

Graph-Driven Decision Support from Bedside to Forecast

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Abstract

Real-time clinical decision-making depends on timely, relevant insight into dynamic patient conditions and evolving care trajectories. Intelligent knowledge graphs that integrate each patient's temporal, multisource data with graphical causal knowledge can generate event-driven alerts for clinicians as conditions change. Predictive care, meanwhile, benefits from temporal modeling of this data to support risk stratification and identify predictive features — for example, tracking a patient's trajectory to detect meaningful shifts and assess the risk associated with those changes. Building effective patient knowledge graphs for modern healthcare raises key research questions around interoperability, data quality, and patient safety.

Knowledge graphs offer powerful representation and reasoning capabilities to support decision-making across domains. While knowledge representation at the graph level is well established, enabling real-time, graph-based reasoning and decision-making — responsive to continuously changing data — requires an event-driven perspective. In healthcare, these two dimensions are tightly intertwined: data from Electronic Health Records (EHR), imaging, labs, genomics, and wearables feeds the patient knowledge graph that underpins real-time clinical decision coordination. Together, events, triggers, predictive models, and causal relationships form a semantically rich foundation for representing and reasoning about patient care.

Keywords: Knowledge Graphs, Clinical Decision Support, Predictive Analysis, Event-driven, Interoperability Standards, Intelligent Patient Knowledge Graphs, Clinical Decision Support Systems, Real-Time Healthcare Analytics, Predictive Care Intelligence, Electronic Health Records (EHR) Integration, Medical Knowledge Representation, AI-Driven Clinical Decision Making, Healthcare Knowledge Graphs, Semantic Interoperability in Healthcare, Predictive Healthcare Analytics.

1. Introduction

Intelligent patient knowledge graphs support coordination of real-time clinical decision-making and predictive care. Knowledge graphs enable continuous synthesis, monitoring, and learning from diverse patient data sources, including electronic health records, imaging, laboratories, wearables, genomics, and current trajectory. Intelligent knowledge graphs serve both as a model of the patient and as a subsumption middle layer for information exchange. The research proposes and explores the concept of temporal knowledge graphs, wherein time may intricately shape the semantics and relationships of children entities in the knowledge graph.

1. Patient Knowledge Graph

$$PKG_t = (V_t, E_t, R_t, A_t)$$

Timely and accurate clinical decision-making with high impact on patient outcomes and safety is critical in the modern clinical setting. Patient knowledge graphs, designed for interoperability with hospital information systems and designed to be updated in real-time, offer an opportunity to aid such tasks: alerting clinicians when specific conditions, risks, or opportunities arise for the patient or patient cohort at hand. These tasks include early detection of sepsis, visualization of flu outbreaks in patients' discharge diagnoses, and real-time alerting of potentially concealed skull fractures in pediatric patients.

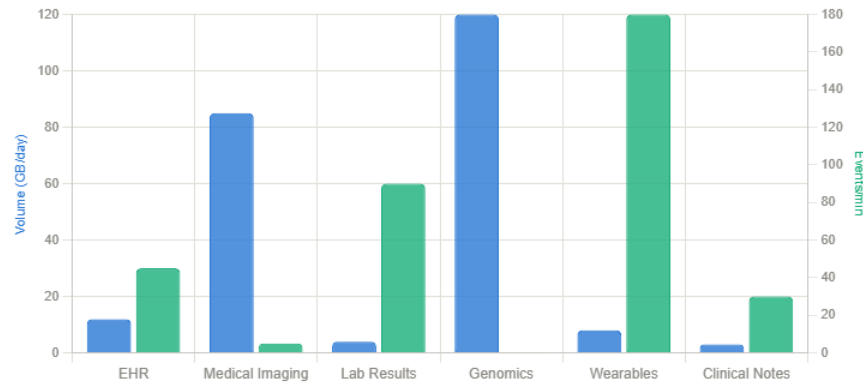


Fig 1: **Data source integration profile** maps the six primary sources (EHR, Imaging, Lab, Genomics, Wearables, Clinical Notes) across two dimensions: data volume and real-time update frequency — reflecting the paper's Section 2A discussion of multi-source ingestion.

A. Interoperability with Clinical Information Systems

Interoperability with clinical information systems—electronic health records (EHR) and decision support tools—facilitates the timely and accurate exchange of clinical data between systems. Timeliness ensures that data arrives as it is created without latency, while accuracy reflects data provenance, trustworthiness, and suitable for clinical inference or alerting. Interoperability standards emerging from HL7 for health care data exchange—Fast Healthcare Interoperability Resources (FHIR), Health Level 7 (HL7), Systematized Nomenclature of Medicine—Clinical Terms (SNOMED CT), Logical Observation Identifiers Names and Codes (LOINC)—help mediate exchange between clinical systems.

2. Temporal Clinical Event

$$e_i = (p_i, c_i, v_i, t_i)$$

Requirements for FHIR-based interoperability mirror requirements for real-time access, data provenance, and governance and supervision. Clinical units should be able to rely on FHIR-based interoperability for their alerting even across different EHR systems. The simple sensor and alert-based model underlying a clinical information system is naturally suited to clinical workflows. Whereas clinical decision support systems typically do not interact with EHRs, the nature of alerting means that, whenever alerts are raised from a knowledge graph instance, the clinical team can receive, evaluate, and act on them in practice.

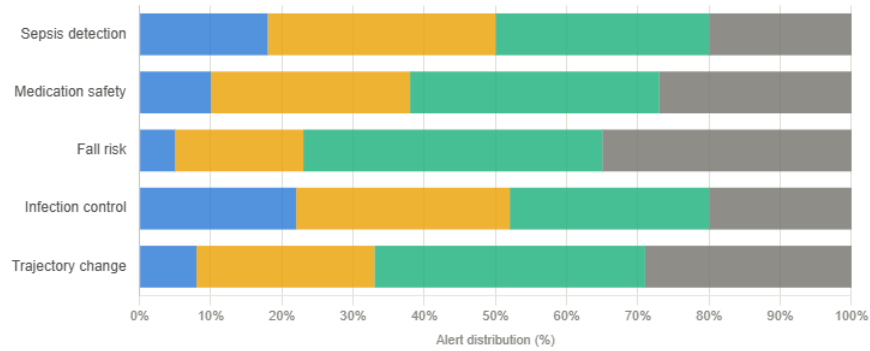


Fig 2: **Alert severity distribution** shows how event-driven clinical alerts (sepsis, medication, fall risk, infection, trajectory) break down by severity level, drawn from Section 3's event-driven inference and alerting framework.

2. Foundations of Knowledge Graphs in Healthcare

Research incorporates patient knowledge graphs to enhance patient safety, achieve real-time clinical decision-making, and enable predictive monitoring and targeted interventions. Successful outcomes hinge on high-quality, trustworthy, focused data.

3. Real-Time Graph Update

$$G_{t+1} = G_t \cup \Delta E_t$$

Considerable volumes of trustworthiness, quality, and real-time awareness would be required to optimally support real-time patient monitoring, decision-making, and predictive care. Definitive statements about the underlying temporal dependencies and causal relationships would point to the emergence and escalation of patient-specific conditions, alerting clinicians along defined paths. Suitable patient-condition-event triples would serve as triggers for alerts, while informative inference-logic rules would stipulate clinician-facing consequences. Clinical workflows frequently make use of alerts, thus offering a familiar frame of reference for rendering a type of real-time patient knowledge graph validatable and verifiable.

4. Event Severity Score

$$S_a = \sum_{i=1}^n w_i x_i$$

Essential data sources encompass electronic health records (EHR), imaging, laboratory test results, wearables, and genomics. Semantic-expression standards (HL7/FHIR for health records, LOINC for tests, SNOMED CT for clinical findings) are thus mapped to a coherent patient-graph ontology. Data ingestion incorporates transformation processes to support manifest semantics. Real-time predictive-monitoring support would emerge from modeling patient-condition-event edges as ternary relations over time-aware entities, with decay functions weighing past-event contributions.

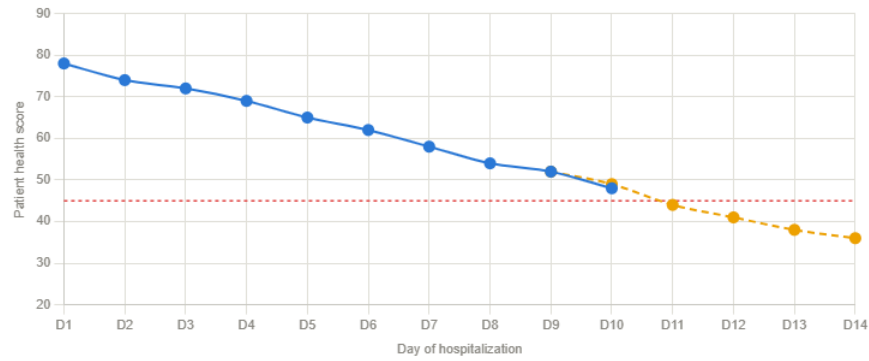


Fig 3: **Temporal trajectory prediction** illustrates how a patient's health score is observed over the first 9 days, then the knowledge graph projects a predicted trajectory across days 9–14, with a risk threshold line — aligning with Section 4A's temporal modeling concepts.

A. Data Sources and Ontologies

Time-aware patient knowledge graphs integrate diverse healthcare data, including clinical, imaging, laboratory, genomic, and sensor information from electronic health records, intelligent wearable devices, and other sources. They support inference-based alerting for real-time clinical decision coordination and serve as templates for machine learning model training. Data populations require automatic semantic alignment, schema mapping, normalization, and quality assurance, with FHIR for electronic health record data and imaging lifting services standardized by the medical imaging data sharing network. Continuous data provenance auditing ensures up-to-date status for all alerts.

5. Risk Prediction Function

$$R_p(t) = f(X_p(t), G_p(t), H_p(t))$$

Event streams deliver messages that represent the occurrence of significant events within the health-care domain. A patient knowledge graph consists of a number of event streams, which are interpreted during the event-driven reasoning process. Each event associated with a given stream represents a fact (relay) within the corresponding patient knowledge graph. An event-driven reasoning mechanism continuously listens for events on the input streams. Upon receipt of one or more events, the reasoning process executes an inference cycle, operating over an appropriate subset of the current graph with respect to the event(s).

7. Patient Trajectory Representation

$$T_p = \{x_1, x_2, \dots, x_t\}$$

Triggers and causal relationships govern which inference rules to apply upon receiving a message from a particular stream. An alert is issued when an inference rule detects that a specified condition has been met. Alerts are typically accompanied by an associated severity level that indicates the priority for resolution. The reasoning process encloses the interactive machine-learning (IML) cycle that identifies which clinician is best suited to address the alert.

Table 1. Healthcare Data Sources for Patient Knowledge Graph Construction

Data Source	Data Type	Standard	Knowledge Graph Entity	Clinical Purpose
Electronic Health Records	Demographics, Diagnoses	HL7 FHIR	Patient, Encounter	Clinical history
Laboratory Systems	Blood tests, Biomarkers	LOINC	Laboratory Observation	Disease monitoring
Medical Imaging	CT, MRI, X-Ray	DICOM	Imaging Study	Diagnostic support
Wearable Devices	Heart Rate, SpO ₂	IEEE 11073	Sensor Event	Continuous monitoring
Genomic Database	DNA Variants	HGVS	Gene Entity	Precision medicine
Medication Records	Prescriptions	RxNorm	Medication Node	Treatment management

4. Predictive Care with Patient Knowledge Graphs

Patient Knowledge Graphs can also help make prognostic predictions about patients. A plethora of machine learning methods exist to predict future values of patients' time-dependent health variables based on their previous trajectories. Machine learning features are computed from the time-dependent health variables in the patients' longitudinal trajectories, and the labels are the future values of the same health variables surrounding the prediction horizon.

8. Alert Trigger Condition

$$A_p = \begin{cases} 1, & R_p(t) \geq \theta \\ 0, & R_p(t) < \theta \end{cases}$$

Predictive modeling with Patient Knowledge Graphs first requires enriching event-driven Patient Knowledge Graphs with time-dependent entities that support the representation of a patient's longitudinal medical history. Time-aware entities comprise time-dependent health variables, which describe the status of patients' internal conditions at each time instant; and temporal edges that characterize time-dependent relationships and interactions of patients with external entities (such as medications or interactions with the healthcare system). The time-dependent health variables, stored in the time-aware entities, provide the target labels of predictive models.

Table 2. Knowledge Graph Ontology Components

Ontology Component Description		Example
Patient Node	Represents patient identity	Patient_ID
Disease Node	Clinical diagnosis	Diabetes
Observation Node	Vital signs or lab values	Blood Pressure
Medication Node	Drug information	Metformin
Laboratory Node	Test reports	HbA1c
Temporal Edge	Time-based relationship	Diagnosed_On
Clinical Event	Hospital admission/discharge	Admission Event
Alert Node	Generated clinical alert	High Risk Alert

A. Temporal Modeling and Trajectory Analysis

Knowledge graphs are not only a schema-agnostic, decoupled information integration architecture but are also a foundation for temporal reasoning. Temporal reasoning is an essential auxiliary feature enabling event-driven inference and beyond since

domain trajectories aggregate distinct event-driven and other time-outdated warnings into non-redundant alerts. By revealing the possible future paths of a patient, trajectory analysis can help identify coming risks or opportunities appealing to clinicians' attention. Patient Knowledge Graphs will directly enable predictive diagnosis by enhancing any temporal modeling approach over EHR snapshots.

9. Clinical Decision Priority

$$P_d = \alpha R_p + \beta S_a + \gamma U_c$$

Knowledge graphs present time-related knowledge with time-aware entities and time-aware edges; each entity contains a time dimension describing its existence duration and each edge can be labeled by its valid period. The relationships between different entities are represented as directed graphs for temporal modeling. Patient trajectories are longitudinal representations of patients moving through time, containing the speed and direction of a moving object. Trajectories with multiple feature levels can be used to define the likelihood of future patients' conditions. Patients' sequential diagnoses or labels can be encoded into longitudinal trajectories to analyze dynamic evolution or transitory. Marker appearance and disappearances can also be utilized as important information to model longitudinal changes of high interest. In summary, temporal modeling and trajectory-based prediction can be treated as time-aware feature engineering, and the Patient Knowledge Graph is capable of generating predictive features with temporal- and trajectory-related knowledge.

Table 3. Event-Driven Clinical Decision Coordination Workflow

Processing Stage	Input	Processing Method	Output
Data Collection	Multi-source healthcare data	Data ingestion	Unified dataset
Semantic Mapping	Clinical records	Ontology alignment	Standardized entities
Knowledge Graph Construction	Standardized entities	Graph generation	Patient graph
Event Detection	Streaming events	Rule engine	Clinical trigger
Reasoning Engine	Trigger events	Graph inference	Risk assessment
Alert Generation	Inference results	Decision support	Physician notification

5. Architecture and Engineering Considerations

Online patient knowledge graphs are routinely populated by increasingly diverse real-time event streams. Designed with decision coordination and predictive care in view, these continually refreshing data products raise considerable architectural and engineering concerns. Candidates include ingestion, transformation, storage, indexing, delivery, and graph update pipelines, all of which must accommodate the schema-less nature of key-value stores. Granular control over event order must be combined with low latency, as well as controlled levels of consistency. Security, including support for privacy-by-design and auditability, must also be considered.

10. Knowledge Graph Embedding Score

$$score(h, r, t) = \phi(h, r, t)$$

Event-driven architecture invites natural horizontal scaling at all levels of data pipelines. Data governance concerns, however, may force constraints that run counter to a rapid-response agenda. Facilitation of New-York-times-style opt-in or opt-out policies for patient-doctor relationships, for example, requires careful management of provenance tracing. As clinical teams delivering care for an individual patient are not typically static over time, the ability to carry patient information across team transitions, and to automatically cease alerting team members no longer actively engaged in a patient's care, becomes crucial.

Table 4. Predictive Analytics Features from Patient Knowledge Graphs

Feature Category	Example Feature	Source	Clinical Significance
Vital Signs	Heart Rate Trend	Wearables	Early deterioration
Laboratory Features	HbA1c	Laboratory	Diabetes monitoring
Medication History	Drug adherence	EHR	Treatment effectiveness
Clinical Events	ICU Admission	Hospital System	Severity estimation
Temporal Features	Disease progression	Knowledge Graph	Risk prediction
Graph Features	Node Centrality	Graph Analytics	Patient complexity

A. Data Integration Pipelines

Data integration pipelines realize the patient knowledge graph's real-time potential from dynamic event streams and information networks. Each incoming knowledge artefact traverses a tailored pipeline for ingestion, transformation, indexing, and



an alert when the condition of a patient satisfies a rule-based condition in an inference knowledge graph.

12. Interoperability Mapping

$$M_s: D_{raw} \rightarrow D_{FHIR}$$

There is a potential impact on clinical outcomes when time-sensitive patient conditions are monitored, or when alerts increase the clinician's awareness of a particular patient condition that had previously been overlooked. Future work includes demonstrating the alerting service, including the capture of event information from the event streams, evaluating the feasibility of defined thresholds and escalation paths, and integrating the alerting service into a novel workflow engine that can coordinate CDSS operational tasks across multiple domains.

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