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Online purchaser segmentation and promotion strategy selection: evidence from Chinese E-commerce market

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Abstract Online customer segmentation is a significant research topic of customer relationship management. Previous literatures mainly studied the differences between non-purchasers and purchasers, lacking further segmentation of online purchasers. There is still existing significant heterogeneity within purchaser-groups. This paper focuses on Chinese online purchaser segmentation based on large volume of real transaction data on Taobao.com, we firstly extracted and investigated Chinese online purchaser behavior indicators and classified them into six types by cluster analysis, these six categories are: economical purchasers, active-star purchasers, direct purchasers, high-loyalty purchasers, risk-averse purchasers and credibility-first purchasers; then we built an empirical model to estimate the sensitivity of each type of online purchasers to three mainstream promotion strategies (discount, advertising and word-of-mouth), and found that economical purchasers are the most sensitive to discount promotion; direct purchasers are the most sensitive to advertising promotion; active-star purchasers are the most sensitive to word-of-mouth promotion; finally, the implications of online purchaser classification for marketing strategies were discussed.

Keywords Online purchaser segmentation · Cluster analysis · Promotion strategy · Sensitivity to promotion strategy

1 Introduction

As an important part of customer relationship management, customer segmentation can contribute to a better understanding of the characteristics of customer behaviors in market, and help sellers to make appropriate marketing strategies according to different customer groups (Raju et al. 2006). With the rapid development of E-commerce all over the

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world, the online customer segmentation has attracted much attention from both business and academia. As for related concepts, in many online shopping studies (Kau et al. 2003; Bhatnagar and Ghose 2004), "customer" could also be called "shopper", who may have one or several of motivations of browsing products, such as, seeking information, communicating, and purchasing some products, etc. In terms of transaction results, shoppers include both the purchasers and non-purchasers.

There are different objectives for the segmentations of three different groups—shoppers, purchasers and non-purchasers. Segmentation of shoppers is helpful to target different groups of all shoppers who include purchasers and potential purchasers (Rohm and Swaminathan 2004), and analyze the differences of behavior characteristics between online purchasers and non-purchasers (Lohse et al. 2000); the objective of non-purchaser segmentation is to investigate the patterns and characteristics of non-purchasers' visiting behaviors, and find out how to stimulate them to make purchasing decisions and turn them into purchasers (Moe 2003); the motivations to study purchaser segmentation are to better understand purchasing behaviors and the determinants of the purchase decision, and develop successful marketing strategies to enhance purchaser loyalty and repeat purchase intention (Wu and Chou 2011). According to the research of Kim and Gupta (2009), repeat purchasers are five times more profitable than new purchasers, and purchaser loyalty is critical for the survival and success of online stores (Chiu et al. 2012). Therefore, the purchaser segmentation is a very important in segmentation area study.

However, although there are comparatively abundant research results in the field of shopper segmentation, and non-purchasing shopper segmentation, there is a relative paucity of research examining typologies of online purchasing shoppers, especially for Chinese C2C E-commerce market, it lacks systematic research of online purchaser segmentation. In recent years, Chinese E-commerce has been experiencing rapid development. TaoBao, the Chinese biggest online shopping website, has become the largest shopping website in the world, with far more transaction account than both eBay and Amazon. By the end of 2011, the biggest daily turnover of TaoBao was 438 million RMB, which is even more than the sum of daily retail sales of Beijing and Shanghai. On the Singles' Day of November 11, 2012, the sales in Taobao broke through 19.1 billion Yuan of RMB. Thus, there is a very large population of and active online purchasers in Chinese C2C E-commerce market.

This paper focuses on the segmentation of Chinese online purchasers and the response sensitivities of different types of online purchasers to promotion strategies. The segmentation study about online purchaser specifically deserves much more attention for several reasons: First, there is still existing significant heterogeneity among purchasers. For example, some purchasers are purpose-oriented directly purchasing type who are very focused and targeted toward a specific purchase (Moe 2003), some purchasers are comparison type, and some are the impulse type-purchasers (Chen and Wang 2010). Second, segmentation study of purchasers has great implication for marketing practice: Different types of purchasers would exhibit different behavioral characteristics in the process of purchasing, and different sensitivity to promotion strategy. The targeted marketing programs based on segmentation information can significantly improve the probability of repurchase. Furthermore, the classification of Chinese online purchasers could be different from that of US online markets due to cultural differences: According to McKinsey research report about Chinese online market, there are some unique features about Chinese online market, such as, Chinese online purchasers are more price-sensitive, and a majority of online transaction is the replacement of offline transaction because of the poor infrastructure of offline market, etc. Therefore, it is quite necessary to investigate the classification of Chinese online consumers specifically, and their specific response sensitivities to different marketing strategies. The understanding of purchaser segmentation will help online sellers to understand the behavior differences among different purchasers, design appropriate promotion plans, then enhance the repeat purchase rate and purchaser loyalty, and form core competition of the online store.

Specifically, based on three million transaction data of purchasers on the platform of Taobao, this paper constructed purchasing behavior indicators and conducted clustering analysis to classify the online purchasers. Then we further studied the sensitivity and adaptability of different types of purchasers to promotion strategies.

The paper proceeds as the following: In Sect. 2, we provide a review of the related literature. In Sect. 3, we use the cluster analysis to classify the Chinese online purchasers based on transaction data on Taobao, and find out that there are six types of online purchaser. Section 4 analyzes the sensitivity of different types of online purchaser and its implications for promotion strategies. Section 5 summarizes the conclusions, and discusses the potential extensions of the research.

2 Literature review

According to the different levels of online market segmentation, current literatures can be divided into three parts, which are shopper segmentation, non-purchaser segmentation and purchaser segmentation. The three parts have different economic meanings and practical applications, and the research of the latter two parts deepens the first.

The studies of online shopper segmentation aim to target different groups of shoppers who include purchasers and potential purchasers, and analyze the differences of behavior characteristics between online purchasers and non-purchasers. Most previous studies classified online shoppers mainly based on demographic or subjective psychological indicators, such as demographic characteristics, consumer motivation, and attitude, etc., which were usually measured by questionnaires. Kau et al. (2003) classified online shoppers coupled with their demographic information and shopping behaviors, and the results from cluster analysis indicated that there were six segments of online shoppers, which were named on-off shopper, comparative shopper, traditional shopper, dual shopper, e-Laggard and information surfer. Rohm and Swaminathan (2004) developed a customer typology based upon motivations and propensity for shopping online, and classified the customers into four types which are labeled convenience shoppers, variety seekers, balanced buyers, and store-oriented shoppers. Bhatnagar and Ghose (2004) applied a latent class modeling approach to segment e-shoppers based on demographics and purchase behaviors, and found that there was a large segment of Internet surfers who dislike buying online, getting the lowest price for commodities does not appear to be a very important attribute for e-shoppers. Soopramanien and Robertson (2007) empirically analyzed the behavioral differences among the purchasers, browsers, and non-Internet shoppers. Barnes et al. (2007) selected some psychological dimensions, such as trust, perceived risk, attitude towards online shopping, shopping pleasure degree, purchasing intention, as the basis for segmentation, and use cluster analysis to classify online shoppers into three types, namely risk-averse skeptics, open-minded online shoppers, and reserved information-seekers, by using the 1123 questionnaire data which was collected from Germany, USA and France.

In order to improve the purchase conversion rate of online stores, some studies focus on non-purchasers, investigating the patterns and characteristics of their visiting behaviors and classifying them. Moe (2003) empirically tested a typology of online store visits according to shoppers' underlying objectives based on page-to-page clickstream data, and found that the non-purchasers could be categorized into browsing, searching, and knowledge-building types. Specifically, browser was significantly less focused, and motivated by the hedonic experience, the objective of searching was to acquire relevant information to help make a more optimal choice, and knowledge building was motivated by learning the operations of the websites or increasing the product information potentially useful in the future. Using web log data, Song and Shepperd (2006) employed vector analysis and fuzzy set theory based algorithms for mining browsing patterns for E-commerce, and verified that the proposed algorithms was more accurate and effective. Ganesh et al. (2010) provided a comprehensive comparison of shopper subgroups between traditional and online formats, found that there were three shopper subgroups that are unique to the online shopping environment, that of e-window shoppers, interactive shoppers, and risk averse shoppers. E-window shoppers were motivated to visit interesting web sites or simply surf the Internet, interactive shoppers scored highest on personalized services and online biding dimensions, and risk aversion shoppers were more concerned about security issues.

Online purchaser segmentation is the further research of shopper typology. The goal of purchaser segmentation is to better understand purchasing behaviors and the determinants of decision making of different types of purchasers, then design targeted marketing plan to enhance repeat purchase rate. Wu and Chou (2011) developed a soft clustering method to classify online purchasers based on purchasing data from online shopping questionnaires, and found several typical segments as following: the first type of purchasers were both frequent shoppers and consumers who spend greatly online, the second type of purchasers were unsatisfied with service and spend little money, the third type of purchasers were reluctant shoppers, who neither shop frequently nor spend much money, the fourth type of purchasers were efficient shoppers, who do not shop frequently, but when they do, they spend a lot. According to the research of Kukar-Kinney et al. (2012), the online purchasers could be categorized to compulsive and non-compulsive ones.

3 Segmentation of online purchasers based on real transaction data

3.1 Conceptual framework

Previous literature has primarily studied the classification of the general shoppers and non-purchasers, while relatively few studies have been done on the segmentation of the core users of E-commerce website—purchasers. This paper focuses on the purchaser segmentation and its application to promotion strategy design based on large volume of real transaction data on Taobao.com. In Fig. 1, we present the conceptual framework for our study. The process of this research can be divided into five steps, which are data acquisition and preprocessing, indicators extraction for online purchasing behaviors, purchaser segmentation, promotion sensitivity analysis, and promotion strategy design.

In the present study, objective transaction data were used to study online purchaser typology considering that he objective transaction data can reflect the real purchasing behavior characteristics better than the subjective survey data. In the step of data acquisition, we obtain the real transaction data by random sampling method from Taobao platform. Then, the transaction data were standardized to eliminate the influences of dimensions of different data items.

We extracted the typical indicators of purchasing behavior from the sampled real transaction data. According to previous literature, although online shopping is a complex process influenced by the factors of products, technologies, sellers etc. (Peng et al. 2008), the effect of all the factors would eventually be reflected in the results of the transactions. That

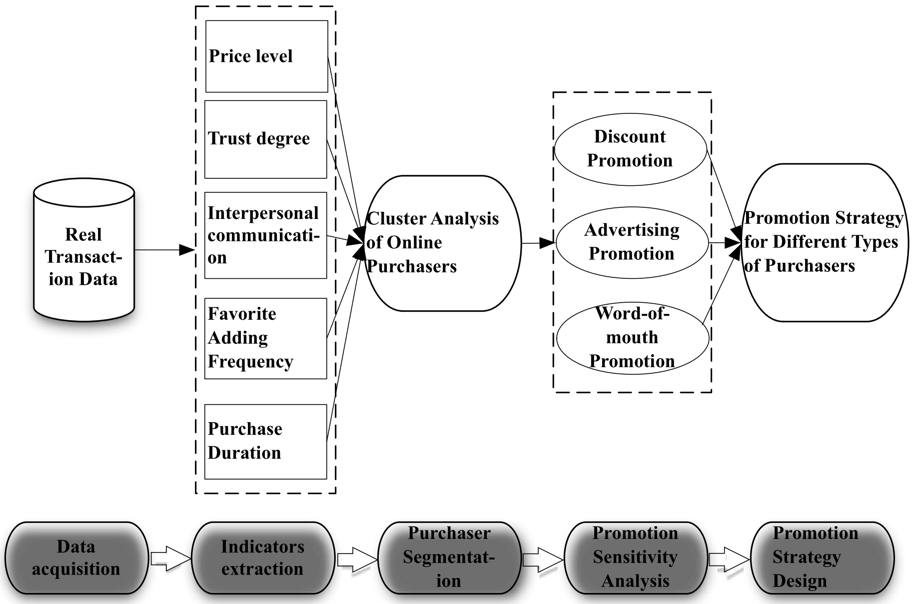

Fig. 1 Conceptual framework

is to say, there is a certain correlation between purchasers' behavioral preferences and the transaction data. Specifically, purchasers' preference for price would be reflected by their selection for high price or low price products, the trust preference can be reflected by their choice for the online stores with high or low reputation (Lin et al. 2006), the purchasers' communication behavior can be reflected by their online reviews (Chen and Xie 2008), and the purchasers' consideration time can be reflected by their visiting time (Song and Shepperd 2006). Besides, lots of purchasers add their preferred products to "Favorites menu", and this behavior indicates the purchase intention. In sum, we extract five behavioral indicators described above for clustering, which are price level, trust degree, interpersonal communication, favorites adding frequency, and purchasing duration.

On the basis of behavior indicators, we classified the online purchasers by using the method of cluster analysis. Then, by building empirical model of sensitivity analysis, we estimated the sensitivity of each type of online purchasers to three mainstream promotion strategies (discount, advertising and word-of-mouth). Finally, the implications of online purchaser classification for marketing strategies were discussed (see Fig. 1).

3.2 Data acquisition

Data source The data in this paper comes from the real transaction data from Taobao (www.taobao.com), which is the biggest Chinese C2C E-commerce website. Specifically, supporting by Alibaba Group Research Center, the data of 3 million transaction records are collected by random sampling method during the period from August 2011 to September 2011, covering 54 kinds of hot products, such as clothing, digital products, household, etc. And each transaction data records all the purchasers' behavior indicators (such as purchaser ID, product ID, price, purchasing volume, the amount of reviews, visiting time, etc.). Some data items related to conceptual framework are shown in Table 1.

Table 1 Purchasing behavior indicators of Taobao

Indicator code	Description
Price	The price that the purchaser paid for goods
Reviews	The amount of Comments the purchaser published
Favorites	The number of products the purchaser saved as Favorite
Reputation	Reputation of shops that purchasers select
Duration	The duration of time the purchaser visited the product website

In order to eliminate the influences of dimensions of different data items, the data standardization is an important basic work for cluster analysis. The descriptive statistic results show that the disparity of every indicator is quite high, and the distribution characteristic is similar to a power law distribution. If we employ cluster analysis on transaction data of power law distribution, it would lead extreme data points to gather together, while most data points can't be effectively distinguished. Hence, every indicator variable needs normalized treatment. Here, we apply the five-level data standardization method, which is similar with Likert Scale. The original data need to be ranked by increasing order of data value, and converted into level data at the scale of one to five according to quantile position: level one represents the lowest value interval, and level five represents the highest value interval. One advantage of this normalization processing method is that it can not only keep consistent with the order of original data, but also reduce the uneven degree of power law distribution, which can effectively distinguish sample points.

3.3 Characteristics indicators of purchase behavior

(1) Preference for price level Traditional economics point out that price is an important factor affecting commodity trading. Generally speaking, price and trading volume are inversely correlated, and the higher the price is, the lower the trading volumes. The rapid development of Internet significantly reduces information search costs, and improves transaction convenience. From this perspective, online price and dispersion degree of commodities would be lower than offline, and price of commodities would tend to be consistent with the level in competitive markets. Besides, it is argued that environment factors of Internet have some inhibitory effect for consumers' sensitivity for price (Shankar et al. 1999). But, real E-commerce data does not support this argument, and some literature pointed out that the price dispersion degree of commodities in real E-commerce websites is usually bigger (Grewal et al. 2003). So in online trading, price is still an important determinant for shopping decision. Xia and Monroe (2004) concluded that segmentation strategies of price in E-commerce websites can improve the purchasing intention and perceived value of shoppers.

Therefore, we select price of commodities recorded in transaction data as the indicator of reflecting purchasers' preference for price, which is denoted as "price" in this paper.

(2) Preference for reputation Trust plays an important role in maintaining the stability and persistence of customers (Anderson and Weitz 1989). In order to build a long-term and harmonious customer relationship, sellers must win consumers' trust (Doney and Cannon 1997). Comparing with offline shopping, online shopping is lack of face-to-face communication, and can hardly judge the quality of commodities due to lack of physical touching. From this perspective, it's argued that the information asymmetry between purchasers and

sellers is more serious, the trust for transaction is more important for the realization of transactions in E-commerce websites, meantime, the trust would also improve purchasers' loyalty. Bart et al. (2005) argued that the factor of trust plays different roles in different types of websites and different kinds of purchasers. Chiu et al. (2012) pointed out that online purchasers' trust degree has positive effect on their repetitive purchasing activities.

We select the reputation of shops visited by purchasers in transaction data as the indicator of reflecting purchasers' preference for reputation, which is donated as "reputation", and the more purchasers tend to purchase commodities from high reputation shops, the more attention the purchaser paid to the trust factors.

(3) Interpersonal communication The consumer psychology theory points out that social interaction need is one kind of psychological motivations which can cause purchasing behavior. Tauber (1972) believed that word-of-mouth communication among consumers with same interests was an important part of social interaction motivation. Alba et al. (1997) found that word-of-mouth interaction plays an important decisive role in selection of online stores. As for the quantitative study of word-of-mouth effects, some studies regarded online reviews as a new indicator of word-of-mouth interaction among consumers, and related empirical research indicates that online reviews have positive effect for transaction volume. In 2010, the research report of McKinsey Consulting about Chinese consumers pointed out, word-of-mouth had become an important source for the dissemination of product information. By analyzing the online reviews data in Amazon, Mudambi and Schuff (2010) found commodity type has some moderate effect for the usefulness of online reviews.

So, we select the numbers of online reviews among transaction data as an indicator for word-of-mouth interaction degree, and it is donated as "reviews".

(4) Favorites adding frequency Favorite saving behavior on website first appeared in the feature set of the Web browser, enabling web visitors to put the websites they like into Favorites, this feature can facilitate the future visits. Similar function can also be found in E-commerce websites, which can be used to collect commodities or shops that visitors like. For example, EBay allows visitors to put some shops that they feel ok into their Favorite Seller List; In Taobao, purchasers can also add their satisficed commodities to "Favorites menu", and this behavior indicates the willingness of repeat purchaser and purchase loyalty.

This paper selects purchasers' favorites adding frequency as an indicator for measuring favorite saving behavior, which is donated as "favorites". We assumed that the more products purchasers adding to favorite menu, the stronger intention they will have to repeat purchase the products. We also argue that these purchasers are loyal shoppers with high repurchase rate.

(5) Purchase duration Online shoppers pay more and more attention to the convenience of saving time in purchasing process (Reynolds and Beatty 2000). Novak et al. (2000) pointed out that visiting time of online purchasers is highly correlated with users' experience of online shopping, which can reflect the effectiveness of market sales. After analyzing click stream data, Rho et al. (2004) found that there is some relationship between visiting time and their purchasing intention.

This paper selects the duration of purchase time as a behavior indicator for distinguishing purchasing type, which is donated as "duration". This indicator reflects the length of the cognitive process purchasers used in making decision. It is argued that the longer the duration time is, the less clear the purchaser targets would be or the more cautious the purchaser would be in making purchase decisions, and vice versa.

Table 2 Cluster result of purchasers from K-means algorithm

Cluster	Economical purchasers	Active-star purchasers	Direct purchasers	High-loyalty purchasers	Risk-averse purchasers	Credibility-first purchasers	Pr > F
Cluster size	30847	27096	18009	15483	11519	9041	
Percentage	27.5 %	24.2 %	16.1 %	13.8 %	10.3 %	8.1 %	
Price	1.4	3.3	1.4	3.4	3.7	3.2	<0.0001
Reviews	1.8	4.2	2.2	3.0	2.1	2.7	<0.0001
Duration	3.9	3.4	1.5	1.6	3.6	1.6	<0.0001
Favorites	1.8	4.0	1.5	3.6	2.3	2.5	<0.0001
Reputations	3.3	3.3	1.8	1.8	2.2	3.7	<0.0001

Notes: Canonical Discriminant Analysis: Wilks' Lambda = 0.054; F-value test: $p < 0.0001$

3.4 Cluster analysis

In order to strengthen the objectivity of analysis results and facilitate stability testing, after removing the purchasers with the same ID, we use random sampling method to collect 100 thousands transaction records from the population samples (nearly 2.9 million unique purchasers). Then, we apply K-means algorithm for cluster analysis based on the five typical purchasing behavior indicators in Sect. 3.3, which are price, reputation, reviews, favorites, and duration.

K-means algorithm is one of the well-known algorithms for cluster analysis, originally known as Forgy's research (Forgy 1965), and it has been used extensively in various fields such as market segmentation etc. (Li et al. 2009). The K-means algorithm for partitioning is based on the mean value of the objects in the cluster, and the main steps are as follows:

Step 1: Initialize centers for K clusters randomly.
Step 2: Calculate distance between each object to K-cluster centers using the distance formula.
Step 3: Assign objects to one of the nearest cluster center.
Step 4: Calculate the center for each cluster as the mean value of the objects assigned to it.
Step 5: Repeat steps 2 to 4 until the objects assigned to the clusters do not change.

The K-means clustering method selects random points as original cluster center, and divides the purchasers into two, three, four, five, six and seven clusters respectively. Determination of the number of clusters is based on the examination of scree plots in cubic clustering criterion (CCC), F-statistics, and the Approximate Overall R-Squared. These are all measures of fit for cluster analysis. In general, the number of cluster is determined by maximizing each value of the three statistics (Rho et al. 2004). After the comparison of test results of CCC, F-statistic and Approximate Overall R-Squared from different cluster number, we finally get six categories of purchasers. The result of cluster analysis is shown in Table 2. Figures 2 and 3 show the scatter plot of clustering result on the first principal component and the second principal component. The purchasing behavioral characteristics of six segments of purchasers are shown in Fig. 4.

3.5 Description of clusters

Economical purchasers This group has the largest proportion (27.5 %) in the purchaser sample. The most prominent behavioral characteristic is that they prefer to purchase low-

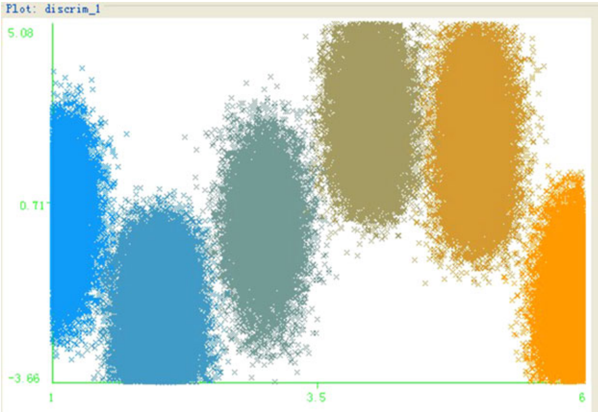

Fig. 2 Scatter plot of clustering result on the first principal component

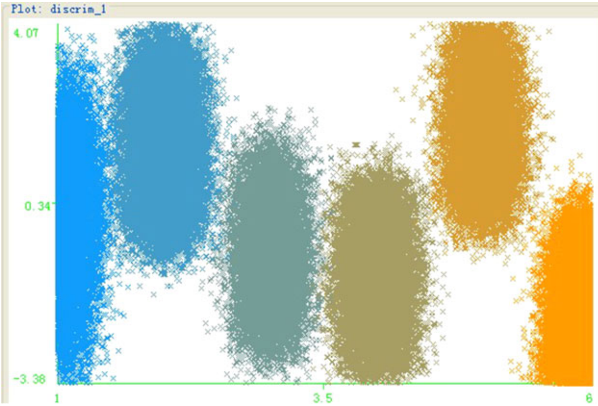

Fig. 3 Scatter plot of clustering result on the second principal component

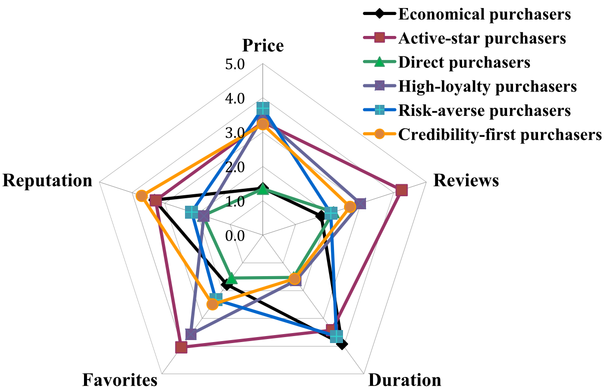

Fig. 4 Behavioral characteristics of six types of purchasers

price commodities and consider a long time to make decision. As seen in the scores of five behavioral indicators of economic purchasers (Table 2), the price indicator is 1.4, which is nearly in the lowest level, the reviews indicator is 1.8, which is the lowest level in sample, while the duration indicator is 3.9, which is the highest level in the six types of purchasers. The economic purchasers are fond of seeking information of commodities online, and compare many similar online stores to get the best prices, so they spend the longest average time in the six types. Besides, the lowest score of reviews indicator indicates that they do not like communicating with others. Specifically, they usually buy the commodities which cost dozens Yuan, such as storage, decorations, digital accessories, etc. Meantime, they also like to visit the stores with higher reputation, and seldom add the commodities to favorite menu. From the above purchasing behavior indicators, we can see that economical purchasers have lots of time to shopping online, with relatively cautious attitude for online purchasing, and prefer to high performance price ratio commodities.

Active-star purchasers This group ranks second in purchaser sample with a percentage of 24.2 %. The outstanding feature of active-star purchasers is that they very like to communicate with others about shopping experiences. So this category of purchasers is the most influential group with the strongest word-of-mouth interaction in the sample. Viewed from the scores of five behavioral indicators, all the scores are above the average level of sample, and the reviews indicator and favorites indicator are both the highest level in the six categories. They also tend to add the commodities that they satisfied to favorites, which indicate that they have strong repurchase willingness. Besides, they spend relative more time for online shopping and purchase the commodities above average price. And they usually purchase some experience goods, such as clothes and bags etc., which cost between dozens and hundreds Yuan. In sum, Active-star purchasers usually have optimistic attitude for online shopping and they are very keen to share their shopping experience with others.

Direct purchasers The proportion of this group is 16.1 % in the purchaser sample. Direct purchasers are task-oriented purchaser with clear targets. The most prominent behavioral feature is that they consider a very short time to make purchaser decision. As for the scores of five behavioral indicators, almost all the indicators are in the lowest score levels in the purchaser sample, specifically, the duration indicator is 1.5, the price indicator is 1.4, the reputation indicator is 1.8, the favorites indicator is 1.5, and the reviews indicator is 2.2. They mainly purchase low-price commodities. Meanwhile, they do not like to communicate with others, and seldom add some commodities into favorites. The difference between direct purchasers and economical purchasers is that they pay more attention to saving time while care nothing about the reputation of stores, and they spend less time on online shopping. From the perspective of specific commodities, they usually purchase virtual goods at the cost of dozens Yuan, such as QQ virtual service, online game equipment, and online shop service. In sum, direct purchasers prefer to buy some low-price virtual goods or services with quickly decision making.

High-loyalty purchasers The proportion of this group is 13.8 % in the purchaser sample. High-loyalty purchasers prefer to buy some high-level commodities with clear preferences. The prominent behavioral feature is that they are very like to add the commodities they satisfied into favorites. As for the scores of five behavioral indicators, there have three indicators above the average level of sample, that are favorite indicator (3.6), price indicator (3.4), and reviews indicator (3.0). There also have two indicators below the average level of sample, which are duration indicator (1.6), and reputation indicator (1.8). They also like to communicate with others about shopping experiences. Yet the difference between high-loyalty purchasers and active-star purchasers is that they spend less time for purchase decision-making and care less about the stores' reputation. This phenomenon implies that they know the commodities well, with high loyalty and history purchasing experience. From the specific commodities, they usually buy furniture, watch, jewelry, etc. In a word, high-loyalty purchasers prefer to spend less time to buy the high-price commodities from their Favorites.

Risk-averse purchasers The proportion of this group is 10.3 % in the purchaser sample. Risk-averse purchasers consider a long time to make purchasing decision for high-level commodities. As for the scores of five behavioral indicators, there have two indicators obviously above the average level of sample, which are price indicator (3.7), and duration indicator (3.6), while the other indicators are in the general level of sample. The difference between risk-averse purchasers and high-loyalty purchasers is that the former spend much more time for purchase decision-making than the latter. They do not know much about the high-price commodities, thus, the high price reflect the level of risk to a certain extent. In order to avoid risk, they spend as much time as possible to compare the commodities information in different stores. From the specific commodities, they usually buy air tickets, hotel reservations, cameras, and laptop computers etc. In a word, risk-averse purchasers usually have cautious attitude for buy high-price commodities, and they tend to spend much more time on the comparison and selection.

Credibility-first purchasers This group has the smallest proportion (8.1 %) in the purchaser sample. The prominent behavioral feature is that they have a strong preference for high-reputation stores. As for the scores of five behavioral indicators, there have two indicators obviously above the average level of sample, which are reputation indicator (3.7), and price indicator (3.2), while the duration indicator is 1.6, far more below the average level of sample, the other indicators are in the general level of sample. They usually spend less time to purchase high-price commodities only care about the online stores' reputation. The difference between credibility-first purchasers and high-loyalty purchasers is that the former make purchasing decision by stores' reputation while the latter mainly by commodity preference. Besides, they are also efficient purchasers laying stress on saving time. From the specific commodities, what they usually buy is just like mobile IP cards and mobile phone recharge cards etc. In sum, credibility-first purchasers are store-focused and prefer to spend less time to buy high-price commodities from high-reputation stores.

4 Sensitivity analysis and implications for promotion strategies

4.1 Empirical model of sensitivity analysis

How to make targeted marketing programs to promote the sales of online products is a major concern for online sellers. The analysis of the classification and behavioral characteristics of online purchasers would be helpful in this aspect. Generally, there are three main promotion strategies used by online shops, one is price promotion, namely improving transaction volume by reducing price; one is advertisement promotion, namely increasing users' click stream by online advertisement, and then improving the trading frequency; And the other one is word-of-mouth promotion, which means attracting more purchasing purchasers by word-of-mouth and comments. Considering heterogeneity of purchasers is an important factor for affecting the effectiveness of promotions, different types of online purchasers concern about different features, and have different sensitivity to different promotion strategies. It is necessary to measure the sensitivity of different types of purchasers to different promotion strategies.

Based on the transaction data of TAOBAO, we select the following measure for each variable (see Table 3).

In order to measure the sensitivity of different types of purchasers for the three promotion strategies, we use double logarithmic model to test the flexibility of each measurement

Table 3 Index selection for sensitivity analysis on promotional methods

Variable	Indicator name	Indicator note	Description
Dependent variable	Transaction volume	*Y*	The volume that purchaser buy during one period
Independent variables	Discount promotion	*price*	The price of commodities that purchaser buy
	Advertisement promotion	*ad*	Investment of commercial advertisement
	Word-of-mouth promotion	*reviews*	The number of comments that purchaser published
		favorites	The frequency that purchaser adding commodities into Favorite Menu
Control variables	Historical sales	*history*	Historical transaction volume of commodities
	Platform protection scheme	*if_protect*	Whether shops that users choose join protection schemes or not

indices for purchasing volume, the specific form of the model is as follows:

$$\begin{aligned} \mathrm{Log}(Y) = \alpha + \beta_1 \log(\mathit{price}) + \beta_2 \log(\mathit{ad}) + \beta_3 \log(\mathit{reviews}) \\ + \beta_4 \log(\mathit{favorites}) + \beta_5 \mathit{history} + \beta_6 \mathit{if\_protect} + u \end{aligned}$$

The test result shows that, the test equations related to the six types of online purchasers have all passed F-test, and every variable has also passed T-test at 5 % significance level, which indicates that price promotion, advertisement promotion, word-of-mouth promotion, have significant effects on transaction volume. From the perspective of model fitting degree, active-star purchasers have the largest adjusted-R^2 value (0.715), which indicates that 71.5 % of the square of the purchasing volume can be explained by independent and control variables; Risk-averse purchasers have the least fitting degree, with adjusted R^2 less than 0.1, which indicates that the three promotion methods have limited explanation ability for cautious purchasers' purchasing behavior. The explanation degree for the rest four kinds of purchasers' purchasing behavior is between cautious purchasers and active-star purchaser (see Table 4).

4.2 Sensitivity analysis on three promotion strategies

The elasticity coefficients of the regression equation show that, different kinds of purchasers have significant different sensitivity for kinds of promotion methods. So as to the common price promotion in E-commerce websites, the negative price elasticity coefficient indicates that the decrease of price has significant promotion for purchasing volume. People with the highest sensitivity for low price are economical purchaser and Direct purchaser, the second highest are active-star purchaser and high loyalty purchaser, while credibility-first purchaser and risk-averse purchaser have the lowest price elasticity. Specifically, in the case of other promotional factors remain unchanged, for every 1 percentage point that commodity price decrease, the above six types of purchasers' transaction volume would respectively rise 0.520, 0.503, 0.350, 0.304, 0.239, and 0.217 percentage (see Fig. 5).

The elastic coefficient of advertising promotion is significantly positive, which indicates that the increase of advertising investment helps to improve purchasers' purchase. Direct

Table 4 Empirical test results of sensitivity analysis

	Economical purchasers	Active-star purchasers	Direct purchasers	High-loyalty purchasers	Risk-averse purchasers	Credibility-first purchasers
Adjusted R^2	0.310	0.715	0.416	0.306	0.058	0.205
F test	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	$<.0001$
price	-0.520^{***}	-0.350^{***}	-0.503^{***}	-0.304^{***}	-0.217^{***}	-0.239^{***}
ad	0.099^{***}	0.049^{***}	0.125^{***}	0.108^{***}	0.092^{***}	0.064^{**}
reviews	0.146^{***}	0.666^{***}	0.303^{***}	0.395^{***}	0.100^{***}	0.357^{***}
favorites	0.035^{ns}	0.140^{***}	-0.015^{ns}	0.145^{***}	-0.020^{ns}	-0.102^{***}
history	-0.082^{***}	0.061^{***}	-0.016^{ns}	-0.019^{*}	-0.026^{ns}	0.037^{ns}
if_protect	0.017^{ns}	0.013^{**}	0.079^{***}	-0.001^{ns}	0.107^{***}	0.080^{***}

Note: ***, **, * respectively represents 1 %, 5 % and 10 % significant level; ^{ns} represents non-significant

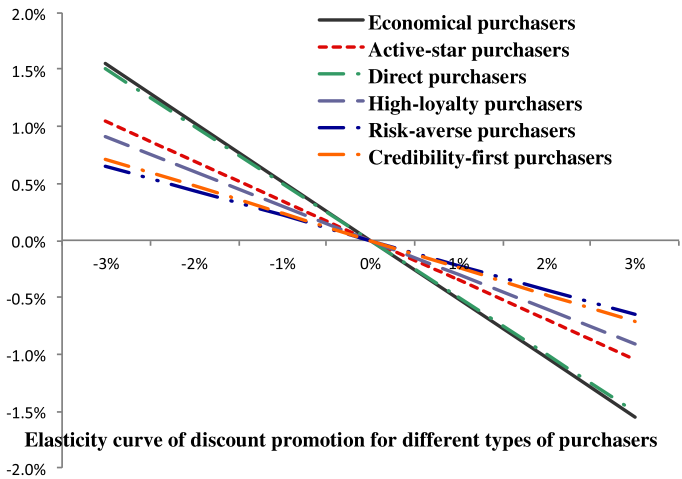

Fig. 5 Sensitivity analyses on six types of purchasers for discount promotion

purchaser and high-loyalty purchaser have the biggest sensitivity for advertisement promotion, followed by economical purchaser and risk-averse purchaser, while credibility-first purchaser and active-star purchasers have the least sensitivity. Specifically, in the case of other promotional factors remain unchanged, for every 1 percentage point that advertisement investment increase, the above six types of purchasers' transaction volume would respectively rise 0.125, 0.108, 0.099, 0.092, 0.064, and 0.049 percentage (see Fig. 6).

The elasticity coefficient of word-of-mouth promotion is significantly positive, which indicates that the increase of purchasers' reviews helps to improve purchasers' purchase. Here, we choose the indicators of reviews and favorites to measure the word-of-mouth behavior. Considering that the coefficients of the variable of favorites are not pass the significant test, so we use the variable reviews to analyze the effect of word-of-mouth on purchasing behavior. Active-star purchasers have the largest sensitivity for word-of-mouth promotion, followed by high-loyalty purchasers, credibility-first purchasers, direct purchaser, and eco-

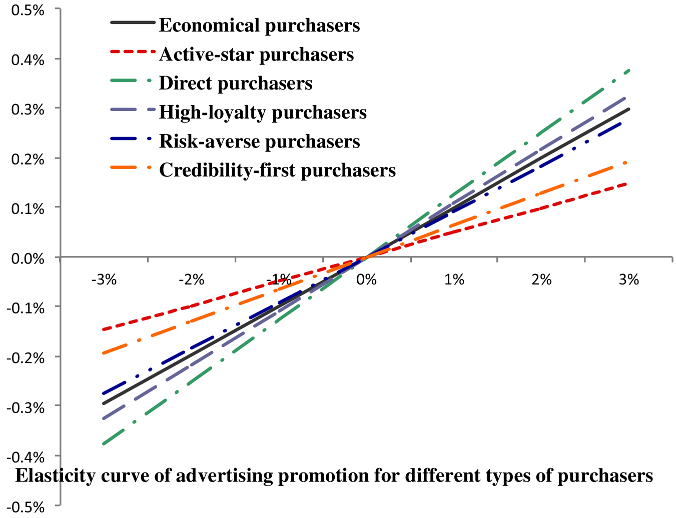

Fig. 6 Sensitivity analysis on kinds of purchasers for advertisement promotion

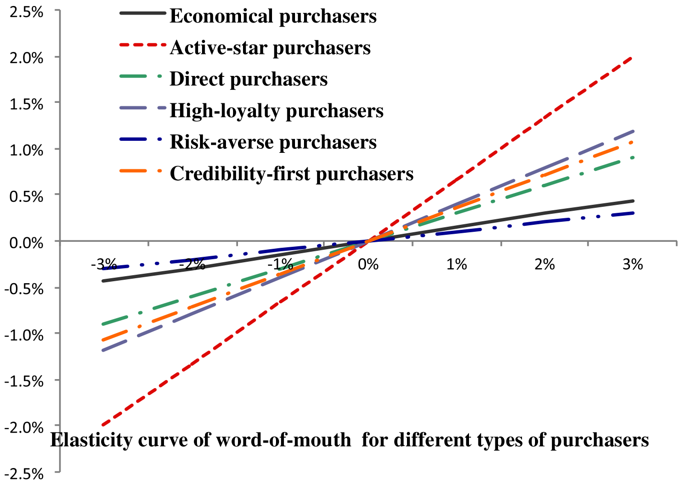

Fig. 7 Sensitivity analysis on kinds of purchasers for word-of-mouth promotion

nomical purchasers and risk-averse purchasers have the lowest sensitivity. Specifically, in the case of other promotional factors remain unchanged, for every 1 percentage point that word-of-mouth comments volume increase, the above six types of purchasers' transaction volume would respectively rise 0.666, 0.395, 0.357, 0.303, 0.146, and 0.100 percentage (see Fig. 7).

4.3 Implications for promotion strategies

As for the types of purchasers' selection for promotion strategies, economical purchasers tend to compare many online shops and commodities and then make a decision. They have the highest sensitivity for price, while the lowest for advertisement and word-of-mouth. So, online shop operators can use low price promotion strategy to attract this type of purchasers.

Active-star purchasers have rich online shopping experience, and are very good at online communication. They love to share with others about their shopping experiences, and meantime, they are easily affected by others' comments, so word-of-mouth promotion is very effective for this type of purchasers. Besides, price promotion can also make them have a more pleasant shopping experience, but it has limited affect. So, shop operators can mainly use word-of-mouth promotion, supplemented by price promotion strategy.

For direct purchaser, they have limited time for purchasing, and they usually buy virtual goods, so it is important whether the goods they need are clearly shown or not, which can help them to make their decision quickly. Virtual goods are usually standardized, and it is easy to verify the authenticity, so price factor has positive effect for purchasers. Shop operators can use advertisement promotion together with price promotion for such purchasers.

For high-loyalty purchaser, they have specific need preference and loyalty, and they love to collect goods or shops that they are satisfied for repeating purchase with relative low sensitivity for price and advertisement. So, shop operators should mainly use word-of-mouth promotion, and try their best to provide related description information and use feelings, and encourage purchasers to collect their goods at the same time.

For risk-averse purchaser, they hold cautious and preventive attitude for online shopping. So to alleviate their fears and worries is an effective way to facilitate transactions realized. Shop operators should provide kinds of protection plans, such as real-name authentication and return with no reason, combined price promotion on this basis for higher purchasing rate.

For credibility-first purchaser, they pay most of their attention to the reputation of shops, while with low sensitivity for advertisement promotion. So, in order to improve this type purchasers' purchasing volume, shop operators should use the way that can improve purchasers' trust, provide some protection plans, and improve purchasers' good comment rate and interaction volume.

5 Conclusions and future studies

Based on the real transaction data from TAOBAO, the biggest C2C E-commerce website in the world, we clustered the purchasers by using refined purchasing behavior indicators into six types: economical purchasers, active-star purchasers, high-loyalty purchasers, direct purchasers, risk-averse purchasers and credibility-first purchasers. These six types have significant differences in many aspects, such as preference for price, communication behavior, collection behavior, time spent on purchasing and the preference for reputation of shops they select, etc. For Chinese online market, economical purchasers consist of over 20 % of the whole online purchaser population, becoming the largest group among Chinese online purchasers.

On the basis of cluster analysis, we build an empirical model to analyze the sensitivity of each type of purchasers to three major promotion strategies: economical purchasers and direct purchasers are most sensitive to price promotion; high loyalty purchasers and direct purchasers are most sensitive to advertisement promotion; active-star type and high loyalty type are most sensitive to word-of-mouth promotion. According to the sensitivity calculation results, we propose different promotion strategies for different types of purchasers. Specifically, economical purchasers are sensitive to low price promotion strategy; active-star purchasers are sensitive to reputation-based strategy, supplemented by price promotion strategy; direct purchasers are sensitive to a combination of both advertising and price promotion strategy; high-loyalty purchasers are sensitive to word-of-mouth promotion combined with encouraging collection behavior; risk-averse purchasers are sensitive to the strategy of enhancing purchasing security for users; credibility-first purchasers are sensitive to the strategies that focus on the improvement of purchasers' trust.

There are several theoretical and practical contributions in this study: First, as for one of the few studies about segmentation of online purchasers, the present study explores the behavioral indicators of online purchasers, the types of purchasers, and their behavioral characteristics, and contributes to the research area of online purchaser segmentation by using large volume of real transaction data, which enhances the validity of clustering results; Second, as one of the biggest online shopping population, Chinese online purchasers deserve much more scientific investigation, this study contributes to the understanding of Chinese online customer behaviors; Third, this study has the practical implications for operation and marketing of e-business by providing the empirical evidence for targeted promotion strategies.

Although this study conducted stability test for transaction data, more other methods, such as purchaser survey by questionnaires about their purchasing type, could be adopted to verify the conclusion of six types of purchasers in the future studies in order to improve the robustness of segmentation analysis. Also, discriminant analysis could be conducted in the future studies to identify the unknown type of purchasers, and analysis of data over a longer period of time could enable the analysis of the changing features of purchaser behaviors, which worth further investigations in the future studies. Furthermore, whether the conclusions of this study based on the data exclusively from Chinese E-commerce market could be generalized to the markets in other culture is an interesting question unanswered yet and worth further studies in the future.

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