Research on Influencing Factors of M-Customer Satisfaction based on Platform Service Quality

Mengjun He [a], Huaigang Wu [b, *] and Ting Yuan

School of Computer Science & Technology, Nanjing Normal University, Nanjing 210046, China

[a]17805003922@163.com, [b]05324@njnu.edu.cn

Abstract

In the Multi-platform access Two-sided Networks,most customers use several platforms to shop. Customer satisfaction with different platform services lead to different dependence of customer to platform. In order to study the factors influencing the m-customer satisfaction, the study builds the evaluation model of m-customer satisfaction based on the HMM method. Customer satisfaction of mobile terminal is studied by combining factor analysis and other methods.The results showed that the applicability of the software, the platform reputation and the corresponding level of logistic, have a significant impact on customer satisfaction. The HMM model can accurately reflect the relative importance of each factor to the m-customer satisfaction.

Keywords

Mobile Terminal; Platform Service Quality; M-Customer Satisfaction; HMM Model.

1. Introduction

With the rapid development of online shopping market, the scale of online shopping customers are increasing as well. E-commerce platforms grow from few initially to many nowadays. Meanwhile, the open environment Internet owns specially makes e-commerce platforms compete fiercely. Multi-platform access is ubiquitous in the bilateral market, and has a profound impact on the marketing activities and pricing strategies of enterprises of e-commerce platforms. In traditional competitive market, the products or services offered by the competitive enterprises usually let the customer choose one or the other option, that is, exclusive demand. But it can be different in the bilateral market, for example, people can make a comparison in Jingdong , Taobao, and Amazon when they are shopping. On the one hand, the behavior of user access to multi-platforms arises because of incomplete replacement of platform services , on the other hand , it is because users can enjoy the benefits from different platforms brought by user scale.

E-commerce breaks the limit of time and region ,making network users ' consuming behavior more likely to change. Satisfied customers can maintain long-term will of purchasing products or services and a low tendency to consumption transfer. So e-commerce platforms are faced with key issues such as how to improve customer satisfaction, how to increase customer reliance on platforms, and how to encourage customers to reuse their own platforms. The bi-directional feature of mobile Internet makes purchasing behavior easier to transfer and more casual to converse platforms, so that customer management is facing a huge impact. We must take effective measurements to maintain the relationship with customers. The huge share of the mobile e-commerce market has brought great attraction to the various e-commerce platforms. However, there are many factors affecting customers' satisfaction with the service quality of e-commerce platforms. How to improve key factors is a consideration in the future. So it is meaningful to study the issue of mobile e-commerce customers' satisfaction to platforms. This paper first investigates to determine mobile terminal - to - platform customers' satisfaction Index System, and then construct factor analysis and HMM model to evaluate customer satisfaction. Finally, actual data are used to analyze the influence level of various factors on customer satisfaction.

2. Influencing Factors of Mobile Customer 's Satisfaction with Platform

2.1 Research on Customer Satisfaction

There have been a large number results about the research on customer satisfaction , including factors of customer satisfaction, evaluation indicators, the formation mechanism, and the application in industry [1]. Many researchers have strengthened research on the field of e-commerce in recent years. In the aspect of customer satisfaction, Xu Donglei and Wang Zuzhu[2]think that customer satisfaction is the certain emotions of customers when they compare their expectation of the products or services with the actual quality, is a mental state based on material perception. Chen Xiangqing [3] thinks that the comparison criteria in the process of achieving customer satisfaction includes the expectation inconsistency pattern, the need inconsistency pattern, perceived performance pattern, perceived fair pattern, in which "expectation inconsistency " is the mainstream pattern of customer satisfaction measurement. Research on the influencing factors of customer satisfaction develops fast as well, but research on the satisfaction of platform service quality is relatively few. Kassim et al. [4] (2010) studied the satisfaction of e-commerce customers in two different cultures in Malaysia and Qatar, showing that customer expectations and perceived quality have an important impact on customer satisfaction in the context of e-commerce, which don't differentiate from each other because of their different cultures. Askariazad et al [5] (2015) found that the reputation of the e-commerce platform has a direct impact on customer expectations, customer satisfaction and customer loyalty when they studied the application of ECSI in the field of B2B e-commerce. Li Weiping, Hu Pei [6] pointed out that social value, seller services, logistics services, etc. will affect the online shopping satisfaction of customers. Xie Peihong, Liu Xia et al [7] found that security privacy, commodity characteristics, information quality, web design , etc. have a positive impact on customer satisfaction in e-commerce through the empirical analysis. Wang Qiaoyu, Qian Huimin [8] pointed out that the unique experience of O2O platform has impact on consumer purchasing decisions. As customers shop on mobile terminal, the performance of mobile phone, data consumption by platform services and other platform practicality will lead customers to give up their shopping willing, for which, Xu Xu et al [9] proved that there is an impact on this by Investigating consumers. The evaluation models and methods of customer satisfaction are as follows: AHP (10), fuzzy comprehensive evaluation method [11], fuzzy analytic hierarchy process [12], etc., which are susceptible to subjective preferences, leading to the irrational weight distribution of each factor. In this paper, we establish the model with actual data base on HMM [13] method to analyze, eliminating the impact of subjective preferences and obtain more accurate relative importance of each index.

2.2 Analysis on Evaluation Index of Mobile E - commerce Customer Satisfaction to Platforms

According to " Research on China Online Shopping Market Report in 2015" , published in June 2016,by China Internet Network Information Center (CNNIC), as of December 2015, the number of China's online shopping users reached 413 million, increasing by 51.83 Million, compared with the end of 2014,a growth rate of 14.3%, and the scale of China's online shopping market still grows steadily. At the same time, the scale of China's mobile terminal shopping users has grown rapidly, reaching 340 million, a growth rate of 43.9%, whose growth rate is 3.1 times that of the overall online shopping market. The use ratio of mobile network shopping increased from 42.4% 54.8%, as shown in Figure 1.So this paper discusses for mobile e-commerce customers.

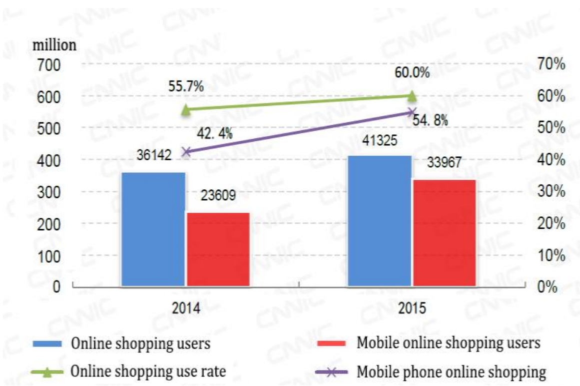

Fig.1 2014-2015 Online and Mobile phone shopping users and rate

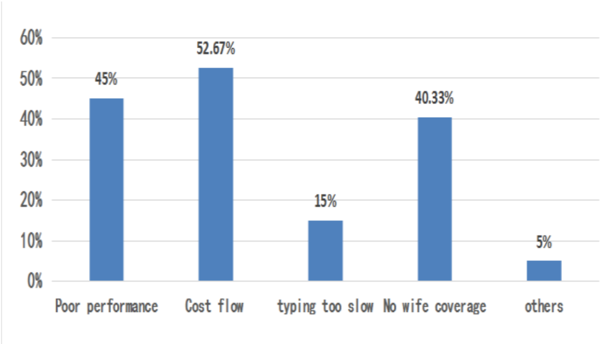

Fig.2 Mobile customer abandon the reason for shopping

According to the need of research, we conducted a questionnaire survey to the relevant experts and business platform related staff. A total of 445 questionnaires were obtained from the paper questionnaires and the questionnaire software. 400 valid questionnaires were filtered and were filtered again to ensure the validity of the questionnaire. These questionnaires were processed with SPSS software, and the indicators such as buyer information, platform quality, technical condition and Internet legal system were selected as the evaluation index. Indicator information includes: (1) the security and convenience of mobile terminal applications and wireless network; (2) the integrity of e-commerce law, Whether the platform website has been certified by three parties; (3) The practicality of the platform commodity, the quality of the website, the brand price of the platform commodity and the promotion activity; (4) the quality of the platform and the reputation of the platform; (5) the personal tendency of the customer, the experience of online shopping, the degree of preference for the goods; (6) the visibility of the platform, the change of the terminal and so on. The survey found that more than 50% of mobile customers will abandon a platform because of its traffic consumption. Customers choose to use package data to shop, and the performance of the phone will also affect the customer's shopping. 45% of customers will give up shopping because of poor performance of mobile phones, as shown in Figure 2. In addition, the security and convenience of applications also affect the experience of shopping. The convenience of mobile devices will increase the frequency of customers to access platforms. Good customer perception will stimulate customers to use the platform again, improving customer satisfaction and the viscosity of the platform. as the channel between customers and sellers, mobile terminal applications allow customers to experience better products and services.

With the development and wide use of the Internet, incomprehensive problems of information has been improved. Customers can compare goods among multiple platforms and brands. The Cost-effective of these platform commodities The cost of each platform commodity has become an important factor in determining their purchase tendency and satisfaction. Using a Tablet PC, mobile phones In a period of time is due to the customers' passion for new things. The use of Alipay, WeChat makes platforms position customer groups faster. The result of the survey shows in Figure 3, 44.5% of customers focus on product quality, and only 8.6% of customers tend to the price of goods, which indicates that in the selection process, price isn't the main factor. Product quality, platform after-sales service, and platform logistics and distribution capabilities have become important factors.

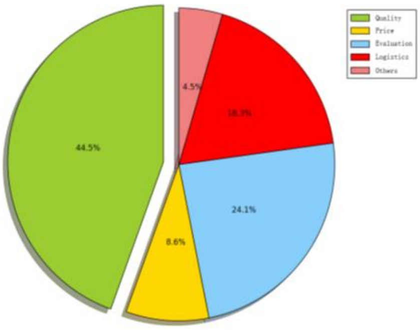

Fig.3 Factors that affect the customer's choice of business

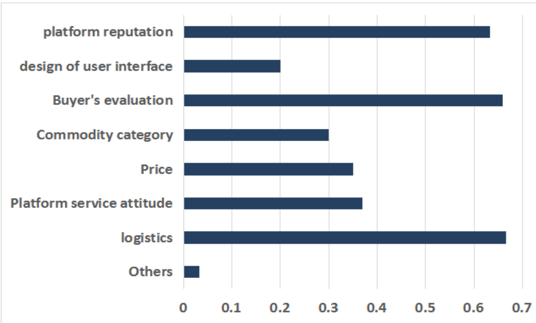

Fig. 4 Factors that affect the customer's choice of goods

In the environment of Internet, as long as customers have computers or mobile terminals, they can randomly select their favorite products without going out, which reduces the number of goods turnover, and thereby reduces the cost of goods transfer. When customers buy products, they prefer high-profile platform sellers. They usually think that the higher the website's reputation is, the higher the usefulness and security of the site are. The higher the satisfaction of the store, more inclined are the customers to visit the products of this store, which is more likely to carry the tendency to shopping in this store . On the contrary, if the customer satisfaction to sellers is low, it is more likely to lose customers. As shown in Figure 4, 63.33% of the surveyed customers will choose a well-known platform to shop, and 66% of the respondents will be affected by the evaluation of goods and give up the purchase of certain goods. It is more important for the improvement of the logistics level. 66.67% of the customers will give up the use of a platform because of the delivery capacity of the platform. In the condition of same goods and same price, the shop's web design, logistics, the type of goods will affect customers' purchase will. Therefore, improving the level of logistics and seller' attitude can make buyers have a greater shopping experience and improve customer satisfaction, which can give customers a good impression Virtually.

3. Construction of Satisfaction Evaluation Model for Mobile e - commerce Customers

By running Python 2.7.12 software, we construct the Recessive Markov model with multiple attributes. Recessive Markov model has no constraint on the number of influencing factor index and the number of recessive states, which can do self-learning continuously with new data any time to adjust its Internal weight parameters, having high capability of training and fault tolerance. As the HMM model has the advantages of high precision, we use the hard factor of historical customer satisfaction as the training set, and selected samples for experiment. The specific settings for the HMM model are as follows:

$U = \{U_1, U_2, ..., U_h\}$ 1) In order to ensure that the input status is the same with the customer satisfaction index of platform, we filtered customer satisfaction factor index, determining that there are 17 observation states, and for the N different observation states, we use to represent ; for the i-th state Observations we use qi to represent. For different observations we normalize them. The formula is as follows:

$$q_i = \frac{q_i - q_n}{q_n} \tag{1}$$

2) Recessive Markov model can not only measure the level of recessive state, but also can calculate the corresponding weight of multiple recessive states, which is defined as the recessive state of the customers. Recessive state is defined as the customer satisfaction degree of platforms: $S_k = (very \quad low, low, medium, high, very \quad high)$. We process the observations with formula (1), making

$\pi \; q_i \in [0,1]$. A represents the transition probability matrix of the recessive state, a matrix of [n x n]. B is the mixed transition probability matrix of n observations and recessive states, and is the initial probability of the state.

$$HMM = (S, A_k, B_k, \pi) \tag{2}$$

3)We train the parameters of the HMM by obtaining data. Because there is no clear way to determine the weight, here we use the factor analysis method to obtain the relative weight of each factor as the correlation degree Cx and k of x factor and k factor. The multiple observation sequences of the index x and the joint probabilities of other k-1 indicators are shown in the following formula (3). O refers to observation sequence of all indicators. Ok refers to the observation of the kth indicator.

$$P(o \mid \lambda) = \frac{1}{K} \sum_{k=1}^{K} \left((C_{x,\ k}) P(O^k \mid \lambda) \right) \tag{3}$$

Parameter formulas of training HMM [13] are as follows: $\xi^k(m,n)$ represents the joint probability that the attribute k is shifted from state m to n. $\lambda^k(m)$ represents the probability that the state of attribute k is m.

The transition probability of recessive state m to n: a_{mn}

$$a_{mn} = \frac{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda)) \sum \xi^k(m,n)}{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda)) \sum \gamma^k(m)} \tag{4}$$

The probability that the observed state in the recessive state m is x: bmx

$$b_{mx} = \frac{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda)) \sum \gamma^k(x)}{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda)) \sum \gamma^k(m)} \tag{5}$$

The probability of the initial state m: π_m

$$\pi_m = \frac{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda)) \gamma_1^k(m)}{\sum_{k=1}^{K} (C_{(x,k)} P(O^k|\lambda))} \tag{6}$$

4) Through the historical observation data, we can train the parameters of the Recessive Markov model. The HMM model can be used to estimate the observation of satisfaction of the next moment. There are some differences between the predictive value and the observations of each index. In this paper, we normalize the error of square root of mean to calculate the error of HMM model. PR(U) represents the predictive value of the Uth observation state. AC(U) represents the actual value of the Uth observation state. n represents the number of observation state; $AC(U)_{\max}$ and $AC(U)_{\min}$ represent the maximum and minimum of the Uth observation state. Normalizing

root-mean-square error can measure the adhesion degree of the model, and smaller the value, the higher the fit degree. The formula(NRMSE) [14] is as follow:

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\frac{PR(U)-AC(U)}{AC(U)\max - AC(U)\min}\right)^2}{n}} \tag{7}$$

4. Experiments and Results

4.1 data description

For the order quantity and relevant comments of Samsung brand notebook desktop SSD, this paper selects the Tmall (which is expressed in T) and Jingdong (which is expressed in JD) platform for data crawling by Web crawler. To improve the information value of the data, we filter the data by removing the redundant information. We choose the sales information and comments from January to July for evaluation. It has been shown that the sales are steadily increasing. However, the differences are quite remarkable in terms of sales in each month of the two platforms. As is shown in Figure 5, in June and July, the sale of Tmall was much higher than the sales of Jingdong, which also illustrates that the customer satisfaction, or the use, of the two platforms is quite different. To explore the factors related to platform satisfaction, we conducted a questionnaire among the professional staff to get the data of the relevant indicator.

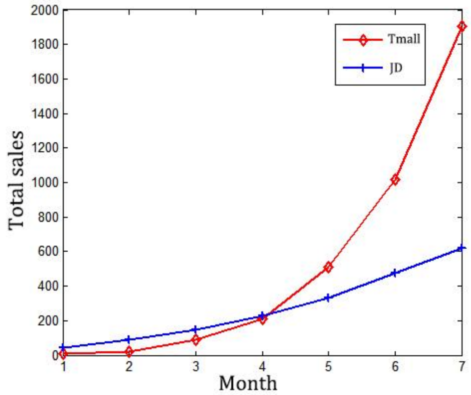

Fig.5 Tmall and Jingdong platform January to July sales

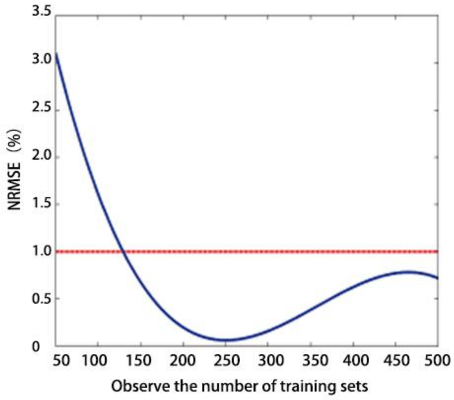

Fig.6 The Model Analysis of the best training set

4.2 Data analysis and model comparison

The importance of each index is not equal, this paper established the HMM evaluation model to get the relative importance of each index through the analysis and comparison of all the indicators.The HMM model is based on the dynamic data to adjust the internal weight parameters, it has high training ability and fault tolerance, it also has high accuracy. In order to test the feasibility of the model, the

HMM model was compared with the common factor analysis model and logistic regression model. The factor analysis is used to aggregate the multiple indexes into a small number of indicators, which can reduce the repeatability and the complexity of the analysis.

Table 1. Factor analysis

Component	Original eigenvalue			Capture squared and loadings			Rotation Sums of Squared Loadings	
	Total	% of Variance	Cumulative	Total	% of Variance	Cumulative	Total	% of Variance
1	16.584	48.775	48.775	16.584	48.775	48.775	8.7	25.59
2	3.17	9.323	58.099	3.17	9.323	58.099	4.787	14.08
3	1.707	5.022	63.12	1.707	5.022	63.12	4.346	12.781
4	1.525	4.485	67.606	1.525	4.485	67.606	3.815	11.22
5	1.171	3.444	71.05	1.171	3.444	71.05	2.227	6.55
6	1.016	2.988	74.038	1.016	2.988	74.038	1.298	3.817
7	0.965	2.838	76.876					
8	0.799	2.349	79.225					
9	0.65	1.912	81.137					
10	0.561	1.65	84.564					
11	0.52	1.528	86.092					
12	0.39	1.148	89.871					
13	0.357	1.05	90.921					
14	0.164	0.484	97.444					
15	0.148	0.435	98.324					
16	0.06	0.176	99.852					
17	0.05	0.148	100					

This paper uses factor analysis to establish the statistical model, in order to analyze the reliability and validity of the evaluation model, this paper normalize the value of index according to the digital statistics and expert experience.

By using the SPSS software, we learn the KMO of the analysis sample values 0.810, and significant probability of the analysis sample is less than 0.01, which explain the index meet the principle of relevance and are suitable for factor analysis. Calculating the eigenvalue and contribution rate of principal components principal component feature calculation value and contribution rate, we establish the factor analysis model as is shown in Table 1.

As can be seen from table 1, the 6 common factors extracted from the 17 indexes of the theory can be used to explain the 74.038 percent of the total change of the variance. Expelling other factors but the six main indexes, we can conclude the most important indexes are: (1) utility of the platform, that is, the ease of use of the application when the customer is using the platform, and the consumption of data flow when browsing products. (2) Platform commodity price. The level of the goods on different platforms is distinctive, such as: the goods on vipshop.com are more expensive that Taobao.(3)Logistics level of the platform.(4) Platform reputation.(5) Safety.(6)Design of the user interface. Combined with the factor analysis table, this paper establishes the normalized linear expression of each index data according to the factor load matrix as follows:

$$f = 0.3456X_1 + 0.1902X_2 + 0.1726X_3 + 0.1515X_4 + 0.089X_5 + 0.052X_6 \tag{8}$$

The comprehensive satisfaction score function is calculated by factor analysis, and the score is compared with the critical value to judge the customer's satisfaction. Put the value of the customer satisfaction factor into the model above to obtain the value of f, calculate the f threshold as the criterion, the significance level of 0.05 confidence interval (-0.2536,0.2536). Calculate the critical value of as the criterion, the confidence interval with a significance level of 0.05 is (-0.2536, 0.2536). we set the value of 0 is the critical point, if the calculated value of f is more than 0, indicating that the customer's satisfaction is high, if the value of f is less than 0, indicating that the customer satisfaction is low, the model discrimination of results is shown in Table 2:

Table 2. Factor analysis model to determine the results

	Discriminate value	Low satisfaction	High satisfaction	Correct rate（%）	false positive rate（%）
Actual value		0	1		
Low satisfaction	0	355	45	88.75	11.25
High satisfaction	1	62	338	84.5	15.5

Logistic regression model is based on a statistical model to predict the future situation, then reflect the future through the regression forecasting model. On the basis of access to index that affect the customer satisfaction, the mathematical model established mathematical model of data between a plurality of indicators, mining the mutual relationship and internal laws between multiple indexes. Logistic regression model solve the defect of assuming constraint of linear equation, without need to meet the independent variable obey the normal distribution and equal covariance hypothesis. However, to avoid the shortage of multiple linear between indexes, we aimed at variable correlation inspection. In order to reduce the error rate of logistic model, we set L=0.42 as the critical point, if the calculated value of L is more than 0.42, the greater the value, the greater the probability that the customer's satisfaction is high, if the value of L is less than 0, the smaller the value, the greater the probability that the customer's satisfaction is low. The calculated results are 0.735 and 0.824, we can come to the conclusion that the fitting degree of regression model is good. The Logistic regression equation is established, and the results of the model are shown in Table 3.

$$Ln(L/(1-L)) = 0.638 - 0.214x_1 + 0.024x_2 - 0.124x_3 - 0.012x_4 - 0.045x_5 + 4.123x_6 \tag{9}$$

Table 3. Logistic model to determine the results

	Discriminate value	Low satisfaction	High satisfaction	Correct rate（%）	false positive rate（%）
Actual value		0	1		
Low satisfaction	0	368	32	92	8
High satisfaction	1	32	368	92	8

By running the Python 2.7.12 software, the historical observation data are analyzed and processed. We found that there are great differences between the T and the J platform sales. We also found differences in customer satisfaction of different platforms through the comparison between the two platforms. We train the HMM model with the previous 500 historical data sets to observe the error size of the normalized root mean square in the model. When the number of training sets of the model is found to be 250, the normalized root mean square error is the least, which is helpful to fit the training sample. When the data set exceeds 475, it leads to overtraining problems, as shown in Figure 6. For deeper research on the effect of training sample size on HMM model, this paper digs more data samples to make a study by Web Crawler. It is found that the optimal number of samples will decrease with the increase of the number of samples, the size of the square root error will decrease as the training sample increases, and the higher the accuracy of the judgment model, as is shown in Figure 7.

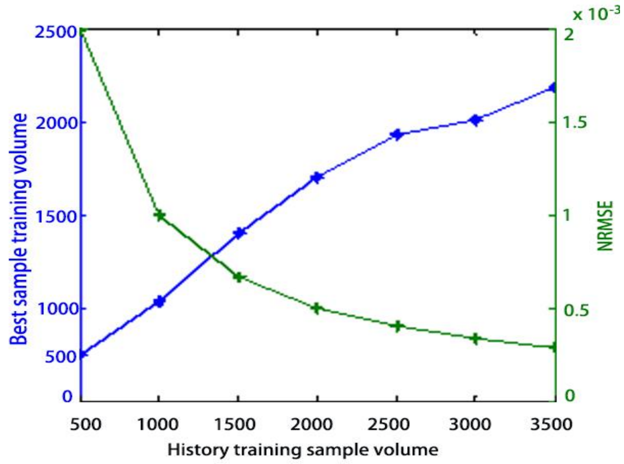

Fig.7 Historical sample set quantitative error analysis

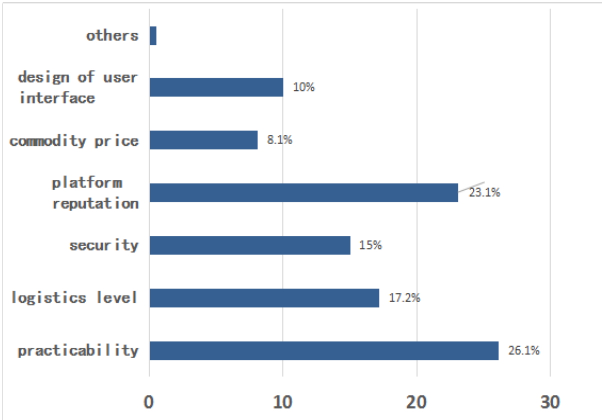

Fig. 8 Factors that affect customer satisfaction with the platform

Since the Hidden Markov Method lacks the ability to interpret the model, it is necessary to further explore the size of the normalized root mean square error (NRMSE). The smaller the value of NRMSE, the better the effect of the model fits, the more accurate the prediction is. In order to judge the level of satisfaction better, this paper chooses the 250 optimal training set of training sets, determine the NRMSE = 0.01 as the critical point, When NRMSE is less than 0.01, judge the customer to be with high satisfaction. When NRMSE is more than 0.01, judge the customer to be with low satisfaction. The results of the model are shown in Table 4.

Table 4. HMM model to determine the results

	Discriminate value	Low satisfaction	High satisfaction	Correct rate (%).	false positive rate（%）
Actual value		0	1		
Low satisfaction	0	491	9	98.2	1.8
High satisfaction	1	9	491	98.2	1.8

In order to make the comparison between the models relatively reasonable, select 500 samples as a training set, try to keep the number of questionnaires similar to the use of HMM model to test customer satisfaction. The HMM model was used to test the customer satisfaction, and the results were compared. In the correct rate, the HMM model was the highest, Logistic followed by the simple factor analysis method. In the misjudgment rate, the simple factor analysis method is the highest, followed by Logistic method, HMM model is the lowest. Compare the accuracy of the three algorithms, HMM model is the highest, and secondly the Logistic regression model, the simple factor analysis model works the worst.

Not only that, HMM model can be relatively accurate to reflect the relative weight of each indicator. Analysis and process the indexes through the data obtained, and then calculate the value of the indexes of HMM. We can come to the conclusion that these six aspects of the platform influence the customers' satisfaction most: practicability, platform reputation, commodity price, logistics level, security, and the design of user interface, as is shown in Figure 8. Enterprises should pay more attention to the practicality of the platform, logistics services and security, improve their ability and service, and enable customers to get better service, reduce customer complaints and improve customer satisfaction. It will eventually bring the platform a good reputation, the frequency of the transactions between business and customer will continue to increase, and cycle of the transactions will be shortened. The customer's trust will continue to increase, and the corporate reputation and customer loyalty will consequently increase.

5. Conclusion

In this paper, we discuss the problem of mobile customer satisfaction in e-commerce platform, and use HMM to analyze customer satisfaction. The result shows that the evaluation model has good prediction accuracy. The HMM model was compared with Logistic regression model and complete factor analysis model. The result shows that the accuracy of HMM model was the highest, followed by Logistic regression analysis. In order to make the model more consistent with practice and reduce the model error, it is necessary to constantly test the training sample data, arrange the experimental simulation and test the model to confirm that the HMM model has high accuracy and effectiveness, thus the HMM model can be used in the study of customer satisfaction. After analyzing the model, we reach the conclusion that factors such as the practicality, reputation, level of logistics, safety and the design of the platform have significant influence on customer satisfaction.

References

[1] Dong Dahai, Wang Keyang. A Review of Western Customer Satisfaction Measurement Model[J].Science of Science and Management of S.& T,2004,(1),p.92-96.

[2] Xu Donglei, Wang Zuzhu. Influencing Factors and Models of C2C E - commerce Customer Satisfaction[J]. Journal of Library and Information Science,2010,(3),p.143-146.

[3] Chen Xiangqing. Analysis on Customer Satisfaction of O2O E - commerce[J]. Journal of Commercial Economics,2016,(14),p.46-48.

[4] Askariazad M H, Babakhani N. An application of European Customer Satisfaction Index (ECSI) in business to business (B2B) context[J]. Journal of Business & Industrial Marketing, 2015, 30(1),p.17-31.

[5] Lin M J, Wang W T. Examining E-Commerce Customer Satisfaction and Loyalty: An Integrated Quality-Risk-Value Perspective[J]. Journal of Organizational Computing and Electronic Commerce, 2015, 25(4),p.379-401.

[6] Li Yuping,Hu Pei. A Study on Influence Factors of E － satisfaction[J].Commercial Research, 2015,(1), p.160-165.

[7] Xie Peihong,Xi Hongmei,et al. An Empirical Study on the Factors Affecting Customer Satisfaction in China 's B2C E - commerce in the Transitional Period[J]. Science Research Management,2011,(10),p.109-117.

[8] Wang Qiaoyu,Qian Huimin. Research on the Influence of O2O Network Platform on Consumers' Purchase Decision[J]. Journal of Commercial Economics,2016,(20),p.53-55.

[9] Xu xu,Liu Hongjun. Evaluation of Mobile E - commerce Customer Trust Based on BP Neural Network Model[J]. Statistics & Decision,2016,(10),p.60-63.

[10] Zhao Jiaying. Evaluation Method of E - commerce Service Satisfaction Based on Fuzzy Analytic Hierarchy Process[J]. Informatization Research,2011,(3),p.52-55.
[11] Pan Yong,Zhao Junmin. Research on Evaluation of Electric Commerce Websites Based on Customer Satisfaction [J]. Journal of Modern Information,2008,(5),p.220-223.
[12] Yang Haoxiong,Wang Wen. A Study on Customer Satisfaction Assessment System of Third Party Logistics[J]. Management Review,2015,(1),p.181.
[13] Li X, Parizeau M, Plamondon R. Training Hidden Markov Models with Multiple Observations-A Combinatorial Method[J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 2000, 22(4),p.371-377.
[14] Mistry S, Bouguettaya A, Dong H, et al. Predicting Dynamic Requests Behavior in Long-term IaaS Service Composition [J]. IEEE International Conference on Web Services, 2015,p.49-56.