Research on Risk Early Warning Mechanism of Medical Equipment Performance Visualization in Big Data Environment

Yi Qin[1], Yuhua Gu[2], Sili Ge[1], Lei Wang[1], Xinmei Gu[1], Yaju Zhang[1]
[1]Audit Department, Nantong Hospital of Traditional Chinese Medicine, Nantong, Jiangsu, China
[2]Device Department, The Second People's Hospital of Nantong, Nantong, Jiangsu, China

Abstract: As the core role of medical equipment in healthcare services becomes increasingly prominent, its performance management has become a key aspect of hospital operations. This paper addresses issues such as the lack of standards, difficulties in data integration, and insufficient dynamic monitoring in traditional medical equipment performance audits, proposing a visual early warning mechanism based on big data technology. By establishing a multi-source data collection platform, a visual interaction system, and a risk warning mechanism, real-time monitoring and dynamic warnings of equipment performance are achieved. The effectiveness of the visual early warning mechanism in improving audit efficiency, optimizing resource allocation, and strengthening risk prevention is verified, providing theoretical support and practical pathways for the digital transformation of internal auditing in hospitals.

Keywords: Big Data; Medical Equipment; Performance; Visualization; Early Warning Mechanism

1. Introduction

1.1 Research Background

With the rapid development of medical technology, the importance of medical equipment in healthcare services has become increasingly prominent. The rising proportion of its investment makes performance auditing a key tool for optimizing the entire lifecycle management of equipment [1]. However, traditional auditing methods still face multiple challenges in practice: Firstly, the lack of a standard system. Although the "Guidelines for Performance Audit of Large Medical Equipment" and the "5E" (economy, efficiency, effectiveness, equity, environmental) model provide a framework for auditing, the dual nature of medical equipment leads to a lack of industry consensus on audit objectives, processes, and evaluation standards. The heterogeneity of audit results from different hospitals reduces their horizontal reference value; Secondly, data governance dilemmas. Large tertiary hospitals need to integrate multi-source heterogeneous data such as equipment revenue, depreciation, usage rate, maintenance costs, failure rates, and patient satisfaction, involving systems like HIS, finance, and material management. Data silos, insufficient standardization, and the inefficiency of traditional auditing tools make it difficult to support precise analysis of massive amounts of data; Thirdly, imbalanced resource allocation. Hospital audit departments have limited human and material resources. In the face of a large number of diverse equipment types, the high cost of comprehensive audits conflicts with limited resources, potentially weakening the actual effectiveness of audits; Fourthly, lagging dynamic monitoring. Equipment performance is significantly influenced by technological iterations, policy adjustments, and market demands. Traditional auditing relies on manual periodic checks, lacking automated data capture and real-time analysis through information technology, leading to delayed audit conclusions that fail to support dynamic optimization decisions for equipment resource allocation. These bottlenecks restrict the deep transformation of medical equipment performance audit from theory to practice, and it is urgent to make breakthroughs through standardization construction, intelligent tool application and resource coordination mechanism.

1.2 Research Significance

Under the impetus of artificial intelligence and information technology, internal audit techniques continue to innovate. The visual risk warning mechanism, as a key area of internal audit innovation, has formed both theoretical and practical foundations [2]. On an international level, IIA's "COSO-ERM-2017" emphasizes the value of integrating risk management (ERM) with business operations, proposing that building a "risk portfolio view" can achieve forward-looking risk prediction and multi-dimensional analysis, providing a theoretical framework for this study; in terms of technology application, tools such as Python, Tableau, and Power BI have realized full-chain closed-loop management from data collection and cleaning, risk modeling to visual warnings, promoting the transition of audits from static sampling to dynamic monitoring; at the policy guidance level, the "14th Five-Year National Audit Work Development Plan" explicitly requires "strengthening audit through technology," advocating the use of big data and cloud computing to build an integrated industry-audit platform; at the hospital level, the rich big data resources brought about by digital transformation also provide a data foundation for the visualization of equipment performance [3-6].

From the perspectives of policy, technology, and data, all conditions for conducting big data audits within hospitals have been met. Therefore, integrating multi-business system data from hospitals, establishing a big data platform for medical equipment performance, developing big data models for medical equipment performance, designing an equipment performance indicator system that meets internal audit needs, and implementing a visual risk warning mechanism will help shift hospital internal audit operations from compliance reviews to value creation, providing core support for organizational risk prevention and strategic decision-making[7-9].

2. Research Methods

2.1 Preliminary Planning

In the performance analysis of medical equipment, data, as a core asset in digital transformation, needs to be structuredly integrated from multi-source heterogeneous data to transform into decision support information. Key data types in medical scenarios include structured data (such as diagnostic records in HIS systems), unstructured data (such as PACS images that require NLP/CV technology for semantic parsing), semi-structured data (such as XML/JSON interface logs from cross-system interactions), social media data (such as user feedback texts from WeChat surveys), and big data (such as data integration platforms). Their collaborative analysis provides the underlying logical support for equipment performance audits.

However, the construction of a performance data platform should be systematically planned with an audit business objective in mind [10]: First, based on core equipment performance indicators, it is necessary to accurately identify highly correlated data through business processes to avoid a decline in analytical efficiency due to data overload; Second, for heterogeneous databases of systems such as HIS, PACS, and finance, during data collection, unified field naming rules, constraints, and data types must be established through SQL scripts, and ETL processes designed to achieve cross-system data cleaning and standardization conversion; Additionally, at the permission management level, database IPs, ports, and read-only accounts must be obtained under management authorization, and patient privacy must be protected through anonymization technology in compliance with the Personal Information Protection Law of the People's Republic of China.

2.2 Hardware Configuration

Under the framework of medical data governance, hospitals implement stringent physical isolation strategies based on the requirements of the Cybersecurity Law of the People's Republic of China and the Data Security Law of the People's Republic of China. They construct a closed internal network environment to ensure the transmission security of patient privacy data and core business data (such as HIS diagnostic records and device operation logs). All data collection, storage, and analysis processes are confined within the internal network topology. Based on this, the platform infrastructure adopts a distributed dual-server architecture: Data servers deploy Power BI Desktop RS, handling the cleaning of multi-source heterogeneous data, ETL (Extract-Transform-Load) processing and storage, data model creation, data analysis, and the establishment of visual reports; Report servers rely on SQL

Server reporting services and Power BI report server to publish visual reports, ultimately forming a data security closed-loop system that provides compliant and reliable technical support for internal audit decisions.

2.3 Selection of Digital Tools

The study uses an easy-to-use integrated low-code tool set in the Microsoft ecosystem:

Power BI Desktop, as a core big data analytics tool, achieves low-threshold data governance—by completing the ETL (Extract-Transform-Load) cleaning and transformation of multi-source heterogeneous data through Power Query components, and building key performance indicator models for equipment performance based on DAX (Data Analysis Expressions). Its visualization engine supports interactive drilling and analysis of data, combined with real-time data refresh functionality (incremental update strategy) to ensure second-level response times for billions of data points, significantly enhancing audit timeliness.

Power BI Report Server Report hierarchical release and permission control in the internal network environment are realized through RBAC (role-based access control), which meets the requirements of local storage of medical data stipulated in the Cyber Security Law of the People's Republic of China.

Power Automate Embedded RPA (robotic process automation) capability to realize automatic text data capture, execution of abnormal value monitoring and early warning, replacing manual repetitive operations.

The whole system architecture adopts a three-in-one mode of "low-code operation-automated processing-security collaboration", enabling non-technical teams to efficiently complete the entire closed loop from data collection, modeling to decision support, providing a reusable methodology framework for the digital transformation of medical equipment performance audit. See Figure 1 for the system architecture diagram.

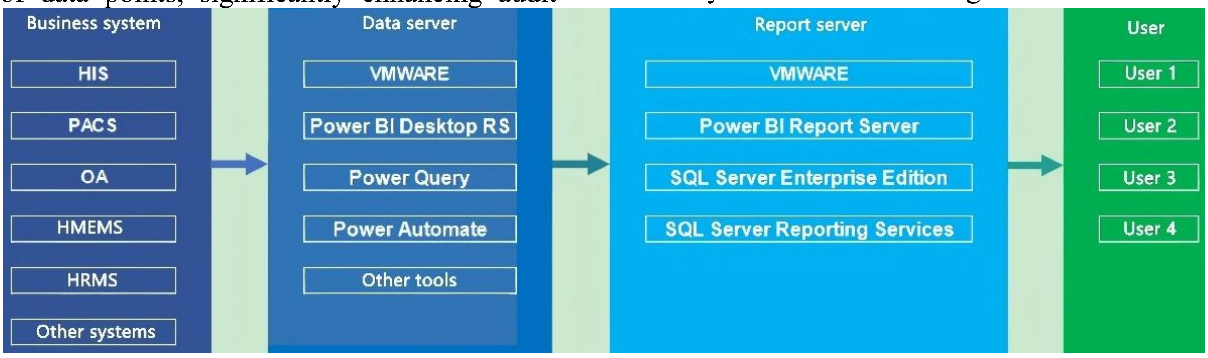


Figure 1. System Architecture Diagram

2.4 Data Collection and Cleaning

2.4.1 Data collection specifications

In the data collection process for medical equipment performance analysis, a series of systematic principles must be followed to ensure the validity and reliability of the data, with the core goal being device performance. 1. When selecting multi-source data, prioritize sources that have broad applicability and greater authority, such as department tables in an integrated platform, to ensure data coverage and accuracy. 2. By precisely filtering fields, use SQL statements to extract useful fields for analysis while discarding unnecessary redundant information, and standardize data formats in advance. This not only reduces resource consumption in the data model but also effectively avoids the risk of memory overflow. 3. Adopt a star schema for architectural pre-design, reasonably plan table relationships and keys, and clearly define the association rules between primary and foreign keys, laying a solid foundation for building an efficient data model. 4. In terms of technical implementation, based on the internal network environment, use Power Query to connect to the production database via ODBC to refresh incremental data. This method not only avoids the complexity of external network gateway configurations but also significantly improves the efficiency of data collection. By following these steps comprehensively, the collected data can be both comprehensive and concise, providing robust data support for subsequent medical equipment performance analysis. The main data tables to be collected from business systems in internal audit practices are shown in

Table 1.

Table 1. Main Data to be Collected by the Equipment Performance Data Platform

outside	source
Equipment income statement	HIS
Departmental tables	Integrate data platforms
Staff table	Integrate data platforms
payroll	Human resources management system
equipment list	Equipment management system
Depreciation statement	Equipment management system
budget sheet	OA
Calendar	Self-built
interest table	network

2.4.2 Data cleaning process

The data cleaning process is designed to build a closed-loop quality control system through the three stages of correction, refinement and validation to ensure the accuracy and reliability of the final data. 1. In the data correction stage, the data types of key fields should be unified, and uniform measurement units and numerical accuracy should be set; 2. Carry out consistency check to ensure that the data structure of non-production database is aligned with that of production database, establish field mapping rules, check the logic of cross-table data (such as the name consistency of employee table and payroll table), and formulate strategies for filling in missing values, removing duplicates and correcting outliers; 3. Improve data, streamline data scale and improve analysis efficiency through operations such as sorting, merging and perspective, use M language of Power Query to add calculation columns that facilitate data analysis (such as creating "discount number" field in equipment depreciation table), and integrate heterogeneous data (such as annual consolidated income summary table) with combined query and additional query. Generate a fact table based on a dimension table (for example, create an accounting classification fact table from an income statement) and so on. 4. In the data verification stage, verify the consistency between model data and source data after collection and cleaning, cross-compare system data (such as PACS device payment data and HIS system income data), verify the timeliness of data according to business time points (such as selection of time points for hospitalization income recognition), and establish a data flow chart to identify risk links. And check the matching degree of the number of records and the summary value of the numeric field. In addition, in order to continuously optimize data quality, a dynamic optimization mechanism should be established to iterate cleaning strategies through analysis results and user feedback, paying special attention to the improvement of field conversion rules and exception handling logic, so as to effectively control data bias, ensure the credibility of analysis conclusions, and provide a high-quality data platform foundation for medical equipment performance evaluation.

2.5 System Function Design and Implementation

2.5.1 Build the model.

Based on the device performance data platform, data association between tables is achieved through primary keys in each data table (ensuring uniqueness and no duplicate values), forming a clear and well-structured data analysis framework to complete the data model design. A star schema is used as the foundation for designing the data model, which is suitable for creating aggregated views and quickly responding to various report requirements. It supports comprehensive analysis of equipment performance from multiple perspectives, significantly enhancing the data analysis process while also simplifying the complexity of subsequent system maintenance and expansion, ensuring the flexibility and scalability of the entire data platform.

2.5.2 Establish equipment performance index analysis system

According to the pre-set objectives of the project, the first step is to design the equipment performance indicator system, followed by implementing the risk warning function. Based on the established data platform, use DAX functions (Data Analysis Expressions) to create necessary calculation columns and measures, thereby supporting the development of the equipment performance indicator system. These indicators include, but are not limited to, key performance indicators such as total asset turnover, revenue growth rate from main business, and budget execution rate [11]. The design of the indicator system should strictly adhere to the needs of internal audit operations, ensuring that the established indicator system not only comprehensively covers the requirements for risk monitoring but also has the capability for continuous monitoring. It should provide solid data support for subsequent risk warnings, making the tracking of equipment performance more efficient and precise, enabling timely responses and adaptation to evolving business needs.

2.5.3 Visualization of monitoring data

Using visual reports to display the performance metrics of devices that audit focuses on is an extremely effective method. Presenting data analysis results in chart form not only clearly conveys complex analytical conclusions but also provides auditors with a new, intuitive, and easily understandable perspective, facilitating their in-depth review of data from multiple dimensions. By leveraging the time and device slicer functions in visualization tools, internal auditors can analyze the performance of each device more meticulously, making it easier to uncover potential audit leads. This approach makes the audit process more efficient and precise, helping to accurately pinpoint issues and support data-driven decision-making processes. As a result, it not only enhances the overall quality of audit work but also ensures that monitoring of device performance is more rigorous and detailed.

2.5.4 Methods of risk warning

Risk warning visualization can help internal auditors identify, prevent, and control risks in advance, enhancing the organizational management level of internal audits and their ability to perceive risks. It helps organizations reduce potential losses during operations and improve the effectiveness of internal controls. In POWER BI, the risk warning function can be achieved through various methods.

(1) Warning through highlighting. This warning method involves setting up "cell elements" within the "visual objects" of a visual report to monitor abnormal values of metrics (measure values). When an abnormal metric triggers the alarm condition, alerts can be issued in the visual report by changing background color, font color, adding data bars, or inserting icons. For example, when displaying main information about equipment, if the budget amount is 0, it will be marked with a red " × ". If there is a lack of bidding process, the field background will be set to red, thus alerting auditors to pay attention to audit clues.

(2) To enhance the accuracy and efficiency of audits, establishing a threshold database for key performance indicators is a significant measure. Clear threshold ranges are set for various performance indicators of concern in audit projects. Once the monitored equipment performance indicators exceed the preset threshold range, they will be highlighted in the report to draw the attention of auditors to these anomalies. For example, the upper and lower limits of the budget execution rate can be set at 90% and 100%, respectively. If an equipment's budget execution rate falls below 90%, or reaches or exceeds 100%, the corresponding budget execution rate value in the report will be marked with different highlights: data with a budget execution rate below 90% will display a green background with red text, while data with a budget execution rate reaching or exceeding 100% will use a blue background for emphasis. This method enables auditors to quickly identify equipment performance issues that require special attention, thus focusing more effectively on potential risk points and optimization opportunities. Through this mechanism, not only is the efficiency of audit work improved, but it also ensures the accuracy and timeliness of equipment performance monitoring (see Figure 2).

(3) Dynamic Risk Warning Line. To more accurately reflect the actual performance of equipment, the concept of a dynamic risk warning line has been introduced for certain performance indicators that change dynamically with external factors (such as seasonal changes and fluctuations in patient volume). For example, the operating profit margin of an equipment can vary depending on different operational environments; therefore, using fixed warning thresholds cannot truly reflect the risk status of equipment usage. To address this issue, we can construct a flexible risk range using one or more variables to provide more precise warnings about equipment performance. Drawing on the principles of the effectiveness coefficient method, considering that industry risks have stage-specific characteristics, the monitoring indicator's operational range is divided into

four levels: No Alert, Low Alert, Medium Alert, and High Alert. Each level represents a qualitative change in the risk degree of the monitored indicator. The specific operation is as follows:

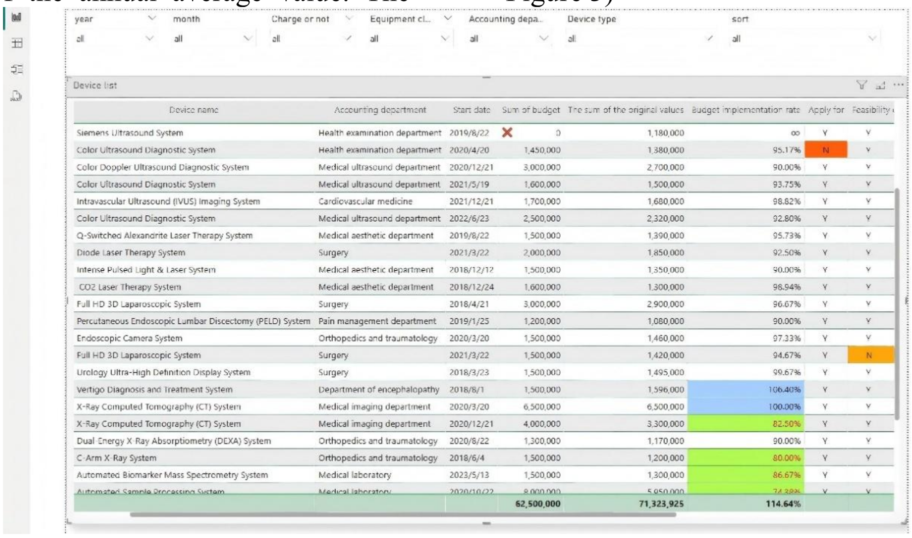
(1) No alarm threshold area: The average annual operating profit margin of the equipment is set as no alarm threshold, which is above the average annual value and defined as a risk-free area.

(2) Light alert threshold area: The interval between the annual average value and the minimum value is divided into three parts. The light alert threshold is defined at the lower third of the annual average value, and the medium alert threshold is defined at the lower two-thirds of the annual average value. The interval from the annual average value to the light alert threshold is defined as the light risk area.

(3) Moderate alert threshold area: the part between light alert threshold and moderate alert threshold is regarded as medium risk area.

(4) Critical warning threshold area: The area below the critical warning threshold is regarded as a high risk area.

In this way, the early warning level can be dynamically adjusted according to the specific value and trend of the operating profit margin of the equipment. This method not only improves the accuracy of risk early warning, but also enhances the effectiveness of equipment performance monitoring. (See Figure 3)



Device name	Accounting department	Start date	Sum of budget	The sum of the original values	Budget implementation rate	Apply for	Feasibility
Siemens Ultrasound System	Health examination department	2019/8/22	0	1,180,000	∞	Y	Y
Color Ultrasound Diagnostic System	Health examination department	2020/4/20	1,450,000	1,380,000	95.17%	N	Y
Color Doppler Ultrasound Diagnostic System	Medical ultrasound department	2020/12/21	3,000,000	2,700,000	90.00%	Y	Y
Color Ultrasound Diagnostic System	Medical ultrasound department	2021/5/19	1,600,000	1,500,000	93.75%	Y	Y
Intravascular Ultrasound (IVUS) Imaging System	Cardiovascular medicine	2021/12/21	1,700,000	1,680,000	98.82%	Y	Y
Color Ultrasound Diagnostic System	Medical ultrasound department	2022/6/23	2,500,000	2,320,000	92.80%	Y	Y
Q-Switched Alexandrite Laser Therapy System	Medical aesthetic department	2019/8/22	1,500,000	1,390,000	95.73%	Y	Y
Diode Laser Therapy System	Surgery	2021/3/22	2,000,000	1,850,000	92.50%	Y	Y
Intense Pulsed Light & Laser System	Medical aesthetic department	2018/12/12	1,500,000	1,350,000	90.00%	Y	Y
CO2 Laser Therapy System	Medical aesthetic department	2018/12/24	1,600,000	1,300,000	98.94%	Y	Y
Full HD 3D Laparoscopic System	Surgery	2018/4/21	3,000,000	2,900,000	96.67%	Y	Y
Percutaneous Endoscopic Lumbar Discectomy (PELD) System	Pain management department	2019/1/25	1,200,000	1,080,000	90.00%	Y	Y
Endoscopic Camera System	Orthopedics and traumatology	2020/3/20	1,500,000	1,460,000	97.33%	Y	Y
Full HD 3D Laparoscopic System	Surgery	2021/3/22	1,500,000	1,420,000	94.67%	Y	N
Urology Ultra-High Definition Display System	Surgery	2018/3/23	1,500,000	1,495,000	99.67%	Y	Y
Vertigo Diagnosis and Treatment System	Department of encephalopathy	2018/8/1	1,500,000	1,596,000	106.40%	Y	Y
X-Ray Computed Tomography (CT) System	Medical imaging department	2020/3/20	6,500,000	6,500,000	100.00%	Y	Y
X-Ray Computed Tomography (CT) System	Medical imaging department	2020/12/21	4,000,000	3,300,000	82.50%	Y	Y
Dual-Energy X-Ray Absorptiometry (DEXA) System	Orthopedics and traumatology	2020/8/22	1,300,000	1,170,000	90.00%	Y	Y
C-Arm X-Ray System	Orthopedics and traumatology	2018/6/4	1,500,000	1,200,000	80.00%	Y	Y
Automated Biomarker Mass Spectrometry System	Medical laboratory	2023/5/13	1,500,000	1,300,000	86.67%	Y	Y
Automated Sample Processing System	Medical laboratory	2020/10/22	8,000,000	5,950,000	74.38%	Y	Y
			62,500,000	71,323,925	114.64%		

Figure 2. Visual Warning

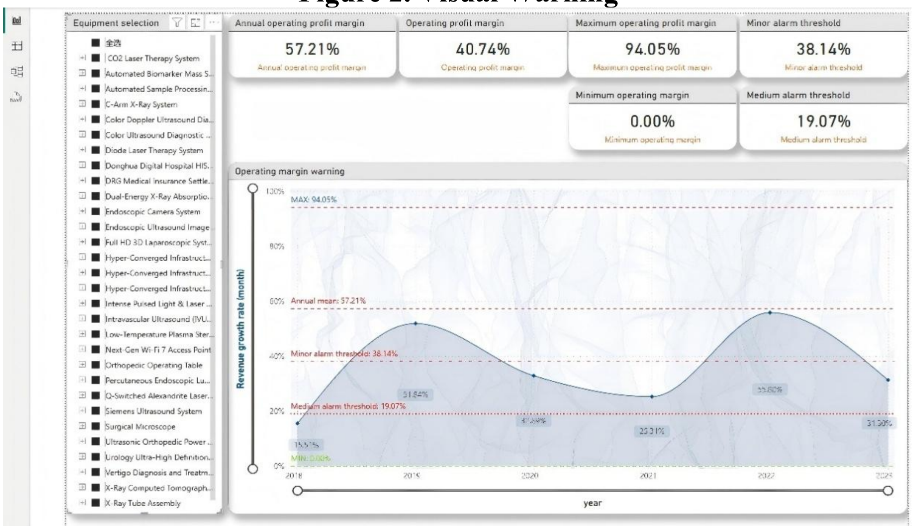


Figure 3. Risk Warning Line

2.5.5 Risk acceptance mechanism

(1) Proactive Risk Acceptance Mechanism. Visual reports have the unique advantage of effectively alerting internal auditors to potential risks through special visual cues. To ensure that internal auditors do not miss any risk, the flexible customization feature of Power BI's visual reports can be fully utilized

to display all key risk indicators from audit projects on a single comprehensive report. This method allows internal auditors to focus solely on the core data and metrics in this single report, thereby gaining a comprehensive understanding of the risk situation.

(2) Passive Risk Acceptance Mechanism. If internal auditors cannot continuously monitor the risk dashboard in visual reports due to time constraints, an automated risk alert mechanism can be adopted to ensure no critical risk alerts are missed. By using customized templates in Power Automate, combined with triggers and Power BI connectors, real-time monitoring of abnormal values in visual reports can be achieved. When a metric data reaches the preset alert threshold, it will automatically trigger the alarm process in Power Automate. Once an alert is triggered, the system will automatically send an email to the internal auditor's inbox, containing detailed alert information. This method not only ensures that potential risk notifications are received promptly even when internal auditors cannot directly access the visual reports but also significantly enhances the responsiveness and flexibility of risk management.

3. Project Implementation Results

(1) Integration of Big Data Technology and Risk Warning: This project successfully applies big data technology to the risk warning mechanism of internal auditing, achieving real-time collection, processing, and analysis of massive amounts of data. This provides more extensive and in-depth data support for internal auditing, enhancing both the depth and breadth of audit work.

(2) Visualization technology enhances risk perception: By leveraging advanced visualization techniques, this project presents the results of risk warnings in an intuitive and easily understandable manner. This approach significantly improves internal auditors' ability to perceive and understand potential risks, making complex data analysis results clear at a glance.

(3) Risk early warning model for innovation: The risk early warning model for equipment performance internal audit based on big data automatically identifies and warns risks through big data analysis and data mining technology. This model not only improves the accuracy and timeliness of early warning, but also marks an important innovation in the risk early warning mechanism.

(4) Transition from Passive to Active Supervision Model: Traditional risk warning mechanisms focus on post-event supervision, whereas this study has achieved a shift towards full-process supervision. By conducting real-time dynamic monitoring and early warnings for internal audit risks related to equipment performance, the internal audit department can identify and address potential issues earlier, effectively preventing the occurrence of risks.

(5) Targeted risk early warning index system: Based on the characteristics of equipment performance and the specific needs of internal audit, this project has established a complete set of risk early warning index system. This system can comprehensively and accurately reflect the status and trend of equipment performance internal audit risks, providing strong support for decision-making.

(6) Application of Interdisciplinary Research Methods: The project adopted an interdisciplinary research approach, integrating theories and technologies from computer science, data science, auditing, and other fields to form a comprehensive research framework. By delving into the internal audit of equipment performance in big data environments, it revealed the intrinsic patterns of risk warning mechanisms, providing new research ideas and methods for relevant fields.

4. Conclusions

In the big data environment of modern hospitals, building a big data model to achieve a comprehensive medical equipment performance visualization risk warning system has shown significant practical importance in internal audits. This system can collect, process, and analyze equipment performance data in real-time, presenting risk conditions in an intuitive visual manner while automatically triggering early warning mechanisms. This technological achievement provides hospital internal audit personnel with a convenient and efficient internal audit risk management tool. Practical applications have demonstrated that this equipment performance warning system not only proves its effectiveness and practicality but also showcases its powerful capability in helping internal auditors promptly identify potential risks within the hospital. Additionally, it offers solid data support for improving internal controls and enhancing refined management levels. Through this system, hospitals can more proactively monitor equipment usage efficiency and performance, ensuring optimal resource allocation, thereby improving overall operational efficiency and service quality. This marks a crucial step forward in leveraging advanced technical means to strengthen hospital management and risk control.

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