

Exploring Browsing Behavior of Product Information in an M-commerce Application: a Transaction Log Analysis

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Abstract. This research aims to describe the information browsing and merchandise purchasing behaviors of the users in an M-commerce application. Data used in this research comes from the transaction logs of 290 heavy users in March 2015. We established the mapping between the request parameters in the log data and information behavior types to further analyze the patterns of browsing behavior. Results indicate that: 1) consumers are most concerned about item details, and actively share their favorite items and shops to other users; 2) the number of viewing times followed a power-law distribution; 3) items that are viewed 9 times are most likely to be purchased. There is a positive correlation between the purchase of items and the numbers of browsing and sharing behaviors.

Keywords: information browsing, information behavior, mobile shopping, mobile electricity business

1 Introduction and Related Research

Mobile e-commerce APPs have become one of the most commonly used APPs in China. As of June 2017, Chinese mobile Internet consumers reached 511 million, accounting for 68.0% of all Chinese mobile Internet users [1]. Research on the information behavior of mobile shopping users is of great significance for deeper understanding of purchasing behavior to improve e-commerce services and promote consumption.

Previous research has examined users' information search behavior using various methods, including user click-through logs, questionnaires, interviews, and experiments [3,4]. Sequence analysis and cluster analysis have also been used to model the characteristics of user information search behavior [4]. Prior research has built a three-level model based on theoretical basis, the search stage, and influencing factors [5]. Yeh found that a website that offers an extended period of product satisfaction guarantee, various kinds of contact information and detailed product information can earn high purchase reaction [6]. Pack found that the information feature, including content and presentation of product, was an important factor determining consumers' site loyalty and decision-making in terms of whether to shop at the store [7].

In this study, we investigated a shopping APP which targets young, white-collar female workers between 23 and 30. The APP now has over 100 million registered users.

More than 5.12 million users shopped with the APP in March 2017, spending about 1 hour per month [2]. This poster aims to model users' information browsing behavior based on log data.

2 Methods

We focused particularly on browsing behaviors relating to items, shops, and the consumer's shopping cart, for example browsing the item detail, browsing the comments on the item, sharing the item with others, etc. Three types of purchasing behaviors were defined: adding items to the shopping cart, placing an order, and making a payment.

2.1 Data collection

The data was obtained from the server log records of a m-Commerce APP during March 2015. We defined a user as a heavy user if he or she continually order items in three consecutive months on this shopping platform, using both PC website and mobile application. By those criteria, we identified 290 heavy users and collected 805,861 server logs after data cleaning. These users browsed 83,743 items and visited 44,467 shops. There were 2,529 orders generated during this timeframe and items totaled 1,954. Table 1 shows the fields in the log that we used in further analysis.

Table 1. Data fields

Field	meaning	field	Meaning
log_date	Login time	items_price	Price of items
hh/mm/ss	Hour/min/sec	request_params	Request parameters
URI	Access link	shop_id	Shop ID
request_name	Name of request	user_id	User ID
user_id	User ID	order_create_time	Order time
item_id	Item ID	pay_time	Payment time
order_id	Order ID	items_sale_num	Sales volume

2.2 Data Preprocessing and Analysis

We followed the following steps to preprocess and analyze the data:

Step1: Data Cleaning. First, we divided the raw logs into fields and removed those that do not have a *user_id* or *item_id*. Then we summarized each user's purchase behavior in the last three months to identify the heavy users. Last, we took out one outlier who bought a same item for more than 400 times.

Step2: Identifying behavior types. The *request_params* field contains 22 different parameters, each of which stands for a specific behavior. We identified the meanings behind them according to the app's development documentation. Some of the meanings are extremely similar. Hence, we summarized those 22 parameters into 10 browsing behaviors and 3 purchase behaviors.

Step3: Statistic analysis. We summarized the data in different dimensions to find patterns, including time, user, item, and behavior types.

Step4: Correlation analysis. We ran a correlation analysis between different browsing behaviors and purchase behaviors using SPSS 22.0.

3 Results

3.1 Characteristics of browsing behavior

The quantity of user log records and records of purchase behavior within one day are shown in Fig.1. The timing of purchase behavior was consistent with the basic trend of browsing behavior but was relatively delayed, which is consistent with the general rule that purchasing decisions are made after full browsing of information obtained by users.

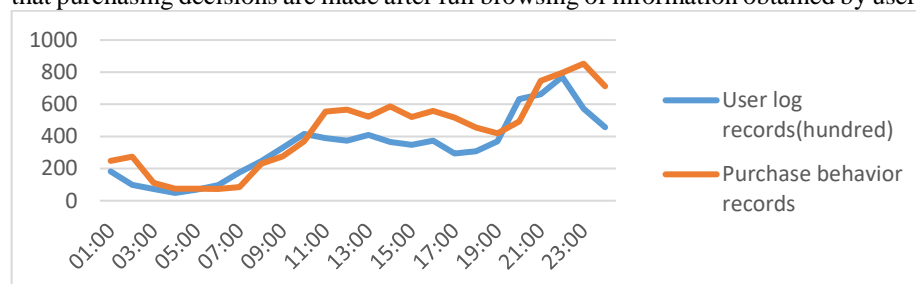


Fig. 1. User log records and purchase behavior records within one day

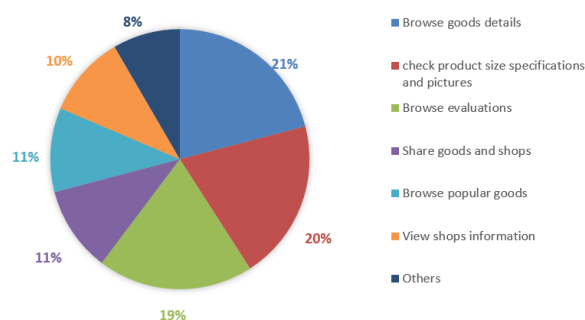


Fig. 2. User log records and accounting analysis

Product details are important, and good items and shops are likely to be shared.

The proportion of different types of browsing behavior are shown in Fig.2. It can be seen that users are not only concerned with details of the products, but also reviews and feedback of other consumers. Consumers tend to browse through the evaluations of sellers in order to obtain a more reliable reference. Generally, users browse for items more often than for shops. They would rather click through a single page of a product that interests them, than entering a store first.

Browsing frequency follows power-law distribution, and 90% of the user's browsing history is below 17 items. 50% of user browsed less than 8 items, and 90% of user browsed less than 17 items. 21.89% items have only been browsed once. The browsing frequency of items follows a power law distribution. In particular, the percentage of items with 7-9 browsing records are larger, possibly because users had a clear preference at this time, and would either continue to browse items or make a purchase decision.

3.2 Characteristics of Purchase Behavior

Users are more likely to buy items that generate 9 server request logs. The general pattern shows that as the number of times an item is browsed increases, the purchase ration increases overall. It was seen that the trends of adding items to a shopping cart, placing orders, and paying were identical. We realized that some consumers would pay for an item directly after viewing the item a couple times, instead of adding the item to the shopping cart before paying. It is theorized that this behavioral pattern emerges from consumers who are familiar with the desired items, and do not need to view details. The number of items that are browsed 7 or more times rises gradually. After this point, the consumer's purchase intent is clearer. The items that are placed orders or paid after being browsed for 9 times have the largest quantity.

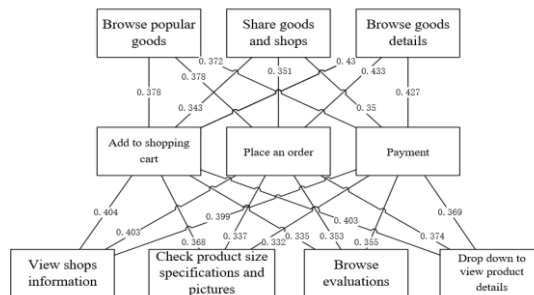


Fig. 3. Correlation analysis of browsing behavior and purchasing behavior

The more times that a user browses a product and shops, the more information they collect and share, and the more likely they are to purchase the items. Correlations of three purchase behaviors and browsing behavior are shown in Fig.3. The purchase behaviors have a high correlation with the 6 types of browsing behavior. It can be seen that the more times a user browses a product and shops, the more information they collect and share, and the more likely they are to purchase the items.

4 Conclusion

This research aims to describe the information browsing behaviors of users who shop online through the mobile shopping applications. We found that consumers seem to be most concerned about the details of items, and actively share their favorite items and shops to others. If users browse items or shops and share the items with other consumers, they are more likely to purchase the corresponding items. Overall, user browsing behavior follows a power-law distribution. Additionally, users may not necessarily pay for items that they add to the shopping cart. However, if users place an order, they will most likely follow through with payment.

Limitations of this study include the fact that some of the server request logs were generated by an automatic loading mechanism of the APP, and thus do not accurately reflect a user's operation. The server request logs were generated by users who frequently use the APP, and the results of this study should be tested and verified further prior to promotion. Furthermore, the logs selected for analysis were generated in the month of March only; perhaps the data would fluctuate outside this specific timeframe. In future studies, we will categorize a user's behavior into different sessions and attempt to develop more detailed models and analysis.

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