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Research on the Participation Motivations of Users in UGC Society Based on DDCM

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Abstract

This study combines satisfaction, achievement motivation, and social identity theories to construct a dynamic discrete choice model (DDCM) to characterize user participation behavior on the Internet UGC platform. The main motivational factors of users participating in the UGC platform are analyzed and extracted, including enjoyment and entertainment motivation, identity motivation, community belonging motivation, and information acquisition motivation from psychological and social interaction. A two-stage estimation method constructs and solves a dynamic discrete choice model. Objective data from Epinions, an online review community, was used to investigate the motivation of users to participate in the UGC platform. The results show that users can gain enjoyment, entertainment, and information acquisition utility by publishing and reading articles in the Epinions community. When users are concerned and trusted by other users in the community, or when their published articles are recognized and praised, users will have a strong sense of identity. The more frequently a user contributes to the community, the more trust they have in other users, and the stronger their sense of community belonging. Finally, some suggestions for developing and managing the Internet UGC platform are put forward based on the estimation results of the model.

Keywords

UGC Society, Participation Motivation, Dynamic Discrete Choice Model, Two-Stage Estimation Method

1. Introduction

In the Web2.0 era, with the rapid development of information technology and popularization of the internet, people are endowed with higher capabilities and more ways to create value. In the past, they were just "consumers" of Internet

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content. Now, they are also "producers". In the internet platform, every user can display their original content and share it with others. This behavior is defined as "UGC", which means user-generated content. UGC has developed rapidly by virtue of its advantages such as proximity to users, high efficiency of resource allocation, flexibility and autonomy, attracting a large number of enterprises and scholars. For every UGC platform, the user's productivity determines the survival and development of the platform. However, in the platform, there is no employment relationship, and users are unable to get direct monetary and material reward most of the time (Park & Van Der Schaar, 2010). So why do users voluntarily invest time and effort in content production? What drives their behavior? What kinds of satisfaction do they get? Understanding these issues is critical to the sustainability of UGC platforms.

At present, most of the researches on user participation motivation of UGC platform are conducted through surveys/questionnaires, and the results are susceptible to subjectivity. Using the actual micro-level data from the Epinions, an online review community, this paper builds up a dynamic discrete choice model to delve into the participation motivations of users in UGC platform. For the solution of the model, we adopt the two-stage estimation method proposed by Bajari et al. (2007).

Our results suggest that users can obtain enjoyment and entertainment utility and information acquisition utility from posting and reading reviews in the Epinions. When users are trusted by others, or their posted reviews are recognized and praised, users will have a strong sense of identity. The higher the degree and frequency of users' community contribution, the more they trust other users in the community, and the stronger their sense of community attachment will be.

2. Research Method

Based on the existing literature (Bajari et al., 2007; Pakes & McGuire, 2001; Gowrisankaran & Town, 1997; Ericson & Pakes, 1995; Rust et al., 1987), this study constructs a dynamic discrete choice model (DDCM) to characterize user participation behavior in Internet UGC society by combining satisfaction theory, achievement motivation theory and social identity theory. The dynamic discrete choice model is a microeconometric model that is widely used in economics and other social science research. For example, Stock and Wise (1990) applied this model to retirement decisions; Imai and Krishna (2004) constructed a dynamic choice model about criminal behavior; It is based on utility maximization theory to study decision makers' action choice problems, which is of great significance for understanding decision-making behavior under different situations. Its basic principles are as follows:

At each time t, $t \in \{1, 2, \cdots, T\}$, the decision maker has a s_t, $s_t \in S$, in which he chooses action a_t from finite set A_t and obtains utility $U(a_t, s_t, \theta)$, where θ is a vector parameter. At the same time, because the decision-maker gains utility in the current time, his state s_t will change and be updated to s_{t+1} at the

next time. The utility $U(a_t, s_t, \theta)$ of a decision-maker can be regarded as consisting of a deterministic component $u(a_t, s_t, \theta)$ and a random perturbation term γ_t:

$$U(a_t, s_t, \theta) = u(a_t, s_t, \theta) + \gamma_t \tag{1}$$

γ_t satisfies independent and identical distribution for different *t*.

Because the utility of the decision maker at time *t* affects the state at time $t+1$ and then affects the utility at the next time, the decision maker will consider the impact of the current action decision on the future utility and make a decision to maximize his total utility:

$$V(s_t, \theta) = \max_{a_t \in A_t} v(a_t, s_t, \theta) \tag{2}$$

$$v(a_t, s_t, \theta) = u(a_t, s_t, \theta) + \beta E\left\{V(s_{t+1}, \theta) \middle| s_t, a_t; \theta\right\} \tag{3}$$

β is the utility discount factor.

The dynamic discrete choice model is a very effective and practical research tool for studying individual choice behavior. Starting from economic theory, it can simulate actual situations and restore individual choice processes by abstracting and describing realistic problems mathematically instead of simply fitting data. By analyzing the magnitude, sign, and significance of parameter θ estimation value of the dynamic discrete choice model, researchers can understand which factors influence decision-makers' action choice and what the direction and importance of their influence are, which provides essential reference basis for understanding and revealing the behavior decision of individuals, enterprises or organizations. On the Internet UGC platform, user participation is a decision-making choice problem. Users can adjust their behavior decisions dynamically better to meet their psychological, economic, and social needs and maximize their total utility. Therefore, the dynamic discrete selection model can be applied to this research.

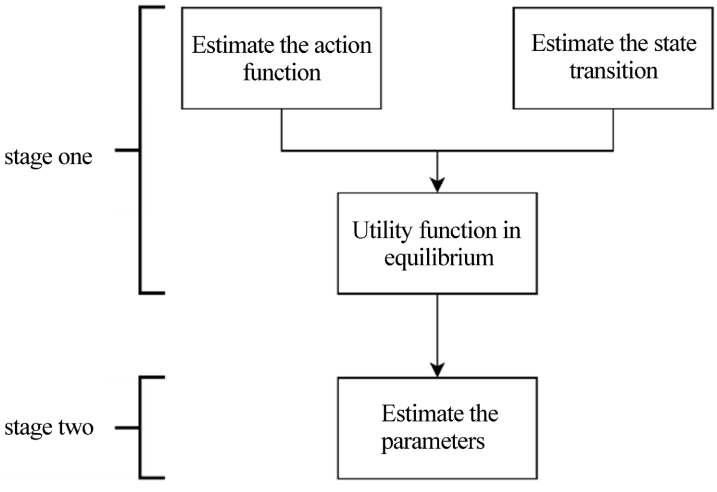

Figure 1. Two-stage estimation process.

To solve the structural model, we employ the two-stage estimation method

(BBL) proposed by Bajari et al. (2007). This method, developed from the work of Rust (1987) and Hotz and Miller (1989), is based on the Markov Perfect Equilibrium (MPE) concept proposed by Ericson and Pakes (1995). It assumes that the behavior of decision-makers in the model follows Markov processes, where each decision-maker's behavior is determined by the current state and random disturbances. The two-stage estimation method, illustrated in **Figure 1**, involves two stages. In the first stage, we solve the decision equation, the distribution, and transition probability of the state variables, and the utility function of the decision maker at equilibrium. In the second stage, we estimate the model parameters by combining the results of the first stage with the equilibrium inequalities of the model. This method has been proven effective for solving various dynamic choice models, including discrete, continuous, or single multi-agent problems (Bajari et al., 2007).

The two-stage estimation process is shown in **Figure 1**.

3. Model Setup

The data sample is from the Epinions, a product review community owned by eBay. It covers a total of 91,338 users, including their home page, trust list, trusted list, list of posted reviews, and comments of other users. For research purposes, we constructed this set of data into a set of panel data, with a period of one month. We selected 210 ordinary users and obtained a total data of 24 periods.

Suppose there are $i=1,2,\cdots,I$ users in Epinions, they need to make posting and reading decisions in each period $t=1,2,\cdots,T$. Let $a_{it}\in A_i$ denotes the action of user i at period t, $a_{it}=\left(n_{ipt},n_{irt}\right)$, among them, n_{ipt} is the number of reviews that user i posts at time t, n_{irt} is the number of reviews that user i reads at time t.

Based on the use and satisfaction theory, we believe that the reason why users voluntarily participate in UGC platform is that in this process, users' enjoyment and entertainment needs, identity needs, community attachment needs and information acquisition needs can be satisfied. Next, this paper will build up a dynamic discrete choice model around these four motives.

1) Enjoyment and entertainment

Enjoyment and entertainment motivation refers to the user's desire for fun and recreation in the process of generating content, which is an important motivation for users to participate in the UGC platform (Aknouche & Shoan, 2013). Users interact with each other on topics they are interested in, sharing their experiences and insights, from which they can obtain emotional comfort and pleasure, and relieve the pressure brought by life. This part of the utility is represented by a function φ_{it}:

$$\varphi_{it}=\theta_1 n_{itp}^2+\theta_2 n_{itp} \tag{4}$$

Here, n_{itp} is the number of reviews posted by user i at period t. The quadratic function is used to take into account that within a certain time, each additional review posted by users brings a sense of amusement with diminishing mar-

ginal utility. In addition, enjoyment and entertainment motivation is an intrinsic motivation of users, but now many platforms will set monetary and material rewards to incentivize active participation. When users post too many reviews due to these external incentives, their enjoyment and sense of entertainment will be squeeze out (Qiao et al., 2017; Kuang et al., 2019).

2) Identity

Identity refers to the confidence and sense of value that users gain from others' recognition and appreciation. This motivation is included in virtually all researches on UGC platform (Song et al., 2014; Chen et al., 2018). By sharing their knowledge, experience and talents that others are interested in, users can obtain recognition and appreciation, thus enhancing their sense of achievement and personal identity. In the utility function, we use ω_{it} to express the identity part:

$$\omega_{it} = \theta_3 P_{it} + \theta_4 TB_{it} + \theta_5 rb_{it} \tag{5}$$

Among them, P_{it} and T_{it} respectively represent the number of praises and trusters that user i has accumulated as of period t, rb_{it} represents whether the user's post is approved by the platform, and the three are state variables:

$$P_{it} = \delta P_{it-1} + p_{it} \tag{6}$$

$$TB_{it} = \mu TB_{it-1} + tb_{it} \tag{7}$$

$$rb_{it} = \begin{cases} 1, & \text{if there is a review is not approved by the platform} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

p_{it} and tb_{it} respectively represent the number of praises and trusters that user i obtained in the period t. δ and μ are the utility attenuation rates and we set them to be 0.8.

3) Community attachment

According to social identity theory, individuals belonging to a particular social group will perceive the emotion and value gained as members of that group. Users with a strong sense of community are more loyal to the platform, so they are more active in content contribution (Song et al., 2014; Hsu et al., 2018). The main factors that affect the community attachment include users' emotional identification with the community and other members, as well as users' degree of participation. The specific form of community attachment utility function is as follows:

$$\tau_{it} = \theta_6 TT_{it} + \theta_7 KS_{it} + \theta_8 h_{it} \tag{9}$$

Here, TT_{it} represents the cumulative number of people that user i trust to as of period t, KS_{it} is the amount of knowledge that has been shared by user i as of period t, h_{it} represents the number of periods since the user last post a review, and the three are state variables:

$$TT_{it} = \alpha TT_{it-1} + tt_{it} \tag{10}$$

$$KS_{it} = \rho KS_{it-1} + n_{itp} \tag{11}$$

$$h_{it} = \begin{cases} h_{it-1} + 1, & \text{if } n_{itp} = 0 \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

tt_{it} and n_{itp} are the number of users trusted and the number of reviews posted in period t, respectively. δ and μ are the utility attenuation rates and we set them to be 0.8.

4) Information acquisition

As a public information gathering center, UGC platforms provide users with valuable information and resources. When users participate in UGC platform, they can learn about things they are interested in, broaden their knowledge scope and improve their cognition level (Ciffolilli, 2003). We use χ_{it} to express the utility of this part:

$$\chi_{it} = \theta_9 KA_{it} \tag{13}$$

Here, KA_{it} is the amount of information that has been acquired by user i as of period t. We represent users' information acquisition by the number of reviews they read. KA_{it} is a state variable:

$$KA_{it} = \alpha KA_{it-1} + n_{itr} \tag{14}$$

n_{itr} indicates the number of reviews that user i read in period t, α is the utility attenuation rate of the acquired knowledge, and we set it to be 0.8.

5) Cost

At period t, the total cost for user i to post and read reviews is:

$$c_{it} = \theta_{10} n_{itp} + \theta_{11} n_{itr} \tag{15}$$

The cost here mainly refers to the time and effort spent by users in posting and reading reviews.

To sum up, the utility of user i in period t is given by U_{it}:

$$\begin{aligned} U_{it} = {} & \theta_1 n_{itp}^2 + \theta_2 n_{itp} + \theta_3 P_{it} + \theta_4 TB_{it} + \theta_5 rb_{it} + \theta_6 TT_{it} + \theta_7 KS_{it} \\ & + \theta_8 h_{it} + \theta_9 KA_{it} + \theta_{10} n_{itp} + \theta_{11} n_{itr} + \nu_{it} \end{aligned} \tag{16}$$

Here, ν_{it} is the random disturbance of utility and it obeys an i.i.d normal distribution.

This research assumes that users are forward-looking and they make decisions to maximize the sum of the discounted values of utility for each period, so their goal is:

$$\max_{n_{itp}, n_{itr}} E_t \left(\sum_{\tau=t}^{\infty} \beta^{\tau-t} U_{it} \right) \tag{17}$$

Here, β is the discount rate, we set $\beta = 0.8$ to balance short-term benefits and long-term utility.

4. Model Estimation Method

Parameters that need to be estimated are:

$\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \theta_8, \theta_9, \theta_{10}, \theta_{11})$.

We use the two-stage estimation method proposed by Bajari et al. (2007) to estimate the model. It assumes that users' behavior is consistent with Markov perfect equilibrium (MPE), which means each user's action decisions are determined only by the current state and random disturbance.

The two-stage estimation process is shown in the above Figure 1.

In the first stage, we estimate the action function and the state transition, then we can get the utility function in equilibrium. According to our hypothesis, the action strategy of user i is determined by the current state s_{it} and the random disturbance ν_{it}, that is $a_i = \sigma_i(s_{it}, \nu_i)$. Therefore, the optimal decision can be estimated as long as the distribution of action strategy under a certain state s and random shock ν is known, which can be obtained from the existing data. To estimate the state transition, we can use the observed value of state variables.

Let $V_i(s;\sigma;\theta)$ represents the utility function of user i in state s, and assume that the action strategy σ_i is in line with the Markov strategy, there are:

$$V_i(s;\sigma;\theta) = E\left[\sum_{i=1}^{\infty} \beta^i U_{it}(\sigma(s_{it}, \nu_{it}), s_{it}, \nu_{it};\theta) \mid s_0 = s;\theta\right] \tag{18}$$

when the state transition and decision equation has been estimated, the utility function $V_i(s;\sigma;\theta)$ can be obtained by forward simulation.

In the second stage, we use the estimation results of the first stage and the equilibrium conditions of the model to estimate parameters. According to the hypothesis, users' action strategy is consistent with MPE, so for any user i in any state s, there are:

$$V_i(s_i;\sigma_i;\theta) \geq V_i(s_i;\sigma_i';\theta) \tag{19}$$

Let x represents a group of (i, s, σ_i'),we define the function:

$$Q(\theta) = \int \left(\min\left\{V_i(s_i,\sigma_i;\theta) - V_i(s_i,\sigma_i';\theta)\right\}\right)^2 \mathrm{d}H(x) \tag{20}$$

where H is the distribution of the set x.

As θ_0 is the true value of θ, then $Q(\theta_0) = 0$. We can minimize the function $Q(\theta)$ to estimate the value of parameter θ.

It should be noted that both $\theta_2 n_{itp}$ and $\theta_{10} n_{itp}$ consist of n_{itp}, so we combine these two terms and estimate them.

5. Empirical Findings

5.1. Data Description

We randomly selected 210 ordinary users as the sample, with complete data throughout the observation period. We gathered information on the number of articles published by these users in each issue, the number of articles read, the number of people included in the trusted network, the number of others included in the trusted network, the number of new comments, etc., in Epinions. We collected data from a total of 24 issues. The number of comments by users is a direct indicator of the number of articles read. Table 1 presents the basic statistics derived from this extensive data set. Over the course of 24 issues, our 210 users collectively posted a total of 32,745 articles and read 1,393,685 articles.

Descriptive statistics for some key variables are shown in Table 2. On average, each user publishes 6.513 articles per issue and reads 277.185 articles, and the average interval between articles is 0.163 issues. The average number of positive

comments received by users in each issue is 275.998, the number of new trusted people is 4.076, and the number of new trusted people is 2.834. rb_{it} is a dummy variable with a mean of 0.04. Descriptive statistics for the key variables are presented in Table 2.

Table 1. Basic statistics of sample data.

Number of users	210
Duration of each period	One month
Number of periods	24
Total number of articles published	32,745
Total number of articles read	1,393,685

Table 2. Descriptive statistics for key variables.

Variables	Mean	Maximum	Minimum
n_{itp}	6.513	35	0
n_{itr}	277.185	3504	0
h_{it}	0.163	7	0
p_{it}	275.998	2484	0
tb_{it}	4.076	48	0
tt_{it}	2.834	51	0
rb_{it}	0.040	1	0

5.2. Parameter Estimation Results

The parameter values estimated in this paper are shown in Table 3:

Table 3. Parameter estimation results.

Motivation	Parameter	Corresponding variable	Estimated value	95% Bootstrap confidence interval
Enjoyment and entertainment	θ_1	n_{itp}^2	−0.6475***	(−0.6579, −0.6230)
	θ_2	n_{itp}	−0.6030***	(−0.6206, −0.5874)
Identity	θ_3	P_{it}	0.2079***	(0.1936, 0.2105)
	θ_4	TB_{it}	0.2415***	(0.2368, 0.2552)
	θ_5	rb_{it}	−0.5693***	(−0.5833, −0.5479)
Community attachment	θ_6	TT_{it}	0.2240***	(0.2198, 0.2363)
	θ_7	KS_{it}	0.2975***	(0.2777, 0.3007)
	θ_8	h_{it}	−0.5638***	(−0.5742, −0.5405)
Information acquisition	θ_9	KA_{it}	0.2812***	(0.2647, 0.2843)
Cost	θ_{11}	n_{itr}	−0.6077***	(−0.6165, −0.5845)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

θ_1 and θ_2 are negative and significant, which explains that the user's enjoyment and entertainment utility presents "inverted U-shape", that is, in a period, user's utility increases with the number of posts at the beginning, and it conforms to the marginal effect degression law. When the number of posts reach a certain number, continuing to post will cause user's utility to decline, confirming the presence of "crowding-out effect". Studies have shown that when users increase their contribution due to some external incentives, such as monetary awards, their internal motivation will be squeezed out. Our estimate θ_2 is a subtraction of the cost θ_{10} of sending a document. θ_2 is a negative number is a result of that θ_2 represent user enjoyment, entertainment utility, and the cost of user posting. In the model, the enjoyment and entertainment terms, as well as the cost term of the utility function expression, all incorporate linear terms of the number of published articles, i.e., $\theta_2 n_{itp}$ and $\theta_{10} n_{itp}$. We can only estimate the coefficient difference of these two terms $\theta_2 - \theta_{10}$, rather than their individual coefficients. This means that the parameter θ_2 we derive are actually a deduction from the user's publishing cost, providing a unique insight into the user behavior modeling process. Therefore, the actual enjoyment and entertainment utility brought by posting a review should be higher.

The significance and direction of θ_3, θ_4 and θ_5 together indicate that praises and others' trust can bring identity utility to users. Many psychological theories have suggested that people have a subconscious tendency to seek approval from others, which is the genetic link and nature of social organisms. As can be seen, compared with the enjoyment and entertainment utility, identity utility is relatively low. That implies that the utility derived from the number of favorable reviews and the cumulative number of trusted users is limited. This result may result from the emergence and existence of "spam users" and "marketing users" alongside ordinary users during the development of UGC platforms. These users frequently comment on others and add a large number of ordinary users to their trust lists to gain more visibility. Praises and trust from them have no value for users, and may also generate a sense of disgust, reducing the effectiveness of users' identity utility.

θ_6 and θ_7 are both positive and significant, showing that the cumulative amount of information shared and people trusted by users in the Epinions can bring positive utility. Users in the community form a social relationship with other users because of their network behavior. In Epinions, the trust network is used to characterize this relationship. This trust network not only reflects the connection between users, but also reflects users' recognition and participation in the community. When users have invested some time and energy in the community and have a deep involvement, they will develop an emotional attachment to the community, from which they can get a sense of belonging. θ_8 is negative and significant, indicating that not actively participating in community will reduce users' community attachment.

θ_9 is positive and significant, which shows that users can increase their utility

by getting information from the Epinions. The result is obvious as UGC platform is an open information gathering center, where users can learn the information they need. The absolute value of θ_{11} is relatively large, which we think may be because users need to spend much time and energy searching for useful information in communities flooded with information irrelevant to them. In fact, this is a problem that many UGC platforms are facing right now. Since any user can post in UGC platform and all kinds of information are mixed together, if the platform do not strengthen the management of users and information, it is difficult for users to conveniently obtain useful information, which is not conducive to the improvement of users' utility.

6. Conclusion and Management Implications

Based on the above results, the main conclusions are summarized as follows.

First, users who post articles on Epinions get enjoyment and entertainment utility. This hedonic utility is "inverted U," which increases with the number of user posts at first. However, the hedonic utility decreases when the number of user posts reaches a specific value. This is mainly because external incentives such as money and material gain have a "crowding out effect" on intrinsic motivation.

Second, users gain a sense of identity when they publish articles that are well-received or gain the trust and attention of others. However, if this kind of praise and trust comes from "junk accounts" such as "marketing numbers", it will not help the user's utility improvement and even have a negative impact.

Third, when users publish more comment articles in the community, participate heavily, and trust other users in the community, they will gain a strong sense of community belonging. They will form stronger emotional ties with the platform, and the stronger the sense of dependence and loyalty to the platform, the more motivated they will be to continue content production and construction on the platform. If users post articles at long intervals, they will also reduce their participation and, thus, their sense of community.

Fourth, the Epinions community can provide users with rich knowledge and experience sharing to meet their information acquisition needs. However, due to the large number of users and the large amount of information on the platform, users need to waste more time searching, filtering, and identifying the information they are interested in and need, which also causes greater utility loss.

Finally, this paper puts forward the following guiding suggestions for the Internet UGC platform to encourage users to participate actively and continuously contribute: 1. When designing incentive mechanisms, we should pay attention to the mutual influence and balance among various mechanisms and fully consider the possibility of external incentives such as money to "squeeze out" users' intrinsic motivation. 2. Feedback mechanisms can be used to strengthen the theory of user management to achieve clear rewards and punishments and improve the quality of the platform's content contribution. Maintaining network order and information security, strengthening content supervision, establishing strict user

screening mechanisms and scientific and practical reporting mechanisms, strictly eliminating illegal information, and creating a safe and healthy network environment. Develop more standardized collaborative production models and systems, improve convenience and intelligence, and reduce user content production and information acquisition costs. In addition, the Internet UGC platform should form its own unique platform culture and positioning, choose the direction suitable for its development, provide users with more innovative and personalized experiences, and obtain long-term development momentum.

The main contribution of this study lies in constructing a structured model based on classical theory and objective data to analyze the participation behavior of users on the Internet UGC platform, explaining the motivation and utility of users' participation without apparent employment relationship and usually unable to obtain monetary reward. This overcomes the problems of previous studies affected by factors such as self-cognitive bias. The conclusions obtained have specific guiding significance for developing and constructing the UGC platform. The author hopes that more scholars will conduct relevant research on this basis in the future, put forward more targeted and constructive opinions, promote the vigorous development of the Internet UGC platform, and achieve more significant value creation.

To reduce the difficulty of model solving, this study sets the utility discount factor and attenuation rate to a known constant of 0.8. A more accurate approach would be to estimate them as unknown parameters, but this would lead to excessive computational complexity and require the development of new algorithms. Future research will focus on improvements and enhancements in this regard.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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