ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

User Life Cycle Research Based on User Consumption Data

Hao Qin[1,*]

[1]*Tianjin University of Commerce, Tianjin, 300134, China*
**Corresponding author: qhao063@163.com*

Abstract: *As the size of mobile Internet users grows, the cost of acquiring customer data increases. It is important to develop targeted acquisition, retention and re-attraction strategies for different levels of users. The consumer lifecycle can be divided into three stages: 1) customer acquisition stage, focusing on attracting new customers; 2) enhance customer value stage, focusing on strengthening consumption vitality and repurchase; 3) customer retention stage, mainly through retention and return measures. Different stages of customer contribution to the enterprise is different, so enterprises should adopt different strategies. In this paper, we use Python to analyze and model the data, and implement targeted marketing for different categories of customers by evaluating the market competitiveness of the enterprise, customer classification, and user profiles.*

Keywords: *consumer data, competitiveness, operation strategy, life cycle*

1. Introduction

1.1 Background of the study

Big data mainly refers to massive data, and big data mining is a series of means, such as selection, exchange, analysis, integration, etc., to process massive data, discover new knowledge, and promote the maximization of massive data, multi-head, intensive use in all aspects of society, to create new value [1-2]. In artificial intelligence, "deep learning", "adversarial learning", "augmented learning" and its corresponding adversarial neural networks and convolutional neural networks are closely related to big data mining. In particular, "adversarial learning", "augmented learning" and their corresponding adversarial neural networks are closely related to big data mining. In particular, "deep learning" in artificial intelligence can make it possible to collect big data and provide enough sample data for user behavior analysis. User behavior is usually a record of a user's use, purchase, and evaluation of a good or service through an intermediate resource, as well as a combination of the user's own underlying information attributes (Attribute 1, Attribute 2, ... , attribute N). User behavior analysis of big data and artificial intelligence is mainly guided by this combination of attributes to collect more detailed data on the behavioral attributes of the target user, including user log information (registration information, online shopping, consumption records, activity trajectories, social interactions, etc.), information on the external environment (growth of mobile Internet users, mobile Internet traffic, self-funded packages, etc.), and information on the user's main body (name, gender, name, education level, interests, residence, etc.). education, interest, address, etc.) [3-4]. User behavior analysis in a narrow sense is to mine and analyze statistics on such data under the assumption of obtaining basic data such as application or communication data in order to discover the usage patterns of users, and to integrate these patterns with other industries to discover the personal preferences of users, and to provide a reliable data basis for enterprise services. User consumption behavior analysis includes six models such as behavioral event analysis, page click analysis, user behavior path analysis, funnel model analysis and user profile analysis. These models can obtain different user behavior data, such as user profiles, active users, retained users, etc., covering user loyalty, response rate, as well as information such as user access page, page stay, bounce rate and jump rate obtained through user behavior tracking [3].

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

2. Problem description and Theoretical Foundations

2.1 Problem description

With the development of e-commerce, the user group is getting bigger and bigger, and enterprises statistically analyze the online shopping behavior of users every year in order to obtain the value information contained in the data. Many users will make multiple purchases, making online shopping become a daily consumption mode. Due to the time-sensitive nature of e-commerce, customers will form certain shopping habits in a relatively short period of time. Therefore, data mining is used to analyze the related shopping behavior data in detail.E-commerce is an important source of big data, the major e-commerce companies have introduced their own e-commerce holiday, the most famous is Taobao's double eleven, double twelve. This paper adopts Taobao a year from November to December 3-4 million consumer orders for analysis and research to explore the relationship between the user's consumption behavior, through the study of effective consumption behavior can provide suggestions for marketing strategy, and based on the consumption behavior of the marketing strategy can greatly save costs, improve the use of budgets, advertising, personalized recommendation of goods for the target group, so as to improve the profitability of merchants.

2.2 Definition of user consumption behavior

User consumption behavior is a series of operations from the generation of consumption demand to the termination of consumption behavior by the user. From the perspective of e-commerce platforms, user consumption behavior is shown in Figure 1 below [5-6]. Consumers first generate demand for goods and then choose one or more e-commerce platforms to select goods. Before purchasing the goods, users will understand the details of the goods, browse the goods information and goods evaluation. If the product can satisfy the consumer, the consumer will make a purchase decision; if it cannot satisfy the consumer's needs, the consumer will go to other platforms or look for other commodities to continue to satisfy their shopping needs, so as to complete this consumer behavior.

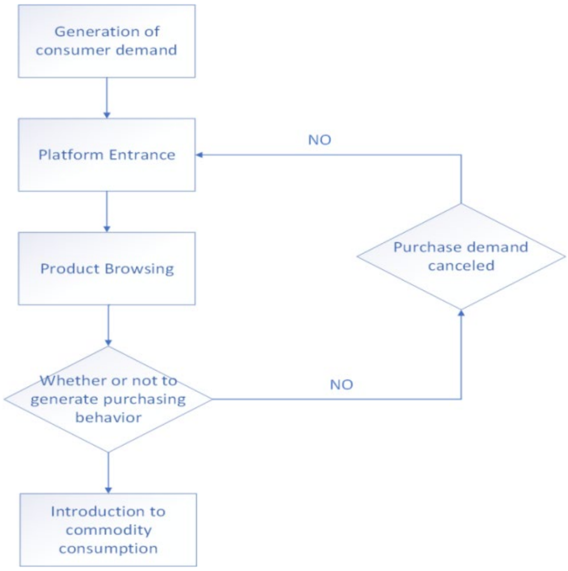

Figure 1: Consumer Behavior Flow

3. User consumption data analysis

3.1 Behavioral Dimension Analysis

3.1.1 RFM Model

RFM is an important modeling tool for measuring customer value and determining how it creates customers. Customer value is presented by three parameters: the customer's most recent purchase behavior, total purchase frequency, and amount spent.

The RFM model shows the complete value picture of individual customers in a more dynamic way,

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

accurately determining the long-term value of a customer over a longer period of time, as well as showing the importance and effectiveness of the decisions made by various marketing tools to impact these three metrics. In RFM, R (Recency) stands for the time of the customer's last purchase, F (Frequency) stands for the frequency of the customer's purchase, and M stands for the amount of the customer's last purchase.

In the business world RFM is often used to send marketing emails to increase the number of transactions between the customer and the company, through RFM can make effective use of funds in response to a greater success rate of the customer, can make the limited budget can be fully utilized.

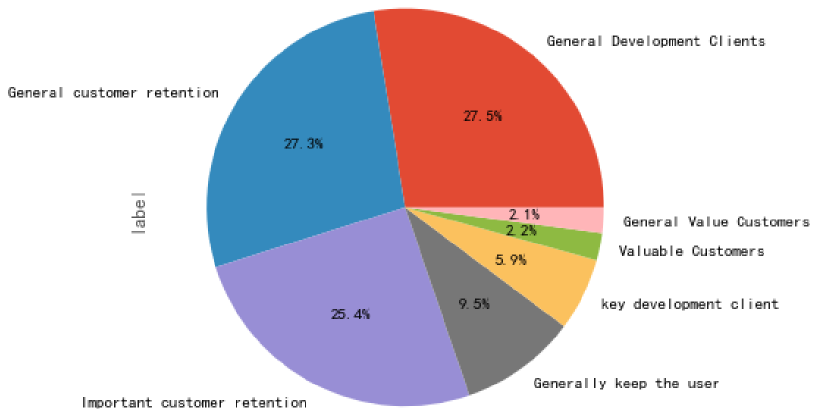

Figure 2: Number of RFM stratified users

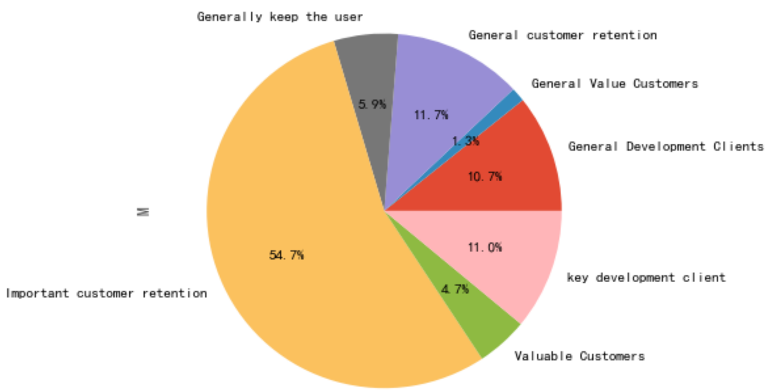

Figure 3: RFM models the amount of money a user spends

Figure 2, Figure 3 shows that the general development of the number of customers accounted for up to 27.5%, but its consumption amount accounted for only 10.7%, consumption accounted for too low, the number of important to maintain the number of customers accounted for only 25.4% but the amount of its consumption accounted for 54.7%. Therefore, when marketers do publicity, within the limited budget should pay attention to the consumption amount accounted for more users and customers, select the higher R value of the user for publicity and marketing can make in the conversion rate is low to improve its conversion rate. The important value of customers in the number of people accounted for the proportion and consumption amount accounted for a small number of this should be related to the sales characteristics of the e-commerce, customer mobility, high loyalty customers are fewer. Among them, the values of R, F and M dimensions are selected by adopting the average value of the respective data columns, and when this model is applied in actual scenarios, the appropriate thresholds should be selected according to the actual situation; in terms of operation strategy, different marketing strategies should be formulated for different classified users in conjunction with the results of RFM's stratified users:1.Important to keep the number of customers accounted for the largest proportion, this part of the customer has a deep hidden value. They have a lot of potential spending power. This category of

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

consumers is widely distributed and numerous, and is an important factor in expanding market share and increasing the profitability of merchants. This type of consumer should take appropriate marketing strategies to stimulate their consumption or increase the frequency of consumption.2.Important to retain customers should take some preferential strategies to stimulate their desire to consume, so that they return and produce consumption value, common strategies are: the issuance of large amount of coupons, appropriate full reduction of preferential policies and so on.3.For important development customers, due to its high value but low frequency, should take appropriate strategies to stimulate its consumption frequency.4.For the rest of the users can be randomly sent at regular intervals, such as text messages, emails and other activities to invite information to promote the return of customers, but do not have to spend too much energy on these users who do not create much value.

3.2 User Dimension

3.2.1 Traffic Indicator Analysis

When analyzing the data, we should also pay attention to the web page traffic analysis, web page traffic in the existence of effective data and invalid data, through the effective web page traffic analysis can accurately analyze the web page of effective data and invalid data so that we can more accurately identify the web page of the degree of attraction of the content of the consumer to better improve the advertisement placement and marketing strategy.

The data is analyzed in python and the data in Table 1 is obtained.

Table 1: User bounce rate

	Number of PV	Number of UV	bounce rate
Total	2999997	9981	0.003327

Where PV is the total number of page views, PV is the number of independent visitors (an IP is considered an independent visitor) that represents a user. Derived bounce rate of about 0.3%. That most of the users into the details of the page to browse the goods, willing to spend time and effort to select the goods, so as to lead to the collection or add a shopping cart and other behaviors to provide the possibility, but also can be a side note that the business ads or activities on the consumer to play a role in attracting the role of the effect is more obvious. And then on the different dates of the visit statistics can be better derived again near the time of the promotional day, consumers on the products and activities of the degree of attention.

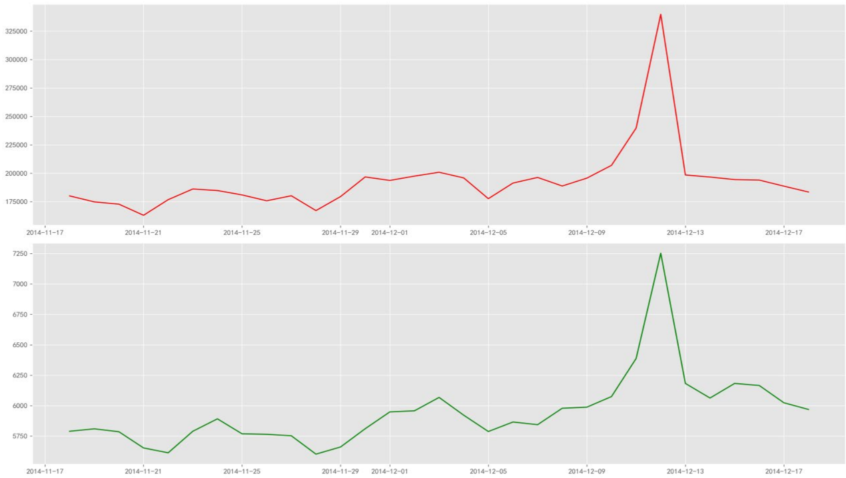

Figure 4: PV(red) and UV(green) trends

As can be seen in Figure 4, independent visitors and total pageviews show a positive correlation. In the promotion day near the total daily page visits and the number of independent visitors have a significant increase, before and after the double 12, pv fluctuates up and down between 100000-20000, uv fluctuates between 4000-6500, in the day of the promotion day to reach the peak page visits rose sharply, proving that the effect of this activity is very good, it can be seen that the vast majority of people to participate in this activity. From the point of view of promotion and marketing, this activity is very successful, and at the same time, it also lays the foundation for the next promotion day. On December 2, the number of visitors reached a small peak, the query learned that the day for the weekend, indicating that the frequency of users in the weekend and the frequency of shopping has increased, can be made for the weekend some of the operation and product push and optimization.

3.2.2 User behavior indicators

The user behavior process can be seen as roughly the following process: clicking on the product, collection of products, add a shopping cart, payment behavior. Analysis of these four user behavior, you can accurately determine when the user interrupts the consumption behavior of the link, can help marketers accurately respond to the strategy and develop a more complete marketing plan. In order for enterprises to realize rapid development, it is indispensable for consumers to continue to be interested in and use the products or services provided by the enterprise. Therefore, how to effectively attract and retain customers is a constant topic for any enterprise. FishbeinMartin, a famous scholar of consumer behavior, pointed out that the most direct way to predict whether a consumer will engage in a particular behavior in the future is to understand the tendency to engage in that behavior.

Table 2: Number of people in each session

shopping session	Number_of_shoppers
Click on the user	5653468
Add to cart users	168546
Favorites	118646
Paying Users	59334

Table2 reflects a series of changes in the behavior of e-commerce users, which can be seen from the initial click users to pay the number of users of the consumer behavior of the number of users show a downward trend. Caused by this series of trends we can make the following assumptions:

Assumption 1: consumers are not satisfied with the products they browse, which can be divided into several aspects: 1: by the impact of product evaluation, consumers will browse the product to comprehensively examine the demand for commodities to meet their needs at the same time will go to the consumer's opinion of the completion of the consumption of the product. 2: the quality of the product, the price is not satisfied.

Assumption 2: when consumers initially selected goods after adding a shopping cart, continue to browse the time period to find the entity alternatives, the alternatives can be divided into several aspects: 1, the shipping time is longer, the consumer demand for a short period of time is more urgent; 2, initially satisfied with the goods, but the price of the goods, postage, or other aspects of the goods to be examined, which led to some users to interrupt their own consumption behavior.

Consumer behavior is an ongoing behavior, and the instability that arises over time is greater, but consumer behavior that changes over time can better reflect consumer behavior patterns over a long enough period of time.

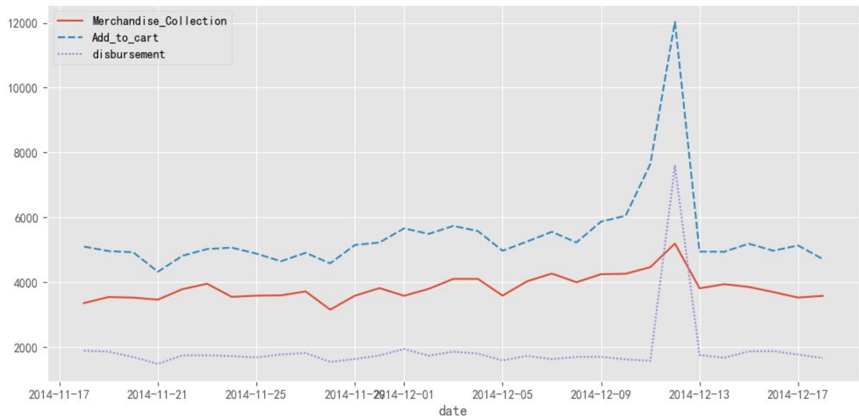

Figure 5: Changes in consumer behavior

Figure 5 reacts to the change of user behavior with the change of date. The number of people who collect, add to cart and pay before December 12 fluctuates around 3,500-5,500, and the trend of change is relatively stable on December 5 and November 25, which is in line with people's needs during normal working days. In December 12 three kinds of behavior have reached the peak, here to reach the peak and the preferential strength of the e-commerce is inseparable, but the actual number of people to pay far less than the number of people to add to the shopping cart, that is, the conversion rate is low. The three behaviors of clicking, collecting and adding purchases are broken down.

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

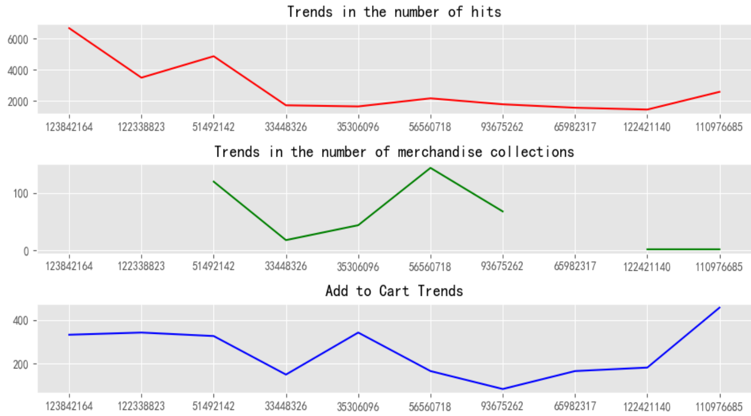

Figure 6: Trends in different behaviors

Figure 6 reflects the number of purchases accounted for the majority of consumers click, collection, join the shopping cart these three behaviors are not necessarily the majority. This process fully reflects the psychological activities of shoppers, in the beginning, will be on the heart of the initial screening of goods, but at this time only into the consumer steps in the product browsing, and then the tentative choice of goods to add a shopping cart, however, in the payment of this step is full of many unknown factors may lead to consumers to interrupt the final consumer behavior. We can analyze the reasons for the interruption of consumption behavior or traffic loss by linking various factors.

3.3 Product Dimension

3.3.1 Analysis of shopping behavior

While shopping carts were originally vehicles used to carry goods, in e-commerce, shopping carts are a functional service [7]. When browsing for products, users add preliminarily selected or intended products to the shopping cart, and users can purchase these selected products when they subsequently perform screening or checkout. Products in the shopping cart are subjectively selected by consumers. Analysis of shopping cart information helps to analyze consumer behavior in depth. Consumers may choose and purchase similar items again after making a purchase, which reflects consumer preferences and goals. Through shopping cart data, it is possible to discover consumers' specific goals and purchase motives, and then predict future purchasing behavior; analyzing the correlation between different products can predict what consumers may be interested in next. These data provide merchants with an effective competitive advantage in the market; studying the information in the shopping cart helps merchants to understand the actual needs of customers, adjust the order of products on the shelves, and analyze the product categories, the number of purchases, and user data in detail in order to make specific preparations [7]. Through the analysis of shopping cart data, merchants can better understand consumer needs and improve service quality and sales efficiency.

For the shopping cart analysis selected goods sales of the top ten products for analysis, the results are shown in Table 3.

Table 3: Commodity consumption statistics

Item_Id	Total
303205878	34
383779671	18
254228319	18
14087919	18
243091690	18
198400340	16
154168523	16
365343482	16
97655171	14
87546522	14

By analyzing the sales volume of the item, the best selling item number is 303205878, which has been purchased a total of 34 times. Then the top 10 selling items were studied for four shopping behaviors are shown in Table 4.

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

Table 4: Commodity consumption behavior

item_id	Click_on_the_product	Merchandise_Collection	Add_to_cart	Number_of_payments
303205878	270.0	10.0	20.0	34.0
14087919	372.0	10.0	16.0	18.0
383779671	16.0	0.0	0.0	18.0
243091690	28.0	0.0	0.0	18.0
254228319	20.0	0.0	2.0	18.0
154168523	16.0	0.0	2.0	16.0
198400340	182.0	4.0	6.0	16.0
365343482	64.0	2.0	6.0	16.0
97655171	646.0	4.0	14.0	14.0
109259240	64.0	0.0	8.0	14.0

Viewing products is the first and key step in consumer behavior, used to determine whether the demand is satisfied. A high click-through rate indicates that consumers keep browsing to determine whether they meet their needs, and then make a second screening of selected products. Therefore, the number of purchases does not necessarily correlate with a high click-through rate, and a low number of favorites and add-to-cart does not necessarily imply a low number of purchases. Studying the top ten product categories to determine their attribution at a strategic and structural level, and especially studying the hot product categories, helps to gain a preliminary understanding of consumer preferences. In addition, analyzing shopping cart information helps to assess consumer interest in attraction tiers with a large number of items to understand the proportionate influence of visual UI design in consumer favoritism.

4. Life Cycle Research

4.1 Lifecycle Consumption Theory

4.1.1 Theory

The theory of life cycle consumption is put forward by American economist Franco Modigliani. The theory is that some rational consumers in the future to predict their own life needs to rationally plan their consumption expenditure and property savings. This rational planning is closely related to the stage of the consumer, different life periods will make different property planning to achieve the most favorable consumer spending and property savings. When the practical factors and the theory are combined, the theory of life cycle consumption can be expressed as follows:$\beta\omega \times \omega\gamma + \beta\gamma\omega \times \gamma\omega$.

c is the annual consumption, $\beta\omega$ is the consumption propensity of wealth, i.e. the proportion of wealth consumed per year, $\omega\gamma$is real wealth, $\beta\gamma\omega$ is the consumption propensity of work income, i.e. the proportion of work income consumed per year, and $\gamma\omega$ is annual work income. Since the consumption planning made by consumers is related to their own period, from this the theory extends another conclusion: the age composition of each stage has an impact on the total consumption and total property reserves in the society. By dividing society into three age groups: young, middle-aged, and old, the different proportions of the three age groups result in different proportions of spending power and property savings.

There are other factors that have an impact on the level of consumption and the capacity to save, such as inheritance tax, which, when there is a high rate of inheritance tax in society, leads to a reduction in the amount of inheritance left and thus an increase in consumption, and when the inheritance tax rate is at a low level, there is an increase in the share of inheritance left, and there are disincentives to consume and produce, which creates a strong social security system and reduces savings, among other things.

4.1.2 Practical application of the user life value cycle

The user life value cycle has the following applications:

1) Not evaluating traffic by a single pathway: current traffic transformations of different pathways are an important guideline, and the life cycle value is an important evaluation index behind the traffic transformation.

2) Explore where consumers' willingness to consume comes from, and based on that, improve the distribution of content to reach the masses. To study the consumption similarity behavior of the

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

high-consumption part of consumers, analyze the content richness and the transient stay of the product characteristics to find out which of the current products meet the consumption standard of the high-value consumer group.

3) Provide different marketing strategies for different life cycles of users to increase the overall value. After categorizing the user profile for each cycle, different strategies can be planned according to the methods derived from the model and the RFM model used to differentiate the methods. Consumers with low lifecycle value will implement targeted product advertising pitches, provide additional strategies to reduce consumer decline, and enhance products and services to recover and organize consumer strategies during downturns.

4.1.3 User Consumption Cycle Analysis

User lifecycle definition: the time interval between the first and last consumption. The longer a user's lifecycle, the more spending money he or she can generate. It is a point of control for companies to earn a greater benefit while extending the consumer life cycle of consumers as long as possible.

Table 5 shows the value of consumption of five users in their own life cycle, the value of consumption generated by a long life cycle is not necessarily high, the life cycle of a short period of time may produce high value but because of its life cycle is too short, in the long run is not necessarily conducive to the generation of high value, but only in the short term to have a higher value of the cycle. A better grasp of the value of the user's life cycle can produce, we can effectively use economic means to extend the life cycle of consumers, increase consumer desire to produce higher consumer value, so that businesses can obtain the maximum benefit.

Table 5: User Lifecycle Value

user_id	price	Life_cycle
100001878	1134	30.0
100011562	178	9.0
100012968	166	29.0
100014060	624	30.0
100024529	540	30.0

The distribution histogram in Figure 7 shows a single peak trend presenting a right distribution, in which the life cycle is less than 20 days, most of the life cycle is more than 30 days, and the frequency is also more than 500. And this data comes from Taobao, now the popularity of e-commerce is very wide, in people's lives everywhere in the figure of e-commerce, so most of the people's life cycle is more than one month. Overall the life cycle of e-commerce users is more stable, without big fluctuations. For consumers of e-commerce, the importance of the life cycle can be appropriately converged under the consumer value, in a certain period of time to make the maximum value of consumption can be generated, so it should be concerned about is the value that can be generated in the life cycle.

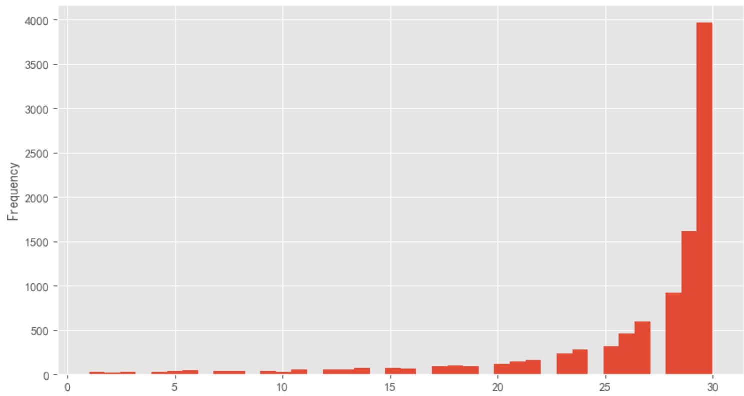

Figure 7: user lifecycle

As can be seen in Figure 7, there is no linear correlation between a user's life cycle and the total value generated during the cycle. Part of the consumption cycle of more than 25 days of users, the cycle of consumption value is greater than the vast majority of the cycle of low users, due to the long life cycle, the consumption amount of time duration, thus the life cycle of high users of the consumption amount of higher than that of the low life cycle of the consumption amount of the user is

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

tending to a greater probability. Customers with a life cycle of 28 days or more have a more stable total value of the life cycle, more concentrated and continuous consumption.

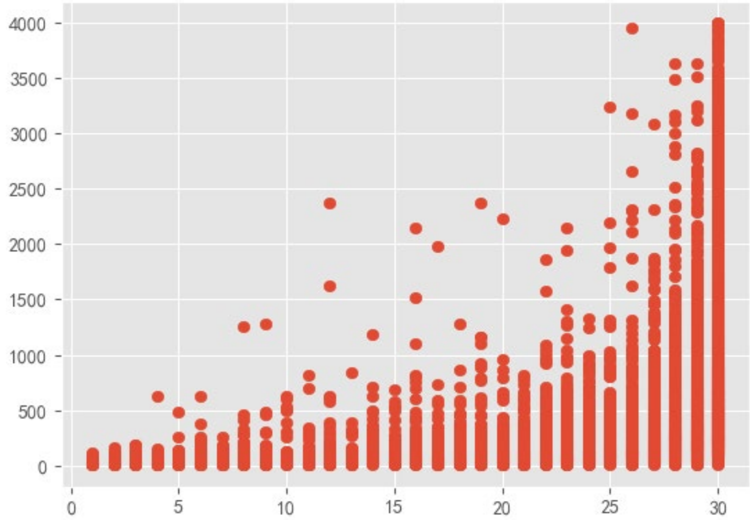

Figure 8: User Lifecycle and Total User Lifecycle Value

As can be seen in Figure 8, there is no linear correlation between a user's life cycle and the total value generated during the cycle. Part of the consumption cycle of more than 25 days of users, the cycle of consumption value is greater than the vast majority of the cycle of low users, due to the long life cycle, the consumption amount of time duration, thus the life cycle of high users of the consumption amount of higher than that of the low life cycle of the consumption amount of the user is tending to a greater probability. And in 28 days life cycle above the customer is a more stable life cycle total value, more concentrated and continuous generation of consumption.

5. Conclusion

This paper analyzes the consumer behavior of users from the user dimension, product dimension and behavior dimension. .Based on the above analysis, this paper draws the following conclusions:

1) The traditional analysis model of customer purchase behavior simply analyzes customer behavior, and it is based on the assumption of customer behavior consistency, ignoring its randomness, the data mining model is based on the premise of customer homogeneity, which is obviously contrary to the current research trend of heterogeneity of purchasing behavior, and the data of customer information it requires is difficult to obtain in most of the Chinese enterprises at present, and in comparison, the stochastic The model uses less customer information, gives full consideration to the characteristics of customer randomness and heterogeneity, and can intuitively calculate the activity of each customer as well as the number of transactions and other results, so it is a more effective method [8-12].

2) Consumer awareness and decision-making behavior in real life is more complex, not as simple as described in traditional economics. With the development of behavioral and experimental economics, there are more and more researches related to it, and with the development of science and technology, there are also many convenient methods and instruments.

3) The research data contains factors such as double eleven and double twelve, and under the interference of the e-commerce promotion day, consumer behavior is more or less affected by the strength of the offer, which results in the inability to very accurately respond to the consumer's consumption and purchase behavior[13-14].

References

[1] Mei Hong. Status quo and future trend of big data development[J]. Transportation Research, 2019,5(05):1-11.
[2] Sun Longjie, Yu Kaijun. Exploration of big data analysis model of library user behavior based on internet of things[J]. Software, 2019,40(06):113-118.

ISSN 2616-5902 Vol. 5, Issue 18: 147-156, DOI: 10.25236/AJBM.2023.051823

[3] Yu Zechuan. Precise positioning and behavior analysis of users based on big data[D]. Beijing University of Posts and Telecommunications,2019.
[4] Pan Huiping. User behavior analysis based on big data and artificial intelligence[J]. Modern Computer, 2021(02):47-50.
[5] Gu Haibin. Research on user consumption behavior analysis method based on large-scale e-commerce data[D]. Jilin University,2016.
[6] Zhu Xuehong. Research on consumption behavior intention of mobile internet users[D]. Nanjing University of Posts and Telecommunications, 2011.
[7] Liao Heng.Research on e-commerce user behavior analysis based on data mining[J]. Marketing World, 2020(34):61-62.
[8] Chunlian Zhang. Research on BG/NBD Prediction Model of Customer Buying Behavior and Its Application[D]. Harbin Institute of Technology, 2006.
[9] Zhai Jinzhi. Analysis of online users' consumption behavior based on big data[J]. Business and Economic Research, 2020(24):46-49.
[10] Wang Sufang. Analysis of mobile user behavior in big data environment[J]. Information Technology and Informatization, 2020(11):250-252
[11] Zhang Wanting,Zhao Min. Research on website user behavior analysis and service recommendation[J]. Intelligent Computer and Application,2020,10(02):71-74.
[12] HU Min,HE Zhenghong,HAN Wei. Research on user behavior analysis system of university network under the background of big data[J]. China Management Informatization, 2020,23 (14):178-179.
[13] Xu Hui. Application and research of web user behavior analysis based on data mining[D]. Yili Normal College, 2016.
[14] Zuo Li. Analysis of the relationship model construction between product sustainable design and user behavior[J]. Knowledge Base, 2020(20):192-193.