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

Load synthetic EHR data
Load real-word EHR data

OHDSI CDM + Standard Vocabulary (PostgreSQL)

Data model

Controller application (Java + Drools)

Alert algorithm validation

DDI CDS Algorithm

RED: Class 1: Avoid Combination
Yellow: Class 2/3: Usually Avoid Combination or Minimize Risk
Green: Class 4: No Special Precautions

OHDSI Vocabulary

Concept Set

Concept

Condition Era
Visit Occurrence
Measurement
Drug Exposure

Patient data

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

Manoj Maddali, MD1, Maunank Shah, MD PhD2

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

www.hivassist.com

**HIV-ASSIST** uses multi-criteria decision analysis

**HIV-ASSIST** improves appropriate selection of HIV Treatment

**HIV-ASSIST** provides accurate Patient specific recommendations

Patient (CD4, comorbidities)

Virus (Viral load, genotype)

+ + +

Pill burden, Drug interactions Treatment history

Evaluate against:
- Tolerability (pills, comorbidities)
- Effectiveness (viral suppression)

**HIV-ASSIST** uses multi-criteria decision analysis

**HIV-ASSIST** improves appropriate selection of HIV Treatment

**HIV-ASSIST** provides accurate Patient specific recommendations

- Ranked ARV recommendations with educational content
- Guidelines 40% appropriate
- Randomized Trial of 118 trainees given HIV-ASSIST or National Clinical Practice Guidelines

Guidelines 40% appropriate

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

Maddali et al. JACM. Oct 2019
Ramirez et al. JGIM. Dec 2019
Ramirez et al. CID. March 2020
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
- < 2 years: 10 days
- ≥ 2 years: 7 days

**Outcomes**

Adherence to Duration Recommendations - Centerline Shift
- Pre-intervention: 24%
- Post-intervention: 88%

Estimated Antibiotic Days Saved over 5 Months: > 2600 days
We created a prototype of the Opportunity Index Dashboard that included features requested by stakeholders.

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

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

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

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.
Predicting Unplanned Readmission Events in Infants with Single Ventricle Disease

App-based Metrics

EHR

O₂Sat

Weight

Event

XGBOOST

68%
Unplanned Readmissions Before Prediction

5%*
Unplanned Readmissions After Prediction

*in offline model evaluation on retrospective data
AI Synthetic Sampling (SynSam) to Boost Machine Learning (ML) Prediction Accuracy for Infrequent Outcome Events

The Problem

Virtual Patient Cohort (N=50,000, Y|Y=1|=1%), 20% Testing Data

- **Sensitivity**: 0.55, 0.70, 0.90
- **Specificity**: 1.00, 1.00, 0.96
- **AUC**: 0.78, 0.99, 0.93
- **F1 Score**: 0.99, 0.99, 0.97

NHANES Asthma Cohort (N=6,177, Y|Asthma ER visit or hospitalization =9%), 20% Testing Data

- **Sensitivity**: 0.19, 0.24, 0.51
- **Specificity**: 0.96, 0.95, 0.88
- **AUC**: 0.57, 0.59, 0.68
- **F1 Score**: 0.87, 0.87, 0.86

A Solution

**Virtual Patient Cohort**
- **SynSam**: AI Synthetic Sampling
- **Y=1**: 1%
- **Y=0**: 99%
- **ML Prediction model Training**: SynSam

**NHANES Asthma Cohort**
- **NHANES**: National Health and Nutrition Examination Survey
- **ML**: Extreme Gradient Boosting
- **Bootstrap**: Random oversampling with replacement

**SynSam**
- 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)
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

Ask
6 questions

Switch
patient and tool

Ask
6 different questions with similar themes

Usability Survey for novel webapp visualization tool

Try it out! legrand.io/fill-view

![Graph showing mean correct response, mean participant score, and mean time to complete each question for novel webapp visualization and current PDF document.]

- Mean correct response (%, t-test p=0.099)
- Mean participant score (%, p=0.036)
- Mean time to complete each question (s, p=0.36)
Prediction of Likely Benefit of Pharmacogenomic Testing Derived from Electronic Medical Record Data

- **Disease Status**: Dis. 1, Dis. 2, ..., Dis. n
- **Procedural Codes**: Proc. 1, Proc. 2, ..., Proc. k
- **PGx Medications**: Med. 1, Med. 1, ..., Med. m
- **Biomarkers**: Gene 1, Gene 1, ..., Gene g

**Receiver Operating Characteristic Curve**
- **AUC**: 0.903
- **Optimized Sensitivity**: 0.857
- **Optimized Specificity**: 0.819
Machine Learning Algorithms Detect and Differentiate Shock in Combat Casualties

<table>
<thead>
<tr>
<th>Training Data: Electronic Health Records</th>
<th>Algorithm Performance</th>
<th>Prognostic Capabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essential Vitals</td>
<td>Detection and Differentiation Models</td>
<td>ML algorithms identify shock before clinician action.</td>
</tr>
<tr>
<td>Diagnosis Time</td>
<td>general shock</td>
<td>A prospective real time silent test at Mayo Clinic will compare algorithm performance to standard of care.</td>
</tr>
<tr>
<td>ICU Patients</td>
<td>- AUC 0.86</td>
<td></td>
</tr>
<tr>
<td>120 Minute Window</td>
<td>- sensitivity 73%</td>
<td></td>
</tr>
<tr>
<td>ICD Codes</td>
<td>- specificity 83%</td>
<td></td>
</tr>
<tr>
<td>Clinician Action</td>
<td>cardiogenic shock</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- AUC 0.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- sensitivity 72%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- specificity 82%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>septic shock</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- AUC 0.88</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- sensitivity 73%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- specificity 82%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>hypovolemic shock</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- AUC 0.71</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- sensitivity 72%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- specificity 79%</td>
<td></td>
</tr>
<tr>
<td>Shock Type Distribution</td>
<td>None 88%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Septic 6%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Cardiogenic 4%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Hypovolemic 2%</td>
<td></td>
</tr>
</tbody>
</table>
Engagement of Clinical Nurses in Text Mining: Enhancing Interpretability and Clinical Relevance of a Fall Prevention Algorithm


- 1% result in death
- 10% result in severe injury
- 30-50% result in injury
- ~1 million patient falls annually

- ~1 million patient falls annually
- ~30-50% result in injury
- ~10% result in severe injury
- ~1% result in death

$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

Manual Annotation

Three Registered Nurses
241 notes annotated

Inter-rater Agreement over Time

Environmental
cognitive
physiological
behavioral
procedures
social
Assessment

F-score
Kappa

0% 20% 40% 60% 80% 100%

Time 1
Time 2
## Impact of EMBED: A User-Centered Clinical Decision Support to Implement EMergency Department-Initiated BuprenorphinE for Opioid Use Disorder (OUD) – The Pilot Study

**EMBED**
- 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

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Baseline</th>
<th>Intervention</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>OUD Pt Receiving BUP in ED or prescription at discharge</td>
<td>3.5%</td>
<td>6.6%</td>
<td>0.03</td>
</tr>
<tr>
<td>OUD Pt Receiving Prescription for Naloxone at ED discharge</td>
<td>6.5%</td>
<td>11.5%</td>
<td>0.009</td>
</tr>
<tr>
<td>Physician Adoption Rate of ED-Initiated BUP for OUD pt</td>
<td>19.2%</td>
<td>32.5%</td>
<td>0.53</td>
</tr>
<tr>
<td>Odds of Physician Adoption following Brief In-Person Training</td>
<td>More than 2x</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Unadjusted RR = 2.16, p = 0.02

Holland et al, AMIA 2020 Clinical Informatics Conference | Conference

NIH National Institute on Drug Abuse
Advancing Addiction Science

Yale University School of Medicine

Author, Session, AMIA 2020 Clinical Informatics Conference
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
Estimating Aspirin Overuse for ASCVD Primary Prevention in the US Veteran Population

Guideline #1
- Age 40-70
- ASCVD Risk*
- Bleeding Risk*
- Cannot compute aspirin overuse

Guideline #2
- Age >70
- No ASCVD
- 3.9% (88,462 people)

Guideline #3
- Age 18+
- Bleeding Risk*
- 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

Privacy Cost = \( F_1(\text{centralized}) - F_1(\text{federated}) \)

Federation Benefit = \( F_1(\text{federated}) - F_1(\text{single client}) \)

Model quality measured via \( F_1 \)-Score

F. Rabe, F. Stieler, B. Bauer; University of Augsburg; Germany
Poster Session 1, AMIA 2020 Clinical Informatics Conference
CDS-based IV-to-Oral Medication Conversion

<table>
<thead>
<tr>
<th>Drug</th>
<th>Per Dose Cost-savings</th>
</tr>
</thead>
<tbody>
<tr>
<td>doxycycline</td>
<td>$17.11</td>
</tr>
<tr>
<td>famotidine</td>
<td>$0.62</td>
</tr>
<tr>
<td>lacosamide</td>
<td>$14.21</td>
</tr>
<tr>
<td>levofloxacin</td>
<td>$1.64</td>
</tr>
<tr>
<td>levothyroxine</td>
<td>$107.05</td>
</tr>
<tr>
<td>linezolid</td>
<td>$42.60</td>
</tr>
<tr>
<td>methocarbamol</td>
<td>$54.10</td>
</tr>
<tr>
<td>rifampin</td>
<td>$67.67</td>
</tr>
</tbody>
</table>

Improved conversion rate from IV-to-PO
famotidine

38% 48%

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,

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

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

<table>
<thead>
<tr>
<th>Prior morbidity</th>
<th>Fold increase in risk</th>
<th>Risk of complications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diabetes mellitus w/o complications</td>
<td>6.30x (+/- 0.33 std)</td>
<td>37% (+/- 10% std)</td>
</tr>
<tr>
<td>Hypertension</td>
<td>2.62x (+/- 0.23 std)</td>
<td>17% (+/- 1.5% std)</td>
</tr>
<tr>
<td>Obesity</td>
<td>2.82x (+/- 0.3 std)</td>
<td>17% (+/- 0.8% std)</td>
</tr>
</tbody>
</table>

Cohort of 29,301 patients with at least 5 years of EHR records and at least 3 visits. Baseline risk for diabetes with complications in this cohort is 5.9%.
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

OCR Analysis via Amazon Textract and NLP Analysis via CLAMP

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

Processing & Data Extraction
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

ML Action Rules for Treatment Recommendation

Sample machine learned association rule built in eTRT knowledge base:

IF R3(<15;20)) AND T_an >= 8
THEN Category(1), Conf. = 94.4%

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?


Results: Evidence, technology, policy, and culture change are needed to optimize the practice of SDM and the development of useful and usable tools.
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
Health Apps for Everyone:
Developing Inclusive User Experience (UX) Criteria

**Developing an assessment criteria to evaluate inclusiveness of health app design that's based on:**

- 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.

**Inclusive UX Criteria**

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

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

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

High Value Exchange

HIE between Metrohealth and Cleveland Clinic in 2014
Decision support and Alerts of Apps for Self-management of Blood Glucose (BG) for Type 2 Diabetes


1 Few apps alert users properly to hypo- and hyperglycemic events...

- 58.8% alerted users
- 37.0% displayed explicit messaging

2 And even fewer provide action prompts to correct BG events...

- Proportion of apps providing action prompts for -
  - Hyperglycemic events: 15.3%
  - Hypoglycemic events: 20.7%

3 Evidencing low levels of decision support or education on BG self-management.

Need for quality control

Immature development of diabetes apps landscape

Jimenez G et al, S49 – May 21, AMIA 2020 Clinical Informatics Conference
Systematic Assessment of Suicide Prevention Strategies in 69 Mental Health Apps


Of the 6 suicide prevention strategies assessed, 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.
A Successful Example of Using FHIR and Epic RESTful APIs in a Clinic Check-In iPad Program

<table>
<thead>
<tr>
<th>Reach and Adoption of iPad Program in 4 Primary Care Clinics</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patient Reach</strong></td>
</tr>
<tr>
<td>66% (4274 uses of 6504 total visits for patients &gt;=18 years)</td>
</tr>
<tr>
<td><strong>Nursing Adoption</strong></td>
</tr>
<tr>
<td>0.3% FHIR and Epic RESTful APIs Failure Rate*</td>
</tr>
<tr>
<td>*encounter mismatches, API did not file data appropriately, network infrastructure issues</td>
</tr>
<tr>
<td>75% (3205 of 4274 times when the Check-In program was used)</td>
</tr>
</tbody>
</table>
The App Rating Inventory (ARI)
A New Tool to Evaluate Mobile Health Apps

When clinicians are confronted by the availability of several hundred apps to help with insomnia, 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?**

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

Robert Ciulla, Ph.D., Session, AMIA 2020 Clinical Informatics Conference
Interoperability Framework and Health Information Exchange

APPLIED CLINICAL INFORMATICS IN VA SYSTEM MODERNIZATION

STANDARDS-BASED FRAMEWORK

Enterprise Architecture

STANDARDS-BASED APPROACH

Business Process Model Notation

PORTABILITY OF HEALTHCARE PROCESS FLOWS

STANDARDS-BASED ONTOLOGY

AMIA 2020 Clinical Informatics Conference
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.

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

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.


Utah Medical Cannabis Process

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.
Panel Discussion: Protecting Adolescent Confidentiality Without Information Blocking

Both State and Federal laws can extend privacy protections for adolescents

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

Both unstructured and discrete data can contain sensitive information

Understand complexity of laws related to adolescent privacy

Develop a governance plan to protect adolescents at your institution

Learn how to use NLP to identify sensitive information in unstructured data
Performance $\rightarrow$

Trade-offs not needed

Care is timely and complete

Trade-offs emerge

Clinical needs are prioritized
Care delays occur

Trade-offs dominate

Urgent needs are prioritized
Routine care is missed

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

<table>
<thead>
<tr>
<th>DoH Sub Domain</th>
<th>Persons (%) with DoH need</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A1c &gt; 9%</td>
</tr>
<tr>
<td>Food Security</td>
<td></td>
</tr>
<tr>
<td>Homelessness</td>
<td></td>
</tr>
<tr>
<td>Electricity</td>
<td></td>
</tr>
<tr>
<td>Transportation</td>
<td></td>
</tr>
<tr>
<td>Daycare</td>
<td></td>
</tr>
<tr>
<td>Income</td>
<td></td>
</tr>
<tr>
<td>Job</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td></td>
</tr>
<tr>
<td>Legal issues</td>
<td></td>
</tr>
<tr>
<td>Personal safety</td>
<td></td>
</tr>
<tr>
<td>Drug-alcohol</td>
<td></td>
</tr>
</tbody>
</table>

- 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.

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

<table>
<thead>
<tr>
<th>DoH Sub Domain</th>
<th>Persons (%) with DoH need</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A1c &gt; 9%</td>
</tr>
<tr>
<td></td>
<td>A1c &lt; 9%</td>
</tr>
<tr>
<td>Food Security</td>
<td>13.0%</td>
</tr>
<tr>
<td>Homelessness</td>
<td>5.0%</td>
</tr>
<tr>
<td>Electricity</td>
<td>4.0%</td>
</tr>
<tr>
<td>Transportation</td>
<td>8.4%</td>
</tr>
<tr>
<td>Daycare</td>
<td>1.0%</td>
</tr>
<tr>
<td>Income</td>
<td>8.0%</td>
</tr>
<tr>
<td>Job</td>
<td>4.4%</td>
</tr>
<tr>
<td>Education</td>
<td>9.0%</td>
</tr>
<tr>
<td>Legal Issues</td>
<td>4.4%</td>
</tr>
<tr>
<td>Personal safety</td>
<td>1.6%</td>
</tr>
<tr>
<td>Drug-alcohol</td>
<td>7.2%</td>
</tr>
</tbody>
</table>

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

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 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%)
- Minorities
- High ADI
- Drug use
- Living alone
- Depression
- Dual Eligibility
- Medicare insurance

Group 2: Medium Readmission (15.7%)
- White patients
- Older patients
- Living alone
- Low ADI

Group 3: Low Readmission (9.5%)
- White patients
- Females
- Low comorbidity scores
- All SDH

SDH By Race-Ethnicity - Readmission Risk Odds Ratios

Pairwise Comparison

- ADI (Area Deprivation Index)
  - Black
  - White
  - Hispanic
- Drug Use
  - Black
  - White
  - Hispanic
- Lives Alone
  - Black
  - White
  - Hispanic
- Depression
  - Black
  - White
  - Hispanic
- Dual Eligible
  - Black
  - White
  - Hispanic
- Insurance (Medicare vs. Commercial)
  - Black
  - White
  - Hispanic

Su and Cannella et al., Session: S03, AMIA 2020 Clinical Informatics Conference
The EQUIPPED Potentially Inappropriate Medication Dashboard: A Suitable Alternative to the In-Person Academic Detailing of Traditional EQUIPPED?

ED Provider Interacts w/ EHR

Nightly Upload

VA’s Corporate Data Warehouse

ED Provider Interacts w/ EHR

Nightly Upload

VA’s Corporate Data Warehouse

EQUIPPED Dashboard

Potential Inappropriate Medication (PIM) Dashboard

Informed by an Evidence-Based List of Medications to Avoid in Older Adults: 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:
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
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
An Infrastructure for Value Set Creation and Maintenance Utilizing a Clinical Interface Terminology (CIT)

CITs Let Clinicians Speak “Clinician”

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

...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 944480000
- 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
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?”

Value sets link clinical terminologies to populations
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)

<table>
<thead>
<tr>
<th></th>
<th>Depression</th>
<th>Domestic Violence</th>
<th>Fall Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Thoughts of Suicide</strong></td>
<td>1% → 14%</td>
<td>0.3% → 6.7%</td>
<td>5% → 18%</td>
</tr>
<tr>
<td><strong>Depression</strong></td>
<td>1% → 14%</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Domestic Violence</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fall Risk</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- 18% domestic violence
- 5% fall risk
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
With these three variables, we can explain about 70% of the variation in a user’s experience with the 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)

Outcomes

Poor performing alerts assessed for optimization with clinical/operational owner

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%
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

Primary Care Provider Clerk

Referral Initiated

Schedule Patient

Specialist Clerk

Primary Care Provider

Loop Closure

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

**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**

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

<table>
<thead>
<tr>
<th>Site</th>
<th>Usability Score (SUS)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>83</td>
</tr>
<tr>
<td>2</td>
<td>80</td>
</tr>
<tr>
<td>3</td>
<td>35</td>
</tr>
<tr>
<td>4</td>
<td>68</td>
</tr>
<tr>
<td>5</td>
<td>83</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>70</td>
</tr>
</tbody>
</table>

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

Garcia et al., S27, AMIA 2020 Clinical Informatics Conference

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

Use Design Thinking to empathize with user

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

Create high-fidelity desktop and mobile prototypes

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.

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
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.

Ongoing training, along with redesigned clinical practices, leads to improved:
- Chart review time
- Documentation time
- Order time

Improve clinician satisfaction with a focus on value of investment.

This investment in people decreases burnout . . . .

. . . and provides stronger physician-patient relationships.

In a fully integrated era of Healthcare IT—EHRs and other technology will play a role in provider burnout.
<table>
<thead>
<tr>
<th>Men from the general public entered the site without clinic referral or active marketing.</th>
<th>Median time on personalized intervention was 8 minutes</th>
<th>Pre-decision users found application acceptable and valuable.</th>
</tr>
</thead>
<tbody>
<tr>
<td>130 men with prostate cancer independently registered and used site</td>
<td>Pre-decision users spent more time on the site.</td>
<td>Next steps include formal marketing campaign and wider dissemination.</td>
</tr>
</tbody>
</table>

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

www.p3p4me.org
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

Nguyen et al., Poster Session 1, *AMIA Clinical Informatics Conference, May 2020*
Automatic real time patient categorization utilizing electronic health record data

Categorization by scoring algorithm

Lab values for 19,906 patients from MIMIC-III

Placement in one of 4 clinical categories

Percent agreement in categorization between physicians & algorithm

<table>
<thead>
<tr>
<th></th>
<th>2) chronically sick</th>
<th>3) acutely sick</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) well</td>
<td>14%</td>
<td>88%</td>
</tr>
<tr>
<td>4) unstable</td>
<td>71%</td>
<td>10%</td>
</tr>
</tbody>
</table>

Categorization by 50 physicians

Lab values for 4 patients each representing one clinical category

Placement in one of 4 clinical categories

Lab values for 19,906 patients from MIMIC-III

Categorization by scoring algorithm

Placement in one of 4 clinical categories

Acuity & change
Do Providers of Different Specialties Vary in Clinical Administrative Burden?

Time Charting After Hours

- Pulmonary Disease
- Psychiatry
- Pediatrics
- Orthopedic Surgery
- Ophthalmology
- Oncology
- Obstetrics and Gynecology
- Neurosurgery
- Neurology
- Internal Medicine
- Infectious Diseases
- General Surgery
- Gastroenterology
- Family Medicine
- Endocrinology
- Dermatology
- Cardiovascular Disease
- Anesthesiology

Time Charting Per Appointment

- Anesthesiology
- Cardiovascular Disease
- Dermatology
- Endocrinology
- Family Medicine
- General Surgery
- Infectious Diseases
- Internal Medicine
- Neurology
- Neurosurgery
- Obstetrics and Gynecology
- Ophthalmology
- Orthopedic Surgery
- Pediatrics
- Psychiatry
- Pulmonary Disease
Disrupting Patient Consent: Managing Health Data Rights Using Blockchain

Current

- Administrative Burden
- Barrier to Interoperability
- Incomplete Clinical Data

Future

- Patient Centered
- Decentralized and Automated
- Private and Secure

vs.
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

Empathy Collaboration Experimentation

Discover Define Develop Deliver

Preliminary user research
Observation Informal user consultation

Personas User scenarios User flows

Prioritize user flows Design low-fidelity wireframe User testing of paper-based wireframe

Design high-fidelity wireframe Usability testing Program the application Evaluation planning

Our Process

7 Personas
NP/PA
Attending
Fellow
Inpatient Nurse
Radiologist
Resident
Unit Assistant

User Testing Sessions

12 User Scenarios 12 User Flows

Paper prototype
- Key screens were designed based on the user flows
- 6 tasks were created for 6 users across 6 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.
## 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

<table>
<thead>
<tr>
<th>Workflows</th>
<th>Lab names</th>
<th>Priority</th>
<th>Order status</th>
<th>Order details</th>
</tr>
</thead>
<tbody>
<tr>
<td>All workflows</td>
<td>Manual</td>
<td>Manual selection</td>
<td>Manual details</td>
<td>Requires manually identifying labs for workup</td>
</tr>
</tbody>
</table>

**Legacy Workflow**

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

**Order details**:

- Requires manually identifying labs for workup
- Requires careful lab selection
- Requires manual selection of priority
- Requires manual status selection
- Requires manual entry of additional details

**Legacy Workflow**

<table>
<thead>
<tr>
<th>Inpatient/ED Bedside</th>
<th>Inpatient/ED IR</th>
<th>Outpatient IR</th>
<th>Outpatient Clinic</th>
</tr>
</thead>
<tbody>
<tr>
<td>General lab names</td>
<td>General lab names</td>
<td>Specialty lab names</td>
<td>Specialty lab names</td>
</tr>
<tr>
<td>STAT</td>
<td>STAT</td>
<td>Routine</td>
<td>Routine</td>
</tr>
<tr>
<td>Immediate</td>
<td>Signed &amp; held</td>
<td>Signed &amp; held</td>
<td>Immediate</td>
</tr>
</tbody>
</table>

**Future-State Workflow**

Each tailored for the respective workflow.

**Future-State Workflow**

<table>
<thead>
<tr>
<th>Inpatient/ED IR</th>
<th>Outpatient IR</th>
<th>Outpatient Clinic</th>
</tr>
</thead>
<tbody>
<tr>
<td>General lab names</td>
<td>Specialty lab names</td>
<td>Specialty lab names</td>
</tr>
<tr>
<td>STAT</td>
<td>Routine</td>
<td>Routine</td>
</tr>
<tr>
<td>Signed &amp; held</td>
<td>Signed &amp; held</td>
<td>Immediate</td>
</tr>
</tbody>
</table>

**Estimated Clicks and Time**

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

**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.
### Content creation

<table>
<thead>
<tr>
<th>Index of Variant Forums</th>
<th>Forums where users can post, search, connect with other users with the same variant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stories and Examples</td>
<td>Situations to illustrate potential challenges and success stories</td>
</tr>
<tr>
<td>Frequently Asked Questions (FAQs)</td>
<td>Participants speak their thoughts aloud as they perform tasks with the website</td>
</tr>
</tbody>
</table>

### 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**

---

**Facilitating Family Communication about Genetic Testing through ConnectMyVariant**

Family communication about genetic risk and testing can facilitate cancer prevention.
Usability of a Word Cloud Visualization of the Problem List

How does the Word Cloud work?

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

“Customize WC to show problems by specific organ systems”

ii. Physician Customization

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

iii. Ease of use

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% decrease
- **Provider Documentation**: 61% decrease
- **Provider Satisfaction**: 83% increase
- **Number of Patient Visits**: 1% increase

Thomas, Poster Session 2, AMIA 2020 Clinical Informatics Conference
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