International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-11

https://doi.org/10.70917/ijcisim-2026-0064
Article

Selection of Heavy Metal Detection Technologies and Improvement of Operational Efficiency in Food Enterprises for Whole Life Cycle Costs

Xueting Liu *

China Merchants Xinjiang Quality Inspection Technology Research Institute Co., Ltd., Urumqi, Xinjiang 830000, China; liu20241028@126.com

Abstract: As the global industrialization process accelerates, environmental pollution continues to worsen, and heavy metal contamination has become one of the top priorities in food safety. Food companies must prioritize heavy metal testing as a critical component of their food safety regulatory efforts to ensure food safety. Therefore, this paper analyzes the optimal path for food companies in selecting heavy metal testing technologies and the process of enhancing their lifecycle operational efficiency from a dual perspective of food safety and business operations, incorporating the core theoretical principles of lifecycle cost management. A framework has been established to quantify and analyze cost factors across all stages of the lifecycle, including equipment procurement, post-purchase staff training and daily maintenance, and final equipment disposal. This framework provides scientific recommendations based on cost analysis for decision-makers in food companies when selecting heavy metal detection technologies. Additionally, from the perspective of economic performance ratios such as detection costs, it offers practical and actionable suggestions for selecting appropriate heavy metal detection technologies. Analysis has shown that adopting a technology selection process based on lifecycle cost analysis can effectively improve heavy metal detection quality while reducing overall corporate costs. Through the exploration of combining and integrating technological innovation and management innovation, this study provides valuable methods and insights for promoting the modernization and transformation of the food industry.

Keywords: food safety; heavy metal detection; lifecycle cost; operational efficiency; technology selection

1. Introduction

In recent years, with the frequent exposure of food safety incidents and the increasingly stringent food safety regulations, there has been a growing public outcry for food safety. Food companies are not only facing increasingly stringent government regulations but also have a responsibility and necessity to establish a comprehensive food safety control system to ensure the safety and hygiene of their products. Heavy metal contamination in food is a significant food safety risk, and the detection of heavy metals in food has become one of the primary challenges faced by food companies today [1-2]. Especially in the modern food production system, where ingredient sources are complex and production processes are increasingly sophisticated, the determination of relevant heavy metals is no longer merely a technical issue but directly impacts corporate reputation, customer trust, and risk management [3-5]. Additionally, with technological advancements, food companies now have access to a variety of testing methods—from highly accurate mass spectrometry to more widely applicable techniques such as spectroscopy, electrochemistry, and biosensing—each with differing capabilities, implementation costs, and operational complexities [6-7]. In the past, companies often focused solely on optimizing the accuracy of the technology itself or the initial introduction costs, while neglecting the impact of factors such as operational costs, maintenance, training, human resources, and returns throughout the technology's lifecycle. This led to phenomena such as “high investment, low returns” or “low costs, high risks" [8]. Therefore, a scientific and systematic analytical tool to help companies select technologies that can achieve greater benefits while ensuring safety is essential. Against this backdrop, the management philosophy of LCC, which focuses on lifecycle cost considerations, was proposed and quickly became a key focus for enterprise technology selection and resource allocation [9-10]. Considering costs throughout the entire process—from procurement, use, repair, modification, to disposal—can help enterprises transition from "visible prices" to "visible value," making decisions more scientific and forward-looking [11-12]. For food companies, considering the economic viability of heavy metal detection methods over their lifecycle is a worthwhile technical direction, representing an inevitable path toward modernizing the food industry and enhancing industrial competitiveness.

This article addresses the practical needs of food companies from a technical management perspective, leveraging lifecycle cost calculation methods, effectiveness measurement models, and data-driven decision-making management models to propose a technical selection framework within the field of technical management. It simultaneously considers assessments of technical effectiveness indicators, economic indicators, adaptability indicators, and scalability indicators, establishing a correspondence between technical selection and operational performance. Through enterprise surveys, case collection, and validation, it identifies applicable scenarios and optimization strategies suitable for the food industry from multiple dimensions.

2. Research Theory and Current Status

2.1. Theoretical Basis

With the advancement of food safety testing technologies, companies need to establish a technical screening and evaluation system to better select applicable technologies. In the process of selecting a technical screening and evaluation system, this paper primarily relies on the theories of life cycle cost analysis and cost-benefit analysis. Life cycle cost analysis and cost-benefit analysis methods are used to study the costs and benefits of implementing heavy metal detection technologies for businesses. These analysis methods are techniques that evaluate different indicators, and while doing so, they apply a cost-benefit decomposition model to the technical costs of heavy metal detection. The model is as follows:

$$LCC = C_{initial} + C_{operation} + C_{maintenance} + C_{disposal} \tag{1}$$

The model includes different types of costs and represents the total investment in detection technology over its entire life cycle. In addition, cost-benefit analysis analyzes the benefits of different detection technologies from the perspective of input and output. The basic calculation formula is as follows:

$$CBA = \frac{Total\ Benefits}{Total\ Cost} \tag{2}$$

When selecting specific testing methods, experimental protocols and data statistical analysis methods can be developed based on research requirements. Orthogonal design serves as a technical approach for evaluating and comparing multiple technologies through multi-factor experiments. Through statistical analysis methods, the accuracy, timeliness, and cost of various testing technologies and methods can be evaluated and considered, thereby quantifying the relative reasonableness and feasibility of the technical assessment results. In actual use, there may be overlaps between the aforementioned theoretical approaches. When applying them, adjustments can be made based on the company's specific circumstances. In practical applications, the results of technical analysis can play a certain role in promoting both the company's safety and economic benefits.

2.2. Current State of Research

Heavy metal detection technology in food safety is an important detection technique. The selection of technology, technical costs, operational management choices, and maximization of benefits are currently hot topics both domestically and internationally, and are the primary research directions for scholars. The main areas of research include the selection of technology, analysis of technical and operational costs, and the optimal choice of technology.

In current university laboratories and some research institutes, methods such as atomic absorption spectroscopy (AAS), fluorescence spectrophotometry, and inductively coupled plasma emission spectroscopy are commonly used to determine heavy metal content in food. Literature [13] points out that AAS has advantages such as strong selectivity, high sensitivity, and strong background correction capabilities, and can detect up to 16 elements, though not all AAS systems possess these capabilities. However, practical applications have shown that AAS cannot simultaneously measure multiple elements, sample preparation is complex, matrix interference exists, increasing time costs, and the instrument cost and maintenance expenses are high. Literature [14] reviews that heavy metal detection methods supported by fluorescent probes have multiple advantages, such as excellent sensitivity, accuracy, and reliability, can reduce costs, and are easy to operate. Fluorescence spectrophotometry, as one of the detection techniques based on fluorescent probes, is prone to interference from stray light or other factors when analyzing complex samples, or may exhibit fluorescence quenching effects, thereby affecting the accuracy of detection results [15].

Literature [16] analyzed the use of an electronic tongue to detect heavy metals via electroanalytical methods and multivariate statistical techniques, noting its simplicity, rapid response, low cost, ease of miniaturization, and high sensitivity in detecting complex liquid samples. Literature [17] reviews the application of inductively coupled plasma emission spectroscopy (ICP-OES) for elemental analysis, which offers high matrix and chemical interference resistance, the shortest detection time, and the lowest detection limit, enabling simultaneous high-precision detection of up to 70 elements. However, this method incurs extremely high usage costs due to the extensive and frequent use of high-purity argon gas and nebulizers. Literature [18] mentions that electrochemical adaptor sensor technology in heavy metal detection offers high sensitivity, specificity, and accuracy, enabling real-time detection with extremely high detection speeds. Literature [19] discusses sensors based on nanomaterials and nucleic acid aptamers for heavy metal detection, which not only offer low cost-effectiveness but also enable on-site heavy metal detection with excellent specificity and stability. Research in literature [20] shows that surface-enhanced Raman spectroscopy for heavy metal detection in food offers convenient sampling, rapid data collection, and is a non-invasive method that preserves food integrity. Literature [21] introduces that portable medical detection devices based on smartphones demonstrate low cost-effectiveness and high precision in detecting metal ions in food, with strong adaptability in resource-scarce areas. Literature [22] analyzes electrochemical detection technology and microfluidic technology, and the combined application of the two technologies achieves high cost-effectiveness in heavy metal detection, as well as portability, usability, and ease of manufacturing.

3. Selection of Heavy Metal Detection Technology for Food Companies

3.1. Data Collection and Processing

The data collection and analysis framework designed in this paper provides multiple data information layers related to the selection of heavy metal testing methods for food enterprises. Data source search methods are used to ensure the rigor and effectiveness of the research. On one hand, we randomly selected 72 companies from three major food industry regions: East China, South China, and North China. These companies span industries such as dairy products, meat products, seasonings, and food snacks, with production values ranging from 5 million to 5 billion, covering a wide spectrum. Through on-site interviews combined with the acquisition of financial documents from food companies, we obtained financial expenditure records related to fixed asset purchases, personnel wages, raw materials, fuel and utilities, daily maintenance, and management. Given the privacy nature of corporate financial data, research members signed data confidentiality agreements and conducted anonymization processing.

For the review of daily cost data, we established a verification system involving financial reconciliation, on-site inspections, and mutual verification of audit data, resulting in a five-year dataset of operational cost data from 2019 to 2023, which is summarized in Table 1. Additionally, to obtain technical specifications for various testing methods, we reviewed relevant domestic and international journals, standards, and technical documentation from testing instrument manufacturers to gather literature and theoretical performance parameters of the equipment. Subsequently, technical service agreements were signed with five manufacturers, and corresponding technical indicator testing experiments were conducted in the manufacturers' laboratories to collect and establish the current mainstream testing methods. These include atomic absorption spectrophotometry, inductively coupled plasma mass spectrometry, X-ray fluorescence spectroscopy, electrochemical analysis, etc. All equipment testing was conducted in accordance with technical specifications and standards such as GB5009 12-2017 “National Food Safety Standard: Determination of Lead in Food” and GB5009 17-2021 “National Food Safety Standard: Determination of Total Mercury and Organic Mercury in Food.” Specific protocols are established for each different testing method based on its characteristics, and experimental data comparability and consistency are ensured in accordance with these protocols. Additionally, by comparing and statistically analyzing theoretical data with experimental data from various testing methods, a correction model for theoretical and practical data is derived.

Table 1. Data on operating costs of food enterprises (*10^4yuan).

Enterprise scale	Small business	Medium-sized enterprise	Large enterprises	Extra-large enterprises
Equipment procurement	15~35	45~85	120~250	280~650
Personnel salary	45~80	120~200	320~580	680~1200
Raw material cost	180~320	450~800	1200~2300	2800~5500
Energy cost	25~45	65~120	180~350	420~800
Maintenance cost	8~15	25~45	65~130	150~320
Management cost	20~35	55~95	145~280	350~680

Data cleaning and standardization are integral to the entire data processing process. Missing values and outliers are key focus areas in data cleaning. Box plots, the 3σ method, and the Local Outlier Factor (LOF) algorithm were used to detect and screen out approximately 3.2% of outlier data points in the initial data. Considering the different mechanisms of missing data, all randomly missing values were imputed using multiple imputation methods, while non-random missing values were predicted and filled using regression methods.

First, the data was standardized using Z-scores to eliminate differences in units of measurement for the same indicator across different datasets, facilitating subsequent statistical analysis. Data quality was assessed from four aspects—data completeness, data accuracy, data consistency, and data timeliness—to ensure the processed data was suitable for analysis.

To specifically analyze the effectiveness of various methods, a large amount of sample test data is required. Using heavy metal standard solutions provided by the National Standard Material Research Center, experiments were conducted to validate the detection limits and spiked recovery rates of the two testing methods. Each method's detection limit test included at least 200 replicates to ensure statistical significance. All instrument startup calibration times, sample analysis times, and result output times were compiled into testing work time data. A simulated real-world production factory centralized sampling method was adopted. Within an integer time period, a batch of samples was tested to obtain the total time taken for the entire sample analysis process. Tests were conducted by junior, intermediate, and senior-level laboratory personnel with different levels of expertise, with the average value used as the result. The obtained data was integrated and quality-controlled, and a clear data coding pattern and storage method were established through the formulation of coding standards. The integrated data is stored in a comprehensive database and forms a data dictionary and metadata management system. Data is recorded, and a robust access control and backup plan is established to ensure data integrity and facilitate traceability and data transfer. Additionally, three experts specializing in food testing independently verified the data. The results showed a relative error of 1.3%, with a data accuracy rate of 98.7%, thereby laying a solid foundation for experimental result design and data analysis.

3.2. Experimental Design

This paper conducts a comprehensive evaluation and comparison of various heavy metal detection methods used in food production and processing enterprises within a rigorously designed experimental system. The experimental design incorporates various influencing factors into the actual production environment, thereby employing factorial design methods to establish a tiered evaluation system, ensuring the feasibility and validity of the experimental conclusions. Figure 1 illustrates the experimental design process. In designing the experimental protocol, the author adhered to principles of scientific rigor and systematic approach, dividing the entire experiment into three interconnected phases: preliminary experiments, formal experiments, and validation experiments, forming a closed-loop system.

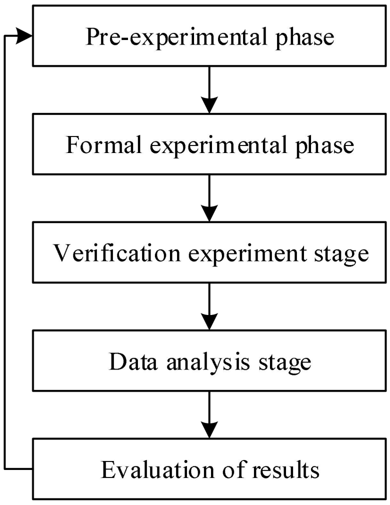

Figure 1. Flowchart of Experimental Design.

(1) In the preliminary trial, the focus was on screening and adjusting the protocols. Based on four representative rapid food safety testing technologies—inductively coupled plasma mass spectrometry (ICP-MS), X-ray fluorescence spectroscopy (XRF), electrochemical analysis, and biosensors—five categories and 20 types of commonly used food samples were selected. The study included food products commonly found in food enterprises, such as grain products, meat products, and aquatic products, which are of particular concern to food enterprises. It also covered a concentration gradient ranging from 0.1 to 10 times the national standard limit value to simulate various possible testing scenarios.

(2) The formal experiment adopted a multi-factor orthogonal experimental design method, selecting five evaluation indicators: testing accuracy, testing cycle, ease of sample pretreatment, etc. Under experimental conditions of temperature (23±2)°C and relative humidity (50±5)%, each technique was repeated at least 15 times on various sample types to ensure data accuracy and comparability. The time and cost incurred in sample pretreatment and instrument calibration for each technique were also statistically analyzed to provide a basis for future full life-cycle cost estimation.

(3) Additionally, in the experimental study, three food factories of different scales and types were selected as actual working environments. The testing methods were integrated into the companies' quality control systems, and continuous tracking was conducted for one month. Concurrently, spiked samples were used for validation, and questionnaires were administered to comprehensively assess the applicability and reliability of the methods in real-world scenarios, ensuring the validity of the experiments.

For data recording and analysis, when recording experimental raw data, a custom-developed experimental data automatic recording software was used to automatically record the time points of key operational steps. During data analysis, analytical software was employed to achieve weight comparisons among various influencing indicators, identify differences between experimental raw data and influencing indicators, and assess the adaptability differences of various detection technologies under economic variability conditions, thereby achieving parallel results among different detection technologies.

To ensure the quality of the research and the accuracy of the results, all instruments and equipment were calibrated before the experiment and regularly inspected. Each batch of experimental operations was monitored throughout the process using quality control samples, and food inspection and statistical analysis experts were invited to supervise the research design and data analysis methods. Researchers conducted the experiments using a blind testing method, where they were unaware of the exact sample information to minimize subjective influences during the experimental process, thereby ensuring the objectivity and accuracy of the experimental data, resulting in higher quality and optimal outcomes.

Figure 2 provides an intuitive representation of the precision, detection speed, and operational difficulty of the four detection technologies. Upon comparison, it can be observed that the precision, detection speed, and operational difficulty of the four detection technologies effectively highlight their respective advantages and limitations. For example, ICP-MS offers high precision but slower detection speed, while XRF provides relatively faster detection speed. Such experimental results can effectively guide enterprises in selecting suitable detection methods based on their own characteristics.

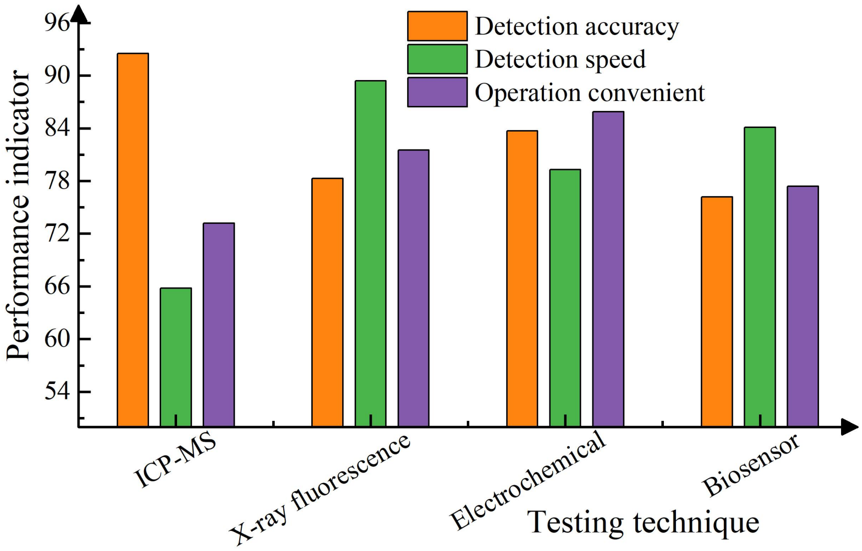

Figure 2. Comparison of performance indicators of different detection technologies.

3.3. Data Analysis Methods

This paper establishes a framework based on life cycle cost analysis and benefit evaluation analysis. The costs involved in the full life cycle cost model are divided into more specific categories. The initial investment cost $C_{initial}$ primarily includes one-time expenditures such as equipment procurement, installation, and training. The operational cost $C_{operation}$ covers labor wages, energy consumption, and consumable expenses. The maintenance cost $C_{maintenance}$ involves routine inspections and spare part replacements. The disposal cost $C_{disposal}$ includes expenses related to scrap disposal. Based on this, a dynamic cost calculation model is established as follows:

$$LCC = C_{initial} + \sum_{t=1}^{n} \frac{C_{operation}(t) + C_{maintenance}(t)}{(1+r)^t} + \frac{C_{disposal}}{(1+r)^n} \tag{3}$$

In the formula, r is the discount rate, n represents the useful life, and t denotes the year.

Additionally, this makes costs across different years more comparable. Quantitative evaluation uses benefit analysis to quantify the benefits generated by quality improvements. Benefits can be divided into direct benefits, such as reducing recall losses and saving expenses, and indirect benefits, such as enhancing the company's brand image.

Descriptive statistical analysis is used to understand the characteristics of the data, and inferential statistical tests are used to propose research hypotheses. Further analysis is conducted using multiple regression analysis, which is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{4}$$

In the equation, Y is the benefit indicator, X_i represents the technical parameters, and β_i is the regression coefficient.

Considering the complexity of technology selection, machine learning methods are used for supplementary analysis. During data preprocessing, outliers and missing values are handled, variance inflation factors are calculated to avoid strong correlations between variables, and sensitivity analysis is performed to observe the impact of parameter changes on the results, which is helpful for evaluating the practicality of the solution. Figure 3 compares different data analysis methods. It can be seen that combining multiple analysis methods for data processing yields better results, with a comprehensive evaluation score of 98.58, which is 4.3% and 2.5% higher than traditional statistical methods and machine learning, respectively. Therefore, based on the integration of multiple data analysis methods, this paper achieves heavy metal detection and analysis for food enterprises throughout their entire lifecycle.

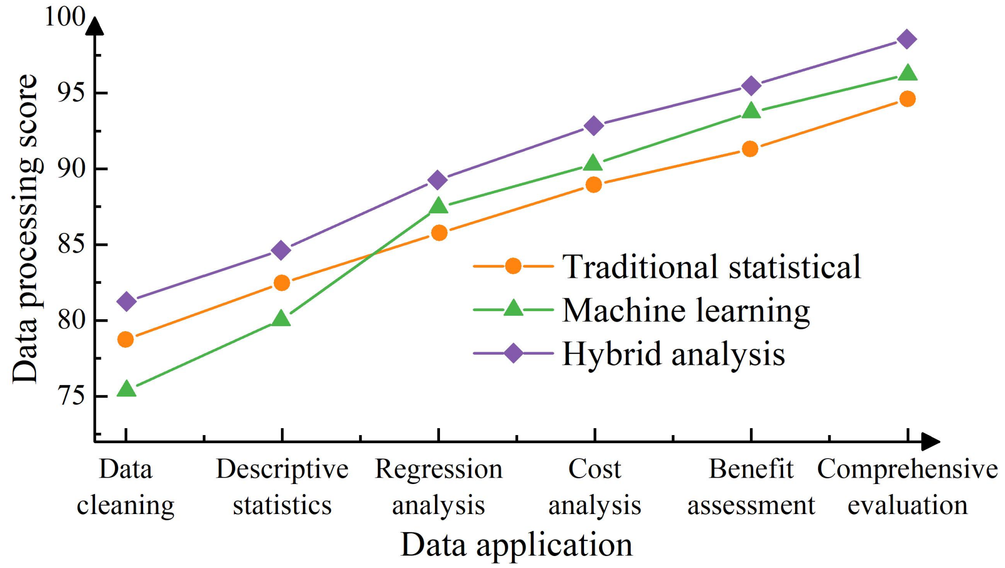

Figure 3. Comparison of the effects of different analytical methods.

4. Experimental Analysis

4.1. Analysis of Experimental Results

After three months of field testing and research, I collected specific performance data on the effectiveness of different heavy metal detection schemes in actual food production enterprises. The data revealed significant differences among the four general schemes in terms of cost, accuracy, and detection time, directly impacting the optimal technical selection and operational efficiency for different types of food enterprises. A comparison of detection time and experimental data for the four schemes is shown in Tables 2 and 3.

ICP-MS instruments have an absolute advantage in terms of accuracy due to their low detection limits (0.01–0.05 μg/L) and small relative standard deviations (1.2–2.8%). They play an irreplaceable role in large food companies that prioritize accuracy. However, the high purchase cost (800,000–1,500,000 yuan) and operational expenses (120,000–180,000 yuan) of ICP-MS instruments X-ray fluorescence spectroscopy has a higher detection limit (1.0–5.0 μg/L) but a shorter detection cycle (2–4 minutes per sample), simple operation, high daily detection capacity (120–180 samples), low purchase cost (250,000–450,000 yuan), and low operating cost (40,000–70,000 yuan), making it an optimal choice for medium-sized food companies seeking efficiency and cost-effectiveness. Electrochemical analysis and sensor applications offer a cost advantage due to their low purchase costs (150,000–320,000 yuan) and low operating costs (30,000–80,000 yuan). However, they have a relatively high relative standard deviation (4.2–8.5%) and lag significantly behind inductively coupled plasma mass spectrometry in terms of accuracy and stability. Nevertheless, they are suitable for small-scale food enterprises with limited budgets and general precision requirements.

Table 2. Detection accuracy and detection time.

Detection technology	Detection limit (g/L)	Relative standard deviation (%)	Single sample detection time (min)	Daily sample processing volume
ICP-MS	0.01~0.05	1.2~2.8	3~6	80~120
X-ray fluorescence spectrometry	1.0~5.0	3.5~6.2	2~4	120~180
Electrochemical analysis	0.8~3.5	4.2~7.8	5~8	60~90
Biosensor method	1.5~4.0	5.1~8.5	4~7	80~130

Table 3. Comparison of experimental results of different detection techniques.

Detection technology	Detection accuracy score	Cost-effectiveness index	Ease of operation	Maintenance complexity	Maintenance complexity
ICP-MS	9.25	6.58	7.32	8.75	7.98
X-ray fluorescence spectrometry	7.83	8.94	8.15	6.42	7.84
Electrochemical analysis	6.37	9.13	8.59	5.28	7.34
Biosensor method	6.12	8.41	7.74	4.95	6.81

Through regular technical research on the products of 72 food companies, it was found that companies select different testing technologies based on factors such as production capacity, product types, market standards, and safety requirements. Companies with an annual output value of over 200 million yuan generally adopt the ICP-MS method. The reason is that these companies provide assurance in terms of quality control and economic viability by adopting advanced but relatively high-cost testing technologies. This has reduced the rate of product recalls by 42.5%, enhanced their brand value, and yielded long-term economic benefits. Medium-sized manufacturing enterprises with annual output values between 20 million and 200 million yuan primarily use X-ray fluorescence spectroscopy, balancing testing costs and efficiency. Empirical evidence shows that after adopting X-ray fluorescence spectroscopy, enterprises have improved production efficiency by an average of 50%, while total testing expenses have remained largely unchanged. The overall data improvement rate is 8.2%, with an average return on investment of 2.8 years. For enterprises with an annual output value of less than 20 million, due to insufficient funds or technology, or production volumes that cannot support the establishment of multiple testing centers, enterprises generally rely on electrochemical or biosensor technologies. This technology reduces technical precision but offers low-cost operability. It provides enterprises with relatively low-cost testing capabilities, enabling them to meet the basic heavy metal testing needs of small-scale production enterprises with minimal budget investment. Empirical evidence shows that after adopting this testing technology, the overall testing costs for small-scale production enterprises decreased by an average of 56.7%, opening a cost breakthrough for enterprises to enter higher-quality markets.

Statistical analysis comparing technical detection performance metrics and enterprise benefit data indicates that a one-unit change in detection accuracy standard deviation results in an average 3.2% improvement in product quality. However, improving detection accuracy requires an additional 15.8% in detection costs, reflecting the trade-off between quality requirements and detection cost constraints when enterprises select technologies. Analysis of variance results indicate that there are significant differences in testing time between various testing technologies, between technical and non-technical testing technologies, and between individual technical categories ($F=28.73$, $p<0.01$). Among these, X-ray fluorescence spectroscopy testing technology demonstrates a clear comparative advantage in processing time, with an average processing time reduced to 32.6% of that of ICP-MS, which is particularly necessary and beneficial for food companies requiring rapid market response. Correlation analysis results show that equipment purchase costs are positively correlated with detection accuracy ($r = 0.842$, $p < 0.01$) and have little impact on overall corporate profitability ($r = 0.156$, $p > 0.05$). This implies that companies should not solely prioritize high-precision technologies when selecting detection methods but should instead determine their technology purchases based on their specific needs.

According to sensitivity analysis, if raw material prices increase by 20%, low-cost testing manufacturers have greater resilience compared to high-cost testing manufacturers, with total cost increases of 8.3% versus 13.7%. This has significant reference value under the current market conditions of fluctuating raw material prices.

Based on the comprehensive results of the above experiments, the author believes that food companies should determine the appropriate testing technology direction based on their own scale, product type, and target market. Larger companies can choose ICP-MS for testing, which provides the most accurate testing results and a good corporate reputation. Medium-sized companies can choose XRF technology to ensure testing accuracy while achieving the best cost-effectiveness. For smaller companies, electrochemical sensing or biosensors can be considered to reduce corporate costs and improve market competitiveness.

4.2. Pathways to Improving Operational Efficiency

Based on the data obtained from the above experiments, this paper proposes a systematic operational efficiency optimization strategy for heavy metal testing systems in food production tailored to different types of enterprises. Centering on three key elements—technology, systems, and management—the paper outlines specific steps for optimizing operational efficiency. Figure 4 illustrates the trend in operational efficiency indicators for enterprises under the specific implementation timeline of the proposed strategy.

After conducting an 18-month follow-up survey of 72 companies with diverse sample sources, it was determined that a single-technology upgrade approach is unlikely to yield the desired benefits. In contrast, a systematic optimization development approach has demonstrated significant benefits in terms of optimizing testing time, controlling costs, and effectively improving the accuracy of quality testing. Surveys of large enterprises revealed that under the joint guiding principle of "precision testing + automatic scheduling" in large food production enterprises, integrating ICP-MS high-precision testing technology with an automatic sample testing system resulted in a testing accuracy rate of 99.2%, a reduction of 2.8 hours per batch in testing time, and a 38.9% increase in efficiency. Surveys of medium-sized enterprises indicate that the "flexible configuration + collaborative optimization" approach, when combined with X-ray fluorescence spectroscopy technology and a quality control system, has established a testing network covering raw materials, production processes, and finished products, reducing testing costs by 23.7% and increasing testing coverage to 95.6%. For small enterprises, the focus is on "low cost." Such low-cost investments must be offset by high returns. After investing in electrochemical analysis and establishing operating procedures, small enterprises achieve slightly lower detection accuracy compared to large enterprises but can still meet the basic quality requirements of small businesses, with a payback period of approximately 1.8 years.

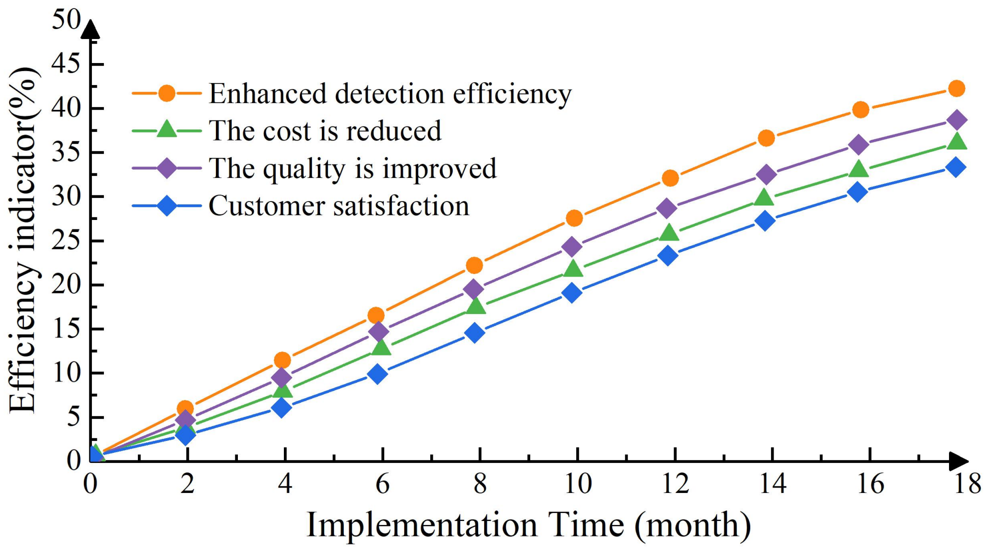

Figure 4. The changing trend of enterprise efficiency improvement indicators.

Improving product operation efficiency is a key component of process optimization. To assist customers in optimizing product testing operation efficiency, this paper proposes a method for enhancing product testing operation efficiency based on value stream analysis. This approach significantly improves product testing operation efficiency through measures such as eliminating non-value-added activities, converting sequential processes into parallel ones, and implementing intelligent scheduling. Through value stream analysis, it was found that the five main activity nodes in the old testing business process—sample registration, sample pre-processing, sample testing and analysis, data calculation and processing, and final report generation—all took a significant amount of time. These processes involved extensive waiting times and repetitive labor, with value-added activities accounting for as much as 42.3% of the total process time. To address these issues, this paper establishes a lean testing product business process and proposes the use of QR code scanners to track samples throughout the entire process. Efficiency is improved by modularizing and batch-processing sample pre-processing, replacing manual calculations with automated data collection, analysis, and data analysis software to enhance processing speed, and introducing standardized report templates for product business processing to further accelerate processing.

Additionally, data-driven operational management innovation is introduced. By establishing a value extraction system for the entire lifecycle of testing data, this approach not only enables cost and efficiency optimization for enterprises through data application but also uncovers the commercial potential and competitive advantages of enterprises by leveraging the intrinsic value of testing data. The testing data application analysis platform proposed in this paper will monitor key testing indicators in real time, automatically identify abnormal patterns and trends using machine learning algorithms, and provide robust data support for quality supervision and risk warning. This will enhance management levels and potentially create new market opportunities and business growth for enterprises.

5. Conclusion

This paper addresses the issue of optimizing the selection of heavy metal detection methods for food enterprises. It employs the life cycle cost (LCC) method to compare and analyze four primary detection technologies across dimensions such as detection accuracy, detection costs, and efficiency. Based on a survey of 72 food enterprises, the paper proposes optimal detection technology configuration models for large, medium, and small food enterprises. The findings indicate that in the food industry, ICP-MS detection methods offer the highest detection accuracy (with detection limits as low as 0.01–0.05 μg/L), but they require significant equipment investment and annual operational costs (800,000–1,500,000 yuan per unit and 120,000–180,000 yuan per year), making them suitable for large food companies with annual operating revenues exceeding 200 million yuan. XRF detection methods can process 120–180 samples per day, with a 35.8% increase in detection efficiency and a payback period of 2.8 years for equipment investment, making it suitable for medium-sized food enterprises. Electrochemical analysis detection methods such as ICPA and ICPC have an annual investment of 30,000–80,000 yuan, with a 56.7% reduction in detection costs and a payback period of 1.8 years for equipment investment, making them suitable for small enterprises with annual sales revenue below 20 million yuan.

Therefore, after improving decision-making through the LCC method, the average product recall rate and inspection equipment utilization rate have both decreased, the total operating cost has been significantly reduced, the value stream has been optimized, and the intelligent scheduling system has reduced the time required for the inspection process. The inspection equipment utilization rate has been improved. Overall, the use of LCC has improved inspection efficiency, controlled inspection costs, and increased production capacity. In the future, data-driven dynamic supervision and control, as well as management innovation, can be applied to food safety management to enhance corporate efficiency and benefits.

References

1. Munir, N., Jahangeer, M., Bouyahya, A., El Omari, N., Ghchime, R., Balahbib, A., ... & Shariati, M. A. (2021). Heavy metal contamination of natural foods is a serious health issue: A review. *Sustainability*, 14(1), 161.
2. Mukherjee, A. G., Renu, K., Gopalakrishnan, A. V., Veeraraghavan, V. P., Vinayagam, S., Paz-Montelongo, S., ... & Ganesan, R. (2023). Heavy metal and metalloid contamination in food and emerging technologies for its detection. *Sustainability*, 15(2), 1195.
3. Zhou, X., Wu, Z., & Dang, J. (2025). The Effect of Regional Food Safety Problems on National Agricultural Export Reputation: Empirical Evidence from The 2013 China's Cadmium-Tainted Rice Incident. *Emerging Markets Finance and Trade*, 1-19.
4. Begum, R., Akter, R., Dang-Xuan, S., Islam, S., Siddiky, N. A., Uddin, A. A., ... & Lindahl, J. F. (2023). Heavy metal contamination in retailed food in Bangladesh: a dietary public health risk assessment. *Frontiers in sustainable food systems*, 7, 1085809.
5. Bair, E. C. (2022). A narrative review of toxic heavy metal content of infant and toddler foods and evaluation of United States policy. *Frontiers in Nutrition*, 9, 919913.
6. Aihaiti, A., Wang, J., Zhang, W., Shen, M., Meng, F., Li, Z., ... & Zhang, M. (2024). Recent advances and trends in innovative biosensor-based devices for heavy metal ion detection in food. *Comprehensive Reviews in Food Science and Food Safety*, 23(4), e13358.
7. Shen, Y., Nie, C., Wei, Y., Zheng, Z., Xu, Z. L., & Xiang, P. (2022). FRET-based innovative assays for precise detection of the residual heavy metals in food and agriculture-related matrices. *Coordination Chemistry Reviews*, 469, 214676.
8. Han, F., Huang, X., & Teye, E. (2019). Novel prediction of heavy metal residues in fish using a low-cost optical electronic tongue system based on colorimetric sensors array. *Journal of Food Process Engineering*, 42(2), e12983.
9. Kambanou, M. L. (2020). Life cycle costing: understanding how it is practised and its relationship to life cycle management—a case study. *Sustainability*, 12(8), 3252.
10. Bradley, R., Jawahir, I. S., Badurdeen, F., & Rouch, K. (2018). A total life cycle cost model (TLCCM) for the circular economy and its application to post-recovery resource allocation. *Resources, Conservation and Recycling*, 135, 141-149.

11. Jaradat, Z., AL-Hawamleh, A., Altarawneh, M., Al-Tahat, S., & Akram Nazzal, M. (2025). Effects of effective ERP system utilization on enterprise economic sustainability through product life cycle cost control. *Journal of Business and Socio-economic Development*.
12. Degieter, M., Gellynck, X., Goyal, S., Ott, D., & De Steur, H. (2022). Life cycle cost analysis of agri-food products: A systematic review. *Science of The Total Environment*, 850, 158012.
13. Ferreira, S. L., Bezerra, M. A., Santos, A. S., dos Santos, W. N., Novaes, C. G., de Oliveira, O. M., ... & Garcia, R. L. (2018). Atomic absorption spectrometry–A multi element technique. *TrAC Trends in Analytical Chemistry*, 100, 1-6.
14. Lai, L., Yan, F., Chen, G., Huang, Y., Huang, L., & Li, D. (2023). Recent progress on fluorescent probes in heavy metal determinations for food safety: a review. *Molecules*, 28(15), 5689.
15. Bose, A., Thomas, I., & Abraham, E. (2018). Fluorescence spectroscopy and its applications: A Review. *Int. J. Adv. Pharm. Res*, 8(1), 1-8.
16. Shimizu, F. M., Braunger, M. L., & Riul Jr, A. (2019). Heavy metal/toxins detection using electronic tongues. *Chemosensors*, 7(3), 36.
17. Khan, S. R., Sharma, B., Chawla, P. A., & Bhatia, R. (2022). Inductively coupled plasma optical emission spectrometry (ICP-OES): a powerful analytical technique for elemental analysis. *Food Analytical Methods*, 1-23.
18. Wang, L., Peng, X., Fu, H., Huang, C., Li, Y., & Liu, Z. (2020). Recent advances in the development of electrochemical aptasensors for detection of heavy metals in food. *Biosensors and Bioelectronics*, 147, 111777.
19. Ullah, S., Zahra, Q. U. A., Mansoorianfar, M., Hussain, Z., Ullah, I., Li, W., ... & Wang, J. (2024). Heavy metal ions detection using nanomaterials-based aptasensors. *Critical Reviews in Analytical Chemistry*, 54(6), 1399-1415.
20. Guo, Z., Chen, P., Yosri, N., Chen, Q., Elseedi, H. R., Zou, X., & Yang, H. (2023). Detection of heavy metals in food and agricultural products by surface-enhanced Raman spectroscopy. *Food Reviews International*, 39(3), 1440-1461.
21. Sivakumar, R., & Lee, N. Y. (2021). Recent progress in smartphone-based techniques for food safety and the detection of heavy metal ions in environmental water. *Chemosphere*, 275, 130096.
22. Li, S., Zhang, C., Wang, S., Liu, Q., Feng, H., Ma, X., & Guo, J. (2018). Electrochemical microfluidics techniques for heavy metal ion detection. *Analyst*, 143(18), 4230-4246.