# DYNAMIC ADOPTION MODEL OF PERSONALIZED ONLINE SERVICES WITH PRIVACY CONCERNS AND WOM EFFECT

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## Abstract

*Privacy concern is becoming one of the most important issues for personalized online services like websites, computer software and mobile apps, especially those offered for free. In this paper, we develop a dynamic adoption model that combines new product diffusion theory with online services privacy, and seek to offer marketing strategies to maximize vendors' profit for online services. We divide the diffusion process into two steps: awareness and adoption, and assume awareness process is mainly influenced by word of mouth effect. The adoption process occurs when benefits adjusted personal information demand level (PIDL) from vendors is lower or close to privacy disclosure tolerance level (PDTL) of consumers. We get numerical solutions for this optimal control problem with two differential equations. Our findings suggest WOM effect, network externalities and the initial state of awareness proportion are effective marketing tools for vendors, and parameters or variables like marginal value for consumer information (MVI), population size and the initial state of adoption amount are less effective. Our study should be considered preliminary with limitations and extensions for future research.*

*Key words: New product diffusion, Privacy concerns, WOM effect, Network externalities.*

# 1	INTRODUCTION

Before the proliferation of online services, there was broad concern about the abuse of personal information in the contexts like employment and direct marketing. The radical development of computing and information technologies have made the personalized online services like websites, computer software and mobile apps available and facilitated collection, processing and trade of personal data (Hann et al. 2007)(Nam et al. 2006). In the late of August 2014, a large number of Hollywood actresses' pictures were stolen and illegally published on websites. Icloud, a typical app of apple mobile devices, was blamed for this issue, and leads to privacy concerns about online services reaching a new level. We are now in an era that any personal privacy can be used without permission, as the so-called privacy property is not in the hand of individuals, but of the service providers and some other third parties (Varian 2006).

However, consumers' willingness to provide privacy seems to contradict their behaviours. It is said that the most important reason why consumers do not make purchases on the internet is the worry about leakage of credit card information (Ernst & Young 1999). Ironically, on the day of November 11th, 2014, Taobao—the biggest e-commerce provider in China, got a trading volume over 57.1 billion RMB( approximately, 9.3 billion US dollars) in a single day, with 42.6% through the mobile devices instead of traditional computers, which means the exposure of both credit card information and all the contract data like address and phone numbers, especially those bounded to their credit cards .

Scholars believe there is a trade-off between the costs and benefits of providing private information which can explain such a paradox, and the benefits can be perceived from monetary rewards and future conveniences (Hann et al. 2007). Markets for personalized online services are fundamentally different from traditional buyer-seller markets as most of the online services are offered for free. However, those service providers still care about the consumers' adoption numbers and the amounts of personal information for some indirect benefits (Chellappa and Shivendu 2007). Some suppliers tend to explore the value of consumers' personal information and offer the potential adopters personalization for privacy trade-off. Others may try to gain some long-run profits. Take the monetary awards in the mobile e-commerce and taxi-calling apps in China for instant, the aim behind these incentive strategies is to grab the market shares on mobile payment field which they believe of strong lock-in effect and the characteristics of "winner takes all" (which has been confirmed a few month ago when two of the biggest taxi-calling apps in China merged with integration plan not yet being announced). In a word, with the venture capital support, they care about nothing but the potential adoption amounts. Besides monetary or subsidy awards, other marketing tools like social media advertising may also have an effect on potential users' decision making for free online services, even though the pricing strategy is not available.

In this research, we seek to suggest a model that is consistent with theories of consumers' behaviour under privacy concern with the assistance of marketing variables like word of mouth effects, and offer advices in accordance with optimum privacy demand path for policymakers. As the users' amount of personalized online service is analogous to the adoption numbers in new product diffusion model with marketing variables, we suggest a framework that is similar to Kalish (1985), but one of the main

variables changed from price to privacy. To the best of our knowledge, this is the first study that combines new product diffusion theory with online services privacy.

The rest of the paper is organized as follows. Related literature is reviewed in section2; in section 3, we present the basic model and discuss its characteristics; in section 4, the optimized strategy with respect to various parameters is discussed, and policy suggestion is offered; in section 5, we conclude with suggestions for future research.

# 2    LITERATURE REVIEW

This study is drawn on two main stream of research: privacy concerns about personalized online services; the diffusion model with marketing variables.

## 2.1    Privacy concerns about personalized online services

Research on the problem of privacy emerged in 1980s, and most of these papers were focusing on the elaborations of relevant concepts. While study on this field was still in its infancy in 1990s, Smith (1994) pointed out privacy information was becoming one of the most important ethical issues of the information age. In 2011, *MIS Quarterly* published several review articles about privacy concerns. Smith et al (2011) and B danger et al (2011) discussed and identified research topics and the relationship between information privacy and other constructs. Based on those two articles, Pavlou (2011) answered two main questions about privacy concerns: where we are now and where we should go. He suggested it does not matter that the concept of information privacy have not yet reach an agreement in the academic circle, what matters is the trade-off between the privacy costs and benefits, which is a topic issue for future study on both theories and practices.

In fact, the trade-off between the costs and benefits of sharing information has been discussed long ago (Posner 1981), and in recent years, some scholars specially tried to explain the trade-off related benefits from the view point of firms' marketing variables, like price (Acquisti and Varian 2005), marketing promotions (Hann et al 2008), and firms' other incentive strategies (Taylor 2004), Hann et al. 2007). However, most of the research are based on empirical or experimental studies and seldom construct mathematical models to offer marketing strategy advices (e.g. Beresford et al. 2012, Preibusch 2013).

Acquisti el al (2007) illustrated the behavioral economics analysis in privacy research, they suggest mathematical models, surveys and experiments should be put together to understand the privacy behavior, and they point out the possibility of studying this problem in the view of neoclassical economics. These narrations are similar to what are shown in the paper published on Science (Acquisti el al. 2015). They believe perceived privacy is uncertainty due to the incomplete and imperfect of information, as well as the uncertainty of preferences. Consumers' decision-making behaviors are affected by endowment effect, pro-social effect, breaking the ice effect, disinhibition effect etc. Also, they mentioned a concept as the malleability of privacy bias, which provide theoretical explanation for building privacy relent models.

As we discussed in section 1, online services put a big challenge on personal information protection, and it is now a commonsense that individuals pay a lot of concerns on these services and have systematic differences in privacy preferences (Hann et al. 2007). Chellappa et al. (2010) suggested the

differences in individuals' concerns for privacy can be valued by privacy cost parameter r with the probability density function f(r) and the cumulative distribution function F(r) to categorize consumers' types. This kind of classification can be drawn into our study to explain individuals' heterogeneity in characteristics towards the perception of privacy risks.

## 2.2 The diffusion model with marketing variables

Bass (1969) introduced a simple epidemic model to depict the new product growth for consumer durables of initial purchases, thus it is called Bass diffusion model, based upon the assumption that the probability of purchase is related to the number of previous buyers due to mass media and word of mouth effects. This work is viewed as one of the most influential articles published on *Management Science* in 55 years and has an extraordinary contribution to forecast market potentials and market shares in both academic research and firms' marketing practices for decades. However, Kalish (1985) argued that the traditional Bass model failed to combine contagion effects with traditional economic variables such as price, which will definitely influence the diffusion process, and a model that can include analyzing the effects of traditional marketing variables will be very useful for managerial perspective (Bass 2004). As Mahajan, Muller and Bass (1990) pointed out, the most useful applications of diffusion models may be for normative purposes other than forecasting, as they can be an explanatory tool to test specific diffusion-based hypotheses. As a result, they concluded a general framework that had been used by several authors in the 1980s (e.g. Kalish 1983) for the dynamic optimization problem.

$$\text{Maximize} \pi = \text{Total discounted profits over the planning period}$$
$$\text{Subject to: A given life cycle growth pattern}$$

Most of studies using this framework consider a single or two marketing variables such as price and advertisement to analyze their effects on product adoption growth. As we discussed above, personalized online services are totally different from traditional economic products as many of them are offered for free, and make the pricing strategy unavailable, but is there any decision variable that plays a similar role to price in the process of interaction between firms and consumers? Luckily we found the one as privacy concerns. Consumers want to maximize their benefits with the privacy cost as low as possible, and service providers try to gain privacy information from those individuals with a reasonable expense including the service cost and other marketing spend (Acquisti 2004)(Chellappa and Shivendu 2010). That is to say, the trade-off between privacy costs and benefits for the consumers is analogous to the trade-off between the charges caused by prices and the perceived utility, and firms can control the levels of privacy exposure as a permission to use services, the way like they plot pricing strategy in order to put an impact on consumers' decision making actions.

Studies derived from Bass model always emphasis that the original model is more applicable for new products with first-time purchases for durable goods, as they believe adoption amounts during the diffusion process is equal to the market sales only under this assumption (Bass 1969, Norton and bass 1987). This is not the case for personalized online service as all. As we all know, online services by the form of mobile apps or computer software can be used for infinite times without wear and tear, and their lifecycle calculated by the time from registration to cancellation of a single user is much more longer than any of the durable products in theory (here we overlook the versioning effect, for

usually they do not occur in a short time and consumers choosing to update those services take a small fraction of the population). In a word, those services can outlive the devices upon which they are operating. Diffusion models applied to services with this kind of attribute is reasonable and sensible.

As for the relationship between marketing variables and adoption growth model, Biottomley and Fildes (1998) addressed three different schools of thought, and they emphasized that price can simultaneously impact upon both the rate of adoption and the size of the market potential. In this study, we followed the framework suggested by Kalish (1985), in which the adoption process is divided into two steps: awareness and adoption. It should be noticed that similar multi-stage decision-making models have been developed in recent research (like Bruyn and Lilien 2008, López and Sicilia 2013, Colapinto el al.2014). Marketing mix like advertising and word of mouth determine the awareness size, and pricing strategy and perceived risks of uncertainty will adjust the market potential. Based on awareness and market potential, the aggregate adoption can be deduced. The major different between these models and ours is that privacy concerns replaces price as the main variable, and marketing potential is adjusted by perceived benefits acquired from monetary awards and future convenience instead of perceived risks of uncertainty, as these benefits are effective ways to  mitigate risk in itself. As a result, the price variable in firm's objective function is replaced by marginal value for consumer information (MVI), and individuals' heterogeneity can be measured by privacy cost parameter other than the perceived valuation of the product (Chellappa and Shivendu 2010, Chellappa et al. 2014), here we defined as privacy disclosure tolerance level(PDTL).

In sum, we integrate some of the above reviewed streams of research and develop a general diffusion model for personalized online services with traditional awareness informed tools that of word of mouth effect and the consideration of a new element as privacy concerns, in order to offer service providers strategies with marketing variables.

# 3    THE MODEL

## 3.1    Individual's behavior

It is now a tendency to study consumers' activity from the stand view of behavioural theory, and following this trend, individual's decision making process, which can be divided into several steps like awareness, interest and final decision is viewed as a way to integrate micro behaviours with macro phenomenon (Colapinto el al.2014). Here we define the dynamic decision making process as a composition of awareness and adoption steps within the diffusion theory framework.

### 3.1.1    Awareness diffusion

With the advent of so-called information exploration era, ways of information transmission changed a lot, and the process of awareness differs a lot from the past with the emergence of viral marketing related to social media and word of mouth influence. According to traditional diffusion theory, mass media influence and word of mouth influence are the most important elements to effect consumer adoption result. In this paper, to facilitate the construction of the model, we assume awareness process is mainly influenced by word of mouth effect instead of advertisement impact for two reasons. Firstly, with the assistance of social media and social network, information flies beyond imagination as recommendations in form of e-WOM is very effective and persuasive. For example, a person got an

amazing experience in using some online service and happily shared this feeling in Face book or twitter (this will be Wechat in China, a mobile app about online community, with the monthly active users amount over 0.4 billion ), many friends would then become awareness and a fraction of those will adopt the same service. If this love-to-share person has a lot of intimate friends or followers, which means he or she is an influential node, the WOM effect would be much bigger than that from the ordinary person. Secondly, The conceptual structure underlying the traditional Bass diffusion model shows that mass-media communication or the external influence presents non-zero at the very beginning and would decrease rapidly over time, while the word-of-mouth communication or the internal influence will increase dramatically from zero at the initial point ( Mahajan, Muller and Bass 1990). Thus, we assumed the word-of-mouth effect is even bigger under the digital age than before, and the mass-media communication in forms of advertisement and other social media can be reduced to some initial value at the beginning of the awareness process. That means word-of-mouth coefficient is the main parameter in the awareness diffusion equation, which we denote as $\beta$. Let $N_0$ be the relevant population size, I(t) be the proportion of the population aware by time t (it is obviously that $0 \le I(t) \le 1$, and the mass media communication can be included in the initial state I(0), and X(t) the number of adopters by t, then the awareness diffusion equation is:

$$\dot{I} = (1 - I)\beta \frac{X}{N_0} \qquad I(0)=I_0 \qquad (1)$$

This equation illustrates the awareness rate is decided by the amount of adopters and the parameter $\beta$. It should be noticed that awareness people who are not the adopters yet at time t may be also influential to diffuse awareness, but this effect is too weak compared to those actual adopters and is not what we concerned in this paper.

*3.1.2    Market potential*

Traditional diffusion model (like Bass 1969) assumes the market potential is constant. However, recent studies point out market potential can be changed due to the dynamic marketing strategy of firms and different levels of perceived benefits of consumers. As most of the online services are offered for free now, privacy concern becomes the major problem individuals care about, and if the personal information demands level (PIDL) from vendors is lower or close to PDTL of consumers, people will take the adoption action.

Let v be the heterogeneity of individuals' attitude toward privacy disclosure and normalized to some value in (0, 1). Accordingly, $f_v(v)$ is the probability density function and $F_v(v)$ the probability distribution function of PDTL. Assumed PIDL from a vendor is R, we may conclude when $v \ge R$, individuals would like to accept the services. However, privacy paradox tells this is far from reality. As consumers' willingness-to-pay privacy attitudes contradict their behaviours in many cases, scholars suggest a trade-off between the cost and benefits of privacy concerns and two major kinds of benefits have been listed as monetary reward and future convenience. Considered monetary incentives are not common phenomenon in general online service marketing strategies even though a hot topic in some specific information products, we focus on the benefits of future convenience in this paper and denote it as u. We assume it is a function of the existing adoption proportion as the more people adopt the services, the better services vendors will offer, which can also be interpreted as 'network externalities' (Brynjolfsson and Kemerer 1996). Another reasonable explanation for u is 'peer

pressure' or a similar concept as 'prosocial effect' (Acquisti el al. 2015). Take online communities apps for example. Exposure of privacy information like phone numbers and contacts is very common for these apps, and may lead to your refusal to adopt them at first, but when you realized most of your friends communicate online and become more intimate, the feeling of isolated by others is rising, meanwhile, considered you are not the only victim of privacy leaking will lower your risk prevention level. All of the above will lead to the faᅟçade of trust. The market potential at R is then the sum of all individuals that value the service at least R-u, and denote as N, the number of individuals that would like to accept the benefits adjusted privacy demand of the service, which is similar to a demand function:

$$N\left[R, u\left(\frac{X}{N_0}\right)\right] = N_0 \int_{v \geq R - u\left(\frac{X}{N_0}\right)}^{\infty} f_v(v)\, dv = N_0 \left\{1 - F\left[R - u\left(\frac{X}{N_0}\right)\right]\right\} \tag{2}$$

### 3.1.3   *Consumers' adoption behaviours*

The total number of potential adopters at time t is the product of I and N, then the net potential is the difference between the total potential adopters and the amount that are already actual adopters, thus we get the adoption diffusion equation:

$$\dot{x} = N(P, u)I - X \qquad X(0) = X_0 \tag{3}$$

Where I is given by the awareness diffusion equation (1) we get above.

## 3.2     Vendor's objective

According to basic economics rules, the vendor's management objective is to maximize its profit even if the product or service is offered for free. In fact, there are several ways for vendors to make profits under this situation, like selling the private information to a third party, or sending advertisements to consumers by processing their preference data, or merely holding these adopters information resource as an advantage to attract more venture capital. In a word, vendors still care about the selling rate and would like to make different strategy according to different values they assumed the information will bring in. Chellappa el al (2010, 2014) define this kind of values as marginal value for consumer information (MVI), here we denote it with a parameter r.

We assume online service vendor owns the ability to differ their product from competitors, which is available in digital products as the updating and versioning cost is much lower than tangible goods. This kind of high heterogeneity means consumers are facing a monopolist when choose a specific service. As a result, the sales rate of the vendor is equal to the adoption rate since online services are similar to durable goods and each adopter only buy one unit, then the mathematical statement of the inter-temporal problem is:

$$\text{Max} \quad \int_0^T rR\dot{X}dt \tag{4}$$

$$\text{s.t.} \qquad \dot{X} = N(R, u)I - X \qquad X(0) = X_0 \tag{5}$$

$$\dot{I} = (1 - I)\beta \frac{X}{N_0} \qquad I(0) = I_0 \tag{6}$$

Where X(0) and I(0) are the initial states of adoption process and awareness process.

We did not add cost variables to this model, as the marginal cost of online service is close to zero. If the total cost is constant or not related to numbers of adopters or the length of time, it will have nothing to do with the final result. Moreover, to simplify our model, we assume fv(v) is uniform distribution in (0, 1) and $u=k\dfrac{X}{N_0}$.

# 4 POLICY IMPLICATIONS

The model above is actually an optimal control problem within economic system and we assume that an internal solution exists. Write the profit $rR\dot{X}$ as $Q(R,\dot{X})$. We use the convention that $\partial$ denotes partial derivative and d is the total derivative. It is an intertemporal optimal problem with a decision variable R and two state variables X and I. Then we get a Hamiltonian H bellow according to maximum principle.

$$\dot{X} = N(R,u)I - X \qquad X(0)=X0 \tag{7}$$

$$\dot{I} = (1-I)\beta\frac{X}{N_0} \qquad I(0)=I0 \tag{8}$$

$$\dot{\lambda}_1 = -\frac{dQ}{dX} - \lambda_1\frac{\partial\dot{X}}{\partial X} - \lambda_2\frac{\partial\dot{I}}{\partial X} \tag{9}$$

$$\dot{\lambda}_2 = -\frac{dQ}{dI} - \lambda_1\frac{\partial\dot{X}}{\partial I} - \lambda_2\frac{\partial\dot{I}}{\partial I} \tag{10}$$

$$H = Q(R,\dot{X}) + \lambda_1\dot{X} + \lambda_2\dot{I} \tag{11}$$

Where $\lambda_1(t)$ and $\lambda_2(t)$ are the adjoin variables, and this Hamiltonian H has a condition $\dfrac{\partial Q}{\partial R} = 0$

We put relative data to the software tools like Matlab and Mathematica and found out analytical solutions are not available, as a result, we decide to reasonably value these parameters and get some numerical solutions. Figure 1 shows the optimal PIDL path and the associated paths of X and I in period T in forms of three-dimensional coordinate, and the arrow indicates the direction of change.
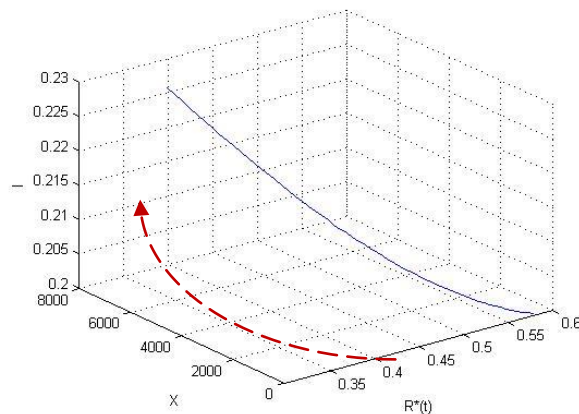


When β =1, $N_0$=100000, r=1, k=1, X(0)=100, I(0)=0.2, T=1

*Figure 1.    Optimal PIDL path and the associated paths of X and I*

In order to check out the impacts of all relevant variables and parameters, we design a computer simulation and input a set of data to see what happens when the values of one parameter changes and others keep constant. Details about the Matlab orders see Appendix1. We get some conclusions based on these observations.

**Lemma 1**. The higher value of β , the more violent of changes of R*(t) during the process, and when β get into some level, R*(t) will present a trend increased at first and then decreased.

We can easily deduce this lemma from the output plot of Matlab when assumed other parameters constant and offer $\beta$ several different values, as shown in Figure 2. When $\beta$ is beyond some level (in this case, the value is above 10), the path of privacy demand curve is obviously concave to the origin. Figure 3 shows results when $\beta$ =50.
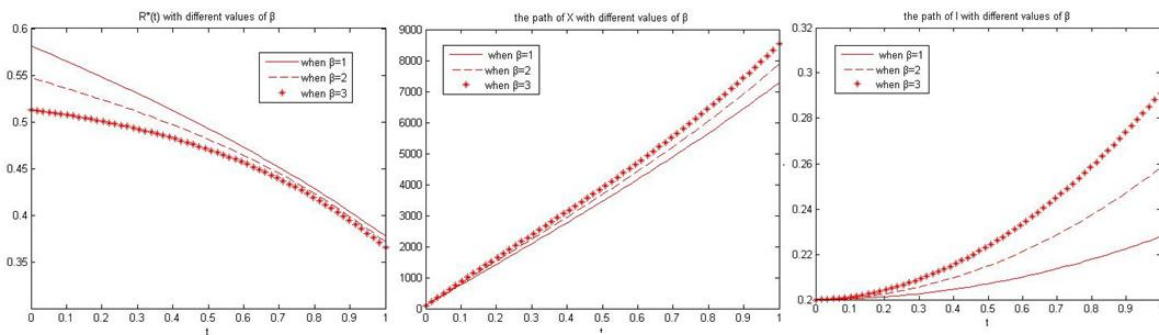


*Figure 2.     Optimal PIDL path and paths of X and I with different values of $\beta$*
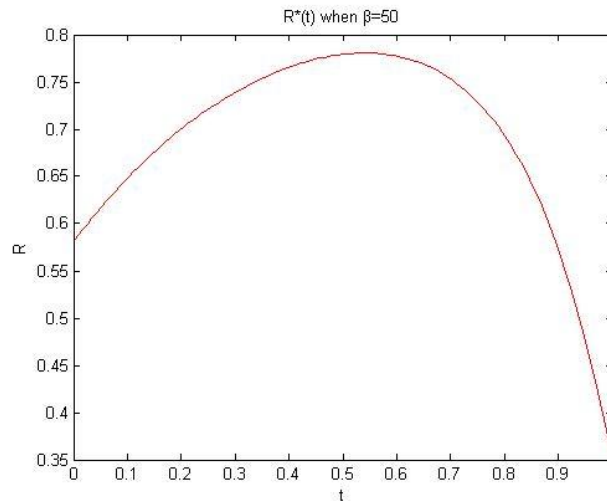


*Figure 3.     Optimal PIDL path when $\beta$=50*

The control for WOM effect coefficient $\beta$ is available via several marketing approaches to make it easier for sharing service information in social network apps. For example, it is common to see some friends show their scores and experiences of playing mobile online games as these apps have options like 'sharing the game to xx' when the game is over. More efficient ways may be offering some incentives in forms of points or cash to those people identified as hubs of social network, and their recommending strength can enhance the WOM effect as well as the coefficient $\beta$ .

**Lemma 2.** Marginal value for consumer information (MVI) is merely related to vendor's profit, and has nothing to do with privacy demand strategy under monopolist condition.

This result (see Figure 4) is contradict to the conclusion of Chellappa et al (2010,2014), as they emphasized the heterogeneity in MVI is the detrimental factor for vendors' strategy. It should be noticed their conclusions are based on the assumption of offering two different types of services as fixed and variable levels, and with coupons cost (Chellappa et al 2010) or duopoly condition(Chellappa et al 2014). In this paper, we focus on online services with installation agreement of clearly privacy disclosure demand, like the mobile apps. Once you agree to install the service, you accept all the privacy disclosure contracts, which is similar to fixed-strategy service with a 'take-it or leave-it approach'. Also, the role of MVI will be totally different in duopoly condition from this paper, which we will explore in future research.
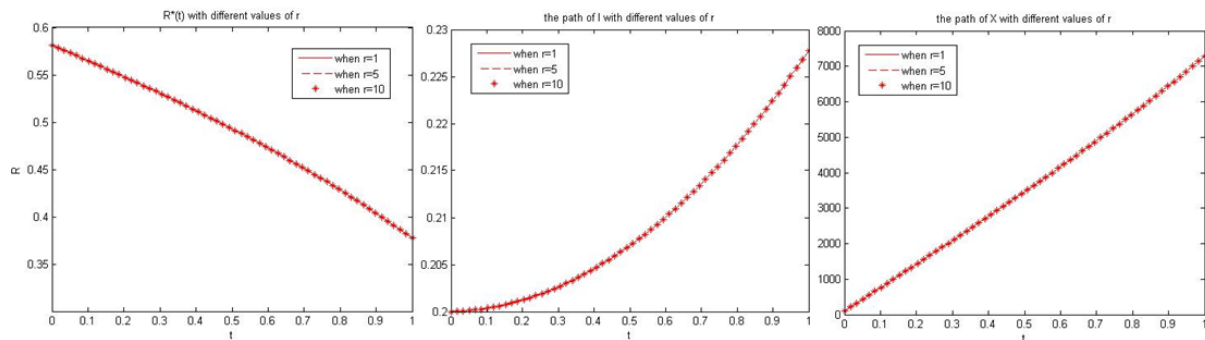


*Figure 4.      Optimal PIDL curve and paths of X and I with different values of r*

**Lemma 3.** Population size has little influence on optimal privacy demand strategy and the path of awareness diffusion, though it has dramatic impact on the speed of adopters' diffusion.

Figure 5 presents this lemma and tells us population size is not an important parameter for making privacy demand management strategy for vendors, even though it has influence on X diffusion curve. Vendors should put more concerns to elements like WOM effect, external network effect and initial state of I and X while doing the marketing research before launch new service or product with privacy concern issues.
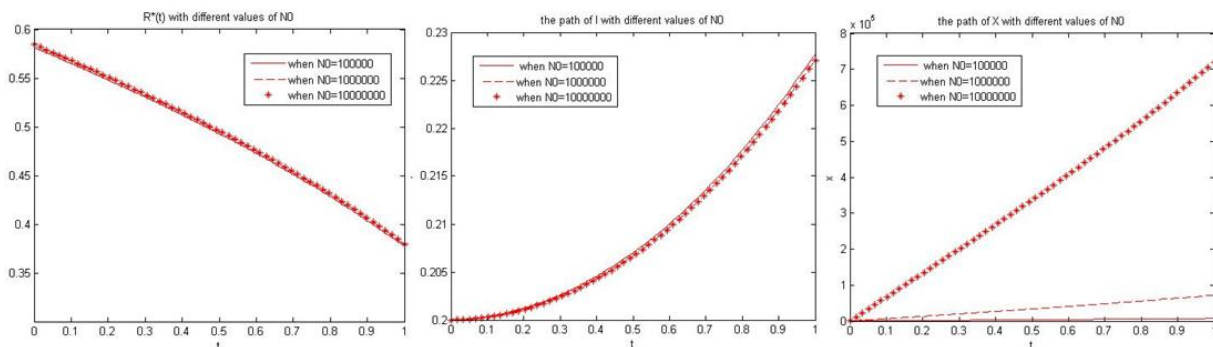


*Figure 5.      Optimal PIDL curve and paths of X and I with different values of $N_0$*

**Lemma 4.** Network externalities is another element that have strong impact to R*(t) curve besides word of mouth effect, even though it will not change its monotonicity.

Like WOM effect, enlarging network externalities is also a hot topic in marketing management, and can be realized by several ways. The more people used the service, the better experiences are is not

confined to the field of social network apps. Many mobile apps like language-learning and curriculum reminder for students, or pregnancy reminder for mothers-to-be tend to build communities for users' interactions. Some vendors also seek to improve lock-in effect by developing users' habits. Take the taxi-driving apps in China for instance, service providers are trying to occupy market share by offering subsidies that almost covers all the taxi fees, as they believe when the market share reaches some level, the competitive landscape will be stable. Figure 6 shows, when network externalities increases, PIDL can be higher at the beginning and lower at the end.
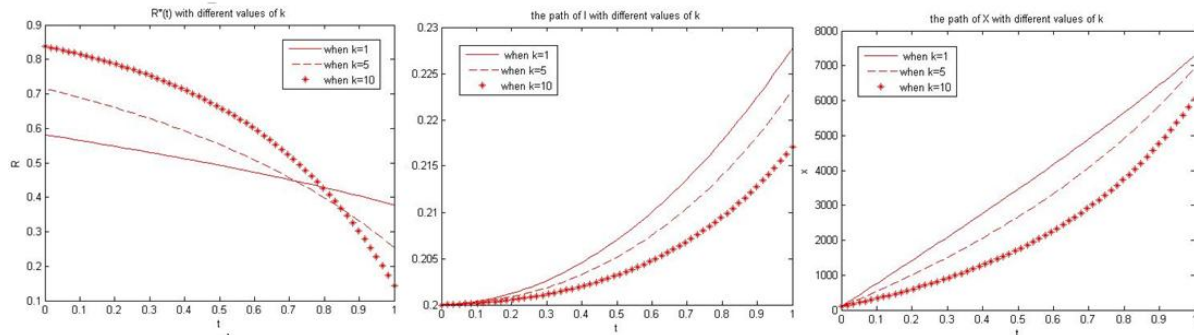


*Figure 6 Optimal PIDL curve and paths of X and I with different values of k*

**Lemma5.** The initial states of I and X have moderate impact on PIDL curve as well as awareness and adoption diffusion curves.1) when I(0) increases, the optimal privacy demand amount is higher at first, and then declines faster. 2) when X(0) increases, the optimal privacy demand curve will be in a lower level, but the shape will remain unchanged.

I(0) refers to the proportion of people that are aware of the service before it is launched out, mass media effect like advertisement is included in the initial state of awareness diffusion process as we discussed above and the result shows it is a noticeable element to affect R*(t). Further research about advertisement effect requires the trade-off between the cost and benefit of mass media advertising be considered. As for X(0), the result is a little surprising, when the initial adopters amount is larger, PIDL at the beginning of the period is lower and would then keep this lower state during the whole strategy process.
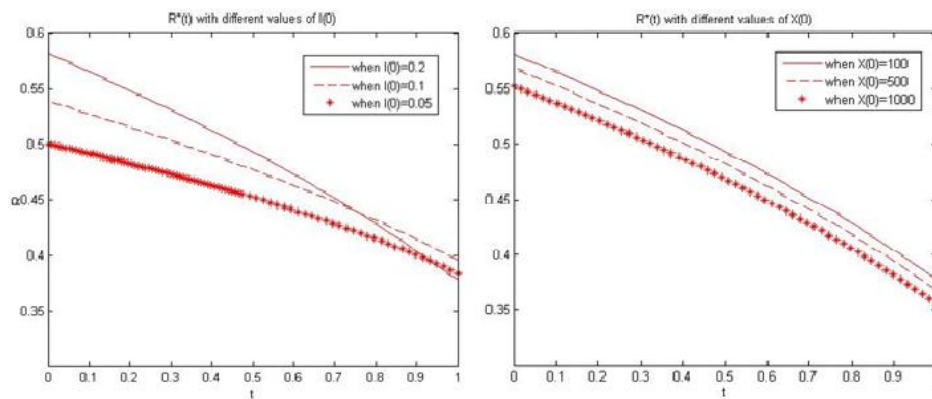


*Figure 7 Optimal PIDL curves with different values of I(0) and X(0)*

**Proposition.** The optimal privacy demanding path of vendors is monotonically decreasing unless the word of mouth effect is very high.

In this model, we have several parameters need to be valued like $\beta$, MVI, $N_0$, r, I(0) and X(0). We can get some inspirations even though WOM effect is proved to be the only reason to make the privacy demand curve increase. That is to say, we can control these parameters to manage the privacy demand amount during the whole period.

# 5    CONCLUSIONS, LIMITATIONS AND EXTENSIONS

## 5.1    Conclusions

In this paper, we seek to offer marketing strategies to maximize vendors' profit for online services, especially those provided for free. We believe privacy concern is what the services users care most instead of traditional marketing variables like pricing. Vendors' profit for per unit use of service can be noted as marginal value for consumer information (MVI), and individuals' heterogeneity as privacy disclosure tolerance level(PDTL) and the users' consumption amount of service is analogous to the adoption numbers in new product diffusion model. Based on these discussion, we suggest a framework that combines new product diffusion theory with online services privacy and divide the dynamic decision making process into awareness and adoption steps. We assume awareness process is mainly influenced by word of mouth effect. As for the adoption process, privacy paradox suggests a trade-off between the cost and benefits of privacy concerns, and we focus on the benefits of future convenience, which is related to 'network externalities'. If the benefits adjusted personal information demand level (PIDL) from vendors is lower or close to PDTL of consumers, people will take the adoption action. The sum of all these individuals is called market potential.

We assume online service vendor owns the ability to differ their product from competitors, which means consumers are facing a situation close to monopolist. As a result, the model is actually an optimal control problem with two differential equations as constraint. With the maximum principles and assistance of Hamilton function, we get numerical solutions, denoted as R*(t), which can offer advices for policymakers with the sensitivity analysis of parameters.

Firstly, effective factors for vendors that have influence on the diffusion process include WOM effect, network externalities and the initial state of I. WOM effect is proved to be the only reason to make the privacy demand curve increase. That means if the vendor can control WOM effect and enlarge it to some level, PIDL can be higher during the diffusion process. Network externalities will not change the monotonicity of R*(t), but still have strong impact on the curve. When network externalities increase, PIDL can be higher at the beginning and lower at the end. Also, the initial states of I have a similar impact on PIDL curve.

Secondly, parameters and variables represent for MVI, Population size and the initial states of X are less effective. MVI is merely related to vendor's profit, and has nothing to do with privacy demand strategy under monopolist condition. Population size has little influence on R*(t), though it has dramatic impact on the speed of adopters' diffusion. As for the initial states of I and X , when X(0) increases, the optimal privacy demand curve will be in a lower level, but the shape will remain unchanged.

However, our study should be considered preliminary with limitations and extensions for future research, which will be discussed below.

## 5.2 Limitations

The main limitation is the neglect of social network effect on diffusion process. We assumed the information about online service is delivered uniformly among potential population by adding a coefficient $\beta$ to awareness equation. However, the delivery process is much more complicate in reality. Some scholars have tried to introduce complex network theory to diffusion models and believe that network density and topology type of social network will directly affect the diffusion curve of new product or service. For example, Rahmandad and Sterman (2008) examined the impact of different network topologies by using the SEIR model. These topologies include fully connected, random, Watts-Strogatz small world, scale-free, and lattice networks, and they found network topology affect the dynamics as expected. Lee el al(2006) focus on new product diffusion on small world network and explained winners-takes-all phenomenon, and they pointed out the new product marketing share with initial installing base is also affected by social network.

These diffusion models with complex network are calculable with the assistance of agent-based models (ABM) using computer technology. Rand and Rust (2011) point out , ABM can be treated as a kind of computer experiment with natural stochastic features to analyze problems with statistical approaches that is fit for empirical data. Trusov, Rand and Joshi (2013) then emphasized the correlation between consumers' network structure and the observed dynamic diffusion results, in another word, different characteristics of networks lead to different presence of diffusion curves. Also, they used the cumulative installation quantity data of 900 Facebook apps to verify low-density, finite-topology feature of potential network under social networks

In a word, the coefficient $\beta$ in awareness diffusion equation is not enough to depict the dynamics of word of mouth effect which is deeply related with potential network. Network structures should be considered in further research.

## 5.3 Extensions

Price has been analyzed as an important single marketing mix variable in diffusion models (Danaher, Hardie and Putsis, 2001), which we substitute for PDTL. However, marketing mix, a concept referred as 'the set of tactical marketing tools that the firm blends to produce the response it wants in the target market' (Kotler el al, 2005), consists of everything the firm can do to influence the demand for its product, like monetary incentives in paid apps and advertisement in group purchase websites or hotel and ticket agent apps. These marketing mixes should be considered in extended diffusion models.

Granted, service vendors tried their best to differ their service from each other, but competition is still a common phenomenon that cannot be neglected and shows duopoly features in many cases. One of the most typical conditions is in the taxi-calling apps market in China. In order to occupy the market share, two biggest vendors, which two take over 98% of the market, are trying to offer subsides to passengers that can cover all the taxi fees and rewards for taxi-drivers with a similar amount for almost two whole years, seemed regardless of their cost. Meanwhile, they keep updating their service levels one after another through innovation and imitation behaviours. The fierce competition tells us the online services market presents prominent duopoly characteristics sometimes, and the assumption of monopoly conditions should be replaced by oligopoly states.

# References

Acquisti, Alessandro and Hal R. Varian (2005), Conditioning Prices on Purchase History, Marketing Science, 24 (3), 367-81.

Alessandro Acquisti, Stefanos Gritzalis, Costos Lambrinoudakis, Sabrina di Vimercati(2007), Digital Privacy: Theory, Technologies, and Practices, Auerbach Publications.

Alessandro Acquisti, Laura Brandimarte, George Loewenstein(2015), Privacy and human behavior in the age of information, Science, 347(1), 509-14.

Acquisti (2004) , Privacy in Electronic Commerce and the Economics of Immediate Gratification, in Proceedings of the 5th ACM Electronic Commerce Conference, New York: ACM Press. 21-29.

Adams A. Users' perception of privacy in multimedia communication[C]. ACM, 1999 Doctoral Consortium 15-20.

Bass, Frank M. (2004), Comments on A New Product Growth for Model Consumer Durables The Bass Model, Management Science, 50 (12_supplement), 1833-40.

Bass, Frank M. (1969), A new product growth for model consumer durables, Management Science, 15 (5), 215-27.

Bélanger, France and Robert E. Crossler (2011), Privacy in the digital age: a review of information privacy research in information systems, MIS Quarterly 35 (4), 1017-41.

Beresford, Alastair R., Dorothea Kübler, and Sören Preibusch (2012), Unwillingness to pay for privacy: A field experiment, Economics Letters, 117 (1), 25-27.

Biottomley, Paul A. and Rovert Fildes (1998), The Role of Prices in Models of Innovation Diffusion, Journal of Forecasting, 17, 539-55.

Bruyn, Arnaud De. Lilien, Gary L. (2008) , A multi-stage model of word-of-mouth influence through viral marketing,International Journal of Research in Marketing, 25(3), 151–163.

Brynjolfsson, Erik . and Chris F. Kemerer (1996), Network Externalities in Microcomputer Software: An Econometric Analysis of the Spreadsheet Market, Management Science, 42 (12), 1627-47.

Chellappa, Ramnath K., Sin Raymond G., and Jia Jia (2014), Competing for Information: A Duopoly of Personalized Service Provision under Privacy Concerns.

Chellappa, Ramnath K. and Shivendu Shivendu (2007), An Economic Model of Privacy: A Property Rights Approach to Regulatory Choices for Online Personalization, Journal of Management Information Systems, 24 (3), 193-225.

Chellappa, Ramnath K. (2010), Mechanism Design for Free but No Free Disposal Services: The Economics of Personalization Under Privacy Concerns, Management Science, 56 (10), 1766-80.

Colapinto, Cinzia. Sartori, Elena. Tolotti, Marco.(2014),Awareness, persuasion, and adoption: Enriching the Bass model, Physica A: Statistical Mechanics and its Applications, 395, 1–10.

Danaher, Peter J.,Bruce G.S.,Hardie, and Putsis JR.Williamp.(2001), Marketing-Mix Variables and the Diffusion of Successive Generations, Journal of Marketing Research, XXXVIII (9), 501-14.

Dou, Yifan, Marius F. Niculescu, and D. J. Wu (2013), Engineering Optimal Network Effects via Social Media Features and Seeding in Markets for Digital Goods and Services, Information Systems Research, 24 (1), 164-85.

Ernst &Young,(1996), The Second Annual Ernst &Young Internet Shopping Study: The Digital Channel Continues to Gather Steam, 26-27.

Gurbaxani, Vijay and Haim Mendelson (1990), An Integrative Model of Information Systems Spending Growth, Information Systems Research, 23-46.

Hann, Il-Horn, Ka Hung Hui, Sang-Yong Tomlee, and Ivan P. L. Png (2007), Overcoming online Information Privacy Concerns An Information Processing Theory Approach, Journal of Management Information Systems, 24 (2), 13-42.

Hann, Il-Horn, Kai-Lung Hui, Sang-Yong T. Lee, and Ivan P. L. Png (2008), Consumer Privacy and Marketing Avoidance: A Static Model, Management Science, 54 (6), 1094-103.

Horsky, Dan (1990), A Diffusion Model Incorporating Product Benefits, Price, Income and Information, Marketing Science, 9 (4), 342-65.

Kalish, Shlomo. (1983), Monopolist Pricing with Dynamic Demand and Production Cost, Marketing Science, 2 (2), 135-59.

Kalish, Shlomo. (1985), A New Product Adoption Model with Price, Advertising, and Uncertainty, Management Science, 31 (12), 1569-85.

Kamakura, W. A. and S. K. Balasubramanian (1988), Long term view of the diffusion of durables, International Journal of Research in Marketing, 5, 1-13.

Kotler, Philip.Wong, Veronica. Saunders,John. Amstrong, Gary, (2005), Principles of Marketing (Fourth European Edition), Pearson Education.

Lee, Eocman, Jeho Lee, and Jonseok Lee (2006), Reconsideration of the Winner-Take-All Hypothesis: Complex Networks and Local Bias., Management Science, 52 (12), 1838-48.

López, Manuela and María Sicilia (2013), How WOM marketing contributes to new product adoption, European Journal of Marketing, 47 (7), 1089-114.

Mahajan, Vijay., Eitan. Muller, and Frank M. Bass (1990), New Product Diffusion Models in Marketing_ A Review and Directions for Research, Journal of Marketing, 54 (1), 1-26.

Nam, Changi , Chanhoo Song, Euehun Lee, and Chan Ik Park (2006), Consumers' Privacy Concerns and Willingness to Provide Marketing-Related Personal Information Online, Advances in Consumer Research, 33, 212-17.

Norton, John A. and Frank M. Bass (1987), A diffusion theory model of adoption and substitution of high-tech products, Management Science, 33 (9), 1069-86.

Pavlou, Paul A. (2011), State of the information privacy literature:where are we now and where should we go?, MIS Quarterly, 35 (4), 977-88.

Posner, Richard A. (1981), The Economics of Privacy, American Economic Review, 71 (2), 405-09.

Preibusch, Sören (2013), Guide to measuring privacy concern: Review of survey and observational instruments, International Journal of Human-Computer Studies, 71 (12), 1133-43.

Rahamandad, Hazhir and John Sterman (2008), Heterogeneity and Network Structure in the Dynamics of Diffusion: Comparing Agent-Based and Differential Equation Models, Management Science, 54 (5), 998-1014.

Rand, William and Roland T. Rust (2011), Agent-based modeling in marketing: Guidelines for rigor, International Journal of Research in Marketing, 28 (3), 181-93.

Smith, H. Jeff , Tamara Dinev, and Heng Xu (2011), Information privacy research: an interdisciplinary review, MIS Quarterly 35 (4), 989-1015.

Smith, H. Jeff ,Managing Privacy: Information Technology and Organizational America, University of North Carolina Press, Chapel Hill,NC, 1994.

Taylor, Curtis R. (2004), Consumer Privacy and the Market for Customer Information, The RAND Journal of Economics, 35 (4), 631-50.

Trusov, Michael, William Rand, and Yogesh V. Joshi (2013), Improving Prelaunch Diffusion
    Forecasts: Using Synthetic Networks as Simulated Priors, Journal of Marketing Research, 50 (6),
    675-90.

Varian, H. R. (2006), Economic Aspects of Personal Privacy, School of Information, University of
    California, Berkeley (http://people.ischool.berkeley.edu/~hal/Papers/privacy/).