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AI-Powered FHIR Interoperability and Risk Analytics

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Abstract

Healthcare information belongs to individuals and communities, and it is imperative to govern control of data stewardship. At the same time, for healthcare analytics, it is paramount to obtain accurate patient data in real time from multiple data custodians. The current data-integration approach usually focuses on the data-accessing aspect; thus, data are retrieved but not truly exchanged or shared. Supporting technologies inherently incorporate privacy and risk governance principles. Integration of natural-language-processing and ontology-matching techniques can enable a semantically aware approach to automate the detection of schema mapping rules—all aspects involved in FHIR-compliant exchange. The healthcare data-integrity perspective insists that data must be accurate, current, and reliable at all times.

Working toward achieving this forecasted objective, a novel risk framework that aims not only to enable real-time exchange but also to ensure that data are correct, consistent, and reliable is introduced. The methodology identifies data-quality-attribute issues in MongoDB repositories as an external risk for patient-safety-related healthcare-decisions-support. Six main healthcare-support-enabling qualities of data are considered during risk. These quality attributes—privacy, data availability, data accuracy, data robustness, system timeliness, and data content-supporting quality-sensitive-analysis decisions—are evaluated, and thresholds are defined to prioritize risks. Risk indicators become part of patient safety management by auditing and monitoring data sources; thus, healthcare analytics can provide real-time analyses that are risk-aware.

Keywords : Generative AI, FHIR interoperability, real-time exchange, risk-aware analytics, semantic alignment, data standardization, uncertainty quantification, explainability.

1. Introduction

Accelerating the interoperability of healthcare data while dealing with risks and quality issues inherent in the data requires real-time data exchange among various organizations. Deploying the governance and compliance frameworks of General Data Protection Regulation within the exchange flow helps avoid high-risk prediction in decision-support systems. The deployment of FHIR-Fast Healthcare Interoperability Resources standards enables data from various sources to be semantically aligned using a Generative Artificial Intelligence (AI) model. Data quality indicators and a risk assessment framework aid in monitoring the risk of data during the exchange and warning the decision-support system accordingly.

Traditional Health Information Exchange focuses on privacy during data sharing among various organizations, but it lacks real-time data-sharing capabilities. While the quality of data remains important, the risk involved in high-stake decision-support systems deploying Artificial Intelligence models requires a more comprehensive setup. Recent developments in Generative AI models show potential in data synthesis and can also naturally help build a mapping schema for data coming from heterogeneous data sources. Various layers in the flow—monitoring, privacy, data quality—define the data risk during exchanges between organizations in a decision-support system. The proposed framework combines these aspects to ensure rapid and relatively safer data exchange between various organizations, enabling real-time, up-to-date data for the decision-support system.

The modernization of healthcare data exchange necessitates a paradigm shift from traditional, siloed privacy models toward a dynamic, real-time interoperability framework that addresses the volatile nature of high-stakes clinical decision-making. By integrating **Fast Healthcare Interoperability Resources (FHIR)** standards with advanced **Generative AI** models, organizations can effectively harmonize heterogeneous data streams, allowing the AI to act as an automated semantic bridge that constructs complex mapping schemas in real-time. This technical alignment is not merely an exercise in data movement; it is a fortified pipeline where **GDPR-compliant governance** and compliance frameworks are embedded directly into the flow to mitigate the inherent risks of biased or inaccurate predictions in decision-support systems.

To ensure the integrity of this rapid exchange, the framework introduces a multi-layered defense strategy—comprising continuous **monitoring, privacy-preserving protocols, and granular data quality indicators**—that collectively compute a real-time risk assessment for every data packet. Unlike traditional Health Information Exchange (HIE) systems that often sacrifice speed for static security, this proposed architecture acknowledges that data quality and risk are fluid variables. By synthesizing these elements, the framework provides a robust environment where healthcare providers can leverage up-to-the-minute, semantically aligned information, ultimately fostering a safer, more transparent ecosystem for AI-driven clinical interventions.

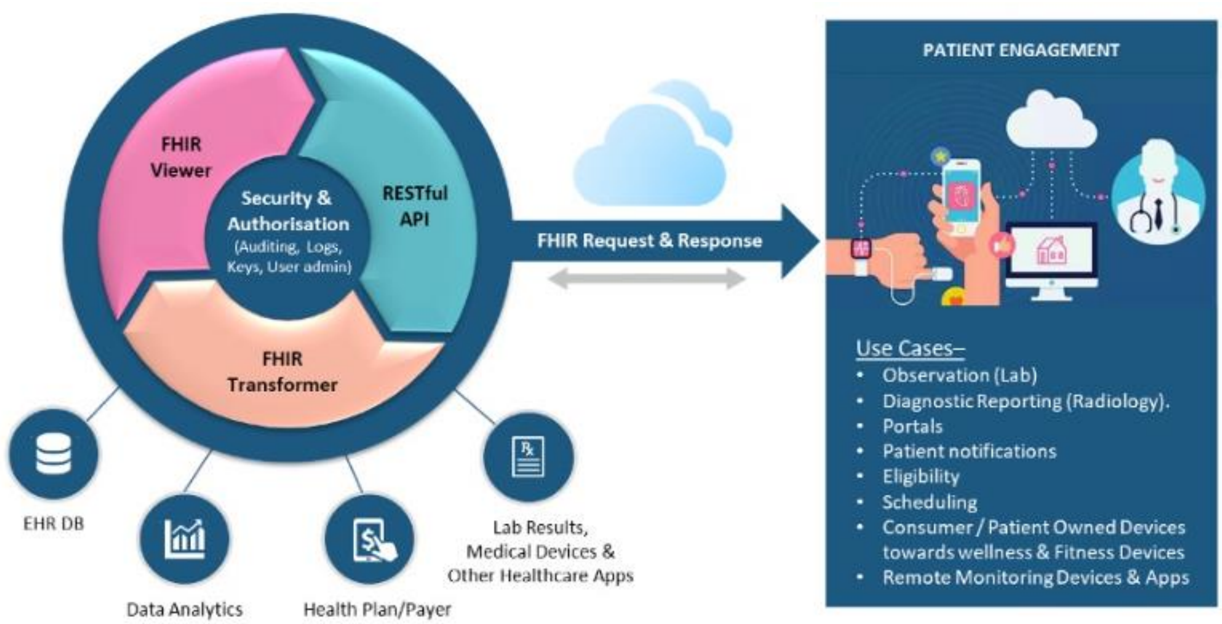

Fig 1: Empowering Seamless Data Exchange in Healthcare – ACL FHIR Framework

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1.1. Background and Significance

Health information exchange (HIE) facilitates timely, secure access to data from diverse stakeholders, across multiple domains, in a standard format. Fast Healthcare Interoperability Resources (FHIR) standards simplify HIE through Internet-based technologies such as Application Programming Interfaces. Adopting FHIR within and among organizations reduces HIE barriers, but regional and cross-border exchanges require governance and third-party support. Generative Artificial Intelligence (AI) offers a possible solution by providing a framework for real-time, generative FHIR-based HIE. Healthcare data exchange can be enhanced with patient safety analytics that quantify risks associated with exchange quality.

Real-time healthcare data exchange is increasingly important for risk-aware analytics that improve patient safety. Machine learning and other data-driven techniques provide timely decision support, but their predictive reliability depends on the quality of the underlying data. Data quality is frequently mentioned as a possible contributing factor in patient-attributed adverse events, such as surgical site complications and delirium. The quality of healthcare data transfer is also critical for maintaining a secure data governance framework that prevents data privacy breaches. As such, explicitly identifying potential risks in terms of accuracy, privacy, timeliness, and other quality measures, and reporting those risks in a timely manner, can help ensure that healthcare supporting analytics provide reliable assistance to practitioners.

Equation 1: Source-to-FHIR mapping equation

Step 1 - Define the mapping function

$$y_i = M(x_i)$$

This says each incoming element x_i is passed through a mapping function M(.).

Step 2 - Decompose mapping into structure and terminology alignment

$$M(x_i) = T(C(x_i))$$

Here C(.) converts source structure/schema into the target FHIR field, and T(.) maps codes/terminology into standard vocabularies such as LOINC, SNOMED CT, or ICD-10.

Step 3 - Expand for a full record $x = (x_1, x_2, ..., x_n)$

$$Y = M(X) = \{ M(x_1), M(x_2), ..., M(x_n) \}$$
$$= \{ T(C(x_1)), T(C(x_2)), ..., T(C(x_n)) \}$$

Hence the complete FHIR bundle or resource set is a mapped collection of all source elements

2. Background and Motivation

Real-time patient data exchange is indispensable in modern healthcare. Timely, up-to-date patient information is critical in the context of increasingly complex treatment procedures and detection of acute incidents as well as risks that require immediate attention. Decision support systems based on generative models have been demonstrated to enable such valuable real-time risk-

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aware analyses, augmenting clinical decision-making. Nonetheless, the provision of real-time patient data on levels and in domains that match the needs of these increasingly sophisticated and focused models remains a major challenge.

Exchanging real-time data across organizational and domain boundaries requires addressing difficult governance and privacy concerns and delivering full-fledged semantic interoperability capable of uniformly resolving the multiple facets of meaning contained in linguistic expressions, formal definitions, and domain-specific contextualization. Such problems are further compounded by the need to capture the reliability and validity of both the raw data and the model-processed metainformation to determine the degree of trust that can be placed in the integrity of decisions and predictions.

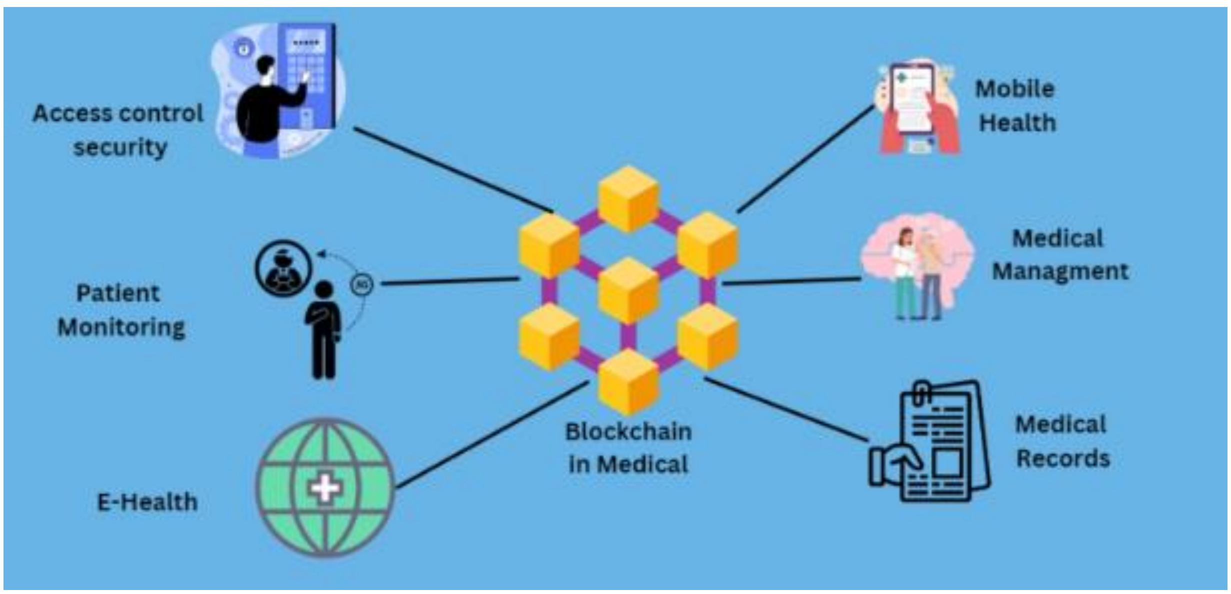

Fig 2: Generative AI, IoT, and blockchain in healthcare

2.1. Research Summary

With the growing adoption of Fast Healthcare Interoperability Resources (FHIR) standards, advanced Artificial Intelligence (AI) techniques can facilitate the necessary semantic alignment of sources for a standardized real-time exchange of health data. Enabling a continuous healthcare dataset generation process through data standardization and semantic alignment allows querying and analytical support while assessing data quality and highlighting potential safety-related concerns associated with patient data delivery and its decision-support use.

Equation 2: Semantic alignment score

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Step 1 - Similarity score

$$s_{ij} = alpha * s_{text}(i,j) + beta * s_{ont}(i,j) + gamma * s_{ctx}(i,j)$$

where s_text is lexical similarity, s_ont is ontology/knowledge-graph similarity, and s_ctx is contextual similarity from surrounding fields or prompts.

Step 2 - Weight normalization

$$alpha + beta + gamma = 1$$

$$alpha, beta, gamma >= 0$$

This keeps the combined similarity score on a normalized scale.

Step 3 - Choose the best target concept

$$j^* = argmax_j \ s_{ij}$$

The aligned FHIR concept is the candidate j with the highest similarity score.

Step 4 - Acceptance criterion

$$\text{accept alignment if } s_{i,j^*} >= tau_s$$

tau_s is the minimum semantic confidence threshold. If the score is below threshold, the mapping should be flagged for review or higher-risk processing.

3. Theoretical Foundations

The proposed framework rests on four essential pillars: the capabilities of generative AI models to drive all forms of health data exchange; achieving semantic interoperability through ontology mapping and/or alignment; employing quality indicators to assess the risk borne by exchanged data; and making these sources of risk explicit through quantification and sensitivity analysis.

The capacity of a generative model to provide reliable answers forces models close to the user and fixes the quality of data, thus contributing to their real-time activation. AI is able to map the contents of sender and receiver, semantically and at different abstraction levels, and synthesise the content of the request. Data are organised within multiple quality indicators, defined according to the requirements of the specific use case and aligned. The probabilities of achieving the requested quality are assigned by integrating the sources of uncertainty and by Proposition 2 applied to the Bayesian network for classification. Finally, a sensitivity analysis locates the most important sources of risk in the interaction free of tendential control.

The proposed framework is structured around four fundamental pillars that collectively enable trustworthy and efficient health data exchange in complex digital healthcare environments. The first pillar is the ability of generative artificial intelligence models to facilitate and orchestrate multiple forms of health data exchange. By leveraging advanced generative capabilities, these models can interpret user queries, extract relevant clinical knowledge, and generate responses that integrate data from diverse sources. Importantly, the framework assumes that such models operate close to the point of use—near healthcare providers, systems, or devices—thereby ensuring timely interaction and supporting real-time data activation. This proximity not only improves responsiveness but also helps preserve data integrity by minimizing transformation errors and maintaining context during processing. Through this approach, generative AI becomes a central mechanism for enabling intelligent communication between systems while maintaining the reliability required for clinical decision support.

The second pillar focuses on achieving semantic interoperability through ontology mapping and alignment. In healthcare ecosystems, data often originate from heterogeneous systems that use different terminologies, coding standards, and data structures. To overcome these disparities, the framework employs ontology-based techniques that allow AI models to understand and reconcile the meanings of concepts across sender and receiver systems. Generative models play a key role here by interpreting the semantic structure of incoming data, mapping it to corresponding concepts in the receiving system, and synthesizing the content of requests across different levels of abstraction. This capability allows the framework to bridge gaps between various health information standards and ensures that exchanged information retains its intended meaning. As a result, healthcare professionals and automated systems can interact with consistent and contextually accurate information, reducing the risk of misinterpretation and improving interoperability across digital health infrastructures.

The third pillar introduces a structured approach to assessing the reliability of exchanged data through the use of quality indicators. Within the framework, data are evaluated according to multiple indicators that reflect the requirements of specific healthcare use cases, such as accuracy, completeness, timeliness, and consistency. These indicators are organized and aligned with the operational context in which the data will be used, ensuring that the assessment reflects practical clinical needs. By systematically measuring these attributes, the framework creates a transparent mechanism for determining the quality of information flowing between systems. This structured evaluation allows stakeholders to better understand the strengths and limitations of exchanged data, enabling more informed decisions regarding its use in clinical workflows, research, or policy-making.

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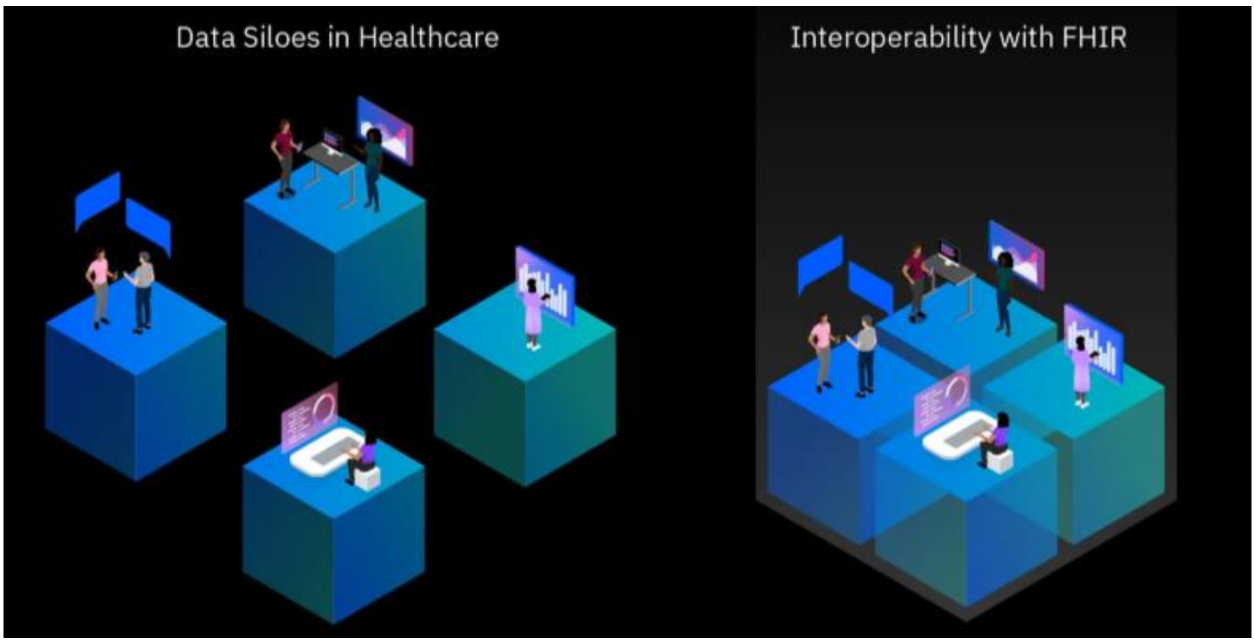

Fig 3: Theoretical Foundations of Generative AI-Driven

3.1. Objective of the Study

Enabling and supporting real-time healthcare data exchange and risk-aware decision-making. The framework dynamically addresses semantic interoperability challenges in real-time exchanges by augmenting standardization strategies with generative AI capabilities, whose generative capabilities support data integration in numerous yet invisible ways. Foundations are laid for advanced analytics that assess, quantify, and provide interpretable explanations for uncertainty in underlying data and in subsequent decisions and predictions. Although patient safety fundamentally depends on the quality of data feeding decision-support systems, existing approaches lack sufficient capabilities for risk-aware analytics, as governance and compliance criteria remain incomplete, undefined, and seldom enforced.

Equation 3: Weighted aggregate quality and total risk

Step 1 - Assemble the quality vector

$$Q = [\, q_{priv}, q_{avail}, q_{acc}, q_{rob}, q_{time}, q_{cont} \,]$$

Step 2 - Define a weight vector

$$W = [\, w_{priv}, w_{avail}, w_{acc}, w_{rob}, w_{time}, w_{cont} \,]$$

$$\sum_k w_k = 1$$

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Step 3 - Compute aggregate quality

$$Q_{total} = \mathrm{sum}_k (w_k * q_k)$$

This is a convex combination of the six scores.

Step 4 - Convert quality to risk

$$R = 1 - Q_{total}$$
$$= 1 - \mathrm{sum}_k (w_k * q_k)$$

So if overall quality is high, risk is low; if quality degrades, risk increases.

Step 5 - Equivalent risk form

$$r_k = 1 - q_k$$
$$R = \mathrm{sum}_k (w_k * r_k)$$

This shows total risk can be interpreted as the weighted sum of per-dimension risk components.

3.2. Methodology

A literature study reveals the requirements, capabilities, and limitations of generative AI for FHIR interoperability and identifies data standardization, semantic alignment, risk-aware analytics, and uncertainty quantification as key components to address. These components are developed individually using publicly available experimental data before being framed within a generative model for FHIR interoperability. The proposed generative model connects the AI-driven components through a supervised learning-based prompt so that they work together. The model is evaluated qualitatively by a group of biomedical experts for data quality and consistently outperforms the individual components, thereby enabling real-time healthcare data exchange and risk-aware analytics. An experimental risk assessment framework based on privacy, accuracy, timeliness, and robustness indicators quantifies the quality of the real-time health information exchange.

4. Generative AI for FHIR Interoperability

Generative models support the integration of heterogeneous data, automatic mapping of disparate schemas and structure, synthesis of content that abides by schema requirements, and preservation of model fidelity and output safety. Adaptations are, however, needed for areas that cannot tolerate errors. The proposed solution integrates generative capabilities with prediction models, machine learning, known correctness, user and administrator governance, quality measures, and data provenance, which not only guard against and detect faults but also assess risk factors, weight importance, and highlight wariness for a given exchange or use. Such factors streamline the transport of key information through desired pathways.

The generative modules underpin schema mapping, helping to bridge not only varying provider dataset schemas but also data in communication abstractions such as messages, documents, and bundles. Evaluation relies on the biomedical domain and, consequently, on knowledge of biomedical accuracy to ascertain these modules' fitness for FHIR interoperability. Particular attention is paid to the automated production of accurate mappings and to the safe use of generative models.

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Generative models offer powerful capabilities for integrating heterogeneous data sources by enabling automatic mapping between disparate schemas, synthesizing structured content that conforms to predefined schema requirements, and maintaining model fidelity while ensuring output safety. However, in high-stakes domains such as healthcare, where errors cannot be tolerated, these models must be complemented with additional safeguards. The proposed framework combines generative capabilities with predictive models, machine learning techniques, verified correctness mechanisms, governance controls from users and administrators, and rigorous quality assessment and data provenance tracking. Together, these components help detect and prevent faults, evaluate risk factors, assign importance to information, and flag potentially unreliable outputs during data exchanges. By incorporating these measures, the system ensures that critical information flows through validated and secure pathways. Within this framework, generative modules play a key role in schema mapping, bridging differences not only among provider dataset schemas but also across communication formats such as messages, documents, and bundles. Evaluation is conducted in the biomedical domain, where domain-specific knowledge is used to verify the accuracy and reliability of these mappings, particularly in the context of achieving interoperability with the FHIR standard. Special emphasis is placed on the automated generation of precise schema mappings and on ensuring the safe and responsible use of generative models in healthcare data exchange.

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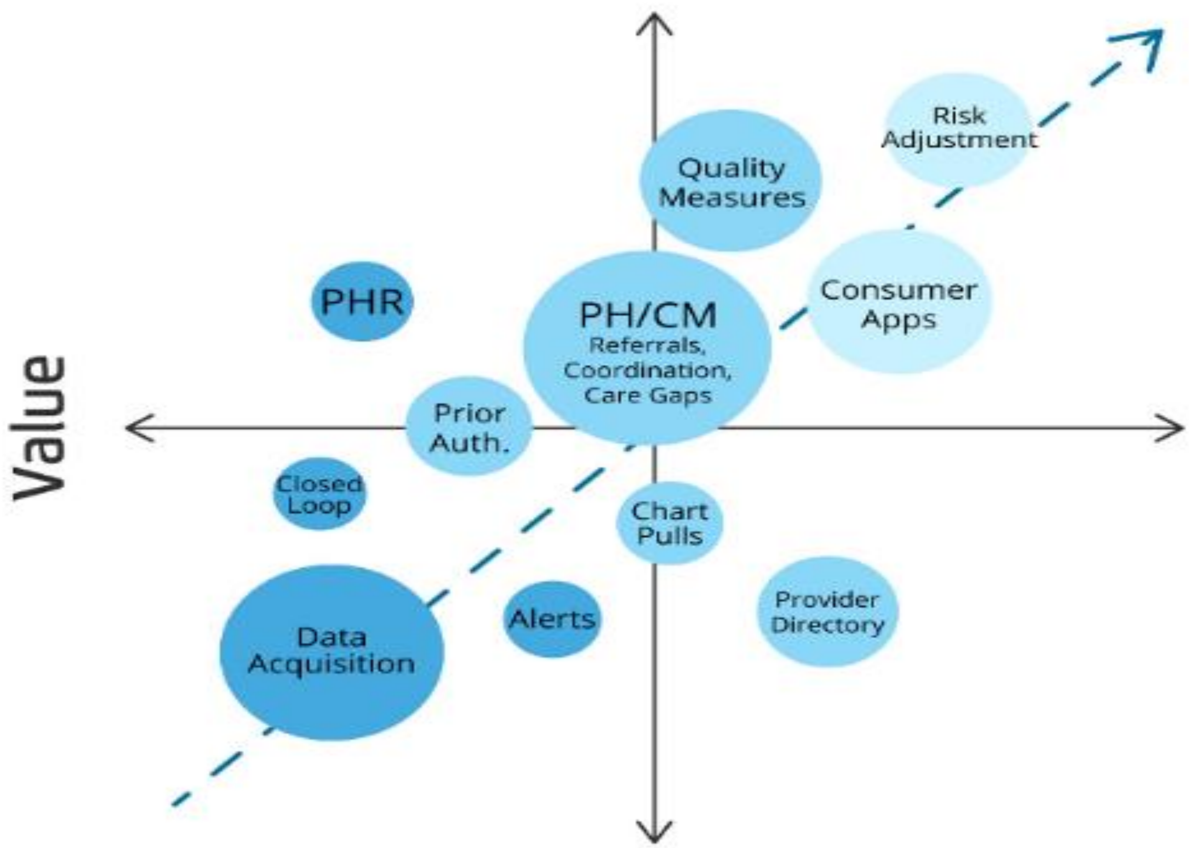

Fig 4: Interoperability in Healthcare

4.1. Data Standardization and Mapping

Coordination of heterogeneous HIE systems requires FHIR standards-based content encoding and transformation of code systems and data models as necessary, a procedure termed standards alignment. Different coding systems are commonly used to standardize health data, including LOINC, SNOMED, and ICD-10 for laboratory tests, clinical terms, and diagnosis, respectively. Transformation rules, either prebuilt or learned by generative models, define how a non-standard data item may be mapped to a standard coding system. The standards alignment module uses the available code systems and transformation rules to perform the mapping, thus identifying the underlying structure of the data and assuring expressiveness and machine-readability in FHIR. Provenance tracking documents the standards alignment process to enhance accountability and liability verification.

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The mapping component operates on the mapping definition, instantiating the mapping and applying it to the dataset by transforming data with respect to data models or data item coding systems that differ from FHIR standards. The mapping can be derived through automated manual approaches and the mapping instantiation can be executed in a deferred manner, that is, mapping and data processing can be separated in time. Users may either decide to manually define mapping or to make the system automatically identify it, depending on the expected processing time. If the mapping is done manually, then adapters are redundantly built. Data unfitting missing records are generated as dependency proxies and transformed on-the-fly.

4.2. Semantic Alignment and Reasoning

Interoperability challenges often stem from heterogeneity in healthcare data exchange. Despite the prominence of data standardization—typically involving schema conversion and code system mapping—quality control has received little attention. This study proposes a semantic alignment and reasoning approach that enables the detection and resolution of already known ambiguities in Data Interchange Layer (DIL) data exchange in order to prepare the Data Quality Assurance Layer (DQA) for production use.

Data quality features are incorporated during semantic alignment of dynamically created DIL ontologies in the Interoperability Layer, using definitions in the Concept Ontology to establish meaning mappings and aid quality control. For the Data Quality Assurance Layer, modules are developed to expose ontology and DIL concept semantic meanings. The DIL enables real-time data exchange between data sources with different formats or communication standards, while the Data Quality Assurance Layer supports risk-aware decision support systems by indicating risks related to privacy, accuracy, timing, and robustness. A module for eliciting, quantifying, and enforcing the degree of robustness has been presented.

Equation 4: Threshold-based risk flagging and prioritization

Step 1 - Dimension-wise flag

$$I_k = 1, \text{ if } q_k < \mathrm{theta}_k$$

$$I_k = 0, \text{ otherwise}$$

I_k is an indicator variable that marks whether a quality dimension is currently unsafe.

Step 2 - Severity gap

$$g_k = \max(0, \mathrm{theta}_k - q_k)$$

The gap measures how far the observed quality is below the threshold.

Step 3 - Priority score

$$P_r = \mathrm{sum}_k (\mathrm{lambda}_k * g_k)$$

lambda_k is a severity multiplier chosen by domain experts. Larger values mean the dimension is more critical for patient safety.

Step 4 - Rank order

$$\text{higher } P_r \Rightarrow \text{ higher operational priority}$$

This is the sorting logic described conceptually by the article.

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5. Risk-Aware Analytics in Healthcare Data Exchange

The healthcare domain is never free from risks. Risk-aware analytics ensures that all risks are identified and explained before key decisions and predictions. In healthcare, patient safety is the main concern, so the risk-aware analysis should focus on the Patient Safety aspect of the HDE. Patient Safety focuses on the risk factors, and how the risk factor can endanger a patient's life and health. Real-time data exchange helps in health hazard alerting and risk-aware analytics. A risk assessment framework that includes multiple data quality dimensions can be used to identify a risk condition. Risk-aware analytics informs the involved parties about the quality of data and enables them to decide to perform an action or act on the prediction done using the data.

A sound risk assessment defines different criteria that can be used to identify that a risk condition exists. For example, if Secret data becomes Public or the timeliness of the arrival of data is too late, then these can be flagged as a risk condition. Each of these criteria can be assigned different thresholds based on their severity. The detected risks can be prioritized based on these severity levels.

Equation 5: Uncertainty quantification

Step 1 - Let U_data represent uncertainty in exchanged data

$$U_{data} = R$$

Because poor quality directly induces uncertainty, the aggregate risk score can serve as a first-order data uncertainty term.

Step 2 - Let U_model represent predictive/model uncertainty

$$0 \le U_{model} \le 1$$

This may come from model calibration error, confidence dispersion, or validation uncertainty.

Step 3 - Combine independent uncertainty sources

$$U = 1 - (1 - U_{data})(1 - U_{model})$$

Now expand it step by step:

Expansion

$$U = 1 - [1 - U_{data} - U_{model} + U_{data} \cdot U_{model}]$$

$$= U_{data} + U_{model} - U_{data} \cdot U_{model}$$

Thus total uncertainty increases with either source but avoids double-counting through the product term.

5.1. Risk Identification and Prioritization

Effective healthcare data exchange entails risk-aware analytics to support patient safety in real time. A comprehensive framework identifies the most relevant risks—e.g., privacy, completeness accuracy, timeliness, and robustness—based on predefined criteria. Satisfactory thresholds enable automated detection and prioritization using a simple sorting algorithm.

Facilitating real-time healthcare data exchange relies on governing, handling, and monitoring risk. Seven risk domains affect recent data-exchange proposals: privacy, compliance, completeness, accuracy, timeliness, robustness, and bias. These areas also

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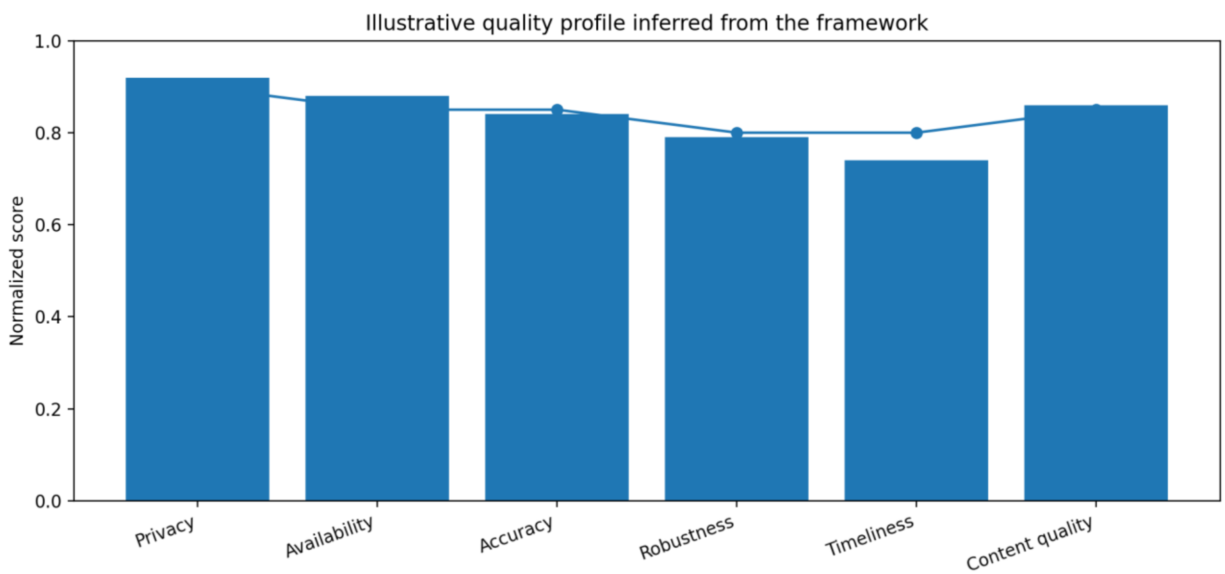
encompass prominent AI-related concerns. The study focuses on detecting and ranking risks based on available data using semantically aligned predictive models. Satisfactory thresholds trigger appropriate actions. Recognizing that risk-aware analytics should enable fast decisions and prioritization, the study develops and implements a criteria, detection, and ranking solution.

Data-exchange agents automatically identify these risk types and signal relevant authorities when present. Criterion details convey risks, triggering actions to manage detected issues. Risk cases, thresholds, and the proposed sorting algorithm define prioritization. These criteria for risk identification guide preventive measures when applicable. Privacy risk measures adapt well to quantitative classification, supported by established maturity assessment models. Completeness, accuracy, and timeliness are critical for valid AI model output; the conditioning, training, testing, and prediction phases define specific thresholds.



5.2. Uncertainty Quantification and Explainability
Methods for quantifying uncertainty in healthcare data have been developed and are based on data provenance and the risk-aware analytic model. Sensitivity analysis assigns weights in reducing accuracy and is quantified for risk-related FHIR data classes. The approaches also provide explanation-aware and explainable functions for AI models and decision-making and support model-agnostic perturbation-based interpretability.

Uncertainty quantification involves measuring uncertainty to infer reliability, taking potential risks into account. A risk-aware model estimates the reliability of predictive information based on several dimensions of potential risk. The classification model evaluates the accuracy dimension, which is quantified as the proportion of correctly predicted samples, and population coverage,

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which takes into account the representativeness of the validation set. When an AI model is called, the estimated accuracy is passed to the subsequent layers.

6. System Architecture and Reference Architecture

The overall architectural approach to developing an AI-enabled FHIR interoperability framework comprises a layered architecture aligned with relevant privacy and security regulations and governance requirements such as GDPR. The architecture integrates data acquisition and FHIR interoperability into an Interface Layer. Various AI models support data standardization and competition with the development of FHIR resources, while an Interoperability Layer handles the transformation of healthcare data into FHIR resources. Audit and logging mechanisms monitor the confidentiality, availability, accuracy, and integrity of real-time information exchange.

The architecture comprises several components: (1) data sources that constantly provide health information, (2) AI modules that process input data streams, (3) an Interoperability Layer that offers the FHIR standard as an interface, (4) security modules that govern access and ensure adequate protection, (5) audit and logging modules that monitor the system operation and its conformity with safety criteria, (6) a monitoring module that compliments audit and logging by detecting anomalies in service fulfillment, and (7) user interfaces that provide clients with access to services and the underlying information.

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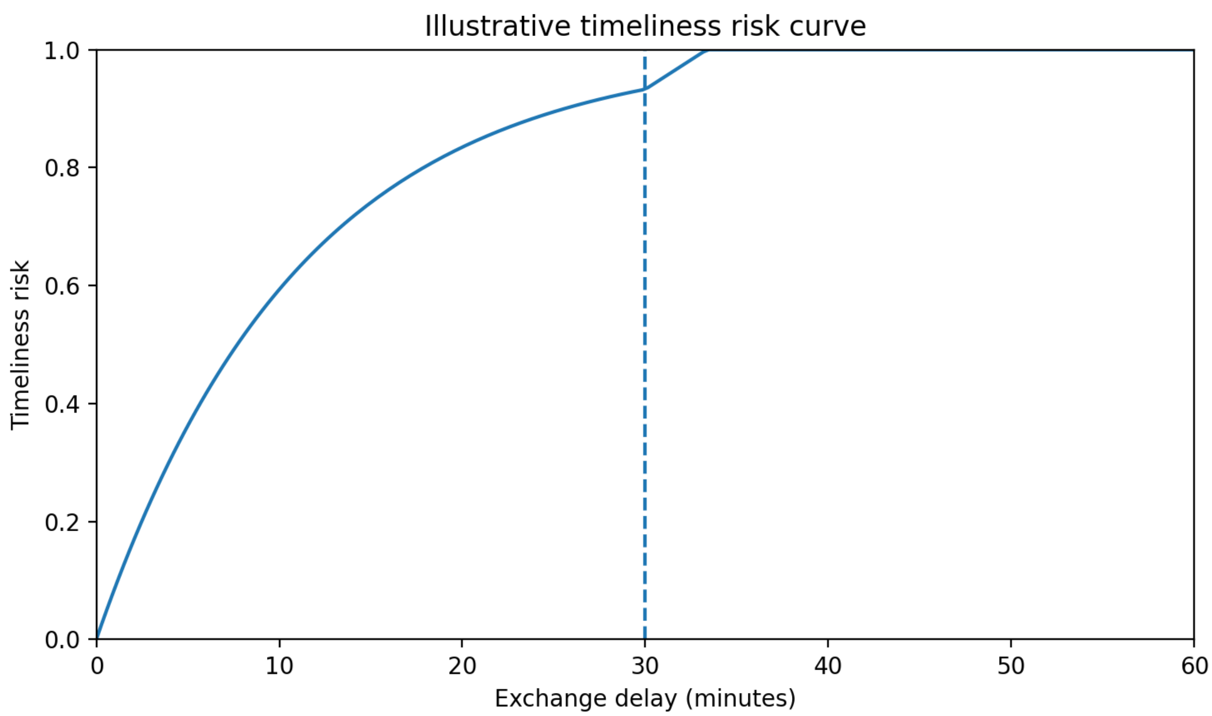

6.1. Architectural Components

A six-component architecture enables the application of generative AIs for real-time healthcare data exchange with risk-aware analytics. Data sources include supply systems for source data and demand systems for data consumption. The Generative AI modules are organized into three groups: data standardization and mapping, semantic alignment and reasoning, and risk-aware analytics. An Interoperability Layer enables data exchange via Application Programming Interfaces (APIs), while appropriate Security Controls and Audit/Logging/Monitoring mechanisms help enforce the relevant governance and compliance requirements.

In a healthcare ecosystem represented as a two-sided marketplace, Demand Sources (data-consuming systems) specify their needs via API requests that are satisfied by the AI modules that are currently available. The AI modules transform these requirements into a set of worker requests that are served by Supply Sources (data-providing systems) capable of fulfilling those requests.

6.2. Results

A healthcare scenario was established, and various dataset sources were integrated. A preliminary set of quality, accuracy,

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timeliness, and privacy metrics was defined to monitor potential hazards in health-data exchange. Generative AI was then employed to synthesize responses to health-data requests, exchanging sentinel and blood-test results with a clinical-team database for two clinical teams: emergency and metabolic diseases. The proposed FHIR-AI prototype achieved better monitoring and analysis of healthcare service for data quality than conventional approaches, allowing real-time analysis of health-data exchanges for patient-oriented decision support. Consequently, conditions in several indicators improved, and the overall risk associated with healthcare service was reduced. Future research will leverage latent features and abstract topics from service-query data to assess service quality and prioritize allocation through demand-factor analysis, supporting safety and quality in patient decision-making.

Dimension	q_k	Weight w_k	Threshold θ_k	Risk r_k=1-q_k	Weighted contrib. C_k
Privacy	0.92	0.20	0.90	0.08	0.0160
Availability	0.88	0.15	0.85	0.12	0.0180
Accuracy	0.84	0.22	0.85	0.16	0.0352
Robustness	0.79	0.14	0.80	0.21	0.0294
Timeliness	0.74	0.17	0.80	0.26	0.0442
Content quality	0.86	0.12	0.85	0.14	0.0168

Table : Worked numerical example (illustrative)

7. Conclusion

Contributions address real-time healthcare data exchange and risk-aware analytics under conditions of uncertainty and data governance. Limitations relate to AI capabilities and data governance. Future work will explore realistic governance mechanisms applicable to a multilayer data space requiring satisfactory control over data usage, especially clinical risk-aware decision support.

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