CRISP-ENABLED RESEARCH SYMPOSIUM

Thursday, March 14th, 2019, 3:30pm to 5:30pm

Johns Hopkins University Tilghman Auditorium
INTRODUCTION AND WELCOME

Christopher Chute, MD, DrPH

Bloomberg Distinguished Professor of Health Informatics
Professor of Medicine, Public Health, and Nursing at Johns Hopkins University
Chair of the CRISP Research Subcommittee
INTRODUCTION AND WELCOME

• Christopher Chute, MD, DrPH, Bloomberg Distinguished Professor of Health Informatics, Professor of Medicine, Public Health, and Nursing at Johns Hopkins University, and Chair of the CRISP Research Subcommittee

OVERVIEW OF CRISP AND THE CRISP RESEARCH INITIATIVE

• Ross D. Martin, MD, MHA, Program Director, CRISP Research Initiative

EXAMPLES OF CURRENTLY SUPPORTED RESEARCH

• UMMS-Friends NavSTAR: Jan Gryczynski, PhD, Senior Research Scientist, Friends Research
• JHU Readmissions, B’FRIEND, Suicide Project: Hadi H.K. Kharrazi, MD, MS, PhD, Assistant Director, Center for Population Health IT (CPHIT), Johns Hopkins Bloomberg School of Public Health
• JHU MESA: Wendy Post, MD, MS – Professor of Medicine and Epidemiology, Division of Cardiology, Johns Hopkins University School of Medicine
• JHU Walgreens: Jodi Segal, MD, MPH – Professor of Medicine, Epidemiology, Health Policy and Management, Johns Hopkins University

CRISP TECHNICAL FRAMEWORK UPDATE

• Michael Berger, CRISP CIO
• Ryan Bramble, CRISP Senior Director of Development and Executive Director, CRISP DC

CURRENT CAPABILITIES AND FUTURE OPPORTUNITIES

• Ross D. Martin, MD, MHA, Program Director, CRISP Research Initiative

CLOSING THOUGHTS

• David Horrocks, MBA, CRISP President and CEO

RECEPTION
OVERVIEW OF CRISP AND THE CRISP RESEARCH INITIATIVE

Ross D. Martin, MD, MHA
Program Director, CRISP Research Initiative
Our Vision
To advance health and wellness by deploying health information technology solutions adopted through cooperation and collaboration.

Our Mission
We will enable and support the healthcare community of Maryland and our region to appropriately and securely share data in order to facilitate care, reduce costs, and improve health outcomes.

Our Guiding Principles
1. Begin with a manageable scope and remain incremental.
2. Create opportunities to cooperate even while participating healthcare organizations still compete in other ways.
3. Affirm that competition and market-mechanisms spur innovation and improvement.
4. Promote and enable consumers’ control over their own health information.
5. Use best practices and standards.
6. Serve our region’s entire healthcare community.

CRISP is a non-profit health information exchange (HIE) serving Maryland, the District of Columbia, West Virginia and the region.
1. The support of research is a valuable but secondary component of CRISP’s mission to share data to facilitate care, reduce costs, and improve health outcomes. CRISP will support research efforts so long as they do not detract from its primary mission.

2. CRISP will contribute to the learning health system by making CRISP-mediated data available to researchers who are participants in CRISP through a well-governed request submission, review, approval, and audit process.

3. CRISP will not replicate services which are available through participating organizations or agencies or serve as a method for bypassing institutional processes for addressing data needs of researchers.

4. CRISP will assess fees to research data requestors in a cost recovery manner in order to cover its actual direct and indirect costs.
5. CRISP will inform patients and their caregivers of the use cases under which their data may be made available for research purposes.

6. CRISP will maintain a public record of its data disclosures for research through regular publication on its website.

7. CRISP will partner with participating researchers to receive feedback on data and service quality and incorporate research results into CRISP offerings.

8. CRISP will periodically evaluate the value of expanding its ability to deliver data in support of research and will seek input from the research community on optimal methods for delivering data in a manner that can support research related to improving care delivery, reducing costs, and improving health outcomes.
CRISP Research Initiative Progress To Date

4/20/2016
Research approved as a new permitted purpose under CRISP Participation Agreement

6/20/2016
State regulatory framework supporting the use of HIE data for research goes into effect

8/10/2016
CRISP Research Subcommittee meets for the first time

11/8/2016
First use case approved – Patient-Consented, IRB-Approved Research

11/28/2016
First research study approved: JHU ALIVE

3/8/2017
2nd use case approved - Combining CRISP Data with HSCRC Case Mix Data for Research

8/31/2017
Four research projects live and using CRISP data
CRISP Research Subcommittee

- Dr. Christopher Chute (Chair) – Bloomberg Distinguished Professor of Health Informatics at Johns Hopkins University
- Dr. Daniel Durand – Executive Director of Research, LifeBridge Health
- Shannah Koss, BA, MPP – Koss on Care, LLC, Consumer Advocate
- Dr. Michael Horberg – Executive Director of Research and Community Benefit, Mid-Atlantic Permanente Medical Group
- Dr. Kate Tracy – Associate Professor and Director of Clinical Translational Research and Informatics Center at the University of Maryland School of Medicine
- Dr. Neil Weissman – President of the MedStar Health Research Institute
CRISP Core Services

1. **POINT OF CARE: Clinical Query Portal & In-context Information**
   - Search for your patients’ prior hospital records (e.g., labs, radiology reports, etc.)
   - Monitor the prescribing and dispensing of PDMP drugs
   - Determine other members of your patient’s care team
   - Be alerted to important conditions or treatment information

2. **CARE COORDINATION: Encounter Notification Service (ENS)**
   - Be notified when your patient is hospitalized in any regional hospital
   - Receive special notification about ED visits that are potential readmissions
   - Know when your MCO member is in the ED

3. **POPULATION HEALTH: CRISP Reporting Services (CRS)**
   - Use Case Mix data and Medicare claims data to:
     - Identify patients who could benefit from services
     - Measure performance of initiatives for QI and program reporting
     - Coordinate with peers on behalf of patients who see multiple providers

4. **PUBLIC HEALTH SUPPORT:**
   - Deploying services in partnership with Maryland Department of Health
   - Pursuing projects with the District of Columbia Department of Health Care Finance
   - Supporting West Virginia priorities through the WVHIN

5. **PROGRAM ADMINISTRATION:**
   - Making policy discussions more transparent and informed
   - Supporting Care Redesign Programs
1. Real-time visit notifications (ADTs)
   • Show events for patients as they progress through the continuum of care
2. Master Patient Index (MPI)
   • Link patients in disparate systems together based on probabilistic matching
3. Provider Panels
   • Track health care relationships to send ENS alerts, create more transparency across programs, and audit CRISP search activity
4. HIE Registries
   • Provide critical information in fast, scalable, and flexible ways
5. Clinical Documents
   • Display patient health information from multiple sources
6. Administrative Data Sets
   • Enable CRISP Reporting Services and Total Cost of Care Model support
CRISP by the numbers

<table>
<thead>
<tr>
<th>Service</th>
<th>Typical Week</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admit, Discharges from Hospitals and Ambulatory</td>
<td>4,159,212</td>
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<tr>
<td>Laboratory Reports Received</td>
<td>964,712</td>
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<tr>
<td>Received Transcriptions/Reports</td>
<td>236,335</td>
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<tr>
<td>Received Radiology Reports</td>
<td>163,407</td>
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<tr>
<td>Encounter Notifications Sent</td>
<td>852,411</td>
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<tr>
<td>InContext Requests for HIE Registry data</td>
<td>470,060</td>
</tr>
<tr>
<td>Delivery of Registry into EMRs</td>
<td>311,040</td>
</tr>
<tr>
<td>InContext Requests for PDMP Data</td>
<td>369,580</td>
</tr>
<tr>
<td>Delivery of PDMP Data into EMRs</td>
<td>95,540</td>
</tr>
<tr>
<td>Patients Searched</td>
<td>61,489</td>
</tr>
<tr>
<td>Patients searched in ULP Portal</td>
<td>41,403</td>
</tr>
<tr>
<td>Patients searched from an EMR</td>
<td>13,606</td>
</tr>
<tr>
<td>Images Viewed</td>
<td>176</td>
</tr>
<tr>
<td>New data sent to MPI</td>
<td>1,833,000</td>
</tr>
</tbody>
</table>
EXAMPLES OF CURRENTLY SUPPORTED RESEARCH
UMMS-FRIENDS NavSTAR

Jan Gryczynski, PhD
Senior Research Scientist, Friends Research Institute
Experiences with using CRISP in the Navigation Services to Avoid Rehospitalization (NavSTAR) study at the University of Maryland Medical Center

Jan Gryczynski, PhD
Friends Research Institute

Christopher Welsh, MD
University of Maryland

This project was supported by the National Institute of Health, National Institute on Drug Abuse (grant R01DA037942)
Friends Research Institute
- Jan Gryczynski, PhD
- Courtney Nordeck, BA
- Robert Schwartz, MD
- Shannon Gwin Mitchell, PhD
- Kevin E. O’Grady, PhD

University of MD Medical Center
- Christopher Welsh, MD
- Art Cohen
- Mike Papa, LCSW-C

Acknowledgements: This project would not have been possible without funding from NIDA, the substance abuse consultation team at UMMC, and the steadfast support of Ross Martin and CRISP.
NavSTAR study

- Builds upon the substance abuse consultation service at the University of Maryland Medical Center.

- **Randomized Clinical Trial** comparing Patient Navigation services vs. Treatment as Usual (TAU) among medical/surgical patients with comorbid substance use disorder (N= 400).

- The ultimate goal of the Patient Navigation intervention is to reduce hospitalizations and ED visits.
NavSTAR was one of the first studies approved to use CRISP for research under the newly-adopted patient-consented research use case.

Language was included in study consent forms in anticipation of CRISP availability.

Continued to collect data on hospital events the old fashioned way.

- Participant self-report at follow-up (using TLFB interview techniques)
- Discharge summary requests to individual hospitals
- EHR review at the UMMS institution (initially UMMC, then added UM Midtown)
Participant Characteristics

- First 200 participants to complete 12 months in the study
  - 47% female
  - 57% African American
  - Mean (SD) age = 45 (12) years
  - 78% met criteria for opioid use disorder (almost all high severity)
  - 42% were homeless based on notes in the EHR
  - By self-report, the sample had mean (SD) of 9.1 (15.3) lifetime medical hospitalizations
## Measuring Hospital Service Utilization: CRISP vs. Conventional Methods

Table 1. Hospital events over a 12-month period as ascertained by different methods
(N= 200 medical patients with comorbid SUD enrolled in the NavSTAR trial).

<table>
<thead>
<tr>
<th></th>
<th>Self-report alone</th>
<th>EHR review alone</th>
<th>Self-report + EHR review</th>
<th>CRISP alone</th>
<th>CRISP+EHR combined</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Any Hospital Utilization</strong> (Inpatient or ED)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Events</td>
<td>261</td>
<td>953</td>
<td>1052</td>
<td>1666</td>
<td>1716</td>
</tr>
<tr>
<td>Unique Participants</td>
<td>105</td>
<td>158</td>
<td>167</td>
<td>181</td>
<td>183</td>
</tr>
<tr>
<td>% of events accurately identified</td>
<td>15.2%</td>
<td>55.5%</td>
<td>61.3%</td>
<td>97.1%</td>
<td>100%</td>
</tr>
<tr>
<td><strong>Inpatient Hospitalizations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Events</td>
<td>145</td>
<td>233</td>
<td>283</td>
<td>421</td>
<td>429</td>
</tr>
<tr>
<td>Unique Participants</td>
<td>83</td>
<td>113</td>
<td>128</td>
<td>143</td>
<td>145</td>
</tr>
<tr>
<td>% of events accurately identified</td>
<td>33.8%</td>
<td>54.3%</td>
<td>66.0%</td>
<td>98.1%</td>
<td>100%</td>
</tr>
<tr>
<td><strong>ED visits</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Events</td>
<td>116</td>
<td>720</td>
<td>769</td>
<td>1245</td>
<td>1287</td>
</tr>
<tr>
<td>Unique Participants</td>
<td>58</td>
<td>126</td>
<td>133</td>
<td>157</td>
<td>158</td>
</tr>
<tr>
<td>% of events accurately identified</td>
<td>9.0%</td>
<td>55.9%</td>
<td>59.8%</td>
<td>96.7%</td>
<td>100%</td>
</tr>
</tbody>
</table>
Self-report methods failed to identify a large number of inpatient hospitalizations.

**Inpatient hospitalizations** (N= 429 hospitalizations among 145 participants)

- Not disclosed in interview, 40.1%
- Correctly reported in interview, 33.8%
- Not interviewed (Deceased), 7.9%
- Not interviewed (Incarcerated), 2.3%
- Lost to follow-up (Unable to locate), 15.9%
Self-report methods failed to identify a large number of emergency department visits.

Emergency department (ED) visits ($N=1,287$ ED visits among 158 participants)

- Lost to follow-up (Unable to locate), 33.0%
- Not interviewed (Incarcerated), 1.2%
- Not interviewed (Deceased), 3.3%
- Correctly reported in interview, 9.0%
- Not disclosed in interview, 53.5%
Utility of CRISP for clinical trials and health services research

- Comprehensive tracking of health service utilization as study outcomes
  - Accuracy and efficiency advantages over conventional methods

- Health economic research

- Monitoring serious adverse events (SAEs) in high-risk studies

- CRISP will be especially useful in studies with populations that have high levels of service utilization and care fragmentation
JHU B’FRIEND
JHU SUICIDE PROJECT

Hadi H.K. Kharrazi, MD, MS, PhD
Assistant Director, Center for Population Health IT (CPHIT)
Johns Hopkins Bloomberg School of Public Health
Using CRISP data for population health research: The geriatric falls and suicide prevention projects

Center for Population Health IT (CPHIT)

Hadi Kharrazi (kharrazi@jhu.edu)
Johns Hopkins University
Bloomberg School of Public Health
Department of Health Policy and Management
Overview

- Population Health Informatics
  - Center for Population Health IT (CPHIT)
  - Risk Stratification
  - New Data Sources

- Use of CRISP data for Population Health Analysis
  - Geriatric Falls (B’FRIEND)
  - Suicide Prevention

- Discussion
  - Challenges & Opportunities
Population Health Informatics
Population Health Informatics → Emerging Field

- Better Health for the Population
- Lower Cost Through Improvements
- Better Care for the Individuals

Triple Aims developed by the Institute for Healthcare Improvement (IHI)
Population Health Informatics \rightarrow JHU CPHIT

JHU Center for Population Health Information Technology (CPHIT)

- **CPHIT** improves the health of populations by advancing cutting edge health IT across all sectors

- **Outcomes:** Healthcare Utilization (e.g., cost, hospitalization, ER admission)
- **Predictors:** Demographics, Diagnoses, Medications, Social Determinants + “new variables”
- **Data Source:** Insurance Claims, EHRs, HIEs, Hospital Discharges
- **Scale:** Populations (n = mil+)
- **Temporal:** Multi-year (t = 3 yrs+)

- Director: Dr. Weiner
- Research Director: Dr. Kharrazi

www.jhsph.edu/cphit
Population Health Informatics → Data Analytic Cycle

Overall Population Health Knowledge Management Process
Population Health Informatics → Claims-based Risk Stratification (ACG)

Management Applications
- Case Management
- Disease Management
- Practice Resource Management
- Needs Assessment
- Quality Improvement
- Payment/Finance

Population Segment
- High Disease Burden
- Single High Impact Disease
- Users
- Users & Non-Users

acg.jhsph.edu
Population Health Informatics → Claims-based Risk Stratification (ACG) (cont.)

**Input Files**

- **Patient File**
  Patient ID, Age, Gender

- **Medical Services File**
  Diagnoses and Procedures

- **Pharmacy File**
  Medications

**Risk Factors**

- Diagnosis-Based Markers
- Pharmacy-Based Markers
- Diagnosis and Pharmacy Markers
- Utilization/Resource Use Markers
- Coordination Markers

**Models**

- Concurrent Cost Risk
- Predicted Cost Risk
- Predicted Hospitalization Risk
Population Health Informatics → Data Sources

Weiner, 2012  http://www.ijhpr.org/content/1/1/33
Use of CRISP data for Population Health Analysis
Baltimore Falls Reduction Initiative Engaging Neighborhoods and Data (B’FRIEND)

Unprecedented public-private partnership in Baltimore City committed to reducing falls in the elderly by 1/3 in three years
B’FRIEND → Data Sources

- **HSCRC** (Maryland’s Health Services Cost Review Commission) – provided us discharge summary data (both inpatient and outpatient) on Baltimore City residents in 2014

- **CRISP** (Chesapeake Regional Information System for our Patients) – Maryland’s health information exchange that aggregates data from all hospitals in Chesapeake region
B’FRIEND ➔ Geographic Factors (Elderly Falls)

Prevalence of falls among elderly in Baltimore City (Census Block Group)
B’FRIEND → Geographic Factors (Elderly Falls) (cont.)

Prevalence of falls among elderly in Maryland (Census Block Group)
B’FRIEND ➔ Year/Month & Age Range
B’FRIEND → Mechanism of Fall
**Predictors and coefficients of the elderly-fall model**

| Predictors                        | Estimate | Std. error | z value | Pr(>|z|) | Significance | OR    | 2.50% | 97.50% |
|------------------------------------|----------|------------|---------|----------|--------------|-------|-------|--------|
| History of fall                    | 1.795    | 0.074      | 24.113  | <2e-16   | ***          | 6.02  | 5.20  | 6.97   |
| Fracture                           | 0.604    | 0.104      | 5.821   | 5.85E-09 | ***          | 1.83  | 1.49  | 2.24   |
| Substance Abuse                    | 0.520    | 0.082      | 6.364   | 1.96E-10 | ***          | 1.68  | 1.43  | 1.97   |
| Parkinson                          | 0.337    | 0.178      | 1.895   | 0.058056 | .            | 1.40  | 0.98  | 1.97   |
| Kyphoscoliosis                     | 0.322    | 0.153      | 2.102   | 0.035519 | *            | 1.38  | 1.01  | 1.85   |
| Sex (female)                      | 0.173    | 0.046      | 3.736   | 0.000187 | ***          | 1.19  | 1.09  | 1.30   |
| Depression                         | 0.146    | 0.068      | 2.141   | 0.032238 | *            | 1.16  | 1.01  | 1.32   |
| Mental Illness                    | 0.128    | 0.065      | 1.980   | 0.047652 | *            | 1.14  | 1.00  | 1.29   |
| Age                                | 0.038    | 0.003      | 14.895  | <2e-16   | ***          | 1.04  | 1.03  | 1.04   |
| Charlson Index                    | -0.053   | 0.009      | -5.711  | 1.12E-08 | ***          | 0.95  | 0.93  | 0.97   |
| Vision                             | -0.211   | 0.057      | -3.689  | 0.000225 | ***          | 0.81  | 0.72  | 0.91   |
| Obesity                            | -0.251   | 0.076      | -3.311  | 0.000031 | ***          | 0.78  | 0.67  | 0.90   |
| Cardiovascular Disease             | -0.313   | 0.050      | -6.301  | 2.95E-10 | ***          | 0.73  | 0.66  | 0.81   |
| Lower Urinary Tract Symptoms      | -0.345   | 0.074      | -4.656  | 3.23E-06 | ***          | 0.71  | 0.61  | 0.82   |
| Hypertension                      | -0.357   | 0.050      | -7.080  | 1.44E-12 | ***          | 0.70  | 0.63  | 0.77   |
| Cancer                             | -0.441   | 0.081      | -5.418  | 6.02E-08 | ***          | 0.64  | 0.55  | 0.75   |
| Lower Back Pain                    | -0.495   | 0.067      | -7.368  | 1.73E-13 | ***          | 0.61  | 0.53  | 0.69   |
| Joint Trauma                       | -0.526   | 0.197      | -2.674  | 0.007487 | **           | 0.59  | 0.39  | 0.85   |
| Lower Extremity Joint Surgery      | -1.069   | 0.182      | -5.870  | 4.36E-09 | ***          | 0.34  | 0.24  | 0.48   |
| (Intercept)                        | -4.372   | 0.197      | -22.249 | <2e-16   | ***          | 0.01  | 0.01  | 0.02   |

Significance codes: 0 **** 0.001 *** 0.01 ** 0.05 . 0.1 * 1
Suicide Prevention Review / Study

Reviewing data linkage strategies and methods to advance youth suicide prevention (funded by NIH P2P)
Addressing Suicide Research Gaps

- OCME (Medical Examiner) $\rightarrow$ [outcome]
- HIE data (admission, discharge, transfers)
- Hospital discharges (i.e., HSCRC)
- Claims (Commercial – MHCC, Medicare, and Medicaid)
- EHR data (Johns Hopkins, Sheppard Pratt, AAMC, PRMC, VHA)
- Child Protection Services & Corrections Data
- Geo-derived Social Determinants of Health (Census, ESRI)
- State-wide VDRS
- ... and other novel data sources
Addressing Suicide Research Gaps (cont.)

Schematic representation of population coverage of various identified data sources in Maryland

- **Population Denominator**
  - Individuals with a suicide death
  - Subpopulation of JHMI patients
  - Patient Population of JHMI, SPHS, or JHCRN
  - Population with a hospital discharge, or insurance claims
  - Population not seeking care in non-federal healthcare setting
  - Total Population of MD

- **Data Source**
  - Medical Examiner data
  - JHMI EHR records that have unstructured data (free text notes)
  - EHR records of JHMI, SPHS, or JHCRN
  - HSCRC, MHCC, Medicare or Medicaid data
  - No data available
Discussion
Discussion ➔ Challenges and Opportunities

- **Data sources/types:**
  - How to compare data types and their added value?
  - What are the limits of each data type? What are we missing?
  - What can be used from unstructured data?

- **Data quality:**
  - How much juice is left in this data type (e.g., claims)?
  - Do objective measures have data quality issues (e.g., BMI)?
  - How can we measure the quality of subjective data?

- **Denominator:**
  - Are we excluding noise or signal?
  - Is this a too big of a cut or too narrow – sample size issues?
  - Patient attribution issues...
Thank you!

Q & A

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JHU MESA
Wendy Post, MD, MS
Professor of Medicine and Epidemiology, Division of Cardiology
Johns Hopkins University School of Medicine
JHU WALGREENS

Jodi Segal, MD, MPH

Professor of Medicine, Epidemiology, Health Policy and Management
Johns Hopkins University
Evaluation

Walgreens aimed to promote medication adherence and reduce unplanned readmissions by expanding the role of the outpatient pharmacy.

Intervention: **Bedside delivery** of medications prior to discharge in 2017
- Medications were delivered directly to the patient’s room by a technician from the Walgreens pharmacy on the hospital campus
- If patient had questions, pharmacist connected via telephone or came to the room.
- Pharmacy staff processed insurance verifications and approvals and collected copayments, just as they would if the patient was at the community pharmacy.

This program was implemented at 14 acute care hospitals in Maryland and we were asked to **evaluate the impact on 30-day readmissions in the 11 hospitals** from which data was expected to be available from CRISP
Does bedside delivery of medication reduce 30-day readmissions relative to usual prescription management in acute care hospitals in Maryland?

[We hypothesized that it does based on results from Walgreens’ evaluation of the program in 2 hospitals in North Carolina.]
Design

- Retrospective cohort study
- Data: CRISP and HSCRC Casemix data
<table>
<thead>
<tr>
<th>Hospital Source Code</th>
<th>Hospital Name</th>
<th>Number of Patients in Source File</th>
<th>Patients Matched in IP</th>
<th>Patients Matched in OBS</th>
<th>Patients Matched in OP</th>
<th>Patients Not Matched</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADVSGAH</td>
<td>Shady Grove Adventist</td>
<td>35</td>
<td>21</td>
<td>*</td>
<td>*</td>
<td>*</td>
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<tr>
<td>ADVWAH</td>
<td>Washington Adventist</td>
<td>1024</td>
<td>661</td>
<td>88</td>
<td>141</td>
<td>134</td>
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<td>CVMH</td>
<td>CalvertHealth Medical Center, Inc.</td>
<td>1599</td>
<td>482</td>
<td>90</td>
<td>927</td>
<td>100</td>
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<tr>
<td>DCH</td>
<td>Doctors' Community Hospital</td>
<td>290</td>
<td>158</td>
<td>26</td>
<td>84</td>
<td>*</td>
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<td>FMH</td>
<td>Frederick Memorial</td>
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<td>343</td>
<td>*</td>
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<td>SAH</td>
<td>Saint Agnes Hospital</td>
<td>843</td>
<td>617</td>
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<td>UMMS_B WMC</td>
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<td>232</td>
<td>177</td>
<td>37</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>All Hospitals</td>
<td>All Hospitals</td>
<td>10,881</td>
<td>6,590 (60.6%)</td>
<td>1,092 (10.0%)</td>
<td>2,473 (22.7%)</td>
<td>726 (6.7%)</td>
</tr>
</tbody>
</table>

Needed to allow flexibility in the date of service (+/- 3 days of intervention)
## Flexibility with Date

<table>
<thead>
<tr>
<th>Difference in Days from Intervention Date</th>
<th>Percent of Patients Matched in IP</th>
<th>Percent of Patients Matched in OBS</th>
<th>Percent of Patients Matched in OP</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3</td>
<td>0.7%</td>
<td>1.2%</td>
<td>1.0%</td>
</tr>
<tr>
<td>-2</td>
<td>1.0%</td>
<td>*</td>
<td>1.1%</td>
</tr>
<tr>
<td>-1</td>
<td>3.0%</td>
<td>3.7%</td>
<td>2.6%</td>
</tr>
<tr>
<td>0  (Intervention Date)</td>
<td>84.8%</td>
<td>90.1%</td>
<td>90.1%</td>
</tr>
<tr>
<td>1</td>
<td>8.0%</td>
<td>3.6%</td>
<td>3.9%</td>
</tr>
<tr>
<td>2</td>
<td>1.9%</td>
<td>*</td>
<td>0.6%</td>
</tr>
<tr>
<td>3</td>
<td>0.7%</td>
<td>*</td>
<td>0.6%</td>
</tr>
<tr>
<td>Total Number of Patients</td>
<td>6,590</td>
<td>1,092</td>
<td>2,473</td>
</tr>
</tbody>
</table>
Comparison Group Matching Strategy

- Age group
- Gender
- Hospital
- Clinical characteristics of the admission/visit:
  - IP or OBS-matched patients: APR DRG for hospital admission
  - OP surgical matched patients: CPT code of procedure based on CPT code on the claim with the highest relative weight
  - ER-matched patients: CCS (diagnosis category) for the primary diagnosis

- Sought up to 5 matches for each intervention patient
- Delivered de-identified data – from 6 months before admission and 30 days after intervention (or index visit)
Patient Data

• Received 10,155 intervention patients and 50,714 non-intervention patients
• Inclusion criteria for study: inpatient admission, eligible for readmission reduced sample to:

  6,167 intervention and 28,546 non-intervention
<table>
<thead>
<tr>
<th></th>
<th>Control N=28546</th>
<th>Exposure N=6167</th>
<th>P-Value</th>
<th>Standardized Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>11531 (40.4%)</td>
<td>2480 (40.2%)</td>
<td>0.7934</td>
<td>0.0041</td>
</tr>
<tr>
<td>2</td>
<td>17015 (59.6%)</td>
<td>3687 (59.8%)</td>
<td></td>
<td>-0.0041</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>8869 (31.1%)</td>
<td>2051 (33.3%)</td>
<td>&lt;.0001</td>
<td>-0.0471</td>
</tr>
<tr>
<td>American Indian/Eskimo/Aleut</td>
<td>50 (0.2%)</td>
<td>8 (0.1%)</td>
<td></td>
<td>0.0258</td>
</tr>
<tr>
<td>Asian/Pacific Islander</td>
<td>636 (2.2%)</td>
<td>89 (1.4%)</td>
<td></td>
<td>0.0602</td>
</tr>
<tr>
<td>other</td>
<td>1489 (5.2%)</td>
<td>281 (4.6%)</td>
<td></td>
<td>0.0278</td>
</tr>
<tr>
<td>unknown</td>
<td>117 (0.4%)</td>
<td>21 (0.3%)</td>
<td></td>
<td>0.0169</td>
</tr>
<tr>
<td>white</td>
<td>17385 (60.9%)</td>
<td>3717 (60.3%)</td>
<td></td>
<td>0.0123</td>
</tr>
<tr>
<td><strong>Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>1315 (4.6%)</td>
<td>236 (3.8%)</td>
<td></td>
<td>0.0399</td>
</tr>
<tr>
<td>not Hispanic</td>
<td>26834 (94.4%)</td>
<td>5862 (95.4%)</td>
<td></td>
<td>-0.0455</td>
</tr>
<tr>
<td>unknown</td>
<td>292 (1.0%)</td>
<td>45 (0.7%)</td>
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<td>0.0327</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>divorced</td>
<td>2685 (9.4%)</td>
<td>636 (10.3%)</td>
<td>&lt;.0001</td>
<td>-0.0302</td>
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<tr>
<td>married</td>
<td>13091 (45.9%)</td>
<td>2619 (42.5%)</td>
<td></td>
<td>0.0685</td>
</tr>
<tr>
<td>separated</td>
<td>561 (2.0%)</td>
<td>149 (2.4%)</td>
<td></td>
<td>-0.0273</td>
</tr>
<tr>
<td>single</td>
<td>8923 (31.3%)</td>
<td>2218 (36.0%)</td>
<td></td>
<td>-0.0996</td>
</tr>
<tr>
<td>unknown</td>
<td>240 (0.8%)</td>
<td>31 (0.5%)</td>
<td></td>
<td>0.0373</td>
</tr>
<tr>
<td>widow/widower</td>
<td>3046 (10.7%)</td>
<td>514 (8.3%)</td>
<td></td>
<td>0.0819</td>
</tr>
<tr>
<td><strong>Primary Payer</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>charity/self pay</td>
<td>1102 (3.9%)</td>
<td>157 (2.6%)</td>
<td>&lt;.0001</td>
<td>0.0734</td>
</tr>
<tr>
<td>commercial</td>
<td>9972 (34.9%)</td>
<td>2265 (36.7%)</td>
<td></td>
<td>-0.0376</td>
</tr>
<tr>
<td>Medicaid</td>
<td>5090 (17.8%)</td>
<td>1307 (21.2%)</td>
<td></td>
<td>-0.0859</td>
</tr>
<tr>
<td>Medicare</td>
<td>11786 (41.3%)</td>
<td>2283 (37.0%)</td>
<td></td>
<td>0.0882</td>
</tr>
<tr>
<td>other</td>
<td>581 (2.0%)</td>
<td>150 (2.4%)</td>
<td></td>
<td>-0.0273</td>
</tr>
</tbody>
</table>
## Lightly Matched (As delivered)

<table>
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<tr>
<th></th>
<th>Control N=28546</th>
<th>Exposure N=6167</th>
<th>P-Value</th>
<th>Standardized Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>APR Severity</strong></td>
<td></td>
<td></td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>extreme</td>
<td>1533 (5.4%)</td>
<td>286 (4.6%)</td>
<td>0.0367</td>
<td></td>
</tr>
<tr>
<td>major</td>
<td>7251 (25.4%)</td>
<td>1558 (25.3%)</td>
<td>0.0023</td>
<td></td>
</tr>
<tr>
<td>moderate</td>
<td>12305 (43.1%)</td>
<td>2851 (46.2%)</td>
<td>-0.0624</td>
<td></td>
</tr>
<tr>
<td>minor</td>
<td>7457 (26.1%)</td>
<td>1472 (23.9%)</td>
<td>0.0508</td>
<td></td>
</tr>
<tr>
<td><strong>APR Mortality Risk</strong></td>
<td></td>
<td></td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>16028 (56.2%)</td>
<td>3652 (59.2%)</td>
<td>-0.0608</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>6515 (22.8%)</td>
<td>1426 (23.1%)</td>
<td>-0.0071</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>4745 (16.6%)</td>
<td>835 (13.5%)</td>
<td>0.0868</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1258 (4.4%)</td>
<td>254 (4.1%)</td>
<td>0.0149</td>
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</tr>
<tr>
<td><strong>Length of Stay Mean(SD)</strong></td>
<td>3.8 (4.2)</td>
<td>3.8 (3.7)</td>
<td>0.8789</td>
<td>0</td>
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<tr>
<td><strong>Total Charges Mean(SD)</strong></td>
<td>15611.6 (14,562.1)</td>
<td>16513.9 (12,799.3)</td>
<td>&lt;.0001</td>
<td>-6.5818</td>
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</tbody>
</table>
Propensity Score Matching

- The propensity scores calculated in a logistic regression model predicting “treat” = 1 (being in exposure group vs control) which adjusted for: gender, age, admit type, discharge disposition, major service, admit source, ethnicity, marital status, primary payer, race, APR severity, APR mortality risk, Length of Stay, total charges, top 20 diagnosis codes and top 20 DRG codes.

- Opted for a 2:1 match using a caliper of 0.05
Propensity Score Matched 2:1

<table>
<thead>
<tr>
<th></th>
<th>Control N = 11,354</th>
<th>Exposure N= 6,009</th>
<th>P-Value</th>
<th>Standardized Difference</th>
</tr>
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<tbody>
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<td>Gender</td>
<td></td>
<td></td>
<td>0.5643</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>4586 (40.39%)</td>
<td>2400 (39.94%)</td>
<td>0.0092</td>
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<tr>
<td>2</td>
<td>6768 (59.61%)</td>
<td>3609 (60.06%)</td>
<td>-0.0092</td>
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</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td>0.9397</td>
<td></td>
</tr>
<tr>
<td>African American</td>
<td>3720 (32.76%)</td>
<td>2000 (33.28%)</td>
<td>-0.01105</td>
<td></td>
</tr>
<tr>
<td>American Indian/Eskimo/Aleut</td>
<td>14 (0.12%)</td>
<td>8 (0.13%)</td>
<td>-0.00275</td>
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</tr>
<tr>
<td>Asian/Pacific Islander</td>
<td>158 (1.39%)</td>
<td>83 (1.38%)</td>
<td>0.00088</td>
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</tr>
<tr>
<td>other</td>
<td>549 (4.84%)</td>
<td>272 (4.53%)</td>
<td>0.01462</td>
<td></td>
</tr>
<tr>
<td>unknown</td>
<td>28 (0.23%)</td>
<td>15 (0.25%)</td>
<td>-0.00422</td>
<td></td>
</tr>
<tr>
<td>white</td>
<td>6887 (60.66%)</td>
<td>3631 (60.43%)</td>
<td>0.00473</td>
<td></td>
</tr>
<tr>
<td>Ethnicity</td>
<td></td>
<td></td>
<td>0.3272</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>491 (4.32%)</td>
<td>234 (3.89%)</td>
<td>0.02168</td>
<td></td>
</tr>
<tr>
<td>not Hispanic</td>
<td>10788 (95.01%)</td>
<td>5730 (95.36%)</td>
<td>-0.01598</td>
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</tr>
<tr>
<td>unknown</td>
<td>75 (0.66%)</td>
<td>45 (0.75%)</td>
<td>-0.01056</td>
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</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
<td>0.9993</td>
<td></td>
</tr>
<tr>
<td>divorced</td>
<td>1204 (10.6%)</td>
<td>628 (10.45%)</td>
<td>0.00499</td>
<td></td>
</tr>
<tr>
<td>married</td>
<td>4856 (42.77%)</td>
<td>2565 (42.69%)</td>
<td>0.00168</td>
<td></td>
</tr>
<tr>
<td>separated</td>
<td>274 (2.41%)</td>
<td>144 (2.4%)</td>
<td>0.0011</td>
<td></td>
</tr>
<tr>
<td>single</td>
<td>4039 (35.57%)</td>
<td>2147 (35.73%)</td>
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<tr>
<td>unknown</td>
<td>53 (0.47%)</td>
<td>29 (0.48%)</td>
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<tr>
<td>widow/widower</td>
<td>928 (8.17%)</td>
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<tr>
<td>Primary Payer</td>
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<td>0.9862</td>
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</tr>
<tr>
<td>charity/self pay</td>
<td>303 (2.67%)</td>
<td>156 (2.6%)</td>
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</tr>
<tr>
<td>commercial</td>
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<td>Medicaid</td>
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</tr>
<tr>
<td>other</td>
<td>282 (2.48%)</td>
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</tr>
<tr>
<td>unknown</td>
<td>8 (0.07%)</td>
<td>5 (0.08%)</td>
<td>-0.0046</td>
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</table>
## Propensity Score Matched 2:1

<table>
<thead>
<tr>
<th></th>
<th>Control N = 11,354</th>
<th>Exposure N= 6,009</th>
<th>P-Value</th>
<th>Standardized Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>APR Severity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>extreme</td>
<td>503 (4.43%)</td>
<td>265 (4.41%)</td>
<td>0.8232</td>
<td>0.00098</td>
</tr>
<tr>
<td>major</td>
<td>2800 (24.66%)</td>
<td>1517 (25.25%)</td>
<td>-0.01351</td>
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</tr>
<tr>
<td>minor</td>
<td>2801 (24.67%)</td>
<td>1454 (24.2%)</td>
<td>0.011</td>
<td></td>
</tr>
<tr>
<td>moderate</td>
<td>5250 (46.24%)</td>
<td>2773 (46.15%)</td>
<td>0.00184</td>
<td></td>
</tr>
<tr>
<td><strong>APR Mortality Risk</strong></td>
<td></td>
<td></td>
<td>0.9833</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>6719 (59.18%)</td>
<td>3570 (59.41%)</td>
<td>-0.00475</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>2655 (23.38%)</td>
<td>1391 (23.15%)</td>
<td>0.00557</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>1538 (13.55%)</td>
<td>811 (13.5%)</td>
<td>0.00145</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>442 (3.89%)</td>
<td>237 (3.94%)</td>
<td>-0.00264</td>
<td></td>
</tr>
<tr>
<td><strong>Length of Stay Mean(SD)</strong></td>
<td>3.6 (3.7)</td>
<td>3.8 (3.5)</td>
<td>0.0503</td>
<td>-0.0555</td>
</tr>
<tr>
<td><strong>Total Charges Mean(SD)</strong></td>
<td>16,152.53 (12805.78)</td>
<td>16,439.63 (12666.40)</td>
<td>0.1584</td>
<td>-0.0225</td>
</tr>
</tbody>
</table>
Standardized Mean Differences

Before PS matching

After PS matching
Who are these patients?

Top 5 DRGs (making up about 20% of sample)
- Total knee or total hip replacement
- Bariatric surgery
- Psychosis
- Spinal fusion (combined)
- Spinal fusion (excluding cervical)
Underway

- Crude estimates of relative risk of readmission
- Propensity score matched relative risk of readmission
- Propensity score weighted relative risk of readmission
- Stratify results by highly prevalent DRGs or diagnoses (exploratory)

- Generate a “disease risk score” which will be risk of readmission
- Weight participants by risk of readmission and examine relative risk associated with intervention
- Examine results in strata of risk of readmission
Team

- Ariella Apfel, MS
- Jeanne Clark, MD, MPH
- Daniel Brotman, MD
- Kenneth Shermock, PharmD, PhD
- Ross Martin, MD, MHA
- HSCRC staff
- H-metrix (Audrey Speter and team)
- Walgreens (Heather Kirkham, Ed Witt and team)
CRISP TECHNICAL FRAMEWORK

Michael Berger, MBA
CIO, CRISP

Ryan Bramble, MS
Executive Director CRISP DC
Sr. Director of Product Development
Architecture
The ‘glue’ for all services - MPI

85 Million Patients at a specific Point of Care (MRN’s)

- Nancy Regan Visited Hopkins (JHH:1234)
  - Regan, Nancy 06/06/1921
  - 1600 Pennsylvania Ave, DC
- Nancy Davis Physician is DR Patel (DRPat:w4w9)
  - Davis, Nancy 06/06/1921
  - 915 Capital Mall Sacramento, CA
- Nancy Davis-Regan has 1 immunization (IMMUNET:39480)
  - Davis-Regan, Nancy 06/06/1921
  - 915 Capital Mall Sacramento, CA
- On a typical day CRISP receives 90,000 new MRN’s like these.
  - Each of those must compare to all 85 Million existing MRN's to find a match.

Combine into 18M distinct Enterprise ID”s

- Roughly speaking … People
- Typical day CRISP creates 6,000 new people.
Most important Data **into** customer EHR

Some data In FHIR App

Very detailed In Portal
InContext App – Clinical Data, Images and SSO to ULP

View diagnostic quality images

SSO into full patient record in ULP

View rad, lab, and transcribed reports
Clinical Query Portals

Mirth Results

ULP
CRISP currently receives Admission Discharge Transfer messages in real-time from:

- All 48 Maryland acute care hospitals
- 9 D.C. acute care hospitals
- 6 Delaware acute care hospitals
- 17 Virginia acute care hospitals
- 29 West Virginia acute care hospitals
- 1 Ohio acute care hospital
- Almost 2/3 of Long Term Care Sites in Maryland

Through ENS, CRISP generates real time hospitalization notifications to PCPs, care coordinators, and others responsible for patient care.
CRISP receives that initial patient list, changes must be submitted to CRISP on a monthly basis.

Examples of changes to the list can include add patient, remove patient, and update patient’s demographics.

A practice can choose to send CRISP an ADT feed of its own in lieu of a patient list.

<table>
<thead>
<tr>
<th>Member_status</th>
<th>Facility_code</th>
<th>PCP</th>
<th>MRN</th>
<th>first_name</th>
<th>middle_initial</th>
<th>last_name</th>
<th>address_line_1</th>
<th>address_line_2</th>
<th>city</th>
<th>state</th>
<th>zip</th>
<th>date_of_birth</th>
<th>gender</th>
<th>ssn</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADD</td>
<td>FACILITY</td>
<td>Dr. Jones</td>
<td>999999</td>
<td>John</td>
<td>K</td>
<td>Doe</td>
<td>33 main st apt 45</td>
<td></td>
<td>baltimore</td>
<td>MD</td>
<td>21230</td>
<td>19990101</td>
<td>M</td>
<td>9999999999</td>
</tr>
<tr>
<td>UPDATE</td>
<td>FACILITY</td>
<td>Dr. Jones</td>
<td>100000</td>
<td>Jane</td>
<td>K</td>
<td>Doe</td>
<td>34 main st apt 46</td>
<td></td>
<td>baltimore</td>
<td>MD</td>
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<td>19990101</td>
<td>M</td>
<td>9999999999</td>
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<tr>
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<td>Dr. Jones</td>
<td>1000001</td>
<td>Jim</td>
<td>K</td>
<td>Doe</td>
<td>35 main st apt 47</td>
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<td>baltimore</td>
<td>MD</td>
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<td>19990101</td>
<td>M</td>
<td>9999999999</td>
</tr>
</tbody>
</table>
• PROMPT – “Proactive Management of Patient Transitions”

• Web-based user interface for clinicians to access notifications (especially non-EP or non-EH members of the Care Team)

Use Case Examples:
- Detect recent admits (IP, ED)
- Detect recent discharges
- Find High Utilizers
- Find Care Team Members
- Perform analytics (utilization by condition, facility, zip code, etc.)
- Manage notifications by status with PROMPT’s real-time status tracking feature
- View patients across multiple patient panels
### Patient Search

**Last Name** (Required)  
Testing

**First Name** (Required)  
Gail

**Date Of Birth** (Required)  
11 25 1965

**Gender**  
Male

**Zip Code**

**SSN**

![Search Results Table]

<table>
<thead>
<tr>
<th>FIRST</th>
<th>LAST</th>
<th>DATE OF BIRTH</th>
<th>CRISP ID</th>
<th>GENDER</th>
<th>ADDRESS</th>
<th>MATCH SCORE</th>
<th>INCLUDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAIL</td>
<td>TESTING</td>
<td>11/25/1965</td>
<td>135155209</td>
<td>Female</td>
<td>225 Greene St Baltimore, MD</td>
<td>Very Likely</td>
<td></td>
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<tr>
<td>GAIL</td>
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<td>11/25/1965</td>
<td>130295764</td>
<td>Female</td>
<td>10 E, WASHINGTON DC, 20001</td>
<td>Very Likely</td>
<td></td>
</tr>
</tbody>
</table>

### Usage Terms and Conditions

I understand that access to the health record is only available for patients with whom I have a treatment relationship and who have not opted out of the HIE, with the exception of data provided by the Maryland Prescription Drug Monitoring Program (PDMP), which is mandated by law.

I understand that as a participant in the HIE, our organization has a responsibility to make sure patients are aware, circumstances permitting, of their right to opt-out of non-PDMP clinical data prior to performing a query.

If I am authorized to access Maryland PDMP data through CRISP, I certify that I understand and will adhere to the regulations outlined in COMAR 20.07.07.

By performing a patient search I accept these terms and conditions.

### Announcements

Unread  Read

### Updates

As of June 8, 2018 the Interstate PDMP is querying DC, DE, VA, WV.
### Diagnoses From Claims

<table>
<thead>
<tr>
<th>Condition</th>
<th>Date Recorded</th>
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<tbody>
<tr>
<td>Abnormality of gait</td>
<td>05/06/2015</td>
</tr>
<tr>
<td>Late effects of cerebrovascular disease, hemiplegia affecting dominant side</td>
<td>11/23/2014</td>
</tr>
<tr>
<td>Late effects of cerebrovascular disease, hemiplegia affecting dominant side</td>
<td>11/03/2014</td>
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</table>

### Procedures From Claims

<table>
<thead>
<tr>
<th>Service From Date</th>
<th>Service To Date</th>
<th>Place of Service</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>01/20/2015</td>
<td>01/20/2015</td>
<td>N MANAGEMENT</td>
<td>Subsequent hospital care</td>
</tr>
<tr>
<td>01/20/2015</td>
<td>01/20/2015</td>
<td>MEDICAL TRANSPORTATION MANAGEMENT</td>
<td>Prolonged service, inpatient</td>
</tr>
</tbody>
</table>

### Care Team

<table>
<thead>
<tr>
<th>Participant Name</th>
<th>Program</th>
<th>Participant Phone</th>
<th>Enroll Date</th>
<th>Disenroll Date</th>
<th>PCP</th>
<th>Care Manager</th>
<th>Care Manager Phone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Providence</td>
<td>My Health GPS</td>
<td>202.555.3000</td>
<td>07/01/2017</td>
<td></td>
<td>Regina Jones</td>
<td>Betsy Smith</td>
<td>202.555.0982</td>
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<tr>
<td>DC Medicaid</td>
<td>Amerigroup</td>
<td>10/01/2015</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Encounters From Claims

<table>
<thead>
<tr>
<th>Event</th>
</tr>
</thead>
</table>
Health Records in ULP

- Laboratory
- Radiology
- Transcription
- Imaging Worklist (In Development)

New! Capability to search inside results
PDMP data available as an app in the ULP with user-friendly features such as sorting by column, inter-state search, and multiple patient selection; PDMP also available directly within certain EHRs.
CRISP’s involvement

• Technology partner for the Maryland PDMP Program
• CRISP serves as access point for clinical providers within:
  • EHR Workflows (InContext)
  • Unified Landing Page PDMP Search
  • Single Sign-On (Mirth Query Portal)
• Credentialing office for all eligible users
• Synergies with outreaching to providers
• Support Maryland PDMP in new technology requirements
  • Reporting & Analytics
  • Clinical user enhancements
  • Deeper integration into clinical workflows
• **Controlled Patient Search**
  - The ability to grant access to ULP but limit your search capability to just a consented roster of patients

• **Notifications when events happen**
  - Send alerts when hospitalizations happen for your consented roster of patients

• **Share your program**
  - At your choosing – let other providers and members of a patient’s care team know that the patient is participating in a research study (via the “Care Team” widget in Snapshot)
What’s Coming?

• More data from C-CDAs
  • CRISP has limited capability to extract data from C-CDAs – we expect to have the capability to extract more information from those documents by the Fall

• FHIR compatibility
  • The majority of CRISP data services will be FHIR enabled – many are already – by the summer.

• Record Location
  • A service that lets consumers know where patient’s have records – allows for more targeted data queries.
DISCUSSION: CURRENT CAPABILITIES AND FUTURE OPPORTUNITIES

Ross D. Martin, MD, MHA
Program Director, CRISP Research Initiative
FUTURE OPPORTUNITIES

• Potential new use case: HIPAA Safe Harbor de-identified data sets of CRISP-mediated data
  • Pre-requisites:
    ▪ Research-specific Opt-Out pathway
    ▪ Patient communications presenting the research opt-out option
    ▪ Normalized clinical data warehouse with robust query tools for creating data sets
OTHER FUTURE OPPORTUNITIES

- Death Data
- Precision Medicine
Discussion
CLOSING THOUGHTS

David Horrocks, MBA
President & CEO, CRISP
Thank You!

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Professor of Medicine, Public Health, and Nursing at Johns Hopkins University
Chair of the CRISP Research Subcommittee
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