Abstract—The rapid popularity of mobile devices especially smart phones has changed human life style greatly. In this paper, we examine the consumer behaviors on several e-commerce platforms based on a large-scale dataset of mobile internet access records for about 3.5 months from a major telecom operator in China, which covers 126,388 users from Shanghai. We provide a preliminary study on users’ daily and periodic online shopping behaviors, as well as the influence of special online shopping events and gender factors. These findings may be exploited by e-commerce providers e.g., for developing personalized recommendation systems to improve their service quality and profit.

I. INTRODUCTION

In the past few years mobile phones have experienced a remarkable evolution and explosive popularization [1]. Meanwhile, e-commerce has a prosperous development and drastically changes traditional commercial relationships, as well as the shopping process for the fast-growing on-line shoppers [2]. With a smart phone at hand, a consumer can check the details of products, compare the prices across various e-commerce platforms, save items into charts and enjoy a number of benefits such as personalization from merchants and recommendation from social networks [4]–[6]. As more and more people purchase online, understanding consumers’ online behaviors becomes more and more important. Based on the behavior analysis, e-commerce companies may enforce corresponding marketing strategies to improve their service quality to keep and gain more consumers.

For online shoppers, searching for ideal products also takes plenty of time and energy, since many of them would purchase products based on their own cost-utility analysis. Facing diverse e-commerce platforms and many merchants, different consumers may exhibit different behaviors because of their diversities in economic status, personal preference and social influence etc. For e-commerce providers, the shortened life-cycles of products and intensified market competition lead to an imperative need to study the consumer purchasing behavior in order to make appropriate marketing strategies [7], such as improving their personalized service and catching consumers’ attention and trust.

Unlike most work of identifying purchasing intent, our work focuses on analyzing consumer online shopping behavior with implicit purchasing intent. Which time period do most consumers make their purchasing decisions? Are there differences between the behavior of male and female users? Do the promotion periods such as November 11 (“11-11”) and December 12 (“12-12”) have special influence on consumer behavior? By analyzing an anonymized dataset from a major telecom operator in China, we try to answer such questions in this paper, shedding light for e-commerce providers and merchants to improve their service quality and profit.

We observed the consumer behavior difference within a day and a week as well as studied the influence of special shopping festivals. In summary, the main contributions of this paper include:

- An overview about the visiting and purchasing fluctuation with two different time granularities (hour and day).
- Empirical evidence about the different consumer behavior considering the factors of gender.
- An observation about the influence of special shopping events on consumer behavior, such as “11-11” and “12-12” as well as the new year, Chinese spring festival and Valentine’s Day.

The remainder of this paper will be organized as following. In Section II, we introduce our dataset of Telecom data and e-commerce platforms used in this paper. Section III analyzes user behavior in detail, considering different time granularity and special online shopping promotion periods. We discuss related research work in Section IV and conclude our paper in Section V.

II. DATASET

A. Data Collection

The dataset contains complete anonymized Internet access records of mobile users in cellular environments, which is
provided by one of the three major mobile telecom operators in China. We collected the anonymized mobile Internet access data for 126,388 users from Shanghai which is the commercial and financial center of China from November 1, 2016 to February 11, 2017. Because of the popularity of WiFi in Shanghai, mobile users can access Internet using WiFi rather conveniently and our Internet access records cannot cover all the Internet access activities but can help to analyze user behavior under cellular environments. Each record contains the following information of an Internet access: anonymized ID of the mobile user, start time of the Internet access, destination URL and reference URL of the access.

B. Data Pre-processing

The collected data is heterogeneous and noisy, including all the active and passive Internet access records. In order to study consumer behavior using these various mobile Internet access records, we need to do data cleaning first. There are a lot of e-commerce platforms in China and for simplified analysis, we chose the 5 most popular ones, which are Taobao (taobao.com), JD (jd.com), Suning (suning.com), Dangdang (dangdang.com) and Vip(vip.com). Taobao and JD are the largest two comprehensive online shopping platforms while Suning, Dangdang and Vip are mainly corresponding to electronics, books and fashionable products respectively. We focused on all the users who have actions on these platforms and extracted all online shopping records at first. Due to the multiple interaction rounds and references of web service requests and response queries on various platforms, there are plenty of redundant records. To identify the unique actions from many redundant interaction records, we identified the item IDs and order IDs and only counted each page visit once for the same item or order. After eliminating redundant records, we obtained 0.4 million unique browsing and purchasing records, related to 28,752 users.

III. CONSUMER BEHAVIOR ANALYSIS

A. Consumer Behavior within a Day

Different consumers have different online shopping time within a day according to their preference and available time. In total, the access peak, purchase peak and successful purchasing ratio peak all occur at 10:00 in the morning, which is at the beginning of work time for most people, as shown in Fig. 1. It seems that many people prefer to do some personal business such as online shopping before work. This may also have some relationship with the delivery strategy of logistics companies because people tend to have their goods delivered as soon as possible and orders paid in the morning usually have priority to be delivered. Another possible explanation is that some users are still on their way to work and therefore have time to visit e-commerce platforms.

However, men and women have quite different consumer behaviors, as shown in the second part of Fig. 1. An obvious purchasing peak occurs in the very early morning around 6:00 for female consumers, which maybe because women have more passion for shopping early. Male consumers tend to finish their online shopping in the morning while female consumers keep browsing and buying nearly throughout the whole day. Moreover, women have more passion for online shopping in the afternoon and an empirical observation is that women tend to be more easily attracted by online shopping, children and small talks etc. in the afternoon in China. Online retailers can carry out more promotion online shopping activities oriented to women consumers to attract their attention and actions.

B. Consumer Behavior within a Week

We tried to find the user behavior difference between workdays and weekends, as shown in Fig. 3. As a whole, users tend to visit and finish purchase on weekdays. The Chinese delivery market is fiercely competitive and thus, the delivery time is quite short for satisfying and winning more customers. On average, an order can be delivered in two workdays. Influenced by the delivery situation, it is quite reasonable to tell why few people choose to buy products on Thursdays. As shown in Fig. 4, male and female users can be divided into two main groups: early workday shoppers and Friday shoppers. Users prefer to do online shopping from Monday to Wednesday probably because they want to receive...
their products on workdays in their companies, while users finishing their online shopping on Friday tend to receive their orders on weekends at home. Weekends are usually used for entertainment and outdoor activities and users tend to spend less time on Internet usage. In addition, users seem to visit e-commerce platforms mainly by wifi which cannot be traced and therefore our result is probably a biased statement.

Since consumers browse and purchase more on weekdays, online retailers can adapt their sale strategies to this phenomenon and organize more promotion activities to attract more consumers and improve their profit.

C. Influence of Special Events

In this section, we investigate the influence of special shopping festivals on consumer behavior in order to aid retailers in their development of marketing programs that can help increase shopping festival sales as well as the total profit throughout the whole year. U.S. Retailers consider two major holiday shopping days as their most profitable: the Friday after Thanksgiving, Black Friday, and the Monday after Thanksgiving, Cyber Monday. Inspired by this, Alibaba held the first “11-11” shopping promotion day on Taobao.com in 2009, storming the online shopping for the very first time. Big promotions in the name of celebrating Nov. 11 Bachelor’s Day usually start at the very beginning of November with huge discounts and give always lined up. There are some other smaller shopping promotion days compared with “11-11”, such as “12-12” and “6-18” as well as some traditional festivals, such as new year, Chinese spring festival, Valentine’s Day etc. Our dataset covers a period including “11-11” and “12-12” of 2016 as well as New Year and Chinese Spring Festival of 2017. Consequently, we can have a rather comprehensive observation about consumer behavior around these festivals and investigate the influence.

From our evaluation, obvious access and purchase peaks occur around “11-11” and “12-12”, as shown in Fig. 5. As mentioned before, “11-11” is an online shopping festival starting several days before the very date. Accessing peaks occur from the beginning of November and in order to decrease the browsing and purchasing pressure of the very day of Nov. 11, many retails choose to bring forward their promotion activities. Considering the purchasing ratio, a higher successful level occurs from Jan. 14, 2017, which is about two weeks before the Chinese Spring Festival. A possible reason is that consumers tend to make some special purchases for the Spring Festival and the need is stronger than usually.

When considering the gender, the result is quite complex and irregular. In average, female consumers have higher accessing ratio while male consumers have higher successful purchasing ratio. More interestingly, both male and female consumers are interested in visiting e-commerce platforms while only male consumers purchase before Valentine’s Day. This phenomenon is inline with Chinese traditional concept of value that a man should buy gifts for his girl friend or wife.

As analyzed above, online retailers can adjust their market strategies to attract more attention from their potential consumers and make their total profit maximum. Special online shopping events are very good opportunities for merchants to finish their annual sale goals while the competition is also very fierce. Proper adjustment for the date maybe make the online retailers benefit from the special online shopping promotion days as well as maximally avoid competition with other shops.

D. Consumer Clustering

Empirically, consumers tend to have different online shopping preference and habits influenced by various factors, such as occupation, social economic status and education
background etc. Understanding consumer behavior difference and can help online retailers to design specific strategies for different consumer groups to maximum their profit. In this paper, we observed that about 85% users have access records to e-commerce websites while have no purchasing actions. Some consumers tend to buy stuff according to their real need and their shopping records are random. In addition to the two kinds of consumers above, another group of users tend to buy plenty of goods during the special shopping events such as “11-11” and “12-12” because of the huge discount. We take the actions of the telecom users in our dataset as features to cluster the online shopping users into several groups.

For consumer clustering, we use $U = \{u_1, u_2, ..., u_M\}$ to represent the consumers access to e-commerce platforms, in which $M$ means the total number of users who have access records to e-commerce platforms. We use $F = \{B, S, P, N\}$ to represent the behavior patterns for each consumer, in which $B, S, P, N$ represent Both(scan and purchase), Scan(no purchase), Purchase(directly purchase without scan) and None(no scan or purchase) respectively. It is easy to understand the consumer behavior of $B, S$ and $N$, while $P$ is also very common for some consumers who prefer to add products into shopping chart first and then need some time for final purchasing decision. In this section, we use K-means clustering algorithm and the input is an array with $D = 110$ dimensions. $\forall u_i \in U$, the corresponding input array is $a_i = [f_1, f_2, ..., f_D]$, in which $f_j \in F = \{B, S, P, N\}(j \in [1, D])$ means the consumer behavior throughout the whole observation period. The number of consumers in our dataset with online shopping actions is 28,752 and the clustering result is shown as Fig. 7(a) when the clusters number is set as 4, in which the X-axis means the number of items scanned and Y-axis means the number of items bought for each user. In Fig. 7(a), the darker the block is, the fewer the number is. Based on the clustering result, most users(78%) only have scanning but no purchasing records. As for the remaining users(22%) who have purchasing actions, 10% only have purchasing records without scanning product details, which is quite normal during the special shopping festivals such as “11-11”, shown as the white block in Fig. 7(b). 8% users prefer to finish their purchasing operations after a plenty of scanning actions to have a comprehensive understanding about the products themselves and different prices across different e-commerce platforms, shown as the red blocks close to the X-axis in Fig. 7(b). The last 4% users tend to make purchasing decisions very quickly after a few scanning operations, shown as the red blocks close to the Y-axis in Fig. 7(b).

IV. RELATED WORK

For the past few years mobile phones have a remarkable evolution and explosive popularization [1]. Meanwhile, e-commerce also has a prosperous development and drastically changed traditional commercial relationships, as well as the shopping process for the fast-growing online shoppers [2]. With a smart phone at hand, the consumer can check the details of products, compare the prices across various e-commerce platforms, save items into charts and enjoy a great many benefits such as personalization from merchants and recommendation from social networks [3]–[6]. The complexity of users’ online behaviors is increasing and understanding consumer online behavior becomes more and more important to know the buildup of successful purchase. Understanding the consumer buying process can make a difference between success and failure in consumer marketing strategies [7].

Research surrounding online shopping analysis has a large body of work [4]–[6], [8], dating back to the early research of purchasing behavior on the Web [2], [9], [10]. The beginning research work focused on the intention identification of users using web service, such as search and browsing [10], [11], which is helpful to improve the quality of a search engine’s results or the attraction of a special website. With the prosperous development of e-commerce and rapid popularization of smart phones, more and more attention are attracted to the user behavior analysis within online shopping. The past research investigated a series of factors leading to successful purchasing results, including motivations, recommendations [12]–[14], personalization, as well as demographic factors, such
as gender, age and residence [15]. This is very useful for e-commerce providers to improve their service quality and competition ability as a result. Our work mainly analyzes user online shopping behaviors using the most popular five e-commerce platforms based on the dataset of telecom, considering factors of gender, workdays and special shopping festivals. In addition, we also studied the purchasing results of the whole day using a time unit of hour and find some interesting results about the most possible “successful” purchasing time periods.

Special shopping festivals have great influence on consumers’ shopping enthusiasm and bring huge profit to online or offline retailers. Esther Swilley et al. [16] examined attitudes and behaviors of shoppers for these two shopping occasions, the Friday after Thanksgiving, Black Friday and the Monday after Thanksgiving, Cyber Monday to help retail managers have a better opportunity to market on these two days with an understanding of consumer intentions for these major shopping occasions based on their findings. Jasmin H. Kwon et al. [17] studied the value of collaborative research on seasonal shopping events and behavior and took Black Friday as a case for study. Chinese online shopping festivals came into being quite later while the influence grows very fast. Juan Liu [18] took a case study of T-Mall “Double Eleven” online shopping event to introduce the change of “11-11” from festive ceremony culture to marketing. Xi et al. [19] tried to analyze the consumer behavior and bandwagon effect with the binary choice model using 1,811 college students as the research objects based on the micro survey data of the “double eleven” online shopping. Our dataset chooses 126,388 telecom users in Shanghai randomly and the results are more general.

V. Conclusion

The popularity of smart phones and prosperity of e-commerce platforms have changed human life style greatly. Meanwhile, the massive mobile data generated brings remarkable opportunities for consumer behavior analysis with the aid of data mining. In this paper, we examine the consumer behaviors using multi-platforms based on a large-scale mobile Internet dataset from a major telecom operator, which covers about 126 thousand users from Shanghai among which nearly half of the users have visited e-commerce platforms within nearly 3.5 months of our study. From our preliminary analysis, we see that male and female online shoppers have quite different behavior and shopping preference. Interestingly, most online shoppers choose to make their purchase at around 10 am., which is the really beginning work time for most people. In addition, we observed that special online shopping festivals such as “11-11” and “12-12” have great influence on consumer behavior in both searching and purchasing products from e-commerce platforms. These findings can be used by e-commerce providers for personalized recommendation system to improve their service quality and profit.

For future work, we currently plan to carry out the research in three aspects. Firstly, we will consider the influence of occupation on consumer behavior. Empirically, people with different occupations have different life styles and social economic status, therefore their attitude and preference to online shopping are also various. Secondly, we will try to find the consumer behavior differences across different regions since different development level and strategies will also have influence on e-commerce market. Finally, we will consider the influence of social relationship on consumer behavior of online shopping since we friends should have similar interests and life styles and we will have more confidence on a product recommended by our friends. We will try to have a comprehensive understanding about consumer behavior and preference when shopping online and then build a recommendation system for different e-commerce retailers to better carry out their market strategies to attract more consumers and gain more profit.

References