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Impact of Electronic Word-of-Mouth to Consumer Adoption Process in the Online Discussion Forum: A Simulation Study

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***Abstract*—**Web-based technologies have created numerous opportunities for electronic word-of-mouth (eWOM) communication. There are many factors that affect customer adoption and decision-making process. However, only a few researches focus on some factors such as the membership time of forum and propensity to trust. Using a discrete-time event simulation to simulate a diffusion model along with a consumer decision model, the study shows the effect of each factor on adoption of opinions on on-line discussion forum. The purpose of this study is to examine the effect of factor affecting information adoption and decision making process. The model is constructed to test quantitative aspects of each factor. The simulation study shows the membership time and the propensity to trust has an effect on information adoption and purchasing decision. The result of simulation shows that the longer the membership time in the communities and the higher propensity to trust could lead to the higher demand rates because consumers find it easier and faster to trust the person in the community and then adopt the eWOM. Other implications for both researchers and practitioners are provided.

***Keywords*—**word of mouth, simulation, consumer behavior, e-business, marketing, diffusion process.

I. INTRODUCTION

THE Internet is a worldwide computer network allowing communication among millions of users and access to different resources. The Internet has enabled individuals all over the world to make their personal experiences, thoughts, and opinion easily accessible to the global communities “at the click of mouse”. This has led to the creation of a diverse online word-of-mouth communities (online forums), where individuals exchange experiences and opinions on a variety of topics ranging from products and services, to politic and world events. A recent survey of DoubleClick also found that the word of mouth plays a very important role in consumers’ purchasing process for many types of products. For some goods, such as electronics and home products, their surveys suggest that product review websites outrank all other media in influencing customer purchase decision [1]. Most of the previous research focused on the impact of electronic Word-of-Mouth (eWOM) on consumer purchasing decision in consumer review type but rarely on forum type. Thus, it is interesting to investigate the effect of eWOM on consumer adoption and decision making process. Marketer, consumer and people who are involved with online communications can utilize the model and the insight to maximize their business benefit and can determine and evaluate sources of information.

The rest of this paper is organized as below. First we provide a review on the literature related to electronic word-of-mouth, vicarious learning and modeling and selected factors influencing the adoption of eWOM. Second, we conduct the preliminary analysis and introduce the research model and the analysis of each factor. Finally, we draw a conclusion for our study and discuss implication for both research and practice.

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II. LITERATURE REVIEW

In this section, we will provide an overview of the literature on electronic word-of-mouth and how it influences purchasing decision. We will also review the relevant literature relating to factors that affect the consumer adoption and decision making process.

Today, the Internet makes possible for consumers to share experiences about a product online. Traditional word-of-mouth (WOM) has proven to play a major role in consumer buying decisions by influencing consumer choice [2], [3], [4], [5], [6]. Electronic word-of-mouth (eWOM) communication refers to any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the internet [7], [8]. Recent evidence indicates that Online WOM is becoming a popular informational source for consumers and marketers [9]. [9] delves into various factors that motivate consumers to engage in online WOM and participate in online forums. The above studies indicated that eWOM is increasingly important to be the source of product information and discussion. Yet few researchers investigate the factors that encourage the adoption of online opinions on forum platforms to customer to buy product. Vicarious learning or modeling refers to process by which people change their behaviors because they observed the actions of other people and the consequences that occurred. In general, people tend to imitate the behavior of others when they see it leads to positive consequences and to avoid performing the behavior of others when they see that negative consequences occur.

Next, the selected factors influencing the adoption process of on-line opinion are discussed. Literatures show that the time of arrival to the market (time decided to enter to the market place) has effect to the consumer decision. Commonly, the first group or innovators that entered to the market makes decision by themselves or the decision was lead by other factors other than joined online communities (forum). According to [10], shown in figure 1, some individual decide to adopt an innovation independently of the decision of individuals in a social system. We shall refer to these as an innovator. All figures 1 to 11 are shown in Appendix section.

This classification in based upon the timing of adoption by the various groups. Apart from innovators, adopters are influenced in the timing of adoption by the pressures of the social system, the pressure increasing for later adopters with the number of previous adopters. We assume that the propensity to trust or convincing limits for the visitors are different. Trust is viewed as a trait that leads to a generalized expectation about the trustworthiness of others. Propensity to trust might be thought of as the general willingness to trust others. People with different developmental experiences, personality types and cultural backgrounds vary in their propensity to trust [11]. The propensity to trust is numerically quantified in our model as the convincing limit which is the limit that consumers unconsciously set when deciding to buy something. The consumer accumulates the information from discussion or assessment point from discussion on a forum. Once the accumulated points exceed the convincing limit, the consumer is considered to possess the judgment whether to buy the product or not. Consumers with low convincing limit are easy to convince but some with higher convincing limit are harder to convince. Consumers generally hold different opinions about quality of the same product. Consequently their product evaluations reflect both quality and individual preferences which are often not readily observable to readers [12]. Thus, we assume that based on different preferences their opinion could be evaluated numerically and randomly following a probabilistic distribution with a given mean and standard deviation. We assume that the forum membership time can affect online consumer decision. For example, if visitor joined the membership of the forum for a long time, consumer may be able to predict poster behaviors toward the topic, they may know that which posters are reliable or can be trusted. We collect the forum membership time from a Web site. www.thaidphoto.com and used it find best-fitted distribution of data to use in our simulation study. The web site is popular among Thai photo enthusiasts with a large number of 17,984 members. The members come to share the experience and opinion on the photo equipments on the web boards. The order of the posting would also affect the visitor decision because typically consumers will read just the recent posts and the opinions of old posts are disregarded. According to uncertainty reduction theory, whenever consumers lack knowledge of a product or of the outcomes of consuming that product, they will engage in uncertainty reduction efforts to mitigate and eliminate the risk associated with the uncertainty and to maximize the outcome value. Consumer can reduce the quality uncertainty by searching for an information sources as online product review or online community such as forum. The consumers with high uncertainty tend to read more reviews or search for related reviews more than consumers who have more knowledge [9]. The search depth or the number of old posts a consumer read back is also a factor in our simulation model.

III. PRELIMINARY ANALYSIS

3.1. Data Collection

We collect the forum membership time from www.thaidphoto.com. First, we generated random number around 300 numbers from Microsoft Excel 2007 (= Rand()) to represent the id number of each membership in the www.thaidphoto.com. The total numbers of membership in the website are 17,984 members. From that random number, we count the membership duration of each member from start to join the website until 22 February 2009. After the raw data are obtained, we used Input Analyzer of discrete-time simulation package "Arena" (version 10) to plot the distribution. The best-fitted distribution of our data is Weibull distribution. The distribution and detail analysis is shown in figure 2.

3.2. Bass Model

The growth model of Bass developed for the timing of initial purchase of new products is based upon an assumption that the probability of purchase at any time is related linearly to the number of previous buyers [13].
The Bass Model is expressed as shown:

$$f(t) = \left[p + q\,F(t)\right]\left[1 - F(t)\right] = p + (q-p)F(t) - q\left[F(t)\right]^2$$

Then solve for F(t) and the solution is

$$F(t) = \left(q - pe^{-(t+C)\,(p+q)}\right) / \,q\;\left(1 + e^{-(t+C)(p+q)}\right)$$

where

- *f(t)* is the rate of change of the installed base fraction
- *F(t)* is the installed base fraction
- *m* is the ultimate market potential
- *p* is the coefficient of innovation
- *q* is the coefficient of imitation

Sales *S(t)* is the rate of change of installed base (i.e. adoption) or demand; *f(t)* multiplied by the ultimate market potential *m*:

$$S(t) = mf(t) = m\left[\frac{(p+q)^2}{p}\right]\left[\frac{e^{-(p+q)t}}{\left(1 + \left(\frac{q}{p}\right)e^{-(p+q)t}\right)^2}\right]$$

IV. RESEARCH MODEL AND RESULTS

This part showed the simulation model that we used to test our assumption. The model is showed below. Factor analysis aims to investigate the effect of changing each factor at different level. We plot the graph of each factor and interpret the result.

4.1. Research model

We can simplify the research model as shown in Figure 3.

4.2. Analysis of Factors

Analysis of Factor aims to investigate the effect of changing each factor at different level.

4.2.1 Effect of coefficient of innovation

From Bass model, we simulate the arrival of innovator by using $m*f(t)$ and setting q to be zero to reflect only the rate from innovator alone. By setting q to be zero, there is no effect from imitation so the rate becomes the rate of innovator alone. From literature, the average value of p from the equation has been found to be 0.02, and is often less than 0.01.(figure 4) In this study, we use 2 values of p in simulation (p= 0.02 and 0.01 and q=0).

In the first case we set p = 0.01 and in the second case we set p = 0.02. We set p = 0.01, q = 0, m = 100 and we simulate t for 1 year and therefore we obtain $f(t)$ value for 1 year. We use average value of $f(t)$ to simulate in the model. Then we plot the graph based on data from the model. The graph of number of imitators and time is shown in figure 5.

As shown in fig. 5, the curves show the effect of the different time interval that the imitator enters the market. In the case where p = 0.02, there was a high demand at the beginning. The rate of imitator demand is high and the mean of time between demands is low. As time passes, demand declines and the rate of imitator demand decreases. On the other hand when p = 0.01 (p is the coefficient of innovation = 0.01), the demand rate is less rapid in the beginning the rate is fading more slowly than that of p = 0.02.

4.2.2 Effect of Membership time

The mean of the membership time indicates number of days that the members join the online communities. From 300 random samples of data, the average number of membership time is 25 days following the Weibull distribution with Beta and Alpha equals to 728 and 1.14 respectively. We want to investigate the effect of membership time toward number of imitators. Thus, we adjust mean of membership time up 15 days and down 15 days by changing the number of 25 in the membership time expression to 40 and 10 respectively. The effect of shifting the mean of membership time to the number of imitators versus time is shown in fig. 6.

As shown in fig. 6, the graph compares the effect of shifting the mean of membership time toward the number of imitators. With the mean of 40 (the green line) the rate of imitator is greater than the rate of imitator with the mean of 10 and 25 at the same number of imitator. The mean of membership time 40 (mean = 40) is lower than the blue line (mean = 10). This means that the more membership time in online communities could lead higher demand rate because it is the easier the consumer to trust the person in the community. (In other words, if we spend more time in the forum, it is more likely that we know the member in the forum whether they post a good review or post the review with bias.) The faster the consumer trusts the post, the more probability he or she will buy the product. Therefore, the number of imitator increases. This situation could be directly applied to the forum with long establishment. If the members in that forum communicate for a long time, there is more chance to trust other posters and reduce the time for purchasing decision. Further empirical investigation for this result would be interesting.

4.2.3. The effect of personal point

The personal point is the numerical assessment point that was given by a review. We assigned personal point randomly to innovator as they entered to the system. In this study, we assume that personal point has an effect on the number of imitator. If point that given to the post is low, it has low effect on the decision and it takes longer time to reach the purchasing decision and therefore the number of imitator will be reduced. With poor review, the reader has to read many posts in order to convince or reaching the purchasing decision or never reach the purchasing decision at all. We want to simulate this assumption. We assign a personal point to the model in order to identify effect of point toward number of imitators. The point ranges between -5 to 5. 5 represent the good post and -5 represent the bias post. The simulation shows the effect of shifting the mean of personal point to the number of imitators versus time in figure 7.

As shown in fig. 7, if we shift the average point given to the post from 3 to 4 (personal point mean4), time spent to reach purchasing decision decreases. Because the review is on average higher, implying higher quality of product, the rate of imitator of personal point mean4 is higher than the personal point mean 3. This indicates that with the good review, people tend to decide to buy more easily and the time to make decision decreases.

Another experiment is to test the effect of personal point together with probability of purchasing. As the quality of product increases, we expect the mean of personal point to increase and then the probability of purchasing the product to increase. As a result, to simulate the effect of increasing quality of product to show the arrival rate of imitators, we change both of these parameters in the same direction at the same time. The base case has the personal point with triangular distribution (TRIA (-5, 3, 5)) and probability of purchasing of 80%. We changed two variables together because these two variables are interrelated. The higher personal point can reflect the good quality of the post. Therefore, probability of purchasing is relatively high if people perceived the post as good quality. The effect of these changes versus time is shown in figure 10. As shown in figure 10, the percentage of purchasing decision will affect directly with the number of buyer in the system. The figure also shows, as the percentage of decide to buy is reduce to 70%, the number of imitator decreases.

4.2.4. The effect of trust

From [10] trust can affect the purchasing decision in online communities. Therefore, the number of imitator is affected by trust as well. If the reader trusts the post or poster, in our model, the reader will give the post more weight. The test was conducted to determine the effect of trust on number of imitator. In the model, we assign the weight into calculation. If a likelihood to trust changes from 80% to 60% (trust 60 line) and 40% (trust 40 line) respectively, time to make decision and number of imitators will be affected as shown in figure 11.

As shown in the figure 11, the graph shows that the probability of trust at 80% gives the lowest value of average of mean of time between demands or the highest rate of purchasing. This can indicate that higher trust can affect the number of imitators by decrease the time between demands and increase the rate of imitators. The time between demand decrease as the tendency to trust increase, resulting in the shorter time period for decision making process.

V. Conclusion

In conclusion, this research is aimed to investigate the effect of each selected factor on information adoption and decision making process. This research has developed the discrete-event model to help understand the factors related to eWOM in the online forum.

We have analyzed the diffusion of innovations in markets with two segments: innovators who are more in touch with new developments thereby affecting another segment of imitators. Our model investigates the effect of factors toward information adoption and purchasing decision. As a result of analysis of factors, we can conclude the results to the following dimension.

• Coefficient of innovation: people tend to enter market quickly and leave market fast with high coefficient of innovation.

• Membership time: membership time has an effect on information adoption and purchasing decision. The longer the membership time in the communities, the lower the time between demands and this is because it is easier to trust the person in the community. In addition, the faster you trust the post, the higher the probability that a customer will buy the product.

• Personal point: personal point has an effect on information adoption and purchasing decision. People tend to make purchase decisions easily and require less time to make decisions when the post score is high or review is good. The personal point is also relevant to probability of making a purchasing decision because if the point given to the post is high, it can express the true value of the product and increase the probability of purchase regarding to the product quality.

• Probability to trust: as the probability to trust increases, the time between demands decreases, thus resulting the shorter the time to reach purchasing decisions on average.

The experiment of various factors will be extensively tested in the future research.

Appendix

Appendix contains the figures 1 to 11.

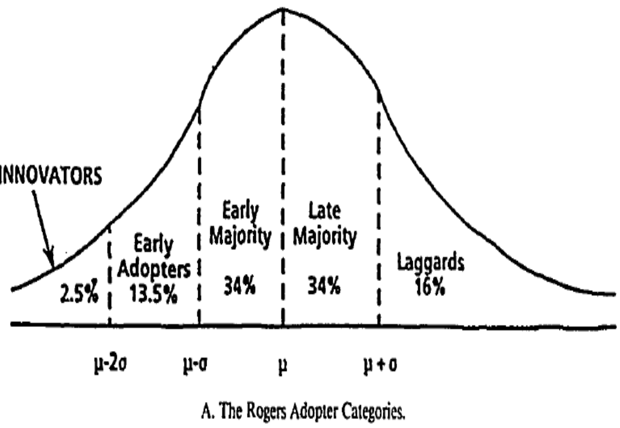

Fig. 1 Rogers Adopter curve

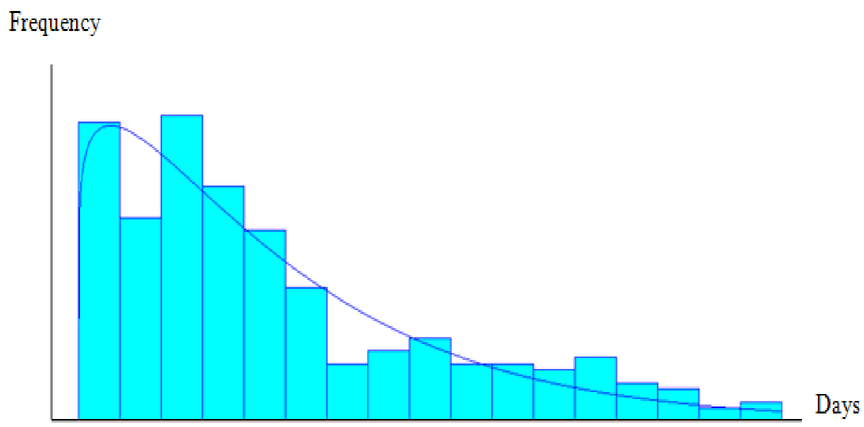

Fig. 2 Weibull distribution of sample membership time

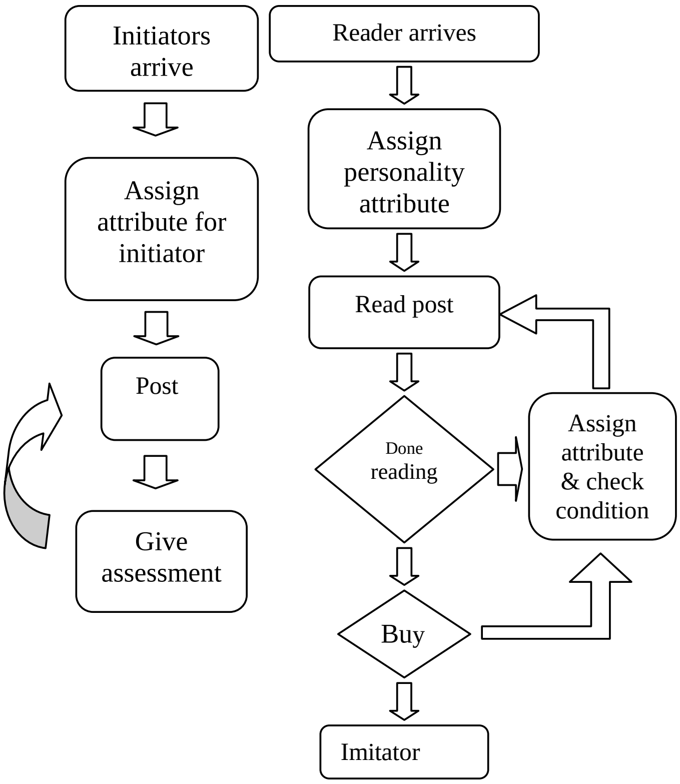

Fig. 3 the flow of initiator and imitator in our model

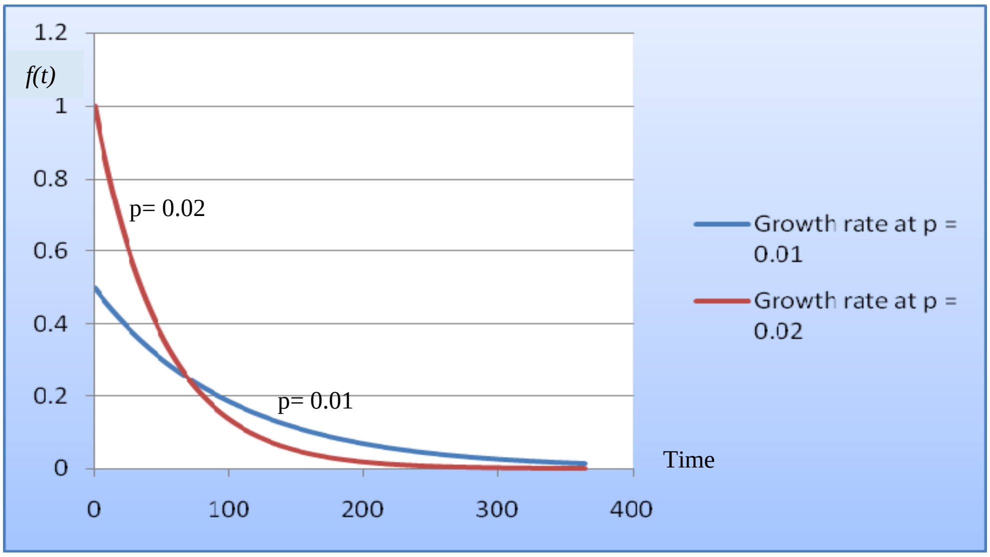

Fig. 4 The arrival rate (as the ratio of total population) of innovator at different time

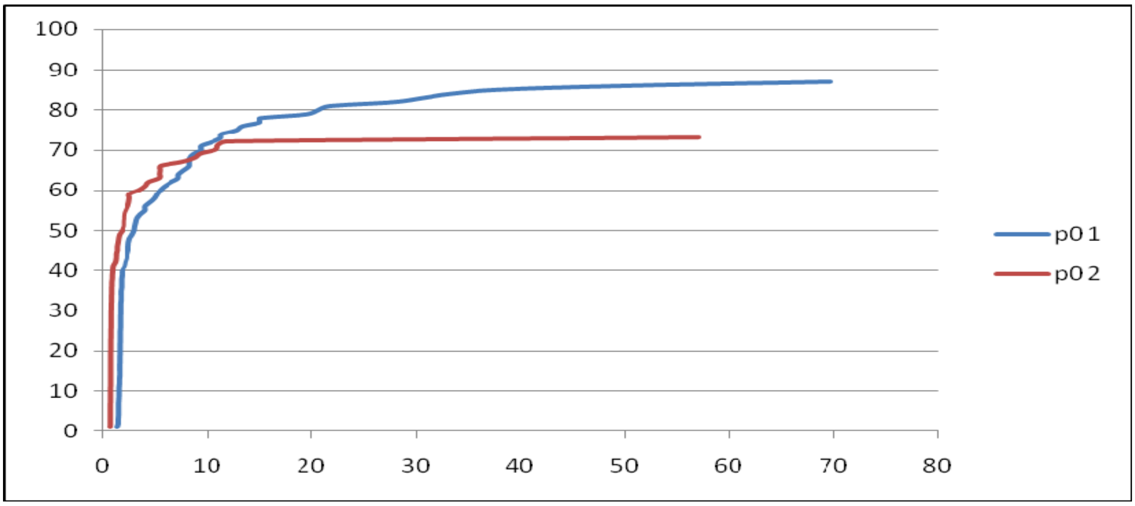

Fig. 5 Effect of Coefficient of innovation on number of imitators

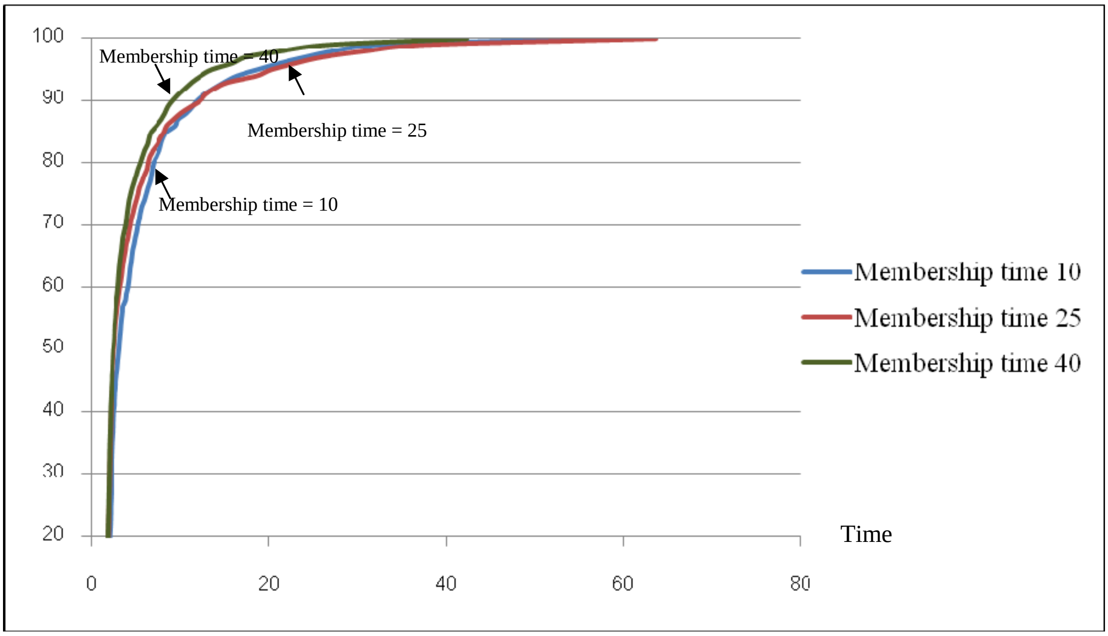

Fig. 6 Effect of Membership time on number of imitators

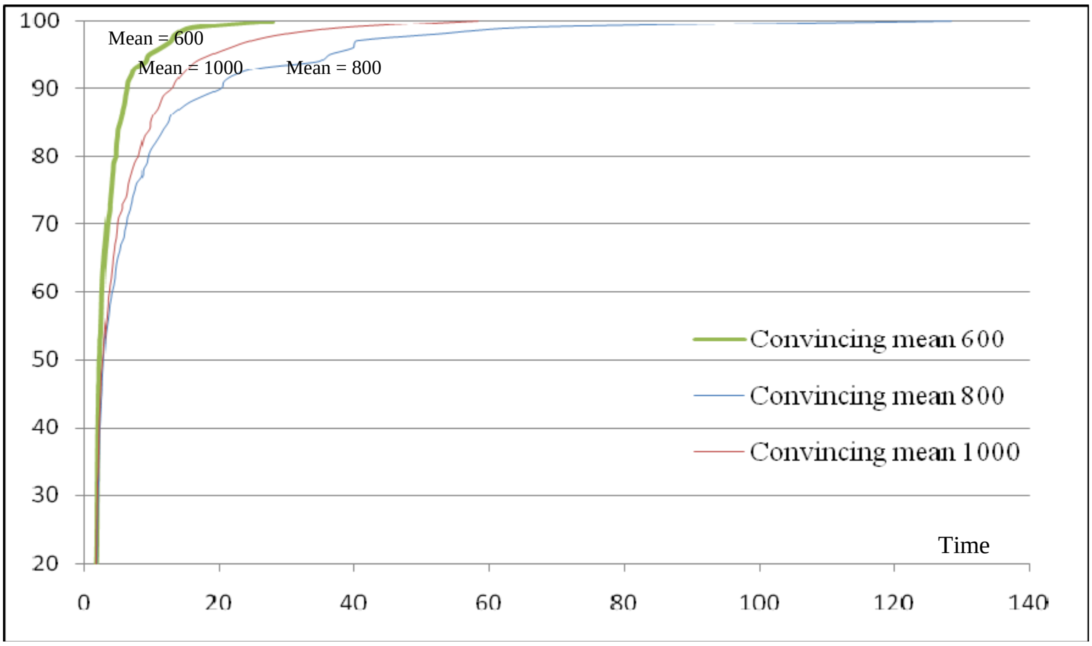

Fig. 7 The effect of changing the mean of convincing level on number of imitators

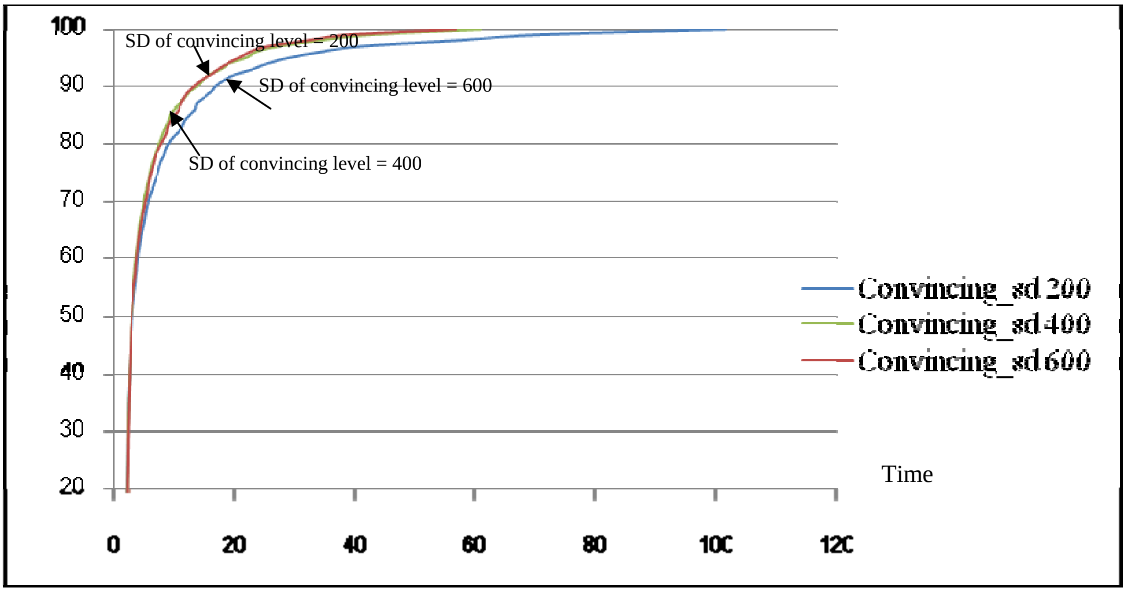

Fig. 8 The effect of changing the standard deviation of convincing level on number of imitators

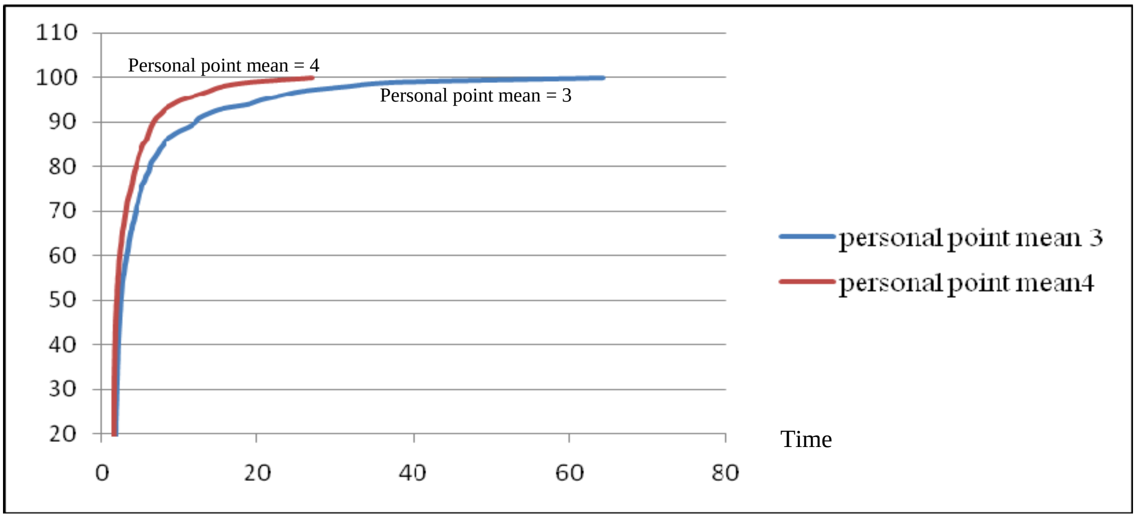

Fig. 9 The effect of personal point on number of imitators

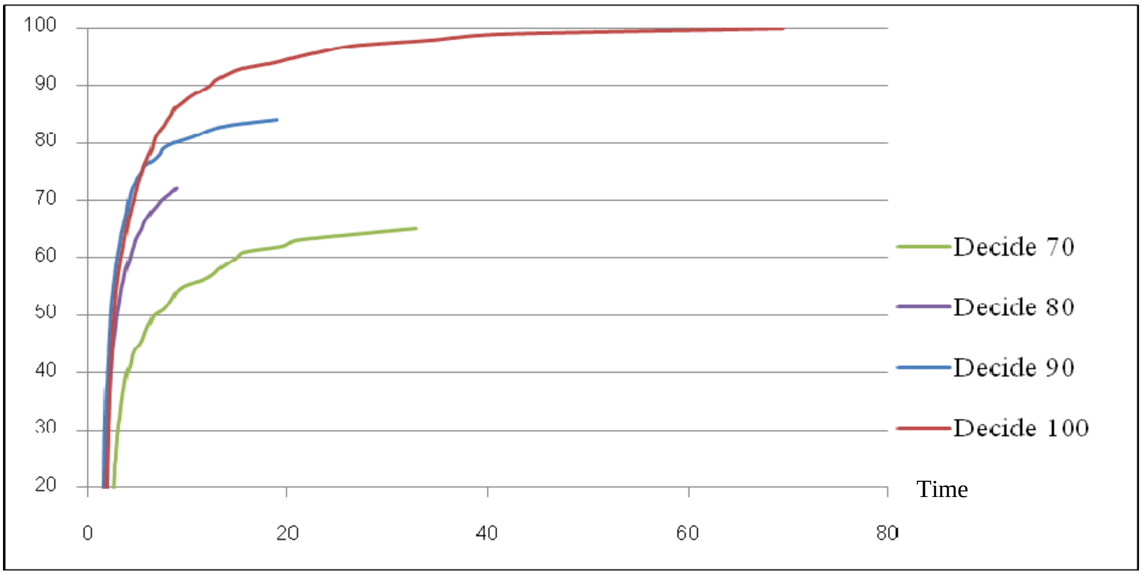

Fig. 10 The effect of personal point and probability of purchasing on number of imitators

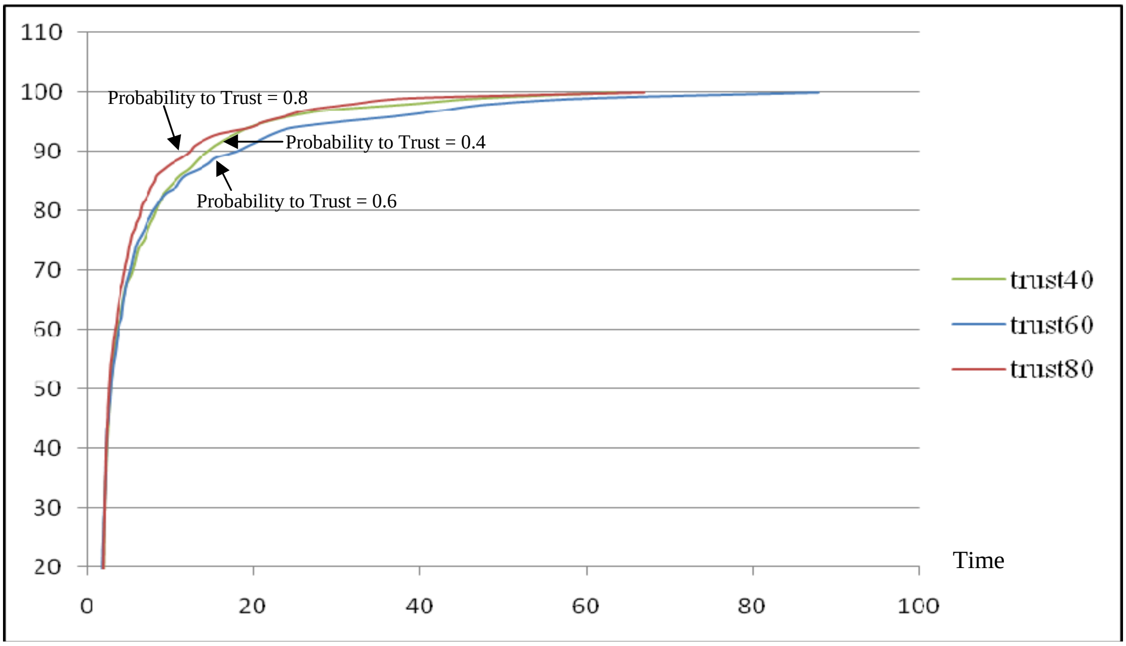

Fig. 11 The effect of trust on number of imitators

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