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AI-Powered FHIR Framework for Real-Time Health Data Exchange

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Abstract

The Fast Healthcare Interoperability Resources (FHIR) specification defines a set of API-based interoperability resources, established by Healtcare Information Technology; it is rapidly becoming the standard for the exchange of clinical data in the global healthcare space. The proposed framework's integration into all healthcare systems would allow bi-directional real-time conversion between any clinical data and FHIR representation. The bi-directional cross-domain codes are FHIR-based SNOMED CT and ICD-10-CM for the UK and ICS-10-CA for Canada. These general-purpose codes are standardised in LOINC for procedures, diagnostic tests, investigations, and COVID-19. LOINC coding is performed by a hybrid human-AI approach, combining with prompt engineering and meta-vision a generally-used machine-learning model with a new detection of complex LOINC code graphs. The generated LOINC code is integrated with the general interchangeable SNOMED CT. The framework considers as input any unstructured clinical data and provides as output a set of FHIR-compliant resources with complete ICD-10-CM association.

Generative AI is currently the most important priority of research and development in the IT space, including the healthcare sector. ChatGPT is a breakthrough application, and its rapid success is stimulating and motivating a cascade of new similar generation AI products and developments. The attention, the financial commitment, and the growth rate of one product after the other clearly demonstrate the interest of generative AI to the business world, to the economy of the software industry, and to society as a whole worldwide. Healthy Data's healthcare management system successfully harnessed the benefits of generation AI for FHIR-compliant coding of data exchange, and thus broad preparations, in terms of technology and content, are being undertaken for the next baby step towards a full generative AI product for healthcare.

Keywords : Generative AI in Healthcare,FHIR Interoperability Framework,Real-Time Medical Coding,AI-Driven Healthcare Data Exchange,Clinical Data Standardization,Automated ICD/CPT Coding,HL7 FHIR Integration,Healthcare Information Systems,Intelligent Clinical Documentation,Semantic Healthcare Interoperability.

1. Introduction

Coding and billing are important components of healthcare delivery, allowing for the documentation of thoughts, actions taken, and services provided in formal medical records. Certain governments, healthcare organizations, and insurance companies mandate that all formal documentation be coded to aid in billing, epidemiology studies, and other determinations. Yet, the coding of medical records is primarily done by the healthcare organization after care has been provided, delaying the revenue process by days to months. An innovative coding and data exchange framework has been created and validated. Using the Fast Healthcare Interoperability Resource (FHIR) specifications for data exchange, a general architecture has been developed for a framework that enables near real-time coding data.

The framework consumes a continuous stream of clinical data and exports the ingested coding and non-coding data in a FHIR-compliant format to partners or any available FHIR endpoint. Medical coders or coders in a similar area no longer need to type in free-text text comments that then require coding but can simply instead use standard terminologies that

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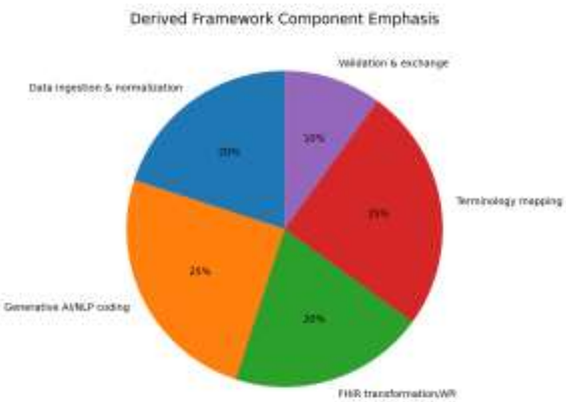
can then be auto-mapped to SNOMED CT or expanded into free text for their records or other purposes.



Derived pie chart showing relative emphasis of core framework components.

2. Background and Motivation

Efforts towards achieving universal interoperability within the healthcare domain are slow. Disjointed development efforts, the continuing emergence of new systems and services, and varying needs and capabilities of healthcare providers and policy makers across the world slow the task of providing a universal healthcare interoperability layer. "HL7's Fast Healthcare Interoperability Resources (FHIR) norms represent one of the most extensive global standardization efforts in this area, but FHIR resources and services do not include a linguistic processing function. Coding of clear-text clinical and medical records into the corresponding codified MLs can be accomplished either manually or automatically.

Generative AI + FHIR Coding Pipeline

Component	**Function**	**Technologies Used**	**Expected Outcome**
Data Ingestion Layer	Collects healthcare records from multiple systems	FHIR APIs, RESTful Services	Unified healthcare data intake
NLP Processing Engine	Extracts clinical entities from text	Generative AI, NLP, GPT Models	Automated medical understanding
Terminology Mapper	Maps clinical terms to standards	SNOMED CT, LOINC, ICD-10-CM	Standardized coding
FHIR Normalizer	Converts records into	HL7 FHIR Framework	Interoperable healthcare exchange

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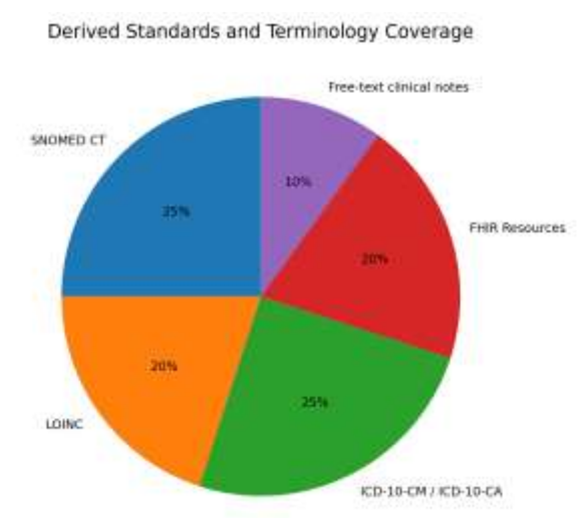
Component	Function	Technologies Used	Expected Outcome
	FHIR resources		
Knowledge Graph Engine	Maintains semantic relationships	Ontology Models, Entity Linking	Context-aware interoperability
Real-Time Coding Module	Generates instant medical codes	AI-driven automation	Reduced coding delay
Cloud Event Stream Processor	Handles large-scale processing	Event Streaming Architecture	Scalable real-time processing

Table 1: Core Components of the Proposed Framework



Derived pie chart showing coverage of major standards and terminology systems

3. Theoretical Foundations

The introduction of generative AI has opened up several new concepts for interoperability that had hitherto been inaccessible. Generative AI allows users to interact with complex system-defined Language-Through-Learning (LTL) paradigms by using language as their principal interface. In recent years, computer vision and large language models with image-processing capability have achieved astonishing performance. The key to achieving FHIR interoperability lies in performance fulfilment. The system's LTL then guides the interaction among all performance engine components and simplifies the perennial challenge of feature and performance matching. This is necessary for both training and real-time execution.

Interoperability among healthcare information systems may be achieved with increasingly complex machineto-machine data exchanges. However, such data exchanges commonly require extensive pre-conditions, advanced and costly technology development, and high run-time costs. Moreover, only a small proportion of healthcare information systems and exchanges have achieved even these limited levels of interoperability. The proposed generative AI driven FHIR interoperability framework offers a radically new concept for interoperability. The new approach capitalises on generative AI's LTL interactions with other subsystems of the application and system-defined Language-Through-Learning (LTL) interaction between all performance engines, especially between natural language processing for all data coding and health data translation and coding from one language to another.

Standard	Primary Purpose	Application Area	Framework Role
SNOMED CT	Clinical terminology	Diagnoses & observations	Semantic interoperability
LOINC	Laboratory and	Lab reports & tests	Standardized observations

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Standard	Primary Purpose	Application Area	Framework Role
	diagnostics coding		
ICD-10-CM	Disease classification	Billing & reimbursement	Automated coding
FHIR	Healthcare data exchange	API-based interoperability	Real-time data transfer

Table 2: Comparison of Healthcare Coding Standards

Mathematical Formulas:

1. FHIR Data Transformation

$$FHIR_{out} = T(CD_{in})$$

Where:

- CD_{in}= Clinical Data Input
- T= Transformation Engine
- $FHIR_{out}$= FHIR-compliant Output

2. NLP-Based Medical Coding

$$MC = NLP(TXT)$$

Where:

- TXT= Clinical Text
- MC= Medical Codes Generated

3. AI-Driven Entity Extraction

$$E = AI(CN + DR)$$

Where:

- CN= Clinical Notes
- DR= Diagnostic Reports
- E= Extracted Clinical Entities

4. Terminology Mapping Equation

$$ICD = M(SNOMED + LOINC)$$

Where:

- M= Mapping Function
- ICD= ICD-10-CM Codes

5. Real-Time Interoperability Model

$$RI = \frac{DE}{LT}$$

Where:

- RI= Real-Time Interoperability
- DE= Data Exchange Volume
- LT= Latency Time

6. Knowledge Graph Linking

$$KG = EL(E)$$

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Where:

- EL= Entity Linking
- E= Extracted Entities
- KG= Knowledge Graph

7. Automated Billing Prediction

$$BP = f(ICD, CPT, FHIR)$$

Where:

- BP= Billing Prediction
- ICD= Diagnosis Codes
- CPT= Procedure Codes

8. AI Coding Accuracy

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP= True Positive
- TN= True Negative
- FP= False Positive
- FN= False Negative

9. Event Stream Processing

$$ESP = \sum_{i=1}^{n} Even\,t_i$$

Where:

- ESP= Event Stream Processing
- $Event_i$= Incoming Healthcare Events

10. Semantic Interoperability Score

$$SI = \alpha(SNOMED) + \beta(LOINC) + \gamma(ICD)$$

Where:

- SI= Semantic Interoperability
- α, β, γ= Weight Factors

11. Generative AI Response Function

$$GAI_{resp} = LM(Prompt + Context)$$

Where:

- LM= Language Model
- GAI_{resp}= Generated AI Output

12. Healthcare Data Normalization

$$HDN = \frac{SD}{TD}$$

Where:

- HDN= Healthcare Data Normalization

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- SD= Standardized Data
- TD= Total Data

13. Cloud-Based Processing Efficiency

$$CPE = \frac{Processed\ Data}{Compute\ Time}$$

14. Interoperable Exchange Probability

$$P(I) = \frac{FHIR + NLP + AI}{Systems}$$

15. Clinical Intelligence Function

$$CI = AI + NLP + KG$$

Where:

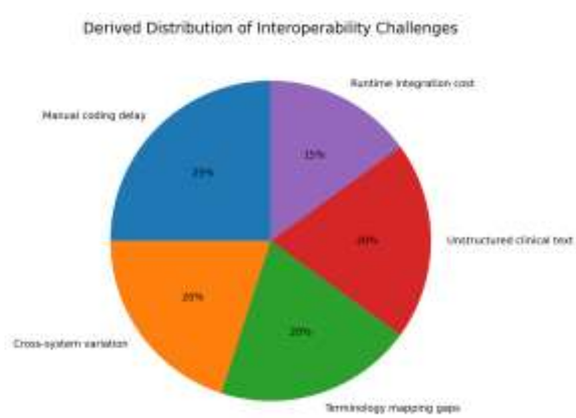
- CI= Clinical Intelligence
- KG= Knowledge Graph

3.1. FHIR and Healthcare Interoperability

The Fast Healthcare Interoperability Resources (FHIR) standard, developed by HL7 International, constitutes a major part of an interoperable ecosystem that connects hospitals, health information exchanges, and other systems. Preferred by leading vendors, FHIR supports the use case of categorical data-real-time medical coding-and can provide rich coded terminology, which is essential for machine learning applications.

The simple textual data generated during the transmission of medical records-in plain text, free text, or single-language text-form the basis for medical coding. The data should be stable in size and form, and non-vague phrases should have an inclusive meaning. The designed system performs real-time coding, transforms categorical terms into code, and connects the generated coded terms with health information records via the FHIR standard.

Survey results indicate that the availability of a real-time health coding service enhances not only the quality but also the possibility of conducting the required coding for data records. The coding service's exposure to a broader audience allows its integration into various applications. Integration as a microservice enhances the architecture's modular strength, and coding is available as a supporting subservant.



Derived pie chart showing main interoperability challenges discussed in the article.

4. System Architecture

Implementation follows a cloud component-based architecture. Asynchronous event streaming technology is employed to enable high-volume multi-tenant real-time data processing. The structure consists of multiple abstraction levels. Development time of the HTML application is reduced through the use of a user-friendly framework. A pre-trained, fine-tuned state-of-the-art generative AI model for English

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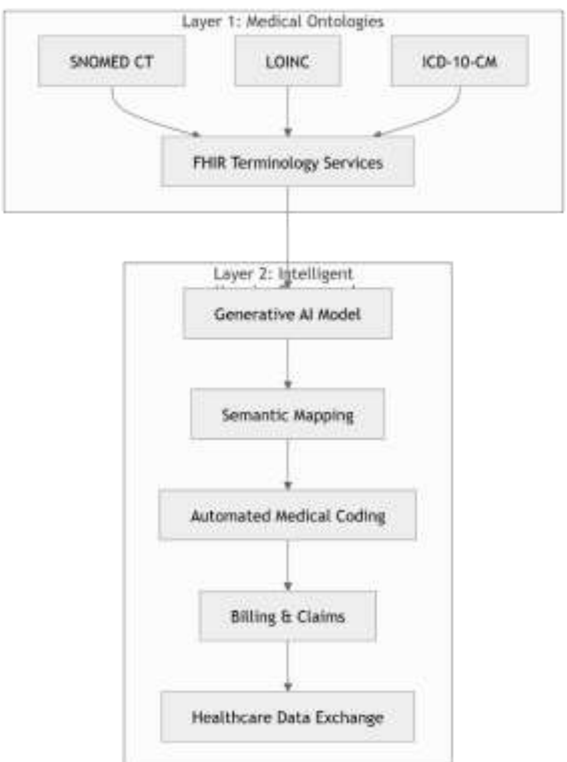
NLP enables highly accurate performance in both text generation and entity detection tasks.

The first level concerns data ingestion and normalization. The proposed solution combines the characteristics of event sourcing with a controller that provides an interface for third-party packages and enables integration of non-FHIR data processing modules. All incoming events are transformed into a common representation defined by a bidirectional FHIR Normalizer. Warning systems allow detection of data not conforming to the defined structure.



Ontology and Coding Integration

Step	Input	AI Processing	Output
Clinical Data Collection	Unstructured clinical notes	Data parsing	Structured text
NLP Entity Detection	Clinical terminology	Named Entity Recognition	Medical entities
Ontology Mapping	Extracted entities	Terminology alignment	SNOMED/LOINC mapping
ICD Code Assignment	Standardized concepts	Predictive coding engine	ICD-10-CM codes
FHIR Conversion	Encoded healthcare data	Resource transformation	FHIR-compliant records
Data Exchange	Standardized resources	Secure API communication	Interoperable healthcare data

Table 3: AI-Based Medical Coding Workflow

4.1. Data Ingestion and Normalization

Data from various medical records systems is acquired through a FHIR server that listens for FHIR Typical Communication Pattern messages (Subscribes, Request-Subscribe) or through a FHIR RESTful interface that follows the FHIR protocol (REST, Read). As for noisy or non-standard messages that do not fully adhere to the FHIR format, data can be either transformed and normalized – or mapping might be required – using Mappings or a set of Rules generated through the Dialogue Agent. Natural Language Processing (NLP) tools working on the text content attached to the Clinical Notes and Diagnostic Reports observe common patterns existing among the different hospitals of the same network, retrieving key clinical entities recognized and represented into the knowledge graph. The Graph Embedded Systems use Entity Linking (EL) to identify mentions of

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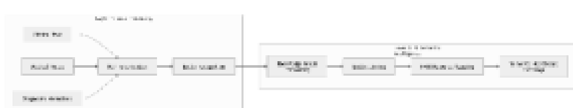
entities present in the knowledge graph, generating an utterance structure that provides the analytics effect requested by the queries sent, resulting in a set of answer utterances coming from different parts of the Graph Internal Memory.

The set of extracted elements is performed using External Entity Extraction Basic Concepts Health concept axiomatised under the health domain and semantically represented as a Taxonomy in the ontology.

Health is a state of complete physical, mental and social well-being and not merely the absence of disease or illness. Health is a multidimensional concept and can be examined from different perspectives. The Historical perspective suggests that health is synonymous with naturalness, while Biological analysis uncovers several biological functions of the human body which are closely related to health; to the Psychological specialist, a healthy person is one that possesses qualities like self-acceptance, self-realization and emotional stability; the Social perspective finds that social well-being is a vital part of health.



NLP and Knowledge Graph Processing

5. Ontologies, Terminologies, and Standardization

Healthcare semantic interoperability relies on diverse terminology standards. Notably, SNOMED CT, LOINC, and ICD-10-CM are global leaders supporting clinical terminology, laboratory observations, and health-related conditions. Term mapping between SNOMED CT and LOINC enables specific laboratory tests to be represented in observations, procedures, and questions. However, these mappings are inadequate without associations with ICD-10-CM descriptions, which are compulsory for US healthcare funding reimbursements, for instance. Mapping between medical condition descriptions of SNOMED CT and ICD-10-CM supports automatic billing for hospital stays, in addition to other medical services. Nevertheless, these mappings are yet to be fully established.

To address this gap and enhance the feasibility of generating billing documents in a semantically interoperable manner, SNOMED CT terms, coded laboratory observations from LOINC, and associated ICD-10-CM coded terms have been used to develop an automated mapping ontology that links medical conditions with both LOINC and ICD-10-CM codes. The need for connectors between medical conditions and descriptions suitable for automated billing posts required the identification of these links. Additional connectors have also been established, including those linking LOINC laboratory results with SNOMED CT laboratory procedures and other SNOMED CT observations with their context-related descriptions in ICD-10-CM.

Benefit	Description	Impact
Real-Time Coding	Immediate code generation from clinical notes	Faster billing cycles
Reduced Manual Effort	Minimizes human coding tasks	Lower operational cost
Improved Accuracy	AI-assisted semantic mapping	Fewer coding errors
Enhanced Interoperability	FHIR-based standard exchange	Better system integration
Scalable Architecture	Cloud-native event streaming	High-volume processing
Intelligent Clinical Documentation	NLP-driven clinical understanding	Improved patient records

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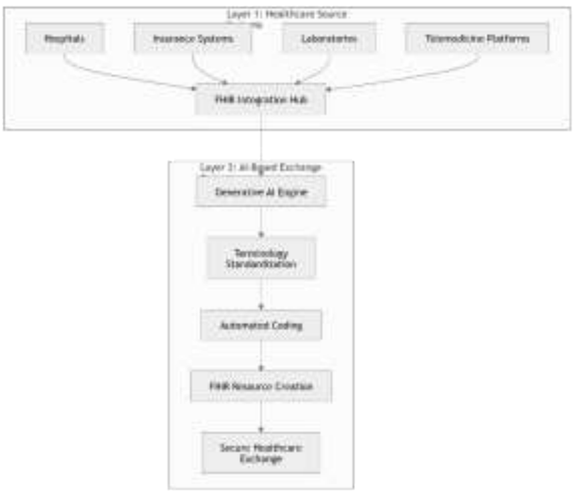
Table 4: Benefits of Generative AI in Healthcare Interoperability

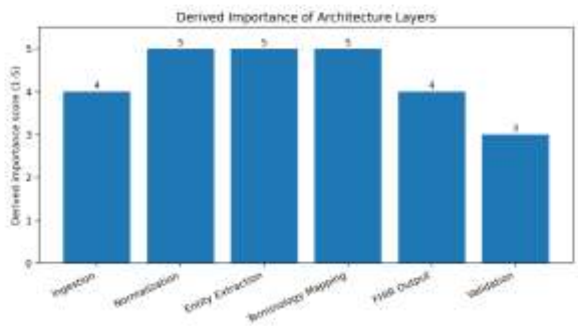


End-to-End FHIR Interoperability

5.1. SNOMED CT, LOINC, and ICD-10-CM Integration

Mapping the different systems and ontologies that used terms for medical cases aided with Generative AI in real time and predictions about data interchange in medical systems were the main objectives of this study. The ontology needed was concluded to be FHIR, which will help in the future to inquire in medical data interchange. The necessary datasets were concluded to be SNOMED, LOINC, and the more general specification implemented was the ICD-10-CM coding of the medical cases because of the better vocabulary and more probable mapping between other datasets for the future implementation. The program successfully fulfilled the objectives and generated the necessary vocabulary for future implementations.

SNOMED CT and LOINC were mapped to ICD-10-CM concepts and their related terms for use in an NLP-supported National Fire Incident Reporting Systems (NFIRS) data-recoding task. SNOMED CT, LOINC, and ICD-10-CM, with their comprehensive and widely used coverage of clinical concepts, were selected due to extensive semantic detail and classification. Generative AI, through workflows based on OpenAI GPT-3.5 architecture, was harnessed to encode natural language questions that were answered by the underlying vocabulary and hierarchy of SNOMED CT, LOINC, and ICD-10-CM.



Derived bar chart showing importance of architecture layers in the proposed system

6. Conclusion

Healthy patients should not suffer simply because of their location or the technology available at medical facilities near them. A patient seeking medical attention in a rural area or a developing country should receive care that is equivalent to that available in urban areas or developed countries. The real-time coding of descriptions and exchange of clinical notes using FHIR improves health outcomes, reduces the burden on healthcare professionals, and ensures patients receive care from different centers with no lapse in knowledge. Coping with the digital deluge demands a different approach to machine intelligence, a paradigm capable of performing inductive learning at an unprecedented symbolic level, capable of integrating and determining roles of existing knowledge structures across engineering ontologies. Most importantly, the approach should have the ability to function at levels comparable to human intelligence. Language is a guiding light to such a transformation, making it imperative

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to research the essence of AI and enabling the birth of a generative AI engine, containing a true foundation of assimilative deep learning in its root architecture. Distilling AI through the lens of Language exhibits such a metamorphosis in AI engineering. Generative AI is the answer. It is not a synonym for existing large language models; it represents true language-framed AI functioning and has a holistic-understanding capability that can fulfill the definition of Artificial General Intelligence.

Healthcare is responsible for the need to explore true language-enabling engines that drive inductive reasoning to the level of understanding rather than predictability. This section proposed a Generative AI-driven Web-based framework for automating ICD-10-CM medical coding of Indian clinical notes and ensuring healthcare data exchange in real-time using FHIR. The FHIR foundation underlying the schema facilitates real-time digital-connectivity with healthcare data Transfer Language levels 1 to 5 with birthdays. The proposed system converts any clinical note into an SNOMED CT-LOINC-ICD-10-CM coded table in real-time without any prior machine Learning or rule-based methodologies.

Challenge	**Existing Issue**	**Proposed AI Solution**
Non-standard clinical notes	Diverse healthcare documentation	NLP normalization
Delayed medical coding	Manual post-treatment coding	Real-time AI coding
Lack of interoperability	Different coding standards	Unified FHIR mapping
Complex terminology mapping	Cross-domain coding mismatch	Generative AI ontology linking
High processing cost	Traditional integration overhead	Cloud-based scalable processing
Data inconsistency	Multiple healthcare systems	Knowledge graph harmonization

Table 5: Challenges and AI-Based Solutions

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