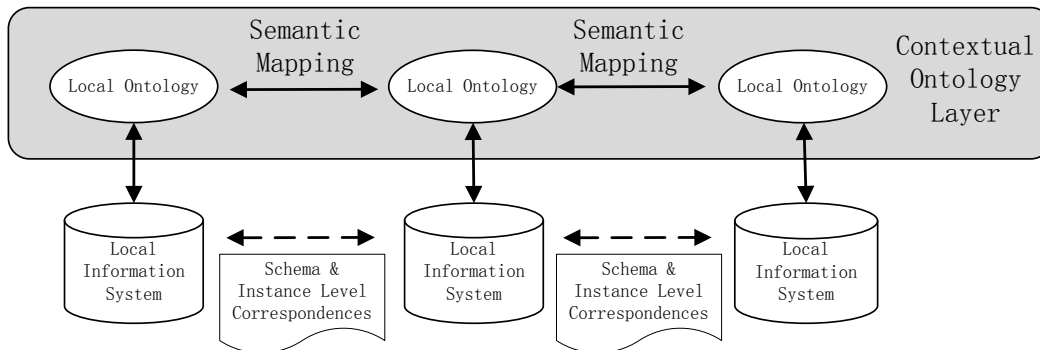


Figure 2. Contextual Ontology Layer

Contextual ontology is used to produce an understanding of the states of the DVA environment which is based on domain-specific definitions (Little and Rogova 2009). Because in DVA the core operation enterprises (i.e. VE leaders) keep stable to a certain degree, the whole context of this virtual business circumstance remains a certain degree of stability. Here the notion context was carried out through views, aspects, roles, and workspaces. It is used to label the belonging of information elements when mapping performed between two representations. Semantic Mapping process explores semantic correspondence including schema-level and instance-level correspondence between heterogeneous data sources (Zhao 2007). Schema correspondence refers to tables and attributes in different information systems that used to describe the same entity type and properties. And instance correspondence represents the items or records which stand for the same entity in different information systems. Based on stable context, the semantics of each enterprise information system is defined locally but also from a DVA wide shared contextual vocabulary, which contains basic schemas of the DVA domain. Based on these schemas, more complex semantics according to autonomous system's characters are easy to build. In such method, the local ontologies of each partner organizations in DVA are comparable, a balance between DVA partner consensus and autonomy is able to be built, thus the cost and effort of semantic mappings to build schema-level correspondences between inter-operation enterprises are under control, a lot of technologies of inter-ontological mapping might be used during this process, such as taxonomy alignment (Jung 2008), SWRL rules (YeYang et al. 2008), cluster and classification analysis (Zhao 2007). In the meanwhile, as long as source from certain basic contextual vocabulary, new entities (e.g. new organization, third party) gain easy access to the DVA system interoperability by subscribing to extended ontologies.

More details about contextual ontology with the language in enabling semantic interoperability can be found in (Little and Rogova 2009; Rifaieh and Benharkat 2006; StrangLinnhoff-Popien et al. 2003).

The lowest layer is DVA infrastructure agent layer. All DVA participants are represented by local intelligent agents. Those agents encapsulate locally deployed services, functions, knowledge, and various internal management methods, provide and release queried results to communication partner agent without exposing actual local service method. From the alliance

collaborative perspective, participant agent functions according to the DVA network life-cycle, which includes steps for alliance establishment, reacting to change requests and breach status, and alliance termination. Accordingly, the agent provides service interfaces with operations for initiating alliance entrance, message exchanges, collaboration re-negotiations, breach reaction, and alliance departure. Particularly, it has to deal with monitoring the behavior of the network and adapting to collaboration changes in terms of network membership and breach management. The function of monitoring and reorganizing are not isolated from each other. For example, once collaboration changes or breach situations are detected by intelligent agent and if those cause a major fault in DVA network which acknowledged by participants, a breach management or reorganization process will be triggered, potentially causing changes in the DVA community partnership and collaboration structure. Furthermore, this layer enables organizational agents to collaboratively manage the DVA network consistency. For instance, in the situation of movement, adding or replacing participant of the network causes requests to change the collaboration point to the new participant's location, and recreate the bindings between new locations.

4. Conclusion

DVA network is the result of strategic alliances of flexible partners for achieving competitive advantage. Such strategic alliances require outstanding flexibility of partnership management. This agility of partnership enables firms to adapt or modify their extended partner network when original sources are no longer available, or they need access to resources, competency or assets that are not resident in the current value network.

For DVA collaboration management, interoperability is a fundamental issue. In our paper, interoperability is defined as the capability to collaborate — an effective capability of mutual communication of information, commitments, and inclinations, requests and results. In general it covers technical, syntactic, and semantic interoperability. Technical interoperability means that messages and requested results can be transported from one participant to another freely across organizational boundaries. Syntactic and semantic interoperability insure the messages content are understood in correct and the same way by the senders and receivers. This includes semantic mapping—transformations of information representation or messaging sequences.

Based on analysis of challenges and requirements in DVA cooperation context, the proposed integrated collaboration framework promises supporting for autonomously administered peer services or organizations that collaborate in a loosely coupled alliance.

However, to extent DVA collaboration capability research, pragmatic interoperability would have to be included, which captures the willingness of alliance partners for the actions necessary for the collaborative participation. Deeper research is needed from the pragmatic perspective. Specifically, process-awareness in terms of collaborative business process model is needed, which must be augmented with nonfunctional aspects related to business policies.

References

1. Fung, R.Y.K., Chen, T.S., Sun, X., and Tu, P.Y.L. "An agent-based infrastructure for virtual enterprises using Web-Services standards," *International Journal of Advanced Manufacturing Technology* (39:5-6), Nov 2008, pp 612-622.

2. Grefen, P., Mehandjiev, N., Kouvas, G., Weichhart, G., and Eshuis, R. "Dynamic business network process management in instant virtual enterprises," *Computers in Industry* (60:2) 2009, pp 86-103.
3. Jung, J.J. "Taxonomy alignment for interoperability between heterogeneous virtual organizations," *Expert Systems with Applications* (34:4), May 2008, pp 2721-2731.
4. Little, E.G., and Rogova, G.L. "Designing ontologies for higher level fusion," *Information Fusion* (10:1) 2009, pp 70-82.
5. Nurmilaakso, J.M. "Adoption of e-business functions and migration from EDI-based to XML-based e-business frameworks in supply chain integration," *International Journal of Production Economics* (113:2), Jun 2008, pp 721-733.
6. Ouksel, A.M., and Naiman, C.F. "Coordinating context building in heterogeneous information systems," *Journal of intelligent information systems* (3:2) 1994, pp 151-183.
7. Pinto, H.S., and Martins, J.P. "Ontologies: How can they be built?," *Knowledge and Information Systems* (6:4), Jul 2004, pp 441-464.
8. Ray, S.R., and Jones, A.T. "Manufacturing interoperability," *Journal of intelligent Manufacturing* (17:6) 2006, pp 681-688.
9. Rifaieh, R., and Benharkat, A.N. "Sharing semantics among enterprise information systems with contextual ontologies: theory and practice," *Int. J. Metadata Semant. Ontologies* (1:4) 2006, pp 306-321.
10. Strang, T., Linnhoff-Popien, C., and Fran, K. "CoOL: A context ontology language to enable contextual interoperability," Springer-Verlag Berlin, 2003, pp. 236-247.
11. Studer, R., Benjamins, V.R., and Fensel, D. "Knowledge Engineering: Principles and methods," *Data & Knowledge Engineering* (25:1-2), Mar 1998, pp 161-197.
12. Wadhwa, S., Mishra, M., and Chan, F.T.S. "Organizing a virtual manufacturing enterprise: an analytic network process based approach for enterprise flexibility," *International Journal of Production Research* (47:1) 2009, pp 163-186.
13. Wang, E.T.G., Tai, J.C.F., and Wei, H.L. "A virtual integration theory of improved supply-chain performance," *Journal of Management Information Systems* (23:2), Fal 2006, pp 41-64.
14. Ye, F., and Li, Y.-N. "Group multi-attribute decision model to partner selection in the formation of virtual enterprise under incomplete information," *Expert Systems with Applications* (36:5) 2009, pp 9350-9357.
15. Ye, Y., Yang, D., Jiang, Z.B., and Tong, L.X. "An ontology-based architecture for implementing semantic integration of supply chain management," *International Journal of Computer Integrated Manufacturing* (21:1) 2008, pp 1-18.
16. Zhao, H. "Semantic matching across heterogeneous data sources," *Communications of the ACM* (50:1) 2007, pp 45-50.

Crowding In or Crowding Out?

Informational and Normative Social Influence in Online Communities

Chong (Alex) Wang
Information Systems, Business
Statistics and Operations
Management, School of Business
and Management, HKUST
alexwch@ust.hk

Xiaoquan (Michael) Zhang
Information Systems, Business
Statistics and Operations
Management, School of Business
and Management, HKUST
zhang@ust.hk

Abstract

In this paper, we investigate social influence in online communities. By empirically differentiating between social influence carried by online follow- and friend-relationship, we are able to distinguish between normative and informational social influence in user review contributions. Our finding suggests that informational social influence is negative (crowding out effect), while normative social influence is positive (crowding in effect). The value of online social connections should lie in introducing normative pressure that may generate a positive social multiplier effect to increase user participation.

Keywords: Social Influence, Tie Type, Informational Crowding Out, Normative Pressure, User Participation

1. Introduction

Social influence is one of the most important aspects of human society. We live in crowds, and we intentionally or subconsciously influence or are influenced by others through social interactions. Social interactions are shaping our perceptions about the environment, our preferences, and our behaviors through social influence. In economics and sociology literature, social influence and its consequences have been investigated extensively in various contexts such as education, consumer choice, innovation adoption, etc. With the development of Internet technology, especially with the web 2.0 platforms, online social interactions are becoming more and more salient. The way users interact in online communities determines how well they can retain and create value for its users. Chen et al. (forthcoming) argue that social mechanism is one way to motivate participation, alleviate under-contribution, and facilitate value creation in online communities. Contrary to the prediction of the private provision of public goods literature, Zhang and Zhu (forthcoming) find that user contribution to Chinese Wikipedia dropped as a result of the exogenous block of the mainland users. This suggests that online users value the social interactions. Despite these recent developments, there has been little research that directly investigates social influence in the virtual context and its consequences in the literature. In this paper, we intend to fill this gap by investigating the social influences in an online community.

While it is intuitively reasonable that online users' participation is subject to social influence, empirical identification of such influence is a challenging task (Manski 2000). First, social influence could be confounded by the contextual and characteristic similarities among socially proximate actors (homophily). Second, social influence is typically mutually effective which introduces simultaneity to the empirical specification (reflection problem). Third, social proximity (reference group) is tricky to define in different contexts. Economists proposed different methods trying to identify social influence in different empirical settings (Soetevent 2006). In this paper, we implement a panel data linear-in-mean model (Brock and Durlauf 2001) to recover social influence in our empirical context. With panel data structure, we are able to control for individual fixed effects, and to address simultaneity by time-lagged instrumental variables.

As a result, we are able to identify the most relevant reference groups by leveraging information of users' online social networks.

In social psychology, researchers identify three mechanisms through which social influence takes place, namely, internalization, normative pressure, and identification (Cialdini 2004). Internalization refers to the process through which people update their cognition about the environment by observing others. Normative pressure refers to people's tendency to comply with others' expectations. Identification refers to the adoption of prototypical behaviors of a social group. These mechanisms are effective separately or jointly under different contexts of social relationships. Deutsch and Gerard (1955) distinguish between informational social influence and normative social influence. Informational social influence is defined as "an influence to accept information obtained from another as evidence about reality", and normative social influence is defined as "an influence to conform with the positive expectations of another". Related to these concepts, organization and network researchers differentiate between different types of social relationships (ties). Within organization, interpersonal links can be categorized into instrumental ties and expressive (primary) ties (Lincoln and Miller 1979, Ibarra and Andrews 1993). Instrumental ties tend to be weaker, information- or performance-oriented relationships created by task-driven behaviors. In contrast, expressive ties are characterized by intimate links that connect people in terms of similarity in various attributes. Network (tie) types can affect the nature of the social influences (e.g., Umphress et al. 2003).

In the online community context, users nevertheless are connected to different groups of people and are under different types of social influence. The differences in tie types are made more salient when the websites provide functions that help users divide their online acquaintances into categories. For example, Douban.com, an influential Chinese online community website that supports the rating of cultural products such as music, books and movies, allows its users to differentiate their acquaintances between the "follow" relationship and the "friend" relationship. The major difference between the two types of relationships is that the "follow" relationship is one-way and the "friend" relationship is two-way, in terms of how acquaintances can observe each other's activities. In the one-way "follow" relationship, a follower can observe a followee's actions, but a followee cannot observe the actions of a follower. In a two-way "friend" relationship, the actions are symmetrically observable by both friends. For a focal user, while these two types of online relationships are informationally equivalent (the focal user gets updates about their acquaintances in both cases), these two types of relationships may transmit different social influences. While friends in a "friend" relationship may be subject to normative pressure (a user's action is observable by her friends), a follower in a "follow" relationship is free from such pressure (a followee does not observe the action of a follower).

By observing the social network connections, we are able to clearly identify relevant reference groups for each user in Douban. Based on the theory about tie type and social influence, we use the empirical framework proposed by Cohen-Cole and Zanella (2008a) to separate the informational and normative social influence empirically. Our results suggest significant social influence effects in user review contributions. Interestingly, we find that the informational effect is negative (crowding out effect) while the normative effect is positive. This suggests that when users are exposed to more reviews they tend to reduce their own contribution, which is consistent with the theory of collective actions (Olson 1971). However, when these reviews come from online friends, the conformity pressure dominates the free-riding incentive. Thus, positive social multiplier effects may result from intensive social influence, and enhancing online social interactions to maintain strong normative social relationships is important to the success of online platforms.

2. Empirical Analysis

In this section, we briefly describe our empirical context, empirical strategy, and main results.

2.1 Data Description

Our data is provided by Douban (www.douban.com), a Chinese website for users to rate, review and discuss about cultural products (books, music and movies). Content contributions from registered users include ratings and reviews. After a user rates an item, the rated item will be collected in the user's online profile and is used by automated algorithms to generate personalized recommendations. User reviews are open to the public. Registered users can post comments for others' reviews. Besides these basic functions, Douban also provides its users with two types of social network functions. Online "follow" relationship is a single-directional relationship similar to the follow-relationship in Twitter. Online friend relationship, similar to the one in Facebook, is bidirectional and requires mutual consent from both users. After becoming a follower or a friend to another user, a focal user receives updates of the other user's online activities.

Our data cover user activities and social network structure from March 2005 to August 2008. Friend network was introduced on January 31st 2008. As a result, we only consider a time frame from February 2008 to August 2008, during which both types of relationships are present. In subsequent analysis, we focus on review contribution activities to investigate the social influence effect.

2.2 Empirical Model

Cohen-Cole and Zanella (2008a) propose a model to unpack social influence by their difference in effectiveness with respect to different reference groups. Cohen-Cole and Duygan-Bump (2008) use this method to separate the effects of social stigma from information sharing. Consider the following two models about social influence.

$$(1) R_{it} = \alpha_i + \sum_k \beta_k X_{it,k} + \gamma^{I,FL} \bar{R}_{i,t-1}^{FL} + \gamma^{NI,FR} \bar{R}_{i,t-1}^{FR} + \varepsilon_{it},$$

$$(2) R_{it} = \alpha_i + \sum_k \beta_k X_{it,k} + \gamma^{I,FLFR} \times [\rho \bar{R}_{i,t-1}^{FL} + (1-\rho) \bar{R}_{i,t-1}^{FR}] + \gamma^{N,FR} \bar{R}_{i,t-1}^{FR} + \varepsilon_{it},$$

where R_{it} is the periodic review contribution by user i . These two equations describe the same social influence from different perspectives. Equation 1 is formulated with respect to the reference groups (tie types). The coefficients ($\gamma^{I,FL}$ and $\gamma^{NI,FR}$) represent the combined effect of social influence with respect to the follow relationship and the friend relationship. On the other hand, equation 2 formulates social influence with respect to the types of social influence (informational versus normative). As a result, the coefficients ($\gamma^{I,FLFR}$ and $\gamma^{N,FR}$) represent the effect of different types of social influences. In the model, we also consider the individual fixed effects (α_i) and other control variables (X_{it}). To alleviate the concern of reflexivity, we lagged peer groups' contribution to reflect the direction of causal relationship.

The above two linear-in-mean equations are "equivalent" in that they generate the same variance structure for the error terms. As a result, the coefficients in each of the equations are comparable. This provides a simple way to identify the stand-alone effect of informational and normative influence carried by the two types of relationships. Specifically, we are interested in the marginal effects denoted by ($\gamma^{I,FL}, \gamma^{I,FR}, \gamma^{N,FR}$). One thing to note is that identification depends on the ability of the researcher to determine (exogenously) the existence and the relative strength (ρ in equation 2) of each type of social influence. This formulation reflects that informational social influence is transmitted through both friend ties and follow ties, but only friend ties carry normative influence. With respect to the relative significance of informational influence in both types of relationships, we assume they are equal ($\rho = 0.5$). Another way to look at this formulation is that we are actually comparing the strength of social influences from different reference groups (in equation 1). Theoretically, we attribute this difference in social influence between different tie types to the additional normative pressure between friends.

2.3 Main Results

We estimate the model with a data set that covers 6 months of review contributions by 63,339 users. We calculate the monthly review contributions by the focal users as well as average monthly review contributions by the focal users' friends and users that our focal users follow at the beginning of the period. Other control variables and their quadratic terms are also included in the model. Lagged review comments variables are also introduced to address endogeneity. Key variables in the model are summarized in table 1.

Table 1 Description of Variables

Variable	Definition	Mean	Std. Dev.
Review_Con _{it}	Monthly review contribution by the focal user	0.118	0.789
Avg_Friend_Con _{it}	Average monthly review contribution by the friends of the focal user	0.221	0.845
Avg_Follow_Con _{it}	Average monthly review contribution by users the focal user follows	0.200	0.623
Rev_Com_Write _{it}	Monthly review comments contributed by the focal user	0.330	1.796
Rev_Com_Get _{it}	Monthly review comments the focal user get from other users	0.546	7.370
Degree _{it}	Number of friends of the focal user at the beginning of the period	10.37	25.28
In_Degree _{it}	Number of other users that our focal user follows	13.50	39.21
Out_Degree _{it}	Number of users who follows our focal user	12.71	34.19
Collection _{it}	Number of books, music, and movies added to the user's profile	19.13	52.35

Our dependent variable is a count variable. To address non-normality, in addition to the regression analysis, we also implement a Logit model and a Poisson regression model. In each model, individual fixed effects and all control variables are included. Estimation results for equation 1 are reported in table 2. Based on estimation of equation 2, coefficients for social influences are reported in table 3.

Table 2 Estimation Results

	Regression Model DV: Review_Com _{it}	Poisson Regression DV: Review_Com _{it}	Logit Model DV: I(Review_Com _{it})>0
Avg_Friend_Con _{it}	0.0006 (0.0005)	0.0067 (0.0044)	0.0041 (0.0105)
Avg_Follow_Con _{it}	-0.0027 (0.0009)***	-0.0427 (0.0121)***	-0.0463 (0.0208)**
Collection _{it}	0.0004 (0.0000)***	0.0030 (0.0001)***	0.0079 (0.0003)***
Rev_Com_Write _{it}	-0.0002 (0.0003)	-0.0006 (0.0014)	0.0014 (0.0050)
Rev_Com_Get _{it}	-0.0003 (0.0001)***	0.0009 (0.0003)***	-0.0041 (0.0012)***
Degree _{it}	-0.0003 (0.0001)***	-0.0031 (0.0005)***	-0.0052 (0.0013)***
In_Degree _{it}	-0.0008 (0.0001)***	-0.0017 (0.0004)***	-0.0060 (0.0014)***
Out_Degree _{it}	-0.0013 (0.0001)***	-0.0040 (0.0011)***	-0.0158 (0.0030)***
Degree _{it} ²	5.16e-07 (7.51e-08)***	3.81e-06 (7.50e-07)***	8.60e-06 (2.40e-06)***
In_Degree _{it} ²	2.11e-07 (2.86e-08)***	3.15e-07 (1.34e-07)**	1.37e-06 (4.58e-07)***
Out_Degree _{it} ²	1.49e-06 (1.96e-07)***	5.61e-06 (1.38e-06)***	1.51e-05 (3.79e-06)***
Note: * significant at 10%, ** significant at 5%, *** significant at 1%;			

From table 2, we can see that being exposed to more reviews from other users that the focal user follows has a negative effect on her review contribution. Thus, the information about others' contribution crowds out the focal user's reviews (informational crowding-out effect). On the other hand, friend contribution has an insignificant effect on review contribution. As shown in table 3, based on our model specification, this result translates to a positive normative social influence from online friends. The estimations for all the social influence effects are significant at 1% level. However, since the normative social influence is positive while the informational social influence are negative, the aggregate social influence through friend ties turns out to be insignificant.

Table 3 Coefficients for Social Influence			
	Regression Model	Poisson Regression	Logit Model
$\gamma^{I,FL}$	-0.0027	-0.0427	-0.0463
$\gamma^{I,FR}$	-0.0027	-0.0427	-0.0463
$\gamma^{N,FR}$	0.0033	0.0494	0.0504

One of the major concerns with the reported empirical analysis is that the magnitude of social influence is small (marginal effect of approximately 3% of the average contribution). This may be caused by the fact that online social interactions are weak and thus carry less significant social influences among the users. Online review contributions are mainly determined by the users' attitudes towards the contents. Social influence may only be of second-order importance. The other possibility is that the use of lagged peer contribution variables may not fully reflect the impact of social influence. One way to alleviate this problem is to consider smaller time intervals. We can also estimate a network-influence model to address simultaneity. We also implement another model on social influence by looking directly at book-level review contribution. Due to space limit, these results are not reported here.

3. Conclusion

Modern technologies enable ordinary people to become active information providers. However, online communities suffer from under-contribution. Social mechanisms are identified as one promising way to motivate user participation. In this paper, we investigate the social influence in review contributions in an online community. We differentiate between online follow- and online friend-relationship. While both types of ties transmit information about peers' activities, online friendship carries an additional normative influence. With a simple framework, we separate informational social influence from normative social influence. Our empirical analyses confirm the positive effect of normative social influence and find that the informational social influence in the online community is negative. This research contributes to the literature about social influence as well as the literature on online community participation. We demonstrate that intimate online social interactions may introduce a positive social multiplier effect that eventually increases user participation.

References

1. Brock, W. and Durlauf, S. "Interactions-based models," in *Handbook of Econometrics*, Vol. 5, J.J. Heckman and E. Leamer (eds.), Elsevier Science B.V. 2001, pp. 3299-3380.
2. Chen, Y., Harper, F., Konstan, J., and Li, S. "Social Comparisons and Contributions to Online Communities: A Field Experiment on MovieLens," *American Economic Review*, forthcoming.
3. Cialdini, R.B. and Goldstein, N.J. "Social Influence: Compliance and Conformity," *Annual Review of Psychology* (55:1), 2004, pp. 591-621.
4. Cohen-Cole, E. and Zanella, G. "Unpacking Social Interactions," *Economic Inquiry* (46:1), 2008, pp. 19-24.
5. Cohen-Cole, E. and Duygan-Bump, B. "Household Bankruptcy Decision: the role of social stigma vs. information sharing," Federal Reserve Bank of Boston, mimeo, 2008b.
6. Deutsch, M. and Gerard, H.B. "A study of normative and informational social influences upon individual judgment," *Journal of Abnormal and Social Psychology* (51:3), 1955, pp. 629-636.

7. Ibarra, H., and Andrews, S.B. "Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions," *Administrative Science Quarterly* (38:2), 1993, pp. 277-303.
8. Lin, N., S. Cook, K., and S. Burt, R. *Social Capital: Theory and Research*, Transaction Publishers, New Brunswick, New Jersey, 2001.
9. Lincoln, J.R., and Miller, J. "Work and Friendship Ties in Organizations: A Comparative Analysis of Relation Networks," *Administrative Science Quarterly* (24:2), 1979, pp. 181-199.
10. Manski, C. "Economic Analysis of Social Interactions," *Journal of Economic Perspectives* (14:3), 2000, pp. 115-136.
11. Soetevent, A. "Empirics of the Identification of Social Interactions: An Evaluation of the Approaches and Their Results," *Journal of Economic Surveys* (20:2), 2006, pp. 193-228.
12. Umphress, E.E., Labianca, G., Brass, D.J., Kass, E., and Scholten, L. "The Role of Instrumental and Expressive Social Ties in Employees' Perceptions of Organizational Justice," *Organization Science* (14:6), 2003, pp. 738-753.
13. Zhang, X., and Zhu, F. "Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia," *American Economic Review*, forthcoming.

User Attitude toward Adaptive Interfaces of Mobile Web Services

Zhe Qu
Fudan University
quz@fudan.edu.cn

Jun Sun
University of Texas – Pan American
jsun@utpa.edu

Abstract

This study examines user attitude toward web service interfaces adapted to small display of handhelds. The results of an experiment suggest significant difference in user attitude toward adaptive and nonadaptive interfaces in mobile web services involving tasks of different complexities. This implies that designers of mobile web service need to take user context into account in interface design.

Keywords: mobile web service, interfaces, task context, user attitude.

1. Introduction

Despite the growth of technologies and applications in mobile web services, scholars find that small display size is still the crucial barrier to users' adoption of mobile web services (Anil et al. 2003, Aoyama 2003). Responding to the concern, practitioners and researchers developed several adaptive presentation methods, and the most popular one is known as automatic re-authoring (Adipat & Zhang 2007). Adopted by some established web service providers including Google, Facebook, and Youtube, this method automatically adapts interface design for handhelds of a given display size (Adipat & Zhang 2007). Figure 1 illustrates the difference between the nonadaptive and the adaptive interface designs.

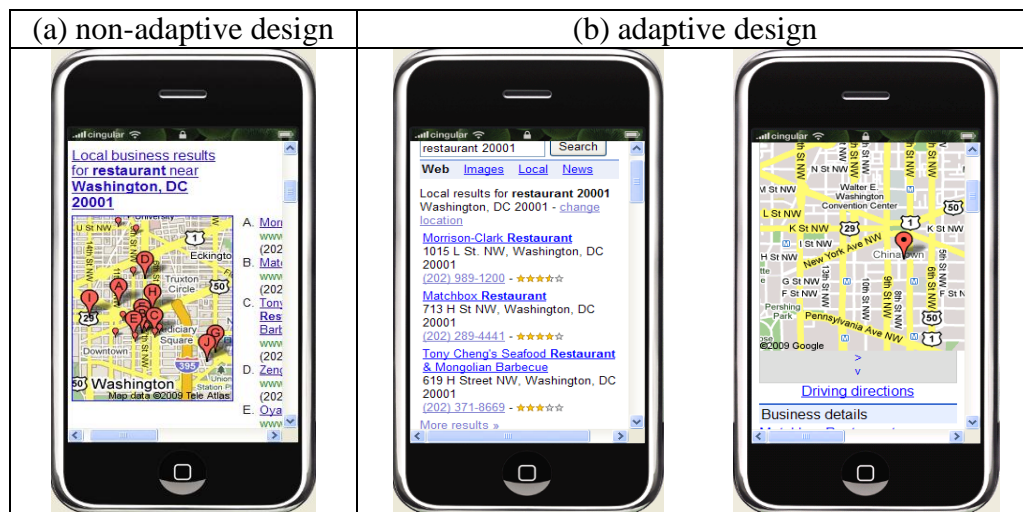


Figure 1: Screenshots of non-adaptive versus adaptive Interfaces

The screen shots present the mobile search results of restaurants near Washington DC. Part (a) displays the search result as designed for desktop viewing (no adaptation): a map that indicates the locations of approximately ten restaurants is displayed next to the text search results. Part (b) displays the adaptive search result. The screenshot on the left of part (b) shows the search result that suppresses the map but discloses in plain text the physical address of each restaurant; users may click on a restaurant name to view the map, which indicates the location of that specific restaurant (the screenshot on the right of (b)).

The nonadaptive and the adaptive mobile interfaces are different for the same web content. The adaptive interface is hierarchical and expandable compared to the nonadaptive interface.

Despite the ongoing effort in the design of adaptive mobile interface, what is missing in the literature is users' attitude toward such adaptation. Do users of mobile web services prefer the adaptation? How does the nature of the task involved in the web service shape users' preference?

To address this gap in the design of mobile web interface, we take a psychological lens to examine users' attitude toward the adaptive mobile interface (content displayed in a hierarchical and expandable fashion) benchmarking with users' attitude toward the nonadaptive interface (content displayed in a flat fashion). We introduce two tasks of different complexity to investigate the impact of task on users' attitude toward the adaptive and nonadaptive mobile interfaces.

2. Conceptual Framework

Abowd and Beale's (1991) well-known interaction framework states that a user communicates with a computer system through input and output components of computer interfaces. The system performs the data processing based on the *input* articulated by the user and presents the *output* for the user to observe.

Take information searching on the Internet for example, a user articulates the key words (e.g. restaurant plus zip code) on the initial input interface of a web service (e.g. the search textbox and buttons of a search engine). Based on the input, the system performs the search and presents the result in the form of an output interface on user-end device (e.g. desktop or handheld). The person observes the output and may articulate further input (e.g. click the links on the page) if he/she wants to know more details.

Although the input and output interfaces are generally present in user's interaction with web services, the interface designs differ across end users' devices. Web services that adopt the adaptive interfaces provide users with the input and output interfaces tailored for the users' handhelds. Such an adaptation has impacts on user behavior in terms of output observation and input articulation. As the screenshots shown in Figure 1 indicate, handheld users searching for local business are only given a short list of search results without a map. If the users want to check out more options or view the map, they need to click various links. Thus, different interface designs imply different rules for users to follow: the communication rule inherent in the adaptive interface is users need to take extra steps to retrieve the complete information.

To summarize, the design of web service interfaces, therefore, has three aspects as related to input interface, output interface and communication rules. Adaptive interface design, in comparison with non-adaptive interface design, has more concise input and output interfaces but more complicated communication rules. Consequently users may have different experiences in their interaction with web services of different interfaces. Such difference in experiences will influence users' future preference to interact with web services of certain input interface, output interface and communication rules.

IS researchers have developed various user acceptance models from a psychological perspective (Venkatesh et al., 2003). Formed on the basis of user experiences with an IS, the psychological constructs in these models were used to predict how likely users are to adopt the IS. However, the unit of analysis in such studies is typically an action of "using" a system, and most existing constructs do not tap user experiences in interacting with a system (cf. Venkatesh et al., 2003). To study how the design of web service interfaces influence user behavior, a psychological construct that reflects user experiences with input interface, output interface and communication rules is needed. A recently developed construct called information system interaction readiness (simply, user readiness) meets the requirement. This construct describes

how a user is prepared and willing to interact with an IS for a certain type of tasks (Sun & Poole, forthcoming). Developed on the basis of Abowd and Beale's interaction framework, this construct has three factors: input willingness, output receptivity and rule observance, corresponding to user attitude toward input interface, output interface and communication rules.

Because adaptive interfaces are intended to make user experiences with mobile web services smoother, they should generally enhance user readiness. We are also interested in whether the nature of a task involved in a web service has any effect on the relationship between the interface designs and users' readiness to interact with the web service. The situated action theory (Suchman 1987, p50) argues that an agent's behavior depends crucially on its circumstances; hence it is important to examine an agent's "situated" behavior and leaving out the circumstances may lead to biased result. This perspective suggests that task nature may moderate the relationship between interface design and users readiness.

To explain the patterns of attitude changes in different settings, Petty and Cacioppo (1986) proposed the elaboration likelihood model (ELM). They suggested that there are two routes of information processing for human beings: the central route and the peripheral route. For relatively complex and difficult tasks, subjects are likely to take the central route; for relatively simple and easy tasks, they are likely to take the peripheral route. Adaptive interfaces require handheld users to explore the hierarchical structure of the content; hence users are more likely to appreciate the special considerations of the web services when the tasks demand central processing rather than peripheral processing. Thus, users may be more ready to interact with web services that employ adaptive interfaces for complex tasks than for simple tasks. We summarize our conceptual framework in Figure 2 and detail the relationship between the constructs in Hypothesis 1 and 2.

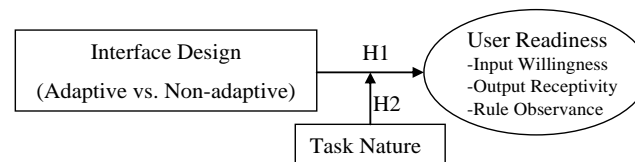


Figure 2: Research Model

Hypothesis 1. Compared with nonadaptive interface design, adaptive interface design enhances user readiness to interact with a mobile web service.

Hypothesis 2. Task nature moderates the effects of adaptive interface design on user readiness: the effects are stronger for relatively complex tasks than for relatively simple tasks.

3. Methodology

The core construct in our conceptual framework is users' readiness to interact with an IS. We examine user readiness toward the adaptive interface in comparison to user readiness toward the nonadaptive interface for the same web content. We select two tasks of different complexity in the comparison. Altogether, 73 college students were recruited for the experiment. In the experiment, the investigators demonstrate to the participants the nonadaptive and the adaptive displays of content through the use of iPhone emulator. Then following the experimental instructions, the participants perform two tasks on their own using the iPhone emulators. The first task is a relatively simple one. The subjects are told that they are travelling in a city and want to look for a nearby restaurant. Using identical key words, e.g. "restaurant 20001", they search through both the nonadaptive interface and the adaptive interface using Google's search engine. The screenshots of the search results are presented in Figure 1. The second task is a relatively complex one. The participants search for a research project using identical key words

(e.g. student's t-test) through both the adaptive and the nonadaptive interfaces on wikipedia.org. The adaptive interface displays the introduction and hides section details in expandable buttons. The nonadaptive interface, in contrast, displays all the information on one page; a participant needs to scroll all the way down to find the example.

4. Results

First, the reliabilities of the user readiness instrument were assessed: the coefficient alpha was 0.910 for overall user readiness, and 0.887 for input willingness, 0.787 for output receptivity and 0.692 for rule observance. This affirmed the internal consistency of responses. To test Hypothesis 1, a t-test was conducted on the index scores of user readiness factors for both tasks. The result (Table 1) shows that all the scores were significantly higher than the neutral point (no difference in preference between the two interfaces) in the Likert scale (i.e. 3). This suggests that adaptive interfaces enhance user readiness, which provides support for Hypothesis 1.

Table 1: Assessment of Instrument and Factors

	Simple Task		Complex Task	
	Mean	$t (H_0: \mu=3)$	mean	$t (H_0: \mu=3)$
Input Willingness	3.37 (0.72)	4.37 ^{Sig.}	4.14 (0.55)	17.68 ^{Sig.}
Output Receptivity	3.37 (0.56)	5.62 ^{Sig.}	4.11 (0.57)	16.60 ^{Sig.}
Rule Observance	3.29 (0.63)	3.92 ^{Sig.}	3.98 (0.58)	14.54 ^{Sig.}

Note: Standard deviations are given in parentheses; Sig. – Significant at 0.001 level.

Figure 3 presents the measurement model, in which nine user readiness indicators are loaded to three latent factors – input willingness (IW), output receptivity (OR) and rule observance (RO). A multi-group analysis was conducted on the two task groups simultaneously, and the pooled fit indices indicate that the measurement model is acceptable (NNFI = 0.953, CFI = 0.969; RMSEA = 0.049).

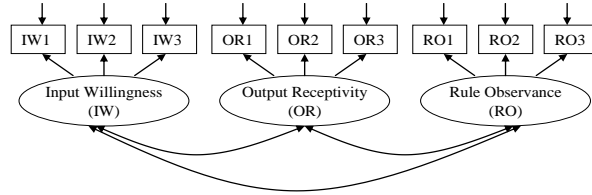


Figure 3: Measurement Model

The multi-group analysis also provides a way to compare the latent means of user readiness factors across the two tasks. The result indicated that the mean differences for input willingness, output receptivity and rule observance were .757, .820, and .887 respectively, and they were all significant at 0.001 level. Because the effect of adaptive interfaces on user readiness differs across the two tasks, there is supporting evidence for Hypothesis 2 that task nature is an important moderator. The results suggest that mobile users generally prefer adaptive interfaces to nonadaptive interfaces, and their preference was more salient when the tasks are relative complex than when the tasks are relatively simple.

5. Conclusion

Appropriate adaptation of mobile interface is a critical success factor of mobile web services. We examine users' attitude toward adaptive mobile interface when they perform tasks of different complexity on handhelds. Our analysis of experimental data shows that adaptive interfaces enhance user readiness to interact with a mobile web service compared to nonadaptive interface. Moreover users prefer more adaptation if the task is relatively complex, but prefer less adaptation if the task is relatively simple. This implies that developers may have to consider the nature of user tasks in designing adaptive interfaces.

6. References

- Abowd, G. D. and Beale, R. "Users, systems and interfaces: A unifying framework for interaction," *HCI'91: People and Computers VI*, 1991, pp. 73 - 87.
- Adipat, B and Zhang, D. "Adaptive and Personalized Interfaces for Mobile Web," 15th Annual Workshop on Information Technologies & Systems (WITS), 2007.
- Anil, S. Ting, L.T. Moe, L.H. and Jonathan, G.P.G. "Overcoming barriers to the successful adoption of mobile commerce in Singapore," *International Journal of Mobile Communications* 1 (1/2), 2003, pp. 194– 231.
- Aoyama, Y. "Sociospatial dimensions of technology adoption: recent M-commerce and E-commerce developments," *Environment and Planning* 35, 2003, pp. 1201 – 1221.
- Petty, R. E. and Cacioppo, J. T. "Communication and Persuasion: Central and Peripheral Routes to Attitude Change," New York: Springer-Verlag 1986.
- Suchman, L. "Plans and Situated Actions: The Problem of Human-Machine Communication," Cambridge University Press, Cambridge, UK, 1987.
- Sun, J and Poole, M.S. "Capturing User Readiness to Interact with Information Systems: An Activity Perspective," *Data Base for Advances in Information Systems*, Forthcoming.
- Venkatesh, V., Morris, M. G. Davis, G. B. and Davis F. D. "User acceptance of information technology: Toward a unified view," *MIS Quarterly* (27), 2003, pp. 425 - 478.

A Value Based Analysis of Web 2.0 Usage

Yi Maggie Guo
College of Business
University of Michigan-- Dearborn
magyiguo@umd.umich.edu

Abstract

The paper proposes a study that investigates continued use of Web 2.0 technologies using the theory of customer values as the theoretical lens. A product or service provides customer with monetary, functional, emotional, social, conditional, and epistemic values. Web 2.0 technologies provide users these values too. Furthermore, we posit that user perceived value has a positive effect on continued use of Web 2.0 technologies. Two site related factors, website quality and communal characteristics, are hypothesized to affect customer values and sense of belonging. A survey study is planned to test proposed research model. In prior research, both utilitarian and hedonic values of IT are recognized. This research further the research stream by including a set of independent and additive values users acquire when using Web 2.0 technologies.

Keyword: Web 2.0, customer values, sense of belonging, website quality, online community

1. Introduction

According to Wikipedia (an example of Web 2.0), Web 2.0 is a collection of technologies that enable users to interact, share, communicate, collaborate, and generate contents, in comparison to users' more passive role in the last generation of Web, in which users mainly receive information provided, and to some extent, dictated by websites. Users participate in Web 2.0 for different purposes, mostly voluntarily with personal motives, such as entertainment, communication, and information acquisition. Their continued use is the goal of websites and benchmark of site success. In this paper we propose a study to understand this phenomenon via the lens of customer values since spending time and effort (maybe money) on Web 2.0 is not too much different from other types of consumption experience from which consumers gain various values. More and more traditional websites, such as online retailing sites, are incorporating Web 2.0 components, such as user comments on products and interactive Q&A. Although the current research focuses on private use of Web 2.0 technologies, it can also provide insights on how business utilizes Web 2.0 technologies to benefit their customers.

2. Research Framework

The phenomenon of Web 2.0 has generated great research interest. A stream of research focused on adoption and then continued use of Web 2.0 by individuals. Technology acceptance model has been extended to study user behavior of social networks (Sledgianowshi and Kulviwat, 2009; Wang et.al., 2008). Other theories also have been applied, such as expectation-confirmation theory, social exchange theory, and social capital theory (Hu and Kettinger, 2008). Various factors have been proposed to affect intention to adopt and use, such as normative pressure, critical mass, trust, computer, self efficacy, enjoyment, information value, perceived risk, structural embeddedness, commitment to the community (Hu and Kettinger, 2008; Nov and Ye,

2008; Sledgianowshi and Kulviwat, 2009; Wang et. al., 2008). In this research we focus on consumer values. Most of the factors in prior studies can be organized in terms of different aspect of consumer values.

2.1 Sense of belonging

The big difference between a Web 2.0 site and a traditional website is the active participation of members during information exchange (Clarke, 2008). Rather than passively receiving information from website, members initiate a conversation or discussion either by posting articles, questions, or pictures. Others can comment and reply. Over time, members with common interest form groups. Some features of Web 2.0 sites facilitate online community building, such as private communication tools. The participatory nature of Web 2.0 makes cultivating a sense of belonging among members a necessity for its success (Lin, 2008). When studying the member participatory behavior in online communities, community identification, a concept defined as the perception of belonging to a online community, is found to positively affect knowledge sharing intentions (Hsu and Lin, 2008) and behavior (Chiu et al., 2006). Thus, **Hypothesis 1:** Sense of belonging has a positively effect on users' continued use of Web 2.0 technologies.

2.2 Customer values

In the original theory of consumption values, five values are presented: functional, emotional, social, conditional, and epistemic (Sheth et al, 1991). Functional value is the product's ability for functional, utilitarian or physical performance through the possession of salient attributes (Sheth et al, 1991). In later research, it is suggested to separate this value into two (Pihlstrom and Brush 2009; Sweeney and Soutar, 2001). The first one is related to price/value for money. Monetary value is defined as "the utility derived from the product due to the reduction of its perceived short term and longer term cost" (Sweeney and Soutar, 2001). It presents good value for money or low price compared with alternatives (Pihlstrom and Brush, 2009). The second is related to performance and quality as "the utility derived from the perceived quality and expected performance of the product" (Sweeney and Soutar, 2001). Some relabeled it as convenience value for mobile service to measure the ease and speed of accomplishing a task (Pihlstrom and Brush, 2009). Others still retain the name functional value (Deng et al, 2009). Although most of Web 2.0 technologies are free, for some websites, members need to pay for more advanced services. For example, to order prints from a photo sharing sites. Thus, monetary value may not be essential as in other types of consumption and consumer decision making, it is relevant to some extent. Functional value is the features and functionalities a Web 2.0 site provides to its member. Users may think a photo sharing site with the ability to tag photos and share photos according to the tag to different groups of friends have more value than a site without this function.

Emotional value is defined as a product's ability to "arouse feelings or affective states" (Sheth et al, 1991). A service or product is often capable of bring emotions (Sweeney and Soutar, 2001), such as a dozen roses. Hedonic value of Web is apparent. People have fun online surfing, searching, communicating, and gaming (Chen et al., 1999). Web 2.0 technologies allow users not only to share image, audio, and videos, but to listen to music and watch television shows and movies. Users are seeking entertainment online.

Social value is defined as enhancement of social self-concept, “the utility derived from the product’s ability to enhance social self-concept” (Sweeney and Soutar, 2001). The social value of a product is related to its association with specific social groups, either positive or negative stereotypic imagery of demographic, socioeconomic, and cultural-ethnic groups (Sheth et al, 1991). Web 2.0 technologies are still considered cool and trendy. Members of these sites may perceive themselves to be cool and trendy by association.

Conditional value is the result of the specific situation or set of circumstances facing the consumer. Certain physical or social contingencies lead to the value. An example is holiday cards that only have seasonal value (Sheth et al., 1991). Certain types of Web 2.0 sites provide conditional values too. For example, an online invitation or event organizing site (e.g., evite.com) is used by members only for special occasions.

Epistemic value is defined as the “capacity to arouse curiosity, provide novelty, and/or satisfy a desire for knowledge” (Sheth et al., 1991). Users gain novelty value from acquiring new knowledge and learning new ways of doing things (Pihlstrom and Brush, 2009). Users learn from reading posts by a blogger and participating in an online discussion of a topic.

Web 2.0 sites provide various customer values to its users. In prior customer value research, customers who perceive higher value have higher probability to remain loyal to the service provider (Deng et al., 2009). If a customer deems the service is valuable, overtime, a bond develops between the customer and the service provider. A sense of belonging may build up in Web 2.0 users especially they gain emotional and social values when using a Web 2.0 site. Thus, we posit the following hypotheses:

Hypothesis 2: Customer values have a positive effect on users’ continued use of Web 2.0 technologies.

Hypothesis 3: Customer values have a positive effect on users’ sense of belonging.

2.3 Website quality

In this research we recognize three aspects of website quality: system quality, information quality, and service quality (Lin & Lee, 2006). System quality is how effective and efficient the website performs. It should be reliable and easy to use. Information quality is the quality of website content. High quality information should be accurate, up-to-date, useful, complete, secure, and easy to access. Service quality is the overall assessment of service delivery. Service quality reflects how the site treats its users, whether in a caring, prompt manner. A high quality website with accurate and helpful information provides user with a range of values, especially monetary, functional, and epistemic values. A reliable and caring provider, here the website, sends out the signal of hospitality, making users “feel at home.” It fosters a sense of belonging in its members. Thus, we posit the following hypotheses:

Hypothesis 4: Website quality has a positive effect on customer values.

Hypothesis 5: Website quality has a positive effect on users’ sense of belonging.

2.4 Communal characteristics

In the heart of Web 2.0 technology is the sharing and community building. More than often Web 2.0 sites provide functionalities to facilitate interaction and relationship building among members. Social interaction ties represents the strength of relationships among members, reflect how

connected members are and how close they are. It can be measured by the amount time spent, communication frequency, and depth and breath of information exchange. Social interaction ties are the result of caring, constructive, responsive norm of a community. Such a community provides high customer values and creates a home feeling for its members. Thus,

Hypothesis 6: Social interaction ties have a positive effect on customer values.

Hypothesis 7: Social interaction ties have a positive effect on users' sense of belonging.

Research model is presented in Figure 1.

3. Research Methodology

A survey study is planned to collect data. Measures of customer values will be based on Deng et al (2009), Pihlstrom and Brush (2009), Sweeney and Soutar (2001). Measures for sense of belonging will be based on Lin (2008). Items measuring website quality will be based on Lin and Lee (2006). Interaction ties will be measured as Chiu et al., (2006). Structural equation modeling will be the main data analysis method.

4. Conclusion

The paper proposes a study that investigates continued use of Web 2.0 technologies using the theory of customer values as the theoretical lens. In prior research, both utilitarian and hedonic values of IT are recognized. This research further the research stream by expand the dichotomy to include a set of independent and additive values users acquire when using Web 2.0 technologies.

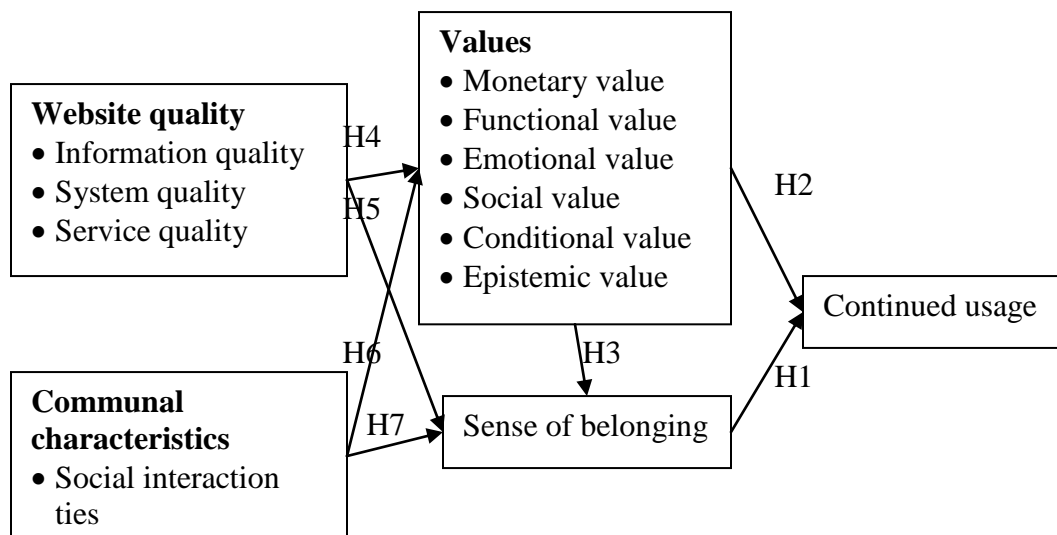


Figure 1. Research framework

References:

- Clarke, R. "Web 2.0 as Syndication," *Journal of Theoretical and Applied Electronic Commerce Research*, 3 (2), 2008, pp. 30-43.
- Chen, H., Wigand, R.T., and Nilan, M.S. "Optimal Experience of Web Activities," *Computers in Human Behavior*, (15:1), 1999, pp. 585-608.
- Chiu, C-M., Hus, M-H., and Wang, E. T.G. "Understanding Knowledge Sharing in Virtual Communities: An Integration of Social Capital and Social Cognitive Theories," *Decision Support Systems*, (42), 2006, pp. 1872-1888.
- Deng, Z., Lu, Y., Wei, K. K., and Zhang, J. "Understanding Customer Satisfaction and Loyalty: An Empirical Study of Mobile Instant Messages in China," *International Journal of Information Management*, 2009, doi: 10.1016/j.ijinfomgt.2009.10.001
- Hsu, C-L., and Lin, C-C. "Acceptance of Blog Usage: The Role of Technology Acceptance, Social Influence and Knowledge Sharing Motivation," *Information & Management*, (45), 2008. pp. 65-74.
- Hu, T. and Kettinger, W. "Why People Continue to Use Social Networking Services: Developing a Comprehensive Model," in *Proceedings of International Conference on Information Systems 2008*, Paris 2008
- Lin, H. F. "Determinants of Successful Virtual Communities: Contributions from System Characteristics and Social Factors," *Information & Management*, (45:8), 2008, pp.522-527.
- Lin, H. F., and Lee, G-G. "Determinants of Success for Online Communities: An Empirical Study," *Behaviour & Information Technology*, (25:6), 2006, pp. 479-488.
- Nov, O. and Ye, C. "Community Photo Sharing: Motivational and Structural Antecedents," in *Proceedings of International Conference on Information Systems 2008*, Paris 2008
- Pihlstrom, M. and Brush, Gregory J. "Comparing the Perceived Value of information and Entertainment Mobile Services," *Psychology & Marketing*, 25(8), 2008, pp. 732-755.
- Sheth, J.N, Newman, B.I., and Gross, B.L. "Why We Buy What We Buy: A Theory of Consumption Values", *Journal of Business Research*, (22), 1991, pp. 159-70.
- Sledgianowski, D., and Kulviwat, S. "Using Social Network Sites: The Effects of Playfulness, Critical Mass and Trust in A Hedonic Context," *Journal of Computer Information Systems* (49:4), 2009, pp. 74-83.
- Sweeney, J.C and Soutar, G. N. "Consumers Perceived Value: The Development of a Multiple Item Scale," *Journal of Retailing*, (77:2), 2001, pp. 203-220.
- Wang, D., Xu, L., and Chan, H. C. "Understanding Users' Continuance of Facebook: The Role of General and Specific Computer Self-Efficacy," in *Proceedings of International Conference on Information Systems 2008*, 2008, Paper 168.

Media Selection Preferences of US College Students: Empirical Evidence and A Proposed Research Model

Jian Tang
Syracuse University
jtang04@syr.edu

Ping Zhang
Syracuse University
pzhang@syr.edu

Abstract

Owing to the development of information and communication technologies (ICTs), people have more choices of communication media than they used to. This study focuses on social communication needs of one of the dominating populations using social media: US college students. It collects evidence on the types and reasons for media use, and applies media richness theory (MRT) to explain media selection preferences. Based on the thematic analysis of data collected from focus groups, we find that MRT can only partially explain the media selection preferences. We then propose a research model that can better explain preferences by this particular population.

Keywords: media selection, media richness theory, social media

1. Introduction

ICTs provide new communication media allowing people more channels for interaction than ever before. Mobile phones offer more than just calls, including text messaging, emailing, and internet access capabilities. In 2007, mobile phone usage per user per month was 748 minutes (World Bank, 2010). In addition to phones, social networking sites, voice over the internet, etc. have gained tremendous popularity. With such a quick and large movement, one would naturally ask: what factors contribute to people's media selection for social communication?

Understanding those factors is meaningful to communication media stakeholders. For media designers, they get a better understanding of users' perceptions and expectations of social communication media. For media service providers, they know what the focal point is to promote their products.

A thorough literature search yielded only limited numbers of empirical studies on people's media selection preferences for social communication purposes, and fewer with theoretical basis. Some studies applied media richness theory (MRT) to explain media selection preferences in organizational and managerial context, indicating that people tended to use richer media to deal with ambiguous and uncertain tasks and to use leaner media to deal with clear and simple tasks (Daft and Lengel, 1984; Daft et al., 1987; Carlson and Davis, 1998; Lee and Lee, 2009). Yet, little research applied MRT to analyze media selection preference in the social communication context. This study provides empirical evidence on people's preferences of media in the social communication context, and uses a theoretical lens to explain such preferences.

2. Literature review

2.1 Studies on Social Media Selection

Previous studies on social media selection compared various media types (e.g. face-to-face, telephone, email, voice mail, and social networking sites), and claimed that media selection was determined by several factors, such as the media's attributes, the properties or the features of the user, content of communication, task equivocality, social presence, and ease of use (Adams et al., 1992; Keil and Johnson, 2002; Yen, et al., 2007; Satofuka et al., 2009). Studies also suggested that individuals made decisions based on their own interactional characteristics (e.g. relationship duration, relationship origin, distance, and communication content) (Mesch, 2009).

2.2 Media Richness Theory

MRT (Daft and Lengel, 1984) posits that media selection is determined by the fit between the richness of media and the richness of information (Daft and Lengel, 1984). The information richness is illustrated by equivocality (the ambiguity and conflicting interpretation of information) and uncertainty (the gap between the information needed and the information available to finish a task). MRT predicts that richest media are used in situations with high equivocality and high uncertainty; fairly rich media are used in situations with either high equivocality or high uncertainty; leaner media are used in situations with low equivocality and low uncertainty (Daft and Lengel, 1984; Daft et al., 1987; Galbraith, 1973). The effect of media richness on information processing was determined by four attributes: (1) Feedback, the time needed to get response from the receiver; (2) Multiple Cues, the number of cues the media can provide, such as voice, body gestures, and eye contact; (3) Language Variety, the broadness of meaning that can be conveyed by the media; and (4) Personal Focus, the ability of the media's customization (Daft and Lengel, 1984; Daft et al., 1987; Dennis and Kinney, 1998; Takeda, 2007).

Although MRT has been a dominant theory in explaining media selection preferences in an organizational and managerial context (Dennis and Kinney, 1998; Webster and Trevino, 1995), some studies suggested that the combination of MRT and other media selection theories could better explain and guide media selection (Carlson and Gordon, 1998; Robert and Dennis, 2005; Yun, et al., 2009). However, these studies failed to distinguish the gap between the predictive statements of theories and the results of empirical studies. Even if the study was based on an empirical study, the participants were asked to choose the media in a hypothetical context (Daft, et al., 1987; El-Shinnaway and Markus, 1992; Otondo, et al., 2008). Conclusions of those studies might not be able to completely support MRT because participants might make different decisions in real situations other than their hypotheses (Dennis and Kinney, 1998). We intend to reveal empirical evidence on factors contributing to media selection for social context, and to examine to what extent MRT could be applied.

3. Research Method

Since we found few empirical studies which systematically identified contributing factors to social media selection, we used an exploratory study with the focus group data collection method. Two pilot studies were conducted to test the effectiveness and accuracy of the protocol and questions. To reflect both gender's views, we recruited one female group (eight participants) and one male group (six participants). They were undergraduates with ages from 19-21 in different departments of a northeast university in the United States. During the sessions, the participants were asked questions on their social communication objects, the types of media used in a variety of situations, and reasons they chose those media. The discussion sessions were audio recorded and transcribed for data analysis.

4. Data Analysis and Results

An inductive (data driven) thematic analysis (Boyatzis, 1998) with ATLAS.ti (v5.6.2) was conducted. The coding schema was initially generated from the two pilots, and then was modified, refined, and finalized with two focus groups. Two raters coded the focus group transcriptions independently, and did inter-rater reliability assessment to ensure the validity of the coding results. Disagreements were resolved through discussions between the two raters and consultations with a third researcher and the final agreement was 100%.

“Media” that the participants used were identified in the data. The most frequently mentioned media were phone calls, text messaging, social networking sites, email, and face-to-face. We examined the richness of these media in light of the four factors in MRT. As Table 1 shows, F2F is the richest media. Phone calls and social networking sites are fairly rich. Text messaging and email are leaner media.

Table 1 Comparative richness of different kinds of media

	Feedback	Multiple Cues	Language Variety	Personal focus
Phone call	Instant	Voice inflection, emotion	High	High
Text messaging	Slower	Word, numbers	Low	Lower
Social networking sites	Slowest	Word, human emoticon, picture	Middle	Middle
F2F	Instant	Physical presence, gesture, eye contact	High	Higher
Email	Slowest	Word, numbers	Low	Lower
Medium richness	<i>F2F > Phone Call > Social Networking Sites > Text messaging > Email</i>			

The data showed four types of reasons for selecting media: 1) characteristics or attributes of media, such as participants’ concerns on instant feedback; 2) relationships with the recipients, such as the closeness of relationships between users; 3) sender’s intentions, like getting acquainted with people; and 4) the characteristics or attributes of the messages, such as the length of message.

Our data analysis also showed co-occurrence frequencies of codes between “Media” and “Why Media,” as listed by gender in Table 2. The numbers indicated that "media’s attributes" is the reason with the highest co-occurrence numbers, followed by "people’s relationships," "message’s attributes," and "sender’s intentions." The differences between female and male students seem relatively minor for various media selection reasons.

Table 2 Numbers of co-occurrence codes in “Media” and “Why Media” (F=Female; M=Male)

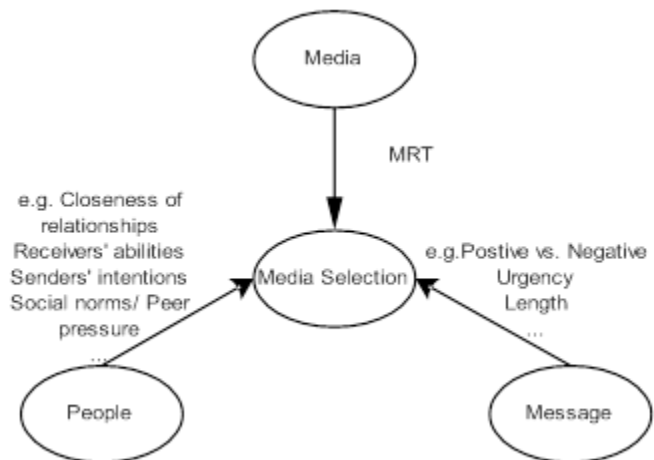
Why Media Media	Media’s Attributes		People’s Relationships		Sender’s Intentions		Message’s Attributes	
	F	M	F	M	F	M	F	M
Phone call	6	3	5	1	1	1	3	0
Text messaging	7	5	3	1	1	0	2	1
Social networking sites	1	2	2	4	2	2	0	1

Face-to-Face	0	2	0	1	0	0	0	1
Email	4	1	1	2	0	0	6	1
Total by Gender	<i>18</i>	<i>12</i>	<i>11</i>	<i>9</i>	<i>4</i>	<i>3</i>	<i>11</i>	<i>4</i>
Total	<i>30</i>		<i>20</i>		<i>7</i>		<i>15</i>	

When we looked back upon the quotations where “Media” and “Why Media” codes co-occurred, we found that text messaging and email were used in situations with low equivocality and low uncertainty. For example, participants used text messaging to get quick answer as opposed to phone call. Email was used for situations such as making appointments. Phone call was mainly used in high equivocality situations with low uncertainty. One male participant said he would like to use phone calls to avoid misunderstanding. F2F was used in ambiguous and uncertain communications. For instance, F2F was used to discuss with professors about their grades.

Media choices resulting from “Media’s Attributes” factors are consistent with the prediction of MRT. However, three factors are beyond the concerns of MRT, one of which is “People’s Relationship.” It includes the closeness of relationship between the sender and the receiver, receiver’s capability, preference and availability, and social norms or peer pressure. For example, several participants said they would not use text messaging to contact their parents because their parents didn’t know how to use it. “Message’s Attributes” was another important influencing factor. Participants preferred to use text messaging to convey negative information to avoid hurting other people’s feelings. The formality of message was also considered by most participants. Email was used to communicate with the potential employers or their professors because it was regarded as a formal communication tool.

Figure 1 A Proposed Model for Social Media Selection



5. The Proposed Model

The proposed model (Figure 1) is a framework incorporating three facets to analyze the reasons for media selection. They are “Media”, “People”, and “Message.” “Media” represents media’s attributes. MRT can explain the richness of the media, but in addition, people also consider practical factors such as the cost of the media. “People” represents individual attributes and social connections. Individual attributes can be demographics, technological skills, and motivations (Satofuka, et al. 2009). Social connection can be relationships between senders and receivers. This facet combines both “People’s Relationships” and “Sender’s Intentions” in the coding schema. “Message” represents the features and content of the message. Examples include

formality, urgency, and the length of the message. The proposed model posits that no single facet can completely explain the media selection preferences in social communication context.

6. Discussions and Conclusion

There are several limitations in this study that we should acknowledge before discussing the findings and their implications. First of all, the sample of US college students was from only one university. Second, results might be restricted by the small data sample. Third, in our proposed model, we considered only the factors identified in our empirical data. There may be other factors that are present in the literature, or might be discovered with larger and broader samples.

We consider several reasons that may result in the inability of MRT to explain media selection preferences in social communication context. First, MRT was proposed in 1980s when it was used to measure the traditional media, such as face-to-face, telephone, written letters, and bulletins. Today, it may not be applicable to social media which has different attributes and functionalities afforded by the modern technologies. Second, in contexts outside the organizational and managerial, people's choices of media are not determined only by media's attributes any more. Social connections and relationships play important roles. Third, MRT didn't analyze the communication purposes and the technological abilities of receivers, leading to an oversimplification of the media selection process. The last reason is that the equivocality and uncertainty are no longer the only two influences on information processing. Formality, length and urgency of message are all influencing factors.

In the proposed model, we claim that "Media", "People", and "Message" are the three facets from which people make decisions about media selection. Further work is necessary to elaborate measures to evaluate the three facets, and a larger dataset is needed to verify the proposed model. This paper suggests that researchers should look at the media selection preference from difference angles, and practitioners should pay more attention to the "People" and "Message" facets when they develop and manage ICTs products for social communication purposes.

References

References are available upon request.

A Model Based Measurement of "Helpfulness" of Online User Review

Qiwei Gan
Texas Tech University
qiweigang@gmail.com

Zhangxi Lin
Texas Tech University
Zhangxi.lin@gmail.com

Jiajia Wang
Southwest University of
Finance and Economics
xiaojiajia198796@sina.com

Abstract

Online user reviews are becoming an important source of information of products and services for customers in addition to the information provided by product/service vendors. Previous studies documented that online user reviews help customers in making purchasing decisions. However, as number of reviews increases dramatically, it creates information overload to customers. "Helpfulness" voting on reviews, a feature provided by some websites, facilitates customers to locate the "helpful" reviews efficiently and effectively. While a growing number of studies attach importance to helpfulness of online reviews in their investigations, such as, website stickiness, online sales prediction, online opinion extraction, etc., a largely uninvestigated issue is the definition and measurement of helpfulness. This paper proposes a model based measurement of helpfulness of online user review which addresses some problems of existing measurements, such as, randomness and subjectivity of reviewers. A better and more accurate measurement can benefit and improve the helpfulness studies.

Keywords: online user review, helpfulness, measurement, text mining

1. Research Background

"Was this review helpful?" is a simple question asked by many websites to readers of online user reviews. It is estimated that this simple question brings 2.7 billion dollars more sales annually to Amazon.com (Spool 2009). What is the "magic" behind this simple question? It helps potential customers locate the reviews with richest and comprehensive information about the products provided by those who had used those products, and then make purchasing decisions based on the information. This facilitation attracts more customers to the websites and also increases the quality and reputation of the website, hence increases sales.

Many existing studies documented the relationship sales and online user reviews and found that online user review has positive impact on products sales (Chen et al. 2008; Chevalier and Mayzlin 2006; Duan et al. 2008). Understanding the importance of online user reviews has been extensively discussed recently in academia (Chen et al., 2004; Clemons et al., 2006; Dellarocas, 2003; Duan et al, 2008; Li and Hitt, 2008) and echoed by practitioners with most product-related websites now providing one or another type of user reviews systems. Online user reviews are regarded as "digitalized word of mouth" (Dellarocas, 2003) and found to be influential on product sales (Duan et al, 2008).

However, the great amount of information available on the Web has created information overload among online users (Brynjolfsson and Smith, 2000; Jones et al, 2004). As the Internet and e-commerce becomes increasingly popular, the types of products available online has grown

rapidly. Online users often find they lack the knowledge and time to decide where to buy, what to buy, and how much they should pay, since there are many competing websites, competing products, and competing prices. Online user review systems, then, provide a way for consumers to share their opinions and experience about specific products. By reading those reviews and then following others' choices, consumers could be more efficient and rational to make decisions. Even though the information overload created by the availability of large variety of products online could be mitigated by referring to online user reviews to some extent, the vast amount of online user reviews created another information overload to consumers. It is virtually impossible for consumers to read all the reviews before making purchase decisions, especially for those popular products. Instead, what consumers really need could be just several the most "*helpful*" reviews. Some websites make this feasible by simply asking anyone who read a review to vote on "was this review helpful to you?" and then provide option to sort reviews based on this helpfulness voting. A growing number of studies attach importance to helpfulness of online reviews, including assessing helpfulness (Kim et al. 2006), helpfulness' effect on sales (Forman and Ghose 2008), and what makes a helpful online review (Mudambi and Schuff 2010).

2. Research problem and their importance

However, this helpfulness voting is not a panacea. There are a couple of unresolved issues. First, there is not any consistent definition of helpfulness. Researchers tend to use the word "helpfulness" flexibly. Second, the measurement of helpfulness, without a clear definition of helpfulness, is different from one study to another. The question "was this review helpful to you?" can be answered either "yes" or "no." The result of answering this question is typically summarized in the form of "20 out of 100 people think this review helpful." In general, this summarized ratio (20/100) is referred to the helpfulness of reviews (Ghose et al. 2008; Liu et al. 2008; Kim et al., 2006). Third, many studies discussed the subjectiveness of online user reviews (Dellarocas 2003; Ghose 2008) and it is the case for the helpfulness voting. Some readers voted on the helpfulness carelessly. Fourth, in our observation, not all online reviews received helpfulness votes, instead, a large part of reviews on some popular websites, e.g. Amazon.com, CNET Download.com (CNETD), do not receive any helpfulness vote.

This paper focuses on the measurement problem. Researchers have used several approaches to measuring helpfulness. For example, Kim et al. (2006) defined the "helpfulness" as the raw percentage of the number of helpful votes divided by the total number of votes. For example, for a review with "20 out of 100 people think this review helpful," the helpfulness is calculated as $20/100=0.2$.

The raw percentage measurement seems intuitive. However, it has some limitations. For example, in one situation, "1 out of 1 people think this review helpful"; in the other situation, "98 out 100 people think this review helpful." The raw percentage measure for the first situation is 1, while the second is 0.98. However, in the first situation, the vote might be just by chance while the second situation has much more credibility. In our observation, there are many reviews with "1 out of 1 people thinks this review helpful" and many reviews with "0 out of 0 people think this review helpful." Another problem would be that for one review, "10 out of 20 people think this review helpful"; for another review, "100 out 200 people think this review helpful". The raw percentage measurements of the helpfulness for both reviews are 0.5. Are these two reviews the

same helpful? The second review has much more votes and provides more statistical evidence. However, online users are hard to distinguish the helpfulness of two reviews.

Another frequently used measurement of helpfulness is a binary indicator, "helpful" or "unhelpful," which is based on the raw percentage (Ghose 2008). If the raw percentage is below a cutoff value (.5 or other numbers), it is unhelpful and if the raw percentage is above the cutoff value, it is helpful.

Both the raw percentage and binary measurement of helpfulness take only the number of helpfulness votes into consideration. Many other factors may affect the accuracy of the measurement, for example, the subjectivity, randomness, and etc. Some users may vote on helpfulness with great subjectivity which may not be fair to the product/service. On the other hand, randomness play a great role in the reviews due to great uncertainty in an online context. It is virtually impossible for a reader to read all the reviews and vote on all reviews. Some users choose to vote on some reviews simply due to randomness.

A third measurement of helpfulness is found in Liu et al. (2007) who manually coded the helpfulness of reviews as good, fair, and bad according to informativeness, readability and subjectivity of reviewers. However, they did not take into consideration of helpfulness votes, which is an important summarization of user experience.

This research proposes to address this problem from a model-based perspective. First, we construct a model with a random effect, which takes the randomness into consideration. Second, we further develop this model taking consideration of review text analyzed by text mining techniques. By using text mining techniques, the subjectivity of reviewers can be mitigated to some extent. This model seems better and more accurate than the raw percentage and binary measurement.

A better measurement of helpfulness will help website designers to better present the "helpfulness" of user reviews by providing an option to rank the reviews in terms of the helpfulness calculated by the model. It facilitates users to quickly locate the most helpful reviews. In doing so, more users will be attracted to the websites and may increase sales. A better and more accurate measurement of helpfulness also enables researchers to correctly estimate those reviews without any helpfulness votes. Some studies used helpfulness as an important factor to study online user reviews (Ghose, 2008). However, if their measurement of helpfulness is wrong or very inaccurate, their conclusions may also be wrong.

The other problem of helpfulness is that different customers may think different about the helpfulness of reviews, because each customer thinks from his/her own angle, a review may be helpful to one customer, but may not be helpful to another customer. For example, a review focuses on the delivery of the product is very important to one customer, but may be of little use to another customer. Therefore, the helpfulness of reviews should be "individualized" helpfulness, that is, the helpfulness changes from customer to customer. We believe that each customer tend to have a priority or "mental list" of features that make the review helpful. In this study, we explore some common features and how these common features affect the helpfulness of reviews. Then, when a customer is to view the online reviews, he/she will be asked to rank

these features. Based on his/her ranking (priority), we will provide a ranking of reviews based on customized helpfulness.

3. Related Work

3.1 Helpfulness of Online User Reviews

The primary focus of most extant research are on defining, modeling, and predicting the helpfulness of online user reviews. Several approaches have been suggested to measure, model, and predict helpfulness. As mentioned earlier, Kim et al. (2006) gave an operational definition of "helpfulness" as the percentage of the helpfulness votes, which is the number of helpful votes divided by the total number of votes. Ghose et al. (2008) proposed another binary operational definition of helpfulness. Liu et al. (2007) manually coded the helpfulness of reviews as good, fair, and bad. These definitions are inconsistent and remain in operationalization level. Until very recently, Mudambi and Schuff (2010) provided a clear definition of a helpful review as "a peer-generated product evaluation that facilitates the consumer's purchase decision process" (p.186). We adopt this definition in this paper.

As mentioned earlier, in this paper, we analyze review text to address subjectivity issue. A brief review of text analysis and online user review is presented in the following section.

3.2 Text Analysis and Online User Review

While earlier studies primarily addressed the relationship between online user review valence/volume and product sales (Chevalier and Mayzlin 2006), there is an emerging research arena that pays more attention to the detailed text information generated in the reviews. Pavlou and Dimoka (2006) utilized the content analysis to quantify the feedback text comments on eBay. Their findings suggest that the rich content of feedback text comments plays an important role in building a buyer's trust in a seller's benevolence and credibility. More recently, text mining is gaining more popularity in IS research and various text mining techniques are developed to quantify textual information (Wei 2008; Larsen 2008; Sidorova et al. 2008). Sidorova (2008) used latent semantic analysis, one of the text mining techniques, to discover the intellectual core of IS research. Wei (2008) also used latent semantic indexing to cluster multilingual documents to generate knowledge maps. The "helpfulness" of reviews, by and large, is closely related to the detailed text information contained in the reviews, that is, whether the information is helpful for the viewers to make product choice. Though many extant studies, as discussed above, simply used the ratio of helpfulness votes to represent the information, a few studies have realized the importance of delving deeper into the detailed text analysis (Kim et al. 2006; Ghose et al. 2008; Liu et al. 2007; Liu et al. 2008).

4. Random Effect Model and Text Mining

This study is the first research to have an in-depth discussion on the measurement of helpfulness of online user reviews and by using the best linear unbiased predictor, we are estimating the helpfulness of online user reviews with incorporation of a random effect.

Formally state, for i th review, there are X_i out of n_i people think it helpful, and the probability of the i th review's helpfulness is p_i , then we assume that

$$X_i \sim \text{Binomial}(n_i, p_i)$$

The problem becomes to estimate the probability p_i . The following model is used to estimate the probability p_i ,

$$\text{logit}(p_i) = \mu + \beta C + \alpha_i, \quad \alpha_i \sim N(0, \sigma_\alpha^2)$$

Where μ is the intercept, α_i is a random effect variable for each review, C is an $n \times 1$ vector of n characteristics of reviews text using text mining results and β is a $1 \times n$ vector of coefficients of those characteristics.

Best linear unbiased prediction is used in linear mixed models for the prediction of random effects. BLUP was derived by Charles Roy Henderson. Best linear unbiased predictions (BLUPs) of random effects are equivalent to best linear unbiased estimates (BLUEs) of fixed effects. The distinction arises because it is conventional to talk about estimating fixed effects but predicting random effects, but the two terms are otherwise equivalent.

In this paper, characteristics of reviews text are derived from one of text mining techniques, the latent semantic analysis, which provides a number of single value decomposition factors for each review.

5. Future Work

Limited by scope and space here, we do not provide the model estimation and detailed text mining procedure and analysis at this stage. Our aim of the paper is to propose the research model. This proposal is feasible in several ways and is also our direction for the future work. First, online review data are available and easy to collect from popular websites such as amazon.com, download.com, etc. Second, the well known statistical software package SAS provides a GLIMMIX procedure that is a powerful random effect estimation procedure and will be used to estimate our model. Third, SAS Enterprise Miner, a SAS data mining solution, provides a powerful text mining tool and can perform a vast range of text mining tasks, such as latent semantic analysis.

Reference

1. Brynjolfsson, E., and Smith, M.D. "Frictionless commerce? A comparison of Internet and conventional retailers," *Management Science* (46:4) 2000, pp 563-585.
2. Chen, P.Y., Wu, S., and Yoon, J. "The impact of online recommendations and consumer feedback on sales," the International Conference on Information Systems, 2004, pp. 711-724.
3. Chevalier, J.A., and Mayzlin, D. "The effect of word of mouth on sales: Online book reviews," *Journal of Marketing Research* (43:3) 2006, pp 345-354.
4. Dellarocas, C. "The digitization of word of mouth: Promise and challenges of online feedback mechanisms," *Management Science* (49:10) 2003, pp 1407-1424.
5. Duan, W., Gu, B., and Whinston, A.B. "The dynamics of online word-of-mouth and product sales -- an empirical investigation of the movie industry," *Journal of Retailing* (84:2) 2008, pp 233-242.
6. Forman, C., Ghose, A., and Wiesenfeld, B. "Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets," *Information Systems Research* (19:3) 2008, pp 291-313.
7. Ghose, A., and Ipeirotis, P.G. Estimating the Socio-Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics SSRN, 2008.
8. Kim, S.M., Pantel, P., Chklovski, T., and Pennacchiotti, M. "Automatically assessing review helpfulness," the 2006 Conference on Empirical Methods in Natural Language Processing, Association for Computational Linguistics Morristown, NJ, USA, 2006, pp. 423-430.

9. Larsen, K.R., Monarchi, D.E., Hovorka, D.S., and Bailey, C.N. "Analyzing unstructured text data: Using latent categorization to identify intellectual communities in information systems," *Decision Support Systems* (45:4) 2008, pp 884-896.
10. Li, X., and Hitt, L.M. "Self-Selection and Information Role of Online Product Reviews," *Information Systems Research* (19:4) 2008, pp 456-474.
11. Liu, J., Cao, Y., Lin, C.Y., Huang, Y., and Zhou, M. "Low-quality product review detection in opinion summarization," *Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, 2007, pp. 334-342.
12. Liu, Y., Huang, X., An, A., Yu, X., Giannotti, F., Gunopulos, D., Turini, F., Zaniolo, C., Ramakrishnan, N., and Wu, X. "Modeling and predicting the helpfulness of online reviews," *Eighth IEEE International Conference on Data Mining, IEEE*, Piscataway, NJ, 2008, pp. 443-452.
13. Mudambi, S.M., and Schuff, D. "What makes a helpful online review? A study of customer reviews on Amazon.Com," *MIS Quarterly* (34:1) 2010, pp 185-200.
14. Sidorova, A., Evangelopoulos, N., Valacich, J.S., and Ramakrishnan, T. "Uncovering the intellectual core of the information systems discipline," *MIS Quarterly* (32:3) 2008, pp 467-482.
15. Spool, J. "The Magic Behind Amazon's 2.7 Billion Dollar Question," 2009.
16. Wei, C.P., Yang, C.C., and Lin, C.M. "A Latent Semantic Indexing-based approach to multilingual document clustering," *Decision Support Systems* (45:3) 2008, pp 606-620.

Online User Reviews and Professional Reviews: A Bayesian Hierarchical Approach to Model the Mediating Role and Time-Variant Impact

Wenqi Zhou
The George Washington University
wenqi@gwmail.gwu.edu

Wenjing Duan
The George Washington University
wduan@gwu.edu

Abstract

We propose a Bayesian hierarchical mediation model to examine the impacts of two sources of Word-of-Mouth information — online user reviews and professional reviews in the context of software download. Our empirical results indicate that the impact of extreme user reviews on software download varies over time and such variation is moderated by product variety. The increase in product variety strengthens the impact of positive user reviews, while weakening the impact of negative user reviews. Furthermore, professional reviews influence software download both directly and indirectly through their impacts on online user reviews. Receiving positive professional reviews leads to more software download, yet receiving very negative professional reviews has a negative impact on the number of download.

Keywords: Online User Reviews, Professional Reviews, Bayesian Hierarchical Mediation Model

1. Introduction

Consumers are facilitated by Internet technology to expediently exchange their experiences and learn from others' recommendations about product information, which significantly influences their decision making in online market (Godes and Mayzlin 2004). The two most prominent and commonly discussed sources of this digital Word-of-Mouth (WOM) effect are professional reviews and online user reviews, the latter of which has two most important attributes: valence and volume (Neelamegham and Chintagunta 1999). There is an extensive body of research on the impact of either online user reviews or professional reviews (Basuroy et al. 2003; Duan et al. 2009). There is, however, lack of attention on how these two resources of information work together to influence consumer decision making. Because of the broad reach of Internet, nowadays consumers can easily have accesses to these two sources of WOM information. For example, many popular websites, such as CNETD (www.download.com) and Amazon readily provide both user reviews and editorial reviews for their products. Consumers are even shown to search for multiple WOM information sources across websites (Park et al. 2009). However, it is unclear from literature about the way consumers analyze and integrate user reviews and professional reviews to formulate their evaluations and make decisions. It could be misleading to independently interpret the impact of either user reviews or professional reviews without recognizing their interrelationship.

The major objective of this paper, therefore, is to open the “black box” of the process through which user reviews and professional reviews jointly influence user choices. Specifically, we investigate two related issues by adopting a Bayesian hierarchical mediation model on a panel data set of software download in CNETD. One issue is that how volume of user reviews

mediates the impact of professional reviews on user choices. Reinstein and Snyder (2005) discuss that the surprisingly large influence of professional reviews on box office revenue could be partly due to the indirect effect of professional reviews through user-generated WOM in addition to their direct effect. This finding suggests the mediation mechanism wherein professional reviews→volume of user reviews→user choices. Unlike the abundant user-generated WOM information, professional reviews are only provided by a small group of well-trained professionals on a very limited number of products. Consumers are motivated to engage in both offline and online WOM activities partly in order to enhance their own self-worth (Dicher 1966; Hennig-Thurau et al. 2004). As a result, consumers are more willing to write reviews on products receiving professional reviews, especially obtaining higher evaluations, for the potential to attract other consumers' attentions and then show their connoisseurship. More WOM activities lead to more user choices (Godes and Mayzlin 2004), resulting in the mediated impact of professional reviews on user choices. We find that professional reviews influence software download partially mediated by volume of user reviews. The fact that a product has received professional reviews both directly and indirectly influence download via its impact on volume of online user reviews. Overall receiving very negative professional reviews significantly reduces a product's download, whereas receiving positive professional reviews contributes to more download.

In order to provide a broad picture about how both user-generated and professional WOM information influence user choices, it is also important to correctly interpret the relationship between valence of user reviews, another attribute of user-generated WOM information, and user choices. Therefore, the other issue explored in this study is how the impact of online user reviews varies over time and is moderated by product variety. Zhu and Zhang (2010) find that product popularity information moderates the impact of online user reviews. Zhou and Duan's paper (2009) demonstrates a significant interaction effect between product variety and online user reviews, implying a moderating effect of product variety on the impact of user reviews. Yet, they do not go a step further to fully explore the variation of the impact of user reviews caused by the change of product variety. And neither of those two studies considers the existence of other moderators, which is sufficiently addressed by a hierarchical structure embed in the empirical model in this study. We find that the impact of online extreme user reviews varies over time, which is mainly caused by the moderating effect of product variety, while neutral user reviews' influence on software download does not change over time. The increase in product variety strengthens the impact of positive user reviews, while suppressing negative user reviews'.

2. Data

We conduct this study in the context of online software download at CNETD, which is a leading online platform for software download. Our data was collected weekly for four categories between Aug. 2007 and Feb. 2008. These categories are Digital Media Player, Download Manager, File Compression and MP3 Finder, which includes popular downloaded categories and also categories with different application purposes. We extract following information on every software program listed in each category on a weekly basis: software name, date added, software characteristics, total download, last week download, average user ratings, number of user ratings and CNET ratings. CNETD only provides editorial reviews for selected software programs (usually the popular ones). Since every category represents a unique group of software with similar functions, we define each category as a single market.

3. Bayesian Hierarchical Mediation Model

3.1 Model Setup

To facilitate illustrating our model setup, we first introduce the notation as following,

Y_{it} = number of weekly download of software i at week t ,

X_{it} = control variables: $X_{it1} = LOGTOTALDOWNLOAD_{it}$ (log transformation of cumulative number of download of software i at week t), $X_{it2} = WEEKLYRANK_{it}$ (weekly download rank of software i at week t), $X_{it3} = FREEPRICED_{it}$ (a dummy variable measures if software i is free-to-try at week t), $X_{it4} = AGE_{it}$ (days since software i has been posted), $X_{it5} = AGESQ_{it}$ (square term of AGE_{it}),

$WEEKLYVARIETY_t$ = total number of software programs listed in the category at week t ,

$USERVAL_{it}$ = average user rating for software i at week t (one to five scale with half points),

$USERVAL^R_{it} = USERVAL_{it} - 3$,

$USERVAL^R SQ_{it}$ = square term of $USERVAL^R_{it}$,

$USERVOL_{it}$ = number of user reviews software i has received by week t ,

$PROD_{it}$ = a dummy variable measures if software i receives CNET editorial rating at week t ,

$PROVAL_{it}$ = CNET editorial rating software i receives at week t (one to five scale with half points).

We note that a minor linear transformation of user ratings would help differentiate user reviews with different valence level. Instead of including $USERVAL_{it}$ in the model, we consider $(USERVAL_{it} - 3)$. For parsimony, we name the new variable $USERVAL^R_{it}$. In order to assess the nonlinear impact of different level of user ratings, we also include a quadratic term of $USERVAL^R_{it}$, denoted by $USERVAL^R SQ_{it}$. Zhou and Duan (2009) empirically demonstrate that the impact of neutral user reviews does not depend on the level of product variety. Therefore we build up a hierarchical structure on the coefficient on $USERVAL^R SQ_{it}$ to capture the moderation effect of product variety on the impact of user reviews. We allow the coefficient on $USERVAL^R SQ_{it}$ random over different time, which vary along weekly product variety with an error term δ_3^t . This error term is indispensable in the sense that it can control for all other unobserved situational variables varying across time, other than product variety, that may also moderate extreme user reviews. Since only less than 20% of software programs have received CNET editorial reviews, in order to measure the impact of professional reviews, we include two terms, $PROD_{it}$ and $PROD_{it} * PROVAL_{it}$, to both capture the impact of valence of professional reviews and differentiate products with professional reviews from those without. As for products without CNET ratings, $PROVAL_{it}$ value is irrelevant to model estimation and thus specified as zero for simplicity. The following is the detailed Bayesian hierarchical mediation model setup:

$$LOG(Y_{it}) = \beta'_1 + \beta_2 * USERVAL^R_{it} + \beta'_3 * USERVAL^R SQ_{it} + \beta_4 * PROD_{it} + \beta_5 * PROD_{it} * PROVAL_{it} + \beta_6 * USERVOL_{it} + \beta_x * X_{it} + \varepsilon_i + \varepsilon_{it}$$

$$\beta'_j = \alpha'_1 + \alpha'_2 * WEEKLYVARETY_t + \delta'_j, j=1,3$$

$$USERVOL_{it} = \lambda_1 + \lambda_2 * PROD_{it} + \lambda_3 * PROVAL_{it} + \sigma_{it}$$

$$\varepsilon_i \sim N(0, \tau_{au}, e), \varepsilon_{it} \sim N(0, \tau_{au}, y), \delta'_j \sim N(0, \tau_{au}, \delta), \sigma_{it} \sim N(0, \tau_{au}, \sigma), i=1, \dots, I; j=1,3; t=1, \dots, 26.$$

,where β_x is a coefficient matrix on control variables with a dimension of 1 by 5.

3.2 Empirical Results

Vague priors are specified for all unknown parameters. We then estimate the model using Markov Chain Monte Carlo (MCMC) method. We conduct a convergence diagnostic to ensure “true” parameters are recovered and thus the estimates are reliable. Due to limited space, here we only report and discuss results from one category – Digital Media Player, which are consistent

with other three categories’.

As shown in Table 1, the coefficient on $USERVAL^R_{it}$ (β_2) is significantly positive, which suggests that the impact of neutral user reviews is positive. As expected, most of the coefficients on $USERVAL^R SQ_{it}$ (β_3^t) are significantly positive over the data collection period as shown in Figure 1a, which plots β_3^t by week. This finding shows that the impact of extreme user reviews denoted by $\beta_2 + 2*\beta_3^t * USERVAL^R_{it}$ varies significantly over weeks. The result also suggests that in most weeks, positive/negative user reviews exert a stronger/weaker impact on software download than neutral reviews. As demonstrated in Table 1, the expected value of β_3^t can be explained as $-0.14(\alpha_1^3) + 0.0004(\alpha_2^3) * WEEKLYVARIETY_t$, which implies that the variation of the impact of extreme user reviews is moderated by product variety. The addition of one more software program would change the impact of extreme use reviews on software download by $2*0.0004(\alpha_2^3) * USERVAL^R_{it}$. The higher/lower the positive/negative ratings are, the more their impact on software download increases/decreases due to the increase in product variety.

Table 1. Estimation Results of Bayesian Hierarchical Mediation Model for Category of Digital Media Player			
		Mean	S.D.
INTERCEPT (α_I^3)	α_I^1	2.505	0.278
	α_I^3	-0.141	0.029
$USERVAL^R_{it}(\beta_2)$		0.181	0.014
$WEEKLYVARIETY_t$	α_2^1	0.004	0.001
	α_2^3	0.0004	0.0001
$PROD_{it}$	β_4	-0.848	0.074
	λ_2	21.550	9.415
$PROD_{it} * PRODVAL_{it}$	β_5	0.382	0.020
	λ_3	32.560	3.661
Indirect impact of valence of professional reviews ($\lambda_3*\beta_6$)		0.009	0.001
Total impact of valence of professional reviews ($\beta_5+\lambda_3*\beta_6$)		0.391	0.020
DIC		184349.000	
Note that Boldface type indicates the significance of estimators, namely the 95% posterior credible interval does not cover zero.			

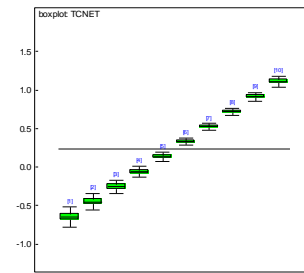
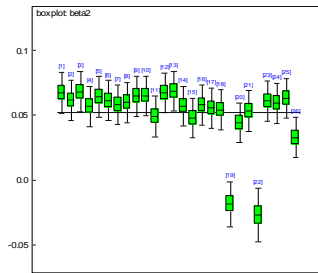


Figure 1a. Box Plots for Coefficients on $USERVAL^R SQ_{it}$ (β_3^t) **Figure 1b. Total Impact of Receiving Professional Reviews**
Note that the middle line denotes the mean and its vertical length denotes the 95% posterior credible interval.

The results also provide implications on the total impact of receiving professional reviews on user choices. The direct impact is estimated as $\beta_4 + \beta_5 * PROVAL_{it}$, which varies along with the valence of professional reviews. The indirect impact to measure the amount of mediation is estimated as $(\lambda_2 + \lambda_3 * PROVAL_{it}) * \beta_6$, which depends on the valence of professional reviews as well. The total impact is simply the summation of these two impacts. Therefore, to

deduce the total impact, we conduct a series of estimations for the summation term at each possible value of $PROVAL_{it}$, i.e. 0.5, 1, ..., 4.5, 5, which is illustrated by a series of box plots in Figure 1b. We can see that valence of professional reviews is helpful to promote software download. However, receiving professional reviews with valence lower than 2.5 leads to decreased software download. Only professional reviews with valence higher than or equal to 2.5 can result in more download.

4. Concluding Remarks

To our best knowledge, our paper is the first empirical study that identifies the mediation role of volume of online user reviews on the link from professional reviews to user choices. Mediation analysis conducted in a Bayesian framework overcomes the limitation of standard frequency mediation approach, which has the difficulty with obtaining a robust estimation of standard deviation for testing a mediated effect. On the other hand, MCMC sampling method, which naturally comes with Bayesian approach, could easily solve this issue by employing the simulation. This paper is also the first to hierarchically model the moderation role of product variety on the impact of online user reviews. The standard moderation approach to include an interaction term in the model is at risk of neglecting other unobserved situational moderators (e.g., promotional event). These factors would be left into error term and cause the endogeneity problem. Instead, we use a hierarchical approach to control those noises in moderator equation, and thus isolate them from modeling the time-variant impact of online user reviews.

References

1. Basuroy, S., Chatterjee, S., and Ravid, S. A. "How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power and Budgets," *Journal of Marketing* (67:4), 2003, pp.103-117.
2. Dichter, E. "How Word-of-Mouth Advertising Works," *Harvard Business Review* (44:6), Nov-Dec 1966, pp.147-166.
3. Duan, W., Gu, B., and Whinston, A. "Informational Cascades and Software Adoption on the Internet: An Empirical Investigation," *MIS Quarterly* (33:1), 2009, pp.23-48.
4. Godes, D., and Mayzlin, D. "Using Online Conversation to Study Word of Mouth Communications," *Marketing Science* (23:4), 2004, pp.545-560.
5. Hennig-Thurau, T., Gwinner, K.P., Walsh G., and Gremler, D.D. "Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet?," *Journal of Interactive Marketing* (18:1), 2004, pp.38-52.
6. Neelamegham, R., and Chintagunta, P. "A Bayesian Model to Forecast New Product Performance in Domestic and International Markets," *Marketing Science* (18:2), 1999, pp.115-36.
7. Park, J., Gu B., and Konana P. "Impact of Multiple Word-of-Mouth Sources on Retail Sales," in *Proceedings of the 30th International Conference on Information Systems*, Phoenix, AZ, 2009, December 17th -19th.
8. Reinstein, D. A., and Snyder, C.M. "The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics," *Journal of Industrial Economics* (53:1), 2005, pp.27-50.
9. Zhou, W., and Duan, W. "Product Variety, Online Word of Mouth and Long Tail: An Empirical Study on the Internet Software Market," in *Proceedings of the 30th International Conference on Information Systems*, Phoenix, AZ, 2009, December 17th -19th.

10. Zhu, F., and Zhang, X. M. "Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics," *To be forthcoming in Journal of Marketing*.

Web 2.0 Online Reputation Systems

Weijun Zheng
University of Wisconsin-Parkside
zheng@uwp.edu

Leigh Jin
San Francisco State University
jinlei@sfsu.edu

Abstract

Web 2.0 has transformed how reputation systems are designed and used by the Web. From a review of Web 1.0 online reputation systems and their challenges in use, this paper summarized the characteristics of Web 2.0 online reputation system such as multimedia feedbacks, human-centered, folksonomy or tagging, community contribution, comprehensive reputation, dynamic and interactive systems etc. These new developments promise a path that move towards a trustworthy and reliable new generation of online reputation system.

Keywords: Online reputation system, Web 2.0

1. Introduction

Online reputation system is the primary mechanism used by online community to collect, distribute, and aggregate feedback about participants' past behavior and help people to decide whom to trust, and to encourage trustworthy behavior. As one of the most studied reputation systems, ebay's feedback forum was attributed to the website's overall commercial success (Resnick et al., 2000, Dellarocas, 2003; Jøsang, Ismail, & Boyd, 2007). However, while the importance of online reputation system is certainly evidenced by its wide adoption in electronic commerce, existing online reputation systems have deep problems in their design that potentially weaken their usability and effectiveness (Malaga 2003).

Web 2.0 distinguishes itself from Web 1.0 through its empowerment of ordinary users to create, control, and share web contents, which contribute to collective intelligence (O'Reilly, 2007). The set of Web 2.0 principles has redefined how individuals and businesses should communicate, interact, and transact through the web, and hence revolved the design principle and future path for online reputation systems in particular.

This paper reviews the status quo of existing reputation systems and describes potential directions for future work in Web 2.0 era.

2. Reputation and Reputation Systems

Reputation represents "the beliefs or opinions that are generally held about someone or something" (Oxford English Dictionary). It is "a collective measure of trustworthiness based on the referrals or ratings from members in a community." (Josang et al., 2007, p. 621). Reputation is often characterized as context-specific, multifaceted, and dynamic (Windley, Tew, & Daley, 2007). That is to say, the same products, people or organizations can be viewed completely differently according to the context under which they are evaluated, the criteria they are judged by, and the time when they are judged.

The development of reputation systems is really about creating a framework of references to gauge the credibility of reputation objects. In a web environment where physical cues of a thing or an individual/group is generally missing, online reputation systems form “large-scale online word-of-mouth communities in which individuals share opinions on a wide range of topics, including companies, products, services, and even world events” (Dellarocas, 2003). Depending on its business objective, an online community’s reputation systems can focus on the reputation of different subjects. For example, product reputation would be the main focus of e-commerce websites like Amazon, while new social media sites like youtube, tend to focus more on the reputation of user generated content (video, photo). The latest social networking sites give more emphasis on people's reputation.

3. Web 1.0 Online Reputation Systems

Web 1.0 reputation systems here refer to all reputation systems before the emergence of Web 2.0. Web 1.0 Online reputation systems such as ebay in its early stage captures individual or organization’s reputation primarily through explicit information that is entered in an online system by a user, e.g. rating score or vote.

E-rating is a mechanism to have users input their evaluation for transactions. eBay used e-rating to provide a public view of participants’ past behaviors, in which a central trusted server gathers transaction information, and calculates participant reputation scores. In ebay case, they use +1 for a positive feedback, -1 for a negative feedback, and 0 for neutral. The equation for them to compute reputation scores is simply a sum of all reputation ratings for past transaction.

E-voting also called ballot box communication (BBC) is an enumeration mechanism that aggregates individual votes and offers limited choices of communication to all participating users. The goal of e-voting is to reveal the interests of the mass population and reflect a many-to-one voice (Xia, Huang, Duan, & Whinston, 2007). With simplified options like Yes/No and Good/Poor, E-voting lowers the cost of participation and reduce the time users need to spend on leaving input. This encourages a large number of people to participate. Sites like eopinion.com used e-voting as their Web 1.0 reputation systems.

Some Web 1.0 reputation systems did attempt to collect implicit information for reputation generation. Implicit reputation is related to network behavioral data, for example, how a user navigates through a series of web pages, how much time a user spends in an online store, or how frequent a user visits a site (Jensen, Davis, & Farnham, 2003). Typical implicit reputation collected by Web 1.0 reputation systems are basic access statistics including popularity by evaluating view rankings, number of visitors, and number of comments etc. Those access statistics are often released in conjunction with e-rating and e-voting scores. However, the scope and depth of implicit information used in Web 1.0 reputation systems are very limited.

Although Web 1.0 reputations systems can affect behavior of participants in online communities and induce beneficial outcomes, they often fail because of some weaknesses: misrepresented feedback, pseudonyms, lack of portability and inaccurate reputation calculation (Resnick et al. 2000, Malaga 2004). First, online reputation often misrepresents the performances of community participants and could be artificially inflated or deflated by the malicious actions of participants. For example, one participant could blackmail another and threaten to post negative

feedback that is unrelated to actual performance. Participants could also collaborate and rate one another positively, and collude against a competitor by providing negative ratings. Second, the anonymity characteristic of many online communities makes it very difficult for reputation systems to identify participants and trace their prior histories. Lacking a history make trust rating impossible because there is nothing to base a prediction of future behavior. Third, reputation accumulated in one community cannot be shared on another site either because participants' reputation could be considered proprietary and prohibited from sharing out of the community that generates those reputations, or because the methods and time-periods used by different communities are not consistent and often difficult to be converted from one to the other. Finally, an overall reputation score that is often a simple sum of each individual reputation rating is unable to compare participants who have pure positive ratings and those who have the same overall scores but the scores are from a sum of both positive and negative rating. A general reputation score also doesn't reflect the multifaceted nature of the reputation of a participant.

4. Web 2.0 Online Reputation Systems

Since its inception, the Web 2.0 movement have influenced many facets of Internet culture and inspired innovative companies to create newer reputation systems to better service customers in the global economy. Its principles redefine how individuals and businesses should communicate, interact, and transact through the web (Lessig, 2006). In general, Web 2.0 encourages users' participation and creativities, captures individual actions to produce collective results, uses mass data volume matters and facilitates community and network building among users, and supports open data exchange with open standards. Online reputation systems designed through Web 2.0 technologies and principles therefore have shown very different features and patterns from Web 1.0 online reputation systems. Next table summarizes their major differences.

Table 1 A Comparison of Web 1.0 and Web 2.0 Reputation Systems

Web 1.0 Reputation Systems	Web 2.0 Reputation Systems
Score/scale/text	Multimedia input
Explicit action required	Implicit reputation derived
Product centered reputation	Human centered reputation
Individual contribution	Community contribution
Static/Reactive	Dynamic/ Interactive
Single dimension	Comprehensive

Multimedia inputs Web 2.0 Reputation Systems encourage users to create and share reviews in the multiple formats including texts, images and videos. In contrast, most Web 1.0 reputation systems tend to use scores/ratings only to aggregate reputation. Multimedia feedback contains richer information and help to reduce the misinterpretation of reputation scores, therefore complement to the score rating used by Web 1.0 reputation systems. For example, one product's images can really provide a good sense of product dimension by comparing it with other familiar objects. Images taken using the digital camera under review not only testify the product quality in a way, but also enable viewers to make their own judgment about product reputation.

Folksonomy Tagging, one of the signature applications of Web 2.0 (Vander Wal, 2005), has also been incorporated in the design of Web 2.0 reputation system. Tagging technology allows

community members easily tag the focal item according to their own definition/classification. Tags generated by members can imply implicitly the reputation of a subject. For example, more customers tag a particular product indicates that more people could be interested in it. Some Web 2.0 reputation systems go even further to display a “tag cloud” where the most popular and most current tags about the subject will be highlighted among all tags.

Human centered Web 1.0 reputation systems mostly target at products that are to be evaluated. Reputation scores in those systems typically are about the reputation of products. Many Web 2.0 reputation systems however start to establish reviewers’ reputation. Not only each reviewer’s profile is displayed along the review he or she made, many Web 2.0 reputation systems also ranked reviewers according to the quality of their review, the correctness of their review, and total number of their reviews etc. The change of reputation focus from products to human permit Web 2.0 reputation systems to improve member participation and the reliability of their feedback. Amazon, for example, now rewards reviewers with various “badges” to signify different contributions they made to the community.

Community contribution Web 2.0 technology such as tagging has let the management and creation of online communities very easily. Reputation information in many Web 2.0 reputation systems can be tied very closely with particular community online, therefore specifying the context generating the reputation. For instance, a typical community profile can lists the number of customers, the number of products and the number of discussions in the community, when the last time any activity happened in this community is etc. All these numbers in combination informs viewers about the context of reputation generated by this community. In addition, using Web 2.0 technologies, many websites are connecting like-minded customers into community of practices that allow community members share product knowledge and help each other solve problems through reviews, discussion forums, and comments. By providing these communication channels, those websites actually include communities into their reputation systems, therefore relying on collective efforts of community members to generate reputation for a subject.

Dynamic system Web 2.0 reputation systems start to consider time factor in their reputation formation. One typical example of this development is to allow members to revise their feedback if they make a mistake. This feature is particularly helpful when the member’s experiences with using the product change over time, and would like to reflect those changes in his/her review. In addition, some Web 2.0 reputation systems also permit community members rights to response to the other reviewers’ post or rating and possibly requesting a change on unfair evaluation.

Comprehensive reputation Web 2.0 reputation systems typically count every contribution from any member in the community, therefore provides various opportunities for customers to participate, from less intimidating ones, such as tagging a product, to more daunting ones, such as writing a guide about how to do bird photography. In contrast to Web 1.0 reputation systems where reputation is solely from the ratings generated by the raters, Web 2.0 reputation systems takes full advantage of members’ community participation, specifically, every tag, every review, every discussion, every images, every lists and guides contributed by customers can be associated with a reputation score and will contribute to members’ reputation. Such a vast coverage of members’ online behaviors in reputation formation apparently provides multi-dimensional measures for reputation.

5. Conclusion

Web 2.0 has transformed how reputation systems are designed and used by the Web. This paper attempts to distinguish Web 2.0 and Web 1.0 reputation systems. It notes several

distinguished features of Web 2.0 reputation systems. These new developments reflect Web 2.0 design principals and promise a path that move towards a trustworthy and reliable online reputation system in the future. Further researches in this area is clearly needed and likely very productive.

References

1. Dellarocas, C. (2003) "The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms." *Management Science*, 49(10), October : pp. 1407 – 1424.
2. Jensen, C., Davis, J., Farnham, S., (2003) "Finding Others Online: Reputation Systems for Social Online Spaces", *Proceedings of the SIGCHI conference on Human factors in computing systems: Changing our world, changing ourselves*, April 20 - 25, Minneapolis, Minnesota, USA , pp. 447 – 454.
3. Jøsang, A., Ismail, R., and Boyd, C. (2007) A Survey of Trust and Reputation Systems for Online Service Provision, *Decision Support Systems*, 43(2), March, pp. 618-644.
4. Lessig, L. (2006) "The Ethics of Web2.0: YouTube vs.Flickr, Revver, Eyespot, blip.tv, and even Google". Lessig blog', Oct 20th, Available online at: http://www.lessig.org/blog/2006/10/the_ethics_of_web_20_youtube_v.html [last accessed 02/06/09].
5. Malaga, R. (2003) "Web-Based Reputation Management Systems: Problems and Suggested Solutions", *Electronic Commerce Research*, October, pp. 403-417.
6. O'Reilly, Tim (2007) "What is Web 2.0: Design Patterns and Business Models for the Next Generation of Software." *Communications & Strategies*, No. 1, First Quarter, pp. 17-37.
7. Resnick, P., Zeckhauser, P., Friednam, E. and Kuwabara K. (2000) "Reputation Systems," *Communications of the ACM*, (43:12), December, pp.45-48.
8. Vander Wal, T. (2005) "Folksonomy Definition and Wikipedia." Blog entry: www.vanderwal.net, 2nd Nov. Available online at: <http://www.vanderwal.net/random/entrysel.php?blog=1750> [last accessed 02/05/09]
9. Xia, M., Huang, Y., Duan, W, and Whinston, A.B. (2007) "Implicit Many-to-One Communication in Online Communities", *Proceedings of the Third Communities and Technologies Conference*, Michigan State University, London: Springer pp. 265-274