Research on Consumer Classification and Service Quality Satisfaction of Agricultural Products Based on RFM-SERVQUAL Model

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Abstract: At present, the rapid development of e-commerce, effectively identifying the individualized needs of consumers and improving the service experience of consumers is a key factor for e-commerce companies to gain competitive advantage. This paper introduces the RFM model for the first time to study the field of agricultural products e-commerce, and provides new ideas for the consumer segmentation of agricultural products e-commerce platform. Based on the improved SERVQUAL evaluation method, the quality satisfaction of agricultural products online shopping service is studied to explore the agricultural products. Commercial consumers' personalized service needs to provide practical development strategies.

1. LITERATURE RESEARCH

1.1 Consumer Value Classification

In the consumer value classification method, WY Chiang consumer value starts from the improved RFMDR model, divides the online shopping market into three markets, and classifies consumers [4]. CH Cheng applies the quantized values of RFM attributes and k-means algorithms to rough set theory to identify consumer characteristics to enhance consumer relationship management [5]. Yang Bin (2015) proposed a data processing using RFM model, combined with K-Means algorithm and association rule mining Apriori algorithm for two-stage consumer association classification method to extract consumer information and classify association analysis for consumers [6]. YL Chen integrates the frequency, frequency and currency (RFM) concepts presented in the market literature and develops a new algorithm for generating all RFM sequence patterns from consumer purchase data to generate valuable value for managing consumer decision-making behavior. Information [7]. Lu Bin (2013) uses the RFM model to classify consumers and uses CRM as the core marketing system to conduct marketing strategies for different optimization combinations [8].

There are also many applications in the classification of consumer value. In terms of price setting, Frow P believes that the value proposition is two-way learning generated when consumers participate in determining the price. The value of the relationship based on the consumer expands the previous discussion of the value proposition. The growing common pricing has been explored [9]. Section's consumer value prediction model proposed in commodity development research to predict the development of new products, to meet consumer demand, to increase market profit and share must focus on the development of new products [10]. In the field of air traffic, Mohaupt M classifies consumer relationships by assessing the impact of consumer expectations on revenues, combining time-distribution information selection to maximize expected value in opportunity-cost
comparisons, and revenue management based on consumer value [11]. Lin Xu predicts consumer churn in a hybrid process neural network based on Fourier orthogonal basis function in mobile communication [12]. In order to solve the problem of commercial banks identifying consumers, Peng Y constructed the company's comprehensive evaluation model for the evaluation and classification of consumer value of commercial banks from the reality of commercial banks [13].

According to the relevant research of experts and scholars, in terms of methods, experts and scholars have used the RFM model to divide the consumer value and get better research results. This article draws on the foundation of the previous experts and scholars to continue to use the RFM model to gain a deep understanding of consumer value. In terms of applications, consumer segmentation has successfully guided many traditional marketing management practices, but most of the research is based on the technical level, lack of comprehensive use in related fields, and research in the field of e-commerce is even more lacking. However, with the rapid development of e-commerce platform, the importance of consumer segmentation has become more and more prominent. Therefore, this paper applies RFM model to e-commerce field for research, and provides reference for the division of e-commerce platform online shopping consumers.

1.2 Service Quality Study
Brysland A believes that the SERVQUAL model has been used in many public service environments to assess the quality of service offerings, from consumer expectations and actual content received, and to use SERVQUAL tools to improve process management and strategic planning [14]. The Stodnick M study attempts to fill the gap in traditional service management concepts in the educational environment [15] by applying SERVQUAL scale, a fully validated and widely used service operational structure. The Rezaei J study proposes a model for evaluating the quality of baggage handling systems, which greatly improves overall passenger satisfaction [16]. Win S uses the appropriate SERVQUAL quality of service measurement model to determine the nature of the relationship between service quality and expected customer behavior in the rental market [17]. Datta KS surveys the five dimensions of service quality based on the SERVQUAL model and identifies the gap between perception and expectations, examining the service standards [18] of management education providers at seven campuses in the UAE.

The service quality model has been widely used, providing reference for reference to the management of various fields. This paper applies the SERVQUAL model to the field of agricultural products e-commerce to explore its service quality and propose marketing recommendations.

1.2.1 Research on Service Quality Evaluation
The basic SERVQUAL scale has five dimensions: tangibility, reliability, responsiveness, assurance, empathy and 22 specific evaluation indicators. However, with the complexity of e-commerce platform services, some scholars have conceptual and empirical views. Depart from the criticism of the traditional SERVQUAL model and improve the indicator system [19].

He Hong (2016) discussed the service quality improvement strategy of e-commerce O2O mode based on the service remediation perspective in the research of service remedy-based E2O mode service quality improvement, emphasizing that the majority of service negligence of e-commerce platform is due to lack of organization. Caused by service mechanisms and service remediation mechanisms [20]. Liu Xiaofeng (2015) also added the compensatory dimension in the B2C e-commerce enterprise service quality evaluation research, which is based on reliability, service completion, system effectiveness, empathy, security, responsiveness, and compensability. The six dimensions [21]. It can be seen from the above research that most scholars have preliminary ideas on the improvement of service quality of e-commerce platform, and explore the two service quality dimensions of experiential and compensatory. N Seth also proposes that the traditional service quality model can not meet the platform. The need for development, the existing research also complements the service quality model from other aspects [22]. Therefore, this paper combines the expert group method to improve the specific division of service quality affecting e-commerce platform. Based on its original five dimensions, it adds two experiential and compensatory service quality dimensions. A service quality indicator, which divides the service quality of agricultural products e-commerce platform.

2. RESEARCH DESIGN
2.1 Establishment of Indicator System
The primary purpose of this study was to establish a universal scale structure for measuring the quality of service for agricultural e-commerce platforms. The basic information of consumers is mainly collected by the RFM
model, which consists of the total amount of consumption, time interval, and number of purchases. Consumers' evaluation of the e-commerce platform mainly uses the improved SERVQUAL scale structure to collect, mainly based on the original five dimensions, adding two experiential and compensatory service quality dimensions, which together constitute empathy. Improved SERVQUAL model based on seven dimensions of ease of use, reliability, assurance, responsiveness, compensability, and experiencing.

2.2 Design and Distribution of The Questionnaire
This study adopts the questionnaire survey method, selects the agricultural products e-commerce platform consumers to issue questionnaires for pre-investigation, pre-investigation links through the manual screening of customers who purchase agricultural products online 191 questionnaires, through the data feedback to improve the questionnaire scale, delete There are 7 items in the questionnaire, and 9 items of the questionnaire are improved. Finally, 22 items of the formal questionnaire are formed. On September 2, 2017, the second formal questionnaire was issued. As of October 30, 2017, 330 questionnaires were distributed online, and 330 questionnaires were collected. The total questionnaire recovery rate was 100%, and the invalidation, missing, incorrect filling, etc. were excluded. There were 49 unqualified questionnaires, and a total of 282 valid questionnaires, the effective rate of the questionnaire was 85.4%.

2.3 Descriptive Statistical Analysis
The descriptive statistical analysis of the sample includes variables such as gender, age, monthly income, occupation, and online shopping period of agricultural products. The detailed data is shown in Table 1:

| Variable          | Count   | Percentage |
|-------------------|---------|------------|
| Gender            |         |            |
| Male              | 97      | 34.4%      |
| Female            | 184     | 65.2%      |
| Male to female ratio | 1:2  |            |
| Age distribution  |         |            |
| 18-24             | 111     | 48.2%      |
| 25-34             | 69      | 20.9%      |
| 35-44             | 57      | 20.6%      |
| 45-54             | 23      | 8.2%       |
| Under 18          | 4       | 1.4%       |
| Over 54           | 2       | 0.7%       |
| Monthly income    |         |            |
| 2501-5000         | 123     | 35.8%      |
| 1001-2500         | 58      | 17.2%      |
| 5001-10000        | 56      | 16.3%      |
| 10,000 or more    | 13      | 3.8%       |
| Occupational      |         |            |
| Students          | 89      | 31.2%      |
| Private enterprise employees | 57 | 16%      |
| Self-employed     | 41      | 14.5%      |
| State-owned       | 30      | 10.3%      |
| Foreign-funded    | 31      | 10.9%      |
| Government        | 28      | 1.0%       |
| Retirees          | 16      | 0.6%       |
| Online shopping   |         |            |
| 2 years           | 65      | 23%        |
| 3 years           | 59      | 20.9%      |
| 4 years           | 55      | 18%        |
| 5 years           | 41      | 13.4%      |
| 6 years           | 22      | 7.6%       |
| More than 7 years | 19      | 6.7%       |

3. EMPIRICAL ANALYSIS
3.1 Reliability Detection
The Conbach's Alpha structural validity test was used to import the questionnaire data into SPSS for reliability testing. In this paper, SPSS21.0 is used to analyze the questionnaire data, and the Alpha coefficient value of the overall scale is 0.928>0.90, which indicates that the internal consistency of the questionnaire is excellent, among which the ease of use (0.882), reliability (0.672), and guarantee (0.703). The reliance (0.766), experiential (0.915), and compensatory (0.841) online consumer service quality satisfaction scales have reliability values greater than 0.6 and lower than the overall reliability value. Therefore, the e-commerce platform service quality is considered. The internal consistency of the measurement data of the scale is high.
Table 1. Reliability Analysis

| Survey scale | Cronbach’s Alpha | item count |
|--------------|-----------------|------------|
| Ease of use  | 0.882           | 4          |
| reliability  | 0.672           | 3          |
| Guaranteed   | 0.703           | 2          |
| Responsiveness | 0.766       | 3          |
| Experiential | 0.915           | 3          |
| Compensatory | 0.841           | 3          |
| Total amount | 0.928           | 18         |

3.2 Consumer Value Classification

3.2.1 Consumer RFM Analysis

The time from the last sample purchase of each consumer is obtained from the sample data of the questionnaire, and sorted in order of near and far. After sorting, the entire consumer set is divided into 5 equal parts, and the purchase time is five points closest to the current time. One consumer is marked as a score of 5, and one-fifth of the consumers who purchase the farthest from the current time are marked as a score of one. In a similar way, consumers are scored separately according to the frequency of their purchases and the total purchase amount, so that each consumer has 3 scores reflecting their RFM status. As shown in the figure, the score crosstab of the RFM of Table 2 is obtained, and the purchase behavior of the consumer is analyzed.

Using SPSS to draw RFM binning count chart based on consumer data, as shown in Figure 1, the consumer data classification is relatively uneven, in which the customer purchase frequency is low, the number of consumers is small, consumers are mainly concentrated in high segmentation, consumption The total amount is mainly concentrated in 3 or 4 points, and the time interval is more evenly distributed. The time interval of the sample consumer data is 1 point, the purchase frequency is 2 points, and the time interval is 2 points, and the purchase frequency is 3 pieces of missing consumer data.

Table 2. RFM Score Crosstab

| Recency score | Monetary score | Total |
|---------------|---------------|-------|
|               | 1     | 2     | 3     | 4     | 5     |       |
| 1 Frequency score | 1     | 2     | 1     | 2     | 0     | 2     | 7     |
| 2 Frequency score | 3     | 6     | 8     | 5     | 6     | 8     | 33    |
| 3 Frequency score | 4     | 1     | 1     | 1     | 1     | 1     | 5     |
| 4 Frequency score | 5     | 2     | 2     | 3     | 2     | 2     | 11    |
| 5 Frequency score | 11    | 12    | 11    | 9     | 13    |       | 56    |
| Total          |       |       |       |       |       |       | 58    |

| Recency score | Monetary score | Total |
|---------------|---------------|-------|
|               | 1     | 2     | 3     | 4     | 5     |       |
| 1 Frequency score | 1     | 0     | 1     | 1     | 1     | 0     | 3     |
| 2 Frequency score | 2     | 3     | 5     | 4     | 4     | 3     | 19    |
| 3 Frequency score | 3     | 2     | 3     | 3     | 3     | 2     | 13    |
| 4 Frequency score | 4     | 1     | 3     | 3     | 1     | 2     | 10    |
| 5 Frequency score | 5     | 1     | 2     | 2     | 3     | 1     | 9     |
| Total          | 7     | 14    | 13    | 12    | 8     |       | 54    |

| Recency score | Monetary score | Total |
|---------------|---------------|-------|
|               | 1     | 2     | 3     | 4     | 5     |       |
| 1 Frequency score | 1     | 0     | 1     | 1     | 1     | 0     | 3     |
| 2 Frequency score | 2     | 9     | 3     | 6     | 8     | 6     | 32    |
| 3 Frequency score | 3     | 0     | 0     | 1     | 0     | 0     | 1     |
| 4 Frequency score | 4     | 3     | 4     | 4     | 2     | 4     | 17    |
| 5 Frequency score | 5     | 2     | 3     | 2     | 3     | 2     | 12    |
| Total          | 14    | 11    | 14    | 14    | 12    |       | 65    |

| Recency score | Monetary score | Total |
|---------------|---------------|-------|
|               | 1     | 2     | 3     | 4     | 5     |       |
| 1 Frequency score | 1     | 0     | 1     | 1     | 1     | 0     | 3     |
| 2 Frequency score | 2     | 2     | 6     | 3     | 4     | 3     | 18    |
| 3 Frequency score | 3     | 2     | 2     | 1     | 4     | 2     | 11    |
| 4 Frequency score | 4     | 0     | 2     | 2     | 1     | 1     | 6     |
3.2.2 Consumer Cluster Analysis

According to the data obtained from the survey, the value of each consumer's time interval (Recency), purchase frequency (Frequency), and total amount of money (Monetary) from the latest consumption to the present is obtained. K-Means clustering analysis algorithm is applied. Consumers with similar consumer values are clustered.

According to the K-Means clustering analysis algorithm, the R, F, and M indicators in each cluster are compared with the overall average of R, F, and M, and the number of clusters is set to four. Four different types of consumer value classifications. Wherein, if R is higher than the average value of the overall R is marked as high, the average value lower than the overall R is marked as low, if F is higher than the average value of the overall F, the average value lower than the overall F is marked as low, If the average value of M above the overall M is marked as high, the average value below the overall M is marked as low. Since the original data cannot meet the requirements of data analysis, the original data needs to be properly converted, and the data is logarithmically transformed to obtain standardized data.

Cluster analysis based on the RFM model yields the following results:

Among them, R, F and M were tested by ANOVA analysis of variance, and the significant index Sig.<0.05 was obtained, which proved that the difference of R, F and M was extremely significant, which was suitable for cluster analysis. The clustering analysis of consumer value is based on the average as the criterion of the high and low. The result shows that the user attribute of cluster 1 is Q9(M) low-Q8(F) low-Q7(R) is high, that is, less cost, shopping Users with lower frequency but more recent activity are defined as A; user attributes of cluster 2 are Q9(M) low-Q8(F) low-Q7(R) is low, ie less cost, shopping frequency is lower and not recently Active user, defined as B; user attribute of cluster 3 is Q9 (M) high - Q8 (F) high - Q7 (R) is low, that is, users who spend more, have higher shopping frequency but are not active recently, define C; cluster 4 user attributes are Q9 (M) high - Q8 (F) low - Q7 (R) high, that is, the user who spends a higher, less frequent shopping frequency but is more active, is defined as D.

281 consumers are divided into four categories, belonging to A (M low - F low - R high) 22 people, belonging to B (M low - F low - R low) a total of 102 people, belonging to C (M high - F low - R low is 103, and the total number of consumers belonging to D (M-F-L-R-high) is 54.

Table 3. Final clustering center

| Clustering | A   | B   | C   | D   |
|------------|-----|-----|-----|-----|
| Q9         | 1.13| 2.36| 3.63| 3.19|
Table 4. ANOVA analysis of variance

| Cluster | Mean Square | df | Mean Square | df | F     | Sig. |
|---------|-------------|----|-------------|----|-------|------|
| Q9      | 52.630      | 3  | .204        | 277| 258.154 | .000 |
| Q8      | 2.445       | 3  | .110        | 277| 22.177  | .000 |
| Q7      | 24.262      | 3  | .152        | 277| 159.561 | .000 |

Table 5. Number of samples per cluster

| Cluster | Count |
|---------|-------|
| A       | 22.000 |
| B       | 102.000 |
| C       | 103.000 |
| D       | 54.000 |
| Valid   | 281.000 |
| Missing | 1.000  |

3.3 Service Quality Research
Firstly, KMO and Bartlett sphere tests are carried out on the sample data of 18 service quality indicators, and the test value KMO > 0.8 is suitable for factor analysis. The Bartlett value is reasonable and the data has correlation, which is suitable for factor analysis.

Secondly, using the principal component method to extract factors, the eigenvalue is greater than 1 to extract 6 factors, and the 6 factors have a degree of variance for the population variance, which better explains the population, although the number of extracted factors is different from the number of dimensions designed. However, the total results of the study were not affected, so the following six factors were extracted as the research objects, and the influence items with load values greater than 0.6 in each factor were selected for the main study. Among them, Q1, Q2, Q3, Q4 and Q5 are the main influencing factors of the first factor, Q13, Q14 and Q15 are the main influencing factors of the second factor, and Q16, Q17 and Q18 are the main influencing factors of the third factor. Q8, Q9 and Q12 are the main influencing factors of the fourth factor, Q10 and Q11 are the main influencing factors of the fifth factor, and Q6 and Q7 are the main influencing factors of the sixth factor.

Table 6. Rotated Component Matrix

| Component | 1  | 2  | 3  | 4  | 5  | 6  |
|-----------|----|----|----|----|----|----|
| Q1        | .846| .103| .215| .110| .038| .198|
| Q2        | .751| .088| .002| .451| .066| .098|
| Q3        | .801| .153| .076| .096| .251| .101|
| Q4        | .820| .205| .073| .068| .166| .194|
Q5 The product information provided by this platform is very specific and comprehensive.
Q6 The actual product and product description of the platform are consistent.
Q7 The information displayed on this platform is true.
Q8 This platform can provide a safe and secure payment environment, such as payment control.
Q9 The platform has standardized management regulations and rules and regulations for the settled merchants.
Q10 The platform's after-sales (return, etc.) consulting service responds quickly.
Q11 The platform is efficient in accepting orders and processing orders.
Q12 The logistics distribution of the platform can arrive on schedule.
Q13 This platform has interactive games about products.
Q14 The platform has offline experience activities for products: such as "Orchard Base".
Q15 The platform has a phone asking for the user experience status.
Q16 The platform will compensate for the failure to deliver the goods on time.
Q17 The platform has a variety of compensation mechanisms for failing to meet customer needs, such as cash compensation, coupon compensation, etc.
Q18 The platform works with third-party insurance institutions to provide consumers with protection.

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations

4. Development strategies and recommendations
According to the K-Means clustering analysis algorithm in the previous section, the R, F and M indicators in each cluster are compared with the overall average of R, F and M, and four different types of consumption are obtained through cluster analysis. Value classification. Taking the SERVQUAL model as a reference, after the principal component analysis, the load value of the first factor greater than 0.6 is mainly distributed in the SERVQUAL model dimension. The load values greater than 0.6 in the second factor are all distributed in the experience. In this way, it is observed that the load values of six factors greater than 0.6 are sequentially distributed in ease of use, experience, compensability, guarantee, responsiveness, and reliability. After comprehensive analysis, six factors are named according to this rule. The spider web map is drawn with the six
factors as the sub-coordinates, and the overall mean value of each factor of different categories of consumers is obtained, and the structure of the spider web is observed.

4.1A
According to the results, it is found that A has a higher overall evaluation of service quality, mainly biased towards responsiveness, and the compensatory score is the lowest. Such consumers have contingency and less cost for the e-commerce platform, although it is not an e-commerce platform. Loyal consumers, but through realistic marketing promotion, has greater development potential. Based on the sample data, the compensation indicators should be improved for such customers. Enterprises should fully improve their compensation mechanisms, understand whether customer rights are effectively protected, pay attention to the real needs of such consumers, and open up on the premise of maintaining the original service quality of enterprises. Innovation, maintaining original satisfaction, and increasing new satisfaction, improve compensatory indicators, and believe that the company is the best choice through improved service quality.

4.2B
B is less expensive in terms of quality of service dimensions, less frequent shopping and less active recently. The scores of these factors are not evenly distributed, and the overall score is low, and the experiential score distribution is the lowest. The degree of satisfaction expressed by B is generally not high, and it gradually shows a negative tendency for the development of enterprises. The satisfaction of such consumers will affect their purchasing behavior. The agricultural products e-commerce enterprises should improve the service quality of the e-commerce platform as a whole for such consumers, and should focus on strengthening the experiential improvement of such consumers, and provide consumers with characteristic platform activities to meet the consumer demand. Enhance the sense of participation of consumers, make up for the satisfaction of such consumers with experience, and improve the satisfaction of such consumers from all aspects.
4.3 C
The C attribute is costly, the shopping frequency is high but it is not active recently. The overall evaluation of this type of consumer is evenly distributed compared with other consumers, and the overall score is low, and the guarantee score is the lowest. Enterprises should increase the overall improvement, especially the weak service in the service quality, listen to the opinions of these consumers when using agricultural products platform to purchase agricultural products, and maintain the platform environment system to increase the trust of consumers on the platform. To improve the guarantee of the platform. Such consumers bring relatively low profits to enterprises, but they are also an important part of enterprise development. They should maintain the loyalty of such consumers to the platform through appropriate marketing efforts.

![Figure 4 Cobweb structure C](image)

4.4 D
The attributes of D are higher, the shopping frequency is lower but recently active. This type of user has a high overall evaluation of the service quality of the e-commerce platform, among which the evaluation of experience is the highest and the responsiveness index is relatively low. For such consumers, the company should strengthen its responsiveness, establish relevant consumer feedback mechanisms, solve consumer problems in a timely and effective manner, and enable timely communication between the platform and consumers to enhance consumer satisfaction. Promote consumer continued consumption on the platform.

![Figure 5 Cobweb structure D](image)
5. Research outlook

With the rapid development of agricultural products e-commerce platform, the competition of agricultural products e-commerce platform is increasingly fierce, accurately grasping the needs of each type of consumers, and developing a precise service marketing strategy is the key to the success of the agricultural e-commerce platform. The segmentation of consumer value is the primary prerequisite for service marketing. The study of consumer value segmentation and service quality helps the platform to better classify consumer demand, provide consumers with quality platform services, and the development of the business platform is of great significance. In this paper, the RFM model is combined with the improved SERVQUAL evaluation model to obtain consumer information to classify consumers of agricultural products e-commerce platform, and four types of consumers are derived and different service marketing strategies are discussed. However, this study still has the following shortcomings: (1) However, the importance of RFM is not equal for different products, so it is more effective to consider the weight of RFM and then divide the customer base. (2) Since this research is mainly focused on service quality, the scope of research on e-commerce platform satisfaction is limited, and this method can be extended to other perspectives of agricultural products e-commerce platform, which has reference significance for online shopping consumer value.

References

[1] China Network Economy Annual Monitoring Report [A]. Irene Consulting Series Research Report (No. 5, 2017) [C]. Irene Consulting Co., Ltd, 2017.

[2] Xu Qin. Consumer Value Management and Application Based on Data Mining [D]. Changsha University of Science and Technology, 2012.

[3] Liu F, Xiao B, Lim E T K, et al. The Art of Appeal in Electronic Commerce: Understanding the Impact of Product and Website Quality on Online Purchases[J]. Internet Research, 2017(4):00-00.

[4] Chiang W Y. To mine association rules of customer values via a data mining procedure with improved model: An empirical case study[J]. Expert Systems with Applications, 2011, 38(3): 1716-1722.

[5] Cheng CH, Chen Y S. classification the segmentation of customer value via RFM model and RS theory [J]. Expert Systems with Applications, 2008, 36(3): 4176-4184.

[6] Yang Bin. A Two-stage Consumer Association Classification Method Based on RFM Model Data Mining[J]. Statistics & Decision, 2015(07):77-79.

[7] Chen Y L, Kuo M H, Wu S Y, et al. Discovering recency, frequency, and monetary (RFM) sequential patterns from customers’ purchasing data[J]. Electronic Commerce Research & Applications, 2009, 8(5):241-251.

[8] Liu Bin, Zhang Jindong. Analysis of Marketing Decisions of Commercial Banks Based on RFM Model[J]. Statistics & Decision, 2013(14):65-67.

[9] Frow P, Reisman R, Payne A. Co-Pricing: Co-Creating Customer Value Through Dynamic Value Propositions[J]. Social Science Electronic Publishing, 2015.

[10] Section. A CBR-Based and MAHP-Based Customer Value Prediction Model for New Product Development[J]. Scientificworldjournal, 2014, 2014(3):459765.

[11] Mohaupt M, Hilbert A. A customer value-based airline revenue management approach considering both opportunity costs and misclassification of heterogeneous clients[J]. Journal of Revenue & Pricing Management, 2015, 14(5):321-341.

[12] Lin Xu. Research on Telecom Customer Churn Prediction Based on Customer Value Classification in 3G Environment[J]. 2016, 06(1):28-36.

[13] Peng Y. Evaluation and Classification of Commercial Bank Customer Value[C]// International Conference on Business Intelligence & Financial Engineering. IEEE Computer Society, 2011:682-686.

[14] Brysland A, Curry A. Service improvements in public services using SERVQUAL[J]. Managing Service Quality, 2012, volume 11(11):389-401.

[15] Stodnick M, Rogers P. Using SERVQUAL to Measure the Quality of the Classroom Experience[J]. Decision Sciences Journal of Innovative Education, 2010, 6(1):115-133.

[16] Rezaei J, Kothadiya O, Tavasszy L, et al. Quality assessment of airline baggage handling systems using SERVQUAL and BWM[J]. Tourism Management, 2018, 66:85-93.

[17] Win S. A SERVQUAL approach to identify the influences of service quality on leasing market segment in the German financial sector [J]. Benchmarking An International Journal, 2017.

[18] Datta KS, Vardhan J. A SERVQUAL-Based Framework for Assessing Quality of International Branch Campuses in UAE: A Management Students’ Perspective[J]. SAGE Open, 7(1):215824401667629.

[19] Brajaballav Kar. Service Quality and SERVQUAL Model: A Reappraisal [J]. Amity Journal of Operations
Management, 2018, 1(2):52-64.

[20] HE Hong. Study on service quality improvement of e-commerce O2O model based on service remediation[J]. Commercial and Economic Research, 2017(18):61-64.

[21] and M Liu Xiao Feng Bai Xuejiao. Study on Service Quality Evaluation of B2C E-commerce Enterprises[J]. Foreign Trade and Economics, 2015(04):87-91.

[22] Seth N, Deshmukh S G, Vrat P. Service quality models: a review[J]. International Journal of Quality & Reliability Management, 2005, 22(9):913-949.