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How to Measure The Operating Efficiency of Internet Group-Buying Platform?

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Abstract

In order to measure the operating efficiency of internet group-buying platform, this study sorts and analyses the transaction data from a large group-buying platform in China, defines the concept of matching efficiency as the measuring index of operating efficiency and the conversion-rate indicators in each stage of matching process. The definition and analysis of matching efficiency of internet group-buying platform fills up the deficiency in internet operating efficiency measurement domain.

Keywords: Big-data; Group-buying platform; Matching efficiency; Discount level

1. Introduction

With the soaring development and penetration of internet, online shopping is becoming increasingly popular and more and more netizens are joining in. By December, 2014, online shoppers in China had reached 361 million and the rate of online shopping had increased to 55.7%. As a rapid-developing mode of on-line shopping, group-buying boasts of 173 million users and a usage rate of 26.6 % among netizens [1].

To group-buy, internet users make use of the internet as an information exchange platform and trade with sellers on the group-buying websites, which will charge for their services or benefit from the price differences. The core of group-buying lies in demand accumulation and quantity discount [2]. In other words, in group-buying, a certain number of buyers form a group through internet and buy the same goods at a low discount.

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The biggest difference between group-buying and ordinary on-line shopping is that it is cooperative, that is, consumers must cooperate with another, get the upper hand in quantity and obtain a large discount in price [3].

The speedy expansion of group-buying has brought challenges as well as opportunities to group-buying websites and platforms. According to the 2012 Annual Data Monitoring Report on Group Purchasing in China, by the end of 2012, a total number of 6177 group-buying websites/ platforms had come into being while 3482 ones had closed down, a death rate of 56%. 2695 ones were in operation, fewer than the 3200 ones at the end of 2010[4].

The fierce competition, products quality problems and lack of commercial integrity have all led to the massive closedown of the group-buying websites, but the key issue is that they didn't secure stable customers. In order to do so, the management must pay close attention to and monitor the operation efficiency of the website and try their best to convert those visitors to buyers or clients. At present, the study on the operation efficiency of websites is scarce and there are only some discussions about CTR (click-through rate) [5-7], page views and website loyalty [8-9] ， but all these cannot systematically measure the operating performance of websites. In addition, due to confidentiality, researchers cannot obtain the relative operation data of websites, which further restrains the study on website operations.

Therefore, this paper comes up with the concept of matching efficiency to systematically measure and monitor the operation efficiency of group-buying platforms. The research team has worked with a large touring group-buying platform and obtained relevant operation data of 7991 products for 171 days. This paper illustrates in detail how matching efficiency is calculated and analyzes how the discount level, pricing and product category influence matching efficiency. This research not only fills the gaps in group-buying platform measurement study but also provides practical guidance for the development of those platforms.

2. Literature Review

2.1. Two-sided market

Group-buying platform is a typical two-sided market. A two-sided market consists of two groups of agents or multiple agents: (1) the agents interact with one another through an intermediary; (2) the participation or involvement of each entity will affect other members. The intermediary is what is often called a platform and each entity has their own position on either side [10]. Andrei Hagiu and Julian Wright define multi-sided platform as "an organization that creates value primarily by enabling direct interactions between two (or more) distinct types of affiliated customers."[11] Two-sided markets are different from the suppliers that trade in basic ways. In the traditional value chain, value flows from left to right, that is, from cost to profit. However, in a two-sided market, cost and profit stand hand in hand on both left and right sides as at both sides of the platform are different end-users. When a platform provides services, cost is generated and subsequently profit is gained from both sides of the platform. Generally speaking, one side of the platform can enjoy free charge. The economy of the platform depends on agencies' choice of platforms and the pricing decision of other competitive platforms [10].

In the past decade, the two-sided or multi-sided markets have been constantly studied in the fields of economics and strategy researches. Related literature has studied how payment networks interconnect credit holders and retailers and how electronic game systems connect game players and game developers. Meanwhile, the studies on two-sided markets have aroused the attention from business community as two-sided markets are quite common in IT industry and the findings of the studies are closely related to the new strategies and decision making in real practice [11].

2.2. Measurement of platform operating efficiency

The existing literature takes such parameters as page views (PV), website loyalty and CTR into consideration when they measure the operation efficiency of websites or platforms. Page views have always been the major concern of both the intellectuals and business people and have served as a standard to measure the success of online retailers and websites. Especially at the preliminary age of e-commerce, the cumulative data were used by numerous managements as the basis to measure the performance of a website, for example, the number of unique visitors or the total visits in a set time[12]. However, performance measured merely by PV and the average visits by individual internet users may mask the dynamic changes of those visits (for example, the changes of the visiting frequencies) for these figures can be misleading because of the changing of customers, such as the inflow of new visitor, who may visit more frequently and the dropout of experienced old customers.

In addition, more and more online sellers have realized that PV is not necessarily a useful indicator and it is the visitor loyalty that affects their operation a lot. The reason is simple: although there will be new visitors surfing the internet every day, the increasingly fierce competition makes the acquisition of new visitors all the more difficult and costly, which in turn motivates the managements to attach more importance to website loyalty[13-14]. It means that websites will shift their competition from attracting new visitors to maintaining the existing visitors [15]. Many scholars have measured user loyalty from different perspectives. Danaher has pointed out that visit duration is a concept closely related with loyalty — longer visit duration indicates better advertising effect, higher repeat visit rates and higher profit expectation [16]. Based on the clickstream data, Moe and Fader come up with a behavioral model of individual visits and conversion in order to use purchasing conversion rate to measure the performance of a website [17]. Repeat visit rate and visit depth are also used by some scholars to measure user loyalty [8-9]. However, to the online platforms, whose essential task is to promote trading, user loyalty as a measurement is impartial as it cannot fully reveal the information about transactions.

Another commonly-mentioned indicator is CTR (click-through rate). CTR is a way of measuring the success of an online advertising campaign for a particular website. CTR is obtained by dividing the number of users who clicked on an ad or product on a web page by the number of times the ad or product was delivered (impressions). It is one of the most commonly used measurements to check products appeal or ad qualities. It can show how attractive an online product or an advertisement is in certain period of time. The higher the rate is, the more likely a product is bought. Just as user loyalty cannot fully reflect the effect of platforms on promoting transactions, neither can CTR. Therefore, there have been so far no effective parameters that can systematically measure the operating efficiency of online platforms.

2.3. Factors affecting operating efficiency of platforms

Many factors may affect the operating efficiency of platforms. To group-buying platforms, the most influential factor is certainly quantity discount, which is quite different from the traditional concepts but is one of their kinds. All-unit discount and incremental discount are the two common forms of quantity discount. All-unit quantity discount means all the units in an order can enjoy the discount while incremental discount gives discount only to those units beyond a given amount. All the companies offering group-buying services adopt the all-unit discount model in order to treat all the buyers equally and encourage them to get involved as early as possible to elicit bandwagon effect.

According to related researches, quantity discount can certainly do a good job to enhance transaction efficiency under the economy of scales as an effective device [19-21]. Monahan extends the concept of economic order quantity (EOQ) by developing the idea of optimal price-quantity schedule [20]. The suppliers offer the schedule and the buyers decide accordingly the optimal amount they will order to achieve the maximum profits. Lee and Rosenblatt furthered the study by allowing suppliers (sellers) to get different lot sizes from the buyers and to encourage buying at the beginning of a season through the strategy of quantity discount in order to reduce the environmental risk characterized by demand uncertainty [19]. Weng combined transaction efficiency with channel alliance incentive and found that under price-sensitive demand and economy of scales quantity discount is an effective device to realize maximum profits and channel coordination[21].

However the researches on the factors affecting operating efficiency of platforms have been adequately done and the affecting factors are still unclear to researchers. Besides the above-mentioned quantity discount, product category and other pricing information may also play a part.

3. Data and Method

The data used in this paper are the clickstream data provided by a group-buying channel of a leading travel search engine in China. With the help of convenient, personalized and advanced price comparison technology, this tourism website offers such deeply-integrated information as domestic and international air tickets, hotels, and vacationing and visa service. Consumers can inquire about the latest price of tourism products and compare the services and prices according to the online information. Meanwhile, it posts all kinds of pay-per-click advertisements that aim at brand promotion and successful trading. These advertisements are targeted at potential high-end consumers and try to help companies promote and sell their products or services effectively to realize precision marketing. The data cover a time span of over six months, from January 1st, 2012 to June 19th, 2012. The data are collected on a date basis and thus are of date data type, each of which records in detail the relevant information of all the online products each day. Altogether, 181727 pieces of information are collected, covering 7991 group-buying products.

In order to ensure the integrity and exhaustiveness of the information, the data of some of the products have been rejected in the process of data sorting. To be specific, they are (1) products that were put online before January 1st, 2012 and stayed online less than 15 days; (2) products that would be off shelf after June 19th, 2012 and stayed online less than 15 days; (3) products whose starting date and closing date are between January 1st, 2012 and June 19th, 2012 but stayed online less than 15 days. According to those standards, 2762 products have been sorted out. After the data sorting, 151227 pieces of information of 4955 products (64.73% of the total products) are retained, the average online time is 30.52 days and 90.3% of all the products stayed online for no more than 50 days, among which 32.8% stayed for 25-31 days.

The data cover such variables as product ID, shelf-display-quantity, CTR, orders, paid orders, market price, group-buying product, discount level, product category and order types.

In order to illustrate how the data are sorted, the variables are clarified in the following table:

Table 1. Variable Clarification

Name of the Variable	Corresponding formula	Variable clarification
Product ID	$id(x)$	The only ID of product x
Product name	$N(x)$	The only name of product x , but sometimes the name of a small number of products will be changed to promote sales.
Shelf-display-quantity	$S(x_i)$	The cumulative display quantity of product x within its display time. Shelf-display-quantity refers to the times visitors browse the display page of a product when they enter a group-buying channel.

CTR	$C(x_i)$	The cumulative visits or clicks on product x within its display time. When a consumer accesses a group-buying channel, clicks on an advertisement and reads the detailed information of a product, there comes one click.
Order number	$\mathrm{SD}(x_i)$	The number of orders of product x on the i^{th} day. To put the product into the shopping cart and thus place an order is the last step before final purchasing, and it is also a unique step for online shopping.
Paid orders	$\mathrm{SP}(x_i)$	The paid orders of product x on the i^{th} day, which equal the number of sold products.
Market price	$PM(x)$	the nominal price or initial price of product x
Group-buying price	$PG(x)$	The trading price of product x on the group-buying channel, usually the discounted price of the market price
Discount level	$D(x)$	The discount level of product x
Product category	$E(x)$	The product categories of the products x , altogether 7 categories
Order type	$H(x)$	the order types of product x , altogether 3 types: express, QR code and Camel voucher

4. Matching Efficiency: Definition and Measurement

4.1. Matching Transaction

A matching body is a virtual entity characterized by its services. It not only provides matching services for the transaction participants but also tries to maximize its own profits. The maximum profits are realized by maximizing business volume, which trying its best to facilitate deals between the transaction agents. Therefore, the matching body has to maximize both its own profits and the gains of the two transaction parties – the seller and the buyer participating in the transaction. In the e-commerce system with the auto-matching function, the transaction parties do not need to search each other by themselves because the matching body will do so for them. It will maximize the trading range and optimize the interests of all sides to match the trading pairs and consequently facilitate the deals. The most important factors in matching are transaction type, transaction price and transaction volume.

4.2. Matching Efficiency

Matching efficiency is defined as the number of buyers converted divided by the total number of visitors to the platform during the same period of time. In terms of products, matching efficiency means the number of buyers divided by the total number of visitors who click on the product advertisement.

To product X , if $\sum S(x_i)$stands for the number of visitors who view the product advertisement, that is the shelf-display-quantity while $\sum SE(x_i)$stands for the number of ultimate purchasing (the number of paid orders for group-buying platforms), the matching efficiency is represented in the following formula:

$$DEM(x) = \sum S(x_i) \Big/ \sum SE(x_i) \times 100\% \quad (1)$$

From logging in the website to ultimate purchasing, a visitor has to go through the following stages: click on the advertisement and learn the details of the product, put the product into the shopping cart, input all the necessary purchasing information (place an order), and finally pay for the order. In the process, there exist three conversions: browse-click conversion, click-order conversion, and order-payment conversion. The rate of browse-click conversion, commonly known as CTR, is calculated by the following formula:

$$CTR(x) = \sum S(x_i) \Big/ \sum C(x_i) \times 100\% \quad (2)$$

The rate of click-order conversion can be got from this formula:

$$COF(x) = \sum C(x_i) \Big/ \sum SD(x_i) \times 100\% \quad (3)$$

The following formula is for the rate of order-payment conversion:

$$COP(x) = \sum SD(x_i) \Big/ \sum SP(x_i) \times 100\% \quad (4)$$

Finally, matching efficiency is the product of the three above-mentioned rates. It can be formulized as follows:

$$DEM(x) = CTR(x) \times COF(x) \times COP(x) \quad (5)$$

Based on the above calculating, the matching efficiency of the concerned tourism group-buying website in this research and the three conversion rates occurring in the matching process can be represented in table 2.

Table 2. The mean matching efficiency of the tourism group-buying website and products of various categories

Variable/rate	DEM	CTR	COF	COP	Number of products
Outbound Tour	0.000904	0.7237	0.2406	51.9159	644
International Tour	0.000858	0.7295	0.2471	47.5713	368
Domestic Tour	0.002556	0.6720	0.6364	59.7727	1151
Domestic Long-distance Tour	0.001334	0.6716	0.3613	54.9577	193
Air Tickets	0.001180	0.9375	0.2961	42.4913	88
Tourism Products	0.032472	2.1188	2.1514	71.2352	771
Admission Tickets	0.006918	0.5796	1.7492	68.2318	392
others	0.004467	0.7932	0.8745	64.4026	30
entertainment	0.004702	0.5907	1.0400	76.5354	40
Periphery tour	0.003533	0.5869	0.8586	70.1104	1278
Total	0.007424	0.8836	0.9251	62.633	4955

It can be clearly seen from the above table that the matching efficiency of products of different categories is varied and it is also clear which categories should be improved – outbound tour, air tickets and international tour for their matching efficiency is relatively low. From the perspective of conversion rate, COF is the key issue, so marketing strategies aiming to increase COF should be made and enforced.

5. Conclusion and Implication

Operating efficiency is vital for the survival of group-buying platforms but there are certain limitations in the measuring methods. Due to the restraints in data collection, the measurement of operating efficiency hasn't been adequately studied. Based on the operational data of a large group-buying platform in China, this research collects, analyzes and mines the collected data and defines matching efficiency as the parameter to measure the operating efficiency of websites. In addition, according to the characteristics of matching, the paper defines three stage parameters to calculate matching efficiency, namely, CTR (impression-click conversion rate), click-order conversion rate and order-payment conversion rate.

The implications of this research lie in the following two aspects: First, the studies on operating efficiency of group-buying platforms are insufficient. The present study is innovative and has certain practical value as it not only defines a brand new measuring parameter - matching efficiency, but also defines three stage conversion rates in the matching process. Second, due to lack of first-hand data, the studies on the key parameters have been relatively scant. The collected data and data analyses of this study are original and ingenious.

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