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Meihua Zuo
Huizhou University, Huizhou, 516000, China; School of Management, Guangdong University of Technology, Guangzhou, 510520, China, zuomeihua123@126.com

Hongwei Liu
School of Management, Guangdong University of Technology, Guangzhou, 510520, China, liuhw@gdut.edu.cn

Yonghua Zuo
School of Mathematics and Information Science, Jiangxi Normal University, Nanchang, 330022, China, youghua.zuo@foxmail.com

Hongming Gao
School of Management, Guangdong University of Technology, Guangzhou, 510520, China, hm.gao.normal@gmail.com

Hui Zhu
School of Management, Guangzhou University, Guangzhou, 510006, China, zhuhui@gzhu.edu.cn

See next page for additional authors

Authors
Meihua Zuo, Hongwei Liu, Yonghua Zuo, Hongming Gao, Hui Zhu, and Zhouyang Liang

Researching Dynamic Brand Competitiveness Based on Consumer Clicking Behavior

Meihua Zuo[1,2], Hongwei Liu[2], Yonghua Zuo[3], Hongming Gao[2], Hui Zhu[4], Zhouyang Liang[2]*
[1]Huizhou University, Huizhou, 516000, China
[2]School of Management, Guangdong University of Technology, Guangzhou, 510520, China
[3]School of Mathematics and Information Science, Jiangxi Normal University, Nanchang, 330022, China
[4]School of Management, Guangzhou University, Guangzhou, 510006, China

Abstract: Analyzing brand dynamic competition relationship by using consumer sequential online click data, which was collected from JD.com. It is found that the competition intensity of the products across categories is quite different. Owing to the purchasing time of durable-like goods is more flexible, that is, the purchasing probability of such products changes more obviously over time. Therefore, we use the Local Polynomial Regression Model to analyze the relationship between the brand competition of durable-like goods and the purchasing probability of the specific brand. Finding that when brands increase at a half of the total market share for consumers cognition preference, the brands' competitiveness is peak and makes no significant different from one hundred percent for consumer to complete a transaction. The findings contribute to brand competitiveness for setting up marketing strategy from the dynamic and online consumer behavior's perspective.

Keywords: dynamic process, brand competitiveness, consumer clicking behavior, durable-like goods

1. INTRODUCTION

It is of upmost interest, from a marketing research point of view, to mining the dynamic brand preference cognition of consumers and comprehensively understand their inherent and implicit patterns. Through a brand cognitive process, the specific brand competitiveness among other brands gradually comes into beings [1]. In turn, it eventually impact the consumers purchase decision-making [2]. Brand certainly can bring market competitive benefits to its owners [3]. A general approach of analyzing the cognitive process and competition is focus on enterprises, products, consumers and market structure condition in common sense [4-6], one of the disadvantages is that the aggregate data ignores the sequential and consumer behavior information. Yet, the dynamic cognitive evolution property of thousands of individual consumers toward brands maintains underdeveloped online retailing research.

Considering a shopping process to an online retailing website, produced by a consumer over time as shown in Figure 1. If one search a product, the consumer might reveals brand inertia thorough the memory effect [7], click those familiar and the specific brands have purchased then directly make a purchase decision, whereas the consumer seeks variety for new brands [8]. In the latter, the dynamics cognitive process happens in consumer behaviors, brands competition comes into beings psychologically and lies in the form of sorting brands, and a transaction is completed as an outcome. Specifically, an individual consumer's level of brand inertia may decline over a time period [9], hence the consumer will seek some new brands and cognitive process occurs as well.

* Corresponding authors. Email: zuomeihua123@126.com (Meihua Zuo), liuhw@gdut.edu.cn (Hongwei Liu), youghua.zuo@foxmail.com (Yonghua Zuo), hm.gao.normal@gmail.com (Hongming Gao), zhuhui@gzhu.edu.cn (Hui Zhu), liangzy@gdut.edu.cn (Zhouyang Liang)

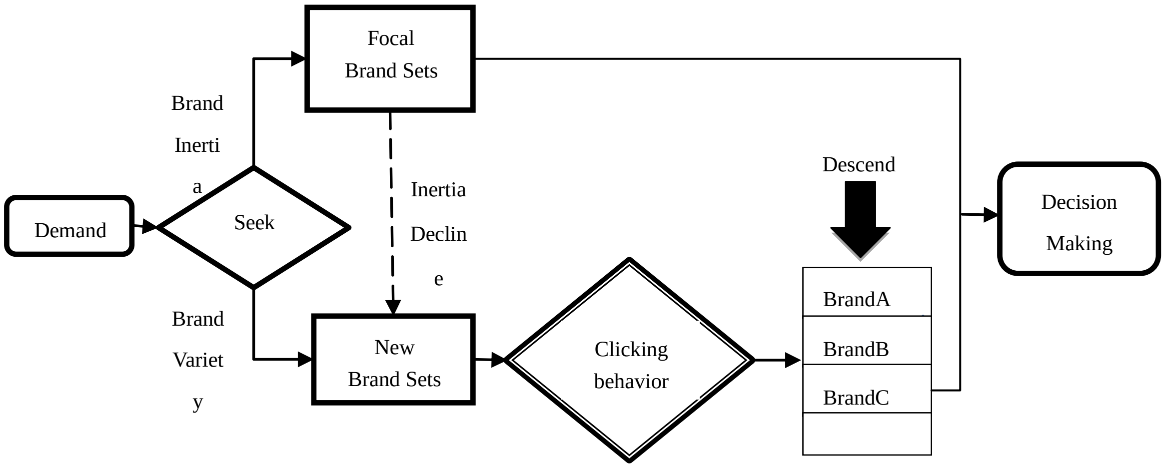

Figure 1. An general online shopping process

2. LITERATURE REVIEW

The brand power could be traced to the article entitled "The Product and the Brand" in the Harvard Business Review [3]. Consequently, the concept of brand competitiveness has been interested by academics and practitioners. There are few about the definitions of brand competitiveness in the prior literature. Brand competitiveness is embedded in brand equity, prior researches state that brand equity is a construct relative to other brands [10] , form an information economics view, Erdem and Swait [11] argue that consumer-based brand equity is the value of a brand as a credible signal of a product's position. Only when consumers pick a brand among other brands with comparing different and conflicting brand equity, then the relative significance of the equity, namely, brand competitiveness in this situation will lead their decision-behavior [12]. That is, brand competitiveness is a relative indicator and gradually formed by brand cognition of consumers. Competitiveness is a comprehensive ability which must be represented by competition or comparison between firms, and aims to expand their market share [13]. From the firm-level of perspective, the competitiveness is usually quantified as productivity or firms' performance [14]. Winzar [12] define brand competitiveness as the market share on a combination of price and brand features, relative to other competitors' price or feature sets. The literature on brand equity and brand competiveness either is analyzed from subjective empirical surveys, or the perspective of product attributes. But it's rarely operated as a relative construct for dynamic consumer brand cognition on their behaviors over time. Since every single interacting behavior, like clicking a brand on an electronic retailer website, could objectively reflect the consumer preference [15]. Following Winzar [12], we conceive brand competitiveness as a brand's behavior share on consumer shopping records online, relative to other competitor brands.

It's necessary for online businesses to understand thoroughly the online behaviors. Especially, one of the most active areas for exploring the online purchase pattern by user activity. The clickstream data are defined as the electronic record of internet usage collected by web servers or third-party services [15] for recording consumers shopping sequence over time. Interaction is a part of human dynamic [16] Such clickstream data made by interacting between consumers and computer could objectively imply the consumer preference [17], even the inherent and implicit brand preference. The more times of a focal brand clicked at a time interval, the higher preference of consumers toward the brand could be. Moreover, brand competitiveness is a proportion of a brand in the market in a certain period of time, relative to other competitor brands [12].The online sequential click behaviors toward brand can indicates the brand competitiveness over time. According to the previous research, brand competitiveness is gradually formed in the process of building brand equity, thus the brand competitiveness has a dynamic characteristic [18]. With the above two characters, we conceive brand competitiveness as a brand's click share on consumer dynamic shopping process, relative to other competitor brands at a time interval. The brand cognitive process is restricted as the process when consumer start to click the brand and purchase it or its product category. We used the real clickstream data set from an e-retailer website for a month to track consumer-individual-level brand cognition process. The dynamic brand cognition process, that is, the user's sequential click share, reflects the evolution of the brand competitiveness.

This paper aims to find out the trend of consumer-based brand competitiveness in a time-variant situation, from the view of human dynamic. The empirical statistic shows that (1) the purchase time distribution follows power laws, and the purchase timing tend to occur later and the purchase elasticity of time is more sensitive for durable-like goods than nondurable-like goods. (2)when brands increase at a half of the total market share for consumers cognition preference, the brands' competition is peak and makes no significant different from one hundred percent for consumer to complete a transaction.

The remainder of the paper is organized as follows. In the next section, we describe the origin of the data set and the statistical description. Then, we depict sequential purchase for different product categories, and modeling the sequential purchase behaviors. Furthermore, the fifth section is depicting the relationship between brand cognition and purchase possibility. We discuss the findings and implications in the last section.

3. DATA SETS

We collected the desensitization clickstream data on the whole March 2016 at JD.com, which is one of the two massive B2C online retailers in China by transaction volume and revenue. The dataset is consisted of 25,916,378 records, which describes of 96087 unique users browsing 23753 commodities, 8 categories of products, and hundreds of brands over time. For the purpose of studying the relationship between dynamic online shopping behaviors and the possibility of purchasing a focal brand. We filtered those consumers who has bought an item at least. The data set is shown in Table 1 as below.

Table 1 . Sumary of data set from JD.com

Category	User	Record	Brand	Purchase	Click	Conversion rate
1	48855	5155842	59	3947	3180842	0.124%
2	37906	2941590	66	4013	1772838	0.226%
3	40076	3320444	82	3405	1986387	0.171%
4	29054	2275133	129	3454	1393602	0.248%
5	88808	9693970	40	7118	5847135	0.122%
6	21903	2189293	127	2437	1326572	0.184%
7	7426	286593	92	106	185176	0.057%
8	8414	53513	18	8	28020	0.029%

From Table1, every single record shown indicates the consumer-brand pair, the total conversion rate of purchase-through-click is 0.156%, which demonstrates that among each 1000 clicks, only 1.6 transactions are completed. Nevertheless, even if there is a large number of records, there is few of brand lying in the categories. The phenomenon implies power-law distribution might exist between brand clicks and purchases. We filter out the inactive and overactive category, those that have less than 2000 purchase and the most one (i.e. category 7, 8 and 5) are out of consideration. Besides, we pick the 2nd and 6th category in our research since (1) their characteristics of the most and least number of purchase may reveals the significant difference of two types of goods, and (2) the conversion rates are approximate and the difference is only 0.00043 .

4. SEQUENTIAL PURCHASE FOR DIFFERENT PRODUCT CATEGORIES

We confirm that the 2nd product category is nondurable-like goods and the 6th is durable-like goods according[19]. The empirical statistics result shows that collective sequential purchase distributions of durable-like goods and nondurable-like goods obey the power law distribution. Nevertheless the exponent of durable-like goods is larger implying that the purchase elasticity of time is more sensitive for durable-like goods than nondurable-like goods. The purchase timing occurring later for durable-like goods is displayed as well.

4.1 Purchase distribution for 2nd and 6th product categories

We observe that the consumer i has clicked M_i brands during a time period $[q_{i1}, q_{it}]$. A session is defined as a sequence of online shopping process, assuming the session ends and the next behavior marks the start of a next session when the consumer i has not any interact with computers for a 30 minute interval. Where q_{i1} indicates the first session (i.e. the beginning interval) of the consumer i search sequence period and the q_{it} denotes the last session correspondingly in March. Hence we observe that consumer i has click M_i brands at sessions $\{q_{i1}, q_{i2}, \cdots, q_{it}\}$, and the number sequence of purchase consumer i at any arbitrary session could be denoted as $p_s(t) = \{p_{q_{i1}}, p_{q_{i2}}, \cdots, p_{q_{it}}\}$. From a collective behaviors point of view, the total number of purchase for all consumers could be expressed as:

$$P_{q_t} = \sum_{1}^{N_{q_t}} p_{q_t} \tag{1}$$

Where N_{q_t} denotes the number of consumers making transaction(s) in the q_t session. For individual consumers in the 2nd and 6th category, the dynamic property of the purchase behaviors is illustrated in Figure 2 and Figure 3. The horizon axis presents the sequential session and vertical axis for the number distribution of purchase. We define a session as a 30 minute interval on that records search[20]. Each dot represents the number of times the consumer purchased the category of products in any given session. Red dots represent the 2nd category of products, while blue triangles for the 6th ones.

From which we could find that the most of transactions completed in the session $[q_{i1}, q_{i20}]$, the fluctuation number of 95% purchase $p_{q_{it}}$ is from 1 to 5 while repurchase could reaches 10 times at most.

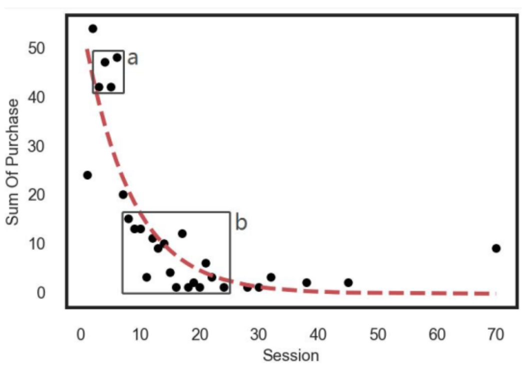

Figure 2. category2 purchased brands distribution

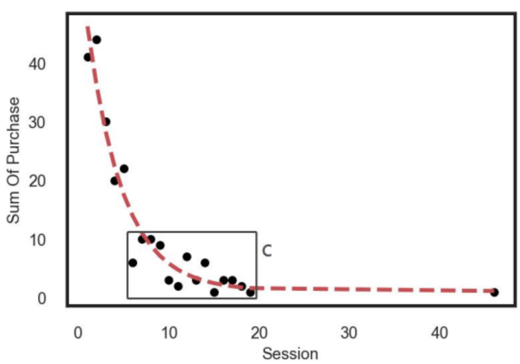

Figure 3. category 6 purchased brands distribution

Figure 2 demonstrates that the purchase behaviors of the 2nd category is concentrated in a and b black rectangle areas. The session $[q_{i3}, q_{i30}]$ are frequent session on which the transactions are concluded while the repurchase intensively distributes in $[0;20]$ and $[40;58]$ intervals. Simultaneously, in figure 3 the C area presents that the consumers prefer repurchasing less than 10 times on the early sessions $[q_{i4};q_{i20}]$ towards the 6th category of products. In short, the online shopping process of these two categories shows significantly difference.

4.2 Mann-Whitney U test for durable-like and nondurable-like goods

Searching durable consumer goods are different from the nondurables. Apparently, one of the characteristics is *high-frequent repurchase* in nondurable goods owing to its relative cheap prices and short service cycle comparing to durable goods. Second attribution is that search or click traffic closes to the sales tendency for most of durable goods[20]implying consumers tend to be prudent to *click more* and search more for learning mass information about the durable products. Due to the difference shown in Table 2, we assume that the 2nd and 6th product categoryare likely to be nondurable-like and durable-like goods. And we analyze the distribution of those two categories based on consumer-brand-pair-level, regarding of individual consumers' repurchase (corresponded to n Rep_n^{2nd} and m Rep_m^{6th}) and click behaviors (corresponded to n $Click_n^{2nd}$ and m $Click_m^{6th}$) for individual brand being more accuracy.

Table 2. The number of repurchase and clicks of the two different products categories

Sample	min	1ST Qu	Median	Mean	3rd Qu	Max
Rep_n^{2nd} (Repurchases of 2ndcategory)	1.00	5.00	15.00	56.85	50.00	2441.00
Rep_m^{6th} (Repurchases of 6thcategory)	1.00	1.00	1.00	1.78	3.00	8.00
$Click_n^{2nd}$ (Clicks of 2ndcategory)	1.00	4.00	10.00	35.72	32.00	1448.00
$Click_m^{6th}$ (Clicks of 6thcategory)	1.00	4.00	10.00	52.58	43.00	2863.00

We find out that these behaviors of individual consumer does not obey the normal distribution through Kolmogorov–Smirnov test and Anderson–Darling test, Therefore we exploit the Mann-Whitney U test, a nonparametric test more widely applicable than independent samples Student's t-test without requiring the assumption of normal distributions to compare the distributions of those two goods categories according to the research[20]. Let the repurchase quantities $Rep_n^{2nd} = \{rep_1^{2nd}; rep_2^{2nd}; \cdots; rep_n^{2nd}\}$ and $Rep_m^{6th} = \{rep_1^{6th}; rep_2^{6th}; \cdots; rep_m^{6th}\}$be arranged in order. Let U count the number of times a Rep_m^{6th} precedes aRep_n^{2nd}. If $P(U \le \overline{U}) = \alpha$ under the below null hypothesis，the test will be considered that P-value is less than the significance level α and the hypothesis $Rep_n^{2nd} \le Rep_m^{6th}$ will be rejected. The Statistic T is the sum of the ranks of theRep_m^{6th}'s in the ordered sequence ofRep_n^{2nd}'s andRep_m^{6th}'s hence the computation U statistics:

$$U = mn + \frac{m(m+1)}{2} - T \tag{2}$$

We proposed the following two hypothesis:

Null Hypothesis 1：the number of repurchase behaviors of individual consumer in the 2nd product category is less than the 6th product category ($Rep_n^{2nd} \le Rep_m^{6th}$).

Null Hypothesis 2：the number of click behaviors of individual consumer in the 6th category is less than the 2nd product category ($Click_m^{6th} \le Click_n^{2nd}$).

The test shows that $U\ statistic = 3889800; P\ value = 0.000$, rejecting the null hypothesis 1, neither does the null hypothesis ($U\ statistic = 77881000; P\ value = 0.002$). In other words, the 2nd category is significantly *higher frequent repurchase* and *lower clicks* than 6th. Drawing a conclusion that the 2nd category is closed to nondurable goods while 6th is approximately durable goods.

4.3 Modeling the sequential purchase via power-law function

Due to the difference between 2nd and 6th categories, we analyze the number distributions of purchase between the nondurable-like and durable-like goods. For clarify, we draw the log-log plot of the collective purchase distributions and we find that the sequential collective purchase distribution could be fitted well by power-law distribution from Figure 2 and figure 3. We find that the fitting curves of these two categories of products are subject to the power law distribution, but the parameters of the distribution are inconsistent.

At each session q_t, we assume that the number likelihood of purchase is denoted as:

$$P_{q_t} \propto q_t^{-\beta} \tag{3}$$

Let's take the logarithm of the above equation for fitting by the least-squares method, we get

$$\ln P_{q_t} = \ln \alpha - \beta \ln q_t \tag{4}$$

Then，we can estimate the parameters according to equation (4), and transform into the power-law function (3). Result shows that purchase distribution of the 2nd category, namely nondurable-like goods obeys $P_{q_t} = 15.1 \cdot q_t^{-0.049}$. And the exponent β of the durable-like goods is around 0.094. The bigger β implies that the purchase elasticity of time session is more sensitive for durable-like goods than nondurable goods. From the perspective of economics, possessing durable-like products indicates the demand of this category is decreasing for consumers in the near future.

5. THE RELATIONSHIP BETWEEN BRAND COGNITION AND PURCHASE POSSIBILITY

Online shopping process is exploited to identifying the brand cognitive process based on brand competitiveness revealed in online click behaviors. We next consider the relationship about the brand competitiveness (i.e. click-rate) and the purchase likelihood on individual brands. The click rate $CR(m)$ for B consumers purchasing the m^{th} individual brand on whole shopping process could be deduced by the number of clicks $c_m(s_{it})$ as

$$cr(m) = \frac{1}{B}\left[\sum_{i=1}^{B}\sum_{t=1}^{S(i)} c_m(s_{it}) \Big/ \sum_{i=1}^{B}\sum_{t=1}^{S(i)}\sum_{m=1}^{J(s_{it})} c_m(s_{it})\right] \tag{5}$$

Where the $S(i)$ represents the length of shopping stages for consumer i and $J(s_{it})$ indicates the numbers of the unique brand-clicked depending on consumers brand cognition preference at the stage s_{it}. Besides, the purchase likelihood $PUR(m)$ for B consumers purchasing the m^{th} individual brand is inferred as

$$pur(m) = \frac{1}{B}\left[\sum_{i=1}^{B}\sum_{t=1}^{S(i)} p_m(s_{it}) \Big/ \sum_{i=1}^{B}\sum_{t=1}^{S(i)} c_m(s_{it})\right] \tag{6}$$

The number of purchase at the stage s_{it} for consumer i has defined as $p_m(s_{it})$. The evolution trends between the purchase likelihood $PUR(m)$ and the brand competitiveness $CR(m)$ for the m^{th} individual brand is displayed in Figure 4. Through the figure, we can draw the following conclusions. Firstly, as the click-rate goes, the likelihood of purchase continuously increases, when the brand's click rate reached at 50% of the total click volume, the purchase likelihood of a brand almost reached its peak. However, consequently the likelihood decreases. Secondly, when the click rate reaches 100%, the likelihood of the purchase soar to the peak value.

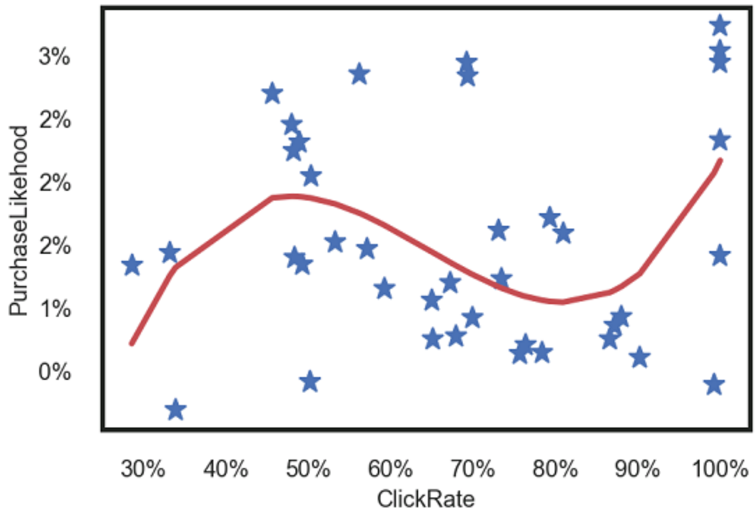

Figure 4. Relationship between brand competitiveness and purchase likelihood

6. CONCLUSIONS

Considering the relationship of the brand competitiveness and the purchase likelihood on individual brands for durable-like goods. When the brand competitiveness is less than fifty percent, consumers tend to seeks a variety for new brands, and their purchase likelihood is positively correlative by the brand competitiveness. Nevertheless, once consumers learn about a focal brand excessively among all brands at a period of time, the purchase likelihood of its products decreases due to the thinner consumer's short-term loyalty to the brand. Till the brand competitiveness runs up to one hundred percent, consumers are most likely to purchase a brand and its product. That indicates brand competitiveness maintain fifty percent of the whole market is most efficient to be profitable, and the performance of costing more to improve the brand competitiveness might make no difference. These findings will provide a reference for brand marketers in developing marketing strategies, the brand of the company should not make excessive advertising for the brand's click. As long as the brand has a 50% market hit rate, then the company can put the funds to improve the quality and to position of the brand market. However, the price and advertising of brand are not taken into consideration, and the economic and marketing information will be elaborated in the future work.

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