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Risk early warning and control of food safety based on an improved analytic hierarchy process integrating quality control analysis method

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ABSTRACT

Food safety risks has received great attention in all world. And the reasonable effectiveness of security warnings can reduce public panic and risk losses. Therefore, this paper proposes an improved risk early warning method for food safety detection data based on the analytic hierarchy process (AHP) integrating the quality control analysis method. The AHP based on the entropy weight can obtain risk values for food safety component data. And the risk matrix of the risk component is obtained by the risk probabilities of the components. Then the corresponding risk levels are calculated using the quality control analysis method to release the risk warning information. Finally, a case study of dairy product safety data from the GuiZhou province in China is conducted to verify the feasibility and reliability of the proposed method. Moreover, the proposed method can scientifically and reasonably determine the risk level information. Furthermore, the risk management is provided to effectively reduce risk losses of the country though relevant quality inspection departments.

1. Introduction

With the rapid development of the economy, the food safety and quality have raised a higher requirement. If making correct and timely warning of food safety, people's fears will be alleviated, and the harm caused by the food security crisis will be reduced. Nowadays, there are more panic and unintended consequences bring by false warnings. And the food safety risk is serious. Meanwhile, more and more food safety problems involving complex food safety data are occurred (Ma, Hou, Liu, & Xue, 2016). Because the food safety risk monitoring foundation of China is weak, it is very important to customize a risk monitoring model based on the basic national conditions (Tang, 2013).

Due to the superior processing characteristics of complex food safety data technology, many dig data analysis and artificial intelligence methods of food safety risk assessment and early warning were proposed (Liu, Li, Yang, & Guo, 2018a; Wang, Yang, Luo, He, & Tan, 2015). Samuel et al. (Samuel, Asogbon, Sangaiah, Fang, & Li, 2017) used the fuzzy analysis hierarchical process (AHP) technique to calculate the global weight of attributes based on their individual contributions and predicted the high frequency risk of patients by training the artificial neural network (ANN) classifier. Wang et al. (Wang & Yue, 2017) formulated an early warning strategy for the safety risks arising from food transportation in the real-time monitoring of food safety to reduce the risk of food supply chain.

With the development of technology, more and more researchers improved the risk model in the food safety early warning field successfully. Lin et al. (Lin, Cui, Han, Geng, & Zhong, 2019) proposed an improved interpretative structural modeling method based on the grey relational analysis to obtain the stratification of food safety risk factors. The multi-level structures model of different factors affecting food safety were obtained. Geng et al. (Geng, Shang, Han, & Zhong, 2019) proposed a novel risk early warning model based on the deep radial basis function (DRBF) integrating the analytic hierarchy process to model complex food safety testing data using the concept of risk weighting, and the early warning of sterilized milk was achieved. In addition, the early warning modeling method combined with the extreme learning machine has also achieved good results (Geng, Yang, Han, & Zhu, 2017a).

Food safety issue is the matter of globalization, which is closely related to life safety, national stability and economic development. The EU has always attached great importance in food safety issues to establish the complete and standardized food safety regulations. Food and

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Feed Safety Alerts (RASFF) was established for food safety early warning, and it is the key tool to ensure the flow of information to enabling swift reaction when risks to public health are detected in the food chain (Tang, Xu, Qu, Zhang, & Hu, 2012). However, RASFF is not a versatile system, which cannot provide a good guarantee for the product quality. In order to meet consumer expectations, the better predictive risk model is built to make food detection and food fraud prevention more effective (Ulberth, 2016).

In order to prevent food safety incidents more effectively, a lot of research work on the top of the food supply chain (Food cultivation and collection) have been done by the researchers to prevent food-borne food safety risks. Hans et al. (Marvin et al., 2013) investigated the potential direct and indirect effects of extreme events such as severe weather and hydrometeorology on various agricultural systems. The study found that the negative impact of serious natural events on food could be minimized by making better use of existing information. Lei et al. (Lei et al., 2017) studied the extreme meteorological disaster effects on grain production in Jilin Province, China. Therefore, early prevention and early detection have a great impact on the prevention of food safety crisis.

Whether natural risk or technical ability, it will have different impacts on food safety risks and generate certain risks (Kaptan, Fischer, & Frewer, 2018). Ross et al. (Ross & Sumner, 2002) adopted a spreadsheet tool in the process of converting qualitative to quantitative values, and the food safety risk values was generated by setting the specified principles for food safety risk assessment within the software. Meanwhile, the risk assessment experiments for foodborne infections was also conducted (Ross & McMeekin, 2003). Furthermore, the specific analytical tools were used to perform quantitative risk analysis for each phase, and a formal conceptual framework for risk nature and risk assessment was established (Jaykus, 1996).

Manning et al. (Manning & Soon, 2013) determined the acceptable mechanism model by using the qualitative or semi-quantitative methods. And the fuzzy logic had a positive effect on the quantification mechanism, but it might also create unacceptable risks in the later stages of the supply chain. Overbey et al. (Overbey, Jaykus, & Chapman, 2017) introduced the relevant literature based on food safety and infectious diseases in social media and concluded on how to use social media best for food safety risk communication. Sadiq et al. (Sadiq & Beauchemin, 2017) developed a new ion chromatography method, which was detected online by inductively coupled plasma mass spectrometry for simultaneous morphological analysis of arsenic chromium and selenium in bio contactable fractions, to determine the toxic portions of these elements. Racicot et al. (Racicot et al., 2018) calculated the median value for each criterion and cluster to quantify the relative importance of the selected criteria in the established risk assessment model, and the risks associated with a group of criteria was estimated. Machine learning technology had also been widely used in the evaluation of food safety analysis (IZSTORu et al., 2017), and had achieved remarkable results in foreign studies (Bisgin et al., 2018; Kim, Awofeso, Choi, Jung, & Bae, 2017).

Faced with a variety of security risk prediction methods, an improved risk early warning method for food safety based on the AHP integrating quality control analysis method is proposed in this paper. Risk values for food safety component data are calculated through the AHP based on the entropy weight to obtain the risk matrix of the risk component. Then the corresponding risk levels are calculated based on the quality control analysis method (Cao, 2018) to release the risk warning information, and the risk warning information is provided to effectively reduce risk losses of the country though relevant quality inspection departments. Finally, the proposed method is applied in risk early warning of dairy product safety data from a GuiZhou province in China. The experimental result shows that the feasibility and reliability of the proposed method is verified. Furthermore, the efficiency of early warning processing can be improved, and the time costs of early warning decisions by warning personnel can be saved.

2. The risk early warning method

2.1. Risk matrix

2.1.1. AHP based on entropy weight

The AHP is a systematic analysis method, which provides a more convincing basis for scientific management and decision-making. The AHP based on the entropy weight has a strong ability to distinguish indicators when the indicators are the same, making the weight distribution more objective and accurate (Geng et al., 2017b; Yan, Zhang, & Zong, 2016a, 2016b).

Set X= $\{X_1, X_2, \cdots, X_n\}$.And the correlation of the nodes is represented by constructing a correlation matrix. The node of $k_{ij}(x)$ is represented by $x_j(1), x_j(2), x_j(3), x_j(4)$, as shown in Eq. (1).

$$k_{ij}(x) = \begin{cases} 0 & x \notin [x_j(1), x_j(4)] \\ \frac{x_{ij} - x_j(1)}{x_j(2) - x_j(1)} & x \in [x_j(1), x_j(2)] \\ 1 & x \in [x_j(2), x_j(3)] \\ \frac{x_j(4) - x_{ij}}{x_j(4) - x_j(3)} & x \in [x_j(3), x_j(4)] \end{cases} \tag{1}$$

Where, x_{ij} is the value of the row i and the column j of the matrix x, and $x_j(1), x_j(2), x_j(3), x_j(4)$ represents four elements of the j column.

When the second node coincides with the third node, the standard correlation function is expressed as shown in Eq. (2).

$$k_{ij}(x) = \begin{cases} 0 & x \notin [x_j(1), x_j(4)] \\ \frac{x_{ij} - x_j(1)}{x_j(2) - x_j(1)} & x \in [x_j(1), x_j(2)] \\ \frac{x_j(4) - x_{ij}}{x_j(4) - x_j(3)} & x \in [x_j(2), x_j(4)] \end{cases} \tag{2}$$

Then, the information matrix is calculated based on Eq. (3).

$$K_{n\times m} = \begin{bmatrix} k_{11} & k_{12} \cdots k_{1m} \\ k_{21} & k_{22} \cdots k_{21} \\ \cdots & \cdots \cdots \cdots \\ k_{n1} & k_{n2} \cdots k_{nm} \end{bmatrix} \tag{3}$$

The matrix normalization is obtained as shown in Eq. (4).

$$k_{ij}^{'} = (k_{ij} - \overline{k_j})/S_j(\text{ i= 1,2,3,}\cdots\text{,n; j= 1,2,3, }\cdots\text{m}) \tag{4}$$

Where,

$$\overline{k_j} = \frac{1}{n}\sum_{i=1}^{n} k_{ij}(j = 1,2,\cdots,m) \tag{5}$$

An orthogonal matrix is obtained by using $R_{n\times m}^{j}$, as shown in Eq. (6).

$$\text{COR} = \text{R}R^{T} \tag{6}$$

Where, i (i= $1,\cdots$,m) the variation coefficient of the evaluation indicator is calculated by using the entropy method as shown in Eq. (7).

$$E_i = 1 + k\sum_{j=1}^{n} r_{ij}\ln r_{ij} \tag{7}$$

Where, k= $1/\ln m$。

If the relevant indicators are highly different, the amount of information is greater (Yan et al., 2016a, 2016b). The weight calculation of the indicator is calculated based on Eq. (8).

$$W_i = \frac{E_i}{\sum_{i=1}^{n} E_i} \tag{8}$$

The weight W can be used to obtain the fused input data $\hat{X}$ as shown in Eq. (9).

$$\hat{X} = X^{T}\text{W} \tag{9}$$

2.1.2. Construction of risk matrix

The possibility of risk occurrence and the impact of risk in risk classification should be considered. Therefore, a risk matrix for risk level assessment needs to be introduced. The risk matrix is a qualitative risk assessment analysis method that combines the probability of occurrence of a hazard with the severity of the hazard. Risks can be characterized and ranked by relevant factors (Markowski & Mannan, 2008), which can visualize risks and help to give reasonable recommendations for the allocation of resources and play an important role in the field of food safety risk management (Banach, Stratakou, Van der Fels-Klerx, Den Besten, & Zwietering, 2016; Liu, Chen, Zhang, & Wang, 2010).

Since the risk index is calculated by the AHP based on the entropy weight, the risk weight generated determines the influence degree of the component on the level index, and thus the level division work is performed.

For the security risk event with the number of risk components n, the basic steps for establishing the risk matrix are as follows.

Step 1: Risk factors x_1, x_2......x_n are determined.
Step 2: The risk values a_1, a_2......a_n are evaluated by the AHP based on the entropy weight, and the risk ranking results are obtained.
Step 3: The probability analysis of the crisis events caused by n risks and n risk probabilities p_1, p_2......p_n are obtained based on the data statistics.
Step 4: The risk matrix is drawn with the risk probability as the coordinate and the risk level as the abscissa.
Step 5: The risk level according to the risk matrix and the risk control factors of different risk levels are determined.

The flow chart of the risk matrix is shown in Fig. 1.

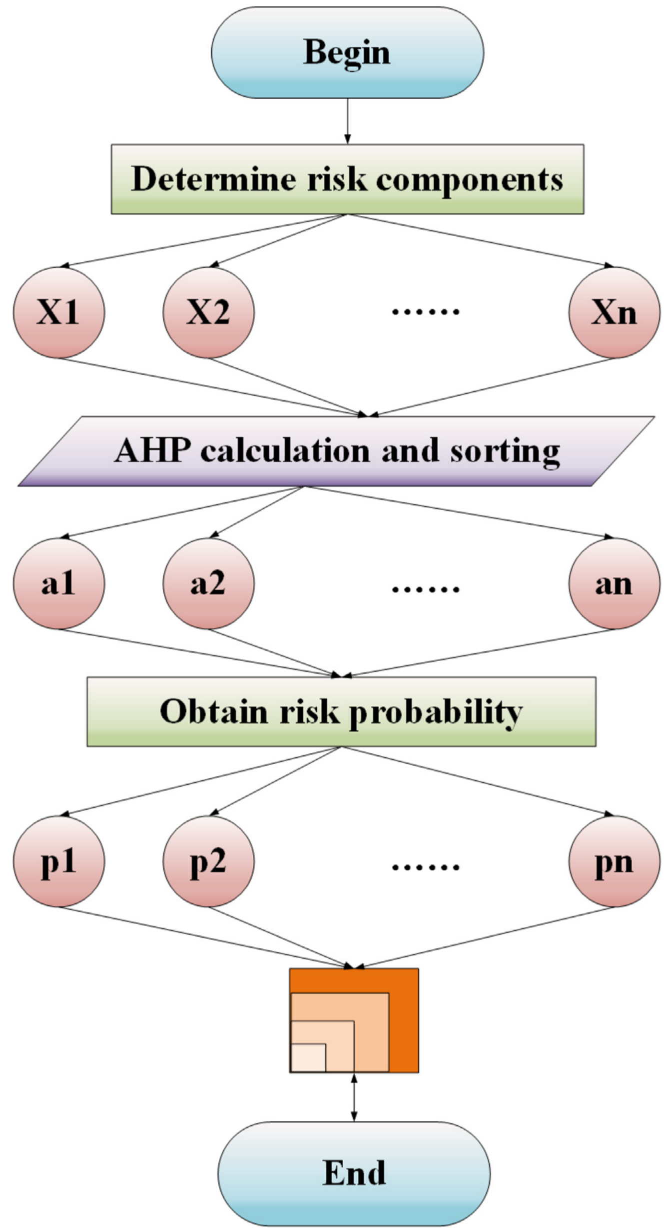


Fig. 1. The flow chart of the risk matrix.

2.2. The quality control analysis algorithm

The detection and control of data quality is the basis of data operation. In the quality management and daily evaluation of data, the quality control chart is an effective method for analyzing monitoring data (Jiang, 2014; Liu et al., 2018b). The data quality control analysis method can directly and accurately reflect the abnormal data fluctuation through the control chart (National food safety standards of China,). The risk value calculated by the AHP is the necessary attribute to draw the risk matrix, and the quality of risk components is analyzed by the data quality control analysis method in sequence by referring to the risk value. Then the result can be used to investigate whether there is abnormal fluctuation inside the data. By calculating the randomness of the risk index and the performance index and determining whether the data component content can fluctuate within the range specified by the state, the further verification of the data risk can be obtained.

When the data is in a normal distribution, the quality control analysis method can judge the extent to which the test data meets the quality standard requirements (specification range, etc.) through the process capability index of the two-sided specification.

The calculation of the capability index and performance index can be used to analyze the fluctuations of the data within the limits of the specification and ensure the quality and safety of the test data.

The quality control limit calculation process is shown as follows, where, UCL represents upper control limit, LCL represents lower control limit.

The mean value is calculated as shown in Eq. (10).

$$\bar{x} = \frac{\sum_{i=0}^{n} x}{n} \tag{10}$$

The range of movement is calculated as shown in Eq. (11).

$$R_s = R_{i+1} - R_i \tag{11}$$

The control limit of the moving range R_s is calculated as shown in Eqs. (12-13).

$$UCL_{Rs} = D_4\overline{R_s} \tag{12}$$

$$LCL_{Rs} = D_3\overline{R_s} \tag{13}$$

The single value X quality control limit is calculated as shown in Eqs. (14-15).

$$UCL_X = \bar{X} + E_2\bar{R} \tag{14}$$

$$LCL_X = \bar{X} - E_2\bar{R} \tag{15}$$

Where D_3, D_4 and E_2 are constants used to group the calculated mobile range and vary with sample size. And D_3, D_4 and E_2 can be obtained in the quality control coefficient table (ASTM Committee E-11 on Statistical Methods, 1976). The detailed data as shown in Table 1.

The double-sided capability index and the one-sided capability index can be obtained by the double-sided specification limit or the single-sided specification limit. The calculated capability index and performance index can effectively evaluate the fluctuation of the analytical data within the specification limits and whether the fluctuations

Table 1
Set control limit parameters.

n	2	3	4	5	6	7	8	9	10
D_4	3.27	2.57	2.28	2.11	2.00	1.92	1.86	1.82	1.78
D_3	*	*	*	*	*	0.08	0.14	0.18	0.22
E_2	2.66	1.77	1.46	1.29	1.18	1.11	1.05	1.01	0.98

Table 2
Capability index and performance index.

Item	index abbreviation	index value	Equation
Actual external item	Act. % Outside SL	0.0%	
Capability index	CP	1.983	$CP = (USL{-}LSL)/6\sigma$
	CPL	1.066	$CPL = (\bar{x}{-}LSL)/3\sigma$
	CPU	2.901	$CPU = (USL{-}\bar{x})/3\sigma$
	CPM	0.677	$CPM = (USL{-}LSL)/6\sqrt{\sigma^2 + (\bar{x} - \mu_0)^2}$
Performance index	PP	1.047	$PP = (USL - LSL)/6s$
	PPL	0.562	$PPL = (\bar{x}{-}LSL)/3s$
	PPU	1.531	$PPU = (USL{-}\bar{x})/3s$
	PPM	0.593	$PPM = (USL{-}LSL)/6\sqrt{s^2 + (\bar{x} - \mu_0)^2}$

are random. Meanwhile, the stability of the data also can be judged by the results of these two indexes, and the monitor of risk fluctuation of the data can be more accurately. The calculation method of the capability index and performance index as shown in Table 2.

Where $\bar{x}$ is the quality control index, s is the standard deviation of all quality control points, μ_0 is the target value, USL and LSL are the upper specification limit and lower specification limit, CP is the process capability index, PP is the process performance index, CPL is the CP lower limit, PPL is the PP lower limit, CPU is the CP upper limit, PPU is the PP upper limit and CPM is the critical path method.

2.3. The process of the risk early warning method

Step 1: The weight of the risk attribute is calculated by the AHP based on the entropy weight, and the risk value of each component is obtained.
Step 2: The risk level of the ingredients is sorted according to the risk value. And the resulting components correspond to nine risk levels can be obtained.
Step 3: The risk probability of each component is calculated.
Step 4: The risk level of each component is determined by the risk matrix.
Step 5: Quality control analysis of each risk component is performed from high to low risk level. Then data risk results and determine risk warning levels can be obtained.
Step 6: The corresponding level of dairy product risk warning information is analyzed.

The flowchart of the improved risk early warning method is shown in Fig. 2.

3. Case study

3.1. Dairy data analysis

The experimental data is derived from dairy inspection data of the GuiZhou province in China (Geng et al., 2019). During the data processing, nine risk assessment indicators are selected for experimentation, including chromium test results, fat test results, arsenic test results, protein test results, acidity test results, mercury test results, lead test results, skim milk Structured data of solid test results and aflatoxin M1 test results. The total number of samples is 1241, and the data composition are shown in Fig. 3.

Normal distribution is the premise of data quality analysis. And the Q-Q graph can provide valid verification of whether the data is normally distributed. In order to verify and ensure the reliability of the quality control analysis results, 30 sets of sample data are randomly selected and tested for normal distribution. The horizontal and vertical coordinates are the standard quantile and the quantile of the input sample, respectively. The inspection principle is shown in Table 3.

Taking the test results of the three components as an example, the experimental results are shown in Fig. 4. It can be judged that the component content data is quantitative data obeying the normal distribution. Therefore, the quality inspection data in this experiment does not need to be further processed.

3.2. The dairy early warning experiment

The weights of the nine risk components are obtained through the AHP based on the entropy weight as shown in Fig. 5.

Through the statistics of the National Food and Drug Administration's data on the unqualified sampling of dairy products from 2014 to the present (Notice of food sampling i, 2014; The Food and Drug Adminis, 2014), 24 cases of sterilized milk violation data are extracted as shown in Table 4, which are used to analyze the risk occurrence probability of each risk component. The results are shown in Table 5.

Combining the risk occurrence probability of each component and the overall priority of the risk components as shown in Fig. 5, the risk evaluation matrix diagram can be drawn as shown in Fig. 6. Then, the risk levels can be classified better and reasonable suggestions can be obtained by the results of the risk matrix.

Through the comprehensive analysis, the risk priority of the components is obtained, and then the specific risk components are positioned. According to the risk matrix analysis results, the quality control analysis method is used to detect the components in turn, and the order is Aflatoxin M1, chromium, arsenic, acidity, lead, protein, HG, fat and Non-fat milk solid.

The non-fat milk solid figure is chosen for analysis, and the rest of the ingredients are not shown one by one for the sake of space. The results are shown in Fig. 7 and Fig. 8:

It can be seen from the result graph that the mean line of the quality control chart is 9.343, the UCL is 10.1642, the LCL is 8.5216, and the LSL is 8.1. According to the national standard, there is no UCL for non-fat milk solids. According to the above introduction, the violation points are marked to facilitate further measures against the violation indicators.

In order to judge the violation of data, the specification limit, quality control limit, and the quality control limit are used for measuring data violation. However, if the data fluctuates within the quality control limits, or if a certain value of the data suddenly occurs, the problem of the data could not be proved, because the randomness of the data need to be determined. This requires that a good use of specification limits is calculated. In order to facilitate the interpretation of the results of the capability index, and reference to the quality control limit, the acidity is taken as an example. And the quality control chart is shown in Fig. 9.

Referring to the calculation of the various indices, Act. % Outside SL is 0%, there is no point outside the free specification limit. According to the graph of the acidity quality control chart, it is in line with the actual data, and all the points are within the specification limits.

These four capability indices with the CP, the CPL, the CPU and the CPM are used to reflect the ability of the analysis process to operate within specification limits and to evaluate different capability indices from different perspectives. The CP is defined as the ratio of the difference between the upper and lower limits of the specification to the fluctuations in the analysis process. The greater the difference between

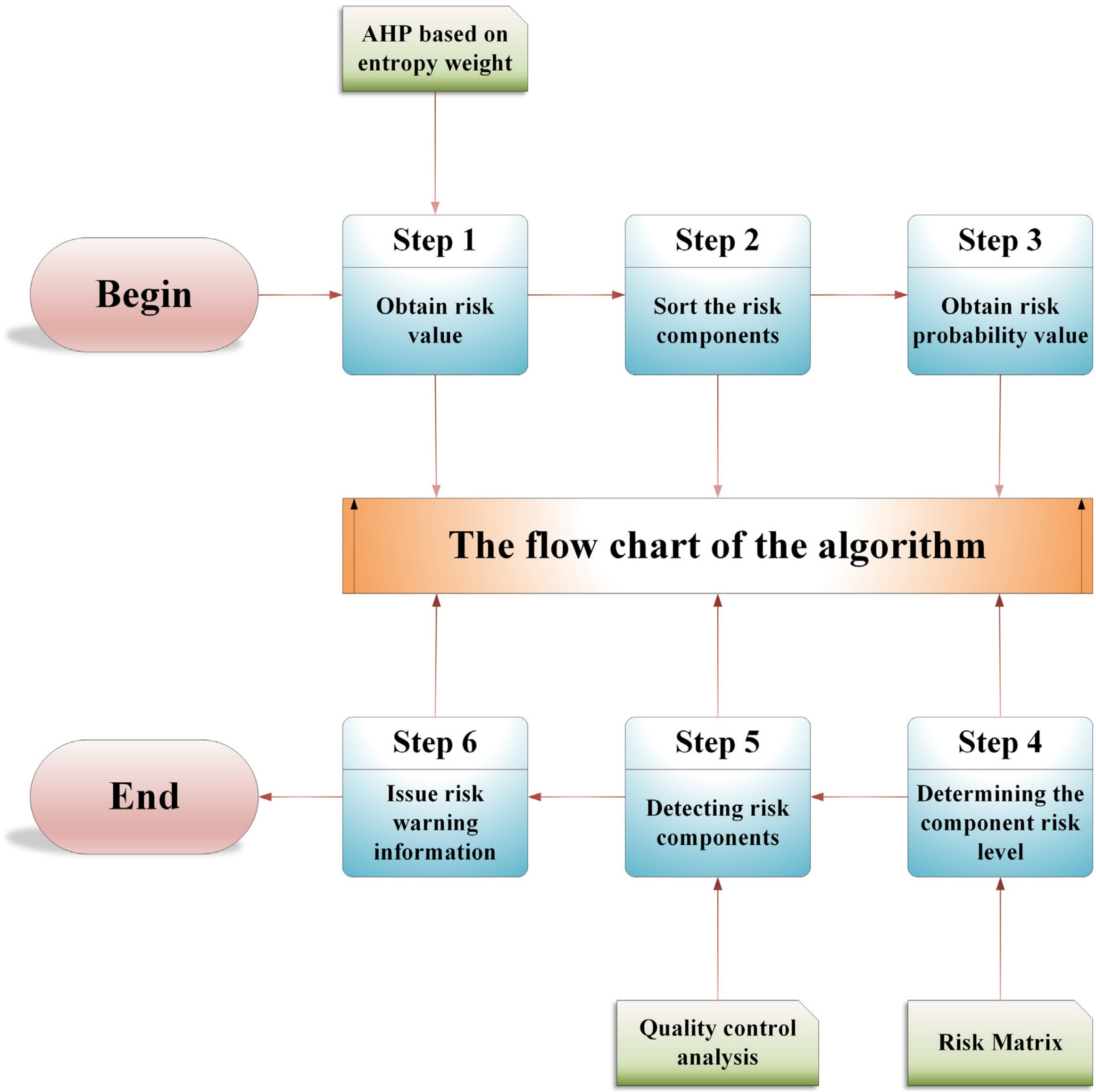


Fig. 2. The flow chart of the improved risk early warning method.

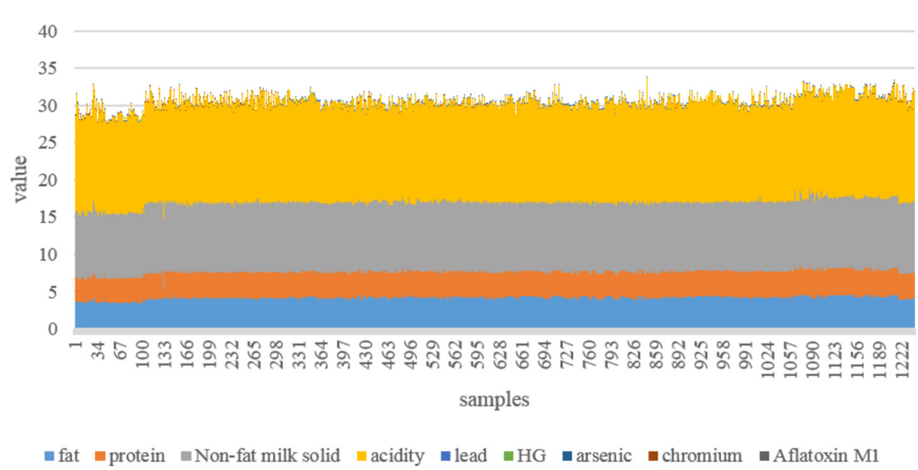


Fig. 3. Dairy inspection data.

Table 3
Q-Q diagram normal distribution test results reference basis.

Point distribution	critical result
The scatter is approximated by a straight line	Normal distribution
The scatter is not near a straight line	Non-normal distribution

the upper and lower limits of the specification, the smaller the data fluctuation, and the larger the CP. If the CP is greater than or equal to 1, the entire analysis process can operate within the specification limits.

As mentioned above, the smaller the data standard deviation, the closer the data distance tolerance is, and the better the data dispersion. Then, the greater the value of the process capability index, the better the process capability is. Otherwise, if the process capability index is small, the process capability of the data is worse. Therefore, through the numerical value of the process capability index, the fluctuation of the data within the specification limits can be judged effectively (Balamurali & Usha, 2016). The specific evaluation method and the corresponding capability index can refer to Table 6.

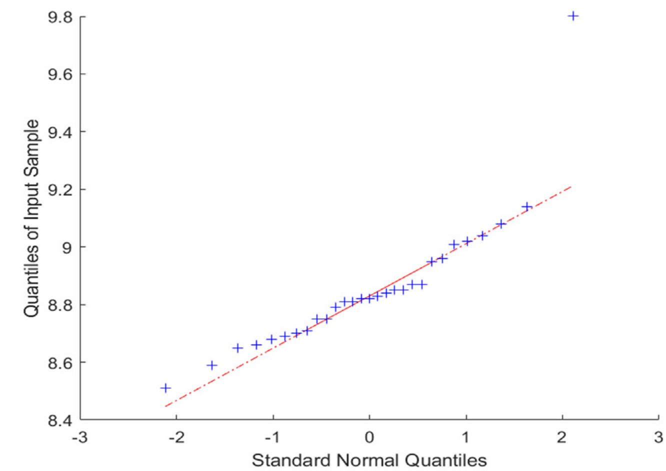
In this example, the value of the CP is 1.983, indicating that the data is not discrete and the data distribution is safe. The CPU is like the CP, and the CPU can feed back the fluctuations and functions of the data within the upper limit of the specification. The value of the CPU is 2.901, indicating that the fluctuation of the data does not exceed the upper limit of the specification set by the data. The CPL feeds back the fluctuations and capabilities of the data above the lower specification limit. For example, fat, non-fat milk solids and protein only need to judge the CPL. The value of the CPL is 1.066, indicating that the experimental data fluctuations should not be below the lower specification limit. Since the fluctuations in the analysis data are not symmetrical, meanwhile, the CPU and the CPL are not close. The difference between the CPM and the CP is that it can judge the activity of the data near the target value, which can be obtained according to the size relationship between the CPM and the CP. When the value of the CP is greater than 1 and approximates the CPM, it can be determined that the data fluctuation is around the target value, and the value of the CPM is 0.677. Therefore, the data fluctuation of the experiment does not surround the target value.

The performance index and the capability index listed in this paper are similar in effect. Meanwhile, according to the publicity and the corresponding name, the corresponding relationship can be obtained, such as the PP relative to the CP and the PPL relative to the CPL. Each performance index is significantly smaller than its corresponding capability index. Therefore, the next conclusion is that the data changes are not random, and such periodic changes may be accompanied by data problems. Although the analysis process is not volatile, the acidity of dairy products have regular changes, and it is necessary to analyze the content data of the components.

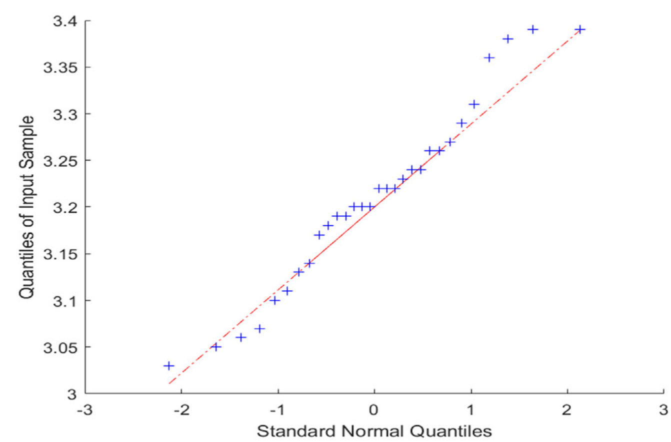
3.3. Analysis of experimental results

The results of the risk matrix can be used to classify the early warning risks of dairy products as shown in Table 7.

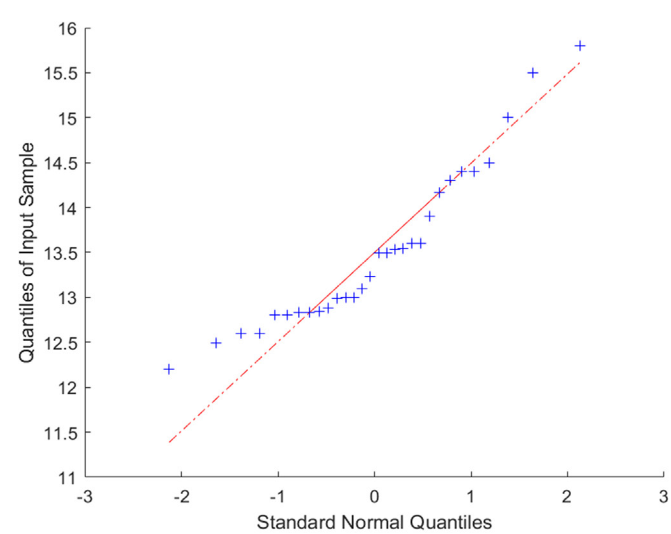
Then, the quality control analysis is used to detect the abnormality of the data, and the specific level of the dairy product safety risk warning can be determined. In order to facilitate the relevant early warning agencies to make appropriate early warning decisions. The loss caused by dairy crisis events in the shortest possible time could be minimized, and the risks could be dealt with in advance, which can bring security to individuals, reducing losses for businesses and panic for the country. Generally, a higher risk security situation will correspond to a higher level. Levels of the high risk should be handled faster and take the most comprehensive measures. Otherwise, the lower warning level can take certain defensive measures to prevent the spread or increase of risks, which also greatly helps the early warning and



Q-Q image detection results of non-fat milk solid components



Q-Q image detection results of protein components



Q-Q image detection results of acidity components

Fig. 4. Q–Q image detection results of non-fat milk solid, protein and acidity components.

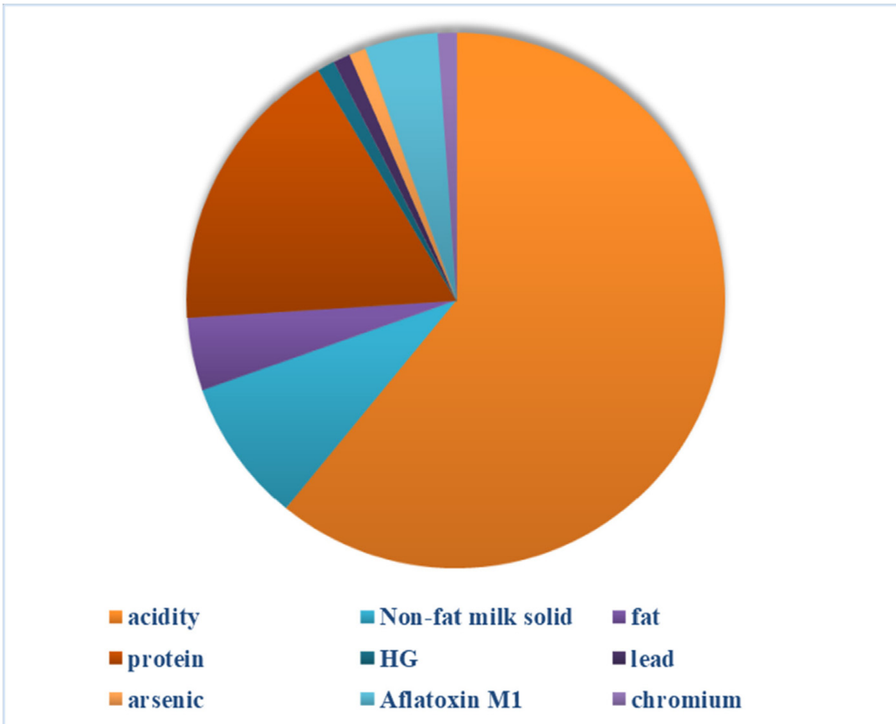


Fig. 5. The risk weights of the safety indicators.

Table 4
Unqualified sterilized milk data.

No.	Sample name	Unqualified item
1	Fresh pure milk	Mold
2	Fresh pure milk	Mold
3	Pure milk	Mold
4	Pasteurized milk	protein
5	Pure milk (sterilized)	Protein, acidity,
6	Fresh milk (full fat pasteurized milk)	Protein, acidity, total number of colonies
7	Full fat pasteurized milk	Mold
8	Fresh milk (pasteurized milk)	Mold
9	(full fat pasteurized milk)	Mold
10	Long-lived pure milk (full-fat sterilized pure milk)	acidity
11	Fresh milk	acidity
12	Xiangxiang Buffalo Milk (Pasteurized Milk)	acidity
13	Pure milk	acidity
14	Pure milk	acidity
15	Fresh milk	acidity
16	Fresh milk (full fat pasteurized milk)	acidity
17	Fresh milk	acidity
18	Student milk (pure milk)	acidity
19	Pure milk (student milk sterilized milk)	acidity
20	Plateau pure milk	acidity
21	Plateau pure milk (full fat sterilized milk)	acidity
22	Pure milk	Fat, protein, non-fat milk solids
23	Pasteurized milk	Mold
24	Pure milk	Non-fat milk solid

processing agencies to solve the problem effectively. Furthermore, dairy companies can also be marked according to the situation and degree of risk and frequency, which can help follow-up quality tracking and risk monitoring, so that enterprises can strengthen self-management and form deterrence.

According to the above content, the dairy product risk is divided into 6 levels, and the warning treatment suggestions for the 6 early warning levels are given as follows:

1) A particularly serious warning signal (level 1). It indicates that the probability of a dairy product quality safety crisis is very dangerous, and market sales or continued production will be significantly affected. Therefore, a first-level warning signal is issued, and special measures are required in the risk control process to minimize product impact and potential hazard regardless of cost.
2) Severe warning signal (level 2). It indicates that the probability of a dairy product quality safety crisis is high. Therefore, the appropriate measures are taken refer to the quality control test results. Meanwhile, the second-level warning signal is issued, and it is recommended to conduct internal discussions and take measures immediately.
3) More serious warning signals (level 3). It indicates that the quality of dairy products has the risk of a security crisis. A three-level warning signal should be issued, and it is recommended to take certain measures to control the adverse effects.
4) Generally serious warning signals (level 4). It indicates that the risk of a dairy safety crisis is less affected. A four-level warning signal should be issued. And it is recommended to take measures as appropriate and make requests to manufacturers according to the actual situation.

Table 5
Probability of risk for each component.

Ingredients	Fat	Arsenic	Aflatoxin M1	Acidity	Non-fat milk solid	Mercury	Chromium	Protein	Lead
Risk probability	0.042	0.01	0.342	0.583	0.083	0.01	0.01	0.167	0.01

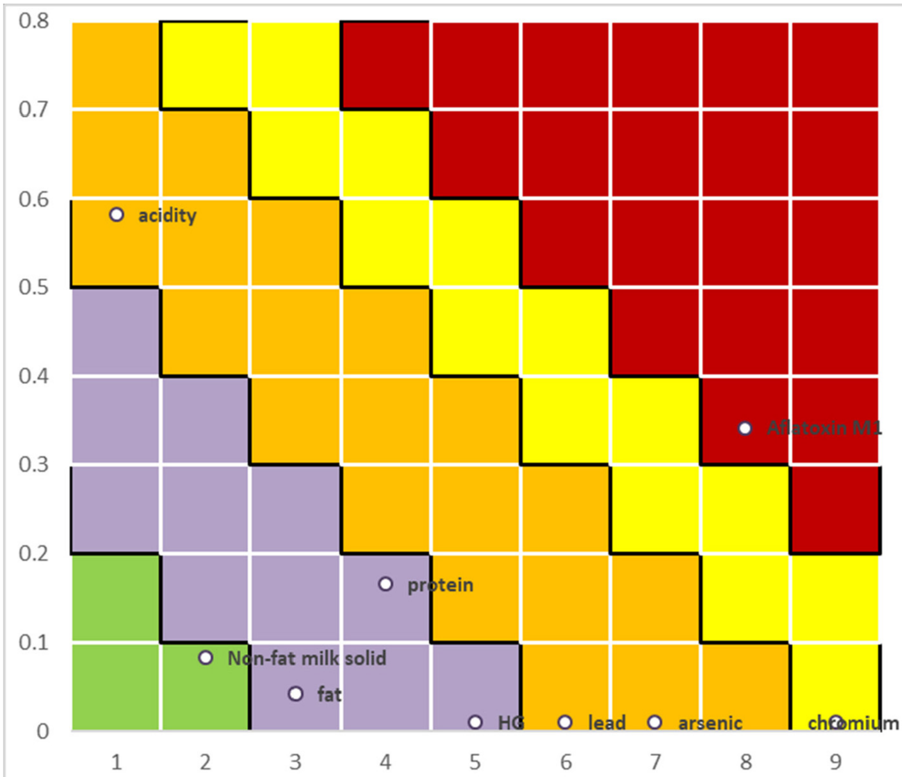


Fig. 6. The risk matrix.

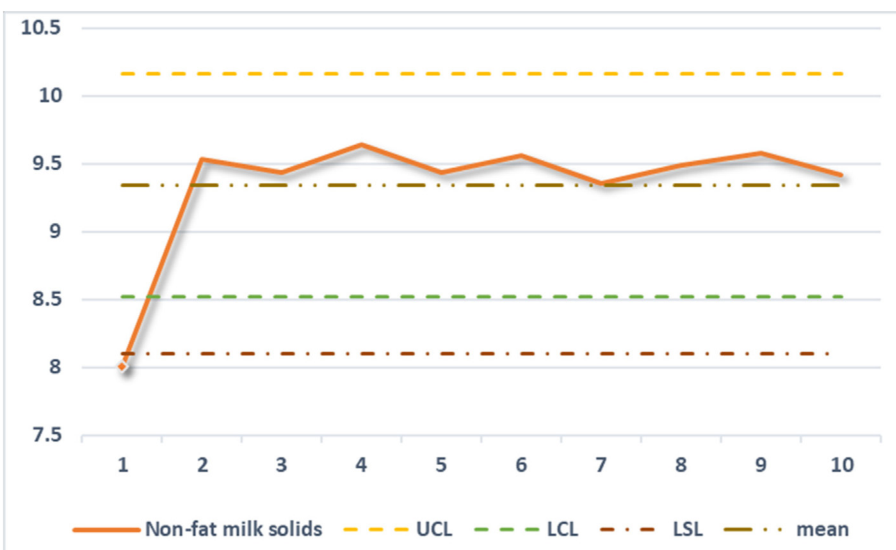


Fig. 7. Quality control chart of non-fat milk solids.

5) Mild warning signal (level 5). It indicates that the probability and impact of the dairy product quality and safety crisis are small. A five-level warning signal should be issued to selectively observe supervision.
6) Risk-free warning. No treatment.

4. Discussion

First, since the RASFF is not a versatile system, which cannot provide a good guarantee for the quality of the product, and the neural network method has low accuracy and easily falls into local optimal solution, an improved risk early warning method based on the AHP integrating the quality control analysis method is proposed. The risk value of risk components obtained by the AHP based on the entropy weigh is converted into quantitative analysis. With the risk weight and the component risk probability results, the risk matrix map can be used to comprehensively evaluate the probability and severity of the risk. Then, the quality control analysis algorithm is adopted. The risk profile of the components is effectively analyzed and the risk level is accurately located by the specification limits, control limits and capability indices.

Second, the proposed method is applied in the risk prediction of the food safety. Nine dairy risk factors are divided into five risk levels by the risk matrix. The warning treatment suggestions for the warning levels are determined by quality analysis results.

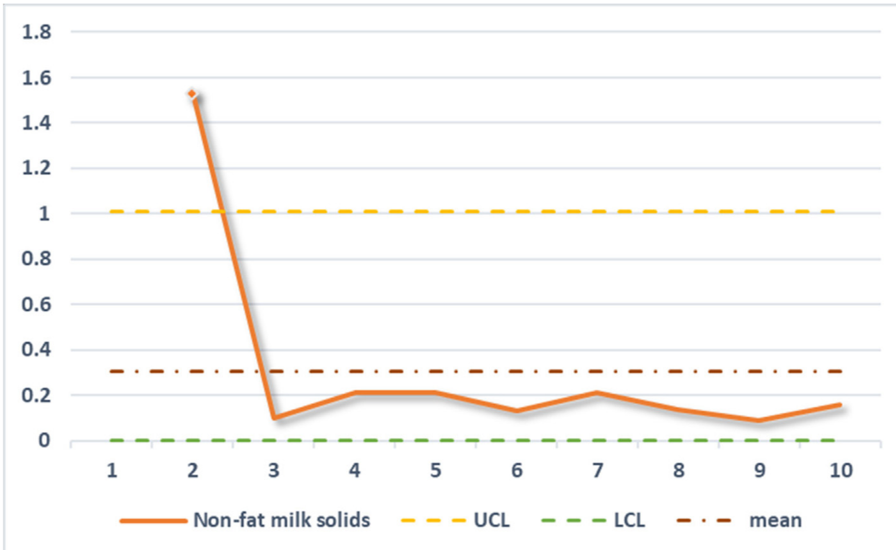


Fig. 8. Range chart of non-fat milk solids.

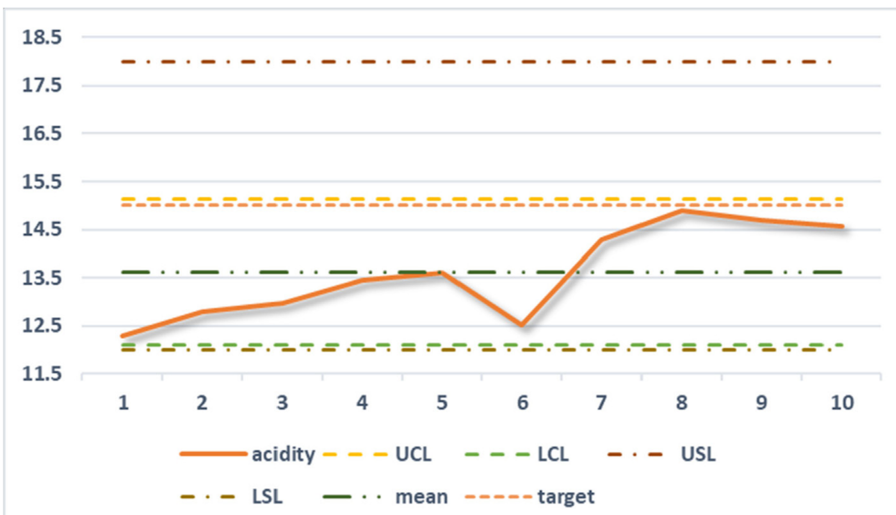


Fig. 9. Quality control chart of acidity.

Table 6
Capability index evaluation references.

CP Radom	level	Evaluation reference
CP ≥ 1.67	1	High process capability
1.33 ≤ CP < 1.67	2	Full process capability, data dispersion security
1 ≤ CP < 1.33	3	Adequate process capability and good data dispersion
0.67 ≤ CP < 1	4	Insufficient process capability, data may exceed specification limits and should be verified
CP < 0.67	5	Serious process capability, serious data violations

Third, when the risk matrix is graded, the level boundaries are artificially set with strong subjectivity. The risk factors that are required to be assessed are relatively determined, resulting in a large difference in the classification of different people. Therefore, more reasonable measures will be taken for the risk division of the risk matrix.

5. Conclusion

This paper proposes a novel risk early warning method of food safety based on the AHP integrating quality control analysis method, which is used in food risk prediction. The AHP algorithm based on the

Table 7
Risk classification description.

Risk level	Basis of division
1	The risk impact of abnormal components is at the fifth level of the risk matrix.
2	The risk impact of abnormal components is at the fourth level of the risk matrix.
3	The risk impact of abnormal components is at the third level of the risk matrix.
4	The risk impact of abnormal components is at the second level of the risk matrix.
5	The risk impact of abnormal components is at the first level of the risk matrix.

entropy weight is used to extract feature variables and form a security risk index. And the component risk probability is combined to draw a risk matrix. Then, the early warning level division of risk components is scientifically and reasonably completed by the visual effect of the risk matrix diagram. Finally, the data quality control analysis method is used to analyze the risk of data and data fluctuations. The risk component is determined and the final risk warning information is released. Meanwhile, the experimental results show the proposed method can reduce the time of positioning risk and the reasonable risk warning evaluation opinions are provided to the risk warning department.

In our further works, the food-borne risks of dairy products should be considered, and some artificial intelligence methods will be integrated to automatically adjust the level boundaries of the risk matrix. In addition, the proposed model can be widely used in other food safety risk warning areas.

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