Fuel Your Digital Health Innovation with HL7® FHIR®

VIVE

2025 02 18

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Chief Standards Development Officer
HL7 International

HL7® International

HL7® International

Organizational Profile

- Not-for-profit (501c6)
- Standards Development Organization
- Founded in 1987
- ANSI-accredited
- Globally trusted

Product Families

- HL7® FHIR®
- HL7® CDA®
- HL7® V2™

HL7® FHIR®
An HL7 International Standard℠

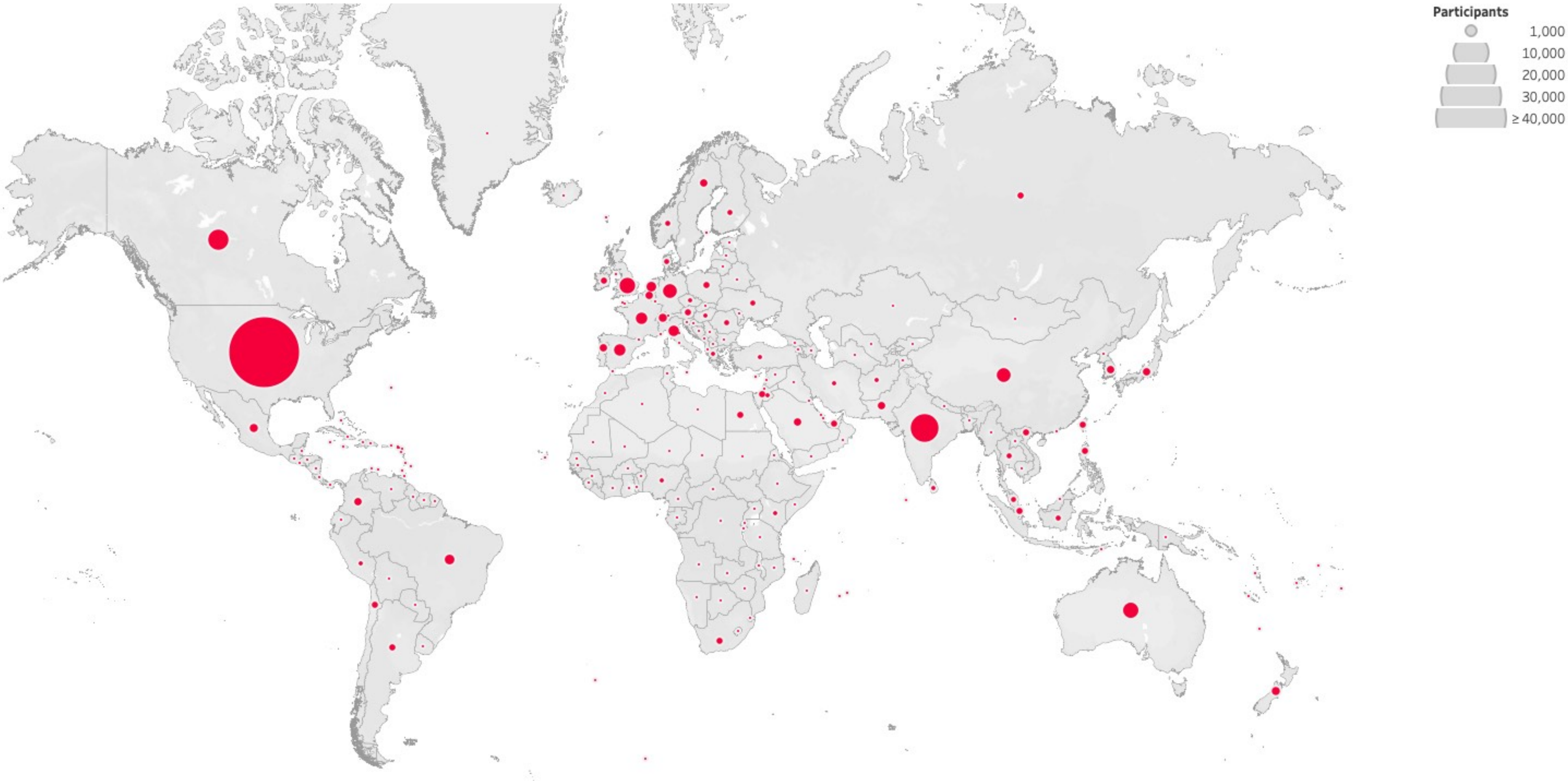
Fast **H**ealthcare **I**nteroperability **R**esources (**FHIR**)

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

Lesson 1:

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


41%
of ED visits are for patients ***with data at another institution***
PMID: 22195094
MEDIC 05
WISHARD
Emergency Medical Services

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

PMID: 22195094

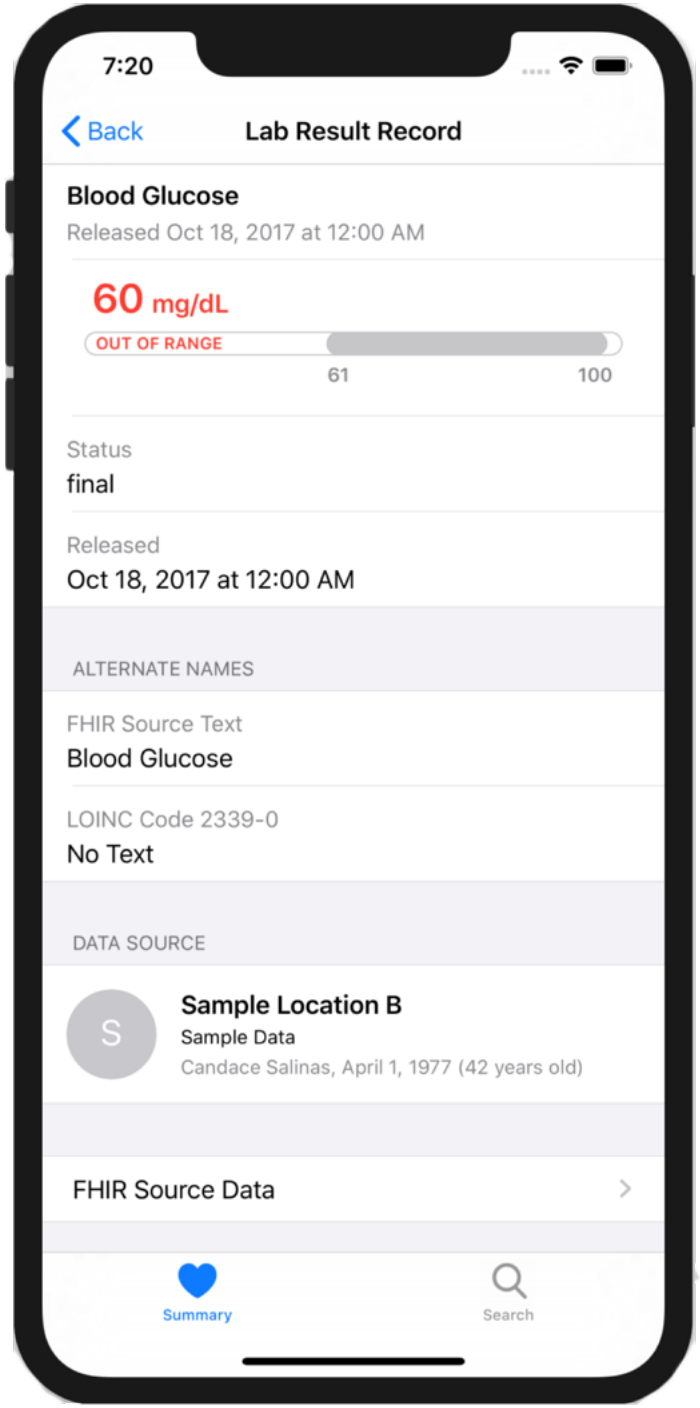

Fixed with FHIR

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

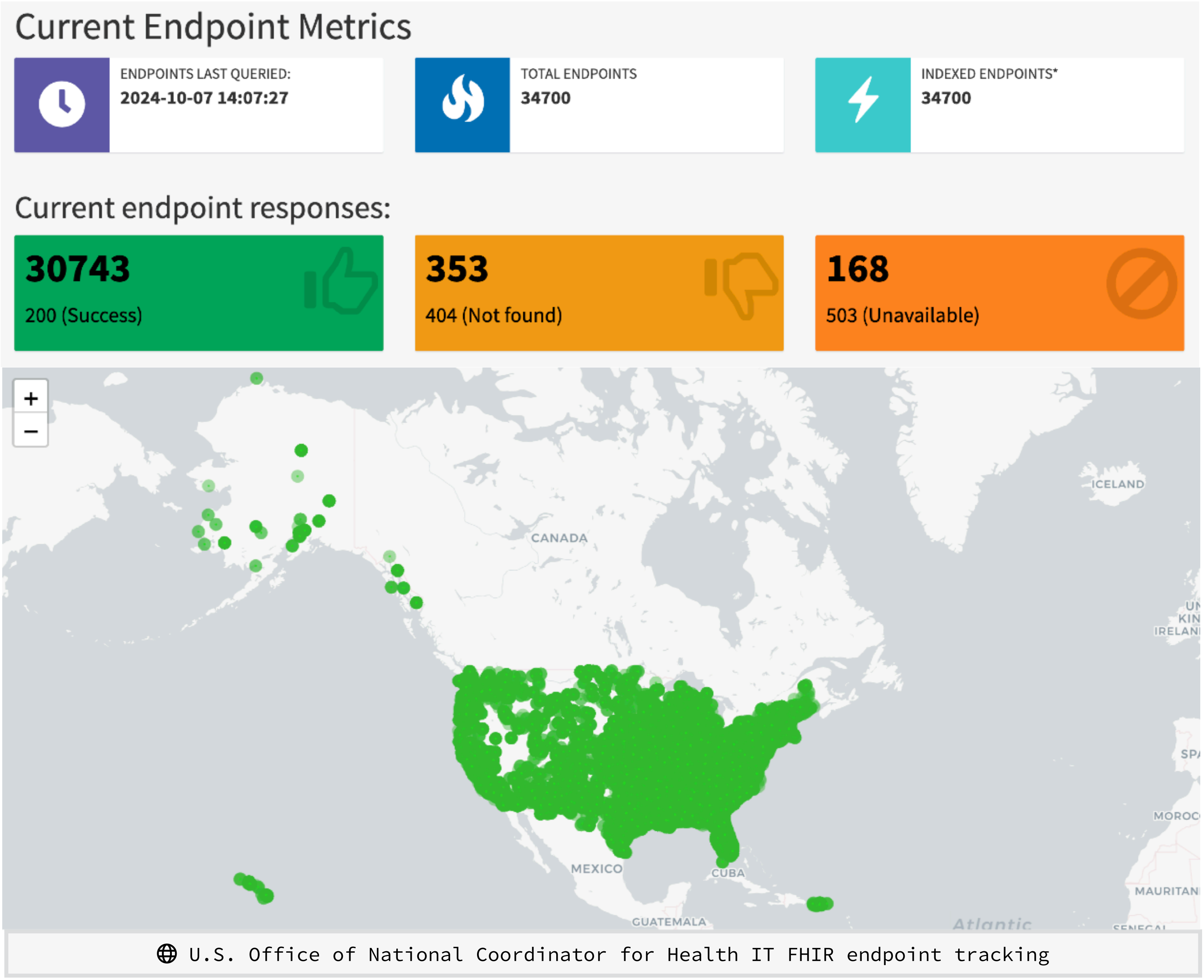
- ONC Cures Act Rule (2020)
- CMS Interop and Patient Access Final Rule (2020)
- ONC HTI-1 Final Rule (2023)
- CMS Interop and Prior Authorization Final Rule (2024)
- Common Agreement 2.0 (2024)

Notice of Proposed Rule Making…

- ONC HTI-2 (2024)



7:20
Back
Lab Result Record
Blood Glucose
Released Oct 18, 2017 at 12:00 AM
60 mg/dL
OUT OF RANGE
61
100
Status
final
Released
Oct 18, 2017 at 12:00 AM
ALTERNATE NAMES
FHIR Source Text
Blood Glucose
LOINC Code 2339-0
No Text
DATA SOURCE
S
Sample Location B
Sample Data
Candace Salinas, April 1, 1977 (42 years old)
FHIR Source Data
Summary
Search



Current Endpoint Metrics
ENDPOINTS LAST QUERIED:
2024-10-07 14:07:27
TOTAL ENDPOINTS
34700
INDEXED ENDPOINTS*
34700
Current endpoint responses:
30743
200 (Success)
353
404 (Not found)
168
503 (Unavailable)
ICELAND
CANADA
MEXICO
CUBA
GUATEMALA
Atlantic
U.S. Office of National Coordinator for Health IT FHIR endpoint tracking

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

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

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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

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

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).

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Research and Applications

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

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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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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

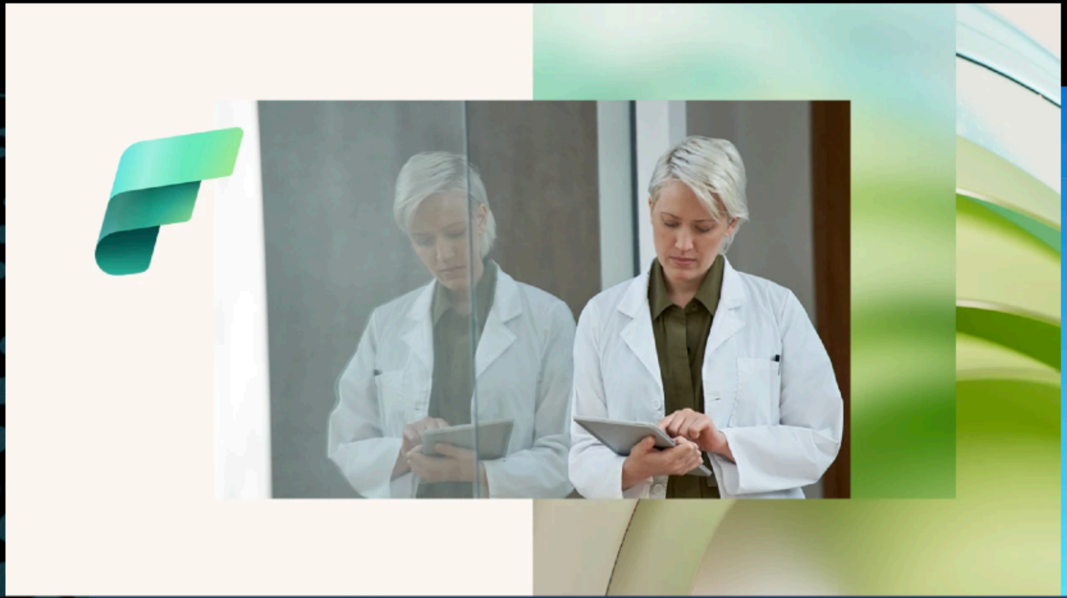
Executives from Amazon, Google, Microsoft and IBM on stage at the CMS Blue Button 2.0 Developer Conference in August 2018. From left: Dean Garfield, Alec Chalmers, Mark Dudman, Peter Lee and Greg Moore. (Microsoft Photo)

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

Geekwire coverage of White House Pledge



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)

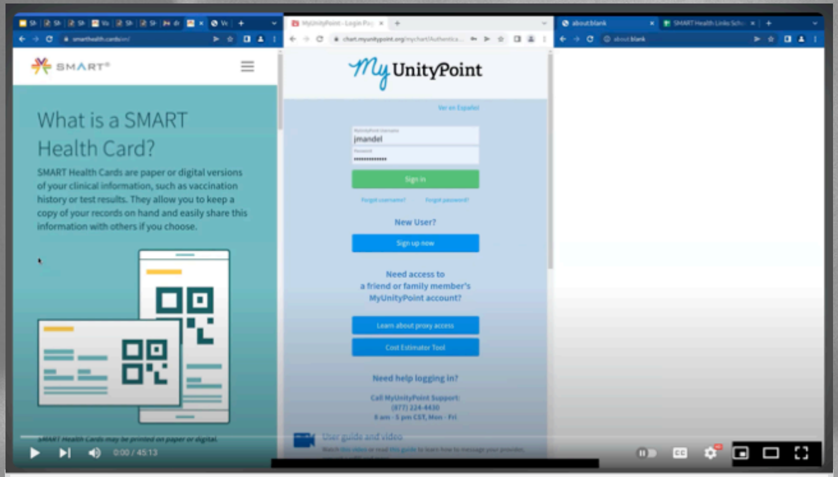
CQL

Standardized clinical knowledge and metrics

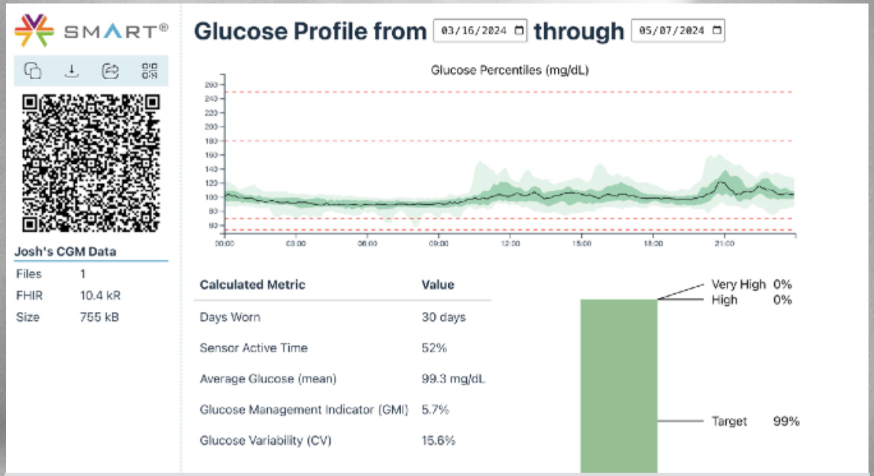
Keep your eyes on this:

HL7 SMART Health Cards and Links

September 2024 Ballot Cycle ➔ anticipated publishing in 2025



SMART Health Links Overview Video



J Mandel's public SHL Demo of CGM Data

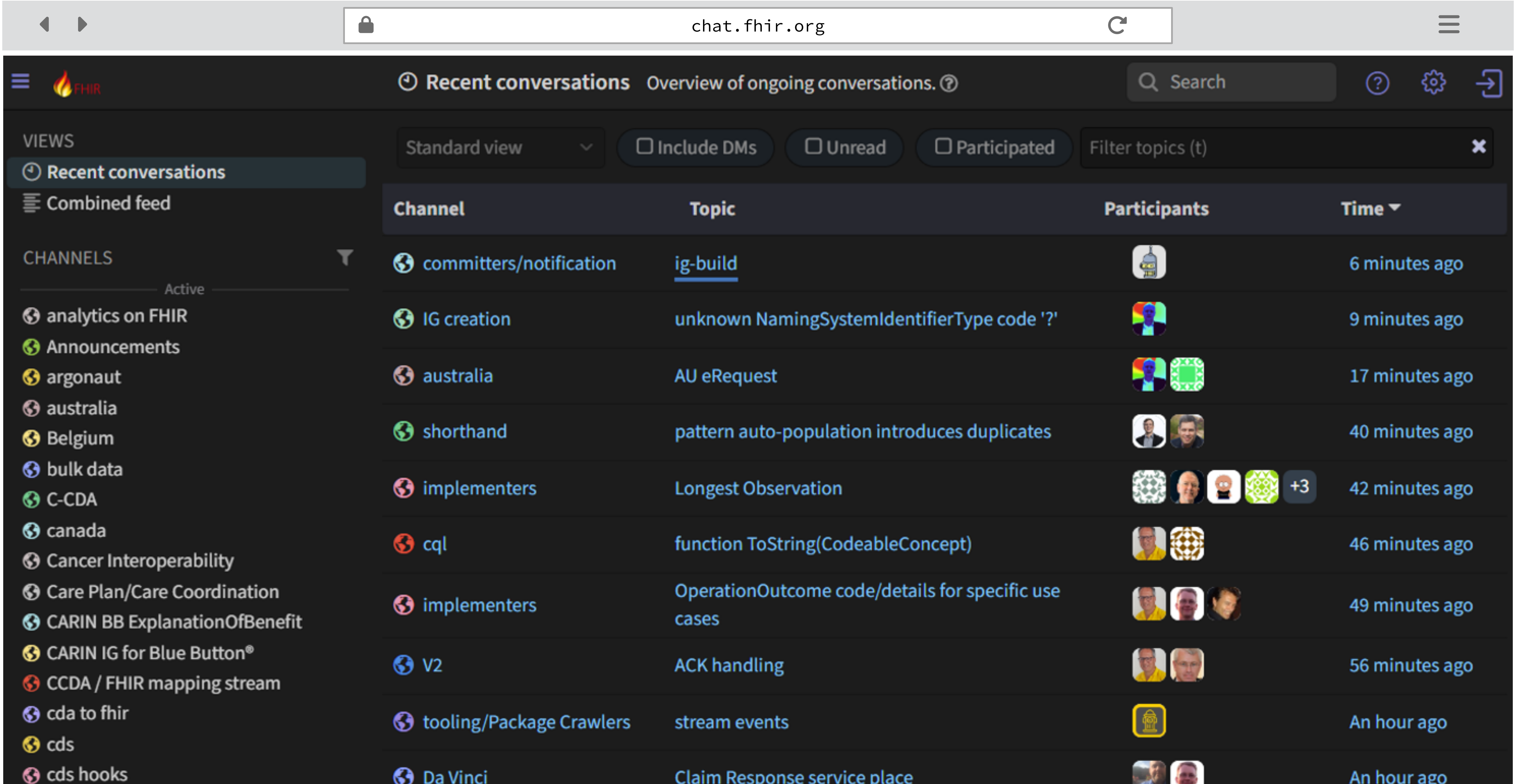
Endless Possibilities

HL7® FHIR®

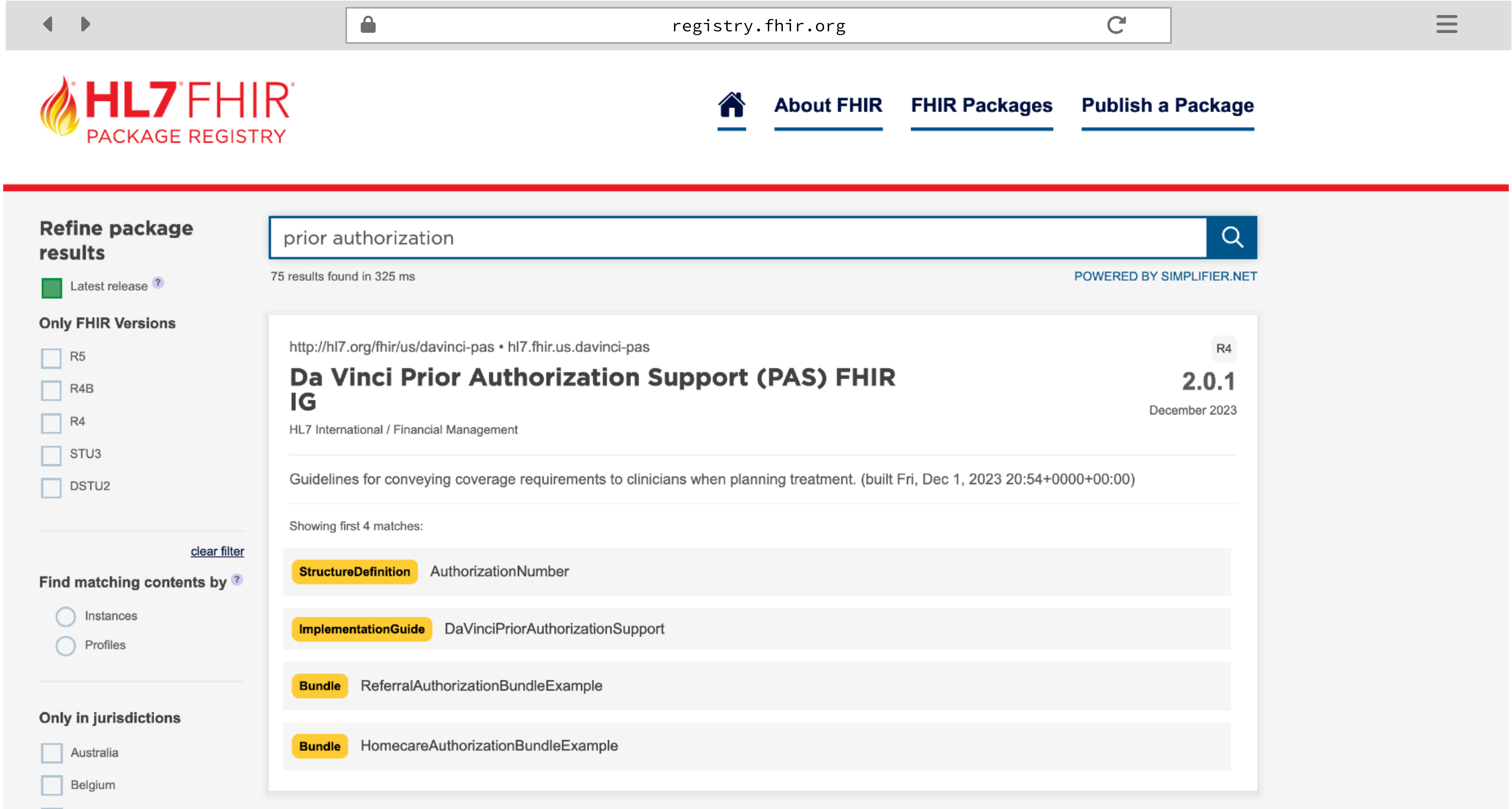
5 Key Resources for Implementers

Connect | Discover | Build on | Test | Learn

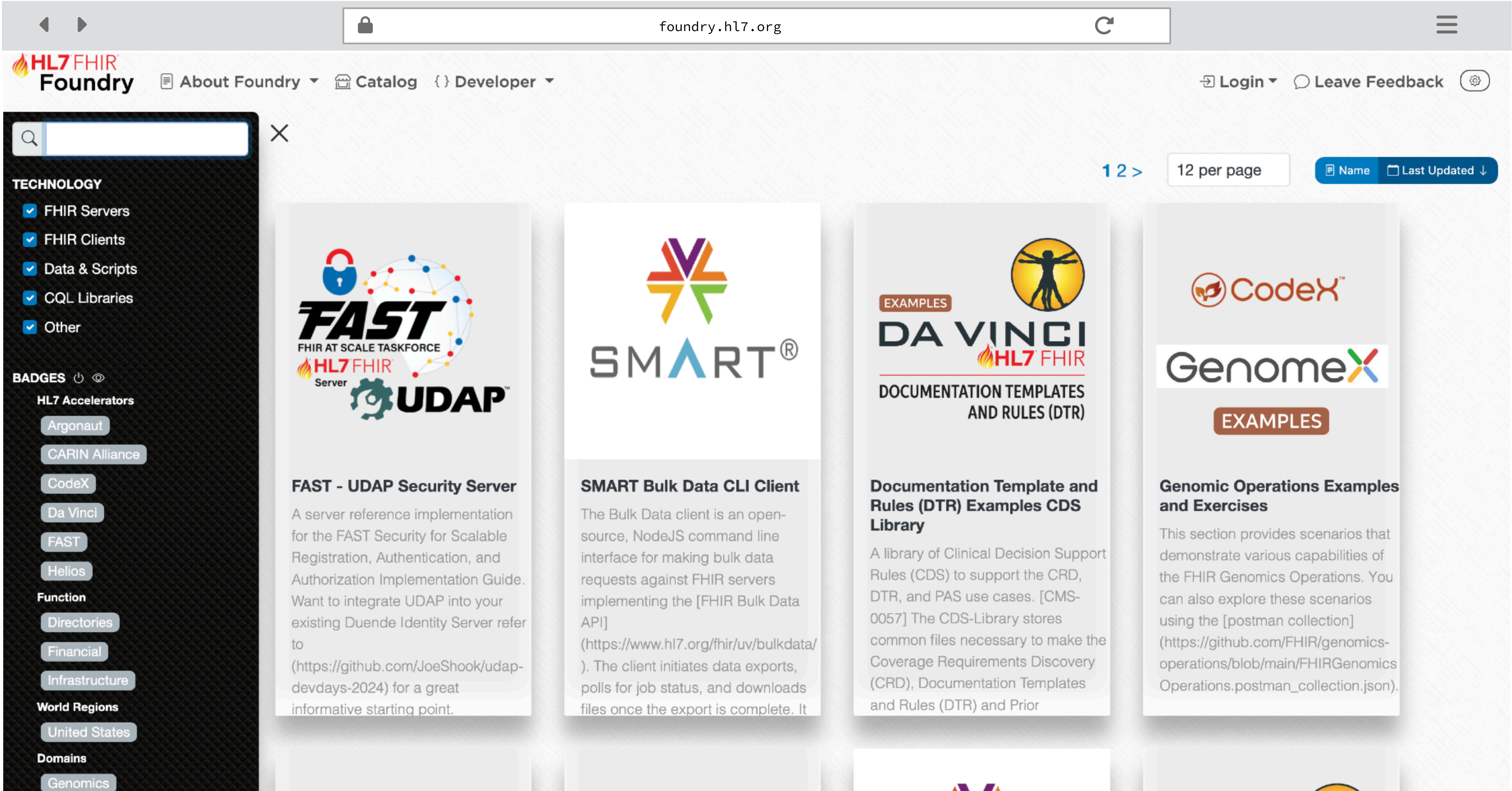
| **Connect:** join the FHIR community online



Discover: find FHIR specifications



Build on: use open source reference implementations



| **Build on:** many other open source tools

Reference Libraries

JAVA

.Net

Delphi

R

Ruby

Python

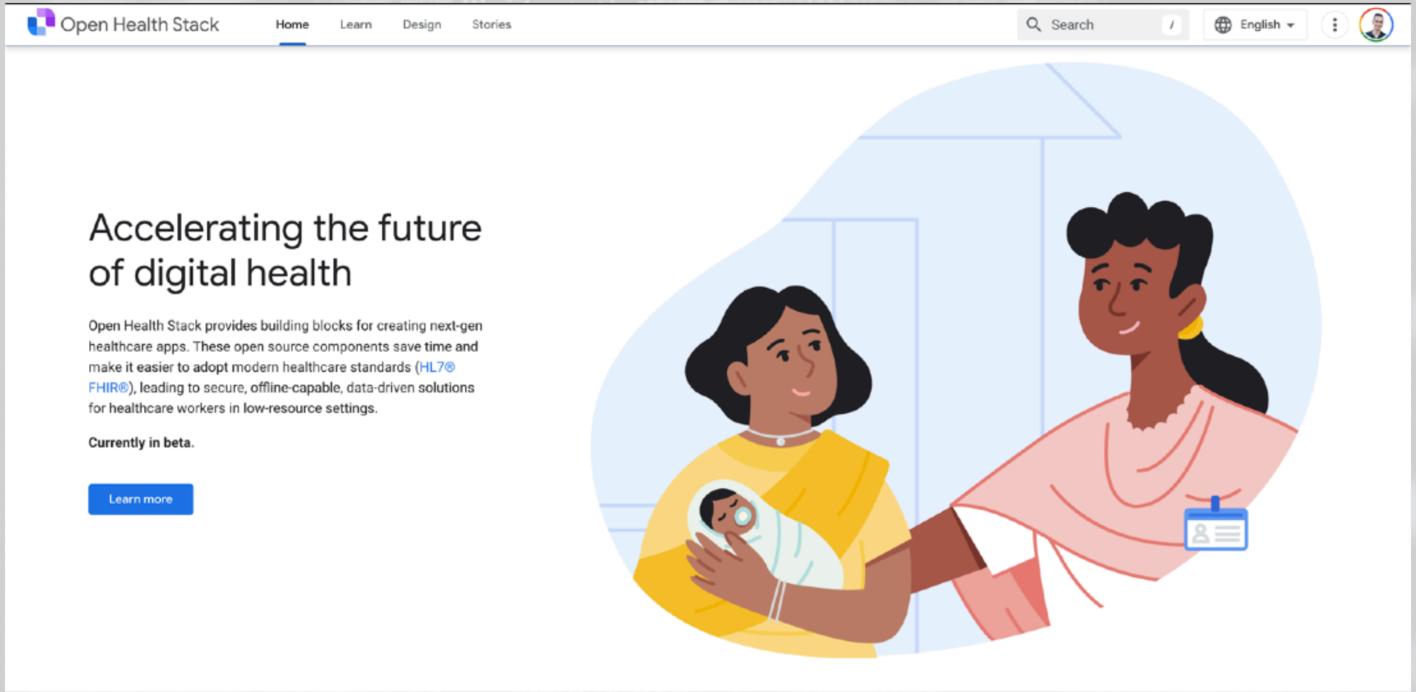
Swift

PHP

Dart/Flutter

Android

Clojure



Example: Open Health Stack

FHIR SDK for Android

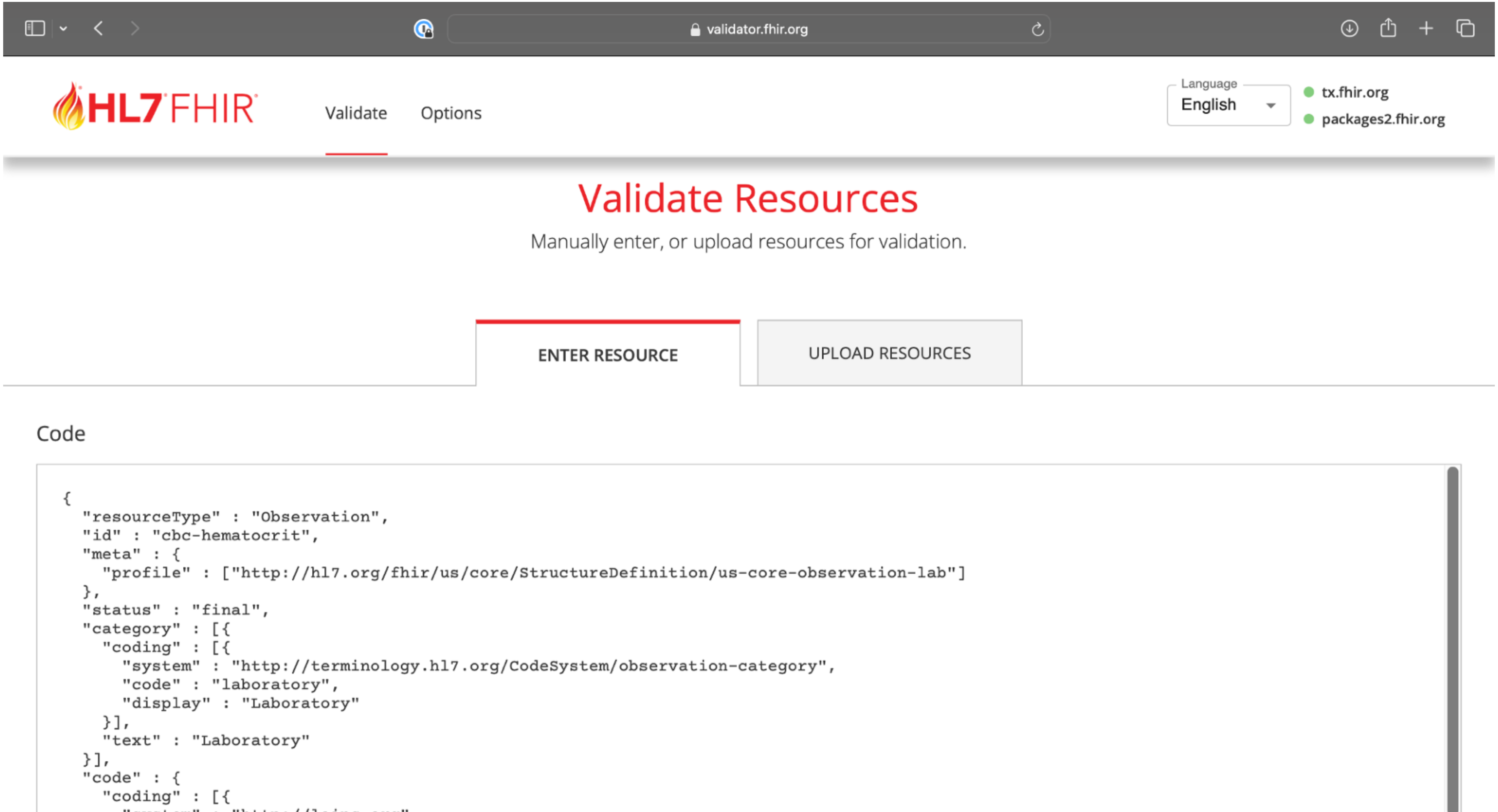
Offline-capable, mobile-first FHIR toolkit (including CQL!) allows developers to create applications helping community health workers in LMICs.

FHIR Analytics

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

Open Health Stack

| **Test:** validate your FHIR content



| **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