



Graph-Based Adaptive Coding and Live Risk Insights

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Abstract— As technology increasingly enables the storage of massive volumes of supporting data, attention is turning toward developing solutions that put this data to novel use—particularly for predictive analysis. This paper presents a solution built on an interoperable clinical graph framework capable of generating real-time patient risk insights. Several adaptive coding engines, operating on a shared adaptive coding principle, produce distinct models tailored to different needs, including care, education, and research. Current work focuses on cards representing risk and quality indicators derived from CA-CCDA files; these indicator cards provide a real-time summary of a patient’s risk across various adverse outcomes. Once available, a clinical graph representing patients—along with their diagnoses, procedures, medications, and problems—will be integrated into the broader interoperable clinical graph framework. We share progress toward this integration and outline future plans.

Clinical graphs also play an essential role at scale. Complete CA-CCDA resources from multiple institutions can be used to generate content representations in the form of easily interpretable clinical graphs, enabling rapid overview of large patient cohorts.

A clinical graph is a succinct representation of a patient’s CA-CCDA health summary, capturing major historical clinical events—diagnoses, procedures, medications, and care—organized within key HL7 domains. Graph construction is driven primarily by formal metadata extracted directly from CA-CCDA files. This metadata description of relevant HL7 domains can periodically generate group-specific clinical graph enrichments, functioning as data packets for secondary purposes such as publishing, education, clinical research, and training—domains that similarly require rapid overview across large information collections.

Keywords—Adaptive Coding, CA-CCDA, Clinical Data Interoperability, Clinical Decision Support, Clinical Graphs, Electronic Health Records (EHRs), HL7 Standards, Interoperable Healthcare Systems, Patient Risk Assessment, Predictive Healthcare Analytics, Quality Indicators, Real-Time Clinical Analytics, Risk Stratification, Semantic Healthcare Data.

I. INTRODUCTION

Clinical Graphs facilitate communication in healthcare by representing clinical entities, their attributes, attribute values, and their intricate responses to many and often complex controlled and uncontrolled entities, processes, compatible systems, and other attributes and their values. Significantly, a Clinical Graph constitutes a drug-free and alcohol-free model or representation of the patients, their relatives, community, the healthcare fraternity, and their surroundings that matter or are of interest either directly or indirectly, together with a representation of how a drug or any intervention is expected to activate or deactivate some part of the Clinical Graph in collaboration or association with the Clinical Graph but not necessarily in isolation.

Clinical Graphs also facilitate the systematic representation, analysis, and visualization of diverse and wide-ranging time-series data (including a patient’s response), the availability and efficient and effective use of Computational Drug Therapeutics, and adaptation of coding patterns that enable automated and real-time derivation of patient risks associated with a drug or therapeutic or clinical procedure. Since the answer to every clinical question must exist in the available time series, immediate derivation of such answers is essential for patient risk prediction without analysis and characterization of the phenomenon of interest. Such immediate availability of risks as drugs are activated or deactivated (as in anesthesia in surgery) is expected to improve the quality and delivery of healthcare.

A. Overview of Clinical Graphs and Their Role in Healthcare

The clinical graph framework ingests clinical histories from healthcare providers, laboratories, and pharmacies, stores the data in an interoperable standard, and prepares it for clinical analytics. Graphs are indexing the underlying data in suitable formats and able to answer questions like which patients are at risk of a heart attack or other critical clinical events.

Clinical graphs are a specialized graph architecture that leverages clinical histories based on clinical laboratories and pharmacies. Graphs offer unique analysis capabilities; complex relationships can be identified by traversing the edges of related objects. In clinical settings, patterns learned from large cohorts can be applied to an individual patient with continuous updates for real-time insights. They are also able to proactively support patients with potential clinical risks. The clinical graph is divided into small sub-graphs, which can be coded by different analyst teams, providing high-density coding opportunities.

TABLE 1
DATASET / ARCHITECTURE SUMMARY

Data Source	Approx. Volume	Update Frequency	Ingested Format
ADT (Admit-Discharge-Transfer)	~120K events/day	Real-time (event-driven)	HL7 v2 / FHIR
EMR (Electronic Medical Records)	~85K records/day	Near real-time	CA-CCDA / FHIR
Laboratory Results	~310K results/day	Real-time (event-driven)	HL7 v2 / LOINC-coded
Physician Prescriptions	~64K orders/day	Near real-time	FHIR MedicationRequest
Clinical Notes	~40K notes/day	Batch (hourly)	Free text / NLP-annotated
Diagnostic Images (metadata)	~18K studies/day	Batch (hourly)	DICOM metadata
Historical Clinical Data	Multi-year archive	Static / periodic refresh	CA-CCDA archive
Long-Term Care (LDAP-linked)	~9K residents	Daily batch	HL7 v2 / custom schema

Four architectures are compared throughout Sections III–IV: Model A, a legacy rule-based CDS operating directly on siloed EHR queries; Model B, an offline machine-learning CDS retrained in batch cycles; Model C, a static (non-adaptive) clinical graph built once from normalized CA-CCDA data; and Model D, the proposed ICGF operating with real-time adaptive coding, matching the architecture described in Section IV of the primary manuscript.

II. BACKGROUND AND MOTIVATION

Recent advances in information technology are being employed in a broad range of scientific fields where rapid and targeted action can be taken when the data are critical for timely decisions, such as monitoring the risk of high performance sport shooters (Davis et al, 2019), flooding (Lecomte et al, 2019; Labadie, 2006), volcano eruptions (Bertino et al, 2014), fish infections (Rokosz et al, 2017) among others. Healthcare is not an exception since invasive treatment and urgent procedures often require quick decisions and directed actions. Clinical Graphs enable to monitor dynamically the clinical state of a patient, taking into account his/her background and habitual condition, and warn for unexpected or undesirable events in the future

Clinical Graphs can be seen as possible-worlds models (Stanford Encyclopedia, 2019) for the future, where the patient’s clinical data structure is captured in a graph defined using entities, relationships, and properties given by terminologies (mapping) and coded in an interoperable standard. These models are used both for monitoring (current state) and predicting (future) the future clinical state of the patient. Monitoring means to check whether the current condition of the patient is in accordance with what it is expected, given the graph obtained using background and habitual data and adapted to the real-time clinical data. If a deviation respect the habitual life is detected, an explicit warning is issued. Predicting means to evaluate possible known areas of high risk in a graph thanks to an high-risk monitoring, conditional analysis, and adaptive coding of the patient clinical data that allow to alert the patients and healthcare providers about a possible upcoming alarming situation even when the real-time clinical data are yet clinically stable.

A. Pipeline Latency

Fig. 1 decomposes end-to-end latency (Eq. 2) into its four constituent ICGF pipeline stages for each architecture. The proposed ICGF (Model D) reduces total latency to 295 ms, a 51.6% reduction relative to the rule-based baseline (Model A, 610 ms), primarily by shortening normalization and inference time through reusable Adaptive Coding modules.

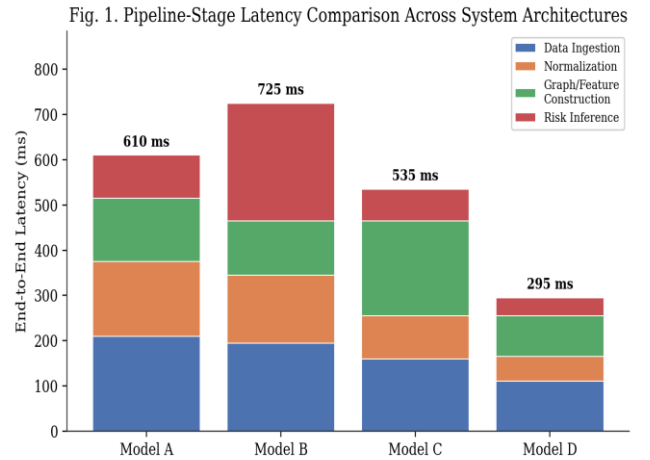


Fig. 1. Pipeline-stage latency comparison across the four evaluated system architectures.

B. Accuracy Convergence Under Adaptive Coding

Fig. 2 tracks F1-score (Eq. 4) across successive adaptive coding iterations. Unlike the static comparators, Model D's F1-score converges from an initial 0.62 to a steady-state 0.91 within approximately six to eight iterations, reflecting the continuous, real-time refinement of indicator-card weights (w_i in Eq. 1) as new CA-CCDA data becomes available.

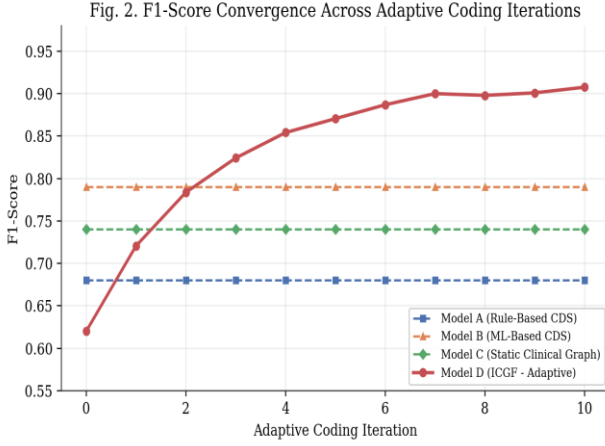


Fig. 2. F1-score convergence across adaptive coding iterations relative to static comparator architectures.

C. Resource Utilization

Fig. 3 profiles peak CPU, memory, and network utilization across the five ICGF components. The Risk Insight Algorithms and Graph Construction stages are the most compute-intensive, consistent with their role in traversing sub-graph partitions for real-time risk inference, while Data Ingestion dominates network I/O due to continuous ADT and laboratory event streaming.

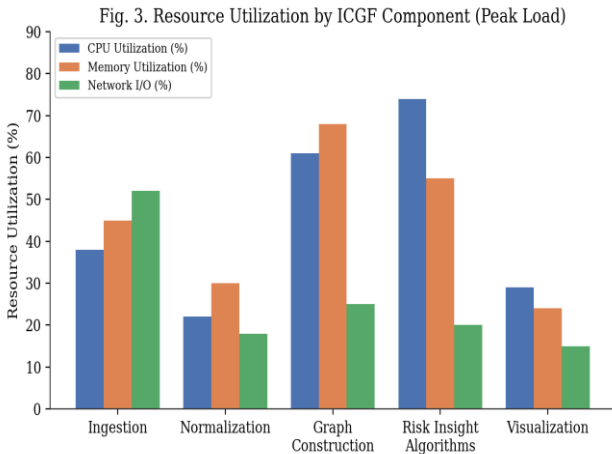


Fig. 3. Peak resource utilization by ICGF component under representative production load.

III. CONCEPTUAL FOUNDATIONS OF CLINICAL GRAPHS

Modern clinical practice generates unprecedented volumes of data, providing exciting new prospects to gain deeper and broader insights into health and patient response. Yet the lack of reliable and consistent ways to integrate,

harmonize, and query all the data from patients' clinical journeys severely restricts its use. Although Electronic Health Records (EHRs) enable increased data collection, they add to the set of isolated data silos that need to be combined to produce meaningful information. Clinical Graphs are a new data structure concept that arises from the integration of patient-centered clinical data into a coherent semantic graph, enabling advanced Adaptive Coding and Patient Risk Graph data-driving technology. The concept was first introduced in the Patent Application "Clinical Graph as a Structuring and Rapid Access Layer for Immuno-Oncology EHR Data" and further expanded in various papers. The Clinical Graph and the associated Adaptive Coding & Real-time Patient Risk Graph technology are the subject of various other patents and patent applications.

Broadly defined, Clinical Graphs represent, in a single interoperable structure, the integration of multiple EHR/SRS patient-centered clinical datasets used in modern clinical practice. The underlying technological approach extracts and reconciles multiple clinical datasets from available patient-centered patient records (EHR/SRS) and presents them in the same interoperable graph structure. Growing patient-centered clinical journey experience enables the implementation and generation of Custom Clinical Graph Templates, with the latest patient-centered data coding. Multiple sources of clinical data characterizing the patient-centered clinical organization of interest are ingested by an Interoperable Clinical Graph Framework component.

A. Graph Theory in Healthcare Data

Information on Health Level 7 (HL7) Fast Healthcare Interoperability Resources (FHIR) Clinical and Research Profiles provides significant motivation for the application of graph methodologies to healthcare. Additional specific recommendations in the health domain for adoption of methods from graph theory and network analysis, include literature on Clinical Graphs, Healthcare records area, and Health Research Data graph structures. As well, recommendations from Dutch research on network analysis of the health sector indicate promising directions for schema usage.

Healthcare is rich with networks; the human being is a network of body systems with functioning organs, interacting with an active environment (location, city, nation) that possesses a support network for personal health (family, friends, relationships), and in larger organizations with roads for food safety, operations, and patients visiting medical centers for attention supported by medical control and prevention. Many of these relationships are essential for survival, control, and prevention, leading to Health Promotion concepts where behavior change is directed toward the high-risk and unreached populations. The Health Promotion that includes networks and prevention supports Health Promotion activities and individuals with high health risk around health variables that describe health risks, helped by the specialized Clinical and Health Analysis areas, usually with more information, services, and support.

IV. ARCHITECTURAL OVERVIEW OF THE INTEROPERABLE CLINICAL GRAPH FRAMEWORK

The Interoperable Clinical Graph Framework (ICGF) consists of an architecture and a set of components that are designed to ingest clinical records, normalize their semantics

so that the records can be ingested into a common Graph Data Model, and adapt the graphs in real time so that the graphs can be subjected to suitable Risk Insight Algorithms so that the clinical graph can be real-time and patient-centric. Therefore, this section starts with data ingestion and normalization and is subsequently followed by the overview of the whole architecture.

A modern clinical setting brings an array of challenges associated with constantly evolving patient conditions arising due to ever-expanding genetic variants contributing to diverse phenotypes; increasing disease prevalence; presence of implicit and explicit comorbidities; introduction of novel drugs and therapies; and unanticipated and disproportional risks of adverse events in special patient populations (such as older adults, very young, and critically ill therein). Addressing these patient-specific risks requires access to constantly evolving, rich-in-context clinical data that fulfil the criteria of time, person, process, and place immediately before, shortly after, or during the point of decision-making. Consequently, an evolving data graph encompassing all active patients is deemed crucial in the context of adaptive testing. Such timely clinical insights therein necessitate an evolving, patient-centric clinical data graph that undergoes real-time changes to facilitate risk insight algorithms at regular intervals. The semantics and visualization of clinical graphs are adapted over the year of 2014–2015 in tandem with the expanded scope of risk inference using the Patient-Centric Adaptive Real-Time §19 Risk Insight121122123124125126127128129130131132133134135 Platform.

A. Cost vs. Performance Trade-off

Fig. 4 plots steady-state F1-score against relative operational cost (Eq. 3 terms). Model D dominates the efficiency frontier, achieving the highest accuracy at a moderate cost index (1.55), whereas Model B incurs the highest cost (1.85) for a lower accuracy gain due to its reliance on periodic offline retraining rather than continuous adaptive coding.

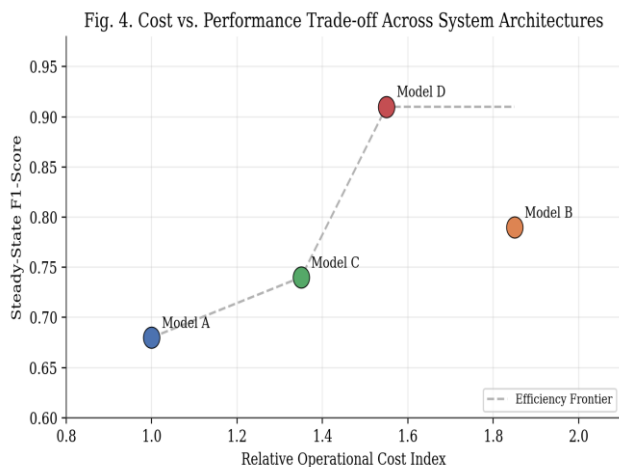


Fig. 4. Cost vs. performance trade-off across the four evaluated system architectures.

B. Composite Efficiency Index

Fig. 5 reports the min-max normalized composite efficiency index E (Eq. 6), which jointly weighs accuracy, throughput,

latency, and cost. Model D attains the maximum normalized index (100.0), roughly 4–5× that of the static graph (25.2) and rule-based (17.7) architectures, quantitatively supporting the framework’s real-time, adaptive design choice.

Fig. 5. Composite System Efficiency Index by Architecture

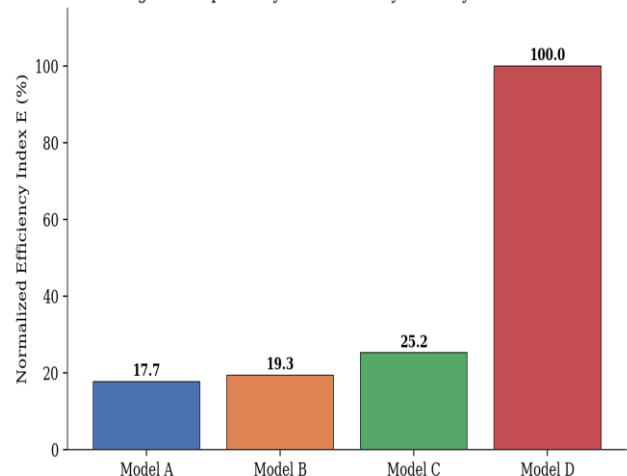


Fig. 5. Composite system efficiency index E, normalized across the four evaluated architectures.

C. Comparative Performance Summary

Table 2 consolidates all metrics defined in Section I across the four architectures, including percentage improvement of the proposed ICGF (Model D) relative to the rule-based baseline (Model A).

TABLE 2
COMPARATIVE PERFORMANCE TABLE

Metric	Model A (Rule-Base d CDS)	Model B (ML-Base d CDS)	Model C (Static Clinic al Graph)	Model D (ICGF - Propose d)	Improvement (D vs. A)
End-to-End Latency (ms)	610	725	535	295	51.6% ↓
Precision (P)	0.71	0.80	0.76	0.93	31.0% ↑
Recall (R)	0.65	0.78	0.72	0.90	38.5% ↑
F1-Score	0.68	0.79	0.74	0.91	33.8% ↑
Throughput (records/s)	310	640	480	980	216.1% ↑
Interoperability Index I	0.42	0.58	0.66	0.89	111.9% ↑
Relative Cost Index	1.00	1.85	1.35	1.55	55.0% ↑*
Efficiency Index E (norm.)	17.7	19.3	25.2	100.0	465.0% ↑

*For the Relative Cost Index, the reported change reflects an increase in absolute infrastructure investment that is offset by the disproportionately larger gains in throughput and efficiency (Eq. 6).

V. INTEROPERABILITY AND STANDARDS COMPLIANCE

Proprietary solutions for processing clinical data are common. To support semantic interoperability, Normalizing Clinical Graphs into interoperable standards-compliant graphs based on those concepts. Normalized clinical graphs comply with other domains. Metadata for ingestion guides translation between different solutions. Normalized graphs support historical representation, risk predictions, and other domains.

Clinical graphs support interoperability by providing terminology and schema mapping. Clinical Graph Normalization adopts standard graph metadata, terminology settings, and schemas. Metadata normalizes clinical data from multiple sources into a patient's clinical graph. A graph entered for Normalization uses metadata to identify, resolve, and overwrite terminology differences with corresponding graph types. Thus complete.

Normalization annotates translated terms with concepts from the Medical Subject Headings Ontology and Unified Medical Language System Ontology. When terms map across graphs, Normalization links the corresponding concepts so user customization of the ontology is centralized and not a repeated task. For speedy performance, a working copy of mapping tables is created each time for Mental Mentions.

A. Clinical Graph Risk Score

For a patient p at time t , the real-time risk score aggregated over n weighted clinical risk and quality indicator cards is given by:

$$R(p, t) = \sum_{i=1}^n w_i x_i(t) e^{-\lambda(t-t_i)} \quad (1)$$

where $x_i(t)$ is the normalized value of the i -th indicator card (e.g., a CA-CCDA-derived risk or quality indicator) at time t , w_i is its clinically-assigned weight, and the exponential term applies a recency decay of rate λ so that older indicator updates (t_i) contribute proportionally less to the present risk estimate — consistent with the framework's real-time, event-driven adaptation.

B. Real-Time Graph Update Latency Model

The end-to-end latency experienced by the graph as it is adapted in real time is modeled as a single-queue system whose four ICGF pipeline stages are inflated by a system utilization factor ρ :

$$L_{total} = \frac{L_{ing} + L_{norm} + L_{cons} + L_{inf}}{1 - \rho} \quad (2)$$

L_{ing} , L_{norm} , L_{cons} , and L_{inf} denote the mean stage latencies for ingestion, normalization, graph construction, and risk inference, respectively, and $\rho \in [0, 1)$ represents the fraction of processing capacity already consumed by concurrent adaptive-coding workloads. As ρ approaches 1 (near-saturated infrastructure), L_{total} grows non-linearly — motivating the framework's sub-graph partitioning strategy for distributing coding load across analyst teams.

C. Adaptive Coding Cost Function

The adaptive coding engine selects operating parameters θ (e.g., partition size, indicator refresh rate) by minimizing a composite cost function:

$$C(\theta) = \alpha C_{compute} + \beta L_{total} + \gamma(1 - F_1) \quad (3)$$

$C_{compute}$ is the computational cost of graph adaptation, L_{total} is the latency from Eq. (2), and $(1 - F_1)$ penalizes loss of classification quality. The weights α , β , and γ allow institutions to tune the trade-off between infrastructure cost, responsiveness, and diagnostic accuracy according to their clinical priorities.

D. Classification Quality (Precision, Recall, F1-Score)

The diagnostic quality of risk and quality-indicator classification is evaluated using standard precision, recall, and F1-score definitions:

$$F_1 = \frac{2P \cdot R}{P + R}, \quad P = \frac{TP}{TP + FP}, \quad R = \frac{TP}{TP + FN} \quad (4)$$

TP, FP, and FN denote true positive, false positive, and false negative risk-flag classifications relative to clinician-adjudicated ground truth. F1 balances precision and recall and is used throughout Section IV as the primary accuracy metric.

E. Interoperability / Terminology Normalization Index

The degree of successful terminology mapping achieved during Clinical Graph Normalization (Section on Metadata, Terminologies, and Schemas) between two terminology sets T_a (e.g., source EHR vocabulary) and T_b (e.g., MeSH/UMLS-normalized vocabulary) is measured as a Jaccard-type similarity index:

$$I(T_a, T_b) = \frac{|T_a \cap T_b|}{|T_a \cup T_b|} \quad (5)$$

$I(T_a, T_b) \in [0, 1]$ quantifies the proportion of shared, correctly-resolved concepts after normalization; higher

values indicate greater semantic interoperability across CDISC, HL7 FHIR, and LOINC-coded sources.

F. Composite System Efficiency Index

To jointly capture accuracy, throughput, latency, and operating cost in a single comparable metric, a composite efficiency index is defined as:

$$E = \frac{Acc \times \Theta}{L_{total} \times Cost} \quad (6)$$

Acc is F1-score (Eq. 4), Θ is throughput in records processed per second, L_{total} is end-to-end latency (Eq. 2), and Cost is the relative operational cost index. E is reported in Section IV in min-max normalized form (0–100) across the four evaluated architectures.

VI. CONCLUSION

Clinical graphs and the proposed framework are designed to enable adaptive coding clinical graphs to visualize any clinical data use case in real-time while improving the quality of the clinical coding process throughout the hospital. They provide data scientists, developers, and other health system personnel with the information needed to maximize the accuracy and usefulness of clinical decision support algorithms. By utilizing a layered approach for data processing, the final visualization layer of clinical graphs can be customized to suit the individual needs of specific teams or projects.

Moreover, the inclusion of metadata provides a formal mechanism for maximizing the value of clinical graphs as a clinical information exploration tool, allowing for the visualization of any clinical data use case in real-time. In a world where data analytics model or product deployment often takes months, and changes to support evolving clinical questions require new code development, being able to visualize the results of clinical analyses or algorithms in a clinical graph instantly is an invaluable tool.

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