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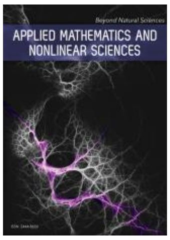

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Analysis of tea culture communication path based on the principal component analysis method

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Abstract

Tea culture is the main component of Chinese traditional culture, and the analysis of tea culture dissemination paths can promote the process of Chinese traditional culture dissemination to the outside world. This paper standardizes the tea culture dissemination paths based on the principal component analysis method. The correlation matrix of the standardized data is tested for sampling suitability, and the eigenvalues and eigenvectors are calculated to derive the principal components. The variance contribution rate and the cumulative contribution rate of the variance of the principal components are calculated, and then the scores of each principal component are derived and evaluated comprehensively. Accordingly, the main communication paths of tea culture are new media communication, museum collection and exhibition, and tea trade. Based on this, this paper analyzes the communication effects of the communication paths, and the results show that: the number of followers of public accounts related to tea culture reached 63,214 in 2021, an increase of nearly 24% compared with 2019. The total number of visitors to the museum collection and exhibition of tea culture was 28,004 in 2021, an increase of 22.7% compared with the previous year. The number of tea exports and export countries both increased significantly in 2021 compared with 2012. It can be seen that the main dissemination paths of tea culture obtained by the principal component analysis method are effective for the dissemination of tea culture and also provide a reference meaning for the dissemination of other traditional Chinese culture.

Keywords: Principal component analysis; Tea culture communication path; Sampling suitability test; Covariance matrix; Variance contribution ratio
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1 Introduction

The key to friendly relations between countries lies in the people being close to each other, and the key for people to be close to each other is the people's heart-to-heart. The bond of heart-to-heart communication is culture [1]. Culture is the sum of the material and spiritual production capacity and the material and spiritual wealth created by human beings in the process of social practice and is the form of social consciousness [2]. Cultural tolerance and integration are the cornerstone of the diversification of world civilization and are the passport to the establishment of a common and inclusive community of human destiny and the common prosperity of multi-ethnic cultures [3]. Chinese tea culture has a long history of thousands of years since Lu Yu's "Tea Sutra" blew the trumpet in the Tang Dynasty. Compared with the coffee-like richness and colorfulness of Western culture, tea culture, which is known for its "quietness and timelessness" constitutes, in a sense, an integral part of traditional Chinese culture. As one of the most popular beverages, along with the tea trade, tea has become a civilizational messenger of Chinese culture out of the country and into the world []-[6]. However, the choice of path is particularly important in the process of spreading tea culture.

Tea is a beverage of Chinese origin. The literatures [7]-[8] show that tea has been shown to have beneficial effects on cancer, obesity, atherosclerosis, diabetes, bacterial and viral infections, and dental caries. Literature [9] shows that with the spread of tea, tea culture has gradually become an embodied form of traditional Chinese civilization and culture. Literature [10] also shows that tea culture is a clear reflection of a country's culture and values. This shows that the development and spread of tea culture have become an important form of cultural exchange. The literature [11] shows that an aggregation of industries related to tea culture is occurring, which provides a solid foundation for the spread of tea culture. Tea culture is not only about tea; it also consists of tea ceremonies, tea virtues, and tea spirit, as well as tea tools and tea paintings. For example, the literature [12] shows that the tea ceremony is an important part of tea culture and has been studied worldwide. However, with the globalization of economic trade and the development of science and technology, the paths of cultural transmission have become more and more varied. For example, the literature [13] points out that since the beginning of the new century, Chinese tea documentaries have used the language of sound and images to show the internalized spirit of the tea ceremony to people all over the world. The literature [14] points out that tea culture can be disseminated by relying on museums. Tea towels in tea culture are sold separately in museums and gallery stores in the UK and other countries. It can be seen that museums are also an important way of spreading tea culture. Therefore the choice of tea culture dissemination paths becomes particularly important. In order to filter out the main dissemination paths from many tea culture dissemination paths, the principal component analysis method was adopted. The literature [15] shows that the principal component analysis algorithm can extract features from relevant factors and then classify them to reduce the features and thus derive the principal components. In this way, the principal factors derived based on the principal component analysis method are more accurate. The literatures []-[19] demonstrate experimentally that the principal component analysis method could perform exploratory factor analysis on the study object and derive principal components by extracting the eigenvalues. It provides the basis for this paper to study the tea culture communication path using principal component analysis. The above literatures confirm that the community has been conducting research on tea culture communication, and some communication paths have been proposed, but these proposed communication paths are lack of the relevant data support and thus are not convincing.

Presently, the common tea culture dissemination paths are literature dissemination, tea trade, museum collections and exhibitions, video narrative, living dissemination, and new media dissemination. Therefore, in this paper, based on the principal component analysis method, the statistical data (i.e. literature number, tea trade amount, museum visitors, video products number, living events number,

number of public account readers, etc.) under different tea culture communication paths are imported into the calculation processes of the principal component analysis method as the original data. The data are standardized, and the standardized data correlation matrix is subjected to a sampling suitability test. The eigenvalues and eigenvectors of the components are calculated to identify the principal components. The scores of each principal component are derived by calculating the variance contribution rate and the cumulative contribution rate of variance, and the main paths of tea culture communication are derived by comparing the scores. If the principal component scores are negative, it means that the path of tea culture dissemination is not important, and the positive value means that the path of tea culture dissemination is effective. In order to verify that the obtained paths are the main paths of tea culture dissemination, we further analyze the performance of tea culture communication under three paths. The increasing number of tea export types from 3 in 2012 to 17 in 2021 proves that the main tea culture dissemination path derived based on the principal component analysis method is convincing.

2 Principal component analysis method

2.1 Basic principle and steps

Principal component analysis, abbreviated as PCA, is an important method of dimensionality reduction and analytical evaluation in multivariate statistical analysis. Due to the correlation of variables, the results of each variable cannot be simply aggregated, which is the basic starting point of multivariate statistical analysis. Principal component analysis has a strict mathematical theory as the basis, and the process of the basic principal component analysis method is shown in Figure 1.

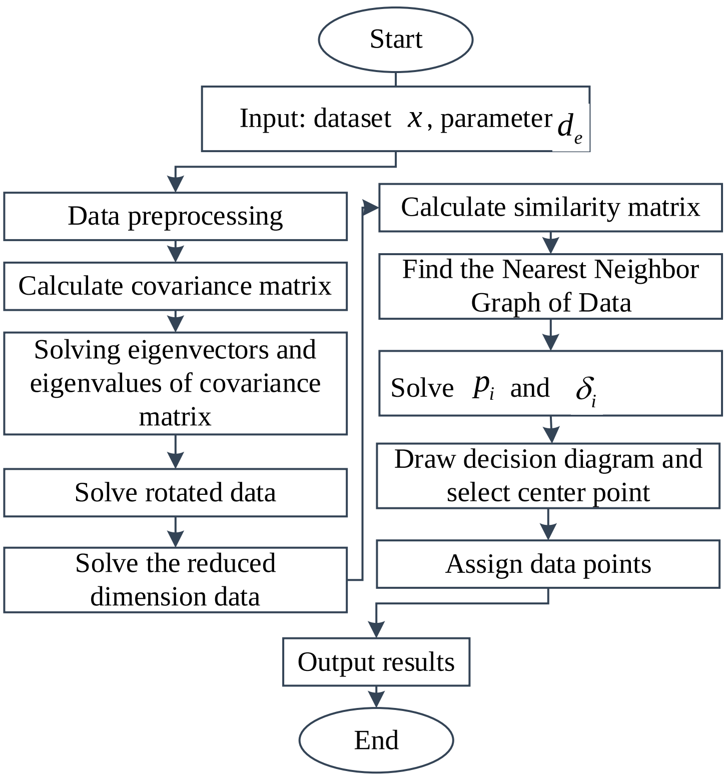


Figure 1. Flow of principal component analysis method

As shown in Figure 1, principal component analysis aims to explain as much as possible of the variance in the original information with fewer variables, i.e., to represent it on an optimal generalizable basis [20]. This shows the mathematical efficiency, physical soundness, and reliability of the independent component analysis method in dealing with redundant targets [21]. The principal component analysis method transforms many highly correlated variables into variables that are independent or uncorrelated with each other. Usually, the number of principal components is less than that of the original variables. They explain most of the variation in the original information and are selected as a comprehensive index of the original information.

In general, principal component analysis is used to identify the main relationships in complex data and allows automatic detection and classification of relevant data during experiments []-[23]. It uses the concept of dimensionality reduction, a multivariate statistical method that transforms multiple indicators into several composite indicators with little loss of information. The composite indicators generated by the transformation are called principal components, and each principal component is a linear combination of the composite indicator variation before the transformation. Usually, when the cumulative contribution of the variance of the current n principal components reaches 90%, these n principal components are generally considered to represent most of the information of the initial data. Therefore, PCA can be used as a powerful data exploration tool to facilitate method development, comparability, and data integration across different experiments [24].

The principal component analysis method processes data consist of P indicators and n samples. The P indicators can be represented by $X_1, X_2, ..., X_p$, which constitutes a P-dimensional random vector of $X = \left(X_1, X_2, ..., X_p\right)$. The $n \times p$-order matrix X of the original data is:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{pmatrix}_{n \times p} \tag{1}$$

Each principal component of the original data also forms a $n \times p$ matrix Z:

$$Z = XA \tag{2}$$

where: A is the transformation matrix from the original data array to the principal component array, and each column of it corresponds to X the unit eigenvector of the covariance matrix of each performance parameter.

It is obtained by a linear transformation of the original data array X, i.e., each principal component is a linear combination of p original performance parameters. A linear transformation of X can form a new composite variable, represented by Y. The new variables can be linearly represented by the original variables satisfying the following equation:

$$Y_1 = U_{11} * X_1 + U_{12} * X_2 + \cdots + U_{1p} * X_p \tag{3}$$

$$Y_2 = U_{21} * X_1 + U_{22} * X_2 + \cdots + U_{2p} * X_p \tag{4}$$

$$Y_p = U_{p1} * X_1 + U_{p2} * X_2 + \cdots + U_{pp} * X_p \tag{5}$$

where: $Y_1, Y_2, \cdots Y_p$ are the 1st, 2nd, and P nd principal components of the original variables.

2.1.1 Data normalization processing

The statistical data under different tea culture dissemination paths in this paper are not identical, and the range of values varies widely; the original data array should be standardized for coordination purposes before calculating the principal components according to the above steps [25].

Assuming that there are P variable for principal component analysis: $X_1, X_2, ..., X_p$, there are n evaluation objects. It can be obtained:

$$\tilde{x}_{ij} = \frac{x_{ij} - \overline{x}_j}{s_j} \tag{6}$$

Where: i is the evaluation object, j is the number of indicators. The value of the j th indicator of the i rd evaluation object is x_{ij}. $\tilde{x}_{ij}$ is the quantified indicator converted from each indicator x_{ij}. $\overline{x}_j$ is the mean value of each column of the original data, and s_j is the standard deviation of each column of the original data.

The calculation formula of $\overline{x}_j$ is:

$$\overline{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{7}$$

The calculation formula of s_j is:

$$s_j = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(x_{ij} - \overline{x}_j\right)^2} \tag{8}$$

where: $j = 1, 2, ..., m$, $\overline{x}_j$ and s_j are the sample mean and standard deviation of the j th indicator, respectively.

Correspondingly, we call:

$$\tilde{x}_i = \frac{x_i - \overline{x}_i}{s_i} \tag{9}$$

Equation (9) is the standardized indicator variable.

The covariance matrix D of the original data array can be calculated according to the following equation:

$$D = \frac{1}{n-1} X^T X \tag{10}$$

where: D is a $P \times P$nd order real pair matrix, and the problem of solving the principal components can be transformed into finding the eigenvalues of D and their corresponding unit eigenvectors.

2.1.2 Correlation coefficient matrix calculation

Some data involve different measures of indicators so that the variance of the indicators is not comparable with each other. For this type of data, it is not appropriate to use the covariance matrix for principal component analysis alone, and the correlation coefficient matrix can be used. The correlation coefficient matrix is the covariance matrix after the standardization of random variables. By standardizing the random variables, the correlation coefficient matrix strips the variance of individual indicators and retains only the correlation between indicators. The correlation coefficient matrix is:

$$R = \left(r_{ij}\right)_{m\times m} \tag{11}$$

where: $r_{ii} = 1$, r_{ij} are the correlation coefficients of the i rd indicator and the j th indicator.

With principal component analysis using covariance matrices, the positive and negative effects of dominance effects are mainly reflected in the influence of the variance of individual indicators. In order to avoid the negative impact of the variance of individual indicators on the principal component analysis, it is natural to think of stripping the variance of individual indicators from the covariance matrix and achieving efficient and accurate data through data compression []-[27]. The correlation coefficient matrix serves this purpose precisely.

2.1.3 Calculating eigenvalues and eigenvectors

When calculating the eigenvalues and eigenvectors, it should be noted that the eigenvalues need to be sorted from largest to smallest.

Calculate the eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$ of the correlation coefficient matrix R , and the corresponding eigenvectors $u_1, u_2, \cdots, u_m$, where $u_j = \left(u_{1j}, u_{2j}, ..., u_{nj}\right)^T$, from the eigenvectors form m new indicator variables:

$$\begin{cases} y_1 = u_{11}\tilde{x}_1 + u_{21}\tilde{x}_2 + \cdots + u_{n1}\tilde{x}_n \\ y_2 = u_{12}\tilde{x}_1 + u_{22}\tilde{x}_2 + \cdots + u_{n2}\tilde{x}_n \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ y_m = u_{1m}\tilde{x}_1 + u_{2m}\tilde{x}_2 + \cdots + u_{nm}\tilde{x}_n \end{cases} \tag{12}$$

where: y_1 is the first principal component, y_2 is the second principal component, and y_M is the m th principal component.

Each unit eigenvector is formed into matrix A in equation (2) in the order of columns and then right-multiplied by the original data array X to obtain each principal component:

$$Z = X\left(\xi_1\xi_2\cdots\xi_P\right) \tag{13}$$

where: $\xi_1, \xi_2, \cdots \xi_P$ is each eigenvector.

2.1.4 Calculate the integrated evaluation value

After calculating the eigenvalues, we need to calculate the information contribution rate and the cumulative contribution rate of eigenvalue λ_j. Where:

$$b_j = \frac{\lambda_j}{\sum_{k=1}^{m} \lambda_k} \tag{14}$$

is the information contribution of the principal component y_j.

$$a_p = \frac{\sum_{k=1}^{p} \lambda_k}{\sum_{k=1}^{m} \lambda_k} \tag{15}$$

is the cumulative contribution of the principal component $y_1, y_2, \cdots, y_p$.

When a_p is infinitely close to 1, the first P indicator variables $y_1, y_2, \cdots, y_p$ are selected as the P principal components instead of the original n indicator variables so that the P principal components can be analyzed in a comprehensive manner. The formula for calculating the composite score is as follows:

$$Z = \sum_{j=1}^{p} b_j y_j \tag{16}$$

The evaluation can be done based on the combined score value.

2.2 Sampling Suitability Test

It is possible to calculate the principal components of a disorganized and unstructured set of data by following the above process, but the results obtained in this way are hardly realistic. In fact, principal component analysis is only applicable to data where the variables are correlated with each other to a certain extent, i.e., this method can only bring out the original associations but not generate new ones. Mathematically, the feasibility of performing principal component analysis is usually portrayed using the sampling suitability test statistic. Its value ranges from 0 to 1. The higher the value, the more intrinsic associations among the variables and the more suitable for principal component analysis. When the sampling suitability test statistic is greater than 0.8, the original data is very suitable for principal component analysis. When its value is less than 0.5, the data is not suitable for analysis. If an exploratory study is conducted on the raw data, the condition can be relaxed to greater than 0.5.

The statistical data (i.e. literature number, tea trade amount, museum visitors, video products number, living events number, number of public account readers, etc.) under different tea culture dissemination paths are imported into the software Matlab, and the sampling fitness test statistic was found to be 0.831, indicating that the tea culture dissemination path can meet the requirement of sampling fitness greater than 0.8 and has the feasibility of conducting principal component analysis.

2.3 Selection of principal components

In summary, it can be seen that the analysis process of the principal component analysis method is actually a computational process. Accordingly, we can derive the calculation process of principal component analysis. The calculation process of the principal component analysis method is shown in Figure 2.

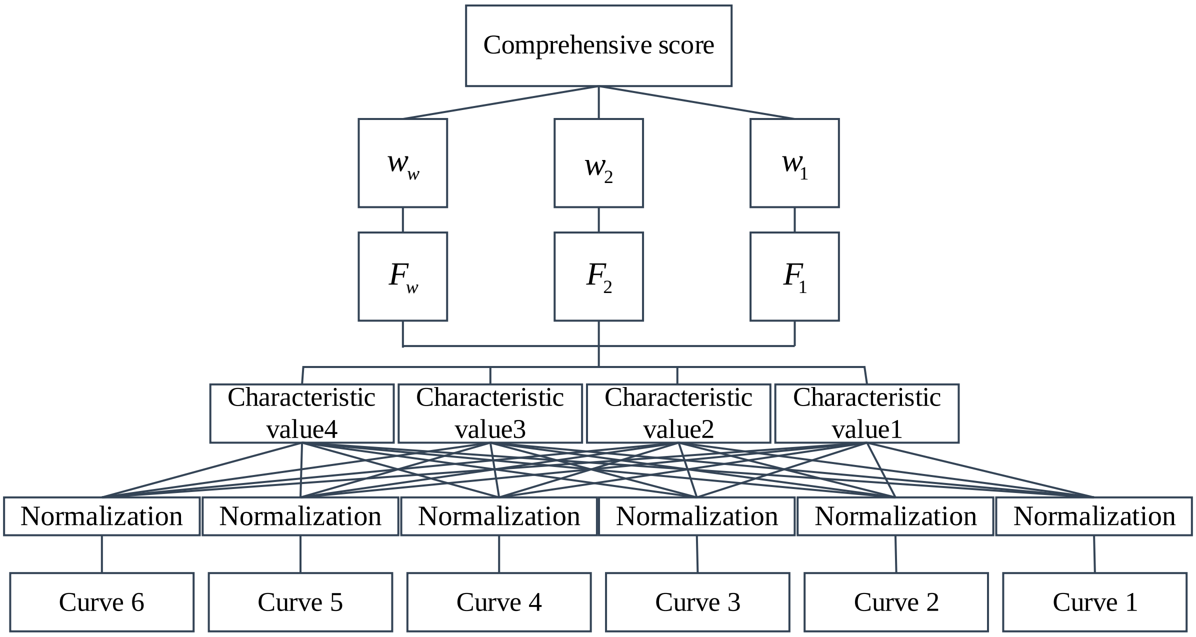


Figure 2. Calculation process of principal component analysis method

From Figure 2, we can see that the calculation of the principal component analysis method is actually a continuous process of dimensionality reduction. When calculating the original data, the data should be standardized, and the process of standardization is also the process of normalization. Through standardization, the original 6 performance parameters can be transformed into 4 principal components to achieve the purpose of simplifying the problem and sifting out the most dominant components.

At present, the popular and common tea culture dissemination paths are literature dissemination, tea trade, museum collections and exhibitions, video narrative, living dissemination, and new media dissemination. The statistical data under above tea culture dissemination paths are input into the calculation process of principal component analysis as raw data, normalized and standardized. Then the eigenvalues and eigenvectors, the variance contribution rate and the cumulative contribution rate of variance are calculated to obtain the comprehensive score of the principal components under each tea culture dissemination path. As shown in Table 1.

Table1. Composite score of the principal components under different tea culture dissemination paths

Tea Culture Communication Path	Composite principal component score
Literature dissemination	-37.33
Tea trade	80.94
Museum collections and exhibitions	85.27
Video narrative	-40.36
Living communication	-30.36
New media communication	96.21

As can be seen from Table 1, the combined principal component scores of the tea trade, museum collections and exhibitions, and new media communication are positive. The composite scores of the principal components of video narrative and living communication are negative. The positive and negative values of the composite principal component scores indicate the effect of tea culture dissemination under different paths. The negative value indicates that the path of the tea culture dissemination effect is not significant, and the positive value indicates that the path is relatively effective. The larger the score value, the better the effect of tea culture dissemination. Comparing the composite scores of the principal components of each tea culture dissemination path, we can see that the 1st principal component of the tea culture dissemination path is new media dissemination, the 2nd principal component is museum collection and exhibition, and the 3rd is tea trade.

3 Analysis of tea culture dissemination path

3.1 New Media Communication

Based on the principal component analysis method, we conclude that new media communication is the 1st principal component of the tea culture communication path. In order to verify it, this paper selects a domestic tea culture public account as a sample and selects its article reading, likes, comments, and the number of public account followers in the past three years for analysis. The change in tea culture public account data is shown in Figure 3.

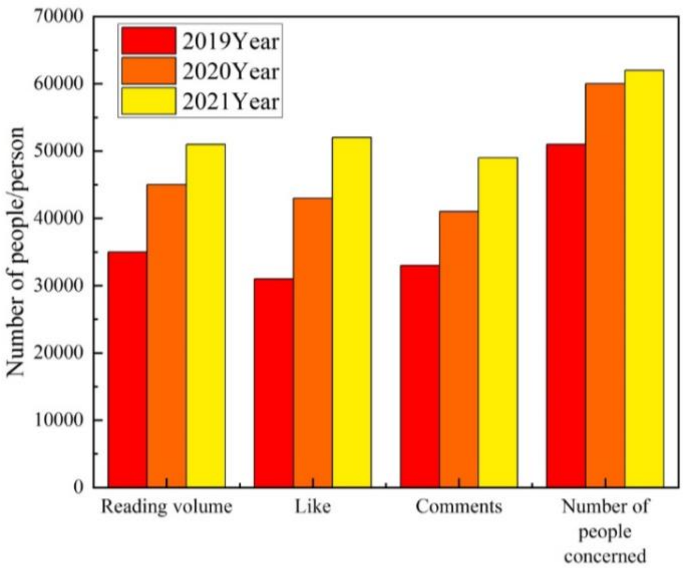


Figure 3. Changes of tea culture public account data

From Figure 3, we can see that both the number of readers, likes, and comments of the articles published by the public account and the number of followers of the public account have kept growing in the past three years. In terms of the number of readers, there are 34,562 people reading articles about tea culture published by the public account in 2019. There are 45,327 people reading the articles in 2020 with an increase of 10,765 people compared with that of 2019. The number of readers in 2021 is 6,009 more than that in 2020, and 16,774 more than that in 2019. In terms of article likes, the number of article likes in 2019 is 31,598, and the number of article likes in 2020 shows an increase of 12,057 compared with 2019. The number of article likes in 2021 increased by 8,491 compared with 2020. The tea culture spread by the public platform is well-received and recognized by everyone. In terms of article comments, the number of article comments about tea culture on the public platform in 2019 is 33,456, higher than the number of likes. There are 41,568 article comments in 2020, an increase of 8,112 compared with that in 2019. There are 48,579 article comments in 2021, an increase of 7,011 compared with that in 2020.

The new media related to tea culture has been widely discussed, and at the same time, it has also promoted the spread of tea culture. In terms of the number of public account followers, the number of public account followers in 2020 increases by 8,821 compared to 2019, and the number of followers in 2021 increases by another 3,369 compared to 2020, reaching 63,214. The number of people following the public account in 2021 increases12,190 compared with that in 2019, nearly 24% over the number of people following the public account in 2019. The number of readings, likes, and comments on tea culture-related articles in public accounts has increased, and the number of public account followers has also increased significantly. This shows that the scope of tea culture communication has expanded through the new media communication path, which is conducive to the spread of tea culture.

3.2 Museum Collections and Exhibitions

Tea culture includes tea genealogy, tea association, tea utensils, tea paintings, etc., and these are mostly shown in the form of museum collections and exhibitions. This is in line with the 2nd principal component tea culture dissemination path based on principal component analysis. In order to verify that museum collections and exhibitions are effective paths for tea culture dissemination, the World Tea Culture Museum in Mengdingshan, Ya'an City, Sichuan Province, China, is selected as the object of analysis, and the number of visitors from China and other countries to its tea genealogy, tea association, tea tools and tea paintings between 2020 and 2021 is analyzed, as shown in Figure 4. The analysis result can be used to prove whether tea culture is effectively disseminated or not under the museum's canonical collection and exhibition dissemination path.

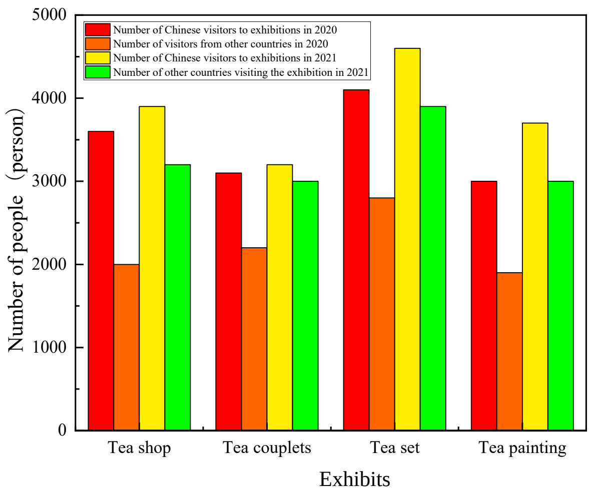


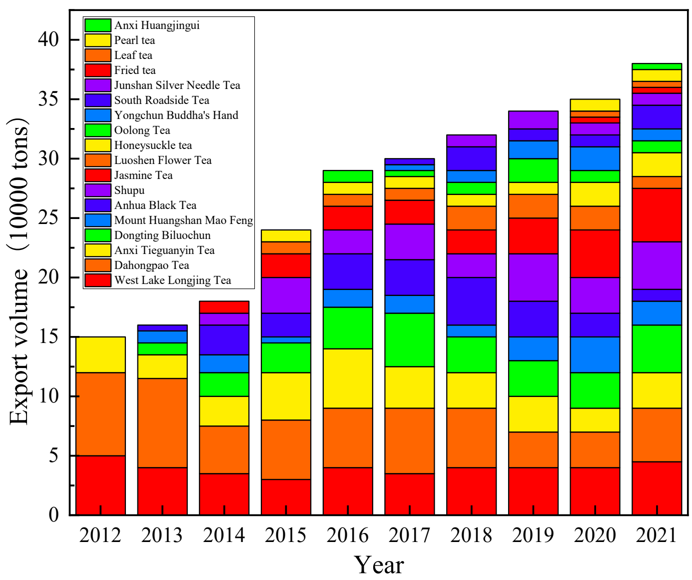
Figure 4. The number of visitors to the exhibits of the Museum of Tea Culture

As we can see in Figure 4, the number of Chinese visitors to the exhibition and the number of visitors from other countries are both on the rise from 2020 to 2021. The number of Chinese visitors to Tea shop increases from 3611 to 3945, an increase of 334. At the same time, the number of foreign country visitors to the tea shop has increased from 2043 to 3197, an increase of 1136. The number of Chinese visitors to the tea couplets in 2020 is 3104, an increase of 114 compared to 2021. The number of foreign visitors to the tea couplets in 2021 is 3002, an increase of 813 compared to 2020. The total number of visitors to tea sets in 2020 is 6,876, while the total number of visitors to tea sets in 2021 is 8,036, an increase of 17%.

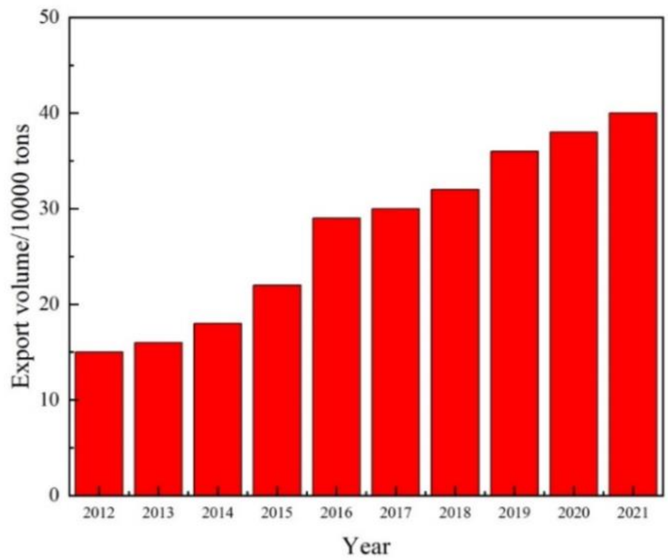
The number of visitors to tea painting in these four exhibits is relatively small, with 3,023 Chinese visitors in 2020 and only increases 586 in 2021, still showing an upward trend. However, the number of foreign visitors increases significantly, from 1,975 in 2020 to 2,997 in 2021, an increase of nearly 52%. In general, the total number of visitors to the exhibits increases from 22,821 in 2020 to 28,004 in 2021, an increase of 5,183 visitors, nearly 22.7%just in one year. With the passage of time and the increase of visitors' reputation, the number of exhibit visitors will continue increasing, The source of visitors will be more and more extensive, and the scope of dissemination will be wider and wider. Through the increase in the number of visitors to the Tea Culture Museum, we can see that the tea culture relies on the museum collection and the exhibition has been widely disseminated.

3.3 Tea Trade

From the ancient Tea Horse Route to the Silk Road, to today's globalization of trade, the spread of Chinese tea culture has been going on along with the tea trade. The export volume of tea and the number of export countries in the tea trade are the best reflections of the tea culture spreading situation. In order to prove that the tea trade is a better dissemination path for the spread of tea culture, this paper plots the volume of tea exports and the number of tea export types and countries from China between 2012 and 2021, as shown in Figure 5.



(a) Chinese tea export varieties



(b) China's tea export volume

Figure 5. Analysis of the overall characteristics of tea exports

The tea trade is the dissemination path of tea culture, and furtherly, the export of tea is the feedback of the effect on the dissemination path of the tea culture. From Figure 5(a), we can see that there are only three major varieties of Chinese tea exports, namely Xihu Longjing, Da Hong Pao, and Anxi Tieguanyin in 2012. By 2013, the varieties of China's major tea exports increase to 6, an increase of 100%. In 2014, the varieties of China's major tea exports increased by 2 compared to that in 2013. The varieties of tea exports from 2015 to 2018 increased by 1 in each year. And by 2018, the varieties of tea exports have increased to 14. By 2019, tea export varieties have covered all the seven tea families in China. The number of tea exports varieties continue increasing between 2020 and 2021, reaching a total of 18 varieties of tea in 2021. The tea export varieties in 2021 increase by 500% compared with 2012.

As shown in Figure 5(b), the tea export volume of China shows a gradual upward trend. The tea export volume is 150,000 tons in 2012, and 160,000 tons in 2013, an increase of 10,000 tons in one year. In 2014, China's tea export volume reaches 180,000 tons, an increase of 20,000 tons compared with the previous year, nearly 12.5%. In 2015 and 2016, China's tea export volume increases significantly. In particular, China's tea exports grow by 290,000 tons in 2016, the largest annual increase in this decade. China's tea exports in 2017 reach twice as much as in 2012. Between 2018 and 2020, China's tea exports still grow steadily. By 2021, China's tea exports have reached 400,000 tons, an increase of 250,000 tons, nearly 170% from the initial 150,000 tons.

According to the results of above analysis on the data related to the number of tea export varieties and tea export volume in China's tea trade, it is clear that Chinese tea culture has spread rapidly and widely overseas along with the tea trade. Because of the advancement of the tea trade, more and more countries and people have learned about different types of tea. Thus, it can be seen that the tea trade dissemination path selected by the principal component analysis method can effectively promote the dissemination of tea culture.

4 Conclusion

In this paper, the statistical data under different tea culture communication paths is standardized based on principal component analysis method, and then the correlation matrix of the standardized data is tested for sampling suitability. The principal components are obtained by calculating the eigenvalues and eigenvectors, and the variance contribution rate and the cumulative contribution rate of variance are calculated to obtain the scores of the principal components. The principal components of the tea culture communication path are evaluated according to the calculated scores as new media communication, museum collection and exhibition, and tea trade. In order to verify the principal components of tea culture dissemination paths derived from this paper, the tea culture dissemination situation under the obtained paths is analyzed, and the following conclusions are obtained:

1) Under the new media dissemination path, the number of followers of public accounts related to tea culture reach 63,214 in 2021, an increase of nearly 24% compared with that in 2019. And the number of article likes in public accounts also increase significantly, with 31,598 article likes in 2019 and 12,057 article likes in 2020, showing an increase of tens of thousands compared with 2019.

2) Under the museum collection and exhibition path, the total number of visitors to the tea culture museum collection and exhibition in 2021 is 28,004, an increase of 22.7% over the previous year.

3) The tea export volumes and export countries in 2021 are both significantly more than those in 2012.The tea export varieties in 2021 increase by 500% compared with 2012.

   It can be seen that the scope of tea culture dissemination increases year by year, and the main path of tea culture dissemination can be derived based on the component analysis method.

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