Research Article

Quality Index Evaluation Model of MPP Sold under the E-Commerce Platform

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1. Introduction

With the development of the times, mobile devices such as mobile phones have become an indispensable part of people’s daily lives. Mobile power has become an essential accessory for mobile devices due to its high power, portability, and versatility. However, the current industry standard for mobile power is not comprehensive and the country does not mandate the quality certification of enterprises, which can easily lead to the introduction of inferior MPP. Because of the frequent occurrence of combustion and explosion accidents caused by the problem of MPP quality, it can be seen that MPP has serious safety problems.

At present, online shopping is one of the main channels for consumers to purchase mobile power. Due to the spatio-temporal and virtuality of online shopping, consumers cannot perceive the quality of products in person. They can only vaguely judge the quality of products based on the product information presented by the seller and the comments of other buyers, so they are easy to buy inferior products and thus have potential safety risks.

The quality problems of MPP are common. However, the evaluation of MPP is mostly carried out by experiment. However, there are a large number of brands, types, and quantities of MPP sold on the e-commerce platform, so the quality inspection cannot be carried out one by one, only sampling inspection can be conducted. At present, the supervision department mostly uses random sampling to select sampling objects for testing, which can easily lead to partial sampling results. Therefore, it is urgent to build an evaluation system that can accurately, objectively, and comprehensively demonstrate the quality of MPP sold on the e-commerce platforms, to provide guidance for supervision and sampling inspection by regulatory authorities and provide reference for consumers to purchase high-quality mobile power supplies.

Currently, the commonly used product quality evaluation method is the comprehensive index method, which can well reflect the influence degree of each quality feature on the comprehensive quality of products [1]. Therefore, the comprehensive index method was adopted to compare the quality of MPP sold under e-commerce platform, and the
2 Mathematical Problems in Engineering

2. Index Selection

The construction of index evaluation model mainly includes four steps: index selection, index optimization, weight determination, and model construction. First, we need to complete the selection of indicators.

The research object is the MPP sold by many e-commerce platforms. MPP has the characteristics of variable capacity, diverse materials, flammable, and explosive, as well as the unique trading patterns, intuitive information, and limited data of e-commerce. Following the principles of purposiveness, scientificity, effectiveness, operability, and comparability [2], the indicators closely related to the quality of MPP sold under e-commerce platforms were selected to form the original indicators.

The data of the research mainly come from the commodity information description in the e-commerce platform, including commodity name, number, weight, origin, shell material, cell type, function, capacity, price, sales volume, favorable rating, cumulative evaluation, charging efficiency, logo, and safety protection. Among them, producing area, shell material, cell type, price, favorable comment rate, cumulative evaluation, charging efficiency, identification, and safety protection all have a certain impact on the quality of mobile power supply, so they can be used as the original indicators affecting the quality of MPP sold on e-commerce platform.

In addition, the network image sampling, inspection results, and product inspection of the brand of mobile power supply all have an impact on the quality and safety of MPP sold on e-commerce platforms. The above data can be obtained through data mining for follow-up research. In summary, the final 16 original indicators are shown in Table 1.

3. Index Optimization

3.1. Source of Sample Data. The sample data are randomly extracted from multiple e-commerce platforms. By collecting and recording the data corresponding to each group of data, 50 sets of initial sample data are obtained. In the initial sample data, the data of brand duplication, the large difference in the index value and lack of partial information were deleted, and the 38 groups finally retained constitute the sample data.

According to the specific content of each original index, the degree of influence on the quality of the MPP sold by the e-commerce platform is different, and the qualitative indicators such as battery capacity, shell material, and battery type are quantitatively processed. For example, for the MPP with a battery capacity of $<10000$ mAh, $=10000$ mAh, and $>10000$ mAh, the value of the battery capacity is determined according to the risk of lower than the calibration capacity and potential safety problems generated under their respective capacities from high to low. For the MPP with flame-retardant material, metal material, and ABS plastic for the shell material, the values of the flame retardancy and the resistance against external impact of the respective materials are determined from high to low. For the MPP of the battery type lithium-ion battery and lithium polymer battery, the value of the battery type is determined according to its stability and safety from low to high.

However, during the actual data collection and processing, it was found that the charging efficiency, output voltage, identified content, and production place are consistent in the 38 sets of sample data and have no effect on the overall research results. Therefore, the above four original indicators are not analyzed in the subsequent statistical analysis. Finally, the original indicators consisting of 12 effective indicators were identified for follow-up studies.

3.2. Index Optimization Principle. The purpose of index optimization is to classify the 12 original indicators into new first-level indicators, extract the original indicators by dimension reduction, and group the indicators with the same characteristics for further research.

Principal component analysis (PCA) is a statistical method that converts multiple indicator problems into less comprehensive indicators, which can make the problem simpler and more intuitive, and the main components are irrelevant, while at the same time ensuring no loss of valuable information [3]. The maximum number of new variable generations is equal to the number of original variables minus one. The new variables are uncorrelated with each other [4]. Because no assumptions are made about variable distributions in PCA, this approach can process any dispersed data [5]. However, using only one method for optimization does not guarantee the authenticity and scientificity of the conclusions obtained. Cluster analysis is the process of dividing a data set into groups or classes and makes the data objects in the same group have higher similarity, while the data objects in different groups are not similar, and the analysis conclusion is straightforward and the form is concise [6]. Considering the intuition of the cluster analysis method and the ability of the corresponding processing variables, it is decided to optimize the original indicators based on PCA and cluster analysis.

3.3. Principal Component Analysis. Using PCA for index optimization includes the following: (1) standardization of indicator data; (2) calculate the correlation matrix of the indicator data; (3) calculate the eigenvalues and eigenvectors of the correlation matrix; (4) calculate the variance contribution rate and the cumulative variance contribution rate to determine the number of principal components; and (5) conduct a comprehensive evaluation of the principal components to determine the principal component name and the composition of each principal component [7].

By sorting the eigenvalues from large to small, the importance of eigenvalues can be obtained, and the contribution rate of corresponding components can also be accumulated. The calculation formulas of contribution $e_m (m = 1, 2, 3, \ldots, p)$ of each principal component and cumulative variance contribution $E_m (m = 1, 2, 3, \ldots p)$ are...
shown in formulas (1) and (2). The greater the variance of the principal component $\lambda_g (\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p \geq 0, \; g = 1, 2, \ldots, p)$, the greater the contribution to the total variance, the greater the variance contribution rate, and the greater the information reflected by the corresponding principal component. The calculated variance contribution rate is shown in Table 2. By analyzing Table 2, since the eigenvalues of the first five principal components are greater than 1 and the cumulative contribution rate is greater than 85%, the two conditions for selecting the principal component by principal component analysis are met so that the number of principal components can be determined to be 5 at the end.

Contribution of the $m$th principal component is as follows:

$$e_m = \frac{\lambda_m}{\sum_{g=1}^{p} \lambda_g}$$

(1)

Cumulative contribution rate of the $m$th principal component is as follows:

$$E_m = \frac{\sum_{g=1}^{m} \lambda_m}{\sum_{g=1}^{p} \lambda_g} \geq 85\%, \; (m \leq p).$$

(2)

After determining the number of principal components, the principal component load $l_{ij} (i, j = 1, 2, 3, \ldots, p)$ is required, which reflects the correlation between the principal component $F_i \; (i = 1, 2, \ldots, 5)$ and the original index $X_j \; (j = 1, 2, \ldots, p)$. The greater the absolute value of principal component load $|l_{ij} (i, j = 1, 2, 3, \ldots, p)$, the greater the impact of the index on the principal component. Therefore, the indicators with relatively large principal component loads in each principal component are selected, and the integrated indicator system of the mobile power quality evaluation model of the e-commerce platform can be constructed. The calculation formula of the principal component load is shown in formula (3), and the calculation results are shown in 3.

$$L_{ij} = \rho(F_i, X_j) = \sqrt{\lambda_i e_{ij}}, \; (i, j = 1, 2, \ldots, p).$$

(3)

By analyzing Table 3, there is a higher load on the first principal component on the selling price and the shell material, indicating that the first principal component reflects the information of these indicators; the selling platform, the battery capacity, and the comments total have higher loads on the second principal component, indicating that the second principal component basically reflects the information of these indicators. The analysis of the third to fifth principal components is the same as above, and the visual results of the PCA are shown in Table 4.

3.4. Cluster Analysis. Cluster analysis is a multivariate statistical analysis method that can automatically classify a batch of sample data based on their many characteristics without prior knowledge [8]. There are currently three common clustering methods. The first is system clustering, which is used to cluster between small samples and cluster variables. The second is clustering of ordered samples. For the interobject clustering of samples with sort order, it is required that the objects adjacent to each other can be grouped together. The third is dynamic clustering, which is suitable for clustering between objects when the sample size is large and is generally processed by the k-means method [9]. Since this paper clusters the original indicators (variables) of small samples, the system clustering method is used for cluster analysis.

System clustering can be roughly divided into three steps: (1) first, each sample is self-contained; (2) the two classes are combined with the smallest distance among all classes into one class; and (3) step 2 is repeated until there is only one class left. Such a continuous process can be represented by a clustering spectroscopy similar to a tree structure.
Generally, the end condition of system clustering is set as maximum and minimum aggregation number and distance threshold. When the minimum component in the distance matrix exceeds a given distance threshold and the number of aggregated classes reaches a given requirement, the algorithm stops. The resulting classification is the result of clustering [10]. For comparative analysis, based on the conclusions obtained from PCA, the minimum clustering number of system clustering is set to 4, the maximum clustering number is set to 6, and the Euclidean distance is used to calculate the distance threshold.

The specific attribution of the variables when the system clustering analysis is clustered into 4 to 6 is shown in Table 5. From Table 5, it is possible to intuitively determine the

| Component | Initial eigenvalue | Sum | Variance (%) | Cumulation (%) | Sum | Variance (%) | Cumulation (%) |
|-----------|--------------------|-----|--------------|---------------|-----|--------------|---------------|
| 1         | 2.743              | 2.743 | 23.103       | 23.103        | 2.743 | 23.103       | 23.103        |
| 2         | 2.368              | 2.368 | 22.219       | 45.322        | 2.368 | 22.199       | 45.322        |
| 3         | 1.655              | 1.655 | 17.727       | 63.049        | 1.655 | 17.727       | 63.049        |
| 4         | 1.304              | 1.304 | 13.429       | 76.478        | 1.304 | 13.429       | 76.478        |
| 5         | 1.074              | 1.074 | 9.823        | 86.301        | 1.074 | 9.823        | 86.301        |
| 6         | 0.953              | 0.953 | 5.078        | 91.379        | 0.953 | 5.078        | 91.379        |
| 7         | 0.886              | 0.886 | 3.017        | 94.396        | 0.886 | 3.017        | 94.396        |
| 8         | 0.654              | 0.654 | 2.308        | 96.701        | 0.654 | 2.308        | 96.701        |
| 9         | 0.414              | 0.414 | 1.602        | 98.303        | 0.414 | 1.602        | 98.303        |
| 10        | 0.311              | 0.311 | 0.827        | 99.175        | 0.311 | 0.827        | 99.175        |
| 11        | 0.146              | 0.146 | 0.621        | 99.796        | 0.146 | 0.621        | 99.796        |
| 12        | 0.060              | 0.060 | 0.204        | 100.000       | 0.060 | 0.204        | 100.000       |

Table 3: Principal component load matrix.

| Indicator                  | Principal component | 1     | 2     | 3     | 4     | 5     |
|----------------------------|---------------------|-------|-------|-------|-------|-------|
| Selling platform           | −0.030              | 0.058 | 0.085 | 0.120 | −0.031|
| Selling price              | −0.792              | 0.392 | −0.097| −0.301| 0.200 |
| Battery capacity           | −0.466              | 0.042 | −0.504| 0.294 | −0.269|
| Shell material             | −0.849              | 0.278 | −0.084| −0.310| 0.145 |
| Battery type               | −0.349              | 0.681 | 0.134 | 0.557 | 0.092 |
| Safety protection          | 0.263               | 0.004 | 0.681 | 0.245 | 0.240 |
| Good proportion            | 0.391               | −0.131| −0.469| 0.372 | 0.511 |
| Comments total             | 0.145               | 0.081 | 0.882 | −0.173| −0.049|
| Network image              | 0.263               | −0.154| 0.329 | −0.143| 0.730 |
| Product testing            | 0.316               | 0.462 | −0.070| −0.572| −0.174|
| Product certification      | 0.418               | 0.516 | −0.260| −0.761| −0.072|
| Inspection result          | 0.050               | 0.098 | 0.192 | 0.495 | −0.202|

Table 4: Principal component analysis results.

| Component                  | Index                                      |
|----------------------------|--------------------------------------------|
| First principal component  | Selling price, shell material              |
| Second principal component | Selling platform, battery capacity, comments total |
| Third principal component  | Battery type, safety protection            |
| Fourth principal component | Inspection result, product testing, product certification |
| Fifth principal component  | Good proportion, network image             |

Table 5: Cluster member.

| Index                   | Six clusters | Five clusters | Four clusters |
|-------------------------|--------------|---------------|---------------|
| Selling platform        | 1            | 1             | 1             |
| Selling price           | 2            | 2             | 2             |
| Battery capacity        | 3            | 3             | 2             |
| Shell material          | 2            | 2             | 2             |
| Battery type            | 4            | 4             | 3             |
| Safety protection       | 4            | 4             | 3             |
| Good proportion         | 4            | 4             | 3             |
| Comments total          | 1            | 1             | 1             |
| Network image           | 1            | 1             | 1             |
| Product testing         | 6            | 5             | 4             |
| Product certification   | 6            | 5             | 4             |
| Inspection result       | 1            | 1             | 1             |
indicators corresponding to the four clusters, the indicators corresponding to the five clusters, and the indicators corresponding to the six clusters.

Finally, the clustering pedigree of the output clustering analysis results is shown in Figure 1. The clustering pedigree diagram shows the combined classes and their coefficient values in each step of the hierarchical clustering analysis, converting the distance between the classes into values of 1–25 and presenting the entire process of clustering from the visual level.

By analyzing Table 5 and analyzing the cluster pedigree from right to left, you can know that no matter whether the hierarchical clustering analysis is clustered into 4 categories, 5 categories, or 6 categories, the two indicators of battery type and safety protection are always in the same category, and the four indicators of selling platform, comments total, network image, and inspection result always in one category.

3.5. Construction of Indicator System. There are some differences in the results of screening the original indicators by PCA and hierarchical clustering analysis. Therefore, it is necessary to contact the actual optimization and integration to determine the final indicator system. The specific analysis process is as follows:

1. In the results of the cluster analysis, when the clustering is 5 categories, the selling price, the shell material, and the battery capacity are in one category. In the results of PCA, the selling price and the shell material are the first principal components, and the battery capacity has a higher load in the first principal component. At the same time, the battery capacity is related to the selling price in actual situations, so the results of the cluster analysis are retained. Therefore, the selling price, the shell material, and the battery capacity constitute a set of first-level indicators.

2. In the results of PCA, the second principal component is the selling platform, the battery capacity, and the comments total. In the previous step, we have divided the battery capacity into the first group of first-level indicators, so we do not analyze it. In the results of cluster analysis, the selling platform, the comments total, the network image, and the inspection result are always in one category. However, the network image and the inspection result have lower loads on the second principal component of PCA, and in practice they are not related to the selling platform and the comments total. Therefore, the selling platform and the comments total constitute the second group of first-level indicators.

3. In the results of PCA, the third principal component includes the battery type and safety protection. In the results of the cluster analysis, the above two indicators are always in one category, and they have a certain correlation in the actual situation. Therefore, the battery type and safety protection constitute the third group of first-level indicators.

4. In the results of the cluster analysis, the product testing and product certification are always in one category. In the results of PCA, the fourth principal component includes the inspection result, product testing, and product certification, and all three of them are the test results of authoritative organizations. Therefore, the results of principal component analysis are retained, and the inspection result, product testing, and product certification constitute the fourth group of first-level indicators.

5. In the results of PCA, the fifth principal component includes the good proportion and the network image. In the results of the cluster analysis, they are not always in the same category. However, the network image is derived from the good proportion, so the results of PCA are retained, and the good proportion and the network image constitute the fifth group of first-level indicators.

After determining the composition of each of the five sets of primary indicators, they need to be named. The first set of indicators refer to the product basic information of MPP, so they are named as the product information; the second set of indicators are related information in the e-commerce platform, so they are named as the platform information; the third group of indicators are related to the security status of the MPP, so they are named as the security guarantee; the fourth group of indicators are the evaluation results of the authoritative institutions, so they are named as the objective evaluations; the fifth group of indicators are all consumers’ evaluation of the goods, so they are named the subjective evaluation. The index system obtained after the indicators is sorted as shown in Table 6.

4. Weight Determination

4.1. Calculation Weight

4.1.1. Analytic Hierarchy Process. One comprehensively utilized multicriteria decision-making (MCDM) strategy is AHP [11–13]. Analytic hierarchy process decomposes the decision-making elements into objectives, criteria, schemes, and other levels, on which qualitative and quantitative analyses are carried out [14]. It can decompose complex multidecision problems into multiple levels and determine the degree of importance through a pairwise comparison between the indicators. The use of AHP to determine the weight of indicators is more systematic, concise, and flexible [15].

The steps of analytic hierarchy process to determine index weights are as follows: (1) construct the hierarchical structure; (2) construct the judgment matrix and assign the value; (3) determine indicator weight; and (4) check consistency of judgment matrix.

The construction of the indicator system has been completed in the above, which is to complete the construction of the hierarchical structure. In this part of weight determination, building a judgment matrix and assigning values is the most important step. According to the
importance of the indicators, this paper uses the five-scale method to complete the construction of the judgment matrix [16]. The judgment matrix is defined by referring to the numbers 1–9 and its reciprocal as a scale, and the importance scale values are as shown in Table 7.

The five primary indicators are recorded as $A_1$ (product information), $A_2$ (platform information), $A_3$ (security guarantee), $A_4$ (objective evaluation), and $A_5$ (subjective evaluation). According to Table 8, the five first-level indicators are compared and assigned separately, and the judgment matrix $A$ is obtained as follows:

$$
A = \begin{pmatrix}
1 & 3 & 1 & 1 & 1 \\
3 & 1 & 1 & 1 & 1 \\
1 & 3 & 4 & 1 & 1 \\
1 & 3 & 1 & 1 & 1 \\
1 & 2 & 3 & 1 & 1 \\
\end{pmatrix}
$$

After the judgment matrix $A$ is obtained, the weighted values of the five first-level indicators are calculated by the arithmetic average method, and the calculation results are shown in Table 9.

4.2. Consistency Check. In the above analysis, the weights of the five first-level indicators are initially obtained. However, this weight is not necessarily valid and desirable. Therefore, it is necessary to calculate the consistency ratio to check the consistency of the judgment matrix and ensure that the weight of the obtained index is acceptable.

Performing a consistency check consists of the following four steps:

(1) Calculate the maximum eigenvalue of the judgment matrix $A$ according to formula (5). The calculation results are shown in Table 8.

$$
\lambda = \frac{1}{n} \sum_{i=1}^{n} (A w)_i w_i
$$

The maximum eigenvalue is the average of the five eigenvalues corresponding to the five first-level indicators $\lambda_{\text{max}} = 26.29749146/5 = 5.25949829$. 

![Figure 1: Clustering pedigree.](image-url)
Computational CI (consistency index): $CI = \frac{\lambda_{\text{max}} - n}{n - 1}$, $n \geq 5$; $CI = 5.25949829 - 5 / (5 - 1) = 0.051899658$.

1. Find the average random consistency indicator, as shown in Table 10.
2. Calculate the consistency ratio: $CR = \frac{CI}{RI}$; $CR = 0.051899658 / 1.12 = 0.0463389804 < 0.1$.

When $CR < 0.1$, it is generally considered that the consistency of the judgment matrix is acceptable; otherwise, the judgment matrix should be appropriately modified. When the judgment matrix passes the consistency test, the calculated result can be used as the weight value of the indicator.

The calculated consistency ratio $CR < 0.1$ indicates that the level is maintained at a significant level, and the judgment matrix is consistent. Therefore, it can be determined that the weights of the five first-level indicators are $A_1$ (product information): 15.55%; $A_2$ (platform information): 6.73%; $A_3$ (security guarantee): 38.08%; $A_4$ (objective evaluation): 27.51%; and $A_5$ (subjective evaluation): 12.13%.

### 5. Model Construction

The weighted linear mathematical model is used to construct the e-commerce platform, MPP quality index, referred to as EMQI. It is linearly weighted by five subindexes of product information, platform information, security guarantee, objective evaluation, and subjective evaluation, as shown in the following formula:

$$EMQI = \sum_{i=1}^{5} \alpha_i \cdot \lambda_i.$$  \hspace{1cm} (6)

Among them, EMQI represents the mobile power quality index for the e-commerce platform, $\alpha_i$ represents the subindicator standard value corresponding to each level indicator, and $\lambda_i$ represents the subindicator weight corresponding to each level indicator.

According to the weights of the first-level indicators obtained, the quality index evaluation model of MPP sold under e-commerce platform is determined as follows:

$$EMQI = 15.55\% \times \alpha_1 + 6.73\% \times \alpha_2 + 38.08\% \times \alpha_3 + 27.51\% \times \alpha_4 + 12.13\% \times \alpha_5.$$ \hspace{1cm} (7)

Among them, $\alpha_i$ is linearly weighted by the corresponding secondary index by the subindicator standard value of the first-level index. The method for determining the weight of the secondary index is the same as above, and the calculation results are shown in Table 11.

Therefore, the final evaluation model is as follows:
Given that \( n = 5 \), it is determined that the value of RI is 1.12.

**Table 11: Weight calculation results.**

| Target                  | First-class targets | Weight | Second-class targets | Weight (%) |
|-------------------------|---------------------|--------|----------------------|------------|
| EMQI                    | \( \lambda_1 = 15.55\% \) | \( \alpha_1 = 37.59\% \) | Selling price      | \( \alpha_2 = 40.29\% \) | \( \alpha_3 = 22.12\% \) |
| EMQI                    | \( \lambda_2 = 6.73\% \) | \( \alpha_3 = 49.31\% \) | Shell material     | \( \alpha_4 = 54.48\% \) | \( \alpha_5 = 37.76\% \) |
| Objective evaluations   | \( \lambda_3 = 38.08\% \) | \( \alpha_4 = 42.68\% \) | Battery capacity   | \( \alpha_5 = 29.56\% \) | \( \alpha_6 = 49.31\% \) |
| Objective evaluations   | \( \lambda_4 = 27.51\% \) | \( \alpha_6 = 41.18\% \) | Selling platform   | \( \alpha_7 = 27.76\% \) | \( \alpha_8 = 41.18\% \) |
| Objective evaluations   | \( \lambda_5 = 12.13\% \) | \( \alpha_7 = 58.82\% \) | Comments total     | \( \alpha_9 = 42.68\% \) | \( \alpha_{10} = 58.82\% \) |
| Platform information    | \( \beta_1 \)       | \( \beta_1 \)       | Battery type       | \( \beta_2 \)       | \( \beta_3 \)       |
| Platform information    | \( \beta_2 \)       | \( \beta_2 \)       | Safety protection  | \( \beta_3 \)       | \( \beta_4 \)       |
| Platform information    | \( \beta_3 \)       | \( \beta_3 \)       | Inspection result  | \( \beta_4 \)       | \( \beta_5 \)       |
| Platform information    | \( \beta_4 \)       | \( \beta_4 \)       | Product testing    | \( \beta_5 \)       | \( \beta_6 \)       |
| Platform information    | \( \beta_5 \)       | \( \beta_5 \)       | Product certification | \( \beta_6 \) | \( \beta_7 \)       |
| Platform information    | \( \beta_6 \)       | \( \beta_6 \)       | Good proportion    | \( \beta_7 \)       | \( \beta_8 \)       |
| Platform information    | \( \beta_7 \)       | \( \beta_7 \)       | Network image      | \( \beta_8 \)       | \( \beta_9 \)       |
| Platform information    | \( \beta_8 \)       | \( \beta_8 \)       | \( \beta_9 \)       | \( \beta_9 \)       | \( \beta_{10} \)     |
| Platform information    | \( \beta_9 \)       | \( \beta_9 \)       | \( \beta_{10} \)    | \( \beta_{10} \)    | \( \beta_{11} \)    |
| Platform information    | \( \beta_{10} \)    | \( \beta_{10} \)    | \( \beta_{11} \)    | \( \beta_{11} \)    | \( \beta_{12} \)    |
| Platform information    | \( \beta_{11} \)    | \( \beta_{11} \)    | \( \beta_{12} \)    | \( \beta_{12} \)    | \( \beta_{13} \)    |

Among them, \( \beta_i \) represents the subindicator standard value corresponding to each secondary indicator.

**6. Conclusion**

The research object of this paper is MPP with frequent safety accidents in the near future. However, online shopping is one of the main channels for consumers to purchase MPP. Due to the virtual and spatio-temporal nature of shopping online, the quality evaluation of MPP in the e-commerce platform is cumbersome and complicated, and the corresponding quality evaluation basis is less, which increases the difficulty for the supervision department to monitor the online sales of mobile power.

This paper comprehensively uses the comprehensive index method, PCA, cluster analysis method, and AHP to construct the e-commerce platform, MPP quality index. This model can provide targeted guidance for the supervision and control of e-commerce platform in the sale of MPP, and the focus of sampling inspection in the next stage can effectively save sampling inspection cost and improve sampling efficiency. It can provide some reference for consumers to purchase MPP online and improve their shopping experience. It can effectively urge MPP manufacturers to improve product quality, safety, and competitive advantage. It is of practical significance to provide technical support for the comprehensive purification of e-commerce network environment.

**Data Availability**

The data used to support the findings of this study are included within the article.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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