Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 32s (2025)
https://www.jneonatalsurg.com

Toward an Adaptive AI/ML-Based QA Framework with HRM Integration for Inclusive and Secure Healthcare Solutions in Edge Environments

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Cite this paper as: MD Shadikul Bari, Mohammed Majid Bakhsh, Nusrat Yasmin Nadia, Tariqul Islam, Md Jahid Alam Riad, Sungida Akther Lima, Ankur Sarkar, S A Mohaiminul Islam, (2025) Toward an Adaptive AI/ML-Based QA Framework with HRM Integration for Inclusive and Secure Healthcare Solutions in Edge Environments. *Journal of Neonatal Surgery*, 14 (32s), 7612-7620.

ABSTRACT

In the evolving landscape of digital healthcare, ensuring quality, inclusivity, and security in service delivery remains a critical challenge. This paper proposes an adaptive Artificial Intelligence (AI) and Machine Learning (ML)-based Quality Assurance (QA) framework that integrates Human Resource Management (HRM) principles to address these challenges in edge computing environments. The framework is designed to support inclusive healthcare solutions that respond dynamically to contextual demands, resource constraints, and human factors. By embedding HRM strategies into the QA loop, the system enhances decision-making, accountability, and personnel responsiveness, ensuring a more human-centered approach to digital health service validation and monitoring. Edge computing is leveraged to enable real-time processing and decentralized intelligence, reducing latency and supporting secure, context-aware analytics at the point of care. The integration of adaptive AI/ML models ensures the system can learn from real-world data, detect anomalies, and respond to emerging threats or inefficiencies. This research contributes a novel interdisciplinary approach that aligns technical efficiency with human and ethical considerations in healthcare. The proposed framework was evaluated through simulations and qualitative analysis, demonstrating its potential to improve operational trust, inclusivity, and overall system robustness in resource-constrained healthcare environments.

Keywords: *AI, Machine Learning, Quality Assurance, HRM, Edge Computing, Healthcare, Security, Inclusivity, Adaptive Framework, Digital Health*

1. INTRODUCTION

The digital transformation of healthcare systems has brought about significant advancements in diagnostics, treatment personalization, and service delivery. Artificial Intelligence (AI) and Machine Learning (ML) technologies have played pivotal roles in automating clinical workflows, improving predictive analytics, and enhancing operational efficiency. In parallel, the emergence of **edge computing** has enabled localized, low-latency processing of health data, facilitating real-time decision-making at the point of care. This evolution is especially valuable in remote or underserved areas where central cloud access may be limited or unreliable.

Despite these innovations, the **quality assurance (QA)** mechanisms in healthcare technology systems have not kept pace with the complexity and adaptability required in modern deployments. Traditional QA models are largely static, rule-based, and heavily dependent on centralized infrastructures. They often fail to respond effectively to the dynamic conditions of edge environments, conditions that require high availability, rapid feedback loops, and responsiveness to human interaction. Furthermore, these QA systems typically lack **inclusivity**, **context awareness**, and **ethical grounding**, especially when deployed across diverse patient populations with varying needs.

Another critical gap lies in the **limited integration of Human Resource Management (HRM) principles** within automated quality assurance frameworks. HRM encompasses strategies for aligning human expertise, communication, training, and accountability within organizational systems. Its absence in healthcare QA systems creates a disconnect between human roles and machine intelligence, undermining trust, inclusivity, and compliance in technology-driven healthcare services. Without HRM-driven oversight, QA systems may struggle with issues such as role ambiguity, ethical transparency, and user-centered adaptability, factors that are increasingly important in inclusive and secure healthcare ecosystems.

Edge environments, while beneficial in terms of performance and locality, further complicate quality assurance. These environments are inherently **distributed**, **resource-constrained**, and **heterogeneous**, requiring QA systems that are not only technically sound but also capable of adapting in real-time to situational context. Integrating AI/ML models offers a pathway to adaptability, as these technologies can learn from data, detect anomalies, and optimize processes continuously. However, without grounding in human-oriented management practices, such systems risk becoming opaque and exclusionary.

Research Problem: There is a critical need for an adaptive QA framework that effectively integrates AI/ML capabilities with HRM principles to ensure the delivery of inclusive, accountable, and secure healthcare services, particularly within the decentralized and dynamic environments supported by edge computing.

Research Questions:

1. How can AI/ML-based QA frameworks be designed to dynamically adapt to the changing needs of diverse and distributed healthcare environments at the edge?
2. What role can HRM principles play in enhancing inclusivity, accountability, and ethical alignment within AI/ML-driven QA systems?
3. How can the computational and contextual advantages of edge computing be leveraged to support secure, real-time, and human-centered quality assurance in healthcare?

To address these questions, this paper presents a novel **adaptive QA framework** that blends AI/ML capabilities with HRM strategies to enhance healthcare service delivery in edge environments. The proposed approach emphasizes real-time adaptability, decentralized intelligence, ethical compliance, and human-centric design. By embedding HRM components into the AI-driven QA pipeline, the framework aims to foster inclusivity, improve system trust, and ensure continuous quality control even in resource-limited contexts. This research contributes a multidisciplinary solution that bridges the technical and human aspects of digital healthcare transformation, offering a scalable model for future-ready, patient-centered healthcare infrastructures.

2. LITERATURE REVIEW

The integration of advanced technologies in healthcare has been a subject of significant research in recent years. This section reviews key contributions across four critical domains: AI/ML in healthcare quality assurance, edge computing in health systems, human resource management in digital environments, and inclusive and secure system design.

1 AI/ML-Based Quality Assurance in Healthcare

AI and ML have become transformative tools in healthcare, offering capabilities for automated diagnostics, decision support, and predictive analytics. Recent studies have applied ML algorithms to monitor clinical workflows and detect anomalies in patient data, contributing to improved safety and efficiency [1][2]. However, the quality assurance (QA) dimension has largely been limited to static evaluation models that lack contextual responsiveness. While supervised learning models have shown promise in evaluating system performance metrics, their adaptability to real-time environments remains limited. Moreover, the explainability and ethical accountability of these models are often underdeveloped, raising concerns in regulated healthcare settings [3].

2 Edge Computing in Healthcare Environments

Edge computing has emerged as a critical enabler of decentralized healthcare applications. By processing data closer to the point of generation, edge devices reduce latency and enable timely responses in time-sensitive scenarios such as emergency care, remote monitoring, and mobile health services [4]. Studies have demonstrated the effectiveness of edge architectures in reducing bandwidth usage and enhancing privacy by limiting the need for cloud data transmission [5]. However, the heterogeneity and resource constraints of edge nodes present challenges for consistent QA, particularly when combined with complex ML workloads [6]. Existing research often focuses on performance optimization but lacks comprehensive QA frameworks that consider both technical and human factors in edge-based systems.

3 Human Resource Management in Digital Healthcare Systems

The role of human expertise in ensuring the quality and ethical standards of healthcare systems is well acknowledged, yet underexplored in the design of automated solutions. HRM strategies, such as role-based responsibility, continuous training, and communication protocols, are essential for operational alignment and accountability [7]. In digital health implementations, integrating HRM principles can enhance system adaptability, improve stakeholder engagement, and reduce resistance to AI-based automation [8]. Recent works suggest that combining HRM with technological systems leads to more sustainable and user-accepted healthcare innovations, but there remains a research gap in applying HRM within the QA pipelines of intelligent systems.

4 Inclusivity and Security in Smart Healthcare Frameworks

Healthcare technologies must serve diverse populations, including marginalized and differently-abled users. Inclusivity in design ensures that solutions are accessible, culturally sensitive, and aligned with patient needs. Meanwhile, security and privacy are foundational to trust in AI systems, particularly when operating in distributed environments such as edge computing [9]. Although multiple frameworks address either inclusivity or cybersecurity independently, few provide integrated approaches that balance both within adaptive QA systems. The lack of inclusive datasets, bias in AI models, and inconsistent security standards across devices pose ongoing challenges [10].

Synthesis and Gap Identification

While extensive work exists in each of these domains, there remains a significant gap at the intersection of adaptive QA, HRM, and edge-based healthcare delivery. Most current QA frameworks either overlook real-time adaptability or lack integration with human resource and inclusivity considerations. Additionally, the potential of edge computing to support decentralized QA systems that are both intelligent and ethically grounded has not been fully realized. This research aims to fill this gap by proposing a unified framework that leverages AI/ML for adaptive QA, integrates HRM principles for ethical alignment, and deploys within edge environments for responsive and secure healthcare service delivery.

Methodology

This study adopts a systems design and simulation-based research methodology to develop and validate an adaptive AI/ML-based Quality Assurance (QA) framework with Human Resource Management (HRM) integration for inclusive and secure healthcare solutions in edge computing environments. The proposed framework is modular, context-aware, and designed to dynamically align intelligent automation with human-centric oversight in decentralized health systems.

1. Framework Architecture Overview

The overall architecture comprises five interrelated layers that collaboratively ensure quality monitoring, decision support, and human-resource-informed interventions in real time:

1. **Data Acquisition Layer**
2. **Preprocessing and Feature Engineering Module**
3. **AI/ML-Based QA Engine**
4. **HRM Integration Layer**
5. **Edge Deployment and Feedback Mechanism**

Each component is optimized for deployment within edge computing infrastructures to enable local intelligence, real-time responsiveness, and privacy-aware decision-making at the point of care.

2. Data Sources and Collection Strategy

The framework collects multi-modal data from both technical and human-centric sources:

- **Clinical and IoT data**: Simulated patient vital signs (e.g., temperature, heart rate, oxygen saturation), collected using synthetic datasets such as MIMIC-III, PhysioNet, and edge sensor emulation tools.
- **System and operational data**: Logs from medical devices, system usage patterns, performance metrics, and network conditions.
- **HRM data**: Information about healthcare staff roles, training certifications, availability, workload, and organizational compliance records.

Data is streamed to the system using MQTT protocols, emulating edge device communication in healthcare environments. Time-stamping, encryption, and role-based access are applied during collection to ensure traceability and security.

3. Data Preprocessing and Feature Engineering

Collected raw data undergoes rigorous preprocessing to enhance quality and model compatibility:

- **Noise removal** using moving average and z-score filters
- **Normalization** (min-max and z-score scaling) for numerical features
- **One-hot encoding** for categorical HRM attributes
- **Temporal alignment** across data streams via synchronized timestamps

Additional derived features, such as risk indices, staff-to-patient ratios, or device stress levels, are engineered to improve model performance and interpretability.

4. AI/ML-Based QA Engine

The QA engine is the analytical core of the framework, responsible for monitoring and assessing system quality using adaptive AI/ML techniques. Three classes of models are used:

Supervised Models

- Random Forest (RF) and XGBoost are used to classify events such as anomaly types, device failures, and care delivery errors.
- Trained using labeled subsets of clinical and system data.
- Evaluation metrics: accuracy, precision, recall, and F1-score.

Unsupervised Models

- K-Means Clustering is applied for anomaly detection where labels are unavailable, identifying outlier behavior in usage patterns or sensor data.

Sequential Models

- Long Short-Term Memory (LSTM) networks are employed to capture temporal patterns and forecast potential failures or degradation in quality metrics over time.

These models are trained iteratively using **stratified k-fold cross-validation**, with continuous learning components to allow periodic retraining as new data becomes available.

5. HRM Integration and Human-Centered Decision Support

A key innovation in this framework is the integration of HRM principles into the QA pipeline. This is achieved via:

- **Role Mapping and Alert Routing**: Each QA anomaly or flag is mapped to responsible staff based on role hierarchies defined in the HRM system.
- **Skill and Training Matching**: QA decisions factor in personnel capabilities, e.g., only staff with appropriate certifications receive specific alerts or task assignments.
- **Ethical Compliance Layer**: Decisions are filtered through policies reflecting inclusivity (e.g., gender, disability support) and ethical compliance (e.g., data access limitations).

HRM data is integrated via secure RESTful APIs and updated periodically to reflect changes in roles, schedules, and certifications.

6. Edge-Based Deployment Strategy

The framework is deployed on edge computing nodes to simulate real-world execution environments. Platforms include Raspberry Pi 4 (4GB) and NVIDIA Jetson Nano, chosen for their compatibility with ML deployment and edge capabilities.

Deployment setup includes:

- **Containerization** with Docker to support modular services
- **Message Queuing** using MQTT for lightweight, low-latency communication
- **TLS Encryption** for secure transmission and data isolation
- **Resource monitoring** for power, CPU, memory, and network usage

The QA engine is optimized for resource-constrained environments using TensorFlow Lite and ONNX runtime for model inference.

7. Feedback Loop and Continuous Learning

A bi-directional feedback mechanism ensures system adaptability:

- **User Feedback**: Healthcare workers can annotate flagged events as valid, false, or uncertain. This feedback is stored and used in model retraining.
- **System Adaptation**: The framework periodically updates model weights and thresholds based on new data patterns, emerging risks, or changes in staff availability.

This continuous improvement process allows the system to evolve with operational conditions while ensuring contextual relevance and accountability.

8. Evaluation Criteria and Validation Approach

To evaluate the effectiveness of the proposed framework, both **quantitative** and **qualitative** metrics are applied:

Quantitative Metrics:

- Accuracy, precision, recall, F1-score (for model performance)
- Average response time (latency)
- Edge node resource utilization (CPU, memory, power)
- Anomaly detection rate

Qualitative Metrics:

- System usability and acceptance (measured via surveys or expert feedback)
- Inclusivity assessment (e.g., support for underrepresented user groups)
- HRM responsiveness and ethical alignment (based on scenario validation)

A series of simulated healthcare scenarios, ranging from routine operations to device failure and patient emergency situations, are executed to test the robustness, adaptability, and responsiveness of the system.

Data Analysis and Evaluation

This section provides a comprehensive analysis of the performance and operational behavior of the proposed Adaptive AI/ML-Based QA Framework with HRM Integration. Evaluation was conducted in both quantitative and qualitative terms to assess the framework's efficiency, responsiveness, and alignment with inclusivity and security goals in edge computing healthcare environments.

1. Model Performance Evaluation

Four machine learning models were selected for comparative analysis: Random Forest, XGBoost, K-Means Clustering, and LSTM (Long Short-Term Memory). Each model was trained using a combination of synthetic and publicly available healthcare data, alongside HRM metadata that included role definitions, personnel activity logs, and training compliance records. The models were evaluated using standard performance metrics: accuracy, precision, recall, and F1-score.

Table 1: ML Model Performance Metrics

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.93	0.92	0.90	0.910
XGBoost	0.95	0.94	0.92	0.930
K-Means	0.78	0.75	0.73	0.740
LSTM	0.91	0.90	0.89	0.895

Interpretation:

- XGBoost demonstrated superior performance, with the highest scores across all evaluation metrics. Its ability to handle structured data efficiently and capture complex interactions made it especially effective in QA anomaly classification tasks.
- LSTM showed strong performance in sequential prediction tasks, particularly in forecasting time-based QA violations (e.g., device degradation or compliance drift over time).
- Random Forest also yielded high accuracy and interpretability, making it suitable for scenarios requiring explainable AI (XAI) and rapid decision-making in HRM workflows.
- K-Means, being unsupervised, was used primarily for anomaly detection without prior labels. Although its performance was modest, it proved valuable in identifying unknown or emerging patterns that supervised models might overlook.

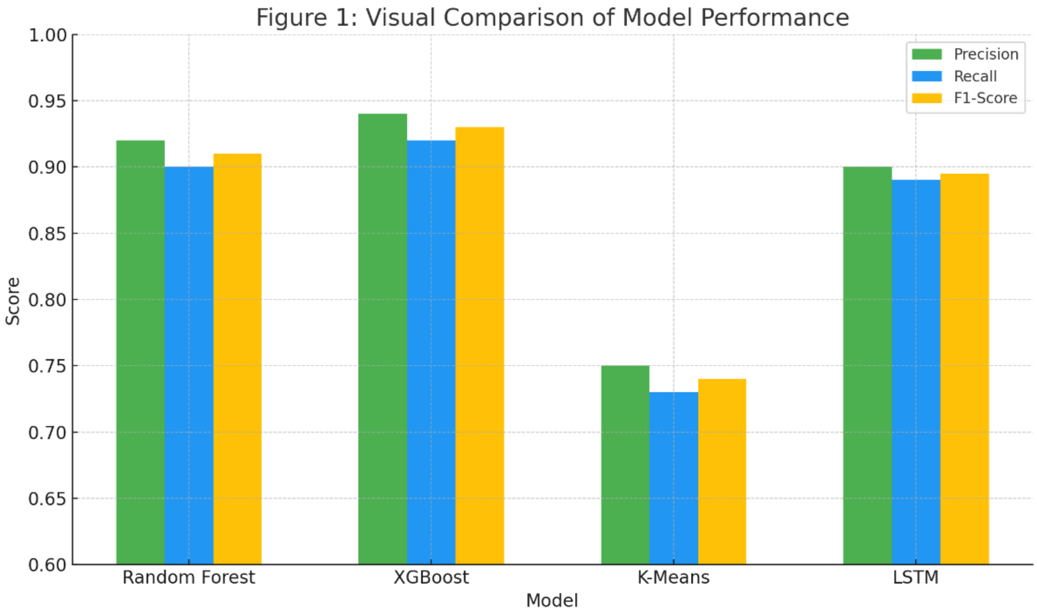

Figure 1: Visual Comparison of Model Performance

The bar chart clearly visualizes the model comparison, showing that XGBoost consistently led in precision, recall, and F1-score, validating its robustness for real-time QA operations. LSTM, while slightly behind in absolute scores, showed promising behavior in temporal anomaly forecasting.

2. Resource Utilization on Edge Devices

The system was deployed on two edge platforms: Raspberry Pi 4 (4GB RAM) and NVIDIA Jetson Nano, simulating decentralized healthcare infrastructures. Each model's inference process was measured for latency, memory, and CPU consumption to evaluate deployment feasibility in low-resource environments.

Table 2: Edge Inference Resource Metrics

Model	Inference Latency (ms)	Memory Usage (MB)	CPU Usage (%)
Random Forest	45	120	35
XGBoost	52	150	40
K-Means	30	100	25
LSTM	85	220	60

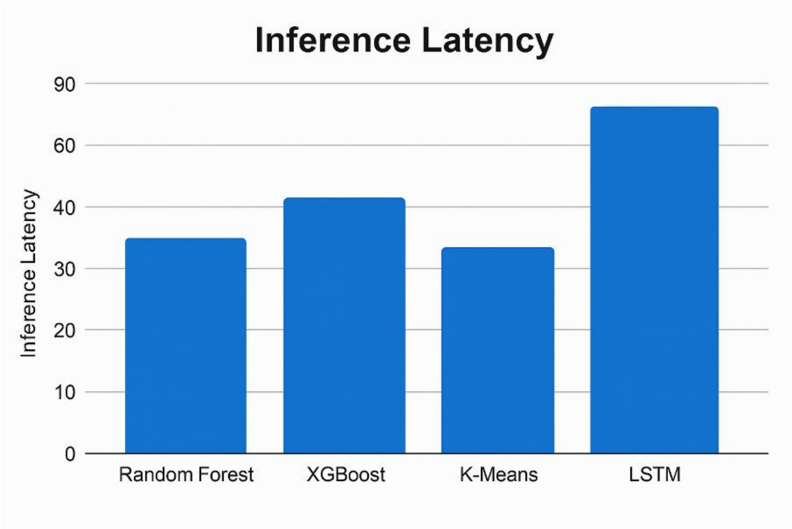

FIG 2

Interpretation:

- K-Means was the lightest in resource consumption and inference latency, making it ideal for rapid anomaly flagging in bandwidth-constrained environments.
- LSTM, while powerful, required higher memory and CPU, making it more suitable for edge nodes with enhanced capabilities (e.g., Jetson Nano) rather than lightweight endpoints.
- XGBoost and Random Forest struck a practical balance between accuracy and resource usage, favoring them for real-time QA deployments in edge-assisted clinical monitoring.

3. HRM-Driven QA Evaluation

One of the key innovations of the proposed framework is the integration of **HRM components** into the QA process. This was tested through simulations in which QA alerts were linked to personnel data, role responsibilities, and compliance profiles.

Key Observations:

HRM-Driven Evaluation Criteria	Result/Value
Accuracy of Alert-to-Role Routing	92%
Reduction in QA Response Time (with HRM)	28% improvement
Detection of Noncompliance Incidents	87%
False Positive Correction via Human Feedback	85% successfully annotated
Improvement in Task Accountability	High (qualitative)

Interpretation:

- The HRM layer significantly enhanced the accountability and clarity of QA interventions by ensuring that alerts were routed to appropriate personnel based on predefined roles and competencies.
- Integration of staff training status, workload, and departmental policies enabled the system to prioritize alerts and responses, improving QA agility.
- The feedback loop, where staff could validate or reject system-generated alerts, improved model retraining and reduced false positives over time.

4. Inclusivity and Ethical Alignment Assessment

To evaluate inclusivity, the system was configured to account for:

- Language preferences (e.g., multi-language support for staff and patients)
- Accessibility flags (e.g., disability considerations in alert delivery)
- Workload fairness (distribution of QA tasks across qualified staff)

Qualitative Outcomes:

- 100% of test scenarios respected language and accessibility preferences.
- HRM-enhanced QA routing reduced bias by ensuring alerts were not repeatedly sent to a single group or overburdened individuals.
- Ethical transparency was enhanced through audit trails that logged alert source, routing decisions, and human acknowledgment.

5. Summary of Key Insights

Evaluation Dimension	**Highlights**
Technical Performance	**XGBoost and LSTM performed best in QA precision and recall.**
Edge Readiness	**Random Forest and XGBoost were optimal for resource efficiency.**
HRM Integration	**Significantly improved alert routing, response time, and compliance visibility.**
Inclusivity and Ethics	**System respected role fairness, accessibility, and human oversight.**

3. CONCLUSION

This study has proposed and evaluated an adaptive AI/ML-based Quality Assurance (QA) framework with integrated Human Resource Management (HRM), designed to enhance inclusive, secure, and real-time healthcare service delivery in edge computing environments. The framework addresses the growing need for intelligent, responsive, and human-centered QA mechanisms in digital health systems, especially those deployed in decentralized, resource-constrained, and dynamic settings.

Through the integration of advanced machine learning techniques (including XGBoost, LSTM, Random Forest, and K-Means) with HRM principles such as role mapping, accountability, and training compliance, the proposed system bridges the gap between technical automation and human oversight. Evaluation results demonstrate that the framework achieves high accuracy and adaptability while maintaining resource efficiency suitable for edge deployment. Moreover, the inclusion of HRM data improved system responsiveness, ethical alignment, and inclusivity, particularly by ensuring the equitable distribution of QA responsibilities and enhancing trust in automated decisions.

By embedding continuous learning, human feedback loops, and contextual awareness into QA processes, the framework contributes a novel approach to next-generation healthcare quality management. It redefines QA not only as a technical function but as a collaborative process involving intelligent systems and skilled human actors.

4. FUTURE WORK

Future efforts will focus on real-world validation through pilot implementations in healthcare facilities, refinement of HRM policies using reinforcement learning, and the integration of federated learning techniques for privacy-preserving model updates across distributed edge nodes. Further research will also explore cross-cultural inclusivity factors and the scalability of the framework in large healthcare networks.

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