

Predictive Analytics in Action: Tackling Readmissions

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Agenda

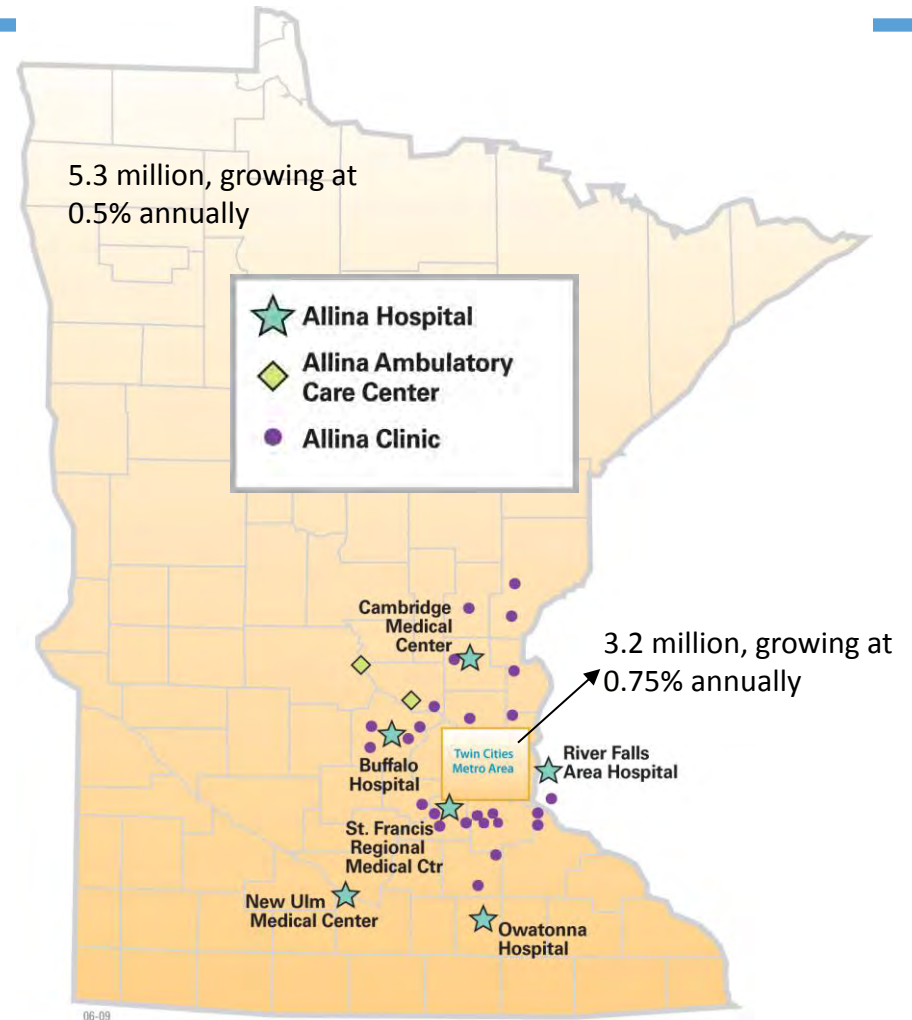
- Background
- Lifecycle
- Current status
- Discussion

Goals for today

- Describe how Allina Health is using data warehousing, predictive analytics, innovative care and technology investment to reduce the number of potentially preventable readmissions within the system.
- Leave plenty of time for discussion
- Learn from you (through your questions and feedback)

About Allina Health

- Largest Healthcare System in the Twin Cities
- 11 hospitals
- 1,658 staffed beds
- 60 Allina Clinics, 22 hospital-based clinics
- 15 community pharmacies
- 4 ambulatory care centers
- Specialty Operations: Transportation, Pharmacy, Lab, Homecare/Hospice
- About 22,800 employees, including 1,200+ employed physicians
- About 5,000 Community Physicians
- **Key statistics**
 - \$3.2 billion in revenue
 - 120,000+ inpatient admissions
 - 1.0 million+ outpatient admissions



Allina's EHR: Excellian

One Patient. One Record.

- First Hospitals and clinics implemented in 2004. All hospitals and clinics complete – Enterprise Applications
- Currently implementing Lab system
- 3 million patient records
- Storage Size: 1.9 terabytes – (adding 4 gig/day)
- 250,000 MyChart users, including e-Visits
- 30,000 Excellian users
- Received the 2007 HIMSS Davies Award for implementation
- Received Stage 6 (Hospital) on the EMR Assessment Model
- Attested for Meaningful Use Stage 1, Year 1 and 2

About the Data Warehouse

- Development
 - In-house, supplemented by outside expertise
 - Began in 2008, provided value to Allina within months
- Current Team
 - 10 x Data Architects (“Data Warehouse Generalists”)
 - 3 x BI Developers (“Data Visualization”)
 - 2 x BI Systems Admins (“Keeping the Lights On”)
 - 1 x Trainer
 - 1 x Manager
- Utilization
 - > 150 active “power” users/month
 - > 500 ad-hoc user queries/day

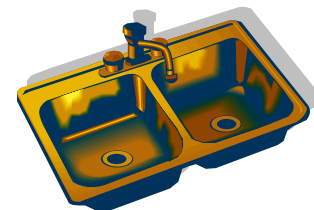
EDW Data Content

From Epic

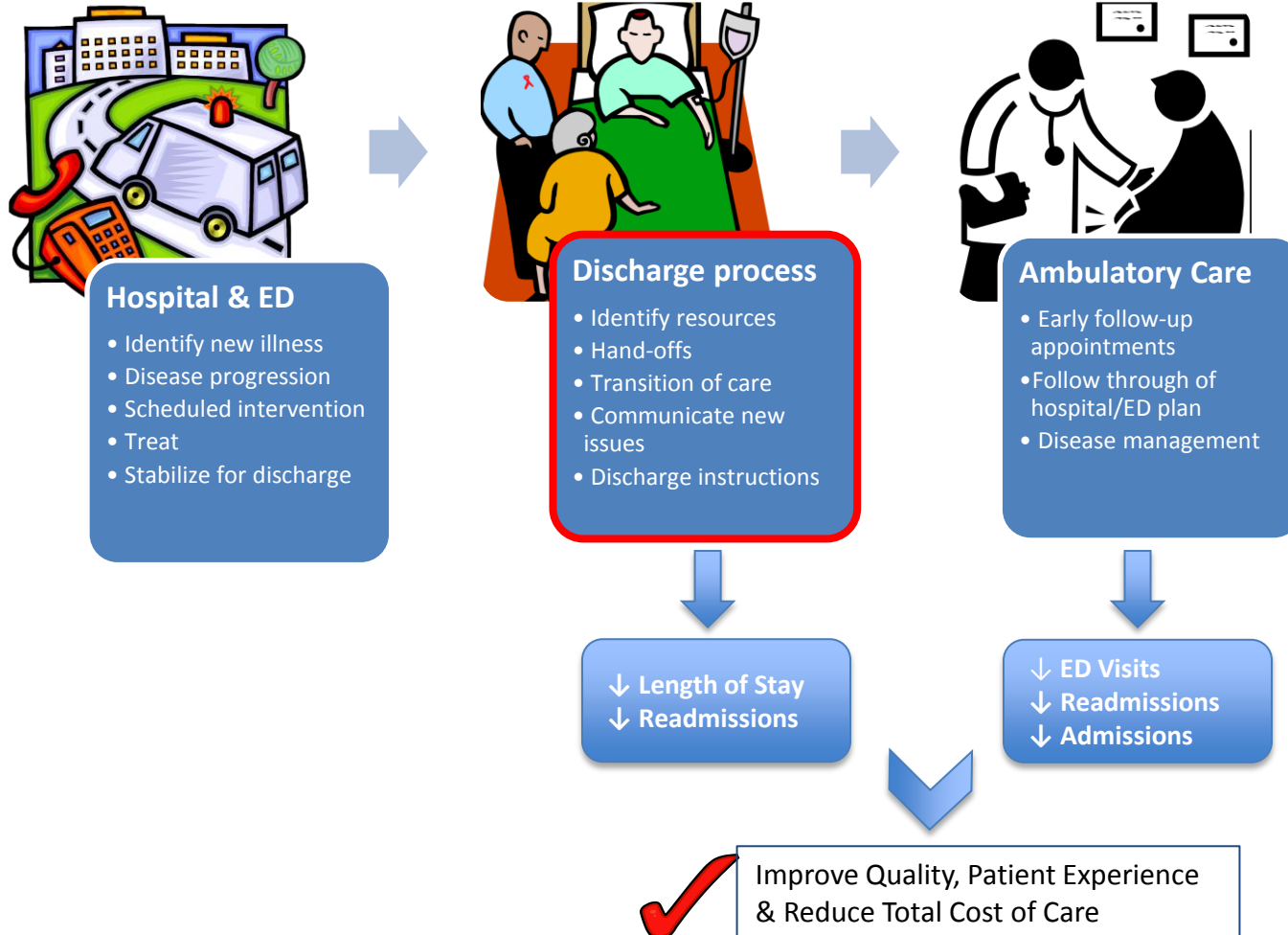
- Patient Demographics and Identifiers
- Surgical Supplies/Implants
- Financial transactions (charges, payments, adj., etc.)
- Results (labs, etc.)
- Encounters and Vitals
- Admissions, Discharges, Transfers
- OR Cases and OR Log
- Ordered Procedures and Medications
- Administered Medications (MAR)
- Medical, Social HX, Problem List
- Flowsheets (subset), Questionnaires
- *(lots more...)*

Other Data Sources

- Pioneer ACO Claims
- HDM (3M Coding)
- Cost Accounting
- Tumor Registry
- Lumedx Apollo (CV Registries)
- Avatar (Patient Satisfaction)
- Premis
- Payroll
- Core Measures



Why are hospital and ED transitions important?



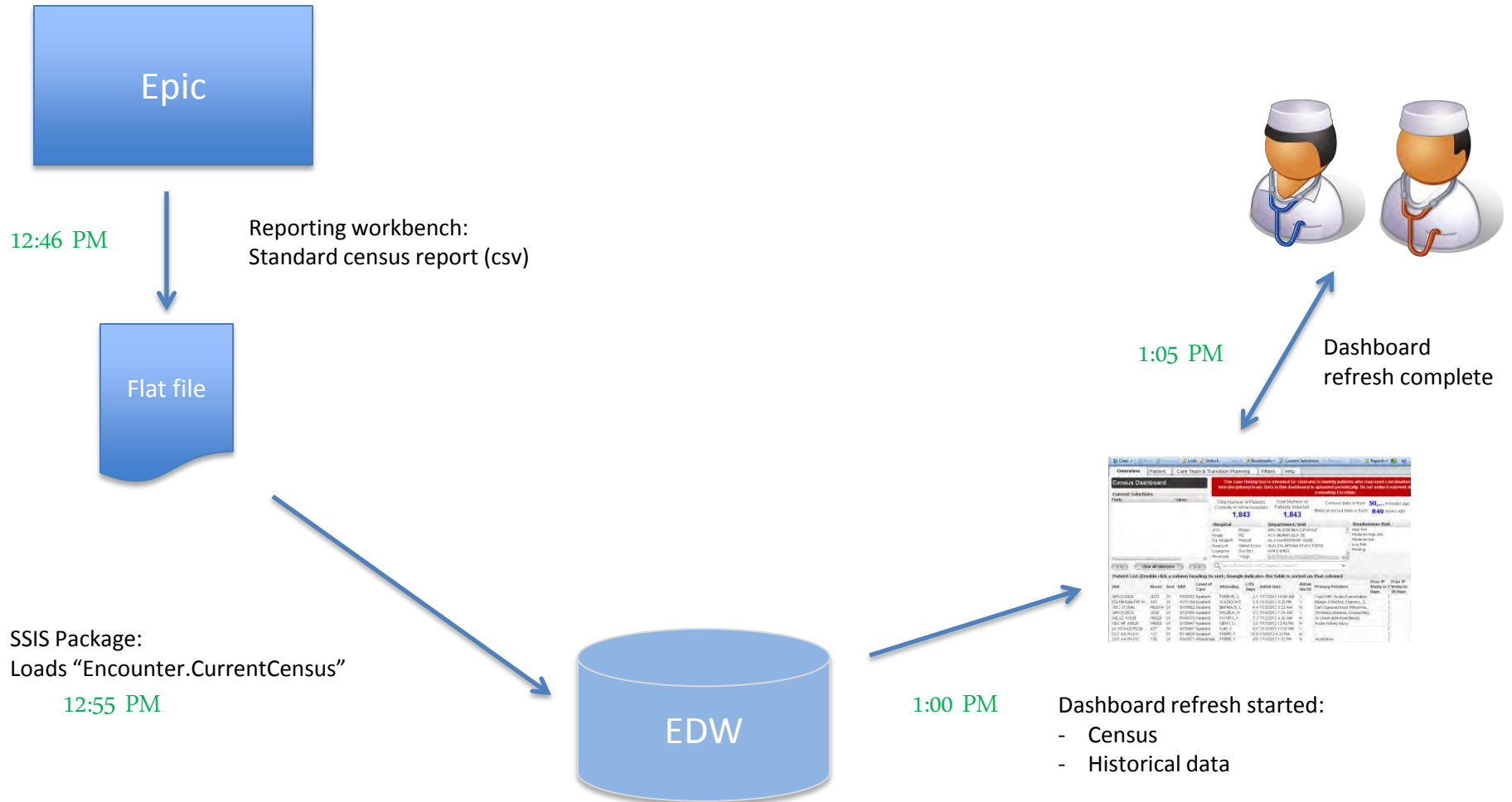
Project Drivers

- Increased readmission focus, statewide and nationally
- Analysis of potential gaps in the way our systems are currently hard-wired to transition patients out of the acute care setting
- Gaps:
 - Information sharing among providers for continuity of care
 - Identification of patients – who is in need of additional help and services?
 - Significant process variation across conditions

Initial Rollout (“Phase 1”)

- Simple dashboard
- No predictive score
- Combination of “quasi real time” and historical data
- Agile development – simplest, easiest to build design which is still useful
- No big up, up-front design
- Lots of “shopping” to potential customers

Phase 1 - Architecture and refresh



Interest in predictive models

- Allina Health: Investing in predictive analytics
 - Better patient outcomes
 - At a lower cost, due to better resource allocation
- Data within the EDW was already well-vetted and used extensively for retrospective analyses
- Hypothesis: could we use the EDW in a proactive manner to improve patient care?

Overview of Readmission Risk Model

- Objective:
 - Create a predictive model accessible for clinicians to identify patients who would benefit from a “Transition Conference” to identify resources for the next level of care
 - *Using a predictive model to identify and intervene with high risk patients can reduce hospital readmissions*
 - Assigns a readmission risk score for 30 day readmissions
- Data & Methodology:
 - Nearly 2 years of data (Jan 2010 – Nov 2011)
 - 180k inpatient discharges (Allina wide).
 - Expanded to discharges of ‘**All**’ conditions
 - Hundreds of variables tested
 - Outcome by forwards and backwards stepwise multiple logistic regression.
 - 70% to train model, 30% to test. The train/test datasets were reassigned hundreds of times to determine confidence levels of final outcome statistics.

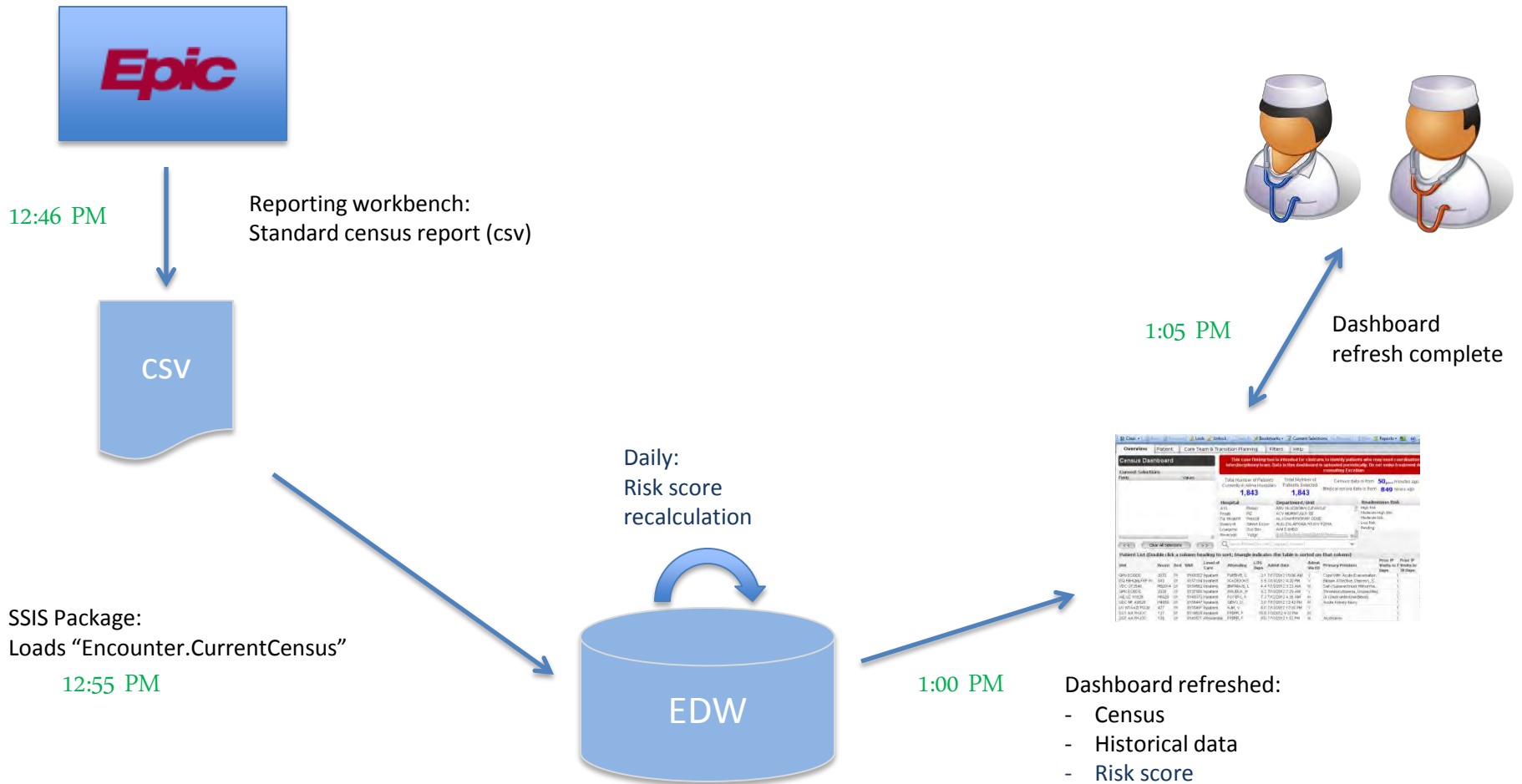
Variables Considered

- **Demographic data**
 - Age
 - Gender
 - Home zip code
 - Marital status
 - PCP clinic
 - Financial Class
 - Language
 - Discharge destination
 - Admit source type
 - Hospital location
- **Clinical data**
 - **Encounter**
 - BMI
 - Weight
 - blood pressure
 - Pulse
 - Temperature
 - Depression (PHQ9)
 - Respiration
 - Etc.
 - **Inpatient values**
 - Nursing assessed functional status
 - Pulse oximetry values
 - Came through emergency department
 - Length of stay
 - Nursing DC assessments
 - Etc.
 - **Medications**
 - OP Medication Count
 - IP Medication Count
 - **Lab**
 - Cholesterol/Calcium
 - Red/white blood count
 - Creatinine/Hematocrit
 - Glucose levels/GFR
 - Hemoglobin/WBC/RBC
 - Other blood values
 - **44 Diagnosis Groupings**
 - If physician entered ICD9's are present in the last 12 months
 - Asthma
 - Cancer
 - CHF
 - Gastro Intestinal
 - COPD
 - Depression
 - Diabetes
 - Renal Disease
 - Respiratory failure
 - Septicemia
 - Etc.
 - **Historical Utilization**
 - Number of inpatients stays in the last 12 months
 - Number of emergency department visits in the last 12 months
 - Etc.

Test of Change (“Phase 2”)

- Minor, but significant, dashboard enhancement – added the risk score with color coding at the patient level
- Intervention - Transition Conferences
 1. Identify potential candidates from dashboard
 2. Schedule conference(s)
 3. Facilitate conference(s)

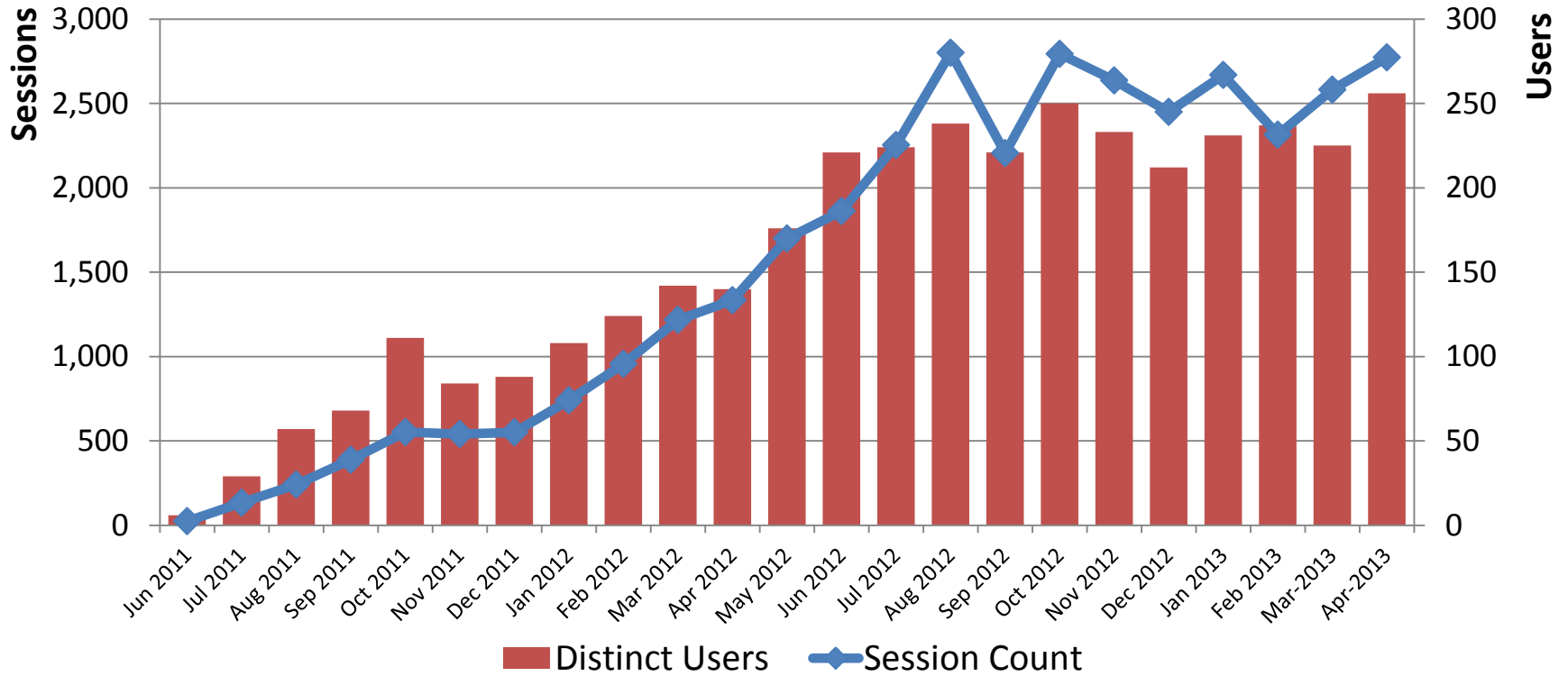
Phase 2 - Architecture and refresh



Census Dashboard Demo

Wish us luck, it's a demo.

Dashboard Acceptance



Post-Testing the Readmission Predictive Model...

- May 1st 2013 (over a **year** after Jan 2012 auto-calculating start for all patients)
 - **675,000** Risk scores
 - **157,000** Unique patients
 - **8,300** Unique patients in the **high risk** category
- **97%** of patient's risk scores have *little or no change* during the stay
 - **75%** of patients will stay within the **same risk level**
 - **22%** of patients will fluctuate between **two** neighboring **risk levels**
- **3%** will fluctuate more significantly
 - Most increase due to major changes in patient status
 - Some due to data delays
- Validation suite was created to verify model accuracy changes over time and data input changes

Comparisons to published models

- Initial Goals
 - c-stat of > **0.7 (moderate discrimination power)**
 - calibration error < **3%**

Model	LACE	CMS	Systematic Review*	Allina Health Readmission Predictive Model
Summary	4 variables: L=LOS, A=Acuity (was ED), C=comorbidity index, E=ED utilization	Claims based, many parameters	Varying depth and applicability	30 clinical and internal variables. Applies to all patients
C-stat	0.68	0.63 – 0.66	0.56 – 0.72	0.73

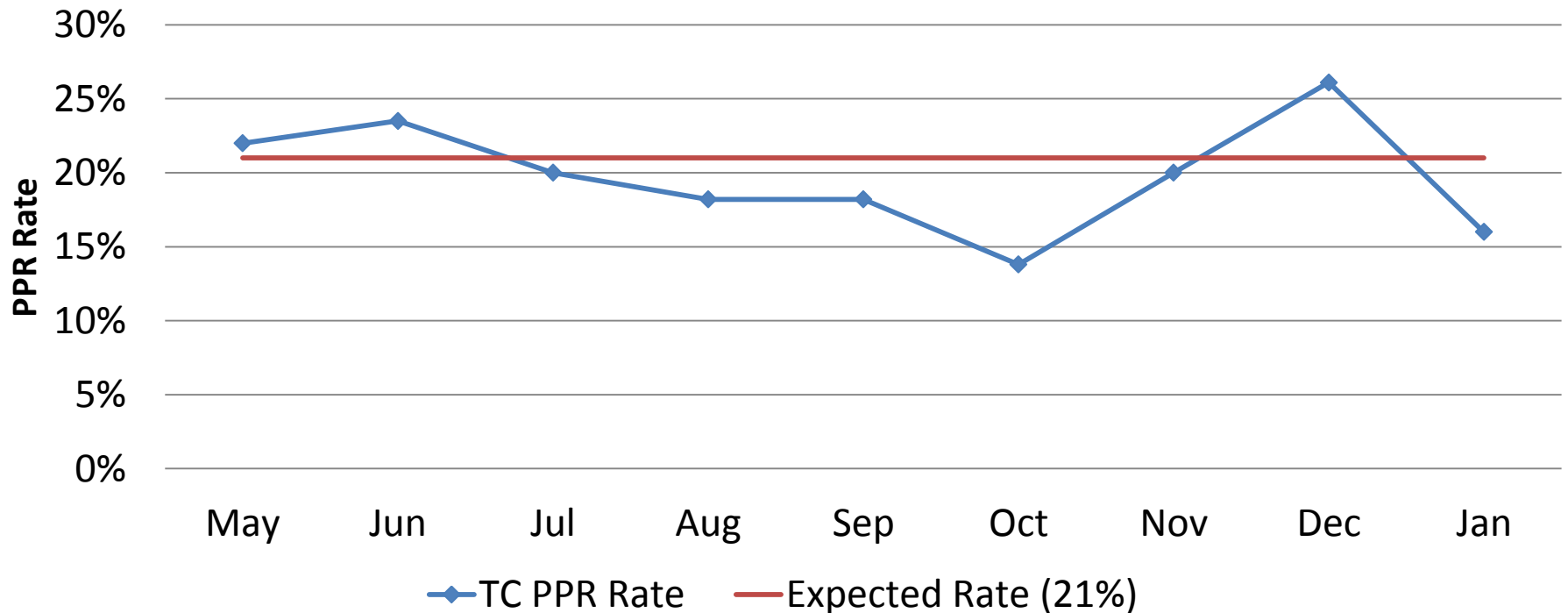
- *JAMA “Risk Prediction Models for Hospital Readmissions”
 - Oct 19th, 2011, Vol 306, No. 15, p 1688
 - 26 Unique models reviewed
 - 14 on claims data.
 - 9 of those 14 had low discrimination ability (c-stat 0.55 – 0.65)
 - 7 with moderate discrimination available during the stay (c-stat **0.56 – 0.72**)
 - 5 at hospital discharge (c-stat 0.68 – 0.83)
 - Vary widely between the groups (one will work great with Asthma but not AMI...)

Why a transition conference?

- Patients and their families continue to experience readmissions
- Patient and caregiver engagement in discharge planning has been proven to decrease readmissions
- Using a predictive model within the EMR to identify and intervene with high risk patients can reduce hospital readmissions
- There are limited clinical resources; an efficient and systematic approach for complex discharge planning is needed
- Hospital payment is tied to readmissions
- New patient experience HCAPHS Care Transitions (CTM-3)

Readmission Rate Over Time

Readmission (PPR) Rate for Transition Conference Patients



PPR = Potentially Preventable Readmissions by 3M™

Transition Conference Summary

- First 800 Transition Conferences for High Risk
 - **15% reduction** in PPRs
 - 10 Allina Health hospitals participated
- Impacts over 100 APR-DRGs
- More patients accepting post acute care
 - Ex. Home Health, SNF, Hospice, TCU

Challenges/Conclusions

- Technical Challenges
 - EDW morning load completion time
 - EDW SLA
 - Licensing
- Conclusions
 - Users find the tool useful and helpful
 - Shifted focus from identification to better care coordination
 - Ambulatory Care management



What questions or comments do you have?

Business card

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