

Fuel Your Digital Health

Innovation with HL7[®] FHIR[®]

VIVE

2025 02 18

Daniel J. Vreeman, PT, DPT, MS, FACMI, FIAHSI, FHL7

Chief Standards Development Officer

HL7 International

HL7[®]
International



Organizational Profile

Not-for-profit (501c6)

Standards Development Organization

Founded in 1987

ANSI-accredited

Globally trusted

Product Families





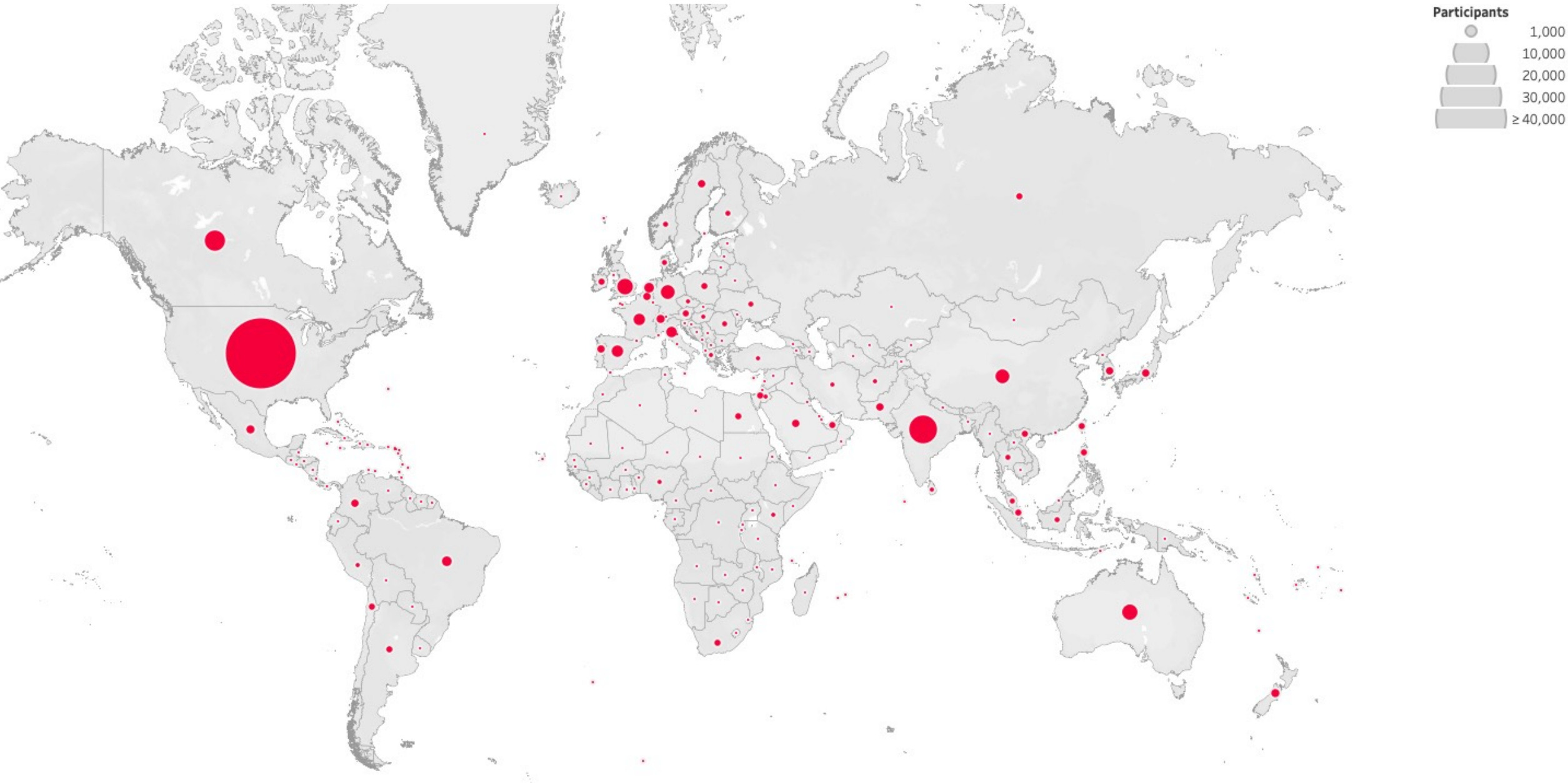
Fast **H**ealthcare **I**nteroperability **R**esources (**FHIR**)

A transformative *open API specification* and *data model* for health information.

Now a decade+ old and a global phenomenon and public good

FHIR: the Web for health data

Propelled by an Active Community Worldwide





Lessons learned the hard way with health data

A close-up, grayscale image of a vintage movie camera. The camera's lens and viewfinder are prominent in the foreground, with a textured metal body. A small circular badge on the top of the camera reads "TURN TO CLEAR VISION". In the background, a blurred city skyline is visible, with the Empire State Building being a notable feature. The overall image has a soft, slightly faded appearance.

Lesson 1:

You're almost certainly *not seeing the full picture.*



41%

of ED visits are for patients *with data at another institution*

Nearly *every ED* in
Indiana shares
patients with *every
other ED* in the state



Fixed with FHIR

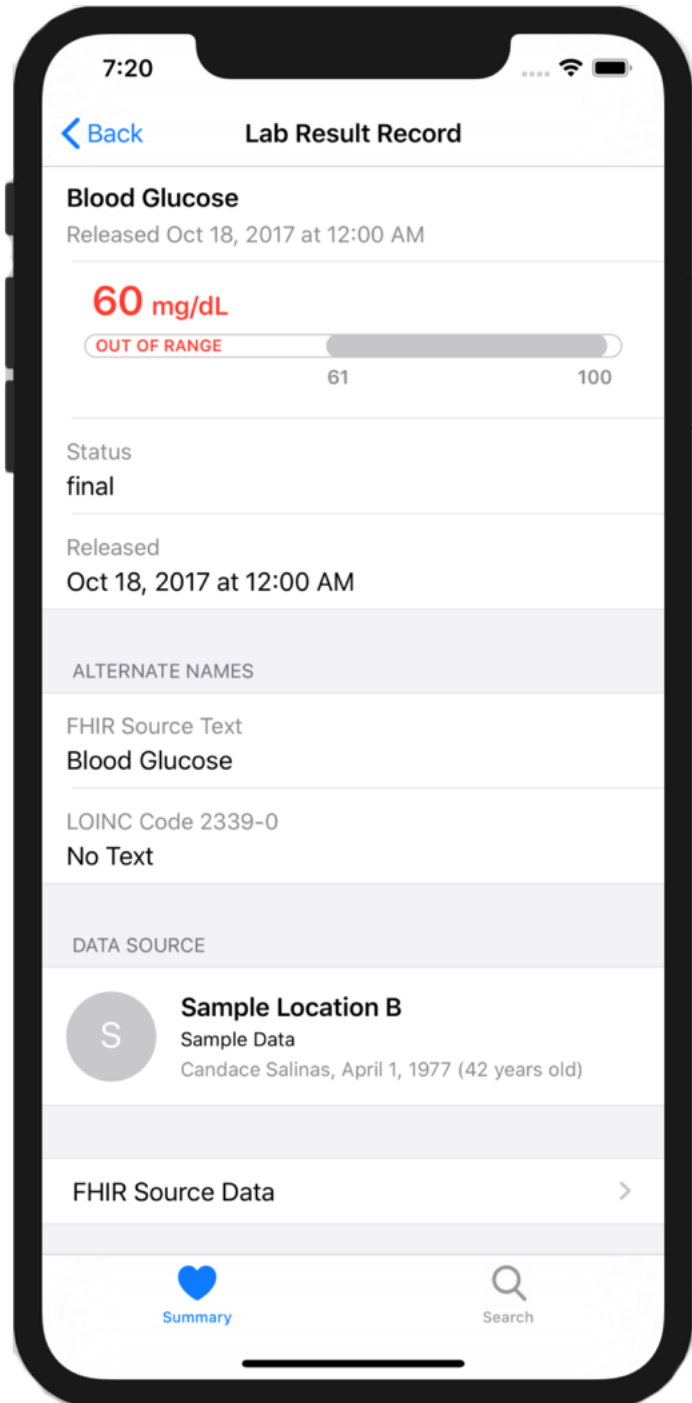


Building a foundation for FHIR-based exchange in the United States

- ONC Cures Act Rule (2020)
- CMS Interop and Patient Access Final Rule (2020)
- ONC HTI-1 Final Rule (2023)
- CMS Interop and Prior Authorization Final Rule (2024)
- Common Agreement 2.0 (2024)

Notice of Proposed Rule Making...

- ONC HTI-2 (2024)



Current Endpoint Metrics



ENDPOINTS LAST QUERIED:
2024-10-07 14:07:27

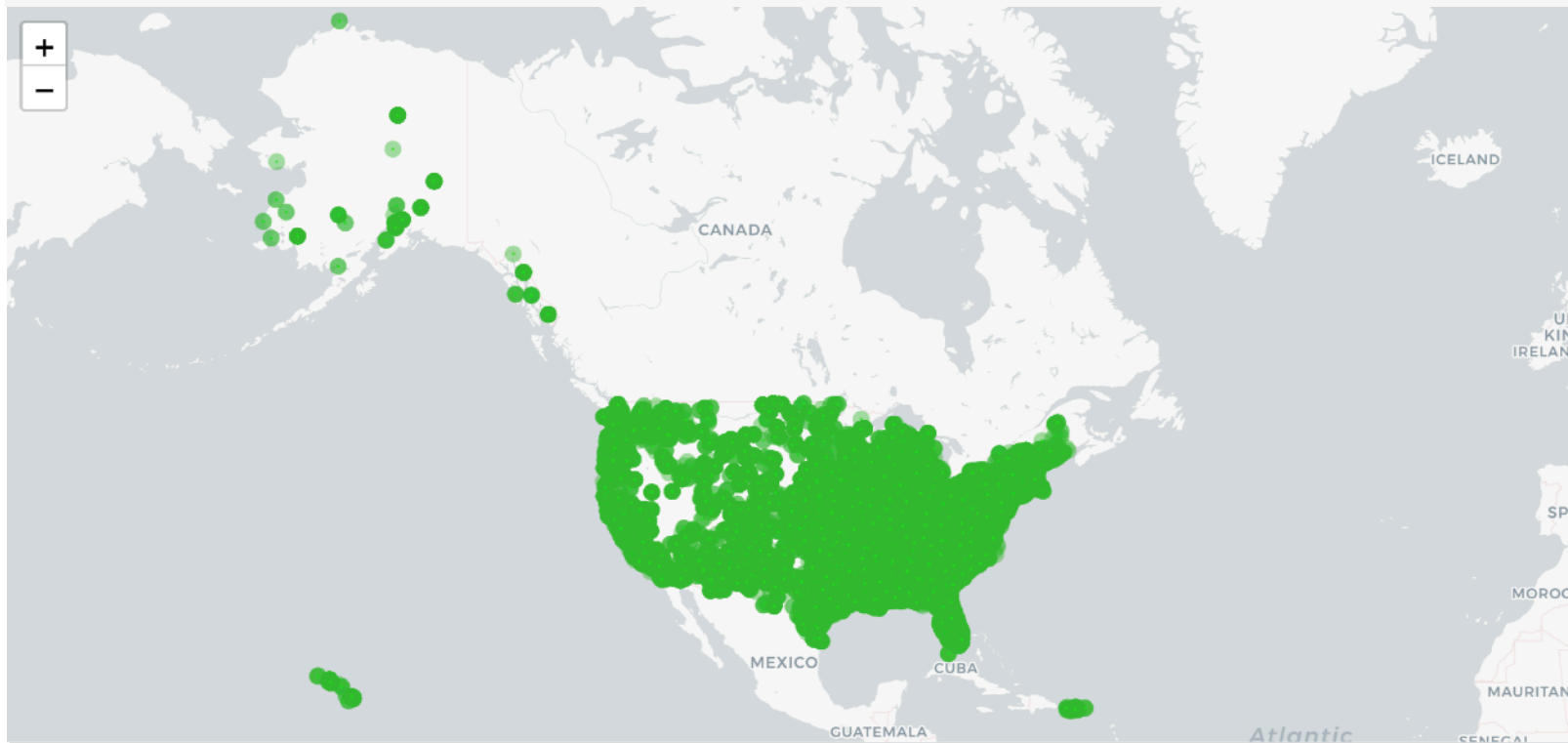
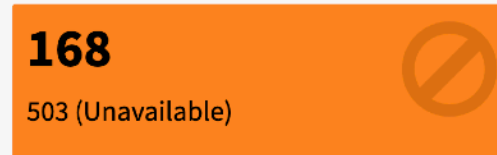
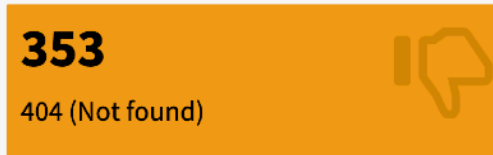


TOTAL ENDPOINTS
34700



INDEXED ENDPOINTS*
34700

Current endpoint responses:



Example Use Cases for FHIR in 2024

Patient Cost
Transparency

Payer Data Exchange

Quality Improvement Core

Adverse Events in
Clinical Research

Central Cancer Registry
Reporting

Digital Insurance Card

Pharmaceutical Quality

Electronic Long-Term
Services and Supports

Value-based Performance
Reporting

Multiple Chronic
Condition Care Plans

SDOH Data Exchange

Electronic Case
Reporting

A woman with long hair is shown in profile, looking towards the right. She is holding a glowing, spherical object in her hands, which appears to be composed of many small, bright particles or data points. The background is dark and filled with out-of-focus light spots, creating a bokeh effect. The overall tone is mysterious and futuristic.

Lesson 2:

AI's magic can sparkle, but insiders know it's ***data work that powers the glow.***

“Everyone wants to do the model work, not the data work”: Data Cascades in High-Stakes AI

Nithya Sambasivan, Shivani Kapania, Hannah Highfill, Diana Akrong, Praveen Paritosh, Lora Aroyo

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Google Research
Mountain View, CA

ABSTRACT

AI models are increasingly applied in high-stakes domains like health and conservation. Data quality carries an elevated significance in high-stakes AI due to its heightened downstream impact, impacting predictions like cancer detection, wildlife poaching, and loan allocations. Paradoxically, data is the most under-valued and de-glamorised aspect of AI. In this paper, we report on data practices in high-stakes AI, from interviews with 53 AI practitioners in India, East and West African countries, and USA. We define, identify, and present empirical evidence on *Data Cascades*—compounding events causing negative, downstream effects from data issues—triggered by conventional AI/ML practices that undervalue data quality. Data cascades are pervasive (92% prevalence), invisible, delayed, but often avoidable. We discuss HCI opportunities in designing and incentivizing data excellence as a first-class citizen of AI, resulting in safer and more robust systems for all.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI.**

lionized work of building novel models and algorithms [46, 125]. Intuitively, AI developers understand that data quality matters, often spending inordinate amounts of time on data tasks [60]. In practice, most organisations fail to create or meet any data quality standards [87], from under-valuing data work vis-a-vis model development.

Under-valuing of data work is common to all of AI development [125]¹. We pay particular attention to undervaluing of data in *high-stakes domains*² that have safety impacts on living beings, due to a few reasons. One, developers are increasingly deploying AI models in complex, humanitarian domains, *e.g.*, in maternal health, road safety, and climate change. Two, poor data quality in high-stakes domains can have outsized effects on vulnerable communities and contexts. As Hiatt *et al.* argue, high-stakes efforts are distinct from serving customers; these projects work with and for populations at risk of a litany of horrors [47]. As an example, poor data practices reduced accuracy in IBM’s cancer treatment AI [115] and led to Google Flu Trends missing the flu peak by 140% [63, 73]). Three, high-stakes AI systems are typically deployed in low-resource contexts with a pronounced lack of readily available, high-quality datasets. Applications span into communities that

“Everyone wants to do the model work, not the data work”:
Data Cascades in High-Stakes AI

Neil S. Davies, Shih-Wei Huang, Hilary J. Dineen, Albert R. Meyer, David J. Foray

Paradoxically, data is the most under-valued and de-glamorised aspect of AI..

An overall lack of recognition for the invisible, arduous, and taken-for-granted data work in AI led to poor data practices, resulting in the data cascades (compounding events causing negative, downstream effects).

CCS CONCEPTS

- **Human-centered computing** → **Empirical studies in HCI.**

[65, 75]). Three, high-stakes AI systems are typically deployed in low-resource contexts with a pronounced lack of readily available, high-quality datasets. Applications span into communities that

Research and Applications

An argument for reporting data standardization procedures in multi-site predictive modeling: case study on the impact of LOINC standardization on model performance

Amie J. Barda,^{1,2} Victor M. Ruiz,^{1,2} Tony Gigliotti³ and Fuchiang (Rich) Tsui^{1,2,4,5,6,7,8,*}

¹Tsui Laboratory, Children's Hospital of Philadelphia, Philadelphia, Pennsylvania, USA, ²Department of Biomedical Informatics, School of Medicine, University of Pittsburgh, Pittsburgh, Pennsylvania, USA, ³Information Services Division, University of Pittsburgh Medical Center, Pittsburgh, Pennsylvania, USA, ⁴Department of Anesthesiology and Critical Care Medicine, Children's Hospital of Philadelphia, Philadelphia, Pennsylvania, USA, ⁵Department of Biomedical and Health Informatics, Children's Hospital of Philadelphia, Philadelphia, Pennsylvania, USA, ⁶Institute for Biomedical Informatics, University of Pennsylvania, Philadelphia, Pennsylvania, USA, ⁷School of Computing Information, University of Pittsburgh, Pittsburgh, Pennsylvania, USA and ⁸Department of Bioengineering, University of Pittsburgh, Pittsburgh, Pennsylvania, USA

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Received 8 September 2018; Revised 22 November 2018; Editorial Decision 10 December 2018; Accepted 20 December 2018

ABSTRACT

Objectives: We aimed to gain a better understanding of how standardization of laboratory data can impact predictive model performance in multi-site datasets. We hypothesized that standardizing local laboratory codes to logical observation identifiers names and codes (LOINC) would produce predictive models that significantly outperform those learned utilizing local laboratory codes.

Materials and Methods: We predicted 30-day hospital readmission for a set of heart failure-specific visits to 13 hospitals from 2008 to 2012. Laboratory test results were extracted and then manually cleaned and mapped to LOINC. We extracted features to summarize laboratory data for each patient and used a training dataset (2008–2011) to learn models using a variety of feature selection techniques and classifiers. We evaluated our hypothesis by comparing model performance on an independent test dataset (2012).

Results: Models that utilized LOINC performed significantly better than models that utilized local laboratory test codes, regardless of the feature selection technique and classifier approach used.

Discussion and Conclusion: We quantitatively demonstrated the positive impact of standardizing multi-site laboratory data to LOINC prior to use in predictive models. We used our findings to argue for the need for detailed reporting of data standardization procedures in predictive modeling, especially in studies leveraging multi-site datasets extracted from electronic health records.

Key words: hospital readmission, heart failure, logical observation identifiers names and codes, predictive modeling, medical informatics/standards

INTRODUCTION

The growing repository of available healthcare data has motivated the healthcare community to improve medical decision-making by integrating knowledge learned from data-driven analyses.^{1,2} Often,

these analyses are geared toward enhancing clinical decision support (CDS) systems with models that predict events of clinical relevance, such as disease risk or progression.² Laboratory data are particularly valuable information in predictive modeling as they can provide in-

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Research and Applications

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Fixed with FHIR

Microsoft, Amazon, other tech giants forge ahead on healthcare data sharing pledge

by James Thorne on · July 30, 2019 at 10:00 am

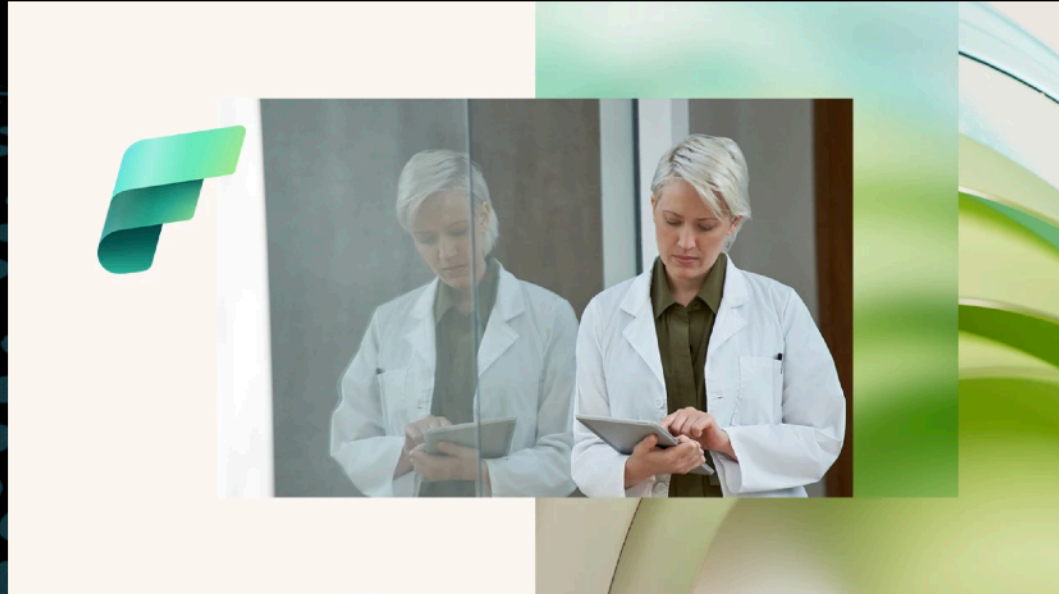


Executives from Amazon, Google, Microsoft and IBM on stage at the CMS Blue Button 2.0 Developer Conference in August 2018. From left: Dean Garfield, Alec Chalmers, Mark Dudman, Peter Lee and Greg Moore. (Microsoft Photo)

This past August, executives from Microsoft, Amazon, Google, IBM, Oracle, and Salesforce **banded together** to promote data sharing in healthcare. Nearly a year later, the world's largest tech companies aren't showing any signs of slowing.

Cloud providers ❤️ FHIR

Big tech vendors were early voluntary adopters and now all have FHIR in their health data solutions



[Healthcare](#) [News and announcements](#) · 7 min read

Power healthcare AI with unified and protected multi-modal healthcare data

By [Umesh Rustogi](#), General Manager, Microsoft Health and Life Sciences Data Platform

October 10, 2024



Announcing general availability of healthcare data solutions in Microsoft Fabric and public preview of healthcare application templates in Microsoft Purview.

Tags



Here are some of the capabilities being released in preview:

Fast Healthcare Interoperability Resources (FHIR) data ingestion. Enables easy ingestion of FHIR data from [Azure Health Data Services](#) in Microsoft Fabric Onelake environment and stores it in the bronze lakehouse as raw newline-delimited JavaScript object notation (NDJSON) files.

Relational FHIR data foundation enables the transformation of FHIR data in bronze to relational FHIR and tabular structure in open data format (delta-parquet) in Silver Lakehouse using highly scalable purpose-built pipelines. This creates a standard-based unified healthcare data model in Silver Data Lake. With support for all FHIR R4 resources, this now enables multiple downstream analytics support for scenarios leveraging the rich clinical, financial (claims and explanation of benefits), and administration data. Healthcare companies and partners can now build analytical scenarios such as quality reporting, population health management, clinical research studies, and operational reporting. It also allows a traditional SQL engine to run on top of the data for a data analyst to conduct ad-hoc exploratory analysis of the healthcare data.



HL7 Product Portfolio



The extended FHIR family unlocks a massive world of opportunity

SMART on FHIR | Bulk FHIR | CQL | CDS Hooks

Cheat Codes for Digital Innovation



Semantically interoperable health data at scale



SMART App
Launch

Standard integration for apps interacting with FHIR data



Bulk

Simple export of big FHIR data (e.g. for model training)



CDS Hooks

Workflow-integrated interaction with CDS (including AI)



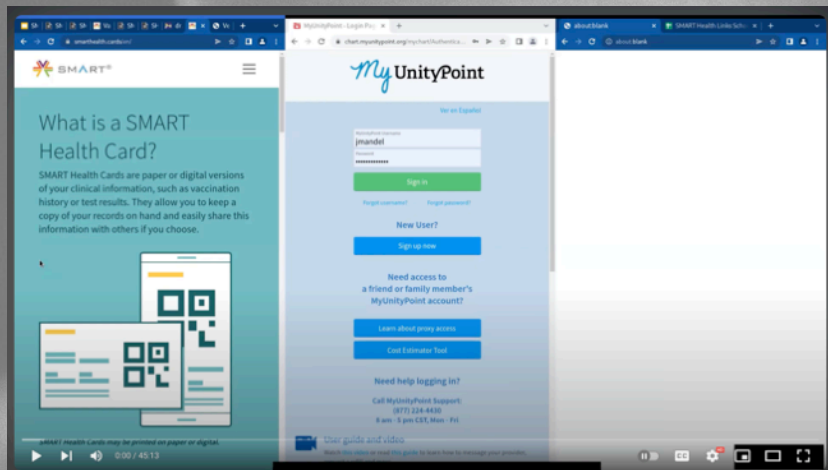
CQL

Standardized clinical knowledge and metrics

Keep your eyes on this:

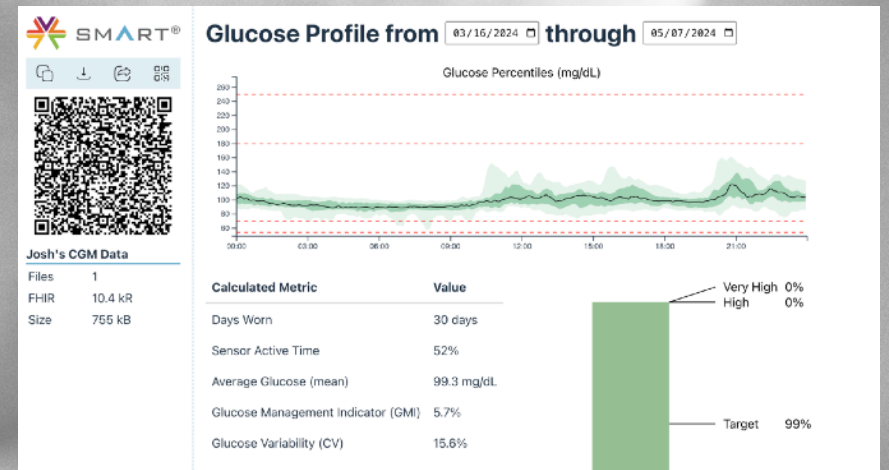
HL7 SMART Health Cards and Links

September 2024 Ballot Cycle → anticipated publishing in 2025



The screenshot shows a video player with three browser windows. The first window displays the SMART Health Card overview, explaining that these cards are digital versions of clinical information like vaccination history or test results. The second window shows the MyUnityPoint login page with fields for username and password, and options for new users or family members. The third window is partially visible on the right.

SMART Health Links Overview Video



The screenshot displays a public SHL demo for 'Josh's CGM Data'. It includes a SMART logo, a QR code, and a glucose profile chart showing glucose levels (mg/dL) over time from 03/16/2024 to 05/07/2024. The chart has a target range and a 'Very High' threshold. Below the chart is a table of calculated metrics.

Calculated Metric	Value
Days Worn	30 days
Sensor Active Time	52%
Average Glucose (mean)	99.3 mg/dL
Glucose Management Indicator (GMI)	5.7%
Glucose Variability (CV)	15.6%

J Mandel's public SHL Demo of CGM Data

Endless Possibilities

ZERO TO ONE | PETER THIEL | Virgin Business

EGO IS THE ENEMY RYAN HOLIDAY P

RYAN HOLIDAY THE OBSTACLE IS THE WAY
The Timeless Art of Turning Trials into Triumph
PORTFOLIO PENGUIN

EXPONENTIAL ORGANIZATIONS ISMAIL, MALONE & VAN GEEST
DIVERSION BOARDS

Value Proposition Design
WILEY

THE STARTUP OWNER'S MANUAL
Steve Blank Bob Dorf

The corporate startup
Tendayi Viki Dan Toma Esther Gons



HL7[®] FHIR[®]

5 Key Resources for Implementers

Connect | Discover | Build on | Test | Learn

Connect: join the FHIR community online

The screenshot shows the chat.fhir.org web interface. At the top, the browser address bar displays 'chat.fhir.org'. The page header includes a 'Recent conversations' title, a search bar, and utility icons. A left sidebar lists various channels, with 'Active' channels highlighted. The main content area is a table of recent conversations with columns for Channel, Topic, Participants, and Time.

Channel	Topic	Participants	Time
committers/notification	ig-build		6 minutes ago
IG creation	unknown NamingSystemIdentifierType code '?'		9 minutes ago
australia	AU eRequest		17 minutes ago
shorthand	pattern auto-population introduces duplicates		40 minutes ago
implementers	Longest Observation	+3	42 minutes ago
cql	function ToString(CodeableConcept)		46 minutes ago
implementers	OperationOutcome code/details for specific use cases		49 minutes ago
V2	ACK handling		56 minutes ago
tooling/Package Crawlers	stream events		An hour ago
Da Vinci	Claim Response service place		An hour ago

Discover: find FHIR specifications



About FHIR

FHIR Packages

Publish a Package

Refine package results

Latest release ?

Only FHIR Versions

- R5
- R4B
- R4
- STU3
- DSTU2

[clear filter](#)

Find matching contents by ?

- Instances
- Profiles

Only in jurisdictions

- Australia
- Belgium

prior authorization



75 results found in 325 ms

POWERED BY SIMPLIFIER.NET

http://hl7.org/fhir/us/davinci-pas • hl7.fhir.us.davinci-pas

R4

Da Vinci Prior Authorization Support (PAS) FHIR IG

2.0.1

December 2023

HL7 International / Financial Management

Guidelines for conveying coverage requirements to clinicians when planning treatment. (built Fri, Dec 1, 2023 20:54+0000+00:00)

Showing first 4 matches:

StructureDefinition AuthorizationNumber

ImplementationGuide DaVinciPriorAuthorizationSupport

Bundle ReferralAuthorizationBundleExample

Bundle HomecareAuthorizationBundleExample

Build on: use open source reference implementations

The screenshot shows the Foundry website at foundry.hl7.org. The page features a navigation bar with "About Foundry", "Catalog", and "Developer" links. A search bar is visible on the left. The main content area displays a grid of project cards, each representing an open source reference implementation. The cards are:

- FAST - UDAP Security Server**: A server reference implementation for the FAST Security for Scalable Registration, Authentication, and Authorization Implementation Guide. It includes a link to a GitHub repository for a Duende Identity Server reference implementation.
- SMART Bulk Data CLI Client**: An open-source, NodeJS command line interface for making bulk data requests against FHIR servers implementing the [FHIR Bulk Data API].
- Documentation Template and Rules (DTR) Examples CDS Library**: A library of Clinical Decision Support Rules (CDS) to support the CRD, DTR, and PAS use cases.
- Genomic Operations Examples and Exercises**: A section providing scenarios that demonstrate various capabilities of the FHIR Genomics Operations, including a link to a GitHub repository for a postman collection.

The page also includes a sidebar with filters for Technology (FHIR Servers, FHIR Clients, Data & Scripts, CQL Libraries, Other), Badges (HL7 Accelerators like Argonaut, CARIN Alliance, CodeX, Da Vinci, FAST, Helios), Function (Directories, Financial, Infrastructure), World Regions (United States), and Domains (Genomics).

Build on: many other open source tools

Reference Libraries

JAVA

.Net

Delphi

R

Ruby

Python

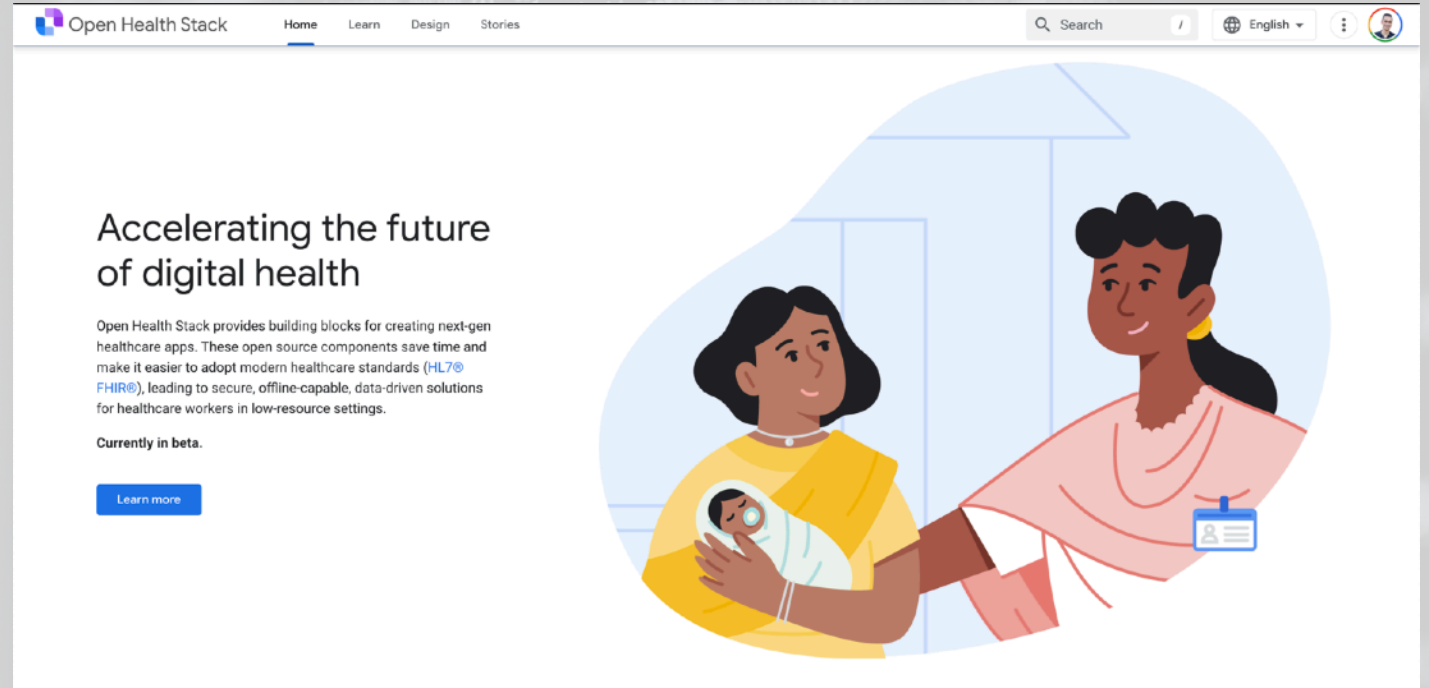
Swift

PHP

Dart/Flutter

Android

Clojure




Example: Open Health Stack

FHIR SDK for Android

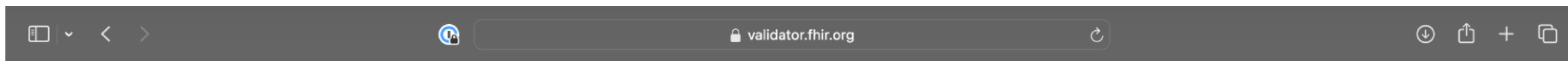
Offline-capable, mobile-first FHIR toolkit (including CQL!) allows developers to create applications helping community health workers in LMICs.

FHIR Analytics

Turn FHIR data into analytics-ready formats for on-prem or cloud processing

 Open Health Stack

Test: validate your FHIR content



Validate Options

Language
English
● tx.fhir.org
● packages2.fhir.org

Validate Resources

Manually enter, or upload resources for validation.

ENTER RESOURCE

UPLOAD RESOURCES

Code

```
{
  "resourceType": "Observation",
  "id": "cbc-hematocrit",
  "meta": {
    "profile": ["http://hl7.org/fhir/us/core/StructureDefinition/us-core-observation-lab"]
  },
  "status": "final",
  "category": [{
    "coding": [{
      "system": "http://terminology.hl7.org/CodeSystem/observation-category",
      "code": "laboratory",
      "display": "Laboratory"
    }],
    "text": "Laboratory"
  }],
  "code": {
    "coding": [{
      "system": "http://terminology.hl7.org/CodeSystem/observation-category",
      "code": "laboratory",
      "display": "Laboratory"
    }],
    "text": "Laboratory"
  }
}
```

| **Learn:** advance *your* FHIR expertise

Education

On Demand

Virtual training events

In person training

Credentialing

Showcase your FHIR knowledge

Helps hirers find qualified people

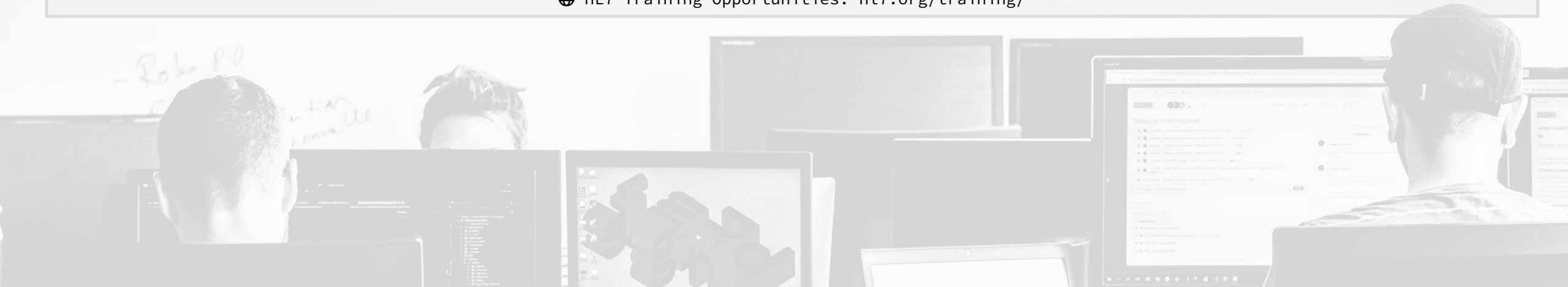
Events

HL7 Work Group Meetings

HL7 FHIR Connectathons

DevDays

🌐 HL7 Training Opportunities: hl7.org/training/



Take Home Messages

Why HL7[®] FHIR[®] ?

Accelerated development

Find top talent

Reduce dev costs

Interoperability + ease of integration

Regulatory compliance

Market access and scalability

Free to focus on innovation

**Let FHIR be the rocket fuel
for your health innovations**

