WHICH FACTORS DETERMINE USER'S FIRST AND REPEAT ON-LINE MUSIC LISTENING RESPECTIVELY? MUSIC ITSELF, USER ITSELF, OR ONLINE FEEDBACK

Completed Research Paper

Jiayin Qi
Beijing University of Posts and Telecommunications
No. 10 Xitucheng Road Haidian District, Beijing, China
qijiayin@bupt.edu.cn

Linghan Liu
Beijing University of Posts and Telecommunications
No. 10 Xitucheng Road Haidian District, Beijing, China
liulinghan@bupt.edu.cn

Yong Tan
University of Washington
Seattle, WA 98195-3226 U.S.A
ytan@uw.edu

Xiangling Fu
Beijing University of Posts and Telecommunications
No. 10 Xitucheng Road Haidian District, Beijing, China
fuxiangling@bupt.edu.cn

Meng Zhao
Beijing University of Posts and Telecommunications
No. 10 Xitucheng Road Haidian District, Beijing, China
xyfzhm@bupt.edu.cn

Angela Xiaoye Zhao
Erasmus University
Burgemeester Oudlaan 50, 3062 PA, Rotterdam, The Netherlands
zhaoxiaoye@hotmail.com

Abstract

In the era of Web 2.0, does online feedback mainly dominant online users' buying behavior, or are user's own preference and product quality still important? Previous studies paid more attention to the influence of online feedback on users' online buying behavior, however this paper focuses on how users' own factors, product quality related factors and online feedback factors together influence a user's buying behavior, and also how does this effect change as time goes by. Taking online music as our research industry and using the data from Last.fm website, this research shows that users' preference and product quality are still the two most dominate factors influencing users' online music listening, while online feedback plays an important role on users' first listening. It is also found that the different influences of crowds and friends.
Keywords: Social media, user behavior, online music

Introduction

The development of the Internet has brought a great impact on the music industry (Peitz and Waelbroeck 2006). Traditional music listening pattern has gone through a transfer from off-line listening to the combination of both off-line and on-line listening. It is acknowledged that online music has gradually changed the way people listen to music.

Online music is a very special good with the following three features. Firstly, online music is a typical hedonic good, for which user's perceived value and the quality of the music are both basically important. Secondly, online music is also a classical information good which is valued for its content. The marginal cost for producing an individual track is very low and the accessing cost for consumers through Internet is also very low, which brings online music have some characteristics of fast moving consumer goods. It makes the popularity of music becomes an essential factors to influence user's choice. Thirdly, online music is an experience good as well. It seems that friend's information will be more helpful.

Traditional value-intention framework developed by Dodds and Monroe in 1985 (Dodds and Monroe 1985) is a typical theory to explore consumer's purchase behavior and this framework is extended by many researchers in different contexts. But, almost all of the extended frameworks just considered factors from consumers and factors from the products, although both of which are involved in perceived customer value. However, the world has entered the Web2.0 era. Anyone is connected with others and is influenced by others. These influences and connections also affect consumer's perceived customer value. Hence, it is worthwhile to extend the traditional value-intention framework. Taking online music as a trial, it is favorable to find how to extend value-intention framework and identify dynamic features of this new value-intention framework in Web2.0 era. Also, is it stable or varietal during the whole consumption process? These are the scientific motivations of this research.

Since music products have such a large rich database and musical preferences are all a matter of personal taste, music recommendation systems are very important for consumers to get their favorite and unknown music. However, until now, the recommendation engines for music have been less successful than that of others. It motivates to find out the key factors influencing consumer's online music behavior, which are very helpful for music's personalized recommendation system design.

Moreover, how to maintain consumers' online music listen activity is also a practical issue confusing managers in this industry. If a consumer is continual active, the likelihood of his/her repeated purchase is high; otherwise, if a consumer is no more active, the likelihood of his/her repeated purchase is low. This is another practical motivation of this research.

The main academic contributions of this research include that the traditional value-intention framework is extended in Web2.0 era and a new value-intention framework is developed to explore the purchasing mechanism of online music and the consumer activity maintaining mechanism. Our research will give a more comprehensive answer for online music providers to design their marketing campaign for new listeners and repeat listeners.

The rest of this research is organized as follows. Firstly, the literature review is presented. Then, the hypotheses development is described. Thirdly, the methodology is presented, including the data collection method, research models, measurement of variables and data analysis. Finally, this research is concluded.

Literature review

Studies on influence factors of user online purchase behavior

Previous research addressed studies on influence factors of user online purchase decisions in two important streams. On the one hand, many scholars studied some traditional influence factors such as price, product information and gender on users online purchase decisions. Dellarocas et al. (2007) and some other scholars found that movie marketing costs and other products information would have positive impact on a movie's box office. Duan (2009) conducted similar research in software industry and found that the number of similar software can have a negative impact on one software download volume. Nel et al. (2009) studied the influence of gender on music download volume. On the other hand, with the

rise of Web2.0, lots of researchers start to pay attention to the effects of users' online reviews, online sales and online social relations on purchasing decisions. Chevalier and Mayzlin (2006) found that consumers concern the content of review much more than they concern simple statistical data. While some researchers have studied the effects of the number of reviews on purchasing decisions, for example, Liu (2006) found the effect of online comments on movies is mainly embodied in the review quantity. And some researchers studied the effect of emotions among comments on purchasing decisions. On studying the sales of film, Dellarocas et al. (2007) found that comments, either negative or positive, always play positive role in movie promotions. Besides, Duan (2009) believed that sales volume is as a significant factor to influence users' purchasing decisions. Moreover, some researchers studied the effect of different social relations on purchasing decisions. Kotler and Armstrong (2005) hold the stance that others' opinion, whether friends or crowd, will significantly influence the users' purchase decisions. After studying the Flixster.com, Lee et al. (2011) found the reviews by crowd are more influential than critics from friends.

To sum up, the studies on the influence factors of online purchase decision can be concluded in three perspectives: price and product information belong to product perspective of influence; users' gender and purchasing motivation belong to user perspective of influence; and customer reviews, sales volume and social relations belong to online feedback perspective of influence.

However, firstly, it can be seen that current scholars mostly base on single perspective of the influential factors to study user's online purchasing decisions, there is no study has been conducted to study users' online purchase decisions in all the three perspectives at the same time. Secondly, it is found that most of the current researchers studied influence factors of first time online purchase decisions, but rarely studied the influence factors of online repeat purchase decisions. Lastly, it seems that most of the current researchers mainly focus on online shop, online bookstore, and film industry and so on, but less researchers study online music. These limitations interested this research to explore whether purchasing behavior of online music will be affected by such three-aspect influence factors as users themselves, music itself and online feedback as well as what kind of different effects will bring to the users' online music first listening and repeat listening behavior.

Studies on influence factors of user online music purchase behavior

Based on the value-intention framework (Dodds and Monroe 1985), Chu and Lu (2007) studied the influencing factors of online music purchase in Taiwan. The study found that the perceived value of online music is a significant factor in predicting the purchase intention of buying online music. Also, the beneficial factor of perceived usefulness and playfulness are identified in addition to the sacrificing factor of the perceived price for assessing the value.

Only Chu and Lu's work is found to be focused on online music purchase behavior research. However, there are three shortages in their framework. Firstly, for online music, the main consumers are young people. It's clear that this tech-savvy young group loves music more than ever and that it remains a vital and passionate part of their daily lives. Young people loves music is not just because of the usefulness of music. Secondly, the price of online music is decreasing sharply in recent years. From a price comparison site www.tunechecker.com, you can get the cheapest downloads from a number of music sites and allows music fans to click through to buy those songs. Thirdly, social network platforms are becoming an important information gathering tools, where new people meet and new friends share their interest in good music and cool music video. At the same time, music social network online communities like Last.fm, Pandora.com, and punkai.com etc. enhance and enlarge the power of social network.

Although there are some limitations about Chu and Lu's work, some enlightenment is still found from their work. The value-intension thought is very helpful to develop a new model. Based on the value-intension theory, two questions are waiting to be explored: what are the new components of consumer perceived value if Chu and Lu's components are denied and what is the new measurement for buying intension if no survey will be conducted.

Studies on online music recommendation systems

Lots of existing commercial music recommender system is based on collaborative filtering of huge amounts of user data. To understand the aspects of music similarity that collaborative filtering captures,

Barrington et al. (2009) compared a recommendation system using collaborative filtering to two canonical music recommender systems: one based purely on artist similarity, the other purely on similarity of acoustic content. In their work, a system was demonstrated, which captures the similarities between acoustic content of songs and the similarities between artists. This system was also argued to take the performance into consideration and be capable to produce the best recommendation seven when collaborative filtering data is unavailable.

In addition, recommender systems associated with social networks often use social explanations to support the recommendations. Sharma and Cosley (2013) presented a study about the effects of these social explanations in a music recommendation context and they found that social explanations have the effects on user preferences, both before and after consumption of a recommendation. For instance, social explanations might influence people's willingness to try out an item because a trusted friend has endorsed it or they want to be able to talk about it with their friends.

In order to build a more effective recommendation system and maximize the potential of combining implicit feedback and explicit feedback, Jawaheer et al. (2010) compared the performances of each type of feedback on a recommendation system. They collected implicit feedback on Last.fm about the tracks played by a user, e.g. the number of times a track is played, commonly known as the play count, and explicit feedback through Last.fm's 'Love a track' or 'Ban a track' feature.

As mentioned above, it can be found that there are some scholars who introduce online feedback factors into traditional collaborative filtering recommendation system. But how to combine online feedback factors, user factors, and music factors is still an unsolved problem.

Hypotheses Development

Chu and Lu (2007) provided a value-intension framework to explore the factors influencing online music in Taiwan. The framework is shown as Figure. 1.

Figure 1. Online music purchase model proposed by Chu and Lu (2007)
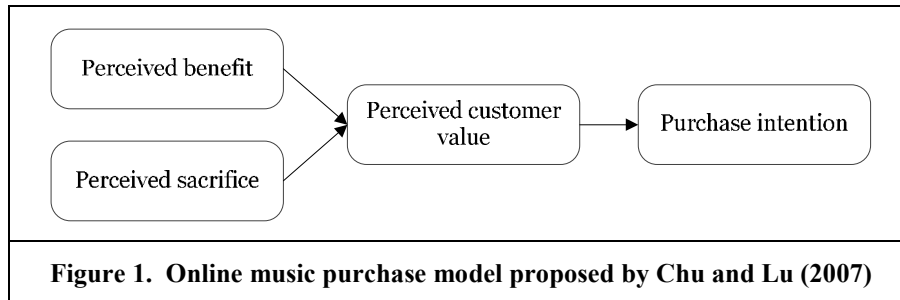
In web2.0 era, consumer's perceived customer value for online music comes from the satisfied needs, the sound quality and the driven powers from online feedback. Users' music listening behaviors are generally influenced by user factors, product factors and online feedback factors. User factors usually refer to the personal preference or the basic information of users. Product factors commonly refer to the characteristics of the music track. Usually, the word of "online feedback" refers to a mechanism harnessing the bidirectional communication capabilities of the Internet to engineer large-scale, word-of-mouth networks (Dellarocas, 2003). Online feedback is a symbol of web2.0 websites, on which users are allowed to post their opinions and observe others' behaviors in a more convenient way. Online feedback produces a great impact on product evaluations and purchase decisions (Tong et al. 2007). In this research, two ways are concluded to perceive a product's quality based on feedbacks from peers: one is to see the explicit feedback behavior of others, such as reviews and ratings; the other one is to see implicit feedback behavior of others, such as actual buying behavior, which is represented as sales volume. Moreover, several researchers divide peers into two categories of group: the crowd or friends (Lee et al. 2011, Abbassi et al 2012). Therefore, the influence factors of online feedback are defined as any potential influence from other's feedback, which include explicit feedback and implicit feedback, both from crowd and from friends. Accordingly, two sources of online feedback information are summarized. One is the reviews or listening behavior information from the group of crowd, the other one is the reviews or listening behavior information from the group of friends. Hence, the online feedback factors can be

divided into crowd feedback factors and friend feedback factors. The relations among the three factors are shown in Figure 2.

Figure 2. Factors Influencing Music Listening Behavior of User
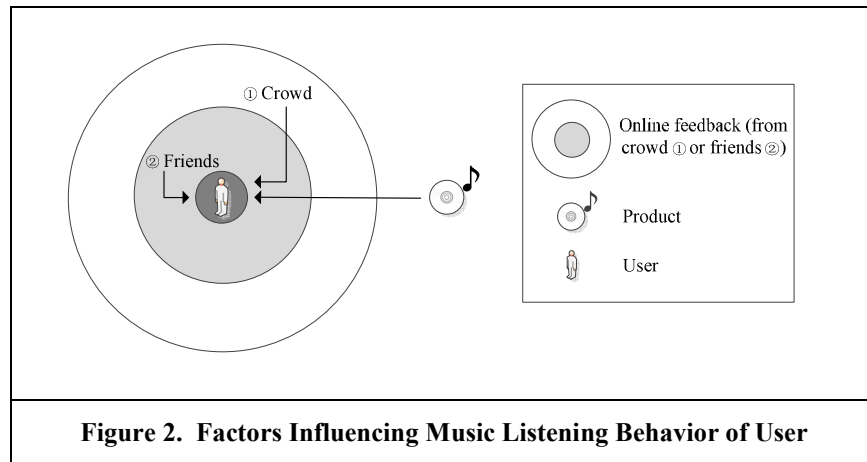
Thus, based on the value-intension theory, the exact antecedents of consumer's perceived customer value for online music are detailed, which are user factors, product factors and online feedback factors, to explore the first purchase mechanism of online music. Based on value-intension theory again, a theoretical model is also developed to determine which factors are the key factors for maintaining a user's activity for an old piece of music. Hence, consumer's online music listening behavior model in Web2.0 era can be presented as follows in Figure 3.

Figure 3. Consumer's online music behavior model
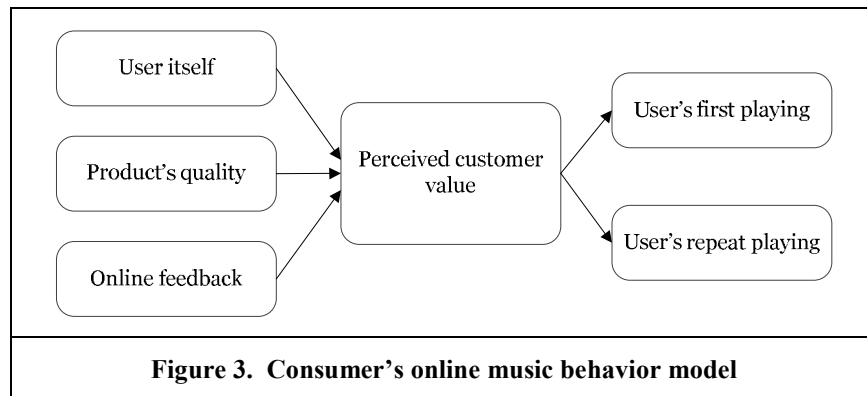
For perceived customer value is a subjective concept, which should be measured by questionnaire survey. However, in this research, it is difficult to conduct the survey because the 1000 target users were selected randomly (Seen in the Data Collection section). The efficiency and the effect of this survey for these users with 190 tracks are also very low. Moreover, it is unpractical to do survey for measuring user's perceived value. On the other hand, the strong positive relationship between perceived customer value and user's buying intention has been confirmed by many studies. Hence, a theoretical model is simplified as follows in Figure 4.

Figure 4. Research model of online music in this paper
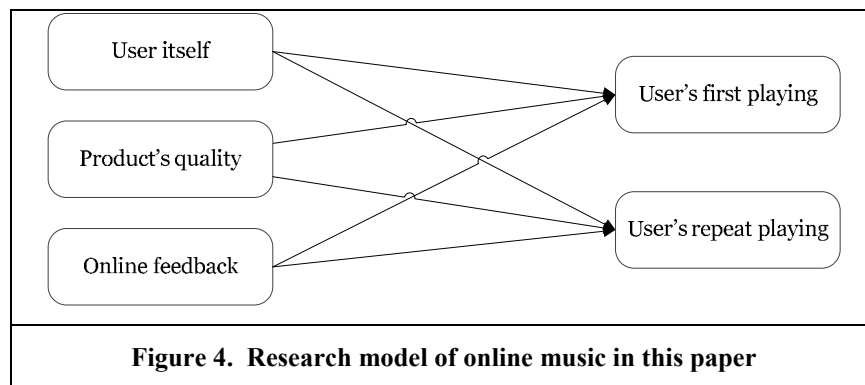
Online Feedback Factors

Impacts of Crowd on User Listening Behaviors

According to the theory of herding (crowd) effect (Nofsinger and Sias 1999; Raafat et al. 2009), personal behaviors will be influenced by the behaviors and thoughts of most people so that he or she follows the actions of the majority. In social psychology studies, herding (crowd) effect lies in two social influence theories, which are informational social influence and normative social influence. Informational social influence is defined as an influence to accept information obtained from another as evidence about the reality with regard to his/her own behavior, and normative social influence is defined as an influence to conform with positive expectations of another, leading to feelings of self-esteem or self-approval (Deutsch and Gerard 1955; Aronson et al. 2005). According to the research on informational social influence, the more uncertain the individual is about the correctness of his/her judgment, the more urgent of the decision-making situation is, and the more professional the others are, the more likely he/she is to be susceptible to informational influences and follows the crowd decisions in making his/her judgment (Allen 1965; Tesser et al. 1983; Baron et al. 1996; Aronson et al. 2005). But when it comes to normative social influence, it is the strength, immediacy, and number of other people from outside the group that affect the target individual's judgment. Strength means the salience, power, importance, or intensity of the outside influence group over the target. Immediacy means closeness in space or time between the outside group and target. Number means how many people there are (Latané 1981). Besides, whether users' behaviors are exposed to the influence source groups is another important factor to determine whether the users will be affected by normative social influence or not (Aronson et al 2005).

Many studies have pointed out that the herding effect resulted from crowd behavior on Internet is an important factor affecting users behavior (Lee et al. 2011; Duan et al. 2009). It is obvious that online music is an experience-type network product. Each user has an anonymous identity on the virtual Internet, which means user's track listening behavior will not be exposed under others' view except his or her friends. According to anonymous effect theory proposed by America psychologist Zimbardo in his famous simulated prison experiment (Haney et al. 1973), it is speculated that the loss of identity would make a user feel a lower importance to others, as well as the farther closeness in space and psychological to other users. That is to say, when a user makes a listening decision for the first time, the impact of informational social influence from crowd is stronger, but the impact of normative social influence from crowd is relatively weaker. Generally, due to the strong positive informational social influence (although the normative social influence is weaker), it can get the following hypothesis:

H1a: Crowd's online feedback is positively associated with a user's first online music listening behavior.

However, the impact of herding effect from crowd will not last long. According to the cognitive response theory (Eagly et al. 1993), people will produce a series of active thinking after they received information from others, these thinking reactions thereby determine the individual's overall response information. As well as we can see from the theories on attitude change (McGuire et al. 1985), an individual's attitude will change as the new information or opinions are accepted. When users make decisions for the repeated listening behaviors, they have established their own judgment about the quality of tracks by their first listening experience and their uncertainty related to the quality of the music is decreased. Thus, the effect of informational social influence on users will be attenuated, that is, in other words, the impact of crowd

will not affect user's repeat listening behavior as strongly as first listening behavior. Therefore, it is reasonable to say that crowd's listening online feedback will influence a user's repeat listening decision less significantly. This leads to the following hypothesis.

H1b: the effect of crowd's online feedback will be attenuated for repeat listening behaviors.

Impacts of Friends on User Listening Behaviors

In the study of social network analysis, there is a common network with a dense, cohesive core and a sparse, unconnected periphery, which is called core/periphery structure (Borgatti 1999). On the basis of social differentiation, Bourgeois and Friedkin (2001) studied the interpersonal ties and they found the distribution of actors in core/periphery structure is generally in multidimensional social space, in which the likelihood and strength of an interpersonal tie are negatively associated with the distance that separates the positions of actors in the social space of a group. Based upon the subjective "type" of social relation, Granovetter (1983) categorized interpersonal ties into strong ties and weak ties, where friendship and family relationship are the typical examples of strong ties.

Being in a circle of strong ties, friends are easier to obtain a user's trust and have an impact on the user. In a research involving 7,000 users in seven European countries, Kotler (2000) stated that 60% of these users' purchase for a new brand is affected by their family members and friends. Bansal and Voyer (2000) pointed out the professional degree of information source had positive impacts on the changes in recipients' attitudes but users tended to believe information with reliable information sources such as information from friends. Previous work on social impact theory (Latané 1981) has demonstrated that the strength of social impact is associated with the distance on the space. Therefore, it will be different between the impact of friends on user's behavior and that of crowd since friends have closer distance to a user.

The impact from friends' online feedback lasts longer than that from the crowd. Unlike the anonymous effect of crowd, a users' identity information will be exposed to his or her friends (the information of the users' listening behavior will be sent to the friends' pages on Last.fm). Except from the informational social influence effect, there is also a normative social influence effect on the users. Several research on the peer pressures of adolescent (Coggans and McKellar 1994; Maxwell 2002) found that the similarities in adolescent's physical proximity, age and lifestyle would influence their behavior easily. In social network, the convergence of thoughts and behaviors among friends will be more obvious, and such convergence and the consistency will not be changed as time flies (Aral and Walker 2011).

Therefore, similar to the impact of crowd on user's listening behavior, users' listening behavior is divided into first listening and repeat listening. Due to the closeness and trustworthy between users and their friends is quite remarkable, the impact of friends on a user's listening behavior will not only come from the informational social influence but also come from the normative social influence. This leads to the following hypotheses.

H2a: Friend's online feedback is positively associated with a user's first listening behavior.

H2b: Friend's online feedback is positively associated with a user's repeat listening behavior.

User Factors

A user's own needs and experiences influence his or her choice of buying behavior (Bosnjak et al. 2007). Therefore, it is important to consider the user's personal preference upon acceptance of a product in the study of user's buying behavior. Kotler (2006) introduced a concept of a "consumer black box" in the consumer behavior research. The theory suggested the external factors such as marketing stimuli as the input of consumer black box, and the buyer responses such as product choice as the output of consumer black box, in which consumer black box is the user's decision-making process based on their own characteristics such as personality. Lee et al. (2011) pointed out that the user's own preferences or tastes affect consumer product adoption and evaluation decisions, and this becomes even more sophisticated when it comes into the social network circumstances.

Online music is an experience good, for which one does not know the value of the product before it is consumed. These experience goods are usually purchased for entertainment or as impulse buying (Nelson

1970; Klein 1998). User preference becomes an important determining factor. Different users have different music preference. In the study of Priest et al. (2004) on the effects of motivational music's relation to gender, age, and frequency of gymnasium attendance, they found older participants expressed a preference for quieter, slower, and generally less overtly simulative music, and the user's preferences for the music will affect their frequency of gymnasium attendance. Therefore, we could see that users' listening behaviors are influenced by their own preference to a large extent. This leads to the following hypotheses.

H3a: User's preference has a positive impact on one's first listening behaviors

H3b: User's preference has a positive impact on one's repeat listening behaviors

Product Factors

There is no doubt that the feature of products is an important factor that users consider in the process of purchase decisions. The traditional consumer decision theories usually consider the product price, quality and value as three of the most important factors determining customer perceived value (Zeithaml 1988). Some researchers have focused on the tangible benefits of conventional goods and services, and some other researchers studied from the customer's subjective perception perspective, they researched on the symbol meaning of the product such as cheerfulness, sociability, elegance feature etc. (Holbrook and Hirschman 1982). According to the symbol theory, all products, no matter how mundane it is, carry on a symbol meaning (Levy 1959). For some products, the symbol value is very rich and outstanding, such as musical recordings，art design, architectural style, paintings and novels (Hirschman and Holbrook 1981). For these products such as music, users need high involvement to experience the quality of the product, and then determine the perceived value it brings (Styvén 2010).

Perceived quality of a product has a direct impact on user's decision-making process, especially for the products that customers have less or no information before they purchased or used (Armstrong and Kotler 2003). When users make a decision on what music to listen for the first time, they have limited knowledge about the quality of tracks that they have never listened before, so they will consider the factors related to the quality of the track, such as the popularity of the track, the well- known level of the singer, time length to make the music etc. Thus, the factors related to the quality of the tracks will impact on user's first listening behavior. This leads to the following hypothesis.

H4a: Product quality-related factors have a positive effect on a user's first listening behavior.

The higher the quality-related factors are, the bigger the probability that the track is qualified will be; the more the track is qualified, the larger a user's perceived value after the first listening will be; the more excellent experience getting from the first listen history is, the chance of this user's repeat listening will increase. This leads to the following hypothesis.

H4b: Product quality-related factors have a positive impact on a user's repeat listening behavior.

Data Collection

Our data is collected from Last.fm website, which was founded in the United Kingdom in 2002 and is one of the world's largest online music community platforms. The reason why this website is chosen as the data source is that users' information, online feedback information and track quality related information can be obtained from this website directly and efficiently. Using "Audioscrobbler", Last.fm builds a detailed profile of each user's musical taste by recording details of the tracks that the user listens to, either from Internet radio stations, or the user's computer or many portable music devices. Each registered user has a profile which displays the most recent songs they have played, and regularly updated charts of their top artists and songs. In addition, Last.fm also provides several communication mechanisms for those interested in using the site socially. Once the friendship is approved by both relational partners, each appears in the others' publicly visible friends list and users can see their friends' most recent listened track list (Baym and Ledbetter, 2009).

A crawling program was developed to get the data by the open API provided from Last.fm. The algorithm of the data crawling program includes three phases. The first phase is to find target tracks and seed users. To minimize history marketing bias, new tracks are initially collected on the top 1000 chart as the target

tracks. Next, we seed users who listened to these target tracks were randomly selected by using "*** (username) is listening to this track" function. The second phase is to acquire target users. To observe users who have both influence effect from crowds and friends, those users who have at least one friend listened to one target track are selected as the target users. The third phase is to get the users' online music listening behavior data. Meanwhile the user demographic and track characteristic data were also collected.

As in sum, 190 tracks, 1000 target users and more than 40000 related friends of these target users are random selected finally (see Table 1). Each target user is with independent characteristics and dispersed in the sample[1].All the listening behavior information of 1000 target users and 42283 friends were extracted during the period of March 22, 2013 to June 28, 2013. A total of 2090000 items of track listening behavior information were collected. After examination[2], there is no essential difference between the sample users and the overall population. The gender ratio was 62% male, 38% female and the average age 24.4 years.

Table 1. General Description of Collected Data(20900000 items in sum)		
Data items	**Description**	**Observation**
User	a. **620 male, 380 female** b. **Age: 1-112 (mean 24.4, standard dev. 7.2)**	**1000**
Tracks	a. **Rank on Last.fm: 5-1000（mean 415.3, standard dev. 298.1)** b. **Related artist: 47 Artists**	**190**
Time period (units: week)	a. **12th , 16th- 25thweek in the year of 2013 (11 weeks in total)** b. **from March 22, 2013 to June 28, 2013**	**11**

Research Model

Basic Model

The dependent variable of this study is an online user's music listening behavior. A standard logistic regression model is employed as our research model since the online user's music listening behavior leads to two results: the user listened to the music or the user did not listen to the music, usually representing as a dummy variable of 0 or 1 value respectively. Ideally, our model is set to estimate the impact of users and their online feedback, and the impact of music factor on users' music listening choice. The general model formula is shown as follows:

$$logit\left(Pr(choice_{ijt})\right) = \beta User_{ij} + \gamma Feedback_{ijt} + \delta Music_{jt} + \varepsilon_{ijt} \qquad (1)$$

Where, $Pr(choice_{ijt} = 1)$ is the probability of user i choose to listen music track j at time t, otherwise $Pr(choice_{ijt} = 0)$means the probability of user i not to choose to listen to the music track j at time t; $User_{ij}$ is the set of user characters of user i, including the demographics of user i reported in online portfolio and the user i's history listening preference and behavior information, such as the preference for an artist or the total time played on Last.fm; $Feedback_{ijt}$ is the online feedback influence which affects on user i to listen track **j** at time t, basically come from crowd and friend two categories, $Music_j$ is the set of characteristics of music track j. β, γ, δ are the coefficients of the model and $\varepsilon_{ijt}$is a residual error term, indicating all the potential influencers that the models have not shown, and the error term satisfies the assumption of $\varepsilon_{ijt} \sim N(0, \varphi)$.

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[1]To our knowledge, each of the username appeared on the track page as "*** (username) is listening to the track" is randomly selected by inherent algorithms of Last.fm. Therefore, as we collected these user's id in different time (five users per hour), we conclude our target users are dispersed in the sample

[2] Firstly, we collected 1millionusers by using snowball sampling method as represent group of the generalization and acquired their basic characteristic information on last.fm. Secondly, we compared the characteristics of our target users to the characteristics of the represent group to see difference and test our samples' relation to the overall population. The gender ratio of the represent group was 67% male, 33% female and the average age 27.6 years (Stander dev.= 9.77).

Measurement of Variables

Dependent Variable

The data on Last.fm contains listening history of each user, providing a great advantage to track the online user's choice of listening on each particular track. Intuitively, the first listening choice is the premise and the foundation for further listening, while the repeat listening choice indicates the user's potential fondness or familiarity of a track. Both the first listening choice and repeat listening choice indicate a good reference to predict to the user's further listening decision or even the final purchasing behavior. Therefore, in this study, the online user's choice of listening music is distinguished into first listening behavior and repeat listening behavior by proposing two dependent variables, which are PlayOrNot$_{ijt}$ and RePlayOrNot$_{ijt}$ respectively.

Table 2. Description of Dependent Variable	
Dependent Variable	**Description**
PlayOrNot$_{ijt}$ (each user has one t value)	**Dummy variable indicating whether user i played the track j for the first time at time t (units: week).**
RePlayOrNot$_{ijt}$ (varied week by week)	**Dummy variable indicating whether user i repeat played the track j during time t (units: week).**

Independent Variable: User level, Online Feedback level and Music level

In order to validate the proposed hypotheses, the independent variables are considered in this study from three dimensions: user level, online feedback level and music level.

(1) User level

The independent variables in user level indicate the influences from user itself on user's listening choice, including the user demographic information such as age (Age_i), gender ($Gender_i$) and user history listening behavior, represented by user online history listening preference for an artist ($Preference_{ij}$) and the total count of tracks ever played by user ($log\_UserPlayCnt_i$). The number of friends ($log\_FriendNum_i$) is also added as one control variable.

(2) Online Feedback level

The independent variables in online feedback level indicate the influences from online feedback factors on user's listening choice, including the listening behavior from others. Two categories are involved: crowd influence and friend influence. In this study, the number of track listeners ($log\_Listeners_{jt}$) and the number of track reviews ($log\_Shouts_{jt.}$) are utilized to represent the impact of online feedback from crowd on user's listening behavior; the number of friend listeners of the track (log$\_FriendListNum_{ijt}$) represents the impact of online feedback from friend on user's listening behavior. Moreover, the variable of the influence coming from crowd, measured by the number of the track listeners ($log\_Listeners_{jt}$) and the number of track reviews ($log\_Shouts_{jt.}$) are acquired dynamically week by week from March 22, 2013 to June 28, 2013, 11 weeks involved[3].

(3) Music level

The independent variables in music level indicate the influences from the music itself on user's listening choice, including duration of track released ($log\_Duration_j$), the time length to prepare the track to be published ($LastAlbum_j$), the well-known level of the artist ($AritstGrade_j$) and the experience of the artist ($ArtistYears_j$). In addition, users on Last.fm will be recommended with similar music once he or she clicked the music. For instance, if a music track appeared to be very popular (shown in front of the track charts), then the probability of a user's listening to the same artist's music will be increased. Considering this fact, a variable is added to represent the best rank of the artists' music appeared on the charts

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[3]**Due to technology limitations, we failed to obtain three weeks (13th -15th week in the year of 2013) data among this time period but it won't affect the final results.**

(*BestRank_top100ⱼ*). **Detailed descriptions of the variables are shown in Table 3.**

Table 3. Description of Independent Variable		
Independent Variable		**Description**
User$_{ij}$	**Age$_i$**	**Self-reported age of user i**
	Gender$_i$	**Self-reported gender of user I (male=1).**
	Preference$_{ij}$	**The preference of user i for the artist of music track j.[4]**
	log_FriendNum$_i$	**The number of user i's friend.**
	log_UserPlayCnt$_i$	**The total number user i played on all songs onLast.fm.**
OnlineFeedback$_{ijt}$ (varied week by week)	**log_Listeners$_{jt}$**	**The total number of listeners of music track j at time t (units: week).**
	Log_FriendListenNum$_{ijt}$	**The number of user i's friend ever listened track j at time t (units: week).**
	log_Shouts$_{jt}$	**The total number of shouts (reviews) of track j at time t (units: week).**
Music$_j$	**log_Duration$_j$**	**The duration from track j released to March 22, 2013 (data collection initial time point).**
	LastAlbum$_j$	**The duration (units: years) from the artist of track j released the last album to year 2013.**
	AritstGrade$_j$	**The popular grade of the artist of track j (points range from 1-10), generated according to the artist rank list on Last.fm.**
	ArtistYears$_j$	**The duration (units: years) from the artist of track j released her first album to time t.**
	BestRank_top100$_j$	**The best rank of the artist of track j in top 100 rank charts.**

Data Analysis

Data Description

The descriptive statistical analysis of the variables is as shown in Table 4. As seen from the table, the mean values of *PlayOrNot$_{ijt}$* and *RePlayOrNot$_{ijt}$* are very small (mean value of *PlayOrNot$_{ijt}$*=0.061; mean value of *RePlayOrNot$_{ijt}$*=0.040), indicating that the listening behavior of a user on a track is a rare event, and probability of the user's repeat listening is smaller than that of the first listening. Besides that, the average age of the users is around 24 with standard deviation value of 7.153, indicating the most of the users in our sample are young listeners. Additionally, 62% of the users in our sample are male (Male =1, mean =0.62).From the general data descriptive statistics, it shows a more apparent trend of younger and masculine users on the Last.fm music website.

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[4]Calculation of the Preference: the preference is the ratio of the number of times a user has played the artist of track j to average number of times a user has played for an artist. Average number of times a user has played for an artist equals to the total number of artist played by the user divided by total number of tracks played by the user

Table 4. Data Descriptive Statistics					
Variable	**Mean**	**Std.Dev.**	**Min**	**Max**	**Obs.**
PlayOrNot$_{ijt}$	0.061	0.240	0	1	190000
RePlayOrNot$_{ijt}$	0.040	0.195	0	1	2090000
Age$_i$	24.376	7.153	1	113	1000
Gender$_i$	0.620	0.485	0	1	1000
Preference$_{ij}$	0.760	4.176	0	283.342	190000
FriendNum$_i$	44.809	44.013	1	198	1000
UserPlayCnt$_i$	37037.15	40242.83	1	276421	1000
Listeners$_{jt}$	88901.98	73162.67	8046	634686	2090
FriendListenNum$_{ijt}$	0.515	5.431	0	3574	2090000
Shouts$_{jt}$	86.36	161.53	1	1554	2090
Duration$_j$	241352.6	74578.89	31000	482000	190
LastAlbum$_j$	2.753	2.685	0	11	190
AritstGrade$_j$	3.305	2.333	1	10	190
ArtistYears$_j$	10.684	12.486	0	49	190
BestRank_top100$_j$	0.209	0.274	0	0.85	190

First Listening Model and Repeat Listening Model

First Listening Model

The first listening model is to examine the impact of user itself, online feedback and music characteristics on users' first playing behavior. The dependent variable $PlayOrNot_{ijt}$ is a binary classification variable, representing whether or not the user i first played the music track j at time t. This model is a dynamic model and different users probably have different but only one time t value. If user i has never played track j during our sampling period, time t will be assumed the end of sampling period: 25th week in 2013 (June 28, 2013). All the data value of other independent variables should be collected before or at time t (the units of time t is week).

$PlayOrNot_{ijt} = \beta_1 age_i + \beta_2 gender_i + \beta_3 Preference_{ij} + \beta_4 log(UserPlayCnt)_i + \beta_5 log(FriendNum)_i + \gamma_1 log(Listeners)_{jt} + \gamma_2 log\_FriendListNum_{ijt} + \gamma_3 log(Shouts)_{jt} + \delta_1 log(Duration_j) + \delta_2 LastAlbum_j + \delta_3 AritistYears_{jt} + \delta_4 ArtistGrade_j + \delta_5 BestRank\_top100_j + \varepsilon_{ijt}$ **(2)**

Repeat Listening Model

The repeat listening model is to examine the effect of user, online feedback and music characteristics on the user's repeat playing behavior. The dependent variable $RePlayOrNot_{ijt}$ is a binary classification variable, representing whether or not the user i played the music track j during time t repeatedly (the unit of time t is a week, period from March 22, 2013 to June 28, 2013, value varied from 12-25 but with gaps). A conditional probability model is also combined in the model analysis to give a better understanding of the repeat listening behavior.

$RePlayOrNot_{ijt}(Or\ given\ PlayOrNot = 1) = \beta_1 age_i + \beta_2 gender_i + \beta_3 Preference_{ij} + \beta_4 log(UserPlayCnt)_i + \beta_5 log(FriendNum)_i + \gamma_1 log(Listeners)_{jt} + \gamma_2 log\_FriendListNum_{ijt} + \gamma_3 log(Shouts)_{jt} + \delta_1 log(Duration_j) + \delta_2 LastAlbum_j + \delta_3 AritistYears_j + \delta_4 ArtistGrade_j + \delta_5 BestRank\_top100_j + \varepsilon_{ijt}$ (3)

Model Diagnostics

In order to be valid, the analysis model has to satisfy the assumptions of logistic regression so as to avoid biased coefficient estimates or very large standard errors for the logistic regression coefficients. Different potential problems in the model result in choosing different model estimation method. In this study, exclude the possibility of heteroscadicity, autocorrelation, multicollinearity respectively and calculate the count R-square in all three models. The results indicate the estimation of the model fits the real value very well and the important and relevant influence factors are found.

Results

In Table 4, the results of logistic regression estimation using equation (2) and (3) are presented. The column of Model 1 in Table 5 shows the First Listening Model results, the column of Model 2-1 shows the Repeat Listening Model results and the column of Model 2-2shows the Repeat Listening Model results with users who have played the track for one time (Given PlayOrNot=1).

Table 5. Logistic Regression Results			
Variables	**Model1: first play** **PlayOrNot**	**Model2-1: repeat play** **RePlayOrNot**	**Model2-2: repeat play** **RePlayOrNot(Given PlayOrNot=1)**
β_1**age**	-0.036***(0.001)	-0.056***(0.001)	-0.053***(0.001)
β_2**gender**	0.395***(0.008)	0.548**(0.009)	0.372***(0.014)
β_3**Preference**	1.040***(0.002)	1.080***(0.003)	0.394***(0.004)
β_4**log_UserPlayCnt**	0.844***(0.008)	0.875***(0.010)	0.365***(0.016)
β_5**log_FriendNum**	-0.102***(0.009)	-0.081***(0.011)	-0.012(0.016)
γ_1**log_Listeners**	2.051***(0.016)	2.023***(0.020)	0.285***(0.029)
γ_2**FriendListenNum**	1.365***(0.012)	1.390***(0.014)	0.600***(0.021)
γ_3**log_shouts**	-0.055***(0.008)	0.040***(0.010)	0.269***(0.019)
δ_1**log_duration**	0.236***(0.023)	0.146***(0.028)	-0.188***(0.044)
δ_2**LastAlbum**	0.059***(0.0021)	0.068***(0.0026)	0.044***(0.0037)
δ_3**ArtistYears**	0.008***(0.0004)	0.006***(0.0005)	-0.005***(0.0007)
δ_4**ArtistGrade**	-0.275***(0.003)	-0.3106***(0.003)	-0.1369***(0.004)
δ_5**BestRank_top100**	-0.517***(0.013)	-0.6127***(0.017)	-0.1768***(0.024)
Constant	-17.53***(0.141)	-17.50***(0.171)	-1.44***(0.266)
Count R2	94.5%	96.3%	66.7%
Pseudo R2	0.336	0.368	0.085
Prob> chi2	0.000	0.000	0.000
Wald chi2(13)	321711.13	255067.93	14046.52
Observations	190000	2090000	127037

Robust standard errors in parentheses* **p<0.01, ** p<0.05, * p<0.1**

The effect of user level characteristics on user listening behavior

The analysis results indicate that user's age (Age_i), gender ($Gender_i$), preference for an artist ($Preference_{ij}$) and the number of tracks played by the user ($log\_UserPlayCnt_i$) are statistically significant in all three models (p<0.01, Model 1, Model 2-1 and Model 2-2). What's more, the degree of these influence to the users' repeat online music listening becomes relatively larger than that to the user who already played the

music for one time: $\beta_{(model\ 2-1)} > \beta_{(model\ 2-2)}$.

In the first listening model, the user preference (*Preference$_{ij}$*) is significant at 1% level. For every one-unit increase in *Preference$_{ij}$*, the log odds of *PlayOrNot$_{ijt}$* increases by 1.040[5], indicating that higher preference for the artist increases the likelihood of the user's listening behavior of that track. This provides evidence for H3a. Meanwhile, the user's preference (*Preference$_{ij}$*) is both statistically significant (p<0.01) in Model 2-1 and Model 2-2, providing evidence for H3b.

The effect of online feedback level characteristics on user listening behavior

The analysis results indicate that, generally, the effect of online feedback has the largest influence on user's listening behavior (top three coefficients: γ_1 (*log_Listeners$_{jt}$*) $>\gamma_2$ (*log_FriendListenNum$_{ijt}$*) $>\beta_3$ (*Preference$_{ij}$*). In the first listening stage, larger listener's number (*log_Listeners$_{jt}$*) increases the likelihood of the user's first listening behavior of this track (as shown in Model 1, $\gamma_1 = 2.051>0, p<0.01$), or in another word, herding effect occurs. In the repeat listening stage, the listener's number appears smaller effect on user's behavior (as shown in Model 2-1, Model 2-2) while the number of friend listeners and the user's preference for artists appears larger effect, indicating the social influence from crowd is attenuated in the repeat listening case. This testifies the hypothesis that social influence from crowd is positively associated with user's first listening but is attenuated for repeating behavior, providing evidence to supportH1a and H1b

However, the number of track reviews (*Shouts$_{jt}$*) is negatively associated with user's first listening but positively associated with user's repeat listening (in Model 1: γ_3=-0.055, p<0.01, in Model 2: γ_3=0.040, p<0.01). It seems that "shout box" of Last.fm provides a good opportunity for users who have listened the music to communicate their feelings with others. People don't need to read others opinion to decide whether to listen a track because the barrier (time and cost) of experiencing a music is much lower than that of exercising a film and it is relatively easy to acquire listening choice of previously unknown tracks (three minutes per song, versus two hours per movie).

Meanwhile, the degree of online feedback influence from friend's listener number to the whole users for first listening behavior (*log_FriendListenNum$_{ijt}$*) becomes relatively larger than that to the users who already play the music for one time in repeat listening behavior (in Model 1, $\gamma_2 = 1.365$;in Model 2-2, $\gamma_2 = 0.600$). It indicates that larger friend listener number increase the likelihood of the user's first listening behavior of this track, while the effect will become smaller for the user who already play the music for one time in repeat listening stage, providing evidence to support H2a and H2b.

The effect of music level characteristics on user listening behavior

The analysis results indicate that the duration of track released (*log_Duration$_j$*), the time length to prepare the track to be published (*LastAlbum$_j$*), the years since the artist started his or her career (*ArtistYears$_j$*), the well-known level of the artist (*AritstGrade$_j$*) and the best ranking of the artist in top 100 (*BestRank_top100$_j$*) are all statistically significant in first listening model and repeat listening models (Model 1, Model 2-1, Model 2-2). This shows the most theory of Hypotheses could be verified very well.

As demonstrated by the results in Table 5, *LastAlbum$_j$* variable is statistically significant with positive coefficient value in all three models (p<0.01). It is an interesting fact, suggesting that the longer an artist prepared for an album, the larger likelihood of users will play the artist's track. It seems that the time length to prepare the track to be published indicate a sign of how long the artist team has spent on producing this new album, reflecting the quality of the tracks. This provides support for H4a and H4b, in which the quality-related factors have impact on user's listening behavior.

In addition, the variable *ArtistYears$_j$* is statistically significant in all three models with positive coefficient value, indicating that the users on Last.fm prefer fame artists who have longer experience. Moreover, the variable *BestRank_top100$_j$*and *AritstGrade$_j$* is statistically significant in all three models with negative coefficient value, indicating that the better ranking of the artist's music is, the higher the Artist well-known level, the larger likelihood of the user will listen to his track (the smaller the number, the higher the rank). As mentioned previously, the popularity of the track could be used to represent the quality of

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[5]The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variable.

music product. Therefore, the best ranking of the artist (*BestRank_top100ⱼ***) provides users an impression that the artist is displaying a high-qualified music work, and then arouses the user's interest to listen the music of artist. This verifies that quality related factors have an impact on user's listening behavior (H4a and H4b).**

Effect of heterogeneity on music listening choice (Random effects)

Since the data is a panel data (both have time series and cross-sectional data), a logistic random effects were analyzed. The results are shown in Table 6.

Table 6. Random effects Logistic Regression Results		
Variables	**Regular logistic**	**Random effect**
Panel level σ_μ		**4.630***(0.007)**
$\beta_1$age	**-0.036***(0.001)**	**-0.158***(0.006)**
$\beta_2$gender	**0.395***(0.008)**	**1.23**(0.061)**
β_3Preference	**1.040***(0.002)**	5.904***(0.032)
$\beta_4$log_UserPlayCnt	**0.844***(0.008)**	3.142***(0.070)
$\beta_5$log_FriendNum	**-0.102***(0.009)**	0.585***(0.068)
$\gamma_1$log_Listeners	**2.051***(0.016)**	12.00***(0.138)
$\gamma_2$log_FriendListenNum	**1.365***(0.012)**	0.0855***(0.0559)
$\gamma_3$log_shouts	**-0.055***(0.008)**	-0.237***(0.061)
$\delta_1$log_duration	**0.236***(0.023)**	-1.515***(0.214)
δ_2LastAlbum	**0.059***(0.0021)**	0.459***(0.019)
δ_3ArtistYears	**0.008***(0.0004)**	0.009***(0.005)
δ_4ArtistGrade	**-0.275***(0.003)**	-1.611***(0.025)
δ_5BestRank_top100	**-0.517***(0.013)**	2.360****(0.114)
Constant	**-17.53***(0.141)**	-78.45*** (1.283)
Observations	2,900,000	2,081,970

Robust standard errors in parentheses* p<0.01, ** p<0.05, * p<0.1**

Except for the number of friend listeners (*log_FriendListenNum***), the subject-specific estimates are observed to be larger in magnitude than in the regular logit model. Among other things, according to this model, the estimate result reports the interclass correlation as 0.968. This coefficient pertains to a latent variable reflecting propensity to choose to listen to a track, indicating the correlation between this music listening choices in any two weeks for the same track selection of same person is 0.97. It is found that 97% of the variance in the music listening behavior choice can be attributed to different individuals and different tracks.**

Summary of Hypothesis Testing Results

From the estimation results of first listening model and repeat listening model, most of the hypotheses get verified, shown in Table 7.

Table 7. Hypotheses Testing	
Hypothesis	**Test Result**

H1a: Crowd's online feedback is positively associated with a user's first online music listening behavior. H1b: The effect of crowd's online feedback will be attenuated for repeat listening behaviors	H1a:Partially Supported H1b:Partially Supported
H2a: Friend's online feedback is positively associated with a user's first listening behavior. H2b: Friend's online feedback is positively associated with a user's repeat listening behavior.	H2a:Supported H2b:Supported
H3a: User's preference has a positive impact on one's first listening behaviors H3b:User's preference has a positive impact on one's repeat listening behaviors	H3a:Supported H3b:Supported
H4a: Product quality-related factors have a positive effect on a user's first listening behavior. H4b: Product quality-related factors have a positive impact on a user's repeat listening behavior.	H4a:Supported H4b:Supported

Conclusion

The objective of this study is to explore the purchasing mechanism of online music and the consumer activity maintaining mechanism. There are several findings of this work:

Firstly, users' preference and products' quality are found to be still the two most stable and lasting factors influencing users' music listening behaviors on the era of Web2.0. In this study, the findings suggest that it is vital for marketers to keep in mind that user's own tastes or preferences and the product quality will always be the essential factors determining consumer's buying decision for online music. Tracking the user's preference and improving the quality of the product will be the fundamental considerations for online music to move on, develop and thrive.

Secondly, herding effect is noted to be obviously outstanding for users' first music listening decision, while it is quite weak for users' repeat music listening decision. The results suggest that the impact of herding effect from crowd on users is mainly come from user informational social influence (Allen 1965; Tesser et al. 1983; Baron et al. 1996; Aronson et al. 2005). While the impact of herding effect from crowd will not last long, particularly for experience goods such as online music, on which users will produce a series of active thinking after they have experienced the music thus they will not be easily influence by crowd.

Thirdly, friends are observed to have power to influence people's life. This research enhanced the understanding of the friend's influence on user purchasing decisions. Moreover, this research helps to improve the user recommendation algorithm and increase the success rate of personalized recommendation to achieve enhanced cross-selling and customer loyalty purposes.

Acknowledgments

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