AMIA 2020 Virtual Clinical Informatics Conference

Visual Abstracts Collection

MAY 19-21

#CIC20

Clinical Decision Support and Analytics

Artificial Intelligence/Machine Learning

Adaptive Clinical Decision Support

Data Sciences

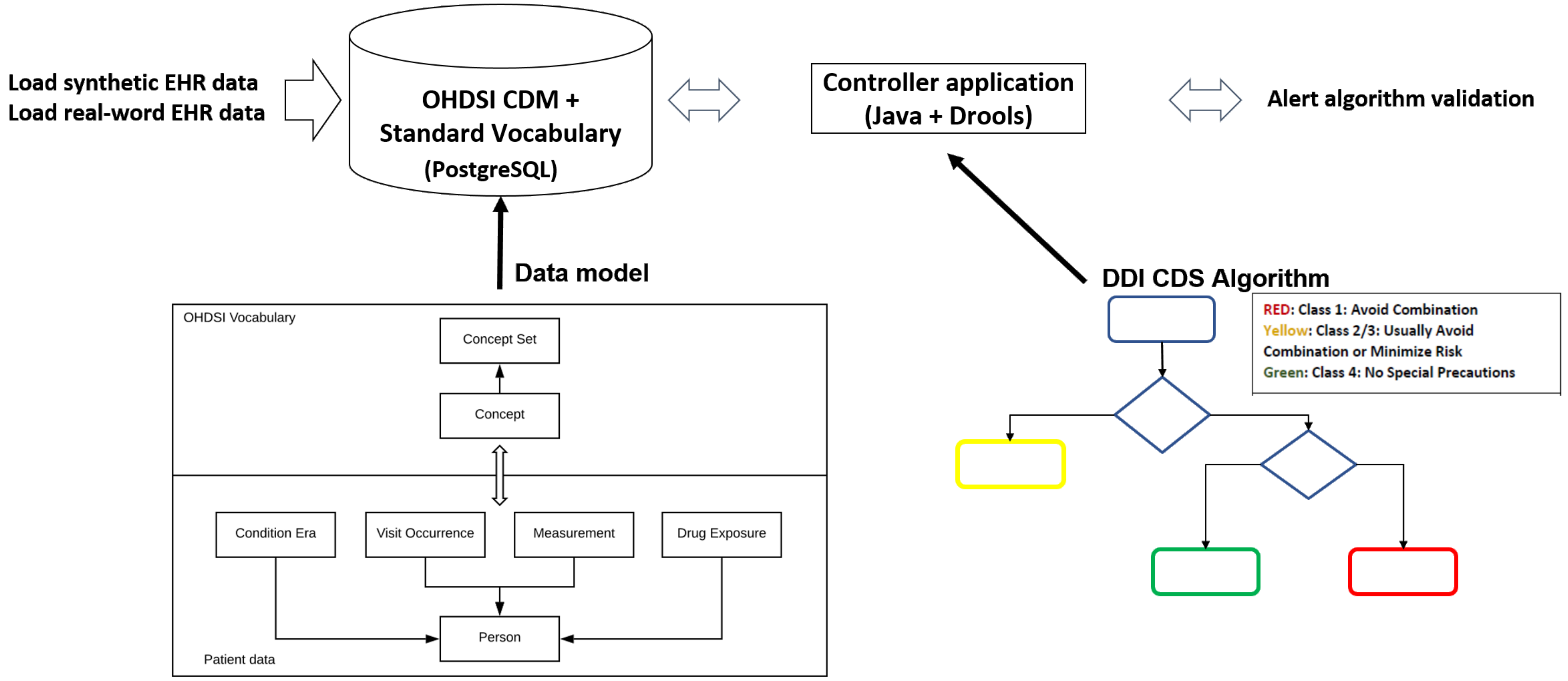
Data Visualization

Governance

Healthcare Big Data Analytics

Precision Health and Genomics

Designing and Evaluating Contextualized Drug-Drug Interaction Algorithms



HIVASSIST

www.hivassist.com

Validation and Impact of **HIV-ASSIST**, an Online Educational Clinical Decision Support Tool to Guide Patient-centered HIV Care

Manoj Maddali, MD[1], Maunank Shah, MD PhD[2]

[1]Department of Medicine, University of California San Francisco, San Francisco, CA. [2]Division of Infectious Diseases, Department of Medicine, Johns Hopkins University, Baltimore, MD.

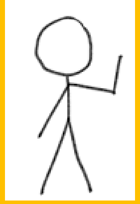
HIV-ASSIST uses multi-criteria decision analysis

Patient

(CD4,comorbidities)

Virus

(Viral load, genotype)



+

+

Pill burden,
Drug interactions
Treatment history

Evaluate against:

- Tolerability (pills, comorbidities)
- Effectiveness (viral suppression)

Ranked ARV recommendations with educational content

HIV-ASSIST improves appropriate selection of HIV Treatment

Treatment choices concordant with HIV experts

HIV-ASSIST

90% appropriate

Guidelines

40% appropriate

Randomized Trial of 118 trainees given HIV-ASSIST or National Clinical Practice Guidelines

HIV-ASSIST provides accurate Patient specific recommendations

84-99% concordant with **HIV experts** at UCSF, Harvard, and Johns Hopkins for both **simple and complex HIV clinical scenarios**

Maddali et al. *JAIDS.* Oct 2019
Ramirez et al. *JGIM.* Dec 2019
Ramirez et al. *CID.* March 2020

UCSF University of California San Francisco

JOHNS HOPKINS MEDICINE

VA

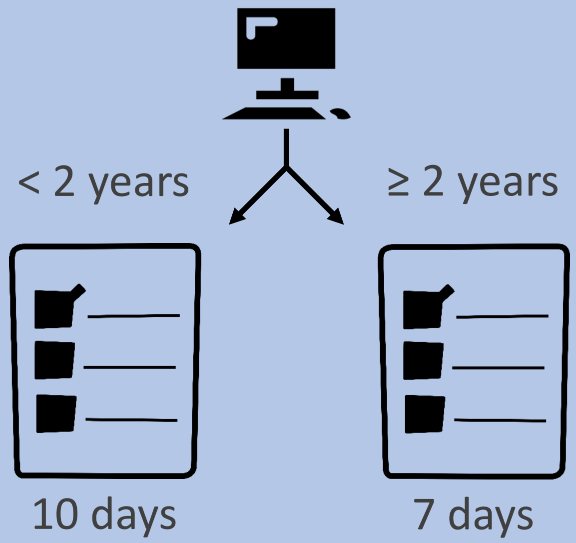
Improved Prescribing of Appropriate Antibiotic Duration for Acute Otitis Media in the Pediatric Emergency Department with a CDS Intervention

Study Population

Single Pediatric Emergency Department

Patients ≥ 2 years, diagnosed with otitis media, & prescribed an antibiotic

Intervention

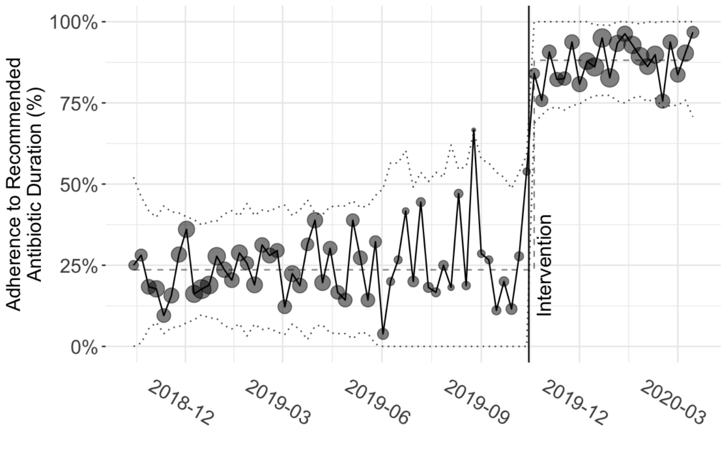


Age-based dynamic order set with preferred default antibiotic duration

Outcomes

Adherence to Duration Recommendations - Centerline Shift

- Pre-intervention: 24%
- Post-intervention: 88%



Estimated Antibiotic Days Saved over 5 Months: > 2600 days

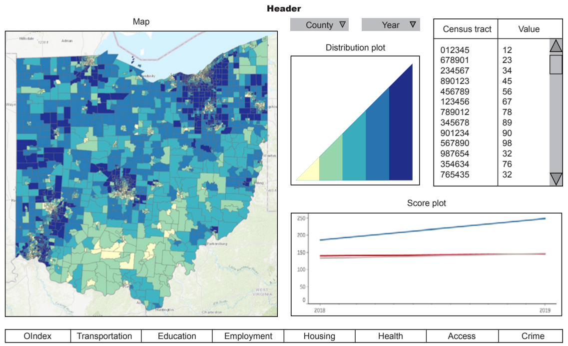
Jonathan Beus, MD, MS

S14, AMIA 2020 Clinical Informatics Conference

Visualizing State Opportunity Index Data: A Dashboard Application to Communicate Area Deprivation Index Information

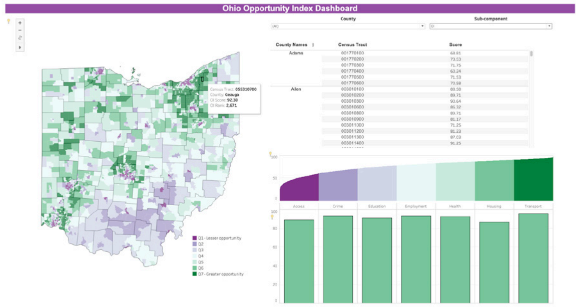
Dashboards that help visualize data may be more meaningful to stakeholders and the public. Our experiences with a user-centered design process present a template for dashboard development in the healthcare context.

Design



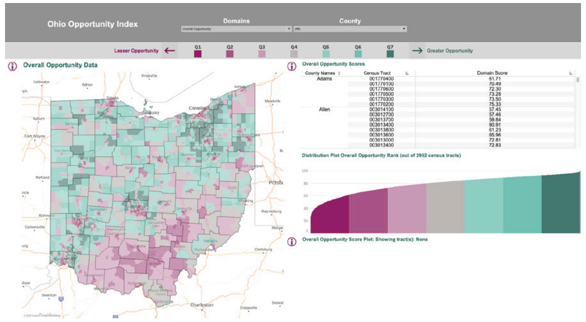
We created a prototype of the Opportunity Index Dashboard that included features requested by stakeholders.

Development



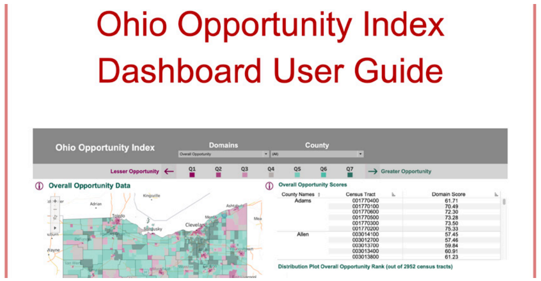
We engineered a functional version of the dashboard by employing Tableau visualization software.

Deployment



We hosted multiple usability sessions, using the feedback to refine the tool’s content, functions, and aesthetics.

Training



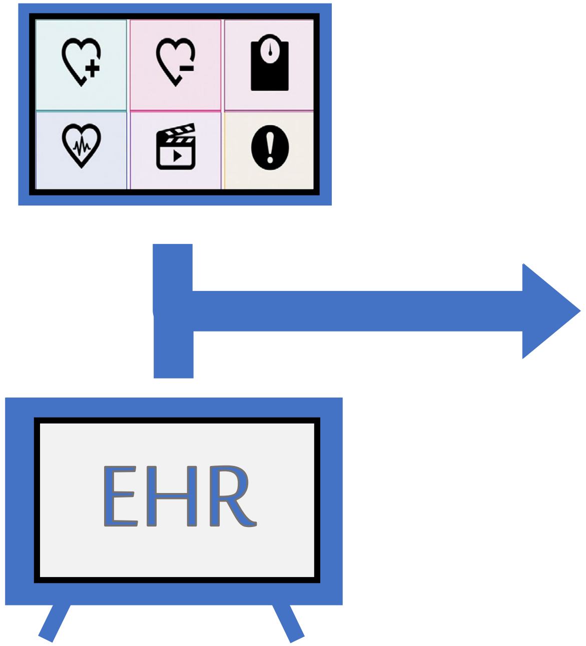
We created a user guide to introduce users to the dashboard and provided in-person training.

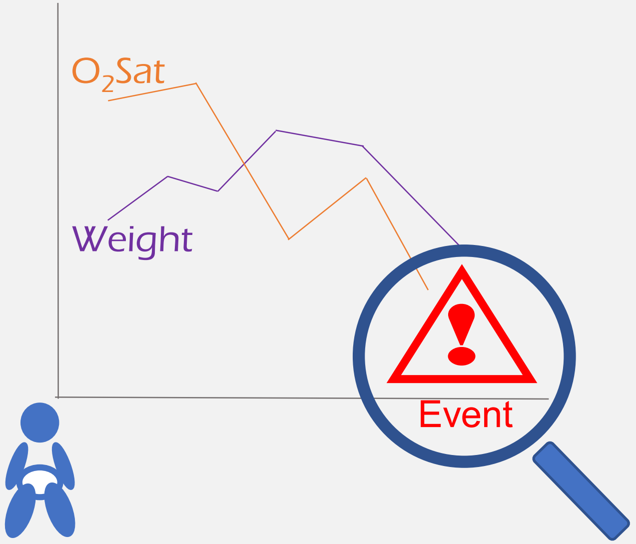
Fareed et al., S15, AMIA 2020 Clinical Informatics Conference

2020

Predicting Unplanned Readmission Events in Infants with Single Ventricle Disease

App-based Metrics





XGBOOST

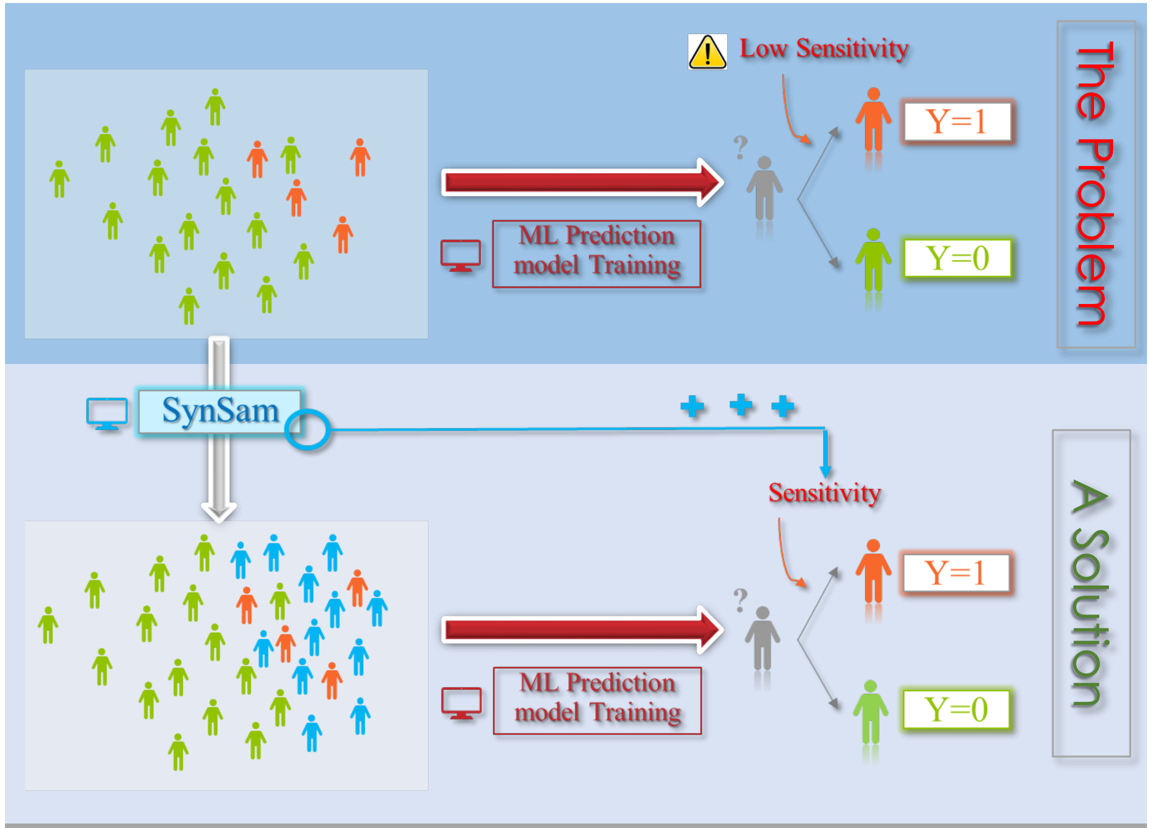
68%
Unplanned Readmissions Before Prediction

5%*
Unplanned Readmissions After Prediction

*in offline model evaluation on retrospective data

KenSci
Children's Mercy KANSAS CITY

AI Synthetic Sampling (SynSam) to Boost Machine Learning (ML) Prediction Accuracy for Infrequent Outcome Events

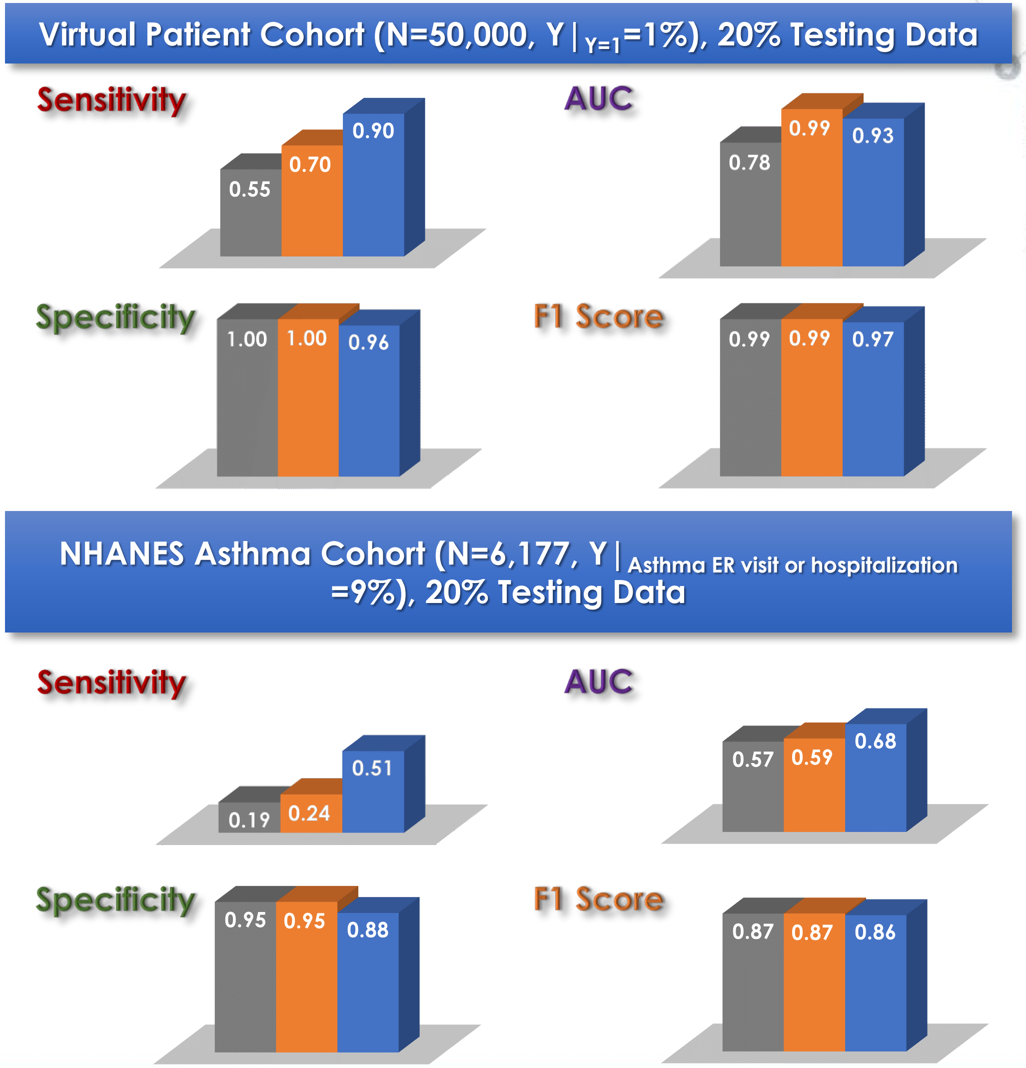


Original Sample without an outcome event (Y=0)

Original Sample with an outcome event (Y=1)

AI Synthetic Sample with an outcome event (Y=1)

Sensitivity: The ability to predict an outcome event that happens (Y=1)



ML

ML + Bootstrap

ML + SymSam

ML: Extreme Gradient Boosting

Bootstrap: Random oversampling with replacement

NHANES: National Health and Nutrient Examination Survey

Gang Fang, Session 24, AMIA 2020 Clinical Informatics Conference

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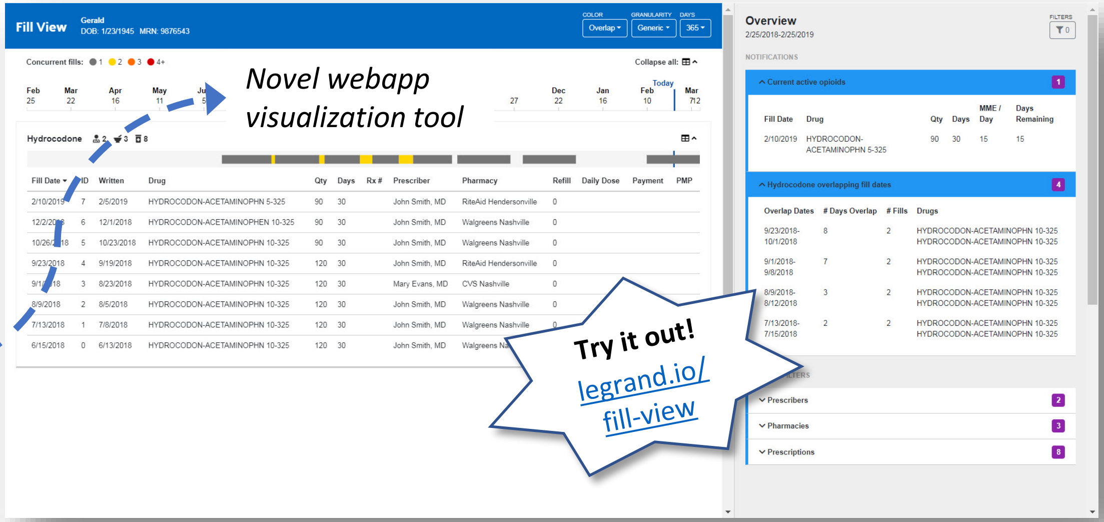
2020

Can Visualizing Opioid Prescription Fill Data Enhance Providers' Understanding and Decision Making?

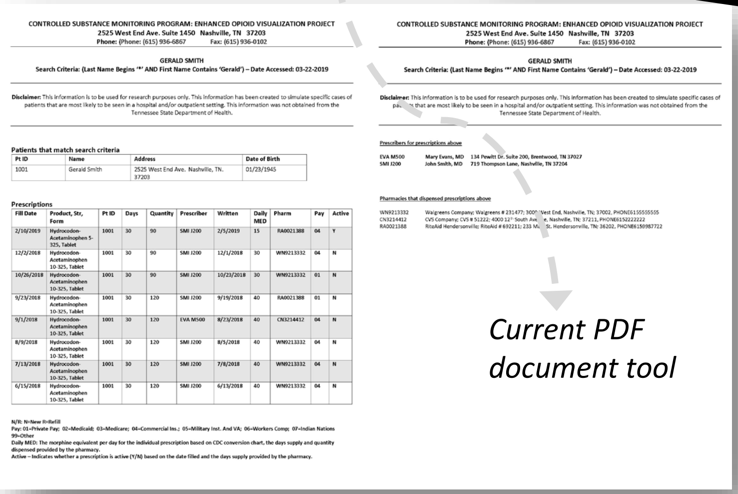
Usability Survey
for current PDF document tool

Randomize
- starting with **novel webapp visualization** or **current PDF document**
- starting patient



Novel webapp visualization tool

Try it out!
legrand.io/fill-view



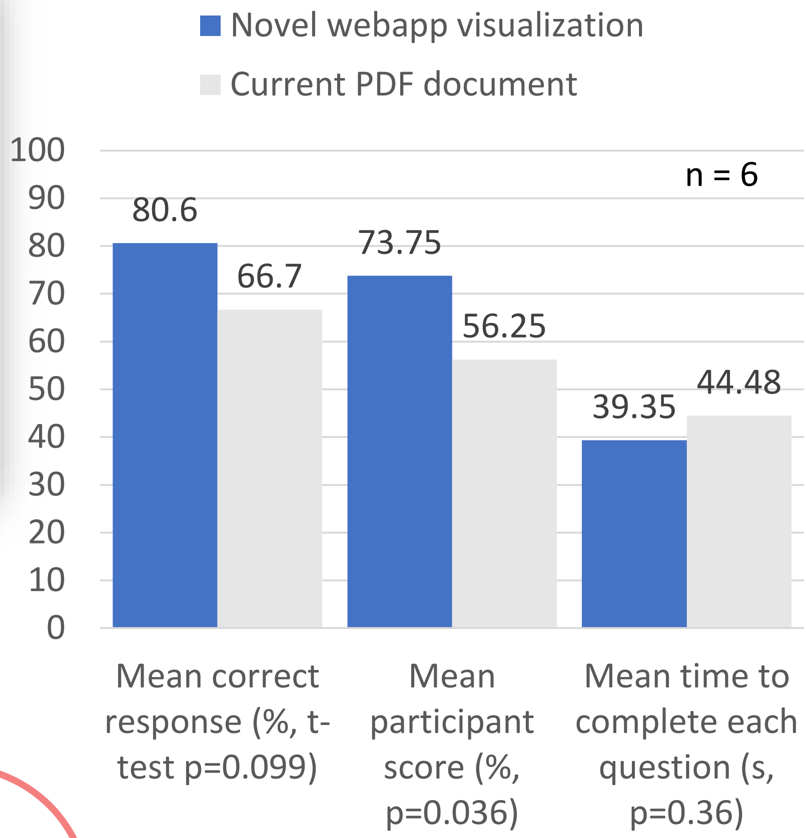
Current PDF document tool

Ask
6 questions

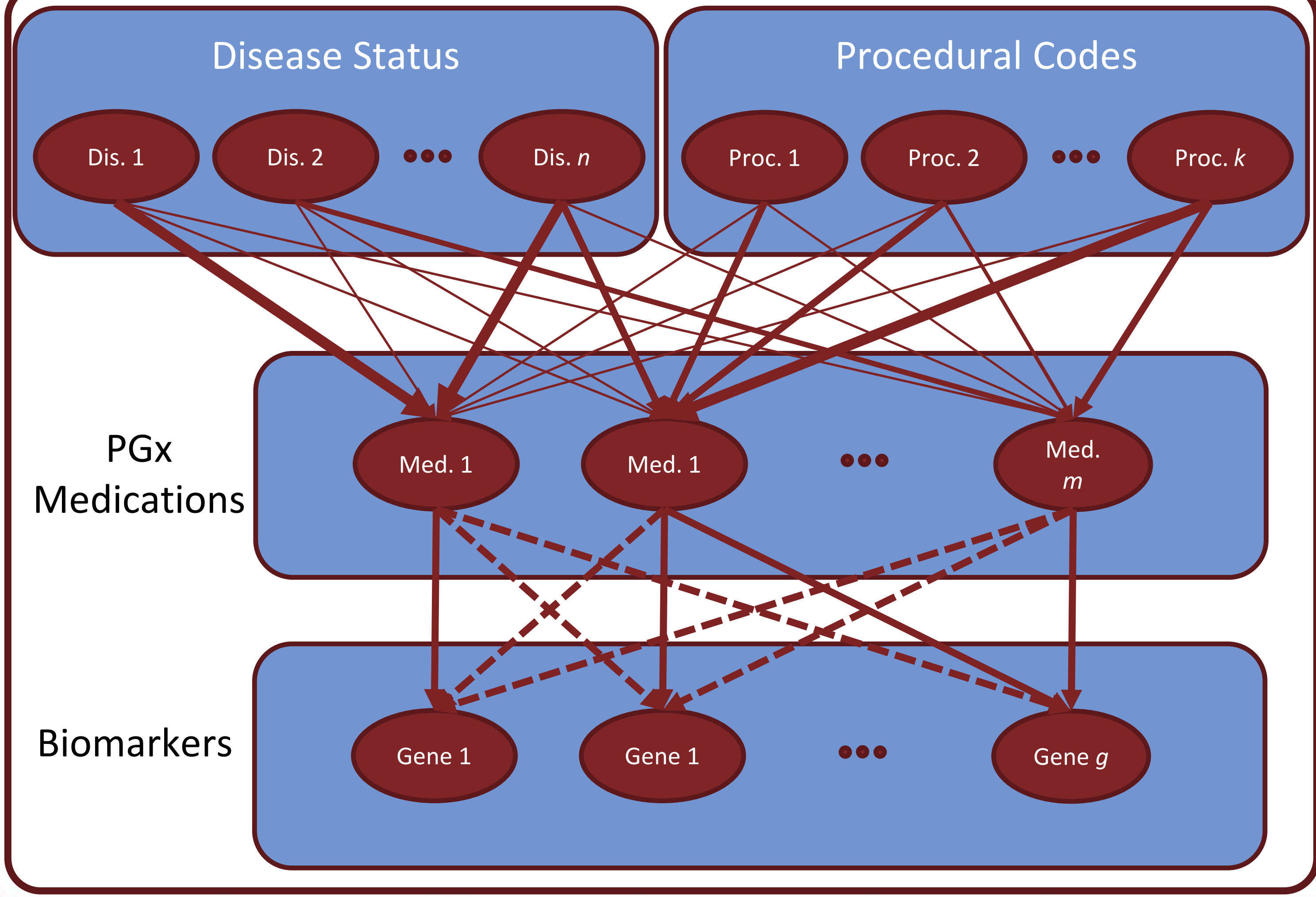
Switch
patient and tool

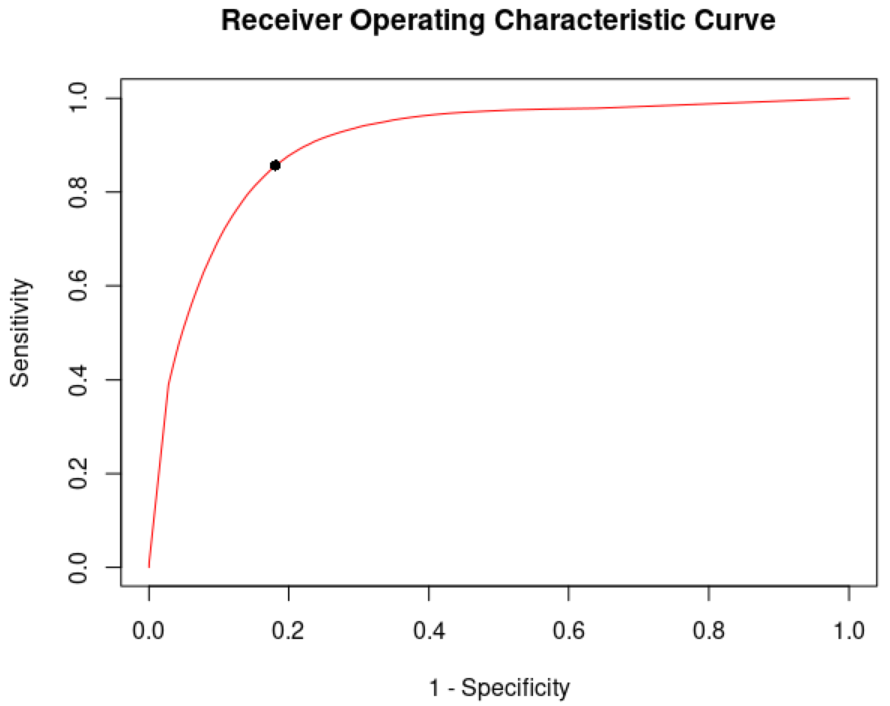
Ask
6 different questions with similar themes

Usability Survey
for novel webapp visualization tool



Prediction of Likely Benefit of Pharmacogenomic Testing Derived from Electronic Medical Record Data





AUC: 0.903
Optimized Sensitivity: 0.857
Optimized Specificity: 0.819

Machine Learning Algorithms Detect and Differentiate Shock in Combat Casualties

Training Data: Electronic Health Records

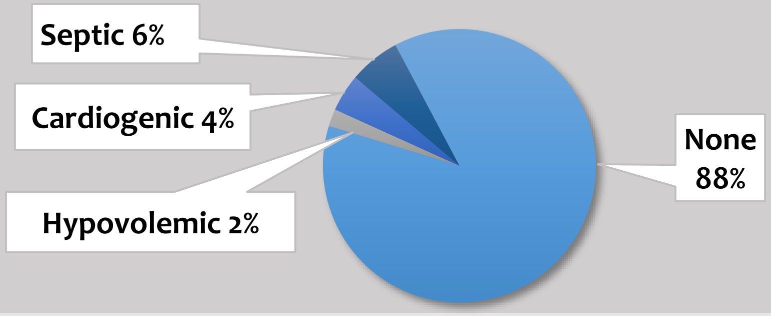
Essential Vitals

ICU Patients
120 Minute Window

Diagnosis Time

ICD Codes
Clinician Action

Shock Type Distribution



Algorithm Performance

Detection and Differentiation Models

general shock
- AUC 0.86
- sensitivity 73%
- specificity 83%

cardiogenic shock
- AUC 0.82
- sensitivity 72%
- specificity 82%

septic shock
- AUC 0.88
- sensitivity 73%
- specificity 82%

hypovolemic shock
- AUC 0.71
- sensitivity 72%
- specificity 79%

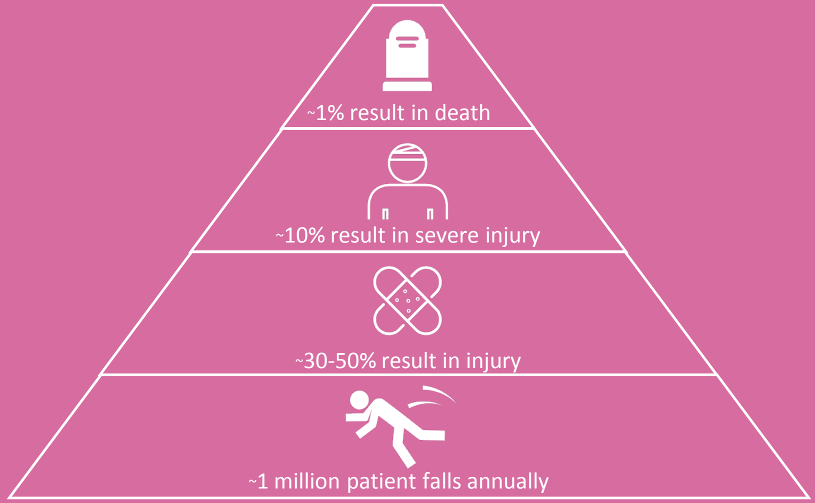
Prognostic Capabilities

ML algorithms identify shock before clinician action.

A prospective real time silent test at Mayo Clinic will compare algorithm performance to standard of care.

Engagement of Clinical Nurses in Text Mining:
Enhancing Interpretability and Clinical Relevance of a Fall Prevention Algorithm

Bjarnadottir RI, Lucero RJ, Snigurska UA, Solberg L, Wu Y, Martinez K, Bolin S, Dwarica S, Thomas J.



$50 billion in associated medical costs

2 hospitals

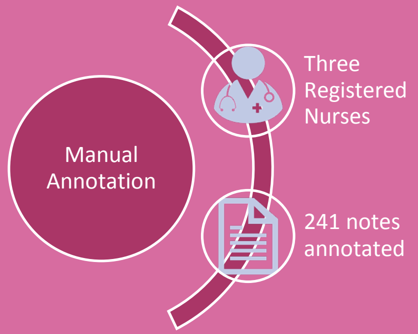
21 med-surg units

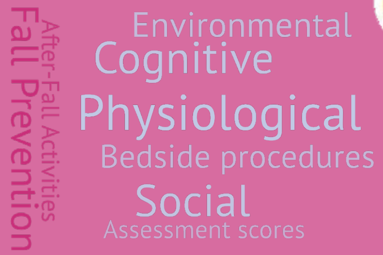
135,739 patients

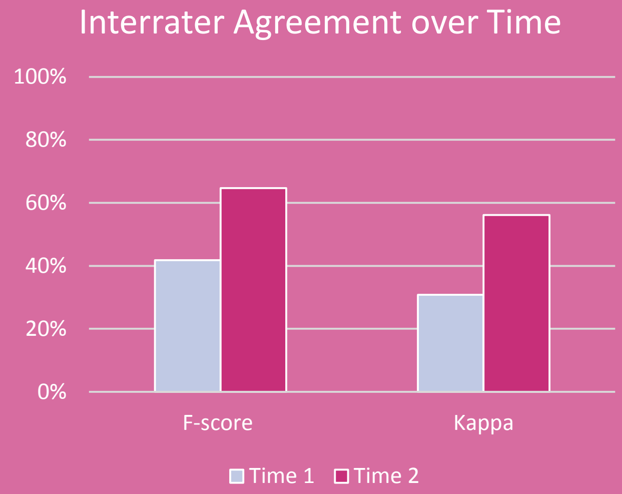
259,610 encounters

5,046,505 RN notes

3,440 fall events







Poster Session 1, AMIA 2020 Clinical Informatics Conference

University of Florida College of Nursing

INFORMATICS PROFESSIONALS. LEADING THE WAY.

Impact of **EMBED**: A User-Centered Clinical Decision Support to Implement **EM**ergency Department-Initiated **B**uprenorphin**E** for Opioid Use **D**isorder (OUD) – *The Pilot Study*

EBD

- *Web-based, EHR Integrated*
- *Flexible, User Centered Clinical Decision Support System*
- *Facilitates EM Department Initiated Buprenorphine (BUP) for OUD patients*
- *Streamlines a complex, unfamiliar treatment algorithm/25 minute workflow into a few clicks*

Findings from Interrupted Time Series

OUD Pt Receiving BUP in ED or prescription at discharge

3.5% ➡ 6.6%

p = 0.03

OUD Pt Receiving Prescription for Naloxone at ED discharge

6.5% ➡ 11.5%

p = 0.009

Physician Adoption Rate of ED-Initiated BUP for OUD pt

19.2% ➡ 32.5%

p = 0.53

Odds of Physician Adoption following Brief In-Person Training

⬆ More than 2x

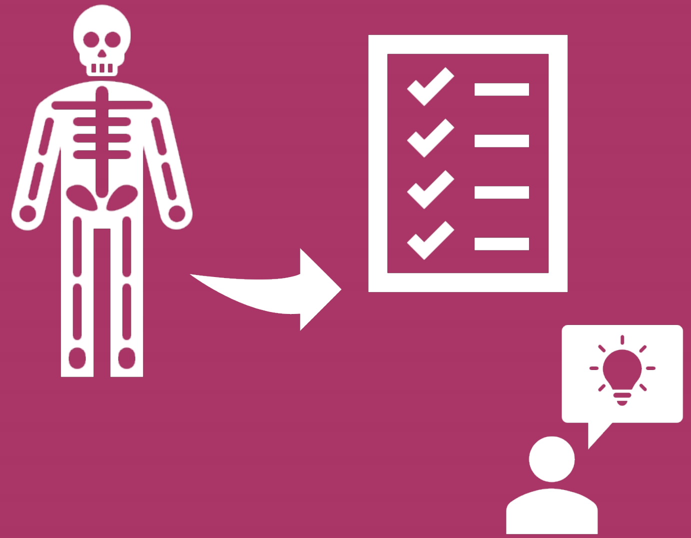
Unadjusted RR = 2.16, p = 0.02

Holland et al, AMIA 2020 Clinical Informatics Conference I Conference

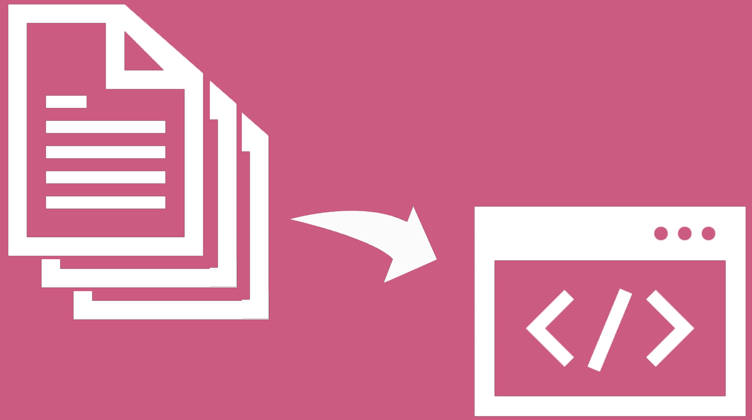
NIH National Institute on Drug Abuse
Advancing Addiction Science

Yale University School of Medicine

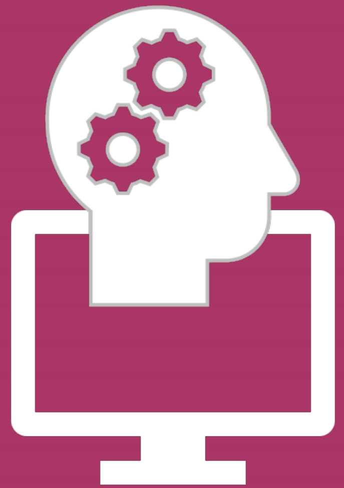
Use of Machine Learning to Predict Severity of Injury from Clinical Documents in Trauma Patients



Injury severity is rated manually by certified trauma coders



Machine learning and natural language processing can use unstructured trauma encounter data



A machine learning algorithm with logistic regression accurately identifies severe chest injuries

Automated methods with natural language processing for identifying severe chest trauma at point-of-care is feasible

Kulshrestha et al., Poster Session 1, AMIA 2020 Clinical Informatics Conference

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Estimating Aspirin Overuse for ASCVD Primary Prevention in the US Veteran Population

Guideline #1	Guideline #2	Guideline #3
Age 40-70	Age >70	Age 18+
ASCVD Risk*	No ASCVD	Bleeding Risk*
Bleeding Risk*		
Cannot compute aspirin overuse	3.9% (88,462 people)	Cannot compute aspirin overuse

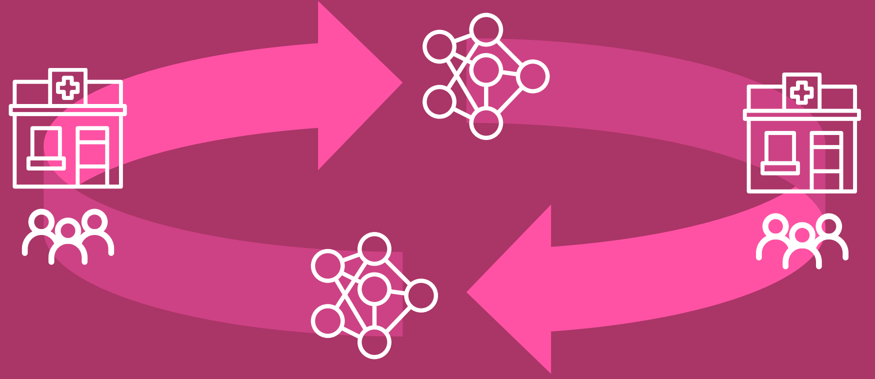
*Unable to define in computer/database terms

Federated Medical Data

How much can Deep Learning Models benefit?

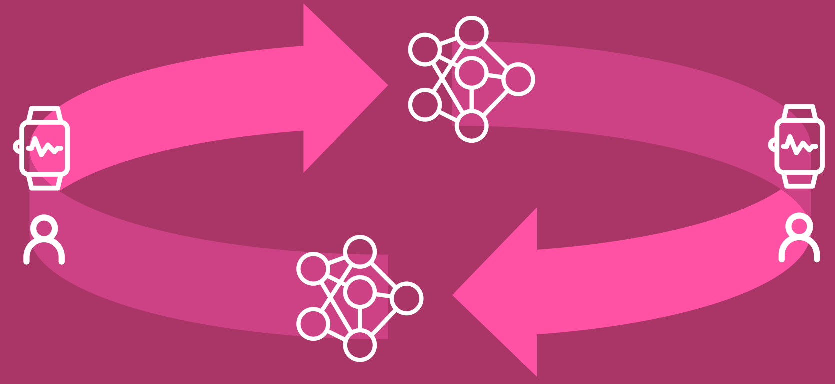
HOSPITAL-SCENARIO

Data from different patients per client



SMARTWATCH-SCENARIO

Data from a single patient per client



Model quality measured via F_1-Score

Hospital: Privacy Cost	Hospital: Federation Benefit	Smartwatch: Privacy Cost	Smartwatch: Federation Benefit
0.03	3.53	2.33	>93

Privacy Cost = $F_{1(\text{centralized})} - F_{1(\text{federated})}$

Federation Benefit = $F_{1(\text{federated})} - F_{1(\text{single client})}$

F. Rabe, F. Stieler, B. Bauer; University of Augsburg; Germany

Poster Session 1, AMIA 2020 Clinical Informatics Conference

2020

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CDS-based IV-to-Oral Medication Conversion

Improved conversion rate from IV-to-PO famotidine

38% → 48%

Drug	Per Dose Cost-savings
doxycycline	$17.11
famotidine	$0.62
lacosamide	$14.21
levofloxacin	$1.64
levothyroxine	$107.05
linezolid	$42.60
methocarbamol	$54.10
rifampin	$67.67

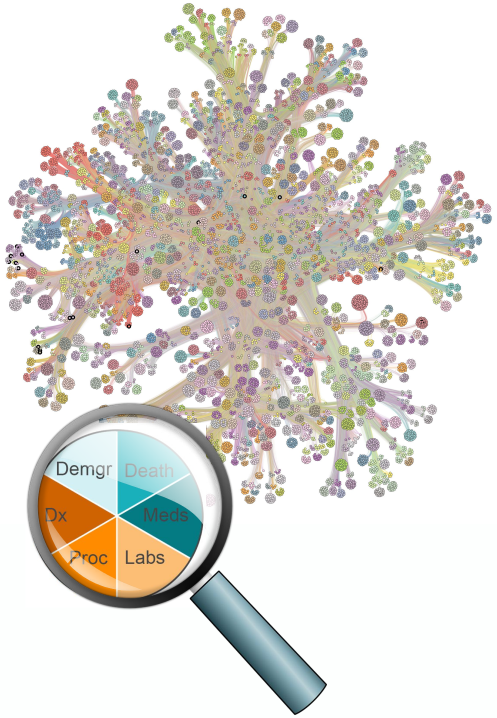
Extrapolated cost savings for all drugs

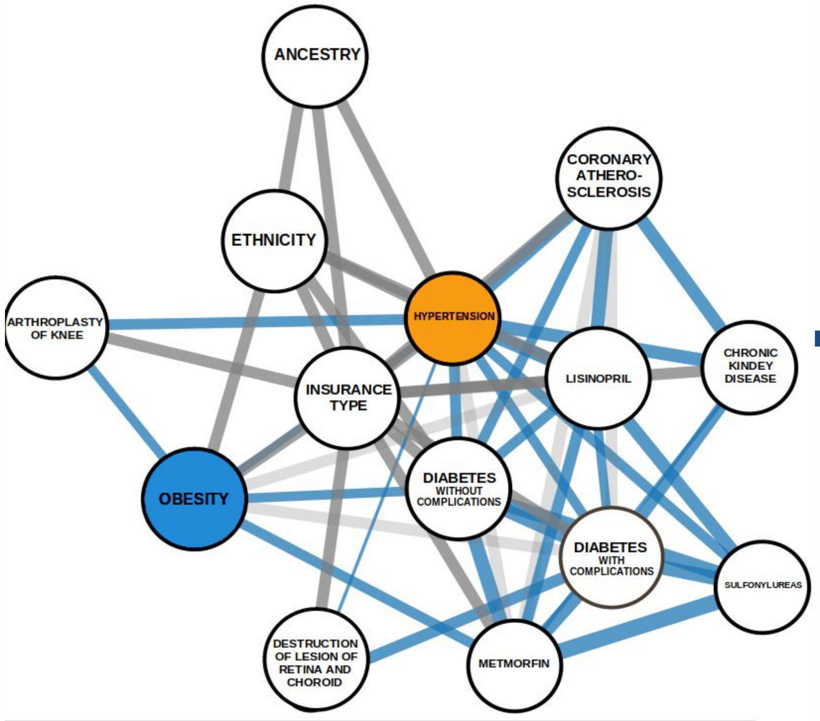
$13,948 at current conversion rate

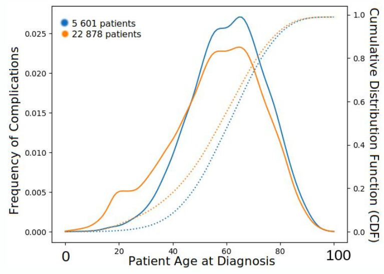
$118,125 annual potential savings

Explainable AI for Discovering the Disease Topology and Outcomes Trajectory of Diabetes Based on EHR

S. Wesolowski, G. Lemmon, A. Henrie, E. Hernandez, J. Lazaro Guevara, M. Pezzolesi, M. Yandell,







Impact of selected Bayes Net risk factors for diabetes mellitus with complications

Prior morbidity	Fold increase in risk	Risk of complications
Diabetes mellitus w/o complications	**6.38x** (+/- 0.28 stdev)	**37%** (+/- 16% stdev)
Hypertension	**2.92x** (+/- 0.23 stdev)	**17%** (+/- 1.3% stdev)
Obesity	**2.82x** (+/- 0.1 stdev)	**16%** (+/- 0.6% stdev)

Cohort of 29,301 patients between with at least 5 years of EMR records and at least 3 visits. Baseline risk for diabetes with complications in this cohort is 5.8%.

Massive EHR Database (1.5m patients)
Automated search for associated clinical variables

Discovering the Topology of a Complex Disease
Bayesian network engine (Explainable AI)

Personalized Actionable Inference
Conditional risks and trajectory prediction

Sergiusz Wesolowski, Poster Session 1 and Reception, AMIA 2020 Clinical Informatics Conference

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Automated methods to identify important, actionable information within scanned and outside EHR documents: Searching the PDF haystack to benefit patients

Latent EHR Data

91 Printed Pages
of Patient Data

Analysis

OCR Analysis via Amazon Textract
and NLP Analysis via CLAMP

Processing & Data Extraction

Correctly Identified:
89% of risk factors found by humans
23% additional risk factors missed by humans

Alexander Kostrinsky-Thomas, Poster Session 2,
AMIA 2020 Clinical Informatics Conference

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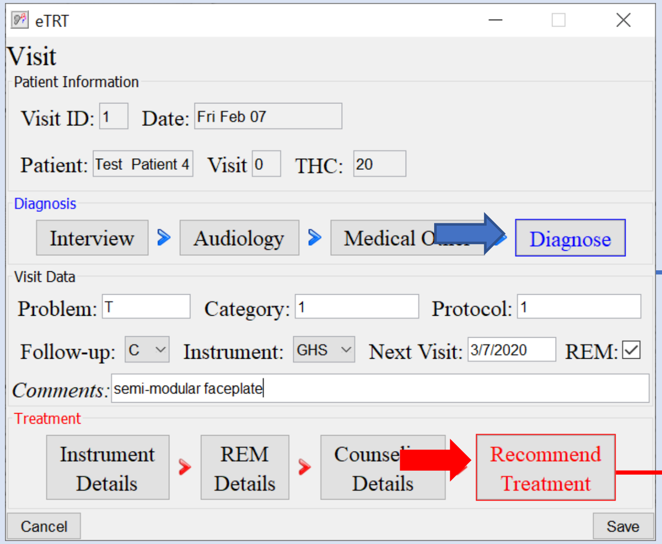
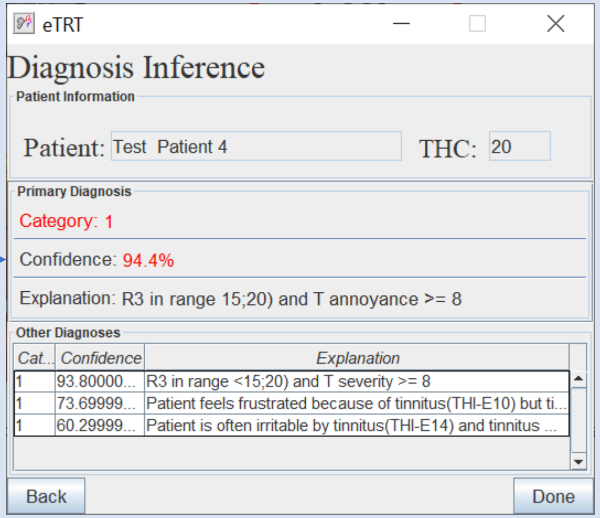
Tinnitus = 15% globally

- **"Phantom auditory perception"**
- No known cure
- **Tinnitus retraining therapy** (TRT) is an effective management technique
- TRT is not widely offered or known
- **eTRT – Clinical Decision Support** System for TRT visit diagnosis and treatment



Data gathered; eTRT system infers accurate diagnosis

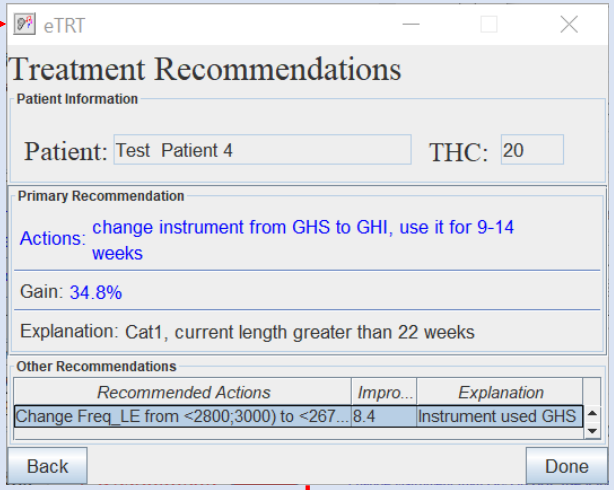


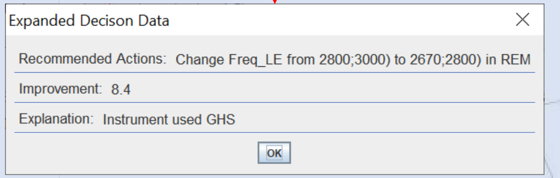
Sample machine learned association rule built in eTRT knowledge base:

IF R3(<15;20)) AND T_an >= 8

THEN Category(1), Conf.= 94.4%

ML Action Rules for Treatment Recommendation





Sample machine learned action rule built in eTRT knowledge base:

IF Ins(GHS): (Freq_LE(<2800;3000) → (<2670;2800))

THEN Change(better), DConf. = 8.4 pp

Interoperability and Informatics Infrastructure

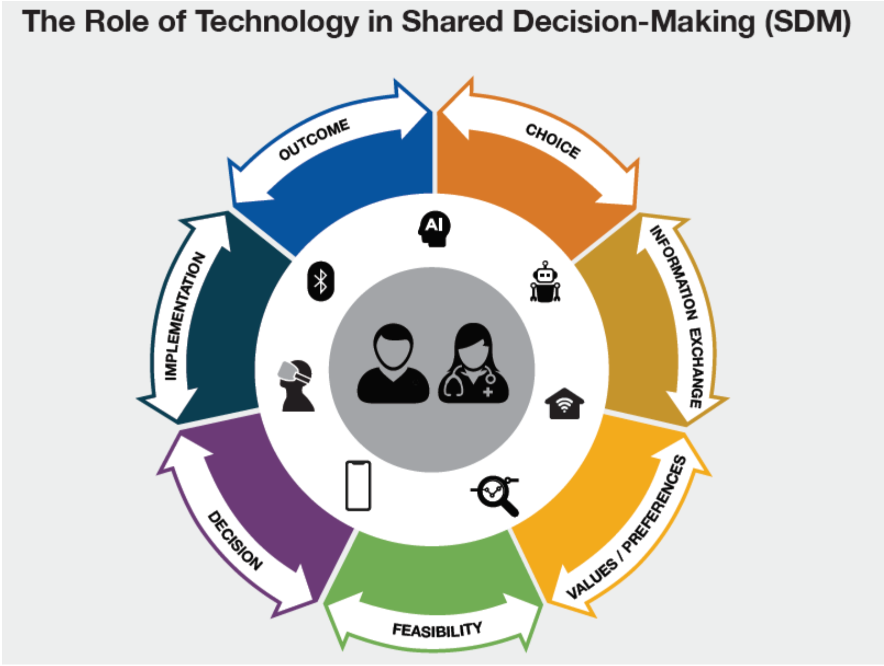
Data and Network Security
Health Apps
Health Information Exchange (HIE)
Health IT Standards (FHIR®, etc.)
HIT/EHR Safety
Informatics Infrastructure
Interoperability
Mobile Technology
Patient-generated Data
Secure Communication
Telemedicine

Technology and Person-Generated Health Data to Enhance Shared Decision Making

Question: How can we improve shared decision making (SDM) processes?

Method: A collaborative consensus approach with multi-stakeholder perspectives valued equally.

Results: Evidence, technology, policy, and culture change are needed to optimize the practice of SDM and the development of useful and usable tools.



K Kim, P Franklin, S Greene, M Edmunds;

S07 AMIA 2020 Clinical Informatics Conference

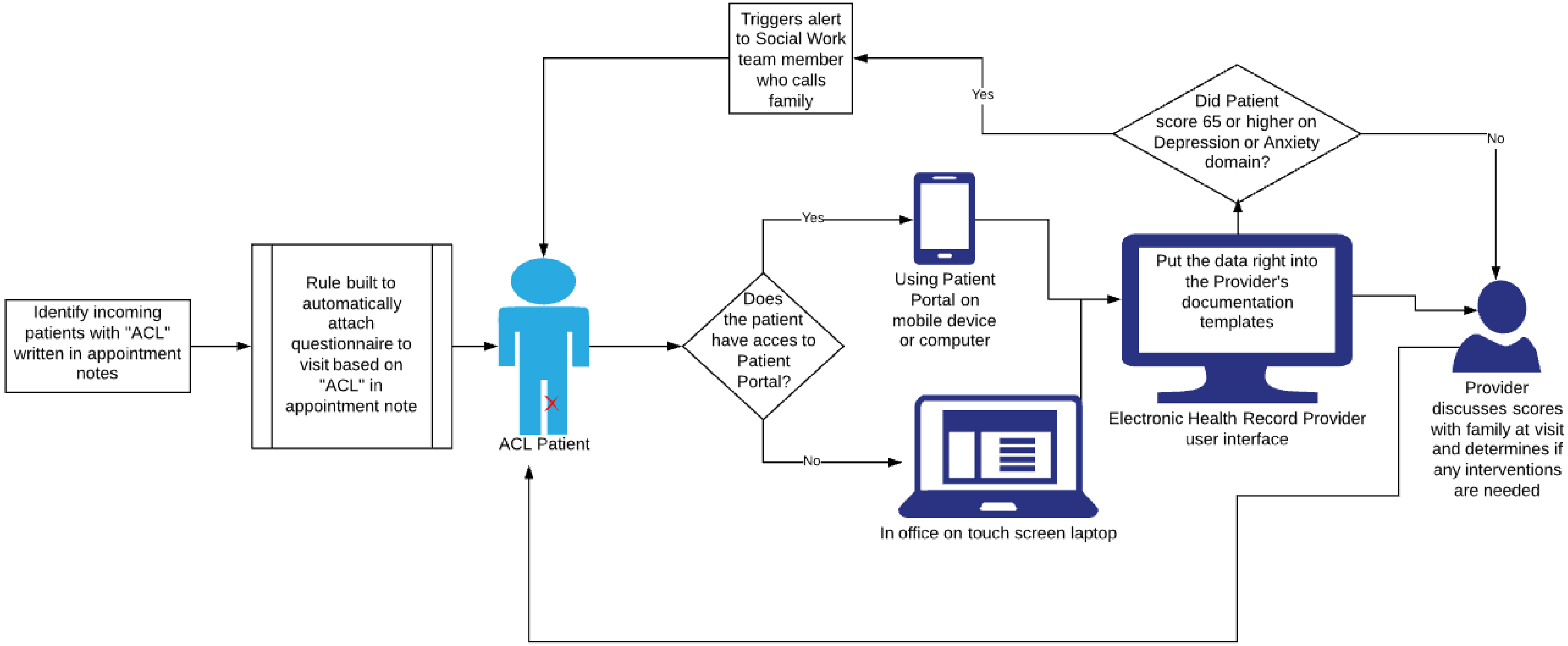
One PROMIS™ at a Time: Implementation of Depression and Anxiety PROMIS™ Domains as a Standard of Care for Adolescents Undergoing Anterior Cruciate Ligament Reconstruction

Identify patient cohort

Identify validated questionnaire

Determine electronic method for questionnaire distribution

Build CDS



Get data in front of providers

Educate providers about the data

Providers discuss data with patient and family

Providers grow to rely on having the data

McNeely L, Riley J, Ganley, T.

Session 17, AMIA 2020 Clinical Informatics Conference

Health Apps for Everyone:
Developing Inclusive User Experience (UX) Criteria

App users may have a variety of physical, cognitive, visual, motor, and/or central nervous system challenges…

<u>Developing an assessment criteria to evaluate inclusiveness of health app design that's based on:</u>

App design for older users

Best practices in universal web/app design

Assistive features in health technology

…So there's a need to incorporate universal design principles and assistive features into app design.

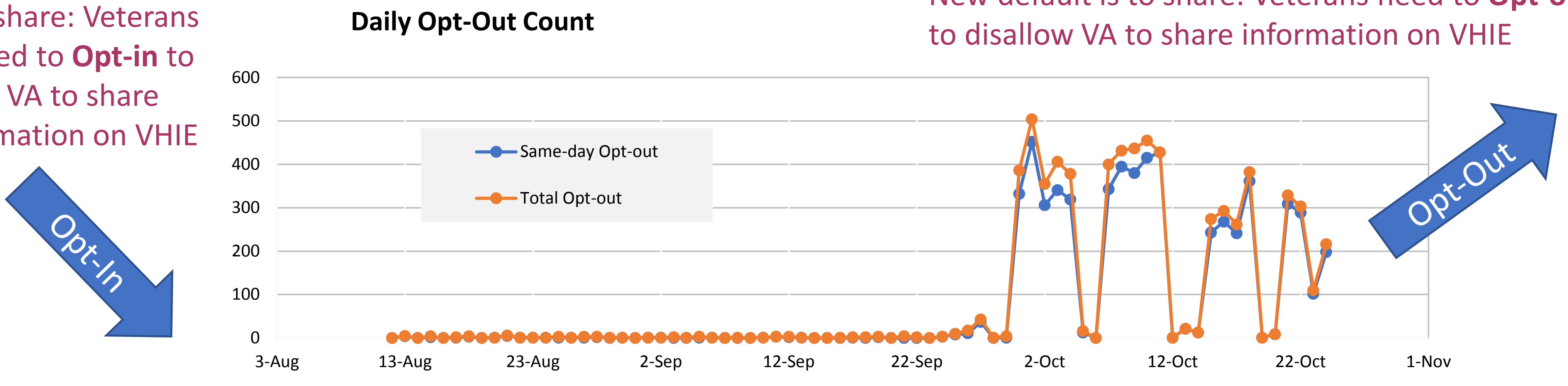
<u>Inclusive UX Criteria</u>

Visual Assesssment	Audio/Sound Assessment	Ease of Use/ Navigation
4 Criteria	*3 Criteria*	*8 Criteria*

Veteran reactions to VHIE changing from Opt-in to Opt-out

Previous default was NOT share: Veterans needed to **Opt-in** to allow VA to share information on VHIE

New default is to share: Veterans need to **Opt-out** to disallow VA to share information on VHIE

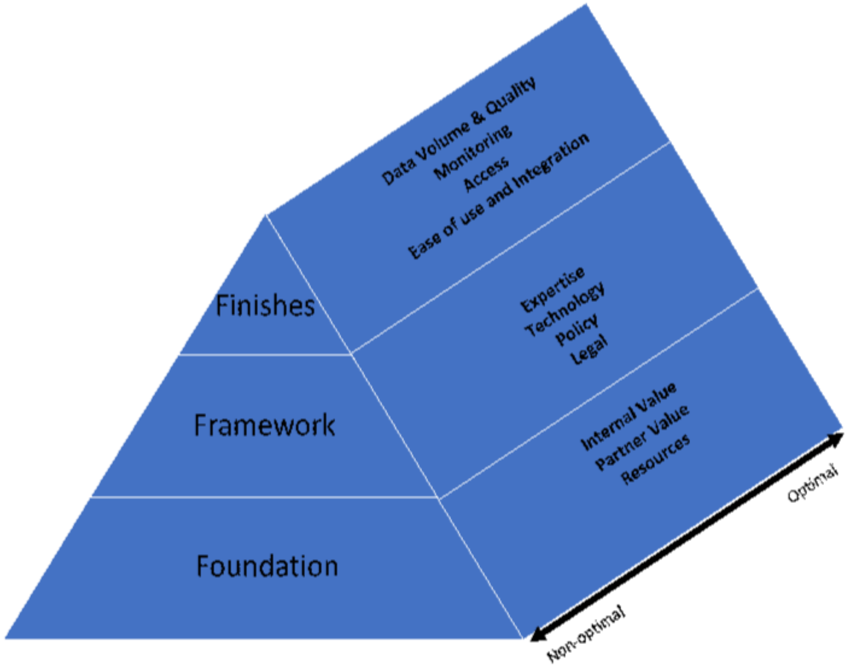


Tracking of this trend was based on **Same-day Opt-in/Opt-out** transactions

Original switch-over date
for VHIE to transition from Opt-in to Opt-out
In communication campaign to Veterans

How to Exchange Health Information like a Boss

Clear the Red Flags to increase exchange

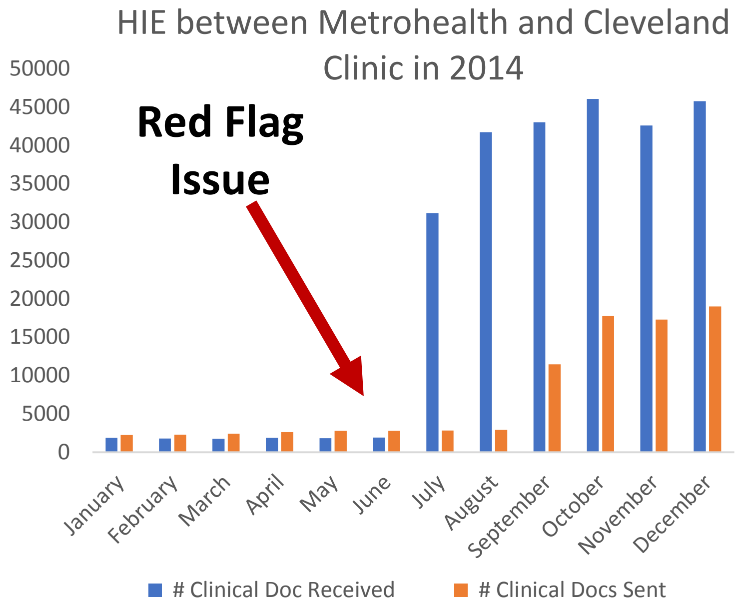


Operational HIE Taxonomy

+

HIE Scorecard

=



HIE Scorecard based on Revised Taxonomy
Assess Readiness, Value, Red Flags Issues

High Value Exchange

Decision support and Alerts of Apps for Self-management of Blood Glucose (BG) for Type 2 Diabetes

Lum, Jimemez. Huang, et al. JAMA. Apr 2019. JAMA

1 *Few apps alert users properly to hypo- and hyper-glycemic events…*

58.8% *alerted users*

37.0% *displayed explicit messaging*

58.4% *alerted users*

32.4% *displayed explicit messaging*

Proportion of apps providing action prompts for -

Hyperglycemic events	*Hypoglycemic events*
15.3%	20.7%

2 *…And even fewer provide action prompts to correct BG events…*

Need for quality control

Immature development of diabetes apps landscape

3 *…Evidencing low levels of decision support or educ ation on BG self-management.*

Systematic Assessment of Suicide Prevention Strategies in 69 Mental Health Apps

Martinego L et al. BMC Med 17, 231 (2019)

Of the 6 suicide prevention strategies assesed, most apps offered 3

94% provided emergency contact information

67% gave direct access to a helpline

51% provided suicide prevention education

But only 5 of the apps included all 6 strategies.

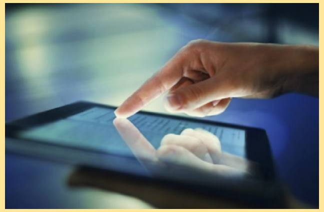
6 ***apps had non-functional crisis helpline phone numbers.***

Apps Examined

51% were health & fitness apps

17% were medical apps

A Successful Example of Using FHIR and Epic RESTful APIs in a Clinic Check-In iPad Program

Reach and Adoption of iPad Program in 4 Primary Care Clinics		
Patient Reach  **66%** (4274 uses of 6504 total visits for patients >=18 years)	**0.3%** FHIR and Epic RESTful APIs Failure Rate* *encounter mismatches, API did not file data appropriately, network infrastructure issues	Nursing Adoption  **75%** (3205 of 4274 times when the Check-In program was used)

The App Rating Inventory (ARI)

A New Tool to Evaluate Mobile Health Apps

Defense Health Agency

When clinicians are confronted by the availability of several hundred apps to help with insomnia, or low back pain, or diabetes (etc.), an apps appraisal tool can help determine which apps are based on reliable information.

What are the best apps to treat **INSOMNIA**?

Search...

1. The process begins with a formal scan of the markets (e.g., find all insomnia-related apps).
2. Apps are then targeted that meet predetermined criteria (e.g., only include insomnia apps that are free and include a sleep diary).
3. The top 10 apps are evaluated with the 28-item **App Rating Inventory (ARI).**

The ARI is divided into three categories:

EVIDENCE

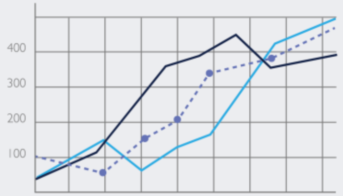
A focus for the **evidence** category is whether the app has been subject to a randomized controlled trial, or is founded on literature-based best-practice guidelines.

CONTENT

The **content** category assesses an app's support for user-generated data and its use of valid external links supplementing the app's content.

CUSTOMIZABILITY

The **customizability** category focuses on an app's ease-of-use and the ability to edit user-generated data.



464 apps have been evaluated with the **App Rating Inventory,** totaling **12,992** data points

CONCLUSION

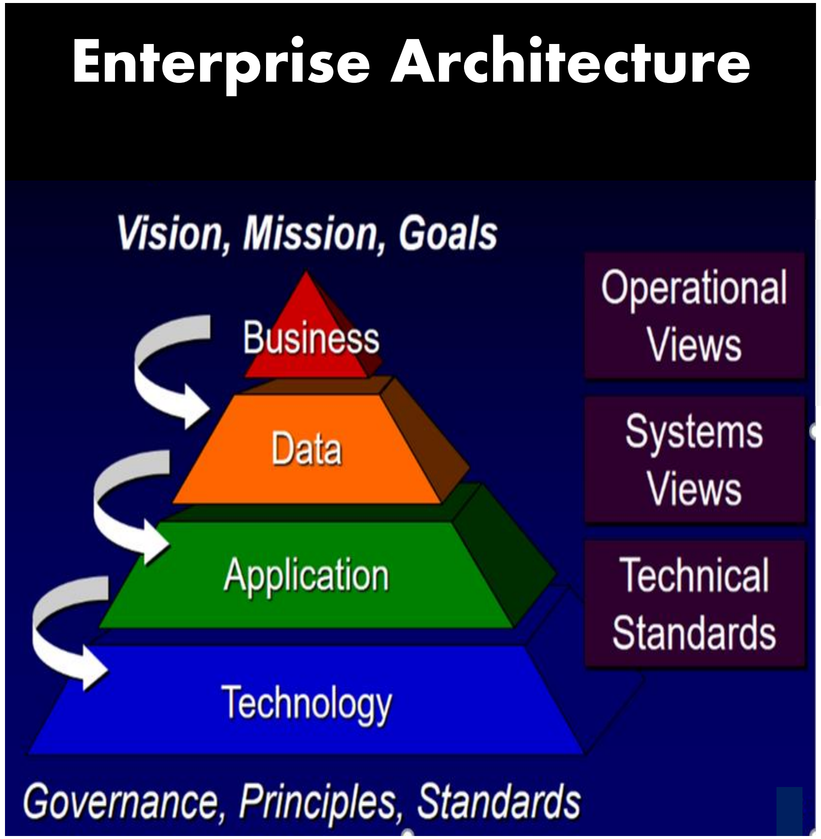
The **App Rating Inventory** was designed with the assumption that effective apps contain:

- Evidence-based content
- Interactive features
- User-generated data storage
- Easy-to-use displays

Interoperability Framework and Health Information Exchange

APPLIED CLINICAL INFORMATICS IN VA SYSTEM MODERNIZATION

STANDARDS-BASED FRAMEWORK

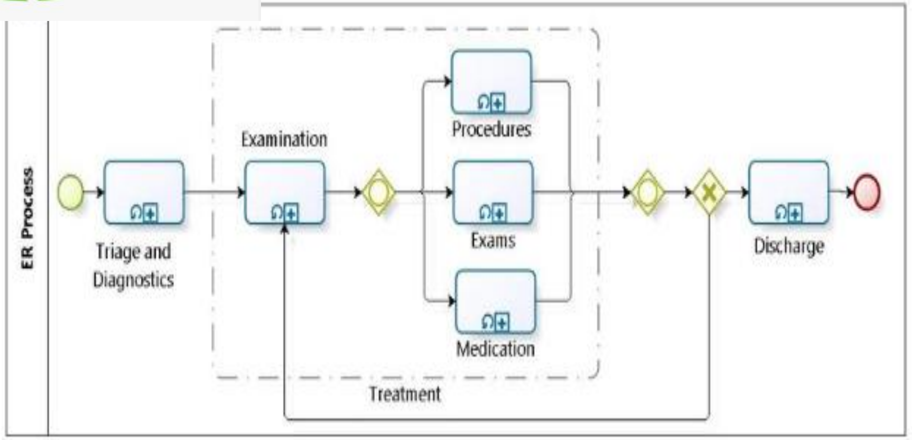


STANDARDS-BASED APPROACH

Business Process Model Notation

BPMN™

PORTABILITY
OF HEALTHCARE
PROCESS FLOWS



STANDARDS-BASED ONTOLOGY

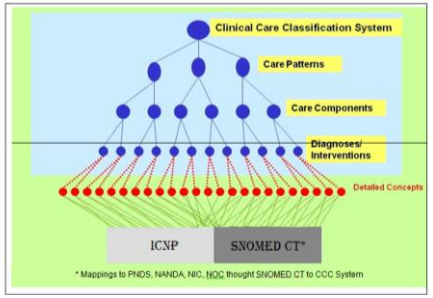
SNOMED CT

LOINC® from Regenstrief

LOINC GROUP

LG34372-9
Body weight

29463-7	Body weight
75292-3	Body weight - Reported --usual
3141-9	Body weight Measured
8350-1	Body weight Measured --with clothes
8351-9	Body weight Measured --without clothes
3142-7	Body weight Stated
79348-5	Body weight --used for drug calculation



Whittenburg, L., Anderson, J.A., Turner, T. Wednesday May 20, 2020
AMIA 2020 Clinical Informatics Conference

2020

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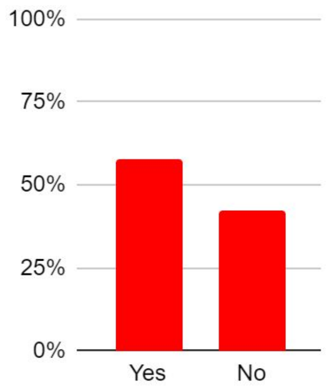
Leadership, Advocacy, and Policy

Affordable Care Act (ACA)
Alternative Payment Models (APM)
Communication Strategies and Change Management
Data Privacy and Security
Disruptive and Innovative Technologies
Ethical, Legal, and Social Issues
Health IT Certification/ USCDI
HIPAA, PHI, EHI
Leadership
Promoting Interoperability Program

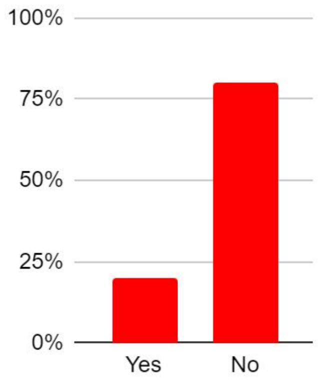
Findings From a Multicenter Survey on Institutional De-identification Practices

An open-ended multicenter survey demonstrated a general lack of standardization of de-identification practices including for structured patient data as well as clinical documentation and imaging.

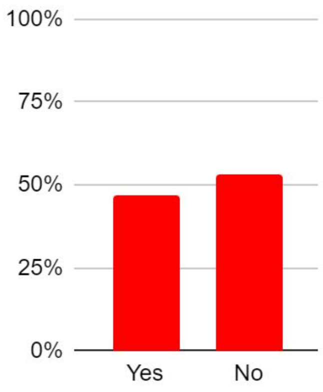
Does your institution have a de-identification service?



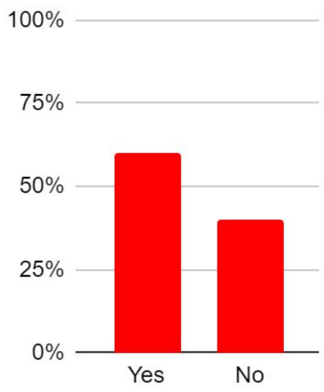
Is a statistical threshold used to decide if anonymization was adequate?



Is your institution de-identifying medical text?



Is there a process for de-identifying imaging results?



Best practice guidelines released by a national organization with input from key stakeholders may be useful to standardize practices among institutions.

Silver Lining in the Dark Cloud of Evolving Cannabis Law and "High" Level Provider EHR Documentation

Farukh Usmani, MD & Carrie Dunford, PharmD

Intermountain Healthcare
Healing for life®

Background

Intermountain created a multidisciplinary Medical Cannabis Workgroup to create electronic health record (EHR) workflows to document cannabis-related patient information within a large, integrated **healthcare system of 24 Hospitals and 215 Ambulatory Care Centers.**

The Federal Controlled Substances Act includes cannabis as a Schedule I drug, which means the drug has a high potential for abuse, has no currently accepted medical use in the United States, and lacks acceptable safety data. Currently, 34 states have passed laws to allow use of cannabis for medical or recreation use creating an incongruence between state and federal law which is a barrier for providers balancing patient care documentation and complying with state and federal law.[1]

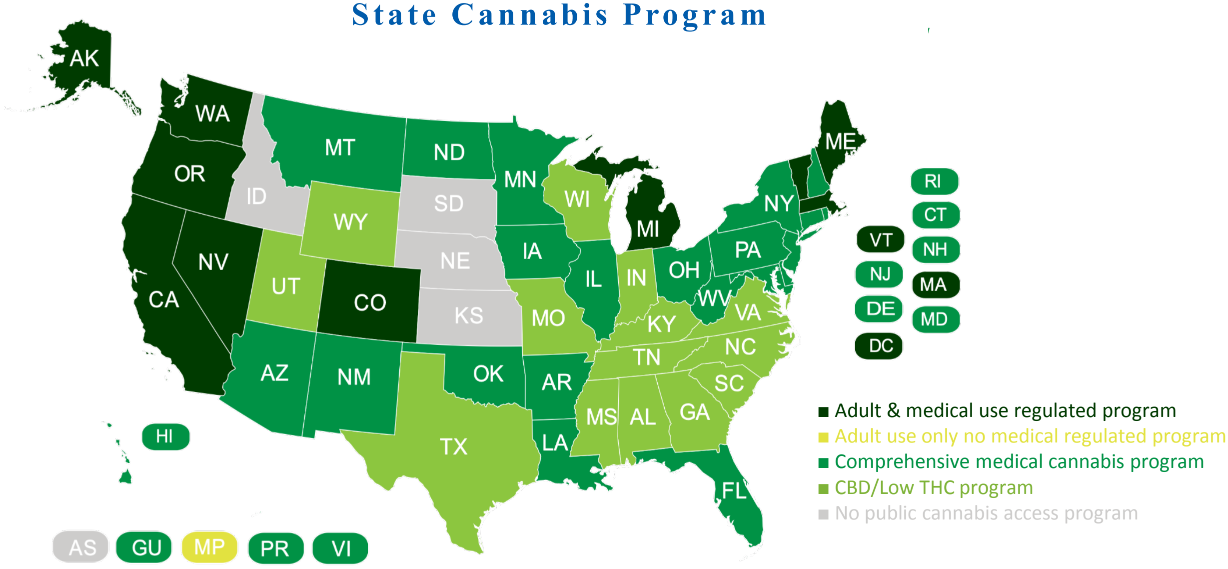
Results

Designed medical cannabis provider documentation module to provide a place in the medical record for transparent care coordination and safe approach to patient care. Developed analytical reports to streamline workflow audits to identify where additional alerts or decision support were necessary. Reports allowed system leaders visibility into patient and provider specific data to meet the needs of all healthcare providers.

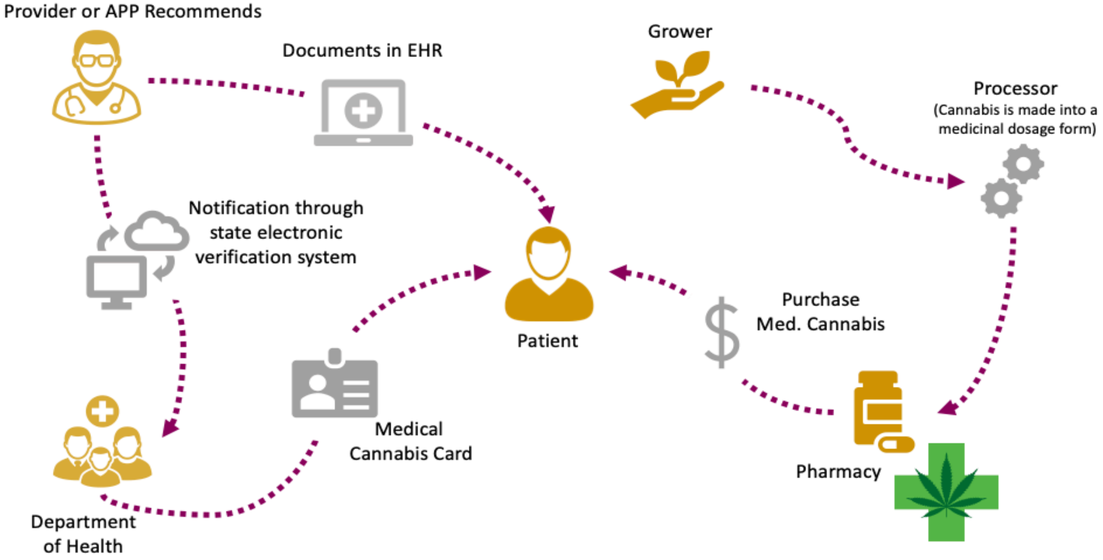
Medical Cannabis Documentation in EHR

200 → 800 (year)

State Cannabis Program



Utah Medical Cannabis Process



Reference [1] :State Medical Marijuana Laws [Internet]. Available from: https://www.ncsl.org/bookstore/state-legislatures-magazine/marijuana-deep-dive.aspx

Disclosure: Under federal law, cannabis remains a Schedule I drug under the Controlled Substances Act, which means the drug has a high potential for abuse, the drug has no currently accepted medical use in treatment in the United States, and there is a lack of accepted safety for use of the drug under medical supervision.

2020

Farukh Usmani, MD; Carrie Dunford, PharmD;
Session # S22, AMIA 2020 Clinical Informatics Conference

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Panel Discussion: Protecting Adolescent Confidentiality Without Information Blocking

Both State and Federal laws can extend privacy protections for adolescents

Understand complexity of laws related to adolescent privacy

Sensitive information can be inadvertently released to parents or guardians through patient portals

Develop a governance plan to protect adolescents at your institution

Both unstructured and discrete data can contain sensitive information

Learn how to use NLP to identify sensitive information in unstructured data

Lee JA, Hoffman J, Sarabu C, Pageler N. *Threading the needle: protecting vulnerable adolescents' confidentiality in the EHR without information blocking.* AMIA 2020 Clinical Informatics Conference S32: 5/21/2020, 9:30-10:30 am PDT.

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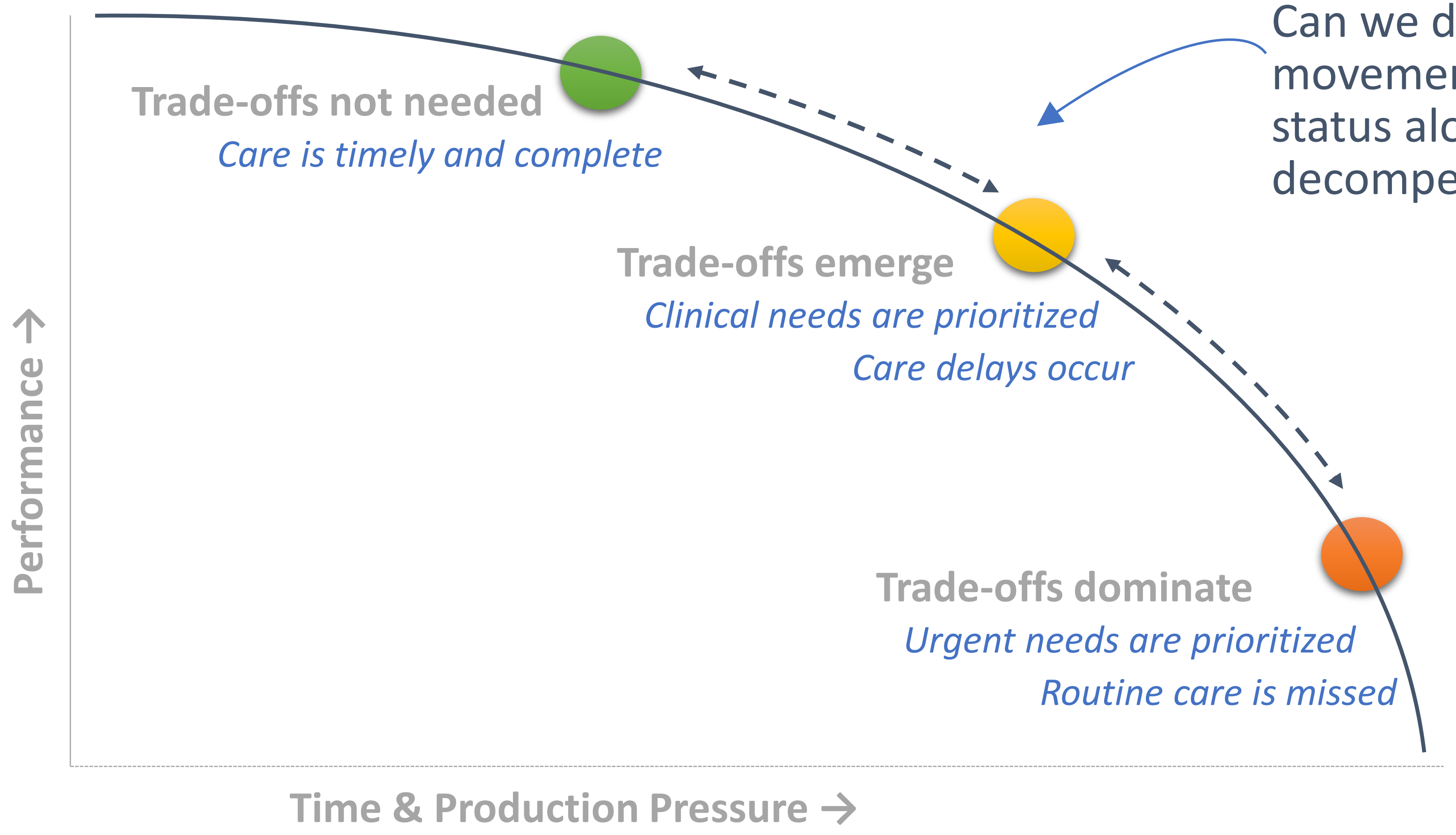


Can we dynamically sense movement in operational status along a care delivery decompensation curve?

Ready or not, Real-time is needed

Learning Health System

Bridging Analytics, Bedside Care, Clinical Documentation, and Education
Generating Evidence for Care Improvement
High Reliability Organizations (HRO's)
Learning Health System
Population Health
Public Heath
Safety and Quality Measurement and Improvement
Social Determinants of Health

Problem: Multiple determinants of health (DoH) tools are in use in healthcare settings, which introduces challenges to interoperability.

Methods: A critical appraisal of evidence-based strategies (psychometric and HIT) was used to develop the DoH Three-Tier Equivalency Scoring strategy.

Results and Application:

DoH Data and Three-Tier Equivalency Scoring

Point of Care		Point of Care and Decision Modeling		Decision Modeling and Analytics	
Diagnosis and Treatment	Referrals	Patient Experience	Care Coordination	Risk Assessment	Research and Quality

- **Tier 1**: Point of Care scoring makes data actionable for intervention.
- **Tier 2**: Scoring to achieve equivalency of domains across tools, settings and populations to make data usable in analytics and algorithms.
- **Tier 3**: Composite scoring that reflects total social, behavioral, psychological, social relationships and environmental burden(s) across settings and health systems.

Health Informatics Journal

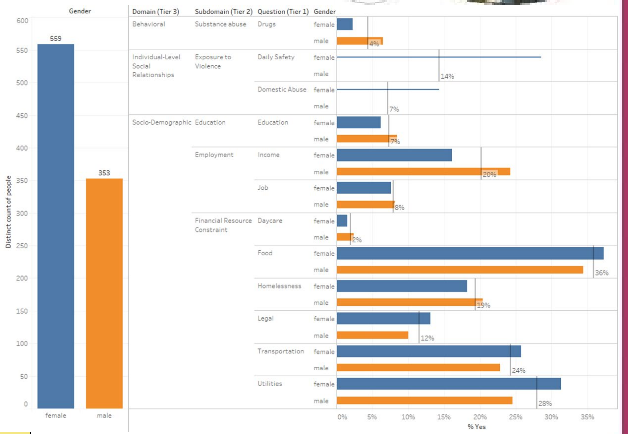
Original Article

An evidence-based strategy to achieve equivalency and interoperability for social-behavioral determinants of health assessment, storage, exchange, and use

Health Informatics Journal
1–12

DOI: 10.1177/1460458219882265
journals.sagepub.com/home/jhi
SAGE

DoH Sub Domain	Persons (%) with DoH need	
	A1c > 9%	A1c < 9%
Food Security	13.0%	7.0%
Homelessness	5.0%	0.2%
Electricity	4.0%	1.0%
Transportation	8.4%	0.6%
Daycare	1.0%	0.2%
Income	8.0%	1.0%
Job	4.4%	0.4%
Education	9.0%	1.6%
Legal issues	4.4%	0.4%
Personal safety	1.6%	0.2%
Drug-alcohol	7.2%	1.8%



Conclusion: Use of the equivalency scoring strategy will increase interoperability, reduce hurdles to information exchange within and across organizations, and decrease redundant data capture.

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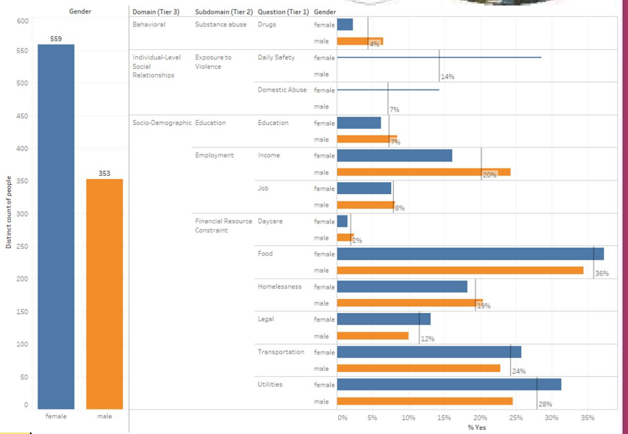


Conclusion: Use of the equivalency scoring strategy will increase interoperability, reduce hurdles to information exchange within and across organizations, and decrease redundant data capture.

The Synergistic Effects of Social Determinants of Health (SDH) and Race-Ethnicity on 30-day Readmission Disparities in an Inpatient Population

HFHS Inpatient Registry:
256,077 inpatient admissions

Primary outcome:
30-day readmission

158,574 unique patients

34,901 readmissions (13.6%)

Mean age 60 years old

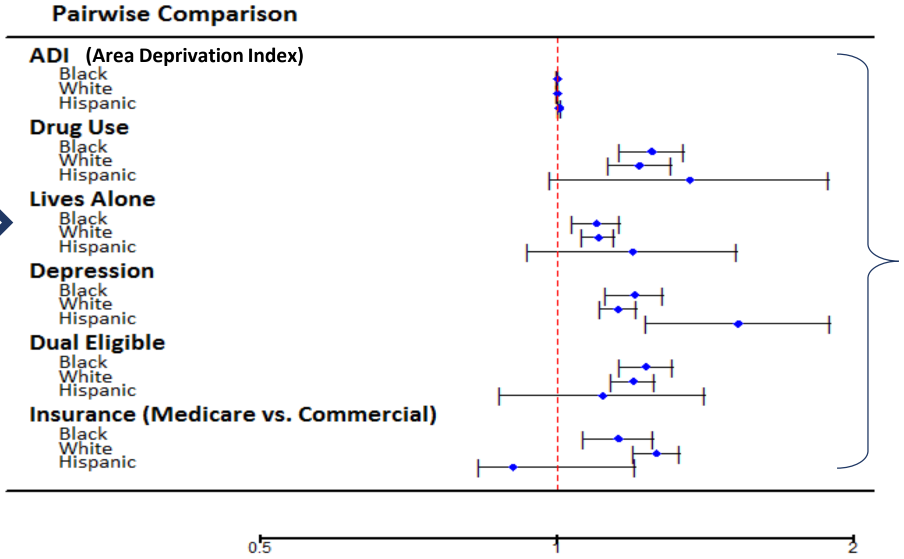
57.7% female

63.0% White

27.0% Black

3.2% Hispanic

SDH By Race-Ethnicity - Readmission Risk Odds Ratios



SDH increase readmission risk similarly across race-ethnicities; however, depression has a particularly large effect on readmission in the Hispanic group.

Latent Class Analysis – Readmission Risk Groups

Group 1: High Readmission (19.5%)

High proportions of
- Minorities
- High ADI
- Drug use
- Living alone
- Depression
- Dual Eligibility
- Medicare insurance

Group 2: Medium Readmission (15.7%)

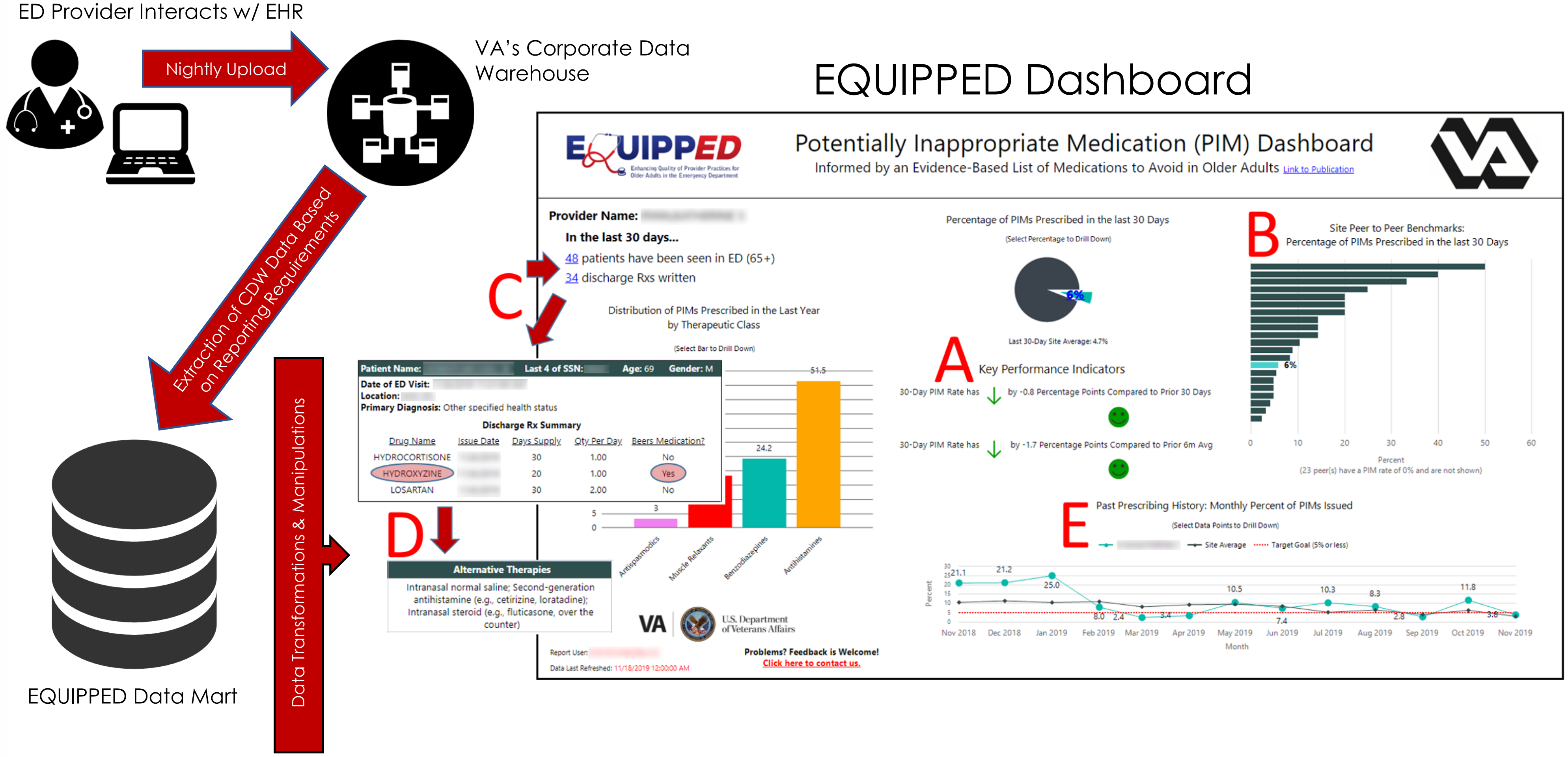
High proportions of
- White patients
- Older patients
- Living alone
- Low ADI

Group 3: Low Readmission (9.5%)

High proportions of
- White patients
- Females
- Low comorbidity scores

Low proportions of
- All SDH

The EQUIPPED Potentially Inappropriate Medication Dashboard: A Suitable Alternative to the In-Person Academic Detailing of Traditional EQUIPPED?



Core Audit & Feedback Elements:

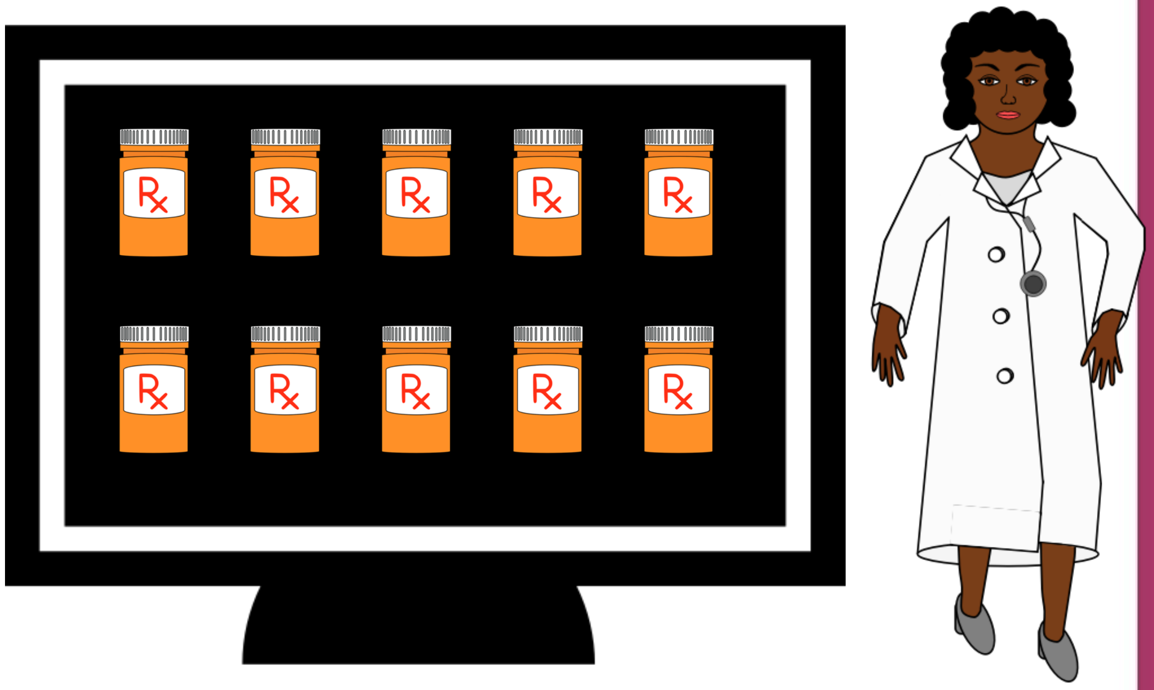
- **A** Key Performance Indicators
- **B** Peer-to-Peer Benchmarking
- **C** Individual Patient/ Encounter Drill Down
- **D** Educational Decision Support
- **E** Longitudinal Performance Tracking

*EQUIPPED = Enhancing the Quality of Prescribing Practices for Older Veterans Discharged from the Emergency Department

In Pennsylvania, providers must search the database of narcotic prescriptions before writing a narcotic prescription. In October 2019 we saw discordant search results on the same patient.

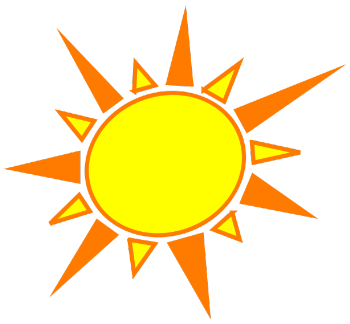
Resident's search results:

Physician Assistant's search results:



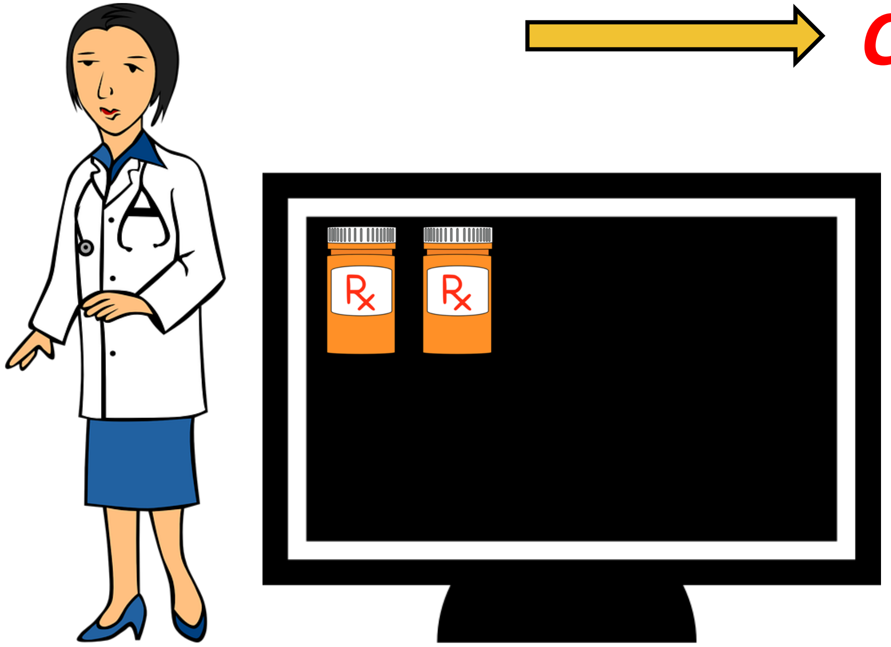
J. Betesh, A. Schettino, J. Lane, J. McGreevey.

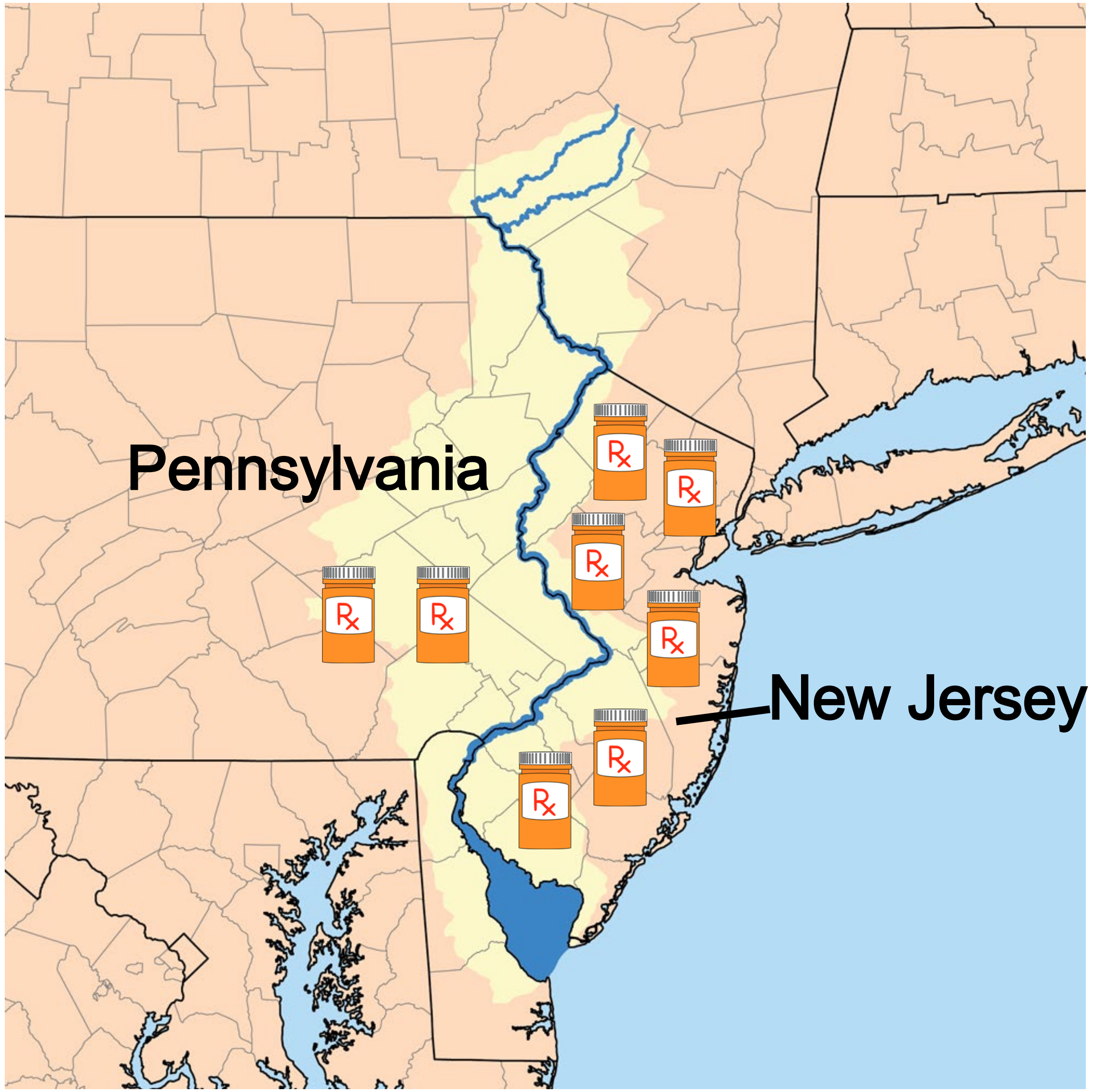
The next morning, searching on the same patient as the day before, both the resident and the physician assistant got the same search results.



Why was this happening?

Cached results





Residents in New Jersey cannot write narcotic prescriptions or search the database. New Jersey prohibits residents in Pennsylvania from searching the database as well. They also cache the results for 24 hours. Anyone who searches within those 24 hours will be limited to the same results as the resident.

New digital care delivery platforms are changing the nature and location of care, how health and services are co-produced, untethered by walls or geographic setting – shaping the design and evaluation of new care interventions and care models.

Novel sources and data types

- Virtual patient care assistants
- Smart devices, sensors, wearables
- Workplace sensors
- Log file & transactional records

Automated Sensing

Digital Twin

Next Gen CDS

AI & Advanced Analytics

Real-time care delivery insight

Panel
Susan C. Hull MSN, RN-BC, NEA-BC, FAMIA @SusanCHull
Michael Wang, RN, MBA
Dana Womack, PhD, RN @DataDragonfly
Rosemary Kennedy, PhD, RN, MBA, FAAN @KennedyNurse

FACILITY HIT ECOSYSTEM CAPABILITY MATURITY MODEL TOOLKIT

How can a facility holistically mature its HIT ecosystem?

ECMM Toolkit is designed to support assessment and prioritization.

Plan for maturing your facility's HIT ecosystem.

J. Shivers, J. Amlung, J. Flowers, T. Cullen
HIT Capability Maturity Model: Strengthening the HIT Ecosystem through Self-assessment
S33: Presentations - Organization Considerations for Achieving Clinical Informatics Success
AMIA 2020 Clinical Informatics Conference

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An Infrastructure for Value Set Creation and Maintenance Utilizing a Clinical Interface Terminology (CIT)

CITs Let Clinicians Speak "Clinician"

What the patient has	What the computer lets you say the patient has
Cerebral calcification	Other conditions of brain
Left knee pain	Pain in joint, lower leg
Breast cancer metastasized to pelvis	Malignant neoplasm of breast (female), unspecified site

…and reap the benefits of detailed "under-the-hood" maps to standardized health vocabularies

Breast cancer metastasized to pelvis
CIT ID: 1845932

- **Primary malignant neoplasm of breast**
  SNOMED CT 372137005
- **Secondary malignant neoplasm of pelvis**
  SNOMED CT 94480000
- **Metastasis from malignant tumor of breast**
  SNOMED CT 315004001
- **Malignant neoplasm of unspecified site of unspecified female breast**
  ICD-10-CM C50.919
- **Secondary malignant neoplasm of other specified sites**
  ICD-10-CM C79.89

An Infrastructure for Value Set Creation and Maintenance Utilizing a Clinical Interface Terminology (CIT)

Identifying subpopulations is critical to health care practice:

"It's early October. We need to make sure all pregnant patients in our practice get an influenza vaccine."

"I want to track how quickly are patients with MI are triaged in my ED."

"Among the patients scheduled for surgery today, which ones are at high risk for serious hemorrhage?"

<u>Value sets link clinical terminologies to populations</u>

An Infrastructure for Value Set Creation and Maintenance Utilizing a Clinical Interface Terminology (CIT)

We describe an architecture and methodology for building and maintaining value sets based on a commercially-available CIT

Value Set Name

Malignant Neoplasm of Prostate, Including Carcinoma in Situ

Scope

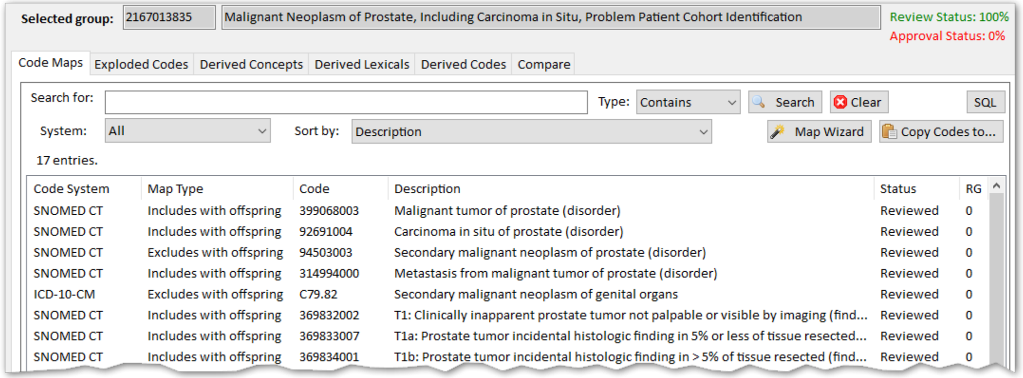
Terms that indicate primary malignant neoplasm of prostate, including carcinoma in situ, used to find patients for analytics or decision support.

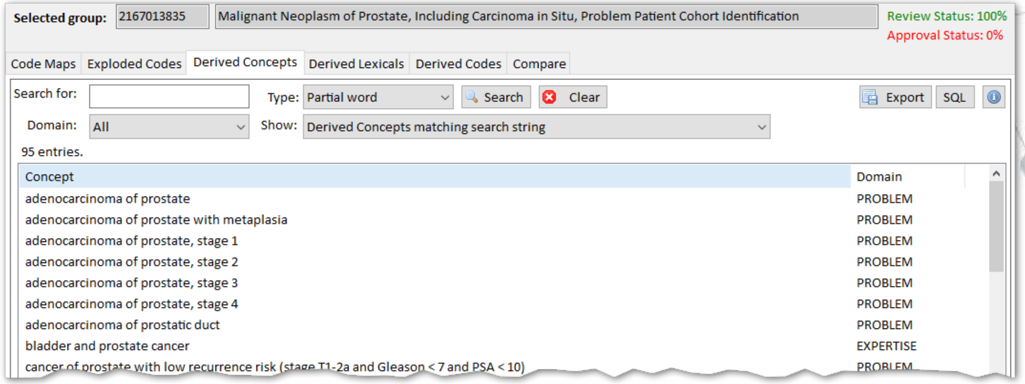
Inclusion

All histopathologies of primary malignancy of the prostate including non-carcinoma tumors, e.g. lymphoma or stromal sarcoma, and including terms that do not specify whether the neoplasm is primary; intraductal carcinoma of prostate.

Exclusion

Metastatic neoplastic disease to the prostate, high grade prostatic intraepithelial neoplasia, atypical intraductal proliferation of prostate, and history or risk of malignant neoplasm of the prostate.





How Medical Trainees Can Use the Electronic Health Record for Clinical Feedback: Four Keys for Compliant and Effective Use

“Is an emergency medicine trainee allowed to follow-up on the results of a lung biopsy for a patient she treated for hypoxia? ”

Clinical Relationship:
Have a direct clinical relationship with the patient

Clinical Question:
Have a defined question answered by the patient’s course

Time:
The question should be answered in a restricted time period

Patient Lists:
Use lists within the EHR to track charts for review

Samuel Yang, MD, MS, Jennifer Lee, MD, Juan Chaparro, MD,

Ignite-Style Talks 2 – Igniting Excellence, Efficiency and Ease of Use, AMIA 2020 Virtual Clinical Informatics Conference

Tablet-Based Screening
Identifies 5x as Many At-risk Primary Care Patients

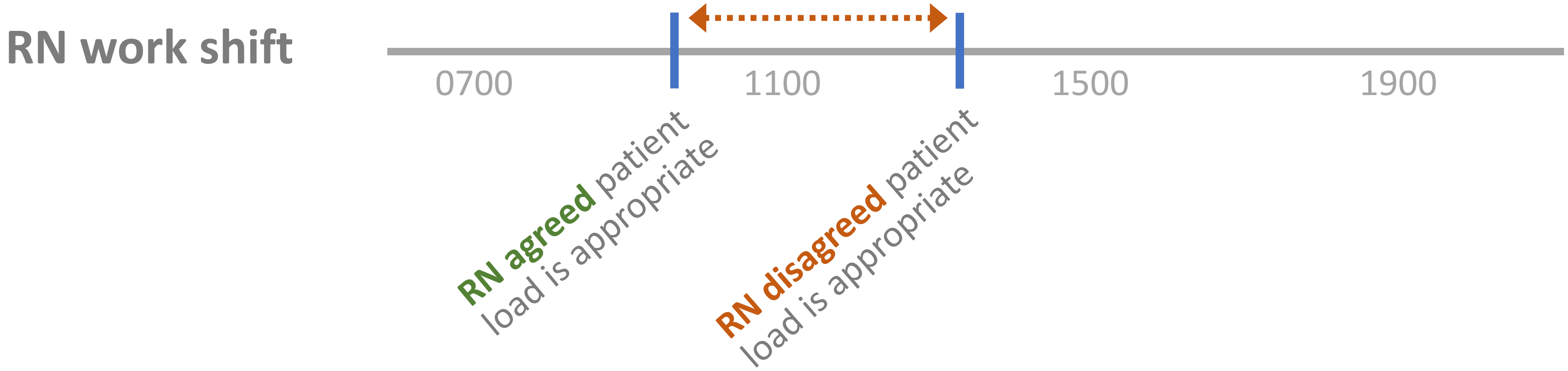
Increase in detection rates using iPad screening in waiting room
(compared to staff-initiated screening)

Depression	Domestic Violence	Fall Risk
1% → 14%		
		
Thoughts of Suicide		
0.4% → 1.5%	0.3% → 6.7%	5% → 18%

Usability, Efficiency, and Experience

Augmented Reality/ Virtual Reality
Care Coordination
Clinical Automation
Clinician Burden/Documentation Burden
Implementation, Optimization
Interprofessional Collaboration
Patient Engagement
Team-based Care
Usability
Workflow Efficiency

Documentation delay of 1st patient assessment may serve as a digital echo of time & production pressure at the bedside



Echoes of Overload: Sensing Clinician Adaptation to Time Pressure

The Arch Collaborative
a KLAS initiative

The Impact of Education, Governance, and Personalization on Clinical EHR Satisfaction

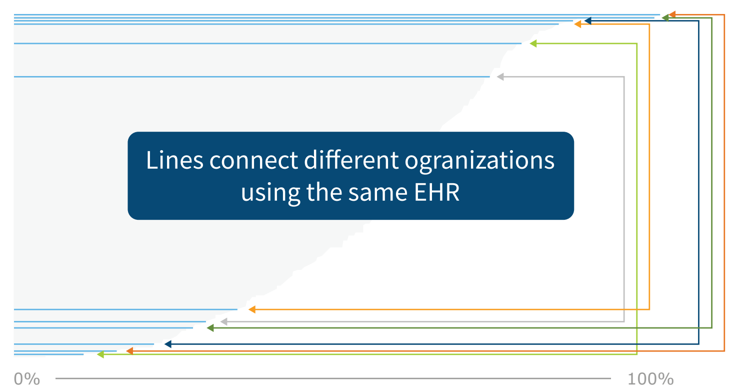
> *I have stopped asking for help because the people teaching make me feel stupid."*
>
> —Clinician, large health system

KLAS Surveyed

130,000 clinicians across 210 healthcare organizations

Percent of Providers Who Are Satisfied

(n=39,072 providers from 189 organizations: each bar is an EHR deployment with >20 responses) (0–100 scale)



Variables That Matter Most

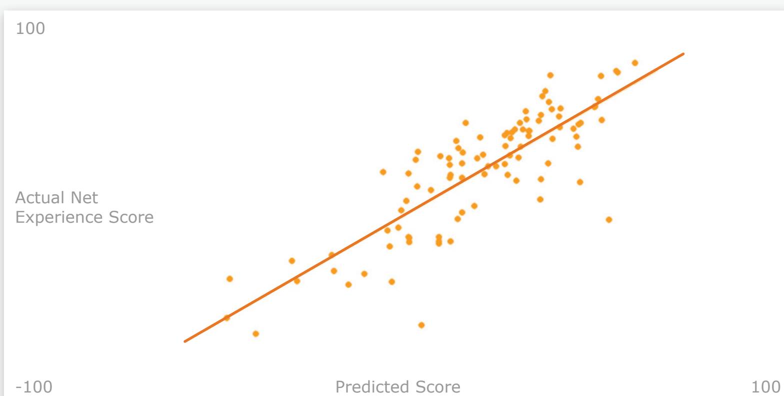
1. Organizational governance
2. Initial and ongoing education
3. Adoption of personalization tools

$r^2=.69$

With these three variables, we can explain about 70% of the variation in a user's experience with the EHR

Predicted Satisfaction vs. Actual Satisfaction

(-100 to +100 scale)



Keys to Success

After analyzing the feedback, KLAS has come up with three keys to a successful EHR:

Reducing the Ignore Rate of Your Clinical Decision Support Alerts within the Electronic Medical Record

Process

Clinical Decision Support Committee regular review of medication and non-medication alerts

Use of visualization software to track alert frequency, overrides and actions

Use of key criteria to target alert optimization

- High (top 20%) or low firing rate (bottom 10%) and low action rate (< 10%)
- Interruptive alert: Y/N
- Target audience (provider, nurse)
- Focus (clinical, administrative)
- Context (inpatient, ED, ambulatory)

Poor performing alerts assessed for optimization with clinical/operational owner

Outcomes

Removal / reduction in non-medication alerts: (examples)

- Removal of sequential compression device (if 'off' or patient 'refused') reminder to nurses → use of alternative workflow (**removal of 4000 alerts/month**)
- Removal of lab status collection (nurse vs phlebotomy) reminder to nurses → use of a silent alert to automatically change status (**removal of 7000 alerts/month)**
- Revise admission order signature by attending reminder (aimed at non-attendings) → **alerts reduced by 78%/month**

Reduction in medication alerts: (examples)

- Epidural – anticoagulation warnings → **alerts reduced by 98%/month**
- Overall medication warnings → **alerts reduced by 39% and 37%** for inpatient and ambulatory contexts, respectively, over last several years
- Overall medication **override rates reduced by 5%**

Zimmerman C., PharmD, Chang R., MD, Medlin R., MD,
Session S12, AMIA 2020 Clinical Informatics Conference

Using a Web-Based Electronic Referral System to Monitor and Track Referral Status

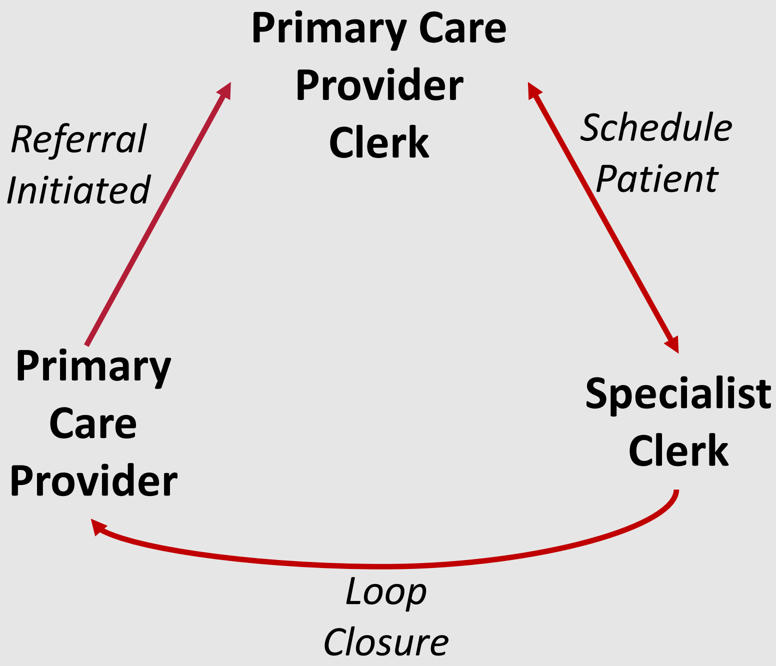
Study Population

Medicaid e-referral network
- 75 sending practices
- 270 receiving practices

Referrals initiated:
- November 2018 → October 2019

Innovation

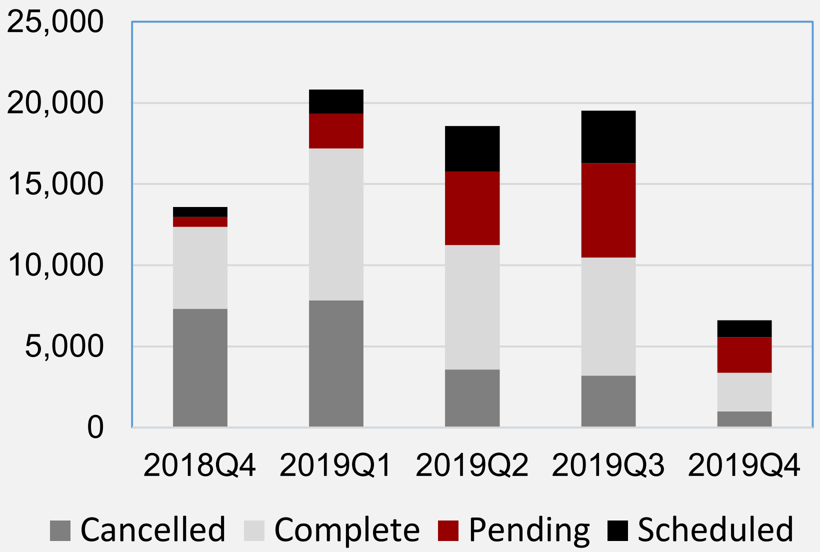
All communication is electronic and logged



Results

79,132 referrals with detailed tracking

Visit Requests by Status



Reynolds E, Van Cain M, Homco J, Lesselroth B, and Kendrick D.

Department of Medical Informatics

School of Community Medicine at the University of Oklahoma

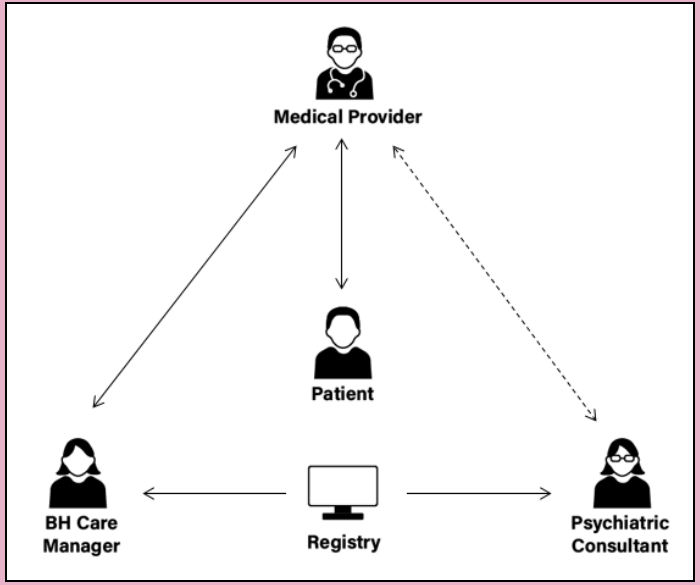
School of COMMUNITY MEDICINE

Development and Use of an Advanced Patient Registry to Support Team-Based Collaborative Care of Perinatal Depression in Community Health Centers

MInD-I

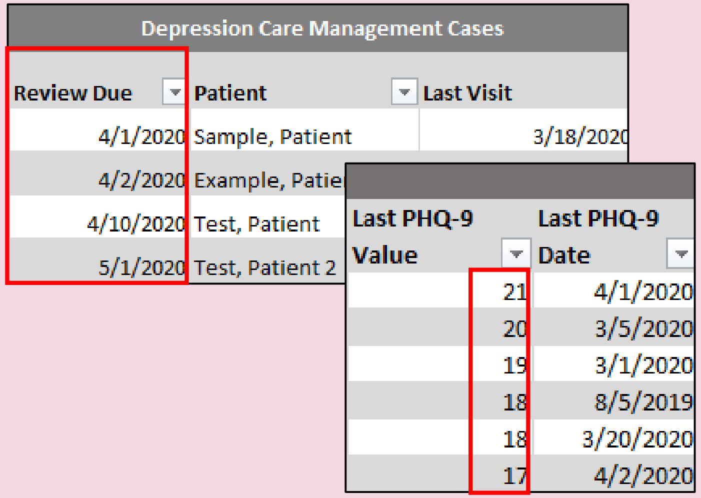
OCHIN

Use Impacted by Presence of Full Collaborative Care Team



Eligible patients added to registry ranged between 14-100% (mean: 85%), higher in sites with full team.

Use Impacted by Technical Complexity of Registry



Initial utilization varied up to 2 months due to technical challenges; all sites utilized by within 4 months of training.

Registry Had High Overall Levels of Usability and Acceptability

Site	Usability Score (SUS)
1	83
2	80
3	35
4	68
5	83
Average	70

Usability scores ranged from 35-83 with an average of 70 (score > 68 indicates greater than average usability).

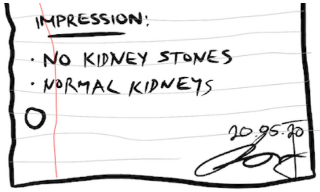
Supported by the California HealthCare Foundation grant #19713 and the National Institutes of Health grant # 1R01MH108548-01

Tess Grover, Ian M. Bennett, Marla Dearing, Mary Middendorf, Amy Bauer, Amritha Bhat, Suzanne Hunter, Rachel Gold, Perry Foley, Melinda Vredevoogd, Whitney Eriksen, Fran Barg

2020

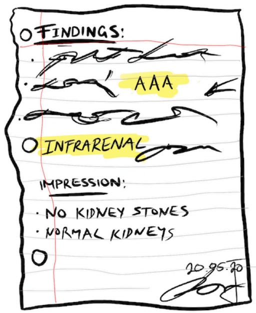
AMIA INFORMATICS PROFESSIONALS. LEADING THE WAY.

1. Aortic aneurysms can be lost to follow-up, especially incidental findings

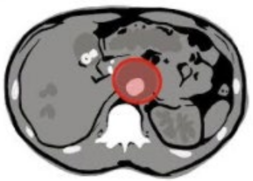


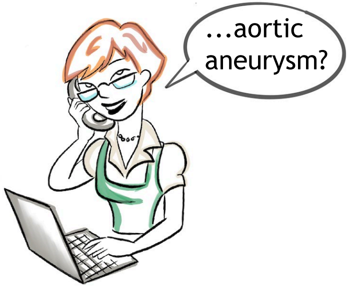
Your kidneys look good! You can go home…

2. Our algorithm searches radiology notes for aneurysm-related terms



3. The Vascular Clinic reviews cases and contacts providers



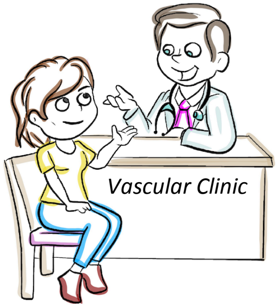


Results in test data:

- Our algorithm found 92% of positive cases

Results in deployment:

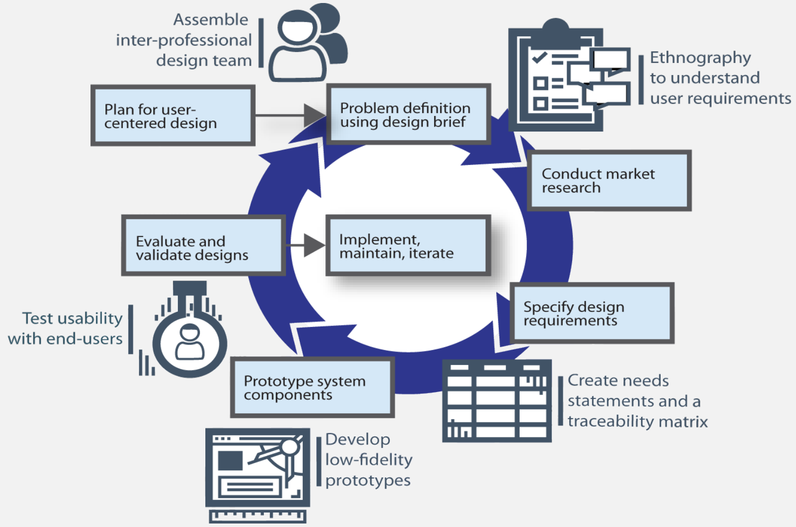
- Vascular Clinic found 80% of flagged cases to be true positives
- 9 cases identified for outreach in the first month



Requirements for Inpatient Handoff Software: Application of Design Thinking to the User-Centered Design Process

User Centered Design process from ideation to execution

Use Design Thinking to empathize with user



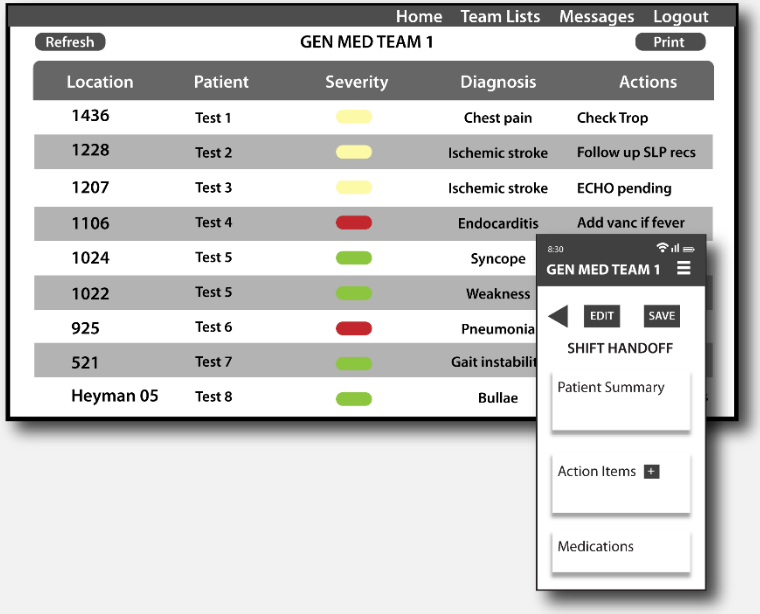
Write needs statements (i.e., user stories)

User Requirements

A **user** needs a way to **do something** to accomplish **a goal.**

A **resident** needs a way to **see all patient tasks** so she **doesn't miss a critical action** at night.

Create high-fidelity desktop and mobile prototypes



R. Yarnall, H. Park, J. Jarshaw, K. Norton, A. Corbett, M. Van Cain, B. Lesselroth
Departments of Medical Informatics and Internal Medicine

AMIA Clinical Informatics Conference, Seattle, May 2020

School of COMMUNITY MEDICINE

From Burnout to Wellness:
Investing in People to Realize the Value of IT Investment

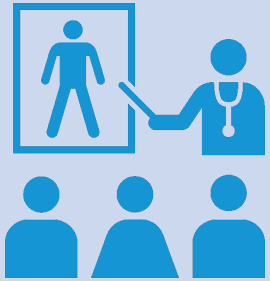
In a fully integrated era of Healthcare IT—EHRs and other technology will play a role in provider burnout

Improve clinician satisfaction with a focus on **value of investment**

Ongoing training, along with redesigned clinical practices, leads to improved:

- Chart review time
- Documentation time
- Order time

This **investment in people** decreases burnout . . .



. . . and provides **stronger physician-patient relationships**.

Lu de Souza, MD; Susan Locke, MD; Michael Ross, MD; John Schultz, MD;
S34 Panel, AMIA 2020 Clinical Informatics Conference

AMIA INFORMATICS PROFESSIONALS. LEADING THE WAY.

UNIVERSITY of WASHINGTON

Public Use of a Web-Based Treatment Decision Aid: The Personal Patient Profile – Prostate

P3P

Men from the general public entered the site without clinic referral or active marketing.

130 men with prostate cancer independently registered and used site

Median time on personalized intervention was 8 minutes

Pre-decision users spent more time on the site.

Pre-decision users found application acceptable and valuable.

Next steps include formal marketing campaign and wider dissemination.

Seth Wolpin, PhD, RN,
Justin McReynolds, MS,
William B Lober, MD, MS,
Donna L Berry, PhD, RN.
University of Washington.

www.p3p4me.org

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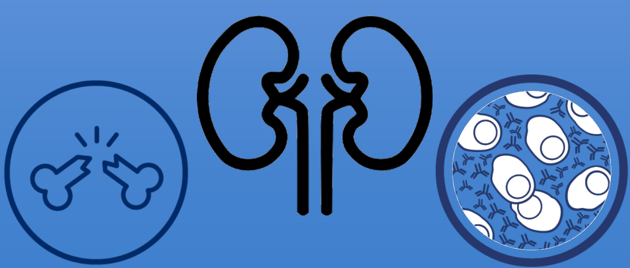
Semi-automated Serum Protein Electrophoresis (SPEP) Reporting Using a Lab-developed Python App

Ghazaleh Eskandari, MD, Paul A. Christensen, MD, S. Wesley Long, MD, PhD

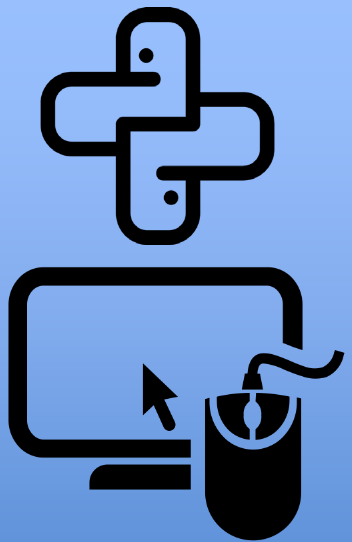
SPEP

An inexpensive method to diagnose different disorders



Traditional manual method

Using the tool



The average daily sign out time:

11 min 13 sec   P=0.01   8 min 2 sec

Human error events:

2.2%   0%

Decreased odds of patient portal adoption (adjusted odds ratio [OR] < 1)

in a cross-sectional analysis of 154,189 adult patients at a non-integrated U.S. healthcare system was significantly ($p<0.05$) associated with…

↑ age	OR = 0.412 (age 65-74)
male	OR = 0.955
African American	OR = 0.770
Hispanic	OR = 0.832
public health insurance	OR = 0.774 (Medicare)
↓ socioeconomic status	OR = 0.891 (zip code)
↑ inpatient visits	OR = 0.709
↑ # comorbidities	OR = 0.746

Automatic real time patient categorization utilizing electronic health record data

Categorization by scoring algorithm

Lab values for 19,906 patients from MIMIC-III → acuity & change → Placement in one of 4 clinical categories

2	3
1	4

Categorization by 50 physicians

Lab values for 4 patients each representing one clinical category → acuity & change → Placement in one of 4 clinical categories

2	3
1	4

Percent agreement in categorization between physicians & algorithm

acuity ↑		
	2) chronically sick 14%	3) acutely sick 88%
	1) well 71%	4) unstable 10%

degree of change →

Nguyen and Pollack, Poster Session 1, AMIA 2020 Clinical Informatics Conference

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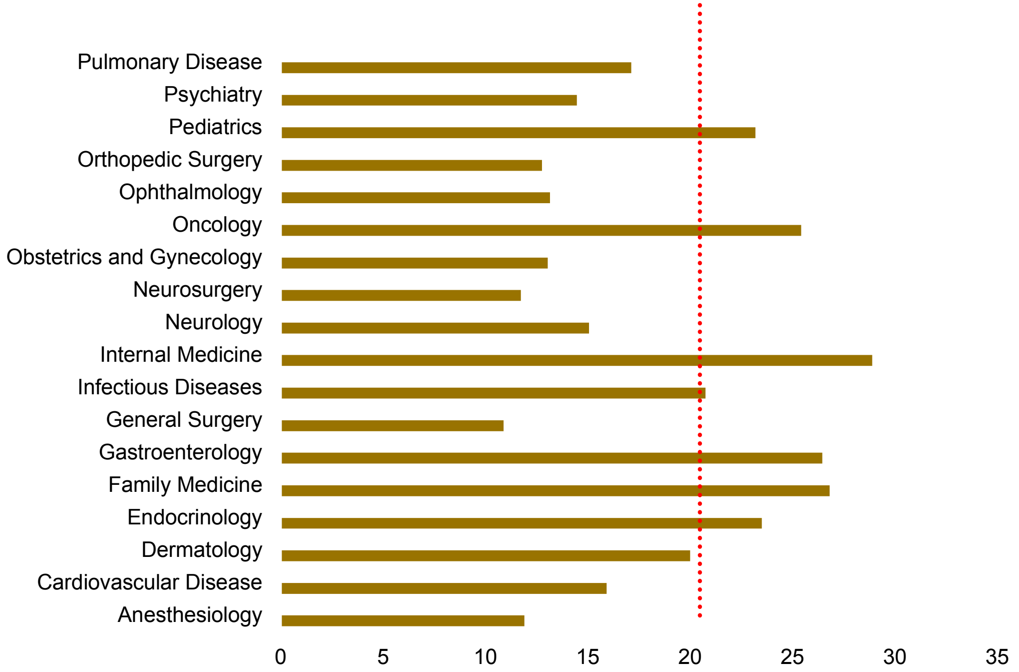
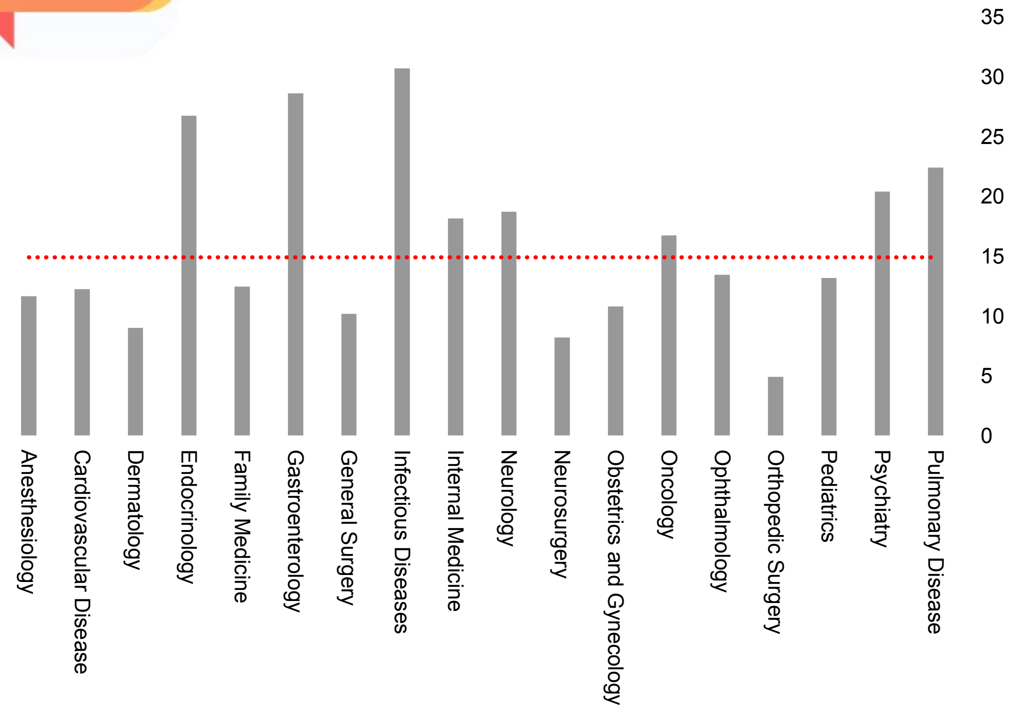
Do Providers of Different Specialties Vary in Clinical Administrative Burden?

Time Charting After Hours



Time Charting Per Appointment



Disrupting Patient Consent: Managing Health Data Rights Using Blockchain

Current

- Administrative Burden
- Barrier to Interoperability
- Incomplete Clinical Data

vs.

Future

- Patient Centered
- Decentralized and Automated
- Private and Secure

Johnson, Weaver, Nachimuthu, Poster Session 2, AMIA 2020 Clinical Informatics Conference

Using Human-Centered Design to Develop ROSTR

An EHR-Integrated Real-Time Online Summary of Team Resources for Care Coordination

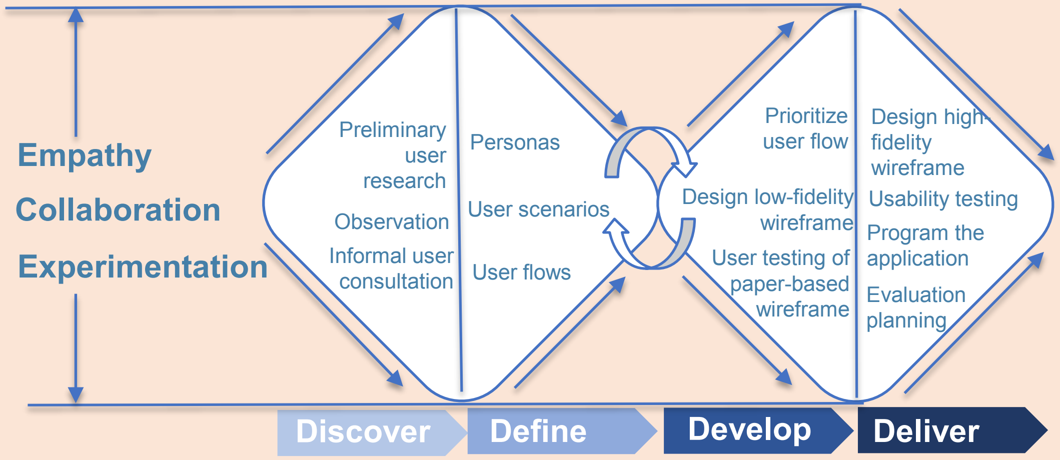
Background

The importance and challenges of real-time care team member identification

- **Breakdowns in care coordination have been shown to significantly impact care quality and patient safety**
- **A patient's care team composition is complex**: There are multiple interdisciplinary roles caring for hospitalized patients
- **A patient's care team composition is constantly evolving:** Based on the patient's status and the shift and rotation of providers

Human-Centered Design Approaches

We situated human factors in the center of the design process to build a tool that can provide accurate and dynamic care team information in real-time.



Our Process

7 Personas

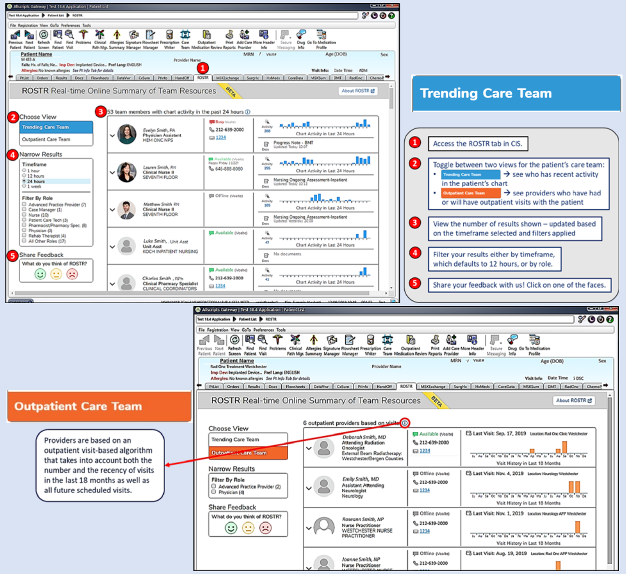
- NP/PA
- Attending
- Fellow
- Inpatient Nurse
- Radiologist
- Resident
- Unit Assistant

→ **12 User Scenarios** → **12 User Flows** →

User Testing Sessions	
Paper prototype	• Key screens were designed based on the user flows • 6 tasks were created for 6 users across 5 roles • Users were asked to think aloud and were prompted to perform real-world tasks
High-fidelity Prototype	• A high-fidelity clickable prototype was designed after incorporating findings for paper prototype testing • 9 tasks were created for testing with 4 users across 4 roles • Results from the user testing were incorporated in the final specifications passed to the development team

Outcome

ROSTR: Real-time Online Summary of Team Resources



Conclusion:

By **designing *with* users,** we brought their voices and insights into the development of the new tool. This allowed us to rapidly **iterate** and **scale up**.

IMPROVEMENTS IN PROVIDER SATISFACTION AND CLINICAL OUTCOMES THROUGH WORKFLOW ANALYSIS AND USER-CENTERED DESIGN OF LUMBAR PUNCTURE ORDER SETS

UCONN SCHOOL OF MEDICINE

A general-purpose lumbar puncture (LP) order set created opportunity for issues with resulting in lab utilization, lab routing, patient safety, and provider satisfaction. After careful analysis of the workflow, we separated it into four major categories, allowing for improved, more intentional, more directed, and deliberate design of workflows, with both tangible and intangible benefits.

Introduction

There was misalignment between foundation LP order sets and provider workflow. Processes need to align to place orders for labs, procedures, etc.

Indications for LPs, the types of labs to order and which procedures to request varies by specialty.

Order sets must be created based on provider indication and applied across an organization regardless of the ordering specialty.

At UConn Health, there was one broad LP workflow that was streamlined into four workflows for inpatient and outpatient services.

Methods

- Review of Epic foundation LP order sets
- Present-state and future-state mapping of LP order sets

Legacy Workflow

Collectively used for Inpatient, Emergency Department (ED), Outpatient LPs at the bedside, in clinic, & Interventional Radiology (IR)

All workflows		
All workflows	No guidance	Requires manually Identifying labs for workup
Lab names	Manual	Requires careful lab selection
Priority	Manual selection	Requires manual selection of priority
Order status	Manual selection	Requires manual status selection
Order details	Manual details	Requires manual entry of additional details

ESTIMATED CLICKS: 91 clicks
ESTIMATED TIME: approx. 5 min

Future-State Workflow

Each tailored for the respective workflow

Inpatient/ED Bedside	Inpatient/ ED IR	Outpatient IR	Outpatient Clinic
General	General	Specialty	Specialty
General lab names	General lab names	Specialty lab names	Specialty lab names
STAT	STAT	Routine	Routine
Immediate	Signed & held	Signed & held	Immediate
Order details +/- specialty add-on labs	Order details +/- specialty add-on labs	Order details	Order details
EST CLICKS: 4 EST TIME: 15 sec	EST CLICKS: 4 EST TIME: 15 sec	EST CLICKS: 6-22 EST TIME: 66 sec	EST CLICKS: 4-20 EST TIME: 60 sec

Results

1. More targeted & intuitive workflow
2. Better clinical decision support
3. Better lab utilization & order routing
4. Fewer clicks & fewer denials
5. Lower propensity for errors
6. Improved provider satisfaction

Conclusion

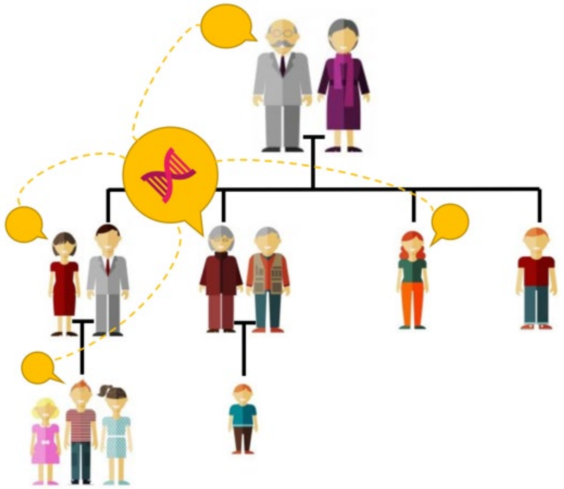
Intentional scenario-driven order set design is imperative for better adherence to clinical standards.

Uju Momah BA, Dirk Stanley MD, Michael Blechner MD
Poster Session 2, AMIA 2020 Clinical Informatics Conference

2020

AMIA INFORMATICS PROFESSIONALS. LEADING THE WAY.

Facilitating Family Communication about Genetic Testing through ConnectMyVariant



Family communication about genetic risk and testing can facilitate **cancer prevention**

Content creation

ConnectMy VARIANT

Index of Variant Forums	Forums where users can post, search, connect with other users with the same variant
Stories and Examples	Situations to illustrate potential challenges and success stories
Frequently Asked Questions (FAQs)	

Usability Assessment

Semi-structured Interview

Ask questions about the experience of using ConnectMyVariant

Think Aloud

Participants speak their thoughts aloud as they perform tasks with the website

User Perceptions

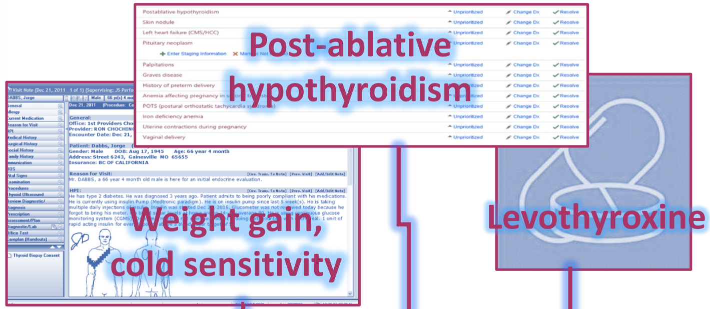
Participants felt overwhelmed with complex genetic information

Participants encountered website navigation issues

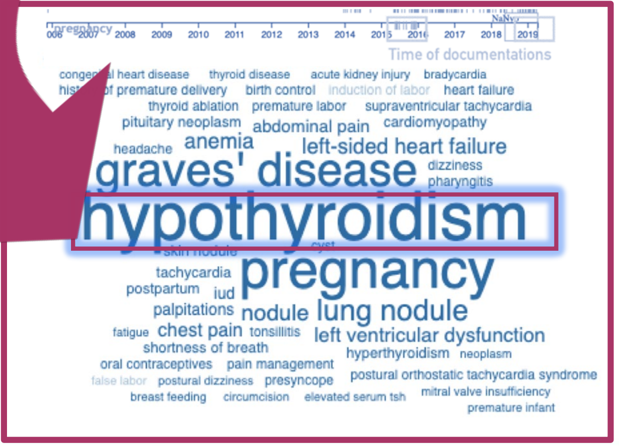
Participants would be willing to share ConnectMyVariant with others

Usability of a Word Cloud Visualization of the Problem List

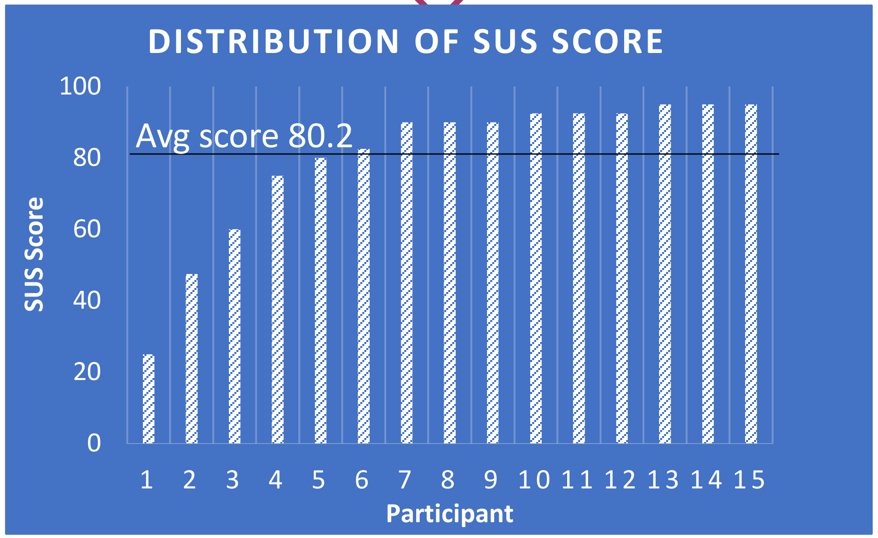
How does the Word Cloud work?



Natural Language Processing



Consecutive sampling of 15 Vanderbilt Internal Medicine physicians to obtain a System Usability Score.



Conclusion: On average, health care providers rated the Word Cloud's usability to be between good (71.4) and excellent (85.5) for its first iteration.

Physician Feedback

i. Accuracy

ii. Physician Customization

iii. Ease of use

"Customize WC to show problems by specific organ systems"

"Zoom function on the timeline bar to look more closely at a patient's problems during a particular time frame/year"

Next steps

I. Improve
II. Repeat SUS across specialties
III. Integrate
IV. Assess impact

Hannah Tan, Dario Giuse, Yaa Kumah-Crystal, Session 2,
AMIA 2020 Clinical Informatics Conference

The Impact of Virtual Transcription Systems on Patients, Providers, and Operations

Time in Charting Activities

↓ 27%

Provider Satisfaction

↑ 83%

Provider Documentation

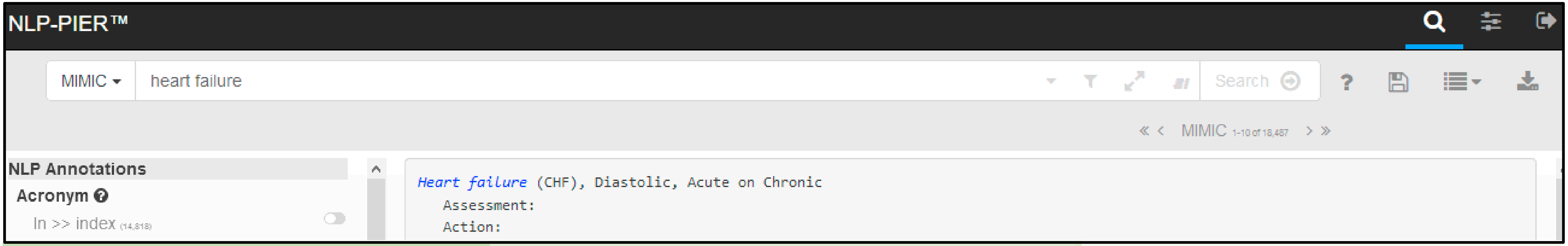
↓ 61%

Number of Patient Visits

↑ 1%

NLP-PIER Redesign:

A Natural Language Processing (NLP) clinical document search interface with updated look and feel and improved functionality



New Features

- Vector based query expansion
- NLP concept searching
- Patient count features

Improved Design

- Encounter view options
- Fixed common bugs
- Query saving across research teams

Updated Look and Feel

- Simplified filters
- More intuitive design
- Usability improvements

Gretchen Hultman, Poster Session 2,
AMIA 2020 Clinical Informatics Conference