



Walgreens

Predicting and Preventing Readmissions:

Opportunities & Challenges



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May 31, 2012

Overview

Introduction

- Why is Walgreens interested in readmissions?

Challenge 1

- Who is at risk?

Challenge 2

- Who is amenable to preventive care?

Challenge 3

- Which interventions can prevent readmissions?

Challenge 4

- What about Roemer's law?



Why is Walgreens Interested in
Readmissions?

Perception



America's #1 pharmacy retailer,
Trusted for over 100 years.



Walgreens is

- Nearly 8,000 community pharmacies
- More than 8,500 total points of care
- Within 5 miles of 70% of the U.S. population
 - #1 in worksite health centers
 - #1 in health system pharmacies
 - #1 in flu immunizations
 - #1 in health testing services
- **6 million consumer visits daily**

Why the Interest in This Topic?

Problem

- Ageing population
- Rising prevalence of chronic disease
- Cost pressures

Opportunity

- ~ 5% of patients account for 50% of emergency bed days
- Unplanned admissions are:
 - Expensive
 - Undesirable
 - Potentially avoidable

Four Major Challenges

- Where Walgreens may be able to add value

Cost of Poor Adherence

The annual cost of poor medication adherence in the US ¹:

Readmissions costs of poor adherence:
\$100 billion ²

\$290
billion

Direct medical



Annual cost of
poor adherence per 10,000
lives

¹Thinking Outside the Pillbox: A System-wide Approach to Improving Patient Medication Adherence for Chronic Disease. NEHI Research Brief, Aug. 2009

²Osterberg L, Blaschke T. Adherence to medication. N Engl J Med. 2005;353(5):487-497

Far Beyond the Corner Drugstore

We have close relationships and interactions with every major stakeholder in healthcare





Challenge 1: Who is at Risk?

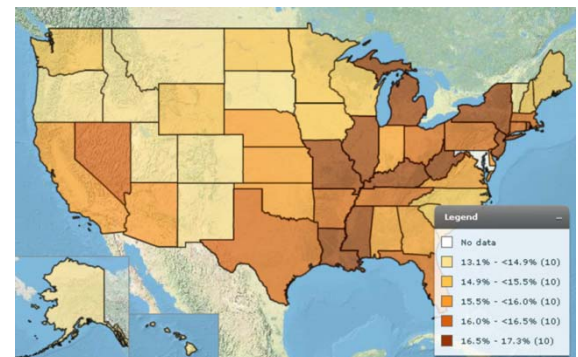
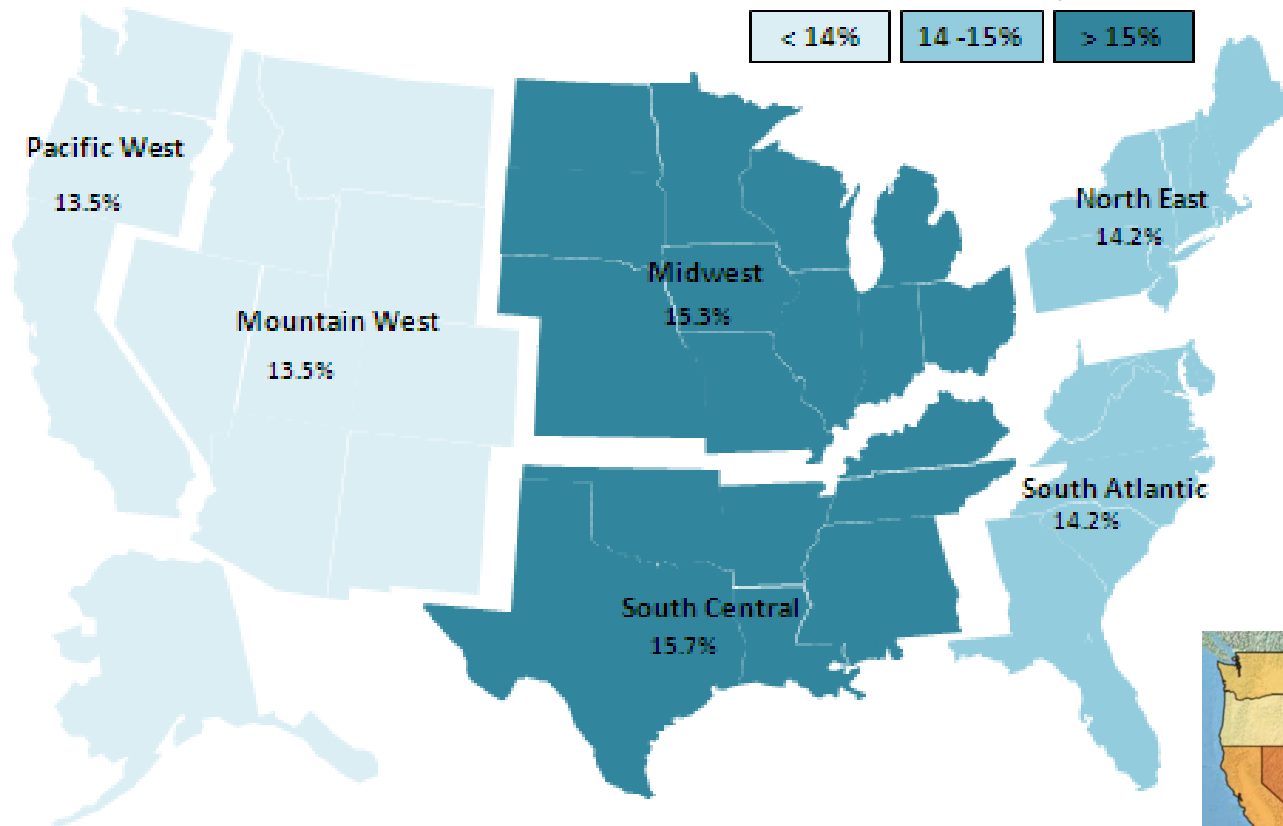
Medicare Readmission Rates

	% Population	Mean Age	% Male	% MH	PMPM
0 admissions	83.4	70	46	21	\$315
0 readmissions	14.1	72	43	54	\$2,636
1 readmission	1.8	72	45	65	\$4,948
2+ readmissions	0.7	68	47	75	\$8,078

Note. Data from 5% Medicare sample in 2010. %MH = proportion with mental health diagnosis

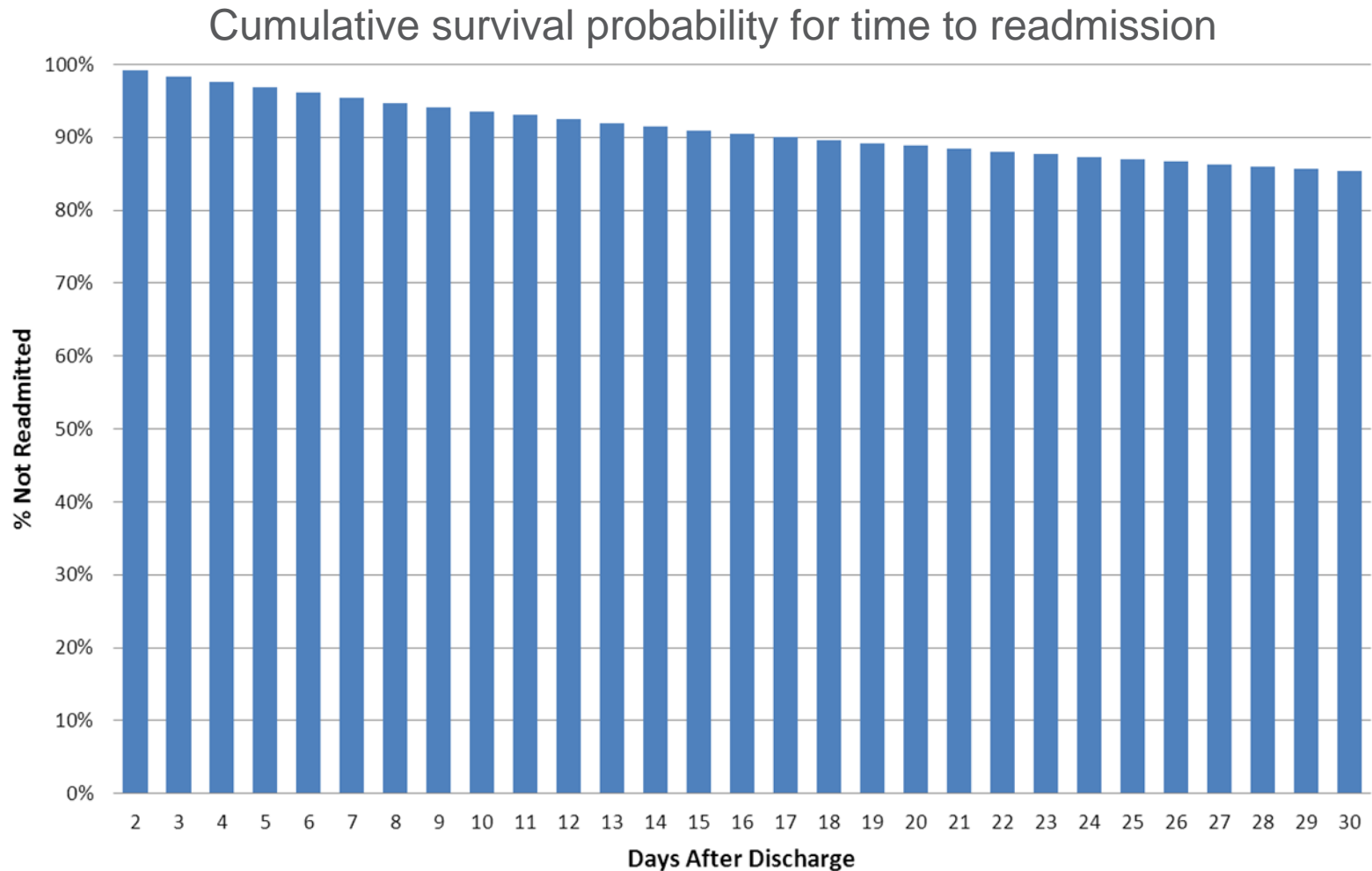
Readmission Rates: Regional Distribution

% of Medicare beneficiaries with at least one 30-day readmission in 2010, by region



Note: Data from 5% Medicare sample in 2010. Inlayed state map from 2009 Dartmouth Atlas data.

Readmission Decay Curve



Note: Data from 5% Medicare sample in 2010.

Case study: UK Evercare Pilots

- A 2002 BMJ study* showed that Kaiser Permanente in California seemed to provide **higher quality** healthcare than the NHS at a **lower cost**
- Kaiser identifies high risk people in their population and offer them preventive care in the community aimed at avoiding hospital admissions

UK Evercare Pilots

- **Comprehensive geriatric assessment**, structured assessment tools, and a physical examination
- **Individualized care plan** agreed with the patient, PCP and other staff
- Patients were then **monitored** and supported in the community by a specialist nurse

*Feachem RG, Sekhri NK, White KL. Getting more for their dollar: a comparison of the NHS with California's Kaiser Permanente BMJ 2002;324:135-143

Retrospective Analysis of UK Evercare Pilots

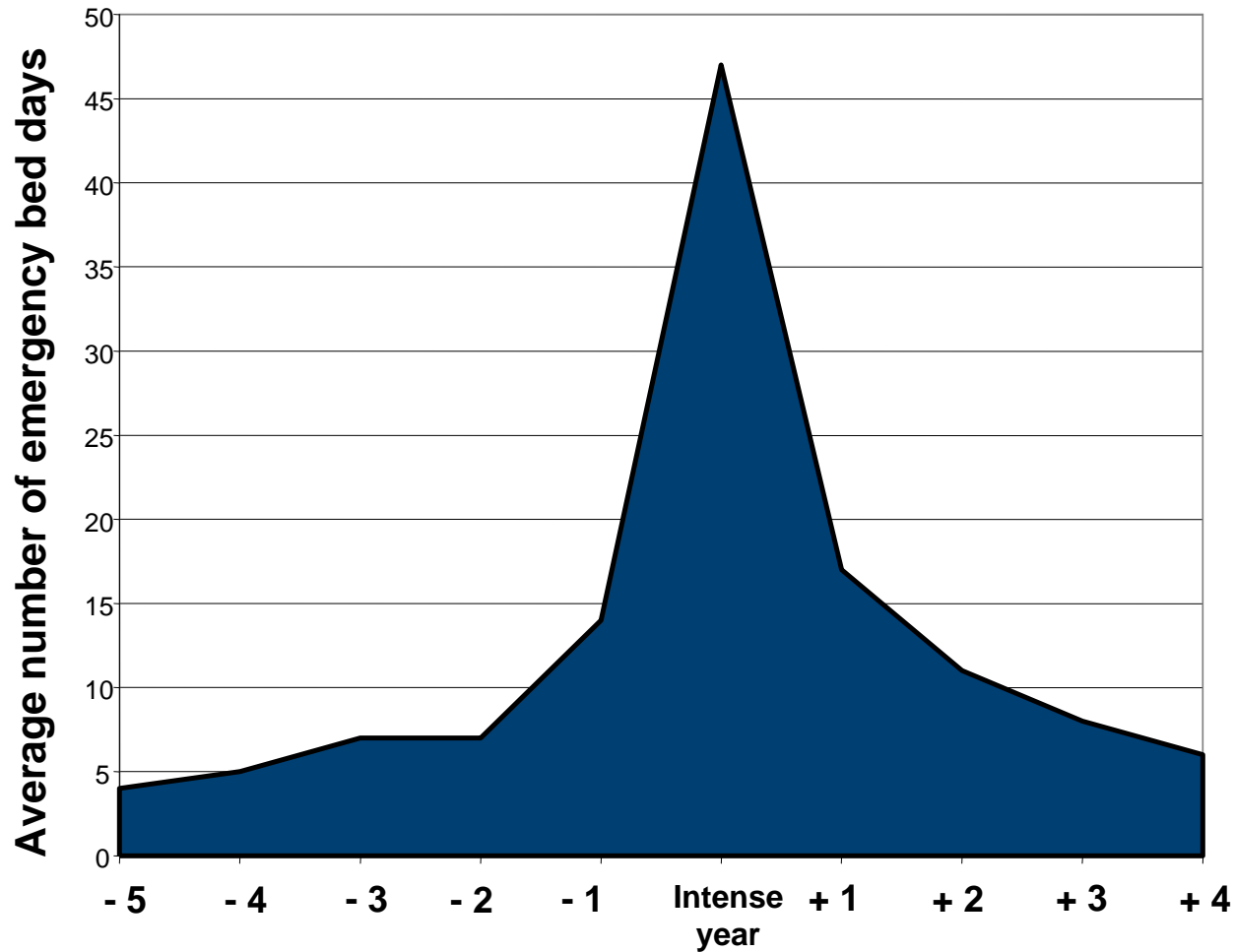
No reduction seen in:

- emergency admissions
- emergency bed days
- mortality



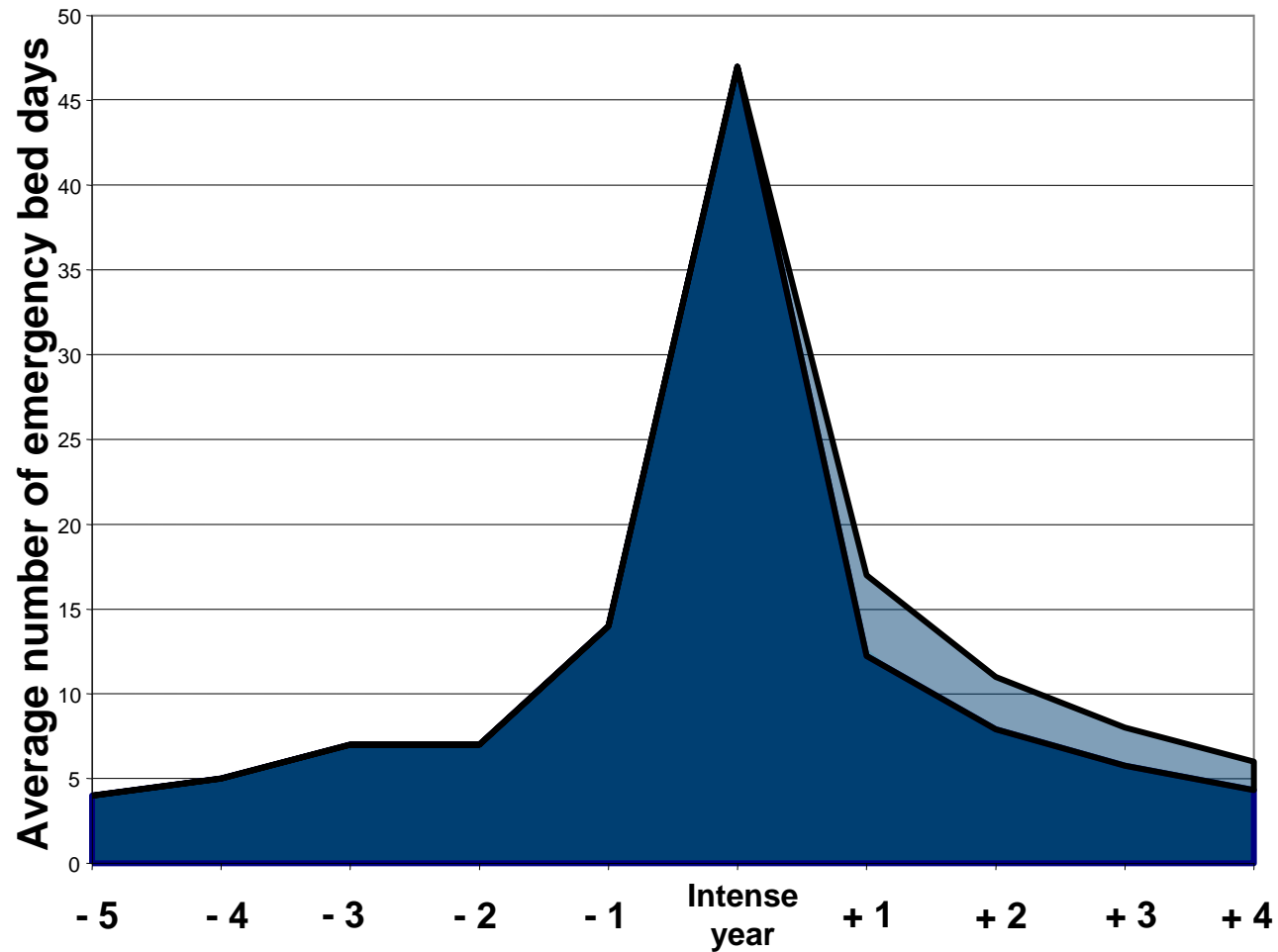
Gravelle H, Dusheiko M, Sheaff R, Sargent P, Boaden R, Pickard S, Parker S, Roland M. Impact of case management (Evercare) on frail elderly patients: controlled before and after analysis of quantitative outcome data. BMJ. 2007;334(7583):31

Importance of Accurate Case Finding



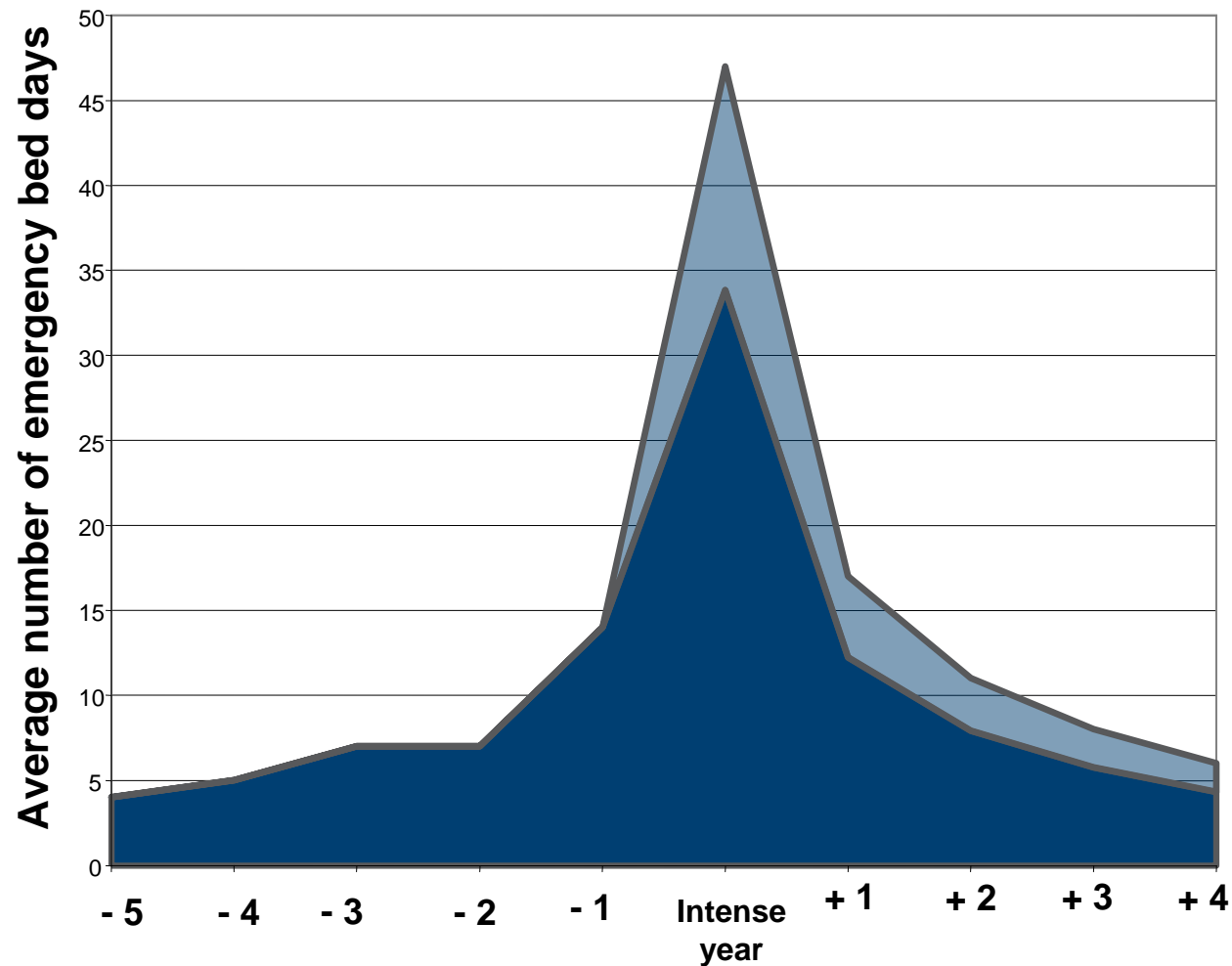
Halliday R. Department of Health analysis of Hospital Episode Statistics for England

Importance of Accurate Case Finding



Halliday R. Department of Health analysis of Hospital Episode Statistics for England

Importance of Accurate Case Finding



Halliday R. Department of Health analysis of Hospital Episode Statistics for England

Preventive Care Can Only Work if Offered to Individuals Who are Truly at Risk

Inaccurate Approaches:

- Threshold models (e.g. all patients aged >65 with 2+ admissions)
- Clinician referrals

Curry N, Billings J, Darin B, Dixon J, Williams M, Wennberg D. Predictive risk project literature review. London: King's Fund, 2005

Referrals by Clinicians

Assessed the predictions made by

- Physicians
- Case managers
- Nurses

“...none of the AUC values were statistically different from chance”



Inability of Providers to Predict Unplanned Readmissions

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BACKGROUND: Readmissions cause significant distress to patients and considerable financial costs. Identifying hospitalized patients at high risk for readmission is an important strategy in reducing readmissions. We aimed to evaluate how well physicians, case managers, and nurses can predict whether their older patients will be readmitted and to compare their predictions to a standardized risk tool (Probability of Repeat Admission, or P_{RA}).

METHODS: Patients aged ≥65 discharged from the general medical service at University of California, San Francisco Medical Center, a 550-bed tertiary care academic medical center, were eligible for enrollment over a 5-week period. At the time of discharge, the inpatient team members caring for each patient estimated the chance of unscheduled readmission within 30 days and predicted the reason for potential readmission. We also calculated the P_{RA} for each patient. We identified readmissions through electronic medical record (EMR) review and phone calls with patients/caregivers. Discrimination was determined by creating ROC curves for each provider group and the P_{RA}.

RESULTS: One hundred sixty-four patients were eligible for enrollment. Of these patients, five died during the 30-day period post-discharge. Of the remaining 159 patients, 32 patients (20.1%) were readmitted. Mean readmission predictions for the physician providers were closest to the actual readmission rate, while case managers, nurses, and the P_{RA} all overestimated readmissions. The ability to discriminate between readmissions and non-readmissions was poor for all provider groups and the P_{RA} (AUC from 0.50 for case managers to 0.59 for interns, 0.56 for P_{RA}). None of the provider groups predicted the reason for readmission with accuracy.

CONCLUSIONS: This study found (1) overall readmission rates were higher than previously reported, possibly because we employed a more thorough follow-up methodology, and (2) neither providers nor a published algorithm were able to accurately predict which patients were at highest risk of readmission. Amid increasing pressure to reduce readmission rates, hospitals do not have accurate predictive tools to guide their efforts.

Received August 27, 2010
Revised January 27, 2011
Accepted January 28, 2011
Published online March 13, 2011

KEY WORDS: readmissions; unplanned; prediction.

J Gen Intern Med 2011;26(7):771-6.
DOI: 10.1007/s11366-011-1003-3
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BACKGROUND

Against the background of rising concerns about both the cost and quality of American medical care, hospital readmissions have come under increasing scrutiny from both outside and within the government.¹⁻³ Hospital readmissions may be a marker for poor quality care, are disconcerting for patients and families, and increase health care costs. Medicare estimates that \$15 billion is spent on the 17.0% of patients who are readmitted within 30 days.⁴

Although it would be ideal to develop interventions that improve the hospital-to-home transition for all patients, given limited resources, some have argued for targeting intensive efforts—such as comprehensive discharge planning, post-discharge phone calls or home visits, and early clinic visits—towards high risk patients. However, such strategies require that we have accurate methods to identify patients at highest risk.

Anecdotal evidence suggests that inpatient providers (physicians, nurses, discharge planners) currently make informal predictions of readmission that affect discharge planning. Such predictions are not new; providers have tried to predict other outcomes, such as mortality and length of stay, in several settings (e.g., intensive care unit, emergency department), with varying success.⁵⁻¹¹ However, the accuracy of informal predictions of hospital readmission is unknown. Several algorithms have also been developed in recent years to predict hospital readmissions, but their use has been limited, because they require information not typically gathered during clinical care, their models are complex and difficult to use, and/or because they are not accurate. A few studies have compared providers with algorithm-based tools to predict readmission and mortality in other settings,⁹ but it remains unknown how well providers' predictions of readmission for general medicine patients compare with published algorithms or how the predictions of multiple disciplines compare with one another.

To reach the ultimate goal of preventing readmissions, identifying the highest risk patients is the first of a multi-step process. Providers would next need to speculate on the reason for readmission before then targeting an effective

Allaudeen N, Schnipper JL, Orav EJ, Wachter RM, Vidyarthi AR. Inability of providers to predict unplanned readmissions. J Gen Intern Med. 2011;26(7):771-6

LACE Model

Length of stay

Acuity

Comorbidity

ER visits in the last six months

C statistic = 0.684

1-point increase in the LACE score
increases the odds of unplanned
readmission by 18% (odds
ratio 1.18, 95% CI 1.14–1.21)



van Walraven C, Dhalla IA, Bell C, Etchells E, Stiell IG, Zarnke K, Austin PC, Forster AJ. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. CMAJ. 2010 Apr 6;182(6):551-7

Trade-off Between Sensitivity and PPV

Cut-off score	Positive predictive value	Sensitivity
50	0.65	0.54
70	0.77	0.18
80	0.84	0.08

Area under the ROC curve (“c-statistic”) = 0.685

Billings et al. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. BMJ 2006;333:327

Current Predictive Models are Suboptimal

“Most current readmission risk prediction models perform poorly...Efforts to improve their performance are needed.”

Implications

- A single, nationwide model is unfeasible
- Additional data points may improve predictive accuracy – possibly including pharmacy data

CLINICAL REVIEW

CLINICIAN'S CORNER

Risk Prediction Models for Hospital Readmission A Systematic Review

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Amanda Salanitro, MD, MS, MSPH
David Kagen, MD
Cecilia Theobald, MD
Michelle Freeman, MPH
Smit Kripalani, MD, MSc

Context Predicting hospital readmission risk is of great interest to identify which patients would benefit most from care transition interventions, as well as to risk-adjust admission rates for the purposes of hospital comparison.

Objective To summarize validated readmission risk prediction models, describe their performance, and assess suitability for clinical or administrative use.

Data Sources and Study Selection The databases of MEDLINE, CINAHL, and the Cochrane Library were searched from inception through March 2011, the EMBASE database was searched through August 2011, and hand searches were performed of the retrieved reference lists. Dual review was conducted to identify studies published in the English language of prediction models tested with medical patients in both derivation and validation cohorts.

Data Extraction Data were extracted on the population, setting, sample size, follow-up interval, readmission rate, model discrimination and calibration, type of data used, and timing of data collection.

Data Synthesis Of 7843 citations reviewed, 30 studies of 26 unique models met the inclusion criteria. The most common outcome used was 30-day readmission; only 1 model specifically addressed preventable readmissions. Fourteen models that relied on retrospective administrative data could be potentially used to risk-adjust readmission rates for hospital comparison; of these, 9 were tested in large US populations and had poor discriminative ability (c statistic range: 0.55-0.65). Seven models could potentially be used to identify high-risk patients for intervention early during a hospitalization (c statistic range: 0.56-0.72), and 5 could be used at hospital discharge (c statistic range: 0.68-0.83). Six studies compared different models in the same population and 2 of these found that functional and social variables improved model discrimination. Although most models incorporated variables for medical comorbidity and use of prior medical services, few examined variables associated with overall health and function, illness severity, or social determinants of health.

Conclusions Most current readmission risk prediction models that were designed for either comparative or clinical purposes perform poorly. Although in certain settings such models may prove useful, efforts to improve their performance are needed as use becomes more widespread.

JAMA. 2011;306(15):1688-98. www.jama.com

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Clinical Review Section Editor: Mary McGee McInerney, MD, Contributing Editor. She encourages authors to submit papers for consideration as a Clinical Review. Please contact Mary McGee McInerney, MD, at mcm001@northwestern.edu.

1688 JAMA, October 19, 2011 • Vol 306, No 15 ©2011 American Medical Association. All rights reserved.

Kansagara D, Englander H, Salanitro A, Kagen D, Theobald C, Freeman M, Kripalani S. Risk prediction models for hospital readmission: a systematic review. JAMA. 2011 Oct 19;306(15):1688-98.

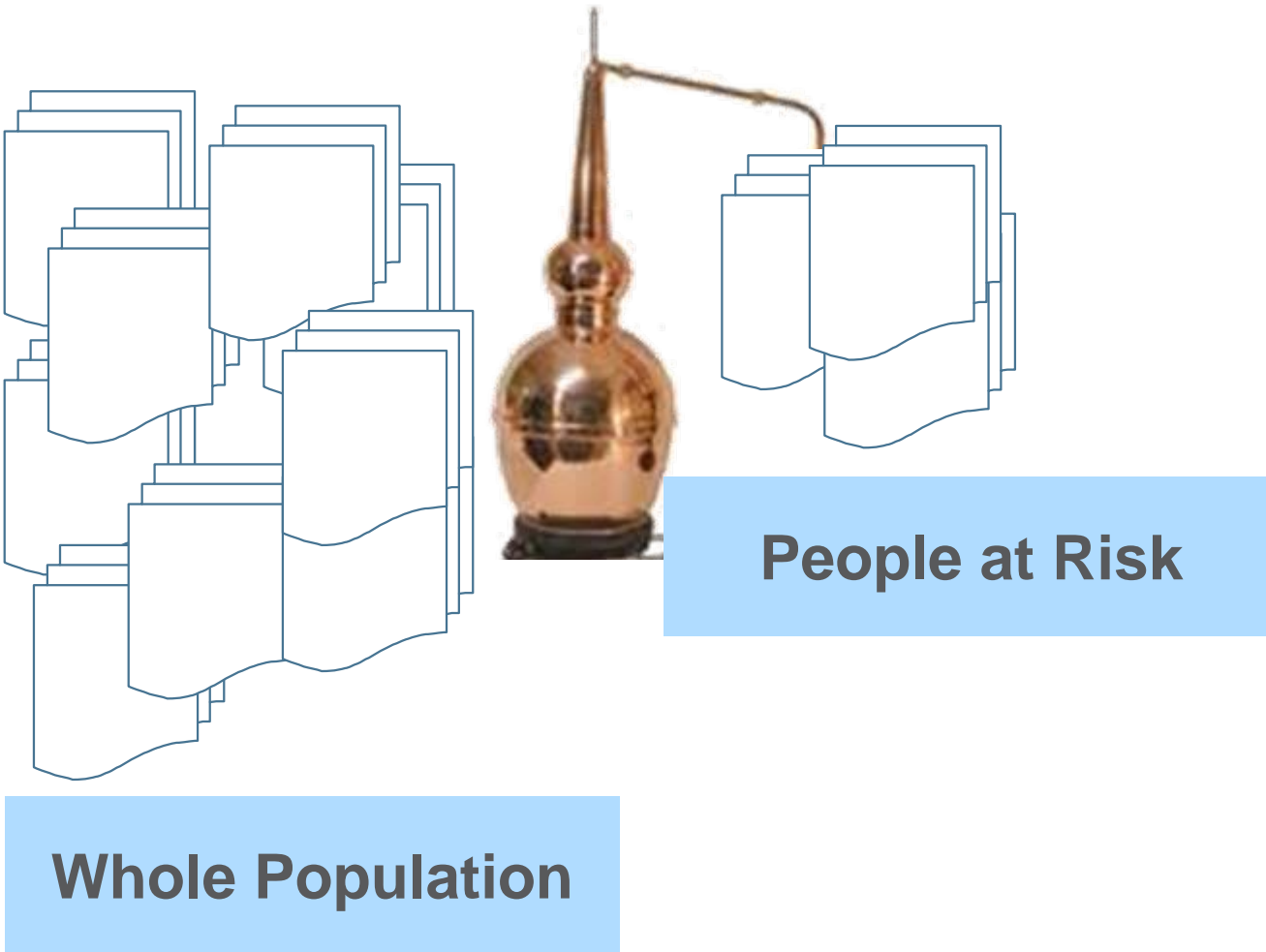


Challenge 2: Who is Amenable to Preventive Care?



Predictive Risk Model

Impactability Model



Approaches to Impactability Modelling

Approach to Impactability Modelling	Efficiency	Equity
Prioritise patients with ACS conditions	✓	✓
Prioritize patients with high “gap scores”	✓	✓
Exclude “difficult” patients	✓	x

Lewis GH. Impactability Models: Identifying the Subgroup of High Risk Patients Most Amenable to Hospital Avoidance Programs. *Milbank Quarterly* 2010;88(2).

Impactability: Top 5 Diagnoses

Cohort	Top 5 Commonest Diagnoses by Cohort
0 readmissions	<ol style="list-style-type: none">1. Pneumonia2. Osteoarthritis3. Septicemia4. Obstructive chronic bronchitis5. Urinary tract infection
1 readmission	<ol style="list-style-type: none">1. Pneumonia2. Obstructive chronic bronchitis3. Septicemia4. Urinary tract infection5. Acute kidney failure
2+ readmissions	<ol style="list-style-type: none">1. Obstructive chronic bronchitis2. Pneumonia3. Congestive heart failure4. Septicemia5. Urinary tract infection

Data from 5% Medicare sample in 2010.

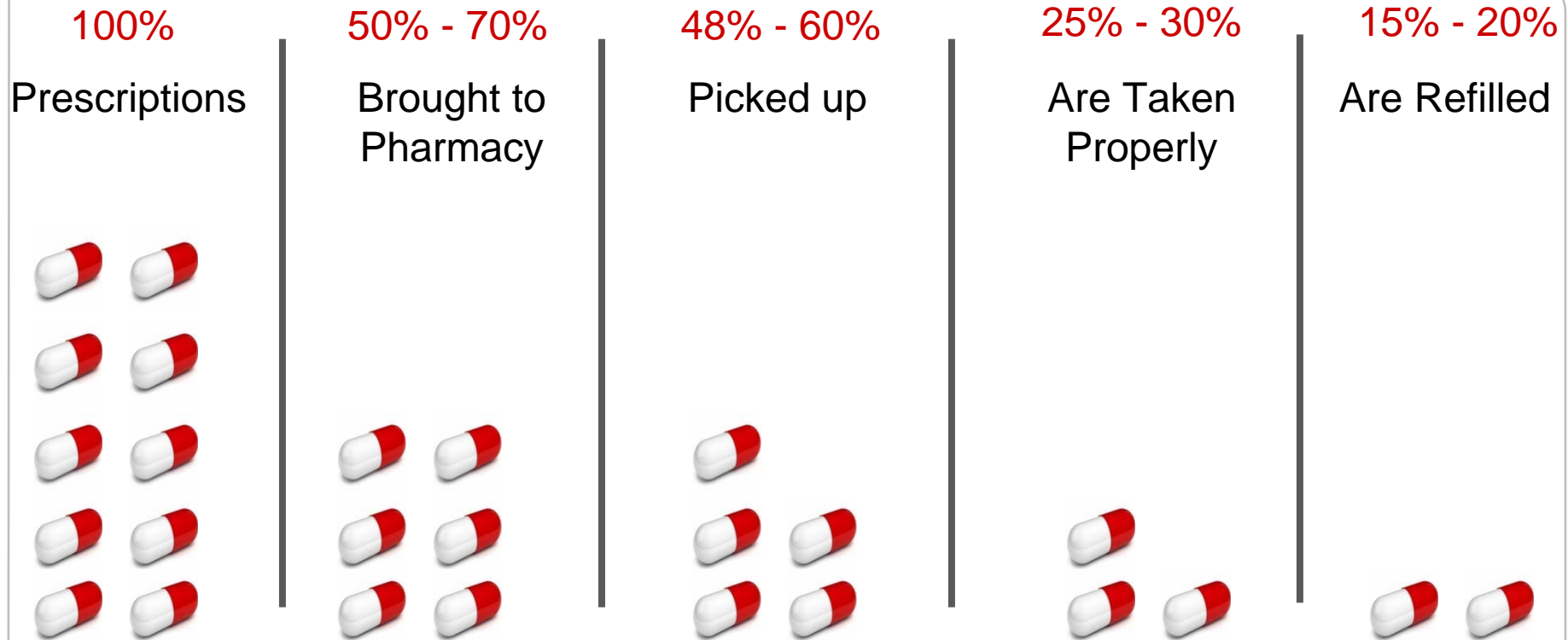
Impactibility: Quality of Care

% of people, by number of admissions/readmissions, who had recommended annual tests performed according to HEDIS guidelines, by disease category, in the previous year

Condition:	CAD	HF	DM	DM	DM	COPD
Annual Test:	LDL	LDL	HbA1C	Eye	Albumin	Spirometry
0 admissions	77%	66%	76%	47%	33%	24%
0 readmissions	63%	55%	64%	65%	42%	23%
1 readmission	57%	52%	58%	61%	39%	23%
2+ readmissions	51%	47%	52%	59%	34%	25%

Data from 5% Medicare sample in 2010. Annual tests relate to HEDIS measures.

Medication Fill Rate as a Potential Additional Predictor Variable



Source: IMS

33 to 69 percent of readmissions attributed to poor medication adherence*

*Osterberg L, Blaschke T. Adherence to Medication. New England Journal of Medicine. 2005;353(5):487-497.



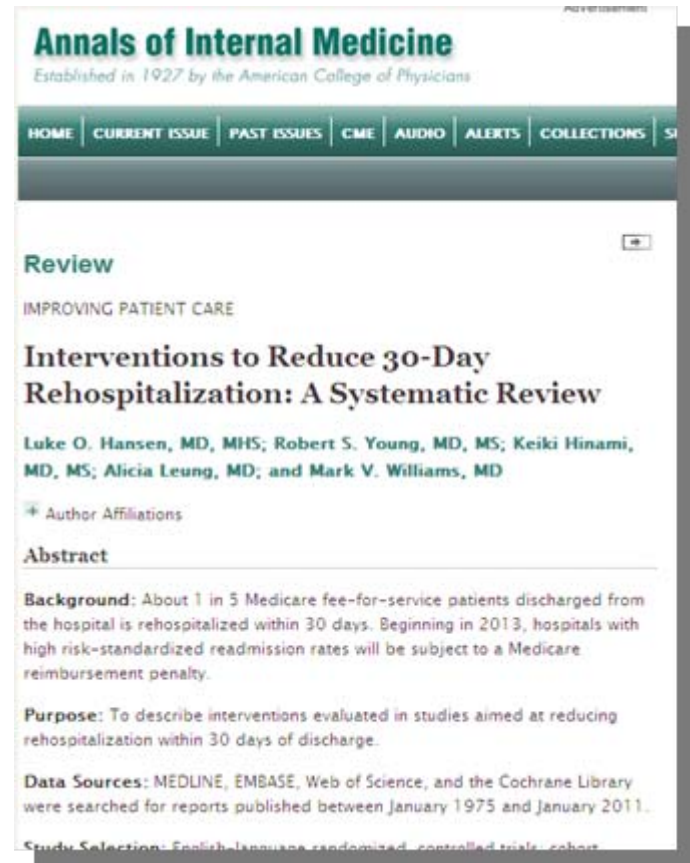
Challenge 3: Interventions to Prevent Readmissions

Meta-Analysis

Classification:

Pre-discharge
Bridging
Post-discharge

“No single intervention implemented alone was regularly associated with reduced risk for 30-day re-hospitalization”



Hansen LO, Young RS, Hinami K, Leung A, Williams MV. Interventions to reduce 30-day rehospitalization: a systematic review. Ann Intern Med. 2011;155(8):520-8.

Toronto Virtual Ward

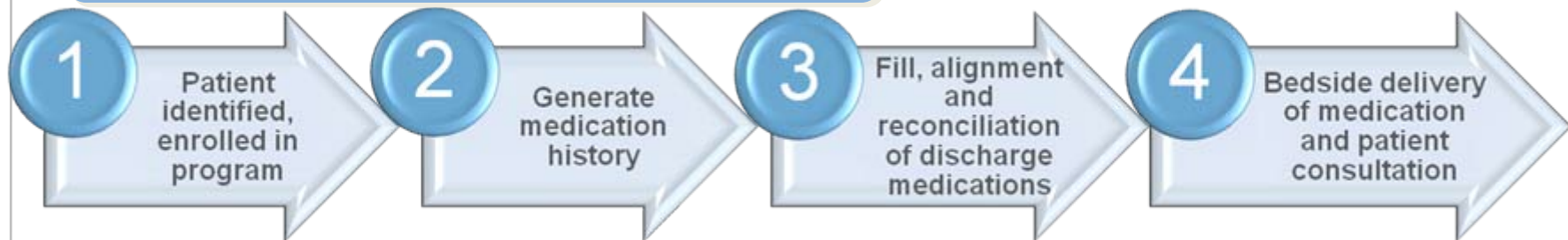
- Offered to patients with a **high LACE score**
- Care at home using the **systems and staffing of a hospital ward** for 30 days post-discharge
- **Bridge** from hospital to home
- Randomized Controlled Trial underway



Lewis GH. Toronto Virtual Wards: useful lessons for NHS hospitals? <http://www.nuffieldtrust.org.uk/blog/toronto-virtual-ward-useful-lessons-nhs-hospitals>

Walgreens Interventions to Prevent Readmission

Hospital Treatment



Post-discharge Care



8 Joint outcomes reporting with health system and IT partner

Challenge 4: Roemer's Law

Roemer's Law

Positive correlation between

- number of short-term general hospital **beds available** per 1,000 population; and
- number of hospital **bed-days used** per 1,000 population

Roemer's Law: A hospital bed built is a hospital bed filled

Contact Information

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