Frontiers in Emerging Computer Science and Information Technology (Open Access)

Volume 02, Issue 08, August 2025,
Publish Date: 08-31-2025
DOI: - https://doi.org/10.37547/fecsit/Volume02Issue08-02 PageNo.07-14

Real-Time Patient Monitoring and Alerting in Hospitals Using AWS Lake House Architecture

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Abstract

A modern data architecture that integrates the capabilities of a data lake and a data warehouse into a single, cohesive platform is an Amazon Web Services (AWS) Lake House. It provides a robust platform for real-time Patient Monitoring (PM). Nevertheless, there is a lack of understanding of Real-Time (RT) PM and alerting using AWS, particularly in its clinical outcomes. Thus, the present research aims to inspect the role of AWS Lake House in RT Monitoring (RTM) of patients and alerting in hospitals. From various secondary sources, the study collects data. As per the study, the AWS-based approach overcomes the challenges faced by the traditional PM system. AWS Health Lake (HL) enables semantic indexing and querying of FHIR-compliant patient records. RT ingestion and alerting require complementary services, such as Amazon Kinesis Data Streams (KDS) for streaming data, AWS Lambda for event processing, Amazon Event Bridge for routing alerts, and Amazon SNS for notifications. Amazon Redshift and Amazon Quick Sight provide low-latency access to patient data for analysis. AWS solutions can permit Healthcare (HC) professionals to have RT analysis, secure storage, along with scalable solutions for heightened HC management and Decision-Making (DM). Moreover, leveraging AWS HL for RTM leads to improved care coordination, personalized treatment plans, and more efficient resource allocation. By leveraging AWS's pay- as-you-go model, HL reduces infrastructure costs for HC organizations, enabling them to allocate resources more effectively. Further, the study finds that AWS allows for early intervention and improved outcomes. Data interoperability is the major challenge of AWS Lake House.

Keywords: *AWS Health Lake, AWS Redshift, AWS Lambda, Patient monitoring, Clinical outcomes*

1 Introduction

In the evolving HC background, the demand for sophisticated PM systems has increased, highlighting the need for RT data analysis and immediate response mechanisms [1]. RT PM involves advanced medical devices that enable continuous observation and analysis of a patient's health data related to heart rate, blood-oxygen saturation, blood pressure, temperature, etc [2]. With a mounting demand for RT along with continuous health monitoring among patients, the HC industry faces a key shift towards digital health technology [3].

The swift advancements in HC technology, coupled with the growing demand for RT PM, have catalyzed cloud services' development [4]. Cloud-based solutions enhance collaboration among HC providers by offering centralized access to patient data, fostering better DM and personalized care [5]. AWS is a subsidiary of Amazon, offering on-demand cloud computing platforms along with APIs to individuals and organization [6]. AWS is a robust leader in HC data management by employing services like Amazon S3, AWS HL, along with AWS Glue for patient data integration, providing HIPAA-compliant storage, and facilitating smooth interoperability of data [7, 8]. HC organizations gain scalability, security, along with RT analytics, which provide HC professionals with actionable understandings for augmenting patient care through the adoption of AWS Cloud [9, 10]

1.1 Background

Several researchers have explored AWS's role in RT PM. For instance, Aditya et al. [11] developed a system for monitoring the patient's activities in real time to determine whether they were normal or abnormal. An alert notification was sent to the respective doctor if abnormal activity was detected. Likewise, Dubery and

Tiwari [12] utilized AWS to link patients with doctors online, aiming to boost productivity along with minimize response time in the HC industry. As per Bouslama and Laaziz [13], the AWS-based system helped reduce hospital workload while ensuring close medical follow-up for patients.

Also, Bingu et al. [14] found that the scalability, flexibility, and safety of cloud computing in HC were evident through the integration of AWS services, such as Amazon SageMaker, Amazon S3, and AWS IoT Core. These services enabled RT data collection, storage, and evaluation, which created opportunities for better resource efficiency, improved DM, and early intervention. According to Bouslama et al. [15]), cloud providers like AWS, Google, and Azure demonstrated similar technical performance levels, including availability, scalability, response time, along with transit delay. Nevertheless, AWS was found to be more cost-effective for data archiving.

Li and You [16] scrutinized intelligent m-health monitoring systems for RT tracking along with the detection of patient conditions. The study reported 98% and 100% accuracy rates for the Im-HMS model. Abu-Jassar et al. [17], employed AWS for RT biomedical data processing in a related study. The findings highlighted minimal latency in transmitting patient data to AWS, and the system had the ability to alert patients and physicians regarding emergency interventions or treatment adjustments.

1.2 Problem Statement and Research Gap

In managing along with monitoring patient health, significant challenges are faced by the global HC system. Traditional centralized HC models suffer from latency issues, bandwidth limitations, along with insufficient scalability, impeding their ability to deliver timely as well as efficient care. These limitations cause poorer patient outcomes as well as create inefficiencies for HC professionals in data handling and DM. A significant research gap exists in the role of AWS in RT PM and alerting, while AWS has been widely adopted in the HC sector. Similarly, there is a lack of studies exploring its impact on clinical outcomes and patient care. Also, existing research focuses on the impact of technologies, such as patient tracking systems, on resource allocation to the researcher's knowledge. Nevertheless, no research has examined the role of AWS HL in HC resource allocation. Therefore, there is a need to bridge the research gap. Thus, the present study aims to investigate the AWS Lake House role in RTM of patients and alerting in hospitals.

1.3 Research Objectives

The objectives of the research are:

To compare the traditional and AWS Lake House approaches for RT hospital PM and alerting.

To evaluate the feasibility and effectiveness of using AWS Lake House for RT PM and alerting.

To assess the impact of RT PM and alerting on clinical outcomes and HC resource allocation.

The remaining part is arranged as: the employed research methodology is described in Section 2. The result is presented as well as discussed in Section 3. Finally, Section 4 concludes the study by discussing the findings, limitations, and implications for future research and practice.

2 Research Methodology

2.1 Research Design

It follows a qualitative approach to collect and analyze the data. This qualitative study aims to analyze AWS Lake House's role in RTM of patients and alerting in hospitals. The study utilizes a qualitative research approach to explore complex social phenomena and meanings in-depth.

2.1.1 System Architecture

HL7 FHIR-based patient monitor data flowing from medical devices into Amazon KDS for RT streaming ingestion is depicted in Figure 1. AWS Lambda processes these streams and passes relevant data to AWS HL, Amazon S3, or Amazon EventBridge. The processed data is structured and indexed in AWS HL for semantic interpretation. Amazon EventBridge routes abnormal events for notification and response to Amazon SNS. RT analytics can be run on Amazon Redshift. Lastly, Amazon QuickSight enables visualization for DM and operational monitoring.

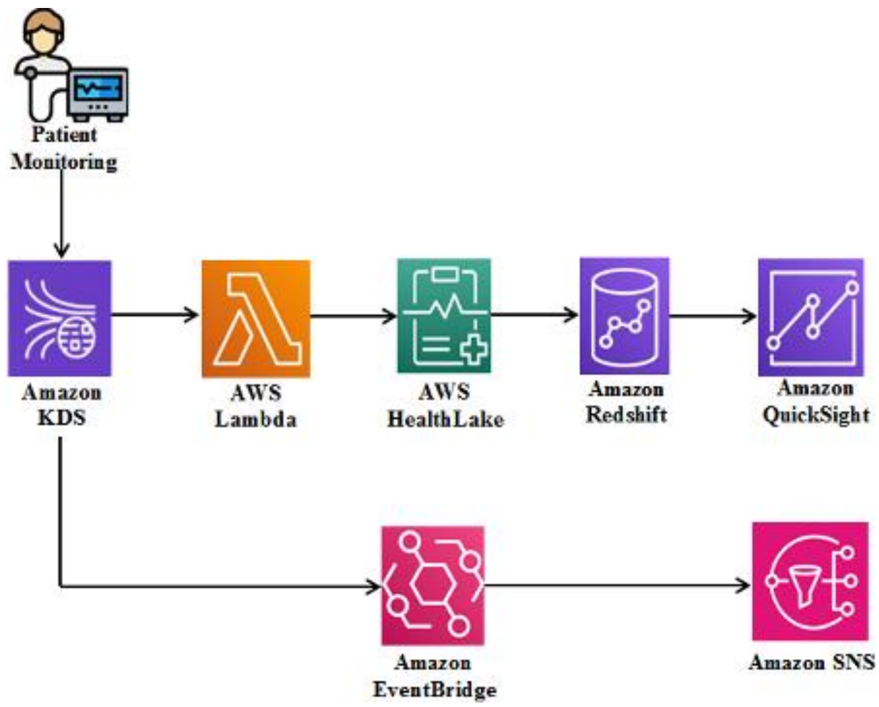

Figure 1: AWS Lake House Architecture for Real-Time Patient Monitoring and Alerting

2.1.2 FHIR Data Ingestion Pipeline

The FHIR data ingestion pipeline (Figure 2) facilitates structured data flow from various HC sources, such as monitoring devices, hospital systems, and EHR platforms. The HL7 FHIR data is delivered in RT through API integration and Amazon KDS. Further, they are transformed using AWS Lambda and stored in Amazon S3. Next, to support HC- specific analytics and semantic structuring, the refined dataset is ingested into AWS HL.

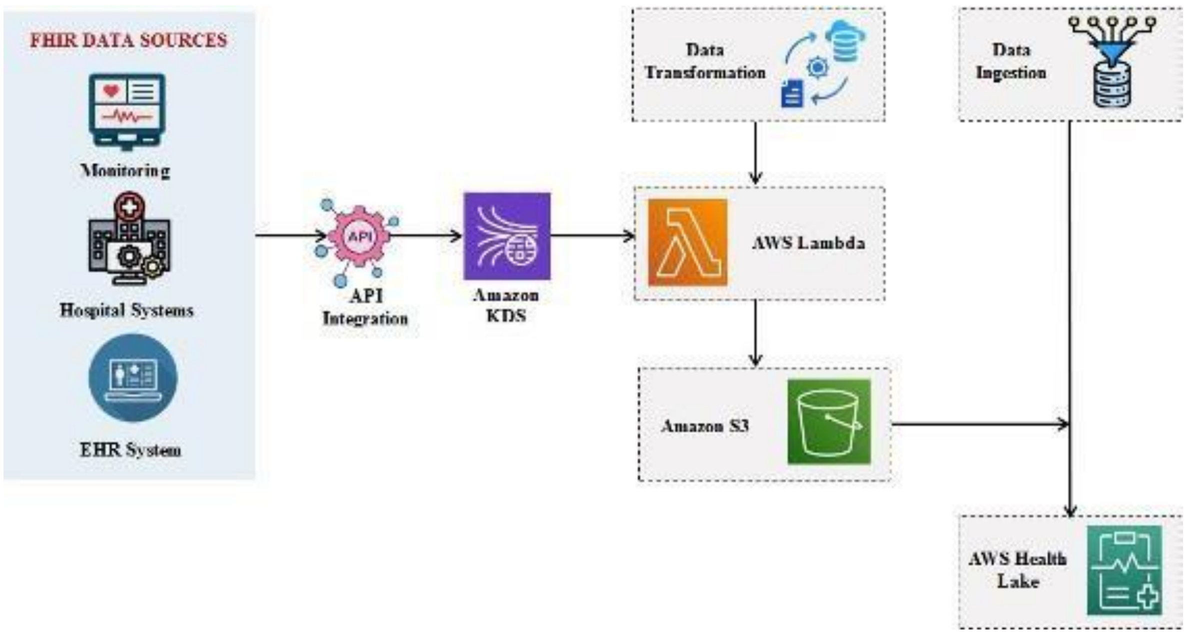

Figure 2: HL7 FHIR-Based Data Ingestion Pipeline into AWS HealthLake

2.2 Data Collection

Through a comprehensive analysis of secondary data, the research has been conducted. Secondary sources are created by individuals who are not directly involved in the events. In academic research and data analysis, secondary data refers to data collected by someone else for other purposes and uses. Generally, secondary research is less expensive along with time-consuming when analogized to primary research since it uses already collected, cleaned, and stored data. This includes a detailed review of existing literature and online sources that pertain to RT PM and alerting. The secondary data are used to generate the

findings and conclusions presented in the study. Examples of secondary sources include:
Books: Books usually offer in-depth examinations of a specific subject matter, providing a detailed analysis based on extensive research and citation of various sources.
Review Articles: A review article is a scholarly publication that compiles and critically analyzes existing research on a specific topic.
Literature Reviews: To summarize the existing research and scholarly literature on a particular subject, literature reviews are often included in research papers or dissertations.
Research Articles: A type of scholarly publication that offers a detailed report of original research findings, presenting new knowledge or insights on a specific topic within a field.

2.3 Data Analysis

To answer complex research questions, the study employs qualitative research methods. The collected secondary data relevant to AWS Lake House in RTM of patients and alerting has been analyzed using qualitative techniques. This involves analyzing the existing data to gain insights beyond the original research question. By leveraging existing data, this study aims to provide a comprehensive understanding of the role of Amazon Redshift and Amazon QuickSight in AWS Lake House for RT patient analytics in hospitals.

2.4 Monitoring and Alerting

The research looks at how observability is critical in cloud-based PM systems. RT performance insights and anomaly detection ensure reliability and safety. Amazon EventBridge routes key alerts, and Amazon SNS sends notifications for rapid response.

2.5 Ethical Considerations

This research accomplishes all the study methods following the relevant guidelines and regulations. When using secondary data, the study adheres to ethical guidelines, including obtaining necessary permissions and protecting the privacy of individuals. Also, the privacy and confidentiality of the information have been maintained throughout the study. The study does not result in any conflict of interest. The results are declared to be presented in a generalized manner.

3 Results and Discussion

3.1 Traditional and AWS Methods in Real-Time Patient Monitoring

RT PM has evolved from traditional, localized systems to cloud-based solutions, offering enhanced capabilities and accessibility. Traditional methods rely on sensors and manual assessments, while cloud-centric systems enable remote and RT data access and analysis. When compared to traditional PM, a cloud-based system, particularly AWS Lakehouse architecture, offers a more flexible and scalable solution. Traditional monitoring often struggles with capacity, scalability, expenditure, and synergy. The comparison between the traditional approach and cloud cloud-based approach for different dimensions in terms of patient health monitoring is represented in Table 1.

Table 1: Comparison of traditional and AWS approaches [12]

Dimension	Traditional method	AWS method
Capacity	Limited	Unlimited
Containers	Local Storage	Cheap Rented Storage
Availability	Limited	24/7 over the internet
Synergy	Not Real-time	Real-time
Expenditure	Upfront cost and maintenance	Pay per use
Scalability	Limited	No limits
Accessibility	Limited	Anywhere, anytime

3.1.1 Challenges

Traditional methods of PM that largely rely on periodic checks and manual assessments have limitations, including delayed detection of critical changes in the patients' condition, limitations of manual or static monitoring, inability to capture subtle changes, and high workload and burnout among HC providers [18]. These drawbacks can hinder the timely and accurate management of patients' health conditions.

- **Delayed detection of critical changes:** The delay in detecting critical changes in a patient's condition is the major issue in the traditional method of PM. Manual monitoring, often involving periodic checks of vital signs, offers a limited view of a patient's condition at specific points in time. This can lead to missed fluctuations, potentially delaying interventions for rapid changes in a patient's health.

- **Limitations of manual or static monitoring:** HC providers manually measure the vital signs, like heart rate, temperature, oxygen levels, along with blood pressure, at scheduled intervals in the traditional PM method. This means that changes between monitoring periods can be missed. Accordingly, any changes in a patient's condition that occur between monitoring periods may go unobserved until the next check.
- **Inability to capture subtle changes:** Some vital signs, including oxygen level, blood pressure, and subtle heart rate variations, can change rapidly or gradually. These changes may be missed during infrequent manual checks, which can delay necessary interventions. Also, fatigue, human error, and potential distraction can impact the accuracy and effectiveness of the manual assessments. This can lead to suboptimal monitoring.
- **High workload and burnout:** Manual PM significantly contributes to the heavy workload of HC professionals, especially nurses and clinicians, due to the time and effort required for routine checks and observations. This can lead to increased stress, potential burnout, and even compromise patient care due to fatigue.

3.1.2 Benefits of AWS HealthLake in Hospitals

AWS brings abundant welfare to HC organizations. AWS HL is a powerful service that is designed to help HC organizations store, transform, and analyze health data at scale [19]. Some of the key benefits are:

- **Interoperability:** By adopting the Fast HC Interoperability Resources (FHIR) standards, HL facilitates seamless data exchange between different HC systems and applications, thereby enhancing interoperability across the HC ecosystem.
- **Scalability:** AWS allows HC providers to effortlessly enlarge their infrastructure along with accommodate augmenting data storage as well as processing needs. This scalability authorizes organizations to grip the mounting volumes of patient information, medical records, along with research data devoid of worrying about capacity constraints.
- **Cost-Effective:** AWS eliminates the necessity for on-premises infrastructure along with reduces maintenance costs. HL reduces infrastructure costs for HC organizations by leveraging AWS's pay-as-you-go model, enabling them to allocate resources more effectively.
- **Secure and Compliant:** AWS HL ensures that patient information remains secure as well as meets rigorous compliance requirements like those mandated by the Health Insurance Portability and Accountability Act (HIPAA) with robust encryption and access controls.

3.2 Effectiveness

3.2.1 Quality and Efficiency of Care by Centralizing and Analyzing Patient Data

AWS Cloud is making HC facilities control with greater operational efficiency, security, along with quality of patient care by employing its cutting-edge cloud computing and AI technologies. AWS solutions permit HC professionals to have RT analysis, secure storage, along with scalable solutions for enhanced HC management as well as DM. AWS Lakehouse architecture enables comprehensive data management, advanced analytics, and ultimately better patient outcomes by combining the strengths of a data lake and a data warehouse. Nevertheless, AWS HL should just be wielded in patient care or else clinical scenarios after review by trained medical professionals implementing sound medical judgment. HC organizations can leverage Amazon S3 and AWS HL to create a HIPAA- compliant environment for consolidating and managing patient records with improved data interoperability. HC providers can consolidate patient information by leveraging

AWS HL, enabling better access to comprehensive patient records and facilitating data- driven DM by providing FHIR indexing and semantic search. This leads to improved care coordination, personalized treatment plans, and more efficient resource allocation [7].

- **Latency:** AWS services are designed to minimize latency in RT data processing. HL, designed for FHIR-based data, offers low-latency access to patient data for analysis. S3, while a cost-effective storage solution, has higher latency than services optimized for RT processing.
- **Proactive Interventions:** AWS enables proactive interventions through its monitoring and alerting capabilities. AWS allows for setting up alarms based on specific metrics, triggering notifications when predefined thresholds are breached. This can be crucial for timely interventions, such as alerting medical staff to a patient's deteriorating condition. Besides, the integration of machine learning with AWS allows for predictive analytics along with early detection of potential health issues.

- **Real-time Data Processing:** For RT data processing in HC, AWS provides various services. For example, Amazon S3 can store raw data and historical information. HC providers can quickly identify anomalies, track patient trends, and make informed decisions by leveraging these services. AWS HL enables RT data ingestion and processing, allowing HC providers to access the most up-to-date patient information for timely DM [19].

3.3 Challenges in AWS HealthLake Implementation

Challenges arise during the conversion of data into the FHIR format when using AWS HL for HC data storage [20]. These challenges and their recommended solutions are presented in Table 2.

Table 2: Challenges of AWS HealthLake in FHIR Data Conversion

Challenge	Description	Recommendation
Healthcare Data Complexity	Unstructured data with different formats makes it complex for AWS to identify, store, and organize the data.	Utilizing AWS Glue for data cataloging and schema discovery enables easier identification and extraction of relevant data elements for FHIR conversion.
Data Quality	Health data comprises inconsistent errors, missing information, along with complications, which could affect FHIR data's accuracy.	Implementing data validation rules within the conversion pipeline can identify and flag data inconsistencies or errors.
Data Mapping and Transformation	Data format conversion is time-consuming along with complex, particularly in unstructured data.	Employ AWS Partners specializing in FHIR data migration and transformation to develop custom mapping solutions tailored to specific data sources.
Technical Expertise and Resources	Converting HC data to FHIR requires specialized knowledge of FHIR, AWS services, and data transformation techniques.	Engage with AWS Partners who offer consulting services and expertise in FHIR data migration and transformation.

3.4 Clinical Impact

3.4.1 Improving Clinical Outcomes

Numerous HC organizations have previously embraced AWS; also, are reaping the welfares it offers. AWS supports predictive modeling for patient outcomes and resource allocation optimization. This accelerates the development of new treatments and supports personalized medicine approaches tailored to individual patient profiles. AWS enables HC providers to extract insights from vast datasets, automate routine tasks, along with enhance DM processes. Empowered patients, along with increased engagement, are caused by RT alerts. When patients are aware that their reported experiences are monitored in RT along with can lead to immediate action, they feel genuinely listened to, and their feedback is valued. This fosters an augmented sense of control over their health management, inspiring them to actively participate in the process. Patients are likely to follow their treatment plans and develop a more collaborative relationship with their providers when they feel heard and know their input matters in their HC decisions. HC organizations have been able to develop predictive models, which detect patients at risk of developing numerous conditions by using AWS's cloud-based infrastructure. This allows for early intervention along with improved outcomes [10, 21].

3.4.2 Impact on Healthcare Resource Allocation

By enabling more efficient and targeted use of resources, RT PM significantly impacts HC resource allocation. Providing continuous data on patient status allows for proactive interventions, early detection of issues, and optimized staffing, thus leading to improved patient outcomes together with reduced HC costs.

- **Optimized Resource Allocation:** It involves leveraging technology to optimize the distribution of resources based on the immediate needs of patients, as determined by continuous monitoring data. RTM allows hospitals to achieve a more optimal patient care.
- **Operational Efficiency and Cost Savings:** Operational costs can be saved through better resource

allocation and improved scheduling efficiencies. The initial investment in integrating the AWS platform has been shown to be offset by long- term savings and improved operational performance in hospitals.

- **Enhanced User Satisfaction:** RTM system significantly improves HC professionals' ability to manage patient flow and allocate resources. The user-friendly dashboards and RT alerts are key features that contribute to these positive perceptions. Such high satisfaction levels are essential for the long-term success and sustainability of any technological innovation in HC [22].

3.4.3 Challenges

Also, there are challenges along with limitations that HC organizations want to consider while AWS brings abundant benefits to the HC industry [5, 22, 23].

- **Data Interoperability:** AWS involves integrating data from various sources with potentially different formats and structures. This heterogeneity makes it difficult to combine and analyze data from these sources in a unified manner for RTM.

Leveraging the FHIR standard can enable seamless data exchange between different HC systems and devices. AWS Glue permits seamless incorporation of structured data across diverse HC platforms.

- **Security and Compliance:** The system collects extensive personal health information, as of heart rate along with blood pressure to sleep patterns as well as daily activity levels. This data becomes vulnerable to unauthorized access and potential breaches when it is transmitted to cloud platforms for storage and analysis. To enhance security, AWS security services like AWS Identity and Access Management, along with Amazon GuardDuty, can be used.
- **Change Management and Training:** The success of any new system depends largely on its acceptance by end users. Comprehensive training programs and effective change management strategies are required to overcome resistance and ensure that clinicians and administrators can fully leverage the new capabilities. For mini- mizing disruptions along with ensuring a smooth transition, HC organizations must carefully plan as well as execute the migration process.

4 Conclusion

Here, the present study examined the role of AWS Lakehouse architecture in the RTM of patients and alerting in hospitals. The study compared the traditional and AWS-based RT PM methods. Also, the study examined the influence of RT PM and alerting on clinical outcomes and HC resource allocation. As per the result, clinical outcomes could be improved with AWS. The challenges of AWS in the HC industry are data interoperability, security and compliance, and change management and training. RTM and alerts could lead to empowered patients and increased engagement. Also, AWS HL could facilitate seamless data exchange between HC systems and applications. Nevertheless, the study utilized secondary data, which might affect the validity of the research findings. Therefore, studies will use primary and secondary data in the future to better understand PM using AWS. Furthermore, potential extensions for the research include implementing more sophisticated machine learning models for predictive analytics and enhancing the user experience for both patients and clinicians.

4.1 Limitations and Future Research

This study utilized secondary data, which might affect the validity of the research findings. Future studies should consider using both primary and secondary data to gain a more comprehensive understanding of patient monitoring using AWS.

Potential extensions for the research include:

Enhancing the user experience for both patients and clinicians in AWS-based healthcare systems.

Investigating the long-term impact of AWS-based patient monitoring systems on healthcare outcomes and cost-effectiveness.

Implementing more sophisticated machine learning models for predictive analytics in patient care.

Exploring the integration of AWS services with other emerging technologies in healthcare, such as Internet of Things (IoT) devices and artificial intelligence.

In conclusion, while AWS Lake House architecture offers significant advantages for real-time patient monitoring and alerting in hospitals, successful implementation requires careful consideration of data management challenges and ongoing evaluation of clinical impacts. As healthcare continues to digitize, cloud-based solutions like AWS are likely to play an increasingly important role in improving patient care and operational efficiency in healthcare organizations.

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