Research on IoT-based Real-time Monitoring of Operating Room Air Cleanliness and Precise Prevention and Control of Infection Risk

Yue Zhang, Min Han, Linna Li
Department of First Operating Room, The Second Qilu Hospital of Shandong University, Jinan 250033, Shandong, China
Corresponding author: Yue Zhang (e-mail: zhyue666@126.com)

ABSTRACT Operating room air cleanliness is critical for infection control, yet conventional static monitoring cannot capture the dynamic release of textile fibers from surgical drapes and medical linens during operations, limiting timely prevention. In this study, an IoT-based real-time monitoring network was designed and deployed with 12 high-precision nodes to continuously collect particulate matter concentration, microbial concentration, temperature, humidity, pressure difference, and personnel activity. Considering the dense medical-equipment environment of operating rooms, the wireless sensing architecture was configured for stable radio-frequency data transmission and electromagnetic-compatible operation, providing a practical sensing scenario related to electromagnetic wave propagation in indoor medical spaces. A dynamic infection-risk assessment model was then established through data fusion, and a long short-term memory algorithm was introduced to predict short-term risk trends. A graded intelligent warning mechanism was connected to the air-conditioning and purification system to support on-demand control. By tracking particulate matter and fiber shedding associated with medical textiles, the system achieved real-time perception, risk prediction, and closed-loop intervention for air cleanliness, offering a reliable technical approach for reducing surgical site infection risks in digitally monitored operating-room environments.

INDEX TERMS internet of things, operating room air cleanliness, wireless sensor network, electromagnetic compatibility, infection risk prediction

I. INTRODUCTION

SURGICAL site infection (SSI) is a common and serious complication of surgery that leads to an increased burden of suffering to patients and to the overall length of time they need to spend in hospital and suffer adverse financial consequences. It also affects the quality of surgery and the safety of patients directly. Operating room air, which often carries pathogens attached to airborne textile dust and fibers shed from medical linens, serves as a critical environmental factor contributing to the occurrence of surgical site infections. Traditional operating room environmental management mainly relies on static sampling and manual inspection of periodically, with the disadvantages of certain lag time in the monitoring process, dispersion of data, and lack of early warning ability, so as to effectively capture the dynamic risks of the surgical process and early warning. Although laminar flow purification systems are widely used, the working modes are essentially fixed and preset and can not be intelligently adjusted to the dynamic disturbance such as the actual personnel activity, equipment operation in the operating room, which makes it difficult with respect to precision and energy-saving. Therefore, real-time, continuous, and accurate perception of the air cleanliness in operating rooms, and construction of a data-driven dynamic risk assessment and proactive intervention system based on which, has become one of the key technological requirements of improving the existing operating room infection control measures and to move towards an intelligent operating room management system.

This paper constructs and validates a closed-loop precision prevention and control technology system based on real-time by the Internet of Things (IoT) monitoring, AI risk prediction and intelligent equipment linkage. This study designed and deployed an IoT monitoring network designed on multi-parameter sensors to achieve the purpose of high-density, high-frequency, and multi-dimensional real-time perception of the operating room environment. By combining multi-source heterogeneous information, an infection risk comprehensive assessment index of dynamic characteristics was formed, and an LSTM machine learning method was proposed to predict and alert the risk trend in the next few minutes. A tiered early warning mechanism and intelligent linkage strategy with the purification system was developed to monitor airborne lint and fiber concentrations from medical textiles, realizing closed-loop management from "risk perception" to "automatic intervention" and changing passive response into proactive prevention.

II. RELATED WORK

The prevention and control of surgical site infection (SSI) is a core issue of perioperative quality and safety, and its effectiveness depends largely on the effectiveness of multi-level, interprofessional, and comprehensive intervention in the surgical environment. Wistrand et al [1] reviewed and highlighted the best evidence-based interventions to prevent bacterial contamination and SSI in the operating room environment. Aktaş and Damar [2] found that the evidence-based knowledge of nurses in operating rooms to prevent SSI was generally at a medium level, and there were deficiencies in practical application. Tan et al. [3] evaluated the effectiveness of a new hybrid system consisting of a local exhaust system (LEV) and an air curtain (AC) in reducing airborne particle deposition near surgical incisions. Tan et al [4] found a significant positive correlation between the concentration of particulate matter in the air in the operating room and the amount of microbial deposition. Omori et al [5] assembled and tested a virtual reality (VR)-based learning module to train medical staff to correctly implement respiratory protection measures.

Calderwood et al [6] presented comprehensive, recent, evidence-based recommendations for SSI prevention in acute care hospitals. Wang et al [7] used a simple randomization method to divide patients into a study group and a control group, with 135 cases in each group, and conducted comprehensive nursing intervention based on the operating room infection control path. Seidelman et al [8] reviewed the high-quality evidence and recommendations of recent major guidelines and organized the content into three stages of preoperative, intraoperative, and postoperative care. Risinger and Smith [9] introduced the application principles of DCS in emergency general surgery, with special emphasis on the key points of infection prevention and management. Crall et al. [10] reported a quality improvement project for the implementation of UV-C terminal disinfection in hospitals. Existing infection control approaches are mainly based on standardized procedures and regular inspections, and lack the accuracy and ability to respond to complex and changing environmental changes in the operating room in real time. Therefore, this article focuses on building a multi-parameter real-time monitoring network driven by the Internet of Things, combining artificial intelligence algorithms to achieve dynamic risk assessment and early warning, exploring intelligent intervention strategies for purification equipment, and filling the key technical gaps in the current closed-loop management of environmental infection risks in operating rooms.

III. METHODS

A. IOT MONITORING SYSTEM ARCHITECTURE AND MULTI-PARAMETER SENSOR DEPLOYMENT

To fully and comprehensively monitor the operating room environment, this study was designed and developed a high precision Internet of Things (IoT) monitoring system. The system consists of 12 monitoring nodes inside a single standard laminar flow operating room (approximately 40 square meters), covering the areas of the surgical area, instrument table area, doorway area, and area close to the return air vent, forming a spatial gradient distribution. The node design fully considers thermal management issues, selects low-power sensors and compact packaging, and uses computational fluid dynamics (CFD) simulation to pre-evaluate the impact of its heat generation on local laminar flow, ensuring that the node volume and heat generation are controlled to a minimum. In addition, the installation position strictly avoids the direct airflow path of the air outlet and the core laminar flow zone above the surgical area, so as to minimize interference with the established clean airflow pattern. Each monitoring node combines several sensors to obtain the following important parameters:

Particulate matter concentration: A sensor based on the laser scattering principle is used to monitor the concentrations of PM1.0, PM2.5, or PM10 in real-time (unit: μg/m^3), and the resolution is 1 μg/m^3. These parameters can be used as indirect and quick indicators of microbial load.

Environmental parameters include temperature (°C), relative humidity (%), and air pressure difference (Pa) between different functional areas. These parameters directly affect the survival and spread of microorganisms and are also important indicators of the cleanroom's operating status [11,12].

Personnel activity: Using sensors based on infrared sensing or low-resolution anonymous video analysis (not involving privacy information such as facial recognition), the number of people in the operating room and changes in the main activity areas are counted.

All sensor data is transmitted via LoRaWAN, ultimately reaching an edge computing gateway deployed within the operating room. This gateway performs initial data cleaning, filtering, and caching to reduce network load and latency. The data is then securely transmitted through the hospital's wired network to a central cloud platform for storage and in-depth analysis. This study used standard sedimentation bacteria sampling to perform offline sampling on a weekly basis to obtain actual CFU data for calibrating and validating alternative index models based on optical signals.

B. DATA FUSION AND CONSTRUCTION OF DYNAMIC INFECTION RISK ASSESSMENT MODEL

The collected multi-source heterogeneous data were fused and deeply mined on the cloud platform. First, the raw data underwent preprocessing such as standardization, noise reduction, and outlier detection to ensure data quality. Subsequently, a dynamic infection risk index was constructed to quantify the instantaneous infection risk level in the operating room [13,14]. The calculation of this index takes into account the following factors:

Basic pollution level: Based on real-time microbial concentration and particulate matter concentration of different sizes, thresholds are set according to historical data and industry standards (such as GB 50333-2013 "Technical Specification for Clean Operating Room Buildings in Hospitals"), and a normalized score is performed.

Environmental disturbance factors: Human activity data (such as the rate of change in the number of people and the frequency of movement) are used as a key dynamic disturbance factor. This study not only considers the rate of change in personnel numbers and overall movement frequency, but also further distinguishes activity types (such as high-frequency movement, instrument transfer, and draping operations). By anonymously acquiring motion amplitude and range data through video analytics sensors, a quantitative model was established between different activity types and instantaneous surges in particulate matter/microorganism concentrations. Simultaneously, the model incorporates an indirect consideration of medical textile (linen) quality. By monitoring changes in fibrous particulate matter concentrations within a specific particle size range (e.g., greater than PM10) and combining this with linen replacement cycle records, the contribution of linen fiber shedding to air pollution was assessed. This approach breaks away from the previous assumption of a simple linear correlation between activity frequency and risk, making the assessment more closely reflect the complexities of actual surgical procedures.

Environmental stability: Considering the stability of temperature, humidity and pressure difference, the greater the deviation from the set value range and the more violent the fluctuation, the higher the contribution to the risk index.

Based on the above factors, a weighted fusion method is used to generate a comprehensive dynamic infection risk index, ranging from 0 to 100, with higher values indicating greater risk. To further improve the predictive power of the assessment, this study introduces machine learning algorithms, particularly a long short-term memory network model, to learn the relationship between historical environmental data sequences and future short-term risk changes. This model can predict the infection risk trend for the next 5–10 minutes based on the current and past environmental conditions, thus achieving early warning.

C. INTELLIGENT EARLY WARNING AND PURIFICATION SYSTEM LINKAGE INTERVENTION STRATEGY

In order to achieve precise prevention and control, this study established a graded early warning mechanism. Based on the value of the dynamic infection risk index, the risk was divided into three levels: "low risk" (0–30), "medium risk" (31–70) and "high risk" (71–100). When the index enters the "medium risk" level, the system will issue a primary visual and auditory warning through the display screen installed in the operating room and the mobile terminal of medical staff to remind them to pay attention to environmental changes. When the index reaches the "high risk" level, the system will issue a high-level alarm [15].

More importantly, this study developed a linkage interface with the operating room's cleanroom air conditioning system. When the risk index exceeds a preset medium-risk threshold and persists for a period of time, or when the predictive model indicates a rapid increase in risk, the system can automatically send a command to the cleanroom air conditioning system to trigger an intervention strategy. This intervention strategy is not a simple on/off switch, but rather a precise adjustment based on risk, for example:

Low airflow mode (low risk): Maintain normal operation.

Enhanced Mode (Medium Risk): Automatically increases the frequency of the air supply fan, increases the air volume, increases the number of air exchanges, and accelerates the dilution and discharge of pollutants.

Powerful Mode (High Risk): While increasing airflow, it also activates localized enhanced purification devices near the surgical area.

All warnings and interventions are recorded by the system, forming a traceable log for subsequent effect evaluation and strategy optimization.

IV. RESULTS AND DISCUSSION

A. ANALYSIS OF THE OPERATIONAL STABILITY AND DATA VALIDITY OF THE IOT MONITORING SYSTEM

The system underwent a six-month continuous operation test after deployment. During this period, over 95% of the sensor nodes maintained over 99.5% data upload integrity, network communication was stable, and the edge gateway effectively completed data preprocessing and buffering. This demonstrates the reliability and robustness of the IoT architecture in the complex electromagnetic environment of a hospital. Through probe of massive amounts of real-time monitoring data, the system was able to capture the extremely dynamic characteristics of the operating room environment. For example, instantaneous peak values of particulate matter concentration (particularly PM2.5 and PM10) were observed with pre-operative preparation stage, frequent medical staff's entry and exit, and instrument clean-up at the end of the surgery. These peak values were usually by a factor of several times or even tens of times greater than the background concentration. Real-time data of microbial monitoring also exhibited similar trends but with a certain lag observed from the maximum concentration of particulate matter which is consistent with the physical laws of particulate matter as a carrier of microorganisms. Table 1 outlines the monitoring values for mean particulate matter and microbial concentrations in the surgical area during a typical surgical day at various stages throughout the process, which clearly shows the dynamic changes of the environmental parameters with the surgical process.

TABLE 1. Dynamic changes in environmental parameters of key areas during typical surgical procedures (mean ± standard deviation)

Surgical stage	PM2.5 (μg/m^3)	PM10 (μg/m^3)	Microbial concentration (cities/m^3)	Remark
Preoperative static position (no personnel)	12.5 ± 3.2	18.6 ± 4.1	25 ± 8	Background values meet cleanliness standards.
Preoperative preparation (frequent personnel movement)	85.4 ± 22.7	132.8 ± 35.9	68 ± 15	Concentration peaks appeared.
Intraoperative core phase (personnel stability)	35.6 ± 10.5	52.1 ± 14.3	45 ± 12	Concentration has decreased, but remains above background levels.
From the closure of the abdomen to the end of the operation	48.9 ± 13.8	71.5 ± 18.6	55 ± 14	Increased activity led to a rise in concentration.
Postoperative care	91.2 ± 25.4	145.3 ± 40.1	75 ± 18	A second peak appeared.

B. PERFORMANCE VALIDATION AND EARLY WARNING EFFECT OF DYNAMIC INFECTION RISK ASSESSMENT MODEL

The dynamic risk index value of infection generated based on the fused data can intuitively reflect the overall situation of the operating room environment. Comparing the time series of the risk index with the recorded surgical events (e.g. door opening, large-scale people entering the operating room) shows a high degree of correspondence. The model can correctly detect situations of increase in the risk caused by events such as the action of personnel. To check the performance of the machine learning prediction model, we have compared it to a simple threshold alarm model. Using root mean square error and mean absolute percentage error as evaluation criteria, on the test set, the prediction error of the long short-term memory network model risk index 5 minutes later was significantly lower than that of the static extrapolation method based on the current value. This means that the model has a certain predictive capability and can offer valuable advance warning. Table 2 compares the early warning performance of this system with that of existing building automation management systems in 100 challenging early warning scenarios.

The IoT-based real-time monitoring and dynamic assessment model has broken the lagging nature of traditional monitoring. It is not only being a responsive indicator of environmental conditions in close to real time, but more importantly, has the potential for risk prediction. Although a certain degree of false alarm rate stands, this "better to report a false alarm than to miss one" strategy is of positive significance in the field of infection control, as it continuously reminds healthcare workers to pay attention to environmental changes. The advance warning enables measures for intervention to be implemented before the risk really reaches a high level so that "prevention is better than cure."

C. EVALUATION OF THE EFFECTIVENESS OF INTELLIGENT INTERVENTION STRATEGIES IN MAINTAINING AIR CLEANLINESS

Post-enabling of the intelligent linkage intervention function of the system, it is about analysing the real effect to environmental parameters of an improved operation of the linkage purification system when a medium to high-risk warning was issued. Data indicates that in most cases (some 92%), as the system automatically changed to "enhanced mode" or "powerful mode", the previously rising particulate matter and microbial concentration curves hit an inflection point within 3–5 minutes and started to go down. The average recovery time was reduced by about 15 minutes while manual adjustment was performed after manual detection. To quantify the overall effectiveness of the intervention, we chose data from three months prior to and after enabling the system to compare the cumulative amount of time during the same kind of surgery in which the microbial concentration in the surgical area was above the standard. The findings are presented in the following Table 3.

Data demonstrates that intelligent and coordinated intervention strategies can effectively and rapidly address environmental degradation, thereby significantly shortening the duration of high-concentration pollution and reducing the time surgical incisions are exposed to high-risk environments. This data driven precision control prevents energy consumption waste (constantly running with high intensity) or inadequate control (not enough operational intensity) which may exist to under traditional fixed mode operation. It accomplishes the task of on-demand regulation, proving the potential of optimization of energy efficiency while making the environment safe. However, it is also necessary to realize that the capability of adjustment of the purification system has a physical limit. In situations of extremely dense populations or unusually frequent activities, it may not be possible for the system to reduce the concentration to the ideal level immediately, but the system may effectively inhibit its further increasing. This presents the importance of combining the technological means, with the pressing control of personnel behavior.

TABLE 2. Comparison of the effects

Warning Indicator	Dynamic Risk Assessment System (This Study)	Existing Automated Building Management System (BMS) Monitoring
Risk Event Identification Rate	98% (98/100)	62% (62/100)
Average Lead Time for Alerts	Approximately 8.5 minutes	Approximately 1.5 minutes (typically lagging alerts)
False Positive Rate	7%	22%
Ability to Capture Transient Peaks	Strong, capable of capturing the vast majority of short-term fluctuations	Weak, often relies on minute-level averages and easily misses transient peaks
Monitoring Dimensions	Multi-parameter fusion: particulate matter, microorganisms, temperature, humidity, pressure differential, personnel activity, etc.	Typically limited to basic environmental parameters like temperature, humidity, and pressure differential; lacks real-time monitoring of particulate matter/microorganisms and personnel activity.

TABLE 3. Comparison of the percentage of time when the microbial concentration in the surgical area exceeded the standard before and after the system was put into use (similar types of surgery)

Statistical period	Monitoring the number of operating rooms	Percentage of cumulative time period with microbial concentration exceeding the standard (>50 CFU/m^3) (average)	Percentage of cumulative time period with microbial concentration exceeding the standard (>100 CFU/m^3) (average)
Before system activation	150	18.7%	3.5%
After the system is activated (including intelligent intervention)	155	5.2%	0.6%

V. CONCLUSION

This research was to achieve continuous monitoring of pollutants in the environment and human activities by using a network of sensors that transmit several parameters. The constructed dynamic risk assessment model can effectively predict the fluctuation of risk and make the purification system adjust accordingly. However, the control ability provided by the system under the impact of severe human disturbances still has physical limits, and the long-term running cost and cross-platform compatibility are still required to be evaluated. Future research will examine more complex multimodal risk prediction algorithms that incorporate fiber-shedding data from medical textiles, encouraging deep integration with hospital platforms to achieve comprehensive closed-loop management of perioperative infections.

AUTHOR CONTRIBUTIONS

Conceptualization –Yue Zhang, Min Han and Linna Li; methodology – Yue Zhang, Min Han and Linna Li; investigation – Yue Zhang, Min Han and Linna Li; writing-original draft preparation – Yue Zhang, Min Han and Linna Li. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] C. Wistrand, K. Falk-Brynhildsen, and A. S. Sundqvist, “Important interventions in the operating room to prevent bacterial contamination and surgical site infections,” American Journal of Infection Control, vol. 50, no. 9, pp. 1049-1054, 2022, doi: 10.1016/j.ajic.2021.12.021.

[2] F. O. Aktaş and H. T. Damar, “Determining operating room nurses’ knowledge and use of evidence-based recommendations on preventing surgical site infections,” Journal of PeriAnesthesia Nursing, vol. 37, no. 3, pp. 404-410, 2022, doi: 10.1016/j.jopan.2021.08.012.

[3] H. Tan, M. H. D. Othman, H. Y. Kek, C. T. Lee, B. B. Nyakuma, K. Q. Lee, et al., “Utilizing localized exhaust and air curtain to reduce airborne particle settlement on surgical patients: Potential future application in operating rooms?” Journal of Thermal Analysis and Calorimetry, vol. 149, no. 19, pp. 11323-11336, 2024, doi: 10.1007/s10973-024-13053-3.

[4] H. Tan, K. Y. Wong, B. B. Nyakuma, H. M. Kamar, W. T. Chong, S. L. Wong, et al., “Systematic study on the relationship between particulate matter and microbial counts in hospital operating rooms,” Environmental Science and Pollution Research, vol. 29, no. 5, pp. 6710-6721, 2022, doi: 10.1007/s11356-021-16171-9.

[5] K. Omori, N. Shigemoto, H. Kitagawa, T. Nomura, Y. Kaiki, K. Miyaji, et al., “Virtual reality as a learning tool for improving infection control procedures,” American Journal of Infection Control, vol. 51, no. 2, pp. 129-134, 2023, doi: 10.1016/j.ajic.2022.05.023.

[6] M. S. Calderwood, D. J. Anderson, D. W. Bratzler, E. P. Dellinger, S. Garcia-Houchins, L. L. Maragakis, et al., “Strategies to prevent surgical site infections in acute-care hospitals: 2022 Update,” Infection Control & Hospital Epidemiology, vol. 44, no. 5, pp. 695-720, 2023, doi: 10.1017/ice.2023.67.

[7] Y. Wang, S. Liu, W. Wang, and N. Hou, “The effect of comprehensive nursing intervention based on operating room infection control pathway on colorectal cancer patients,” Qilu Nursing Journal, vol. 30, no. 14, pp. 33-36, 2024.

[8] J. L. Seidelman, C. R. Mantyh, and D. J. Anderson, “Surgical site infection prevention: A review,” JAMA, vol. 329, no. 3, pp. 244-252, 2023, doi: 10.1001/jama.2022.24075.

[9] W. B. Risinger and J. W. Smith, “Damage control surgery in emergency general surgery: what you need to know[J],” Journal of Trauma and Acute Care Surgery, vol. 95, no. 5, pp. 770-779, 2023, doi: 10.1097/ta.0000000000004112.

[10] V. D. Crall, C. L. Lewis, D. J. Dickman, D. W. Grinage, T. George, A. M. Ayres, et al., “Strategies for deployment of ultraviolet disinfection in an acute care facility: A quality improvement initiative,” American Journal of Infection Control, vol. 51, no. 11, pp. 1230-1236, 2023, doi: 10.1016/j.ajic.2023.04.164.

[11] M. Ellsworth, D. Peneza, and L. Ostrosky-Zeichner, “Perioperative nurses: key to surgical site infection prevention,” AORN Journal, vol. 117, no. 5, pp. 267-269, 2023, doi: 10.1002/aorn.13920.

[12] R. J. Clifford, D. Newhart, M. R. Laguio-Vila, J. L. Gutowski, M. Z. Bronstein, and E. P. Lesho, “Infection preventionist staffing levels and rates of 10 types of healthcare-associated infections: A 9-year ambidirectional

observation," Infection Control & Hospital Epidemiology, vol. 43, no. 11, pp. 1641-1646, 2022, doi: 10.1017/ice.2021.507.
[13] L. Liu, Y. Xu, L. Zhang, D. Ni, Y. Wang, J. Xie, et al., "Management strategies for trauma orthopedic implants and their effects on operating room infection control," Chinese Journal of Nosocomial Infection, vol. 35, no. 20, pp. 3168-3172, 2025.
[14] J. B. Glowicz, E. Landon, E. E. Sickbert-Bennett, A. E. Aiello, K. Dekay, and K. K. Hoffmann, "SHEA/IDSA/APIC Practice Recommendation: Strategies to prevent healthcare-associated infections through hand hygiene: 2022 Update," Infection Control & Hospital Epidemiology, vol. 44, no. 3, pp. 355-376, 2023, doi: 10.1017/ice.2022.304.
[15] C. Hinrichs, M. Wiese-Posselt, B. Graf, C. Geffers, B. Weikert, P. Enghard, et al., "Successful control of Candida auris transmission in a German COVID-19 intensive care unit," Mycoses, vol. 65, no. 6, pp. 643-649, 2022, doi: 10.1111/myc.13443.