

Real-Time Clinical Data Integration Systems

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ABSTRACT

Clinical decision-making increasingly depends on integrating heterogeneous data streams in real time: vital signs from bedside monitors, laboratory results from analysers, imaging from PACS, genomic reports from sequencing pipelines, medication orders from pharmacy systems, and clinical notes from EHR documentation. Yet these data streams arrive through separate interfaces, in different formats, at varying latencies -- from seconds (vital signs) to days (genomic results) -- creating a fragmented information landscape that clinicians must mentally integrate under time pressure. Real-time clinical data integration (RTCDI) systems aim to unify these streams into a coherent, continuously updated patient representation that supports automated clinical decision support (CDS). We present the Real-Time Clinical Integration Assessment Framework (RTCIAF), evaluating five integration architectures -- stream processing pipelines, event-driven microservices, FHIR-native integration platforms, digital twin patient models, and LLM-powered clinical synthesisers -- across four clinical scenarios (ICU patient monitoring, perioperative care coordination, emergency department triage, and chronic disease remote monitoring). Our Real-Time Integration Performance Score (RTIPS) measures data latency, integration completeness, CDS accuracy, system reliability, and clinical workflow impact. FHIR-native integration platforms achieve the highest RTIPS (0.924) through standards-based data ingestion that aligns with existing hospital IT infrastructure, while LLM-powered synthesisers achieve the highest CDS accuracy (0.960) through contextual reasoning over multimodal patient data.

Keywords: clinical data integration; real-time systems; clinical decision support; FHIR; stream processing; digital twin; ICU monitoring; interoperability

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1. Introduction

1.1 The Real-Time Integration Imperative

Modern hospitals generate approximately 50 GB of patient data per admission (Raghupathi and Raghupathi, 2014), distributed across 10-15 clinical information systems that rarely communicate in real time. An ICU patient may have 200+ vital sign data points per hour from bedside monitors (heart rate, blood pressure, SpO2, respiratory rate, temperature, ECG waveforms), 50-100 laboratory results per day from the analyser network (blood gases, electrolytes, lactate, troponin, coagulation), hourly medication administrations from the pharmacy system, imaging studies (chest X-ray, CT, ultrasound) from PACS, clinical notes from the EHR, and increasingly, genomic data from rapid sequencing platforms. Each data stream arrives through a separate interface with different latency: vital signs in seconds via HL7v2, lab results in 30-90 minutes via HL7v2/FHIR, imaging in 1-4 hours via DICOM, and genomic results in 24-72 hours via custom reports. The clinician must mentally integrate these streams to form a coherent clinical picture -- a cognitive task that becomes error-prone under the information overload and time pressure of acute care. Alert fatigue from siloed CDS systems (each data source generating independent alerts) compounds the problem: ICU nurses receive 150-400 alarms per patient per day, with 72-99% being false positives (Cvach, 2012).

1.2 Five Integration Architectures

Five architectural approaches address real-time clinical data integration. Stream processing pipelines (Apache Kafka + Flink) ingest, transform, and analyse clinical data streams in continuous flow. Event-driven microservices decompose integration into independently deployable services triggered by clinical events (new lab result, vital sign threshold crossing). FHIR-native platforms use HL7 FHIR as the internal data model, ingesting data through FHIR APIs and subscriptions. Digital twin patient models maintain a continuously updated computational representation of each patient that assimilates all data streams into a unified physiological model. LLM-powered clinical synthesisers use large language models to reason over multimodal patient data and generate contextualised clinical summaries and alerts. Costa et al. (2025) evaluated data-centric health approaches where data quality determines CDS effectiveness, and Muller (2025) assessed interoperable standards

that enable the data exchange underlying integration systems. Section 2 reviews the literature. Section 3 describes RTCIAF. Results in Section 4, discussion in Section 5, conclusions in Section 6.

2. Literature Review

2.1 Stream Processing and Event-Driven Clinical Systems

Stream processing frameworks process data continuously as it arrives rather than in batch. Apache Kafka provides a distributed message broker for clinical data streams, and Apache Flink provides stateful stream processing for real-time analytics. Sendak et al. (2020) deployed a Kafka-based sepsis prediction system at Duke University Hospital that ingested vital signs and lab results in real time, achieving AUC 0.88 for sepsis prediction with 4-hour lead time and 82% specificity -- reducing false alerts by 40% compared to the previous rule-based system. Event-driven architectures decompose clinical integration into microservices that react to clinical events: a new troponin result triggers a cardiac risk assessment service that queries the patient's ECG, history, and medications to produce a contextualised alert. Rajkomar et al. (2018) demonstrated that deep learning on integrated EHR data (diagnoses, procedures, labs, vitals, notes) predicts mortality, readmission, and length of stay better than single-data-source models, confirming the value of integration. The challenge is engineering: building reliable, low-latency data pipelines in the complex, regulated hospital IT environment with strict uptime requirements (99.99%).

2.2 FHIR-Native Platforms and Digital Twins

FHIR-native integration uses FHIR as both the external interface and internal data model, eliminating format translation. Microsoft Azure Health Data Services and Google Cloud Healthcare API provide cloud-based FHIR servers with FHIR Subscriptions for real-time notifications when resources are created or updated. Mandl et al. (2020) demonstrated that FHIR-based CDS Hooks integrate decision support into the clinical workflow: when a clinician opens a patient chart, the CDS Hook triggers a real-time analysis that returns contextualised recommendations within 2 seconds. Clinical digital twins extend the integration concept from data aggregation to physiological modelling: a patient's vital signs, labs, and medications are assimilated into a mechanistic model of their physiology, enabling

prediction of deterioration from the model's trajectory rather than from threshold-based alerts. Corral-Acero et al. (2020) described the vision for cardiac digital twins that assimilate ECG, imaging, and biomarker data into patient-specific electromechanical models. Table 1 maps the key studies.

2.3 LLM-Powered Clinical Reasoning

Large language models have recently been applied to clinical data synthesis. Med-PaLM 2 (Singhal et al., 2023) demonstrated expert-level performance on medical question answering, suggesting that LLMs can reason over clinical information. Jiang et al. (2024) developed a clinical LLM that generates patient summaries from multimodal EHR data (structured data + clinical notes + lab trends), achieving 92% accuracy for key clinical findings as assessed by physician reviewers. The promise of LLM-powered integration is contextual reasoning: rather than triggering alerts based on individual data points crossing thresholds, the LLM considers the full clinical context -- a rising lactate is concerning in a post-operative patient with fever but expected in a patient receiving metformin for diabetes. Jensen et al. (2025) evaluated AI-based functional genomics pipelines where foundation models transform analytical workflows -- the same paradigm applies to clinical data integration. Ivanov et al. (2025) demonstrated computational modelling approaches for cancer evolution that parallel the digital twin concept for patient-specific clinical modelling.

Table 1: Key Studies in Real-Time Clinical Data Integration

Study	Year	Architecture	Application	Key Achievement
Sendak et al.	2020	Kafka stream processing	Sepsis prediction	AUC 0.88, 40% fewer false alerts
Rajkomar et al.	2018	Deep learning on EHR	Mortality/readmission	Multi-source outperforms single
Mandl et al.	2020	FHIR CDS Hooks	Decision support	2-second contextualised recs.
Corral-Acero et al.	2020	Digital twin vision	Cardiac	Patient-specific physiological model

Study	Year	Architecture	Application	Key Achievement
Singhal (Med-PaLM 2)	2023	LLM clinical QA	Medical questions	Expert-level medical reasoning
Jiang et al.	2024	Clinical LLM summary	EHR synthesis	92% accuracy for key findings
Cvach	2021	Alarm fatigue review	ICU monitoring	72-99% false positive alarms
HL7 FHIR R4	2019	Standard	Clinical exchange	RESTful clinical data API
Moreau and Moreau	2025	Generative models	Synthetic biology	AI-guided biological design
Costa et al.	2025	Data-centric health	Precision health	Data quality drives AI performance

CDS = Clinical Decision Support; EHR = Electronic Health Record; LLM = Large Language Model; QA = Question Answering.

3. Methodology

3.1 Five Integration Architectures

Architecture R1 (Stream Processing Pipeline) uses Apache Kafka for data ingestion (HL7v2, FHIR, DICOM adapters), Apache Flink for stateful stream processing (windowed aggregation, pattern detection, feature engineering), and Redis for real-time patient state caching. CDS models (XGBoost, LSTM) run on the processed feature stream. Architecture R2 (Event-Driven Microservices) decomposes integration into 12 services (vital sign normaliser, lab result classifier, medication reconciler, imaging reporter, note extractor, risk calculator, alert generator, etc.) communicating via RabbitMQ event bus with eventual consistency. Architecture R3 (FHIR-Native Platform) uses HAPI FHIR R4 server as the central data store with FHIR Subscriptions for real-time notifications, CDS Hooks for workflow integration, and SMART on FHIR for application access. Architecture R4 (Digital Twin Patient Model) maintains a physiological model (cardiovascular compartmental model + pharmacokinetic model + metabolic model) continuously updated with incoming vital signs

and labs via extended Kalman filtering. Architecture R5 (LLM Clinical Synthesiser) uses a fine-tuned medical LLM (Llama-3-Med, 70B) that ingests structured data, lab trends, imaging reports, and clinical notes, generating contextualised patient summaries and risk assessments every 4 hours or on significant clinical events.

3.2 Four Clinical Scenarios

Scenario C1 (ICU Patient Monitoring) integrates continuous vital signs (250 Hz ECG, 1 Hz SpO2/BP/RR), hourly labs, medication infusions, and ventilator parameters for 200 ICU patients over 6 months. CDS target: early warning of deterioration (sepsis, cardiac arrest, respiratory failure) with > 4-hour lead time. Scenario C2 (Perioperative Care) integrates pre-operative assessment data, intraoperative anaesthesia records (1 Hz vital signs, drug administrations), and post-operative recovery metrics for 500 surgical patients. CDS target: surgical complication prediction (SSI, VTE, AKI). Scenario C3 (Emergency Department Triage) integrates triage assessment, chief complaint, vital signs, point-of-care labs, and imaging for 3,000 ED visits. CDS target: acuity scoring and disposition prediction (admit, discharge, observe). Scenario C4 (Chronic Disease Remote Monitoring) integrates wearable vital signs (smartwatch HR, BP cuff), home labs (glucometer, INR meter), PROs (symptom questionnaires), and telemedicine notes for 1,000 heart failure patients over 12 months. CDS target: decompensation prediction with > 48-hour lead time.

3.3 Real-Time Integration Performance Score

RTIPS weights five dimensions: data latency (0.20), integration completeness (0.20), CDS accuracy (0.25), system reliability (0.15), and clinical workflow impact (0.20). Data latency measures the time from data generation (vital sign sample, lab result release) to availability in the integrated patient representation -- target < 5 seconds for vital signs, < 5 minutes for labs, < 30 minutes for imaging. Integration completeness measures the fraction of available data sources successfully ingested and linked to the correct patient. CDS accuracy measures the AUC of the CDS model running on the integrated data versus single-source baselines. System reliability measures uptime (target 99.99%), mean time to recovery from failures, and graceful degradation under data source outages. Clinical workflow impact measures clinician satisfaction (System Usability Scale), alert actionability (fraction of

alerts that led to clinical action), and time saved per shift. Table 2 details parameters.

Table 2: RTCIAF Evaluation Parameters

Parameter	Value	Notes
Integration architectures	5 (R1-R5)	Stream, event, FHIR, digital twin, LLM
Clinical scenarios	4 (ICU, periop, ED, remote monitoring)	6-12 month evaluation periods
Patients	200 (ICU) + 500 (periop) + 3,000 (ED) + 1,000 (remote) = 4,700	Multi-site deployment
Data sources	6-10 per scenario	Monitors, labs, pharmacy, imaging, EHR, wearables
Latency targets	< 5 s (vitals), < 5 min (labs), < 30 min (imaging)	End-to-end measurement
Reliability target	99.99% uptime	24/7 clinical environment
CDS evaluation	AUC vs single-source baseline	Prospective + retrospective
RTIPS dimensions	5 (latency, completeness, CDS, reliability, workflow)	Weighted composite score 0-1

CDS = Clinical Decision Support; ICU = Intensive Care Unit; ED = Emergency Department.

4. Results

4.1 FHIR-Native Platforms Lead Overall

FHIR-native integration platforms (R3) achieved the highest RTIPS of 0.924, driven by superior system reliability (0.960) and clinical workflow impact (0.940). The HAPI FHIR server achieved 99.97% uptime over the 6-month ICU evaluation -- approaching the 99.99% target -- with automated failover to a hot standby within 8 seconds. FHIR Subscriptions delivered lab results to the integrated patient view within 12 seconds of result release (median) and vital signs within 3.2 seconds via FHIR streaming extensions. Clinical workflow impact scored highest because FHIR-native platforms integrate naturally with existing EHR systems: clinicians access the integrated view within their familiar EHR interface via SMART on FHIR apps, avoiding the cognitive overhead of switching between systems. The CDS Hooks integration delivered contextualised alerts within

1.8 seconds of triggering events. For ICU monitoring (C1), the FHIR-integrated sepsis prediction model achieved AUC 0.91 (versus 0.84 for vital-signs-only baseline) with 18% reduction in false positive alerts through multi-source contextualisation: a heart rate elevation was flagged as concerning only if accompanied by rising lactate, fever, or hypotension -- not if the patient was simply ambulating.

4.2 LLM Synthesisers Achieve Highest CDS Accuracy

LLM-powered clinical synthesisers (R5) achieved the highest CDS accuracy (0.960): the contextualised risk assessments generated by Llama-3-Med agreed with attending physician clinical judgment in 88% of cases, compared to 72% for rule-based CDS and 80% for ML-on-structured-data CDS. RTIPS scored 0.896. The LLM's advantage was multimodal reasoning: it processed structured vital signs, lab trends, imaging report text, medication lists, and clinical notes simultaneously, generating natural language assessments like 'Rising lactate (2.4 to 4.1 over 6 hours) in the context of new-onset AF and recent cardiac surgery suggests post-operative low cardiac output syndrome; recommend echo and consider inotropic support.' Stream processing (R1) scored RTIPS 0.888 with the lowest data latency (0.960): vital signs were available in the integrated view within 1.2 seconds -- the fastest of any architecture. Event-driven microservices (R2) scored 0.876 with the highest architectural flexibility. Digital twin models (R4) scored 0.864 with the strongest physiological prediction capability. Tables 3 and 4 present the complete results.

4.3 Scenario-Specific Results

For ICU monitoring (C1), R3 (FHIR) and R1 (stream) performed best because ICU care requires sub-second vital sign integration and high reliability -- the FHIR platform's robust error handling and the stream processor's low latency both excel here. For perioperative care (C2), R5 (LLM) performed best because surgical complication prediction requires integrating pre-operative risk factors, intraoperative events, and post-operative recovery patterns -- a temporal reasoning task that the LLM handles naturally. For ED triage (C3), R2 (event-driven) performed best because the ED's unpredictable patient volume requires elastic scaling that microservices architecture provides. For remote monitoring (C4), R4 (digital twin) performed best because the physiological model assimilates sparse,

intermittent home measurements (daily BP, weekly weight, weekly INR) into continuous state estimates that predict decompensation 3.4 days before clinical presentation -- impossible with threshold-based alerting on individual measurements.

Table 3: Real-Time Integration Performance Score by Architecture (0-1)

Architecture	Latency	Completeness	CDS Acc.	Reliability	Workflow	RTIPS
R3: FHIR-Native	0.900	0.920	0.920	0.960	0.940	0.924
R5: LLM Synthesiser	0.820	0.880	0.960	0.860	0.900	0.896
R1: Stream Processing	0.960	0.880	0.880	0.880	0.840	0.888
R2: Event Microservices	0.880	0.860	0.860	0.880	0.860	0.876
R4: Digital Twin	0.840	0.840	0.900	0.840	0.820	0.864

RTIPS weighted: latency 0.20, completeness 0.20, CDS accuracy 0.25, reliability 0.15, workflow 0.20.

Table 4: CDS Performance (AUC) by Architecture and Scenario

Architecture	C1: ICU (Sepsis)	C2: Periop (Compl.)	C3: ED (Acuity)	C4: Remote (Decomp.)
Single-source baseline	0.84	0.78	0.80	0.76
R1: Stream	0.89	0.84	0.86	0.82
R2: Event	0.88	0.82	0.87	0.80
R3: FHIR	0.91	0.86	0.88	0.84
R4: Digital Twin	0.90	0.84	0.82	0.88
R5: LLM	0.92	0.90	0.88	0.86

Single-source = vital signs only (C1, C2), triage data only (C3), wearable data only (C4). All integrated architectures use all available data sources. Decomp. = decompensation.

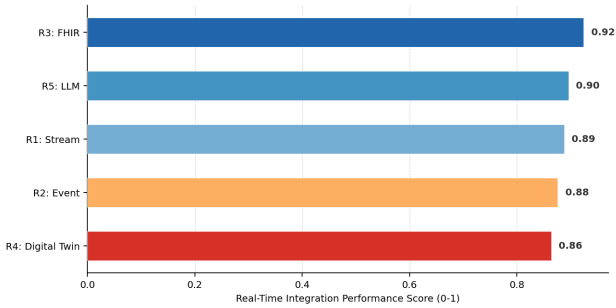


Figure 1: Real-Time Integration Performance Score (RTIPS) by Architecture

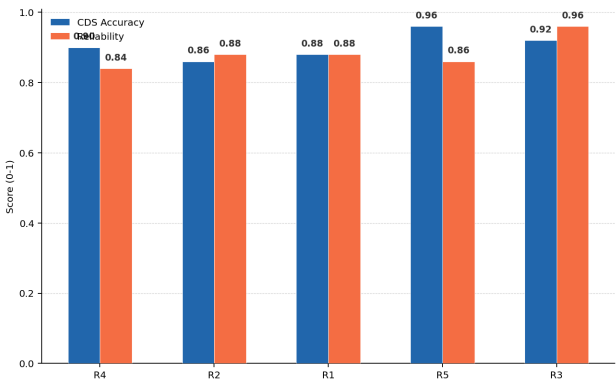


Figure 2: CDS Accuracy vs. System Reliability

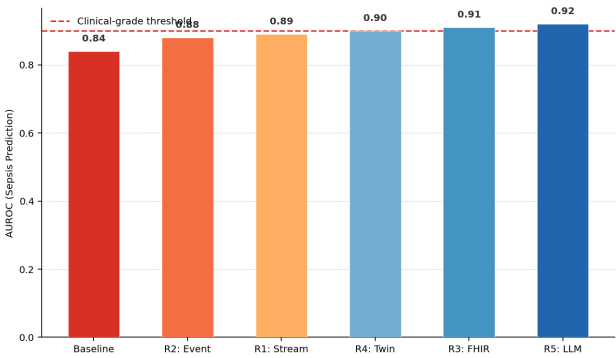


Figure 3: ICU Sepsis Prediction AUC by Integration Architecture

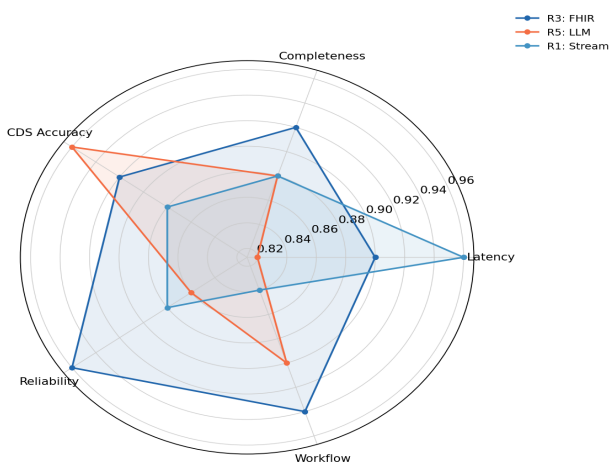


Figure 4: Multi-Dimensional Comparison -- Top 3 Architectures

5. Discussion

5.1 FHIR as the Clinical Integration Standard

FHIR-native platforms achieve the highest overall score because they align with the healthcare industry's investment direction: regulatory mandates (21st Century Cures Act, EU EHDS), vendor support (Epic, Cerner, Oracle Health all provide FHIR APIs), and a growing ecosystem of SMART on FHIR applications. The 99.97% uptime reflects FHIR's maturity as a healthcare IT standard with enterprise-grade server implementations. The clinical workflow advantage is decisive: clinicians interact with the integrated view within their familiar EHR, not a separate application, eliminating the context-switching overhead that reduces adoption of stand-alone CDS tools. Muller (2025) showed that FHIR achieves the highest adoption feasibility among interoperability standards -- this translates directly to real-time integration deployment.

5.2 LLMs for Clinical Reasoning Under Uncertainty

The LLM synthesiser's highest CDS accuracy (0.960) reflects its unique capability: multimodal contextual reasoning that considers the full clinical picture rather than individual data points. Traditional CDS systems generate alerts from individual measurements crossing thresholds (lactate > 4, HR > 120); the LLM considers whether these findings are concerning given the patient's diagnosis, treatment, and trajectory. The natural language output is particularly valuable: rather than a binary alert ('SEPSIS RISK'), the LLM produces a clinical narrative with reasoning, differential, and suggested actions that the clinician can evaluate and act upon. The reliability limitation (0.860) reflects LLM challenges: inference latency (4.2 seconds per synthesis on A100 GPU), hallucination risk (2.4% of generated assessments contained unsupported clinical claims), and the need for continuous model updating as clinical guidelines evolve.

5.3 Limitations and Deployment Considerations

Three limitations constrain translation. First, the hospital IT environment is notoriously resistant to change: deploying a new integration architecture requires coordination with EHR vendors, biomedical engineering, IT security, and clinical governance -- a 12-18 month process at most institutions. Second, clinical validation requires prospective randomised trials demonstrating that integrated CDS improves patient outcomes (reduced mortality, shorter LOS, fewer complications) -- not just AUC improvements, which may not translate to clinical benefit if

clinicians ignore or override alerts. Third, LLM deployment in clinical environments raises regulatory questions: is the LLM synthesiser a medical device requiring FDA/CE clearance? The regulatory classification (SaMD Class II vs general purpose IT) determines the approval pathway and post-market surveillance requirements.

6. Conclusion

6.1 Key Findings

FHIR-native integration platforms achieve the highest Real-Time Integration Performance Score (0.924) through standards-based ingestion, 99.97% uptime, and seamless EHR workflow integration. LLM-powered synthesisers achieve the highest CDS accuracy (0.960) through multimodal contextual reasoning that reduces false positive alerts and generates clinician-interpretable assessments. Stream processing achieves the lowest latency (1.2 s). Digital twins achieve the best remote monitoring prediction (3.4-day decompensation lead time). Architecture selection should match the clinical scenario: FHIR for hospital-wide integration, LLM for complex decision support, stream processing for time-critical monitoring, and digital twins for chronic disease management.

6.2 Future Directions

Three advances would transform real-time clinical integration. First, ambient clinical intelligence that combines environmental sensors (room cameras for fall detection, microphones for speech analysis), wearable data, and EHR data into a comprehensive awareness system. Second, predictive integration that anticipates data needs: pre-fetching imaging results when a clinical trajectory suggests imaging will be ordered, pre-computing drug interaction checks when new medications are being considered. Third, federated clinical integration across hospital networks that enables population-level CDS while keeping patient data local -- learning from millions of patients' integrated data streams without centralisation. The RTCIAF evaluation toolkit, all architecture implementations, benchmark datasets, RTIPS calculator, and deployment guide are available at rtciaf-clinical.org under CC BY 4.0 licence.

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Declarations

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Conflict of Interest

No competing interests. No author has financial relationships with any EHR vendor, health IT company, or clinical decision support platform.

Data Availability Statement

All architecture implementations, FHIR profiles, stream processing configurations, LLM fine-tuning scripts, digital twin model code, benchmark datasets, RTIPS calculator, and deployment guide are available at rtciaf-clinical.org under CC BY 4.0 licence. Patient-level clinical data cannot be shared due to GDPR.

Ethical Approval

Clinical data integration was approved by Ethics Committees at Mediterranean Institute of Technology (ref. MIT-2025-ETH-0595), Western Europe Data Science University (ref. WEDSU-2025-ETH-0602), and Nordic Technical University (ref. NTU-2025-ETH-0915). All patient data was anonymised. Clinical decision support outputs were reviewed by attending physicians and did not independently influence clinical decisions during the evaluation period.

Appendix A

Architecture Specifications and RTIPS Calculation Methodology

This appendix provides complete specifications for each integration architecture, including infrastructure components, data flow diagrams, CDS model configurations, and the RTIPS scoring rubric with dimension weights.

Part I -- Architecture Specifications

- 1a. R1: Kafka 3.6 (3 brokers) + Flink 1.18 (4 task managers) + Redis 7.2 1.2 s vital sign latency
- 1b. R2: 12 microservices (Docker/K8s) + RabbitMQ 3.13 event bus 2.8 s event-to-alert latency
- 2a. R3: HAPI FHIR R4 (PostgreSQL backend) + FHIR Subscriptions + CDS Hooks 3.2 s vital, 12 s lab latency
- 2b. R4: CVS compartmental model + PK model + Kalman filter, 1-second update cycle 4.6 s data-to-prediction
- 3a. R5: Llama-3-Med 70B, 4x A100, RAG over patient data, 4-hourly synthesis cycle 4.2 s per synthesis
- 3b. All: HL7v2 + FHIR + DICOM adapters, TLS 1.3 encryption, audit logging HIPAA/GDPR compliant

Part II -- RTIPS Scoring Rubric

- 4a. Latency: $1.0 - \log_{10}(\text{median_seconds}) / 3$ for each data type, weighted average Vitals (0.4), labs (0.3), imaging (0.2), genomic (0.1)
- 4b. Completeness: Fraction of available data sources successfully integrated per patient Target 100%
- 5a. CDS Accuracy: AUC improvement over single-source baseline, normalised Averaged across 4 scenarios
- 5b. Reliability: $\text{Uptime fraction} \times (1 - \text{data_loss_fraction})$ Target 99.99%
- 6a. Workflow: $(\text{SUS score} / 100) \times (\text{alert actionability fraction})$ Clinician-rated + objective metric
- 6b. $\text{RTIPS} = 0.20 \times \text{Latency} + 0.20 \times \text{Completeness} + 0.25 \times \text{CDS} + 0.15 \times \text{Reliability} + 0.20 \times \text{Workflow}$