A hierarchical Bayesian model in Evaluating Apps Downloading Frequency

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Abstract: - Several purchase models are developed to understand customer dynamic purchasing behavior. The negative binomial distribution (NBD) contains two characteristics which are Poisson purchasing and gamma heterogeneity is shown as a robust method in product purchase frequency. An approach is to develop individual-level estimation by MCMC Bayesian NBD model. Since the smart phone launch to publish, various types of apps are developed and try to approach users. The app can work successfully only when they meet customers' requirements. An empirical exam is to estimate effects that influence download frequency for different type of apps. Three app types, game, social communication and photo editor, are examined. The proposed model can capture app download frequency successfully. The game downloaders are more focus on social and hedonic. The social communication downloaders emphasis on informativeness and price. The photo editor downloaders concern on informativeness and social characteristics. Results can provide valuable designing strategies for companies.

Key-Words: - negative binomial distribution (NBD), MCMC, hierarchical Bayesian model, App

1 Introduction

A various types of apps are developed because of the popular of smart phones. Long-term customers can bring about 95 percent of companies' profits. They also provide stability in sale volume. Companies are trying in retaining their valued customers via apps now. Companies' profits will immediately increase when you spend more of marketing budget on retention and less on new business. Understanding customers' intents and serve as marketing strategies for maintaining long-term customer relationship is important. The app download frequency is one indicator of knowing users' preference and designing a proper app.

Several purchase models are developed to understand customer dynamic purchasing behavior. The purchase frequency model is adopted to evaluate the download frequency in this study. Eskin (1973) first model the purchase trail [7]. The most popular inter-purchase models are exponential and Erland2 [21]. Kalwani and Silk (1980) assume rate parameters followed a gamma distribution for an exponential distribution to model the repeat purchase time [14]. The negative binomial distribution (NBD) contains two characteristics which are Poisson purchasing and gamma heterogeneity. Ehrenberg first introduced to the marketing [6]. The NBD model is shown as a robust method in representing product purchase [18]. Many literatures use the NBD in inter-purchase model [3][16][19].

A growth of computation technology enables researches simulation purchase time stochastically. The hierarchy Bayesian estimates the posterior distribution based on the prior information and likelihood with MCMC are adopting in simulating inter-purchase research. Allenby developed a Bayesian based dynamic inter-purchase time model [1]. Jen et al. (2003) modeled the purchasing frequency by a Bayesian approach and comparing results with a Poisson and a NBD model. The model provide improved estimate of purchase frequency for short purchase customer histories and infrequent interaction with a firm [13]. Wu and Chen (2000) develop a stochastic model to capture the regularity effects in inter-purchase time [22]. Guo (2009) generate the multi-category inter-purchase time model and measuring the influence of product category on customers' inter-purchase [11].

The growth develops in apps cause huge competition in catching customers' interests. This study focuses on finding effects influencing downloading intention for different types of apps.

2 Theoretical Background

2.1 Perceived usefulness and perceived ease of use

The technological acceptance model (TAM) was introduced by Davis [3], built on the theory of reasoned action (TRA). The TAM is used for investigating users' acceptance of information technology [3]. The model proposed that perceived usefulness and perceived ease of use are two important determinates, many researches prove the TAM provides strong conceptual and empirical evidence in technology product adoption.

2.2 TTF(Task Technology fit)

The TTF model was originally proposed by Goodhue and Thompson [10]. IT will be adopted only whether the technology fit users' technology [5]. TTF has also been used to explain user adoption of mobile technologies.

2.3 Price

Price is a critical attributes of purchasing products. High price acceptability leads to high consumer's tradeoff value, and in turn triggers re-patronage intention [20]. It implies price acceptability having a positive relationship with consumer's satisfaction.

2.4 Hedonic

Some research has shown hedonic motivations to have powerful influences on shopping behavior in both traditional and online shopping environments [15]. Hedonic can provide the dominant predictor of attitudes toward download apps.

2.5 Social

The main function of smart phone users is the need of communication. Some apps offer an efficient way in supporting social interactions between individuals and groups. Also, users can share their documents, data, videos, and photographs on their phones.

2.6 Informativeness

Informativeness refers to the ability to effectively provide relevant information [17]. Information is one need function related to download frequency. Apps provide a convenient way for users to gain necessary information in a proper manner.

3 Methodology

3.1 The negative binomial distribution (NBD) model

The Bayes Theorem follows the definition of the conditional probability is stated. If A and B are event with P(B)>0, then $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$. The case of continues parameters is rewritten as $p(\theta|y) = \frac{p(y|\theta)p(\theta)}{\int P(y|\theta)p(\theta)d\theta}$, where θ is unknown parameter and y is a given data. The formula is more commonly expressed as $p(\theta|y) \propto p(y|\theta)p(\theta)$. The p(θ|y) is a posterior and is propositional to the prior p(y|θ) and the likelihood p(θ). The probability estimation of p(θ|y) is improved by combing the prior information of θ.

The Poisson regression model is a fundamental random process which expresses the probability of a number of events occurring in a fixed time interval with the average of event occurred in known and independent increments in non-overlapping time periods. Suppose yi is the ith response variable, the Poisson distribution is expressed as $f(y_i) = \frac{(\lambda_i T)^{y_i} e^{-\lambda_i T}}{y_i!}$ where λ_i is the mean and T is the interval of length. The Poisson regression model can not satisfied real life applications in some reasons.

A fully parametric method of the mix Poisson distribution named NBD model is proposed to modify the shortage of the Poisson distribution. The NBD model assumed that the purchase time by an individual customer followed a Poisson distribution with a parameter λ [2][6]. The negative binomial distribution (NBD) model assumed that the purchase time by an individual customer followed a Poisson distribution with a parameter λ [2][6]. The parameter λ is various across different consumers is set as a gamma distribution. Given the gamma prior assumption on λi with parameters (α, θ), the joint probability function becomes

$$f(yi|\lambda i)\pi(\lambda i|\alpha,\theta)=\frac{(\lambda iT)^{yi}e^{-\lambda iT}}{yi!}\frac{\theta^{\alpha}}{\Gamma(\alpha)}\lambda i^{\alpha-1}e^{-\lambda i\theta}.$$

which results in the marginal distribution of y_i as

$$f(yi|\alpha,\theta)=\int_0^{\infty}f(yi|\lambda i)\pi(\lambda i|\alpha,\theta)d\lambda_i$$
$$=\frac{T^{yi}}{yi!}\frac{\theta^{\alpha}}{\Gamma(\alpha)}\int_0^{\infty}\lambda^{yi+\alpha-1}e^{-(T+\theta)\lambda i}\,d\lambda i$$
$$=\frac{\Gamma(yi+\alpha)}{yi!\,(\alpha-1)!}\left(\frac{T}{T+\theta}\right)^{yi}\left(\frac{\theta}{T+\theta}\right)^{\alpha},yi=0,1,2,\ldots$$

Under again the Gamma prior assumption on λ_i, the posterior distribution of λ_i is

$$\pi(\alpha,\theta|y_i)=\frac{f(y_i|\lambda_i)\pi(\lambda_i|\alpha,\theta)}{f(y_i|\alpha,\theta)}$$

$$=\frac{\frac{(\lambda_iT_j)^{y_j}e^{-\lambda_iT_j}}{y_i!}\frac{\theta^{\alpha}}{\Gamma(\alpha)}\lambda_i^{\alpha-1}e^{-\lambda_i\theta}}{\frac{\Gamma(y_i+\alpha)}{y_i!\,(\alpha-1)!}\left(\frac{T}{T+\theta}\right)^{y_i}\left(\frac{\theta}{T+\theta}\right)^{\alpha}}$$

$$=\frac{(\theta+T)^{y_i+\alpha}}{\Gamma(y_i+\alpha)}\lambda_i^{\alpha+y_i-1}e^{-\lambda_i(T+\theta)},$$

which is a gamma distribution with parameters $(\alpha+y_i,\theta+T)$. The NBD model provides a more flexible estimation of the intensity parameter in the Possion model, which has been used in the marketing prediction [6 13 16].

3.2 The Hierarchical negative binomial distribution (NBD) model

Suppose we observe the number of purchases made in a time-period of length T for each of N households, which are denoted as y = (y1, y2, …, y_N)'. Based on this sample, the unknown parameters (α, θ) can be estimated by three methods. Firstly, let the marginal joint likelihood function be denoted as $l(\alpha,\theta|y)=\prod_{i=1}^{N}f(yi|\alpha,\theta)$. (1)

Potential estimators of (α, θ) is the maximum likelihood estimates which is obtained by maximizing (1).

Assume that the total number of purchases that occur by time T for the i[th] customs follows a Poisson process having rate λ_i, $\lambda_i>0$. Let $Y_{i,j}$ denote the number of purchases made during the period of (t_{j-1},t_j), where t_0 = 0 and $t_{j-1}<t_j$. Assume that Yi has a Poisson distribution with mean λ_iT, where λ_i is the purchase frequency with gamma distribution. The vector,$Y=\{Y_1,\ldots,Y_n\}$, is purchase times in a time period T. The joint likelihood function for the hierarchical Bayesian model can be then represented as

$$l(\Theta|y_i,T)=\prod_{i=1}^{N}p(y_i|\lambda_i)\pi(\lambda_i|\alpha,\theta_i)\,\pi(\alpha)\pi(\theta_i),$$

where $p(y_i|\lambda_i)$ is the Poisson probability mass function, $\pi(\lambda_i|\alpha,\theta_i)$ denotes a gamma probability density function, $\pi(\alpha)$ denotes a prior probability density function of α and $\pi(\theta_i)$ is a prior probability density function of θ_i.

Let $T_j=t_j-t_{j-1}$. We can obtain the conditional probability of $Y_{i,j}$ given $Y_{i,j-1}$ as

$$P\left[Y_{i,j}=y_j|P_{i,j-1}=y_{j-1},\lambda_i\right]=\frac{(\lambda_iT_j)^{y_j}e^{-\lambda_iT_j}}{y_j!}.$$

Under again the Gamma prior assumption on λ_i, the posterior distribution of λ_i is

$$\pi(\alpha,\theta|y_i)=\frac{f(y_i|\lambda_i)\pi(\lambda_i|\alpha,\theta)}{f(y_i|\alpha,\theta)}$$
$$=\frac{\frac{(\lambda_iT_j)^{y_j}e^{-\lambda_iT_j}}{y_i!}\frac{\theta^{\alpha}}{\Gamma(\alpha)}\lambda_i^{\alpha-1}e^{-\lambda_i\theta}}{\frac{\Gamma(y_i+\alpha)}{y_i!\,(\alpha-1)!}\left(\frac{T}{T+\theta}\right)^{y_i}\left(\frac{\theta}{T+\theta}\right)^{\alpha}}$$

$$=\frac{(\theta+T)^{y_i+\alpha}}{\Gamma(y_i+\alpha)}\lambda_i^{\alpha+y_i-1}e^{-\lambda_i(T+\theta)},$$

which is a gamma distribution with parameters $(\alpha+y_i,\theta+T)$. As a result, the marginal probability mass function of Y_j given Y_{j-1} can be derived as follows:

$$P\left[Y_{i,j}=y_j|Y_{i,j-1}=y_{j-1}\right]=\int_0^{\infty}P\left[Y_{i,j}=y_j,\lambda_i=\lambda|Y_{i,j-1}=y_{j-1}\right]d\lambda$$
$$=\int_0^{\infty}P\left[Y_{i,j}=y_j|P_{i,j-1}=y_{j-1},\lambda_i\right]P[\lambda_i=\lambda|\,Y_{i,j-1}=y_{j-1}]d\lambda$$
$$=\int_0^{\infty}\frac{(\lambda T_j)^{y_j}e^{-\lambda T_j}}{y_i!}\frac{(\theta+T_{j-1})^{y_{j-1}+\alpha}}{\Gamma(y_{j-1}+\alpha)}\lambda^{\alpha+y_{j-1}-1}e^{-\lambda_i(T_{j-1}+\theta)}d\lambda$$
$$=\frac{(y_{j-1}+y_j+\alpha-1)!}{y_j!\,(y_{j-1}+\alpha-1)!}\left(\frac{T_j}{T_j+T_{j-1}+\theta}\right)^{y_j}\left(\frac{T_{j-1}+\theta}{T_j+T_{j-1}+\theta}\right)^{y_{j-1}+\alpha},$$

which is a negative binomial distribution with parameters ($y_{j-1}+\alpha,\frac{T_{j-1}+\theta}{T_j+T_{j-1}+\theta}$). Therefore, the conditional expectation of $Y_{i,j}$ given $Y_{i,j-1}$ is $E\left[Y_{i,j}|Y_{i,j-1}\right]=(y_{j-1}+\alpha)\frac{(y_{j-1}+\alpha)T_j}{T_{j-1}+\theta}$. The NBD model provides a more flexible estimation of the intensity parameter in the Possion model. The NBD model has been used new product sale prediction in marketing literatures [6][13][16].

Let $\theta_i=\exp(x_i'\beta)$. A proposed simulation procedure is as follows.

Step 1: Generate λ_i from a gamma distribution with parameters A and B, where A = $y_i+\alpha$ and B = θ_i+ T, i = 1, …, N.

Step 2: Generate β_k, k = 1, …, K from the posterior distribution. The K is the variable number and xiks are dummy variables.

$$\pi(\beta_k|\lambda,\alpha,x_{ik},T) \propto \prod_{i=1}^{N} \frac{\theta_i^{\alpha}}{\Gamma(\alpha)} \lambda_i^{\alpha-1} e^{-\theta_i \lambda_i \pi(\beta_K)}$$

Step3: Denote $\psi_k = e^{\beta_k}$ and ψ_k has a gamma prior distribution with parameter (a_{k0}, b_{k0}). Then we can obtain the posterior distribution of ψ_k as

$$\pi(\psi_k|a_k, b_k, \lambda) \propto \prod_{i=1}^{N} \psi_k^{x_{i,k}} e^{-\sum_{i=1}^{N}\prod_{j=1}^{N}\psi_j^{x_{ij}}} \frac{b_{k0}}{\Gamma(a_{k0})} \psi_k^{a_{k0}-1} e^{-b_{k0}\psi_k}$$

Step4: Generate α from the posterior distribution of α defined as

$$\pi(\alpha|\lambda,\theta_i) \propto \frac{\theta_i^{\alpha}}{\Gamma(\alpha)} \lambda_i^{\alpha-1} e^{-\theta_i\lambda_i}.$$

Step5: Repeat step1 through step3 10000 times.

The estimates are the average values based on the last 500 iterations.

3.3 The Markov Chain Monte Carol Algorithm

The NBD model combines a Poisson distribution for the number of purchases and integrates a gamma random-effect distribution for the individual heterogeneity. Drawback of the NBD model is not providing individual- level frequency estimation. An approach is to develop individual-level estimation by hieratical Bayesian model. Moreover, the MCMC algorithm samples Markov chain based on the Monte Carol principle and is adopting in computing complicate the hieratical Bayesian NBD model. Many researches model the Bayesian analysis by the MCMC method in social science [12]. The MCMC algorithm is adopted in computing the posterior density of the parameter in a hierarchical Bayesian model via a Gibbs sampler. A Gibbs is a straightforward sampling drives from the "divide-and-conquer" to approach high-dimensional problems [12]. Suppose the Gibbs samples the parameter $\theta = (\theta_1, \theta_2, \dots, \theta_n)'$ from a possibility function $p(\theta_i|\theta_{j\neq i}, y)$ sequentially [9]. The algorithm states as follows.

Algorithm of Gibbs Sampler

for i= 1 to # of iteration

$$\theta_1^{i+1} \sim p_1(\theta_1|\theta_2^i, \theta_3^i, \dots, \theta_n^i, y)$$

$$\theta_2^{i+1} \sim p_2(\theta_1|\theta_1^i, \theta_3^i, \dots, \theta_n^i, y)$$

…

$$\theta_n^{i+1} \sim p_n(\theta_1|\theta_1^i, \theta_2^i, \dots, \theta_{n-1}^i, y)$$

end for

A successful application of Bayesian inference problems is shown by the Gibbs sampler [8]. This study use MCMC to simulate hierarchical Bayesian algorithm for purchase frequency problems.

4 Empirical Analysis

Data is collected from people who own smart phones. A total of 234 responses were valid for analysis. The percentage of female and male of the respondents were 53.7% and 46.3%. More than 80% use Android based phone and more than 50% of respondents have been purchased the smart phone more than one year. The most popular brand is Samsung. About 62% of respondents use the smart phone two to five hours per day. Details of the description analysis are listed in Table 1.

Table 1. Description analysis of the Respondents

Variables	Classification	N	%
Gender			
	Female	119	53.4
	Male	104	46.6
Age			
	<=18	11	4.9
	19-25	135	60.5
	26-35	55	24.7
	36-45	16	7.2
	>46	6	2.7
Operation System			
	Android	184	84.0
	IOS	30	13.7
	Windows	5	2.3
Total year of Using the Smart phone			
	< 6 month	26	11.7
	6-12 month	68	30.6
	13-24 month	72	32.4
	25-36 month	30	13.5
	>36 month	26	11.7
Brand			
	Samsung	93	41.5
	HTC	58	25.9
	apple	29	13.9
	Sony	19	8.5
	LG	7	3.1
	Nokia	2	0.9
	Others	16	7.1
Average using time per day			

<2 hrs.	14	6.4
2-5 hrs.	136	62.7
6-8 hrs.	41	18.9
>8 hrs.	26	12.0

A survey questionnaire was asking respondents about their app adopting behavior to rate their importance on a Likert 5-scale. In the first step, we use the principle component method for determining loading factors. Table 2.shows the elements of the factor model on which the principle component method concentrates. The selection principle is maximizing the variance to seek the rotated loading with eign-value larger than 1 based on the Kaiser rule. The Cronbach's α is used to estimate constructs' reliabilities ranged from 0.695 to 0.828. Secondly, the construct are transferred into binary data. If the mean value of scale items for the construct is greater than 4, the construct value is rescaled as 1. Otherwise, the construct value is rescaled as 0.

Table 2 Factor Analysis

	Factor loading	Cronbach's α	Mean	SD
Price		0.77	3.50	0.87
Use apps can save me money	0.823			
I think apps price is reasonable	0.766			
Usefulness		0.797	3.85	0.69
Use apps can make my work more efficient	0.735			
Apps can fulfill my life	0.762			
Apps can save me time in process the work	0.749			
TT_fit		0.828	3.78	0.68
Apps fits my requirements	0.715			
Apps provide suitable services	0.846			
Apps provide suitable functions	0.817			
Ease Of Use		0.811	3.82	0.74
I can clearly know how to operate apps correctly	0.934			
It is easy for me to operate apps	0.732			
Social		0.816	4.03	0.71
Apps fits my social life	0.893			
Apps make my relationship with friends closely	0.736			
Informativeness		0.793	3.92	0.73
Apps make me learn many new knowledge	0.893			
I am satisfy with the app learning service	0.736			
Hedonic		0.695	4.08	0.68
Using apps make me feel interested	0.683			
I feel happy when using apps	0.781			
Satisfaction		0.820	4.01	0.65
I feel satisfied with apps	0.812			
I am very satisfied with apps	0.819			
Overall, I think it is worth in using apps	0.715			

We choose three types of most popular app including game, Social Communication and photo editor as evaluated. Respondents are asked which apps are most used in the last 3 months. Items of each category are listed in Table 3.

Table 3 List of items in each category

Category	Items	Selected	Proportion
Game			
	LINE Pop	111	47.4%
	TempleRun2	59	25.2%
	LINE Bubble	47	20.1%
	LINE Cartoon Wars	44	18.8%
	Subway Surfers	39	16.7%
	Homeran Battle Burst	39	16.7%
	Candy Crush Saga	34	14.5%
	LINE Ice Qpick	32	13.7%
	Come on baby	26	11.1%
	LINE Patapoko animal	24	10.3%
	LINE Hidden Catch	21	9.0%

	Zombie Smasher	14	6.0%
	Mahjong	1	0.4%
	Stone Age	1	0.4%
	Chinese Dark Chess	1	0.4%
	Tower of Saviors	1	0.4%
	Angry Bird	1	0.4%
Social Communication			
	Facebook	169	72.2%
	Line	161	68.8%
	Facebook Messenger	77	32.9%
	WeChat	53	22.6%
	WhataAppMessenger	33	14.1%
	Weibo	30	12.8%
	Skype	21	9.0%
	MoPTT	5	2.1%
	Outsider	2	0.9%
	Twitter	1	0.4%
	Flipboard	1	0.4%
Photo Editor			
	Line Camera	110	47.0%
	Meitu	104	44.4%
	Phototastic Free	74	31.6%
	Baidu magic photo	46	19.7%
	Camera+	44	18.8%
	InstaPlace	28	12.0%
	ThumbaCam	17	7.3%
	ThumbaPhoto Editor	9	3.8%
	Camera 360	9	3.8%
	GirlsCamera	1	0.4%
	Cymera	1	0.4%

Note: N=224

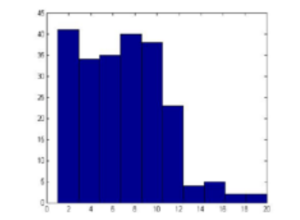
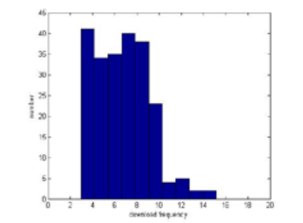
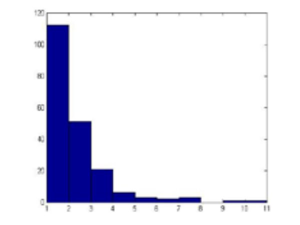
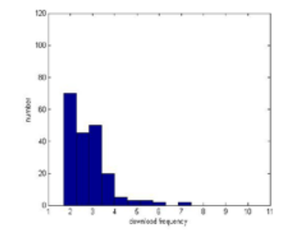
The factors of the ease of use and early adaptor, the economic, convenience, usefulness, and fun and social are set as independent variables for the model. A Markov Chain Monte Carol simulates the Bayesian NBD model. The posterior parameters inferred from the average values based on the last 500 iterations out of 10000 iterations. Each estimation process runs 30 times.

One sample histogram plots of both the observation data and the experience data are shown in Figure 1.The root mean squared error (RMSE) between proposed model and observed data is 15.6983. The average influential parameters are listed in Table7.

Table 4 The download frequency of each category

Catalog	frequency	number	percentage
Game	1	70	29.90%
	2	42	17.90%
	3	51	21.80%
	4	21	9.00%
	>=5	16	6.90%
Social Communication	1	15	6.40%
	2	70	29.90%
	3	58	24.80%
	4	22	9.40%
	>=5	25	10.70%
Photo Editor	1	24	10.26%
	2	53	22.65%
	3	45	19.23%
	4	26	11.11%
	>=5	13	5.56%

Table 5. The downloading frequency of real data and simulation data

	
Real data of Total Catalog	Simulation data of Total Catalog
	
Real data of Game Catalog	Simulation data of Game Catalog

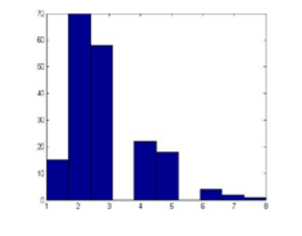
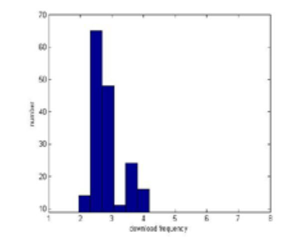
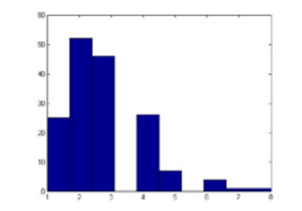
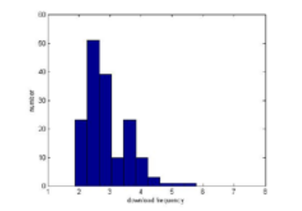
	
Real data of Social Communication Catalog	Simulation data of Social Communication Catalog
	
Real data of Photo Editor Catalog	Simulation data of Photo Editor Catalog

Figure 1. Purchase frequency comparisons

Table 6 RMSE

Catalog	RMSE
Total	21.5904
Game	10.4005
Social Communication	8.9172
Photo Editor	8.1895

Table 7. The influential parameters

Total (N=224)	Game (N=200)	Social Communication (N=190)	Photo Editor (N=162)
Mean (S.D.)	Mean (S.D.)	Mean (S.D.)	Mean (S.D.)
Intercept			
1.01 (0.25)	1.17 (0.43)	1.14 (0.21)	1.22 (0.33)
Price			
0.97 (0.21)	1.13 (0.23)	1.29 (0.44)	1.18 (0.20)
Usefulness			
1.07 (0.25)	1.03 (0.18)	1.24 (0.40)	1.12 (0.20)
TT_fit			
0.98 (0.14)	1.07 (0.22)	1.19 (0.27)	1.20 (0.39)
Ease of Use			
1.07 (0.22)	1.14 (0.21)	1.12 (0.29)	1.20 (0.27)
Social			
1.02 (0.28)	1.17 (0.29)	1.13 (0.29)	1.24 (0.58)
Informativeness			
1.00 (0.25)	1.12 (0.24)	**1.33** (0.44)	**1.28** (0.36)
Hedonic			
1.00 (0.22)	**1.29** (0.66)	1.13 (0.22)	1.21 (0.41)
Satisfaction			
1.08 (0.23)	1.14 (0.30)	1.13 (0.23)	1.19 (0.20)

5 Conclusion Conclusions

There are thousands apps. Some of them are successful and some are not. Knowing user's requirements can design proper apps for low cost. This research applied the MCMC based hierarchical Bayesian model in evaluate the download frequency of app to predict users' adoption behavior. Three different main app categories include the game, the social communication and the photo editor are examined. Results show that the proposed algorithm can capture the data characteristics. The game downloading users are emphasis on hedonic and social. Designers can focus on adding group game to provide enjoyment in playing with friends. The social communication downloader more concern about the informativeness and price. Reasons for using the social communication app are free and can share information with friends. Most communication apps are having a free access policy. The communication app providers must try to speed up the information sharing speed to keep the royalty of users. The photo editor users focus more on informativeness and social. Users can build friendship through sharing their photos. The photo editor app can make a link to information sharing based platform such as facebook or line to exchange information with users' friends. Based on this research, app designers can more focus and make different strategies for different types of apps.

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