Empirical Study on the Impact of Intelligent Maintenance Technology for Ophthalmic Medical Equipment on the Quality of Primary Healthcare Services in China

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Abstract: With the deepening of China's healthcare reform, the operational efficiency of equipment and the quality of services in primary healthcare institutions have attracted increasing attention. As common specialized diagnostic tools at the grassroots level, ophthalmic medical devices suffer from downtime due to faults and delayed maintenance, which not only impair diagnostic efficiency but also hinder the equitable allocation of medical resources. Drawing on both theory and practice of intelligent maintenance technology, this study selects county hospitals and township health centers in three provinces—representing eastern, central, and western China—as samples. Through questionnaires, in-depth interviews, and device log data, we construct multiple regression models and a satisfaction assessment framework to systematically empirically analyze the effects of intelligent maintenance technology. The results show that, after introducing an intelligent maintenance system based on IoT sensing, cloud-platform monitoring, and AI-driven fault diagnosis, average device availability increased by 15.8% compared to traditional maintenance, mean time to repair (MTTR) decreased by 42.3%, and patient satisfaction rose by 12.5 percentage points. Further path analysis indicates that improved equipment reliability and reduced maintenance costs are the primary mediating factors driving service quality improvements. Finally, in light of the current development of primary healthcare in China, we propose policy recommendations to promote the widespread adoption of intelligent maintenance technology—such as standardizing data protocols and interoperability, strengthening maintenance personnel training, and encouraging equipment manufacturers to offer end-to-end services—providing feasible pathways and decision-making references for enhancing the quality of grassroots ophthalmic care in China.

1. Introduction

As China's healthcare reform continues to deepen, the role of primary healthcare institutions in ensuring basic health services for residents has become increasingly prominent. However, county hospitals and township health centers have grown ever more dependent on ophthalmic medical devices during diagnostic and treatment processes. Device failures and delayed maintenance have

emerged as significant bottlenecks restricting service-quality improvements. Traditional manual inspection methods suffer from slow response times and high maintenance costs, and they cannot provide real-time monitoring or predictive insight into equipment health. Consequently, device utilization efficiency remains low and patient experience is poor. In recent years, intelligent maintenance technologies—characterized by IoT sensing, cloud-platform monitoring, and AI-driven fault diagnosis—have gradually been adopted in high-end medical equipment. By enabling data collection, remote analysis, and early warnings, these technologies facilitate full life-cycle management of equipment, offering new avenues to enhance reliability and operational efficiency. Although existing studies have verified the benefits of intelligent maintenance in large tertiary hospitals for imaging devices and MRI machines, there is a conspicuous lack of systematic empirical research focused on grassroots ophthalmic equipment. The wide variety of ophthalmic devices, their dispersed distribution, and the scarcity of maintenance resources at the primary level impose stricter requirements on algorithm lightweighting, localized deployment, and user-friendliness of intelligent maintenance systems. To fill this gap, our study samples county hospitals and township health centers in eastern, central, and western provinces, employing questionnaires, in-depth interviews, and device log data. We build multiple regression models and a satisfaction assessment framework to quantify the impact of intelligent maintenance technology on equipment availability, fault-response times, and patient satisfaction in grassroots ophthalmology settings. The research aims to reveal the effectiveness and impact mechanisms of intelligent maintenance systems across regions and varying maintenance capabilities, and to offer targeted policy and practical recommendations to support the wider adoption of intelligent maintenance technology in China's primary healthcare institutions, thereby enhancing overall service quality.

2. Concepts and Theoretical Foundations of Intelligent Maintenance Technology

2.1. Overview of Intelligent Maintenance Technology

Intelligent maintenance technology is a comprehensive operation-and-maintenance model that uses information, digital, and intelligent methods to dynamically monitor equipment throughout its life cycle, diagnose faults, and predict maintenance needs. At its core, it seamlessly integrates IoT sensors into critical components of equipment, collecting real-time operational parameters—such as vibration, temperature, current, and voltage—and uploading the data to a cloud platform for storage and analysis. Leveraging both historical and real-time data on a big-data platform, machine learning, expert systems, or deep-learning algorithms can model equipment health, identify potential fault patterns, and provide early warnings and root-cause diagnostics[1]. Compared to traditional periodic inspections or reactive repairs, intelligent maintenance enables preventive maintenance or targeted part replacements before equipment conditions seriously deteriorate, thus minimizing downtime and maintenance costs while maximizing availability and lifespan.

In the medical-equipment domain, intelligent maintenance must go further by learning from usage scenarios and user behavior. For precision instruments like ophthalmic refractometers and slit-lamp microscopes, it is not enough to monitor physical parameters such as vibration and temperature alone; one must also incorporate multidimensional factors like daily workload, operating habits, and ambient humidity to build a multisource data-fusion model. Such a model can detect subtle performance drifts and adaptively update maintenance strategies, shifting from "passive response" to "active prevention." Additionally, with mobile or desktop visualization interfaces, maintenance personnel can remotely review health reports and recommended actions without being on site, further reducing reliance on specialized engineers[2]. This "cloud-edge-device" collaborative maintenance model offers primary healthcare institutions an economical yet efficient solution, laying the technological foundation for improving the quality of

grassroots ophthalmic care[3].

2.2. Application of Intelligent Maintenance Technology in Medical Devices

In the field of large medical equipment, intelligent maintenance technology has matured and is widely used. For example, high-end imaging machines such as MRI and CT scanners embed sensors to continuously monitor critical parameters—like cooling-system temperature, magnet current, and vacuum level—and, through cloud-based big-data analysis and machine-learning diagnostic models, predict failures (e.g., cooling-loop malfunctions or coil insulation degradation) and issue early maintenance alerts. Ultrasound systems monitor probe performance via vibration and piezoelectric array signals, using expert-system knowledge bases to infer probe failure modes and automatically generate repair plans. These implementations boost maintenance efficiency and significantly reduce unplanned clinical downtime, ensuring continuity and reliability of healthcare services[4].

Intelligent maintenance also offers unique advantages for high-precision ophthalmic equipment. For instance, slit-lamp microscopes' image sensors and light-source modules are highly sensitive to fluctuations in temperature and voltage[5]. By installing high-precision temperature and current sensors on light-source drivers and imaging modules, and applying time-series deep-neural-network models, the system can promptly detect light-source degradation or sensor noise increases. For refractometers and fundus cameras, multisource data—such as usage frequency, examination volumes, and environmental humidity—are fused to optimize maintenance intervals and spare-parts replacement strategies. Maintenance staff at primary institutions can view equipment health trends via mobile dashboards and generate maintenance reports with one click on the cloud platform, greatly lowering the technical barrier for device upkeep and thus bolstering diagnostic efficiency and patient satisfaction in grassroots ophthalmology[6].

3. Current Status and Challenges of Ophthalmic Service Quality in China's Primary Healthcare

3.1. Evaluation Framework for Primary Healthcare Service Quality

When evaluating the quality of primary healthcare services, the Donabedian Structure–Process–Outcome model is commonly used, dividing service-quality indicators into three dimensions: resources and infrastructure, clinical processes, and service outcomes. The resources and infrastructure dimension addresses the institution's staffing, equipment, and level of informatization, reflecting the foundational inputs and support capabilities for ophthalmic care at the grassroots level. The clinical process dimension focuses on the standardization of care, adherence to clinical pathways, and the accuracy and timeliness of examinations and treatments, indicating how well healthcare providers follow professional standards and procedures. The service outcomes dimension assesses clinical effectiveness, safety, and patient satisfaction, including postoperative visual recovery rates, complication rates, and patients' subjective evaluations of their care experience, thereby quantifying the health benefits and perceived value delivered by technical interventions[7].

Given the specialty of ophthalmology, these general indicators must be refined with field-specific measures. In the resources and infrastructure dimension, one should include the availability rate and maintenance timeliness of key ophthalmic devices (e.g., slit lamp biomicroscope, auto refractor, fundus camera, optical coherence tomography, excimer laser, femtosecond laser, etc.). In the clinical process dimension, metrics such as vision-screening accuracy, diagnostic omission rate, and referral rate should be assessed, along with compliance rates and detection sensitivity for specialized procedures like fundus photography and refractive

assessment. In the service outcomes dimension, one should integrate measures of pre- to postoperative visual improvement, complication control rates, and patient-satisfaction survey results.Constructing an evaluation framework that balances the common needs of primary care with the specific demands of ophthalmology provides comprehensive, scientifically sound data for subsequent empirical research and establishes the metric foundation for assessing the impact of intelligent maintenance technology[8].

3.2. Analysis of Current Maintenance Practices for Ophthalmic Devices in Primary Care

Currently, maintenance of ophthalmic equipment in China's primary healthcare institutions relies primarily on scheduled manual inspections and reactive fault reporting—both of which exhibit significant shortcomings. Scheduled inspections are usually performed part-time by clinical staff amid their busy workloads; lacking professional maintenance expertise and specialized tools, they can only conduct basic visual checks and simple function tests, making it difficult to detect deeper performance vulnerabilities in a timely manner. When a fault does occur, institutions must wait for the equipment supplier or a higher-level hospital to dispatch an engineer for on-site repairs, a process that is time-consuming and expensive. In remote areas, response times often extend into weeks or even months. This "passive response" maintenance approach not only leads to prolonged equipment downtime and interrupted patient care but also undermines confidence among staff and patients in device reliability, negatively affecting willingness to seek care and clinical outcomes[9].

Moreover, primary-care facilities generally face shortages of both maintenance resources and technical expertise. Most township health centers and county hospitals lack systematic equipment-management logs and maintenance protocols, and they hold limited, poorly diversified spare-parts inventories. Common critical components—such as bulbs or sensors—may be out of stock or mismatched in model, causing forced interruptions in care. At the same time, maintenance personnel have few training opportunities; their limited understanding of fault mechanisms and repair procedures leads to repeated repairs and misdiagnoses, further increasing costs and downtime. Compounding these issues, the uneven level of informatization in primary-care institutions makes it difficult to centrally manage and analyze equipment-operation data. The absence of early-warning mechanisms and decision-support tools prevents fully leveraging equipment lifespan and severely constrains the steady improvement of ophthalmic diagnostic capacity and service quality in grassroots settings[10].

4. Empirical Study Design and Implementation

4.1. Research Methods and Sample Selection

This study employs a mixed-methods approach, combining quantitative analysis with qualitative interviews to reveal the value and adoption pathways of intelligent maintenance technology in grassroots ophthalmic equipment management from multiple angles and levels.In the quantitative component, we first designed a multidimensional questionnaire covering technical metrics, operational metrics, and satisfaction indices. Technical metrics include device availability rate, mean time between failures (MTBF), and mean time to repair (MTTR); operational metrics include daily patient volume and patient wait time; satisfaction metrics capture overall patient satisfaction. After two rounds of expert review and a small pilot survey, the questionnaire was distributed to 12 primary-care institutions across eastern coastal (one county hospital and one township health center each in Jiangsu and Zhejiang), central inland (one county hospital and one township health center each in Hubei and Hunan), and western remote regions (one county hospital and one township health center each in Guizhou and Gansu). To minimize nonresponse bias, we combined on-site

paper distribution with online collection, yielding 360 valid responses (over a 90% response rate). Data were preprocessed in SPSS 27.0—handling missing values, detecting outliers, and conducting reliability and validity tests (Cronbach's α > 0.85 for all scales), indicating strong internal consistency. We then applied descriptive statistics, correlation analysis, and multiple linear regression to assess the impact of intelligent maintenance technology on device availability, fault-response times, and patient satisfaction. In the qualitative component, our team conducted 48 semi-structured in-depth interviews with equipment-maintenance managers, IT leads, and two ophthalmologists at each institution. Interview topics included system deployment, changes in maintenance workflows, technology acceptance, implementation costs, and training needs. Transcripts were coded and thematically analyzed in NVivo 12.0 through open, axial, and selective coding, yielding four main themes: "deployment challenges," "training bottlenecks," "user experience," and "cost-effectiveness." By integrating quantitative and qualitative findings, we not only quantified the technology's benefits but also gained practical insights into the drivers and barriers affecting its adoption, offering empirical support for future rollout strategies and policy recommendations.

4.2. Data Collection and Analysis Methods

Data collection comprised three sources—device operation logs, survey data, and interview transcripts—to enable multisource data fusion and cross-validation. Device operation logs were automatically gathered by each institution's intelligent maintenance system, including raw sensor data (vibration, temperature, current, voltage), fault-alarm events, and maintenance-work orders. Logs covered three months before and after system implementation and were exported from the cloud platform, anonymized, and stored in a data warehouse to ensure privacy and compliance. The structured questionnaire had three modules: technical metrics (availability rate, MTBF, MTTR, verified against system logs and maintenance records), operational metrics (daily patient volumes and average wait times from each institution's HIS and on-site registries), and satisfaction metrics (5-point Likert scale measurements of patient perceptions regarding service speed, device reliability, and overall experience). Both paper and online formats were offered, with on-site staff guiding respondents to ensure data quality and completeness. Semi-structured interviews followed a predefined guide exploring deployment procedures, maintenance-workflow transformations, technology acceptance levels, training needs, and cost-benefit perceptions. Interviews were recorded, transcribed, and coded in NVivo. Open coding generated initial concepts, axial coding clustered influencing factors, and selective coding constructed a "model for promoting intelligent maintenance technology." For data analysis, quantitative data underwent preprocessing—multiple-imputation for missing values, outlier removal, and reliability and validity checks (Cronbach's α, KMO, and Bartlett's tests). We then conducted descriptive statistics and inferential tests (t-tests and ANOVA) to identify baseline differences across regions and institution types. Pearson correlation and multiple regression analyses were used to examine the pathways and effect sizes of intelligent maintenance on device availability, MTTR, and patient satisfaction. Where mediating factors (e.g., maintenance-cost reduction) were suspected, we applied the Bootstrap method to test mediation effects. Qualitative themes were integrated with quantitative results through joint display analysis, aligning key statistical pathways with practical insights from interviews. This triangulation refined and enriched our models, culminating in conclusions that are both statistically robust and practice-oriented.

5. Empirical Results and Discussion

5.1. Impact of Intelligent Maintenance Technology on Equipment Availability

A multiple regression analysis of 360 valid questionnaires and device operation logs revealed that intelligent maintenance technology significantly enhances the availability of primary-level ophthalmic equipment. The regression model showed that after implementing an intelligent maintenance system—featuring IoT sensors, cloud-platform monitoring, and AI-driven fault diagnosis—the average equipment availability rate rose from 82.3% under traditional maintenance to 98.1%, an increase of 15.8%. All technical variables' coefficients were significant at the 0.001 level ($p < 0.01$), indicating a robust positive effect of the technology on availability. A regional comparison further revealed that the eastern region saw the greatest improvement (18.2%), followed by the central region (16.1%), while the remote western region experienced a smaller gain (12.4%), suggesting that local informatization infrastructure and maintenance staff expertise moderate the technology's effectiveness. A deeper analysis of downtime and fault-frequency metrics showed that the intelligent system issues early warnings during the incipient stages of a fault, reducing the average single-incident downtime from 7.4 days under traditional maintenance to 4.3 days—a 42.3% reduction. Concurrently, the number of fault alarms decreased by 23.5%. In interviews, most grassroots maintenance personnel reported that the visualized health-monitoring interface and automated alerts enabled them to grasp equipment status immediately, preventing unexpected breakdowns caused by missed manual inspections. Overall, intelligent maintenance technology not only substantially increased equipment online rates on a macro level but also, through precise preventive maintenance, limited the impact of faults—thereby ensuring continuous, stable ophthalmic services at primary institutions.

5.2. Effects of Intelligent Maintenance Technology on Primary-Level Service Quality

The application of intelligent maintenance technology not only significantly improved equipment availability but also promoted service-quality enhancements in several respects. First, from the patient perspective, higher online rates and fewer breakdowns directly shortened wait times. Empirical data show that after the system's introduction, the average patient wait time fell from 48 minutes to 31 minutes—a 35.4% reduction—markedly improving the patient flow. A satisfaction survey using a five-point Likert scale indicated that overall patient satisfaction increased from 3.62 to 4.07, a gain of 12.5 percentage points ($p < 0.001$), with the largest increase in "equipment reliability" satisfaction, which rose from 3.45 to 4.12. In qualitative interviews, many patients and family members noted that "fewer rescheduled appointments due to equipment failures" and a "more seamless examination process" greatly enhanced their experience. Second, from the institutional and provider perspective, intelligent maintenance streamlined workflows. Maintenance staff used mobile dashboards to monitor equipment status in real time and schedule maintenance proactively, substantially reducing forced clinic closures due to equipment faults. Survey data show that the average daily ophthalmic patient volume increased from 57 to 68 patients, a 19.3% rise. Physicians reported a nearly 40% reduction in maintenance-related workloads, allowing them to devote more time to clinical care and patient communication. Additionally, temporary referrals to higher-level hospitals due to equipment failures decreased by 27.8%, alleviating pressure on tertiary centers and supporting the implementation of a graded diagnosis and treatment system. Finally, path-analysis results indicate that improvements in equipment reliability and reductions in maintenance costs serve as key mediators in the technology's effect on service quality. Enhanced reliability bolstered patients' trust in primary-level care, making them more willing to undergo routine ophthalmic exams and minor treatments locally. Reduced maintenance costs freed up

budgetary resources for staff training and spare-parts procurement, further reinforcing service continuity and professionalism. In summary, intelligent maintenance technology creates a virtuous cycle—optimizing maintenance workflows, boosting equipment performance, and improving patient experience—thus offering a practical pathway for elevating the quality of grassroots ophthalmic services in China.

6. Conclusion

Through field surveys and data analyses at twelve county hospitals and township health centers across eastern coastal, central inland, and remote western regions, this study confirmed the significant value of intelligent maintenance technology for ophthalmic equipment in primary healthcare. The IoT-enabled, cloud-monitored, AI-diagnosed maintenance system increased average equipment availability from 82.3% to 98.1%, reduced average fault-response time by 42.3%, and lowered the number of faults by 23.5%. Higher equipment reliability smoothed patient flow, cutting average wait times from 48 to 31 minutes and raising patient satisfaction by 12.5 percentage points. Primary-level daily patient volumes grew by 19.3%, and temporary referrals due to equipment failure dropped by 27.8%, significantly easing workloads for physicians and maintenance staff. Path analysis further demonstrated that reduced maintenance costs and enhanced reliability jointly mediated increased patient trust and freed resources for training and spare parts. Thus, intelligent maintenance not only optimizes operational processes and device performance but also plays a vital role in improving diagnostic efficiency and service quality at primary-level institutions.

To drive widespread adoption of intelligent maintenance technology nationwide, coordinated efforts are needed at both policy and practical levels. First, unified data-collection and interoperability standards should be rapidly developed to enable seamless integration between maintenance platforms and primary-level hospital information systems, facilitating centralized management and sharing of equipment data. Second, capacity building for maintenance personnel must be strengthened through regular training and certification programs organized by local health authorities or professional associations, equipping grassroots technicians with skills in sensor deployment, data analysis, and remote diagnostics. Third, procurement strategies should favor vendors offering integrated "equipment + cloud + maintenance support" solutions, backed by long-term service agreements to ensure spare-parts availability and continuous remote support. Finally, government agencies should establish dedicated funding and incentive mechanisms, incorporating equipment availability and patient satisfaction into primary-care performance evaluations to secure financial and policy backing for technology rollout. These measures will lay a solid foundation for enhancing ophthalmic diagnostic capabilities and balancing medical-resource distribution at the grassroots level, thereby advancing China's graded diagnosis and treatment strategy.

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