Systems for Action
National Coordinating Center
Systems and Services Research to Build a Culture of Health

Strategies to Achieve Alignment, Collaboration, and Synergy across Delivery and Financing Systems

Using Predictive Modeling to Identify Patients Who Need Social Services

Research In Progress Webinar
Wednesday, January 10, 2017
12:00-1:00 pm ET/ 9:00 am-10:00 pm PT

College of Public Health
Center for Public Health Systems and Services Research

Funded by the Robert Wood Johnson Foundation

Agenda

Welcome: **CB Mamaril, PhD**
Research Faculty, RWJF Systems for Action National Coordinating Center,
University of Kentucky College of Public Health

Presenter: **Joshua R. Vest, PhD, MPH**
Director, Center for Health Policy
Associate Professor, Health Policy & Management
Indiana University Richard M. Fairbanks School of Public Health at IUPUI
joshvest@iu.edu

Commentary Speaker:
Michael Shafer, PhD
Director
Center for Applied Behavioral Health Policy
Professor
Arizona State University
michael.shafer@asu.edu

Questions and Discussion: Moderated by Dr. Mamaril

Presenter

Joshua R. Vest, PhD, MPH
Director
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Webinars

Archives

http://systemsforaction.org/research-progress-webinars

Upcoming

Upcoming
Wednesday, January 24, 12-1pm ET/ 9-10am PT **Optimizing Governmental Health and Social Spending Interactions** *Johns Hopkins University Bloomberg School of Public Health* *Principal Investigators: Beth Resnick, DrPH, MPH, and David Bishai, MD, MPH, PhD*
Wednesday, February 7, 12-1pm ET/ 9-10am PT **Strengthening the Carrying Capacity of Local Health and Social Service Networks** *Trailhead Institute in Colorado* *Principal Investigators: Danielle Varda, PhD, and Katie Edwards, MPA*
Wednesday, February 21, 12-1pm ET/ 9-10am PT **Linking Medical Homes to Social Service Systems for Medicaid Populations** *National Committee for Quality Assurance* *Principal Investigators: Sarah Scholle, DrPH, and Keri Christensen, MS*

Thank you for participating in today's webinar!

S4A
Systems for Action

For more information about the webinars, contact:

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111 Washington Avenue #201, Lexington, KY 40536

859.218.2289

www.systemsforaction.org

Speaker Bios

Joshua R. Vest, PhD, MPH, is a health services researcher with interests in organizational determinants and effectiveness of health information technology and systems, specifically the adoption, utilization, and policy issues of technologies that facilitate the sharing of patient information between different organizations. He is widely published and his work has employed a variety of research techniques from large scale database analyses, to geographical information system mapping, to survey research, to qualitative focus groups and interviews. As a former local public health practitioner, Dr. Vest has a particular interest in effective public health information systems including the role of information technology governance structures on local public health departments' adoption of information technology and systems, the structure of state and local public health information systems, as well as an evaluation of email intervention to improve disease notification efforts.

Michael S. Shafer, Ph.D., is a professor in the School of Social Work at Arizona State University’s College of Public Service and Community Solutions where he also holds affiliate appointments in the Center for Health Information Research and the School of Criminology and Criminal Justice. Dr. Shafer is the founding director of the Center for Applied Behavioral Health Policy which has, for the past 25 years, conducted cutting edge research on the adoption and implementation of innovative practices in behavioral health care. Dr. Shafer has authored more than 40 peer-reviewed research articles and generated more than $45 million in grants and contracts that target capacity building and innovation in behavioral health services. Dr. Shafer earned his Ph.D. in Education in 1988 from Virginia Commonwealth University. He has received numerous awards and citations, including recognition from the U.S. Department of Justice for the development of crisis intervention training for law enforcement personnel. Dr. Shafer is a frequent contributor to professional literature and he consults with behavioral health agencies throughout the country.

Using predictive modeling to identify patients who need social services

Joshua R Vest, PhD, MPH

Director, Center for Health Policy

Associate Professor, Health Policy & Management

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This work was supported by the Robert Wood Johnson Foundation through the Systems for Action National Coordinating Center, ID 73485.

Acknowledgements

Kasthurirathne et al 2017 doi: 10.1093/jamia/ocx130

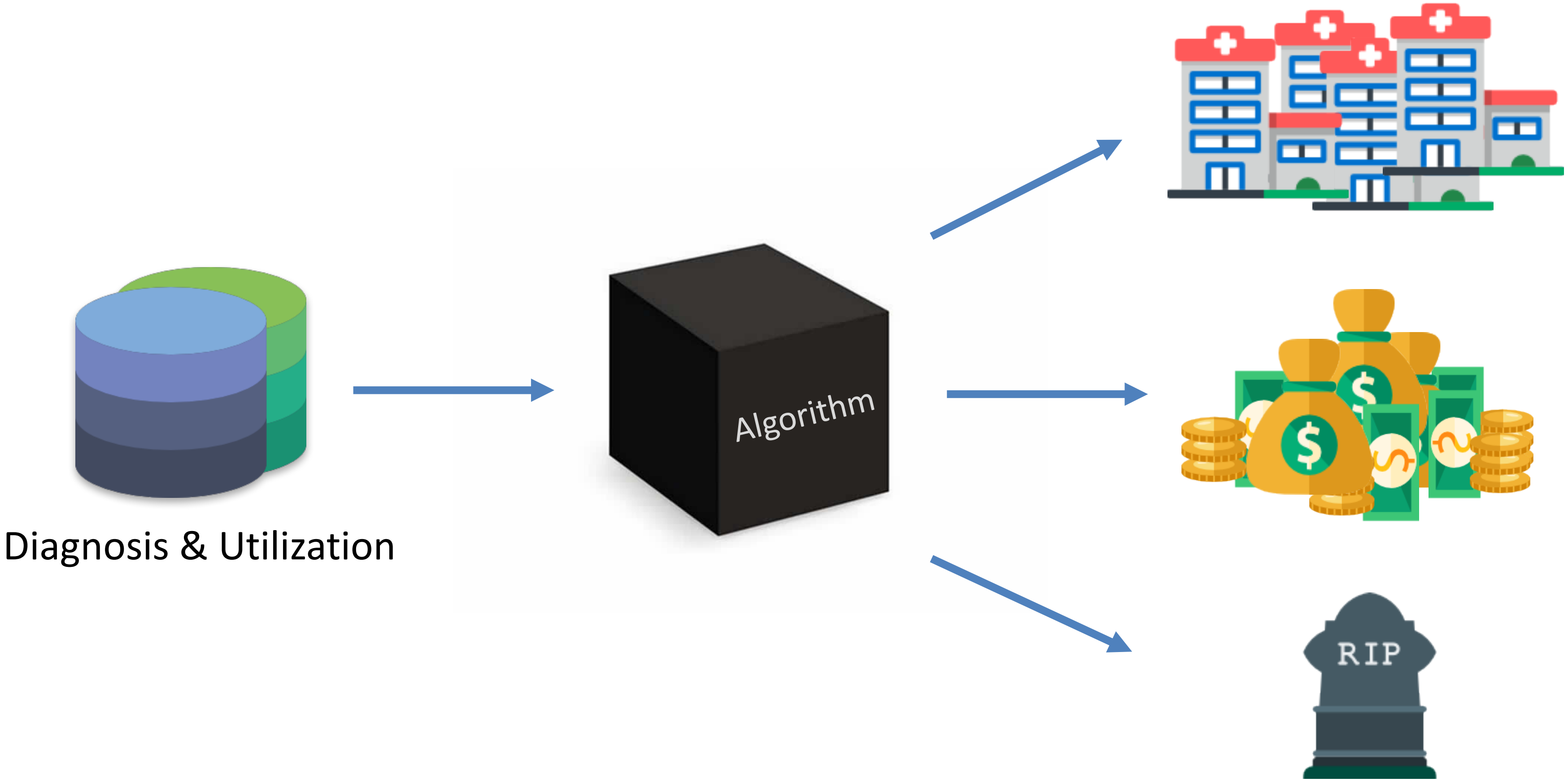
Indiana University

- Suranga N. Kasthurirathne
- Nir Menachemi
- Paul K Halverson
- Shaun J. Grannis
- Jennifer Williams
- Karen Comer

Eskenazi Health

- Dawn Haut
- Jennifer Ferrell
- Donna Burke
- Alisha Jessup

Predictive modeling in health care: statistical approaches to identifying patients at high risk (more *likely*) for negative outcomes



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Predictive modeling is widely applied...

POPULATION HEALTH

By Sabine I. Vuik, Erik K. Mayer, and Ara Darzi

ANALYSIS & COMMENTARY

Patient Segmentation Analysis Offers Significant Benefits For Integrated Care And Support

DOI: 10.1377/hlthaff.2015.1311
HEALTH AFFAIRS 35,
NO. 5 (2016): 769–775

ABSTRACT Integrated care aims to organize care around the patient instead of the provider. It is therefore crucial to understand differences across patients and their needs. Segmentation analysis that uses big data can help divide a patient population into distinct groups, which can then be targeted with care models and intervention programs tailored to their needs. In this article we explore the potential applications of patient segmentation in integrated care. We propose a framework for population strategies in integrated care—whole populations, subpopulations, and high-risk populations—and show how patient segmentation can support these strategies. Through international case examples, we illustrate practical considerations such as choosing a segmentation logic, accessing data, and tailoring care models. Important issues for policy makers to consider are trade-offs between simplicity and precision, trade-offs between customized and off-the-shelf solutions, and the availability of linked data sets. We conclude that segmentation can provide many benefits to integrated care, and we encourage policy makers to support its use.

Sabine I. Vuik (s.vuik@imperial.ac.uk) is a policy fellow at the Institute of Global Health Innovation, Imperial College London, in the United Kingdom.

Erik K. Mayer is a clinical senior lecturer at the Centre for Health Policy, Imperial College London.

Ara Darzi is executive chair of the World Innovation Summit for Health, Qatar Foundation, and director of the Institute of Global Health Innovation, Imperial College London.

Risk Prediction Models for Hospital Readmission

A Systematic Review

Devan Kansagara, MD, MCR
Honora Englander, MD
Amanda Salanitro, MD, MS, MSPH
David Kagen, MD
Cecelia Theobald, MD
Michele Freeman, MPH
Sunil 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 readmission 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):1688-1698 www.jama.com

AN INCREASING BODY OF LITERATURE attempts to describe and validate hospital readmission risk prediction tools. Interest in such models has grown for 2 reasons. First, transitional care interventions may reduce readmissions among chronically ill adults.[1-3] Readmission risk assessment could be used to help target the delivery of these resource-intensive interventions to the patients at greatest risk. Ideally, models designed for this purpose would provide clinically relevant stratification of readmission risk and give information early enough during the hospitalization to trigger a transitional care intervention, many of which involve discharge planning and begin well before hospital discharge. Second, there is interest in using readmission rates as a quality metric. The Centers for Medicare & Medicaid Services (CMS) recently began using readmission rates as a publicly reported metric and has plans

Author Affiliations: VA Evidence-Based Synthesis Program (Dr Kansagara and Ms Freeman), Department of General Internal Medicine (Drs Kansagara and ... Medicine, Vanderbilt University, Nashville, Tennessee (Drs Salanitro, Theobald, and Kripalani).
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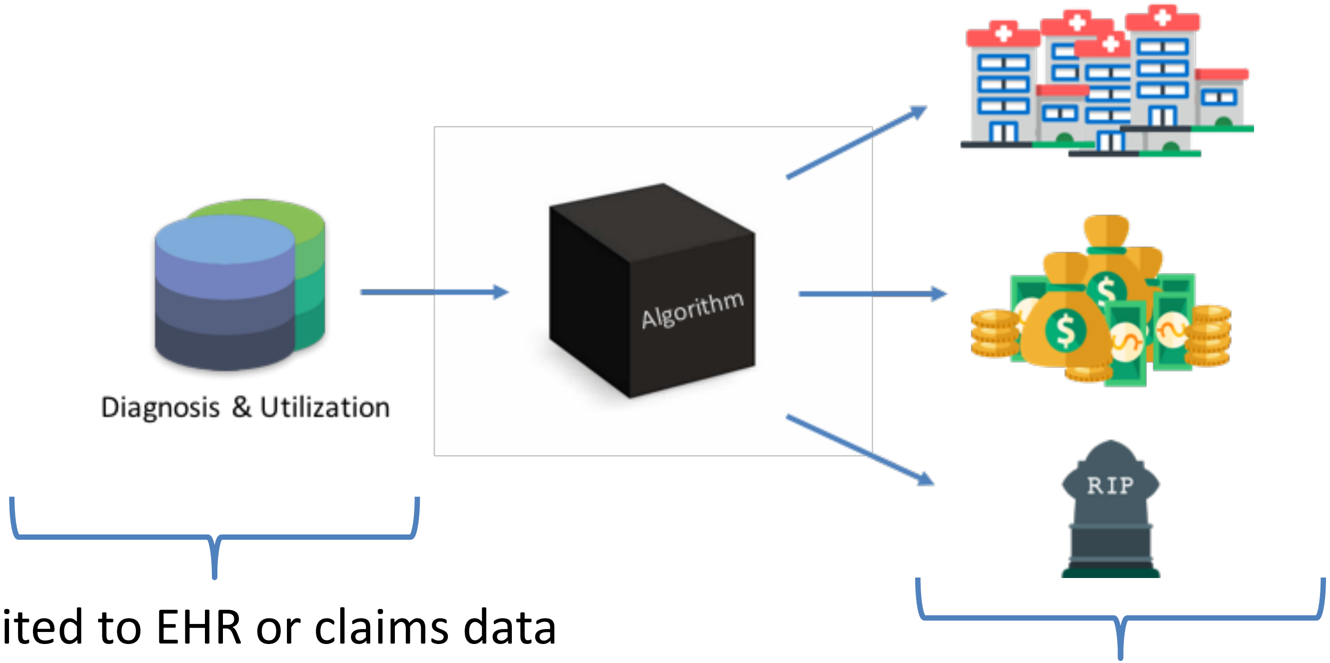
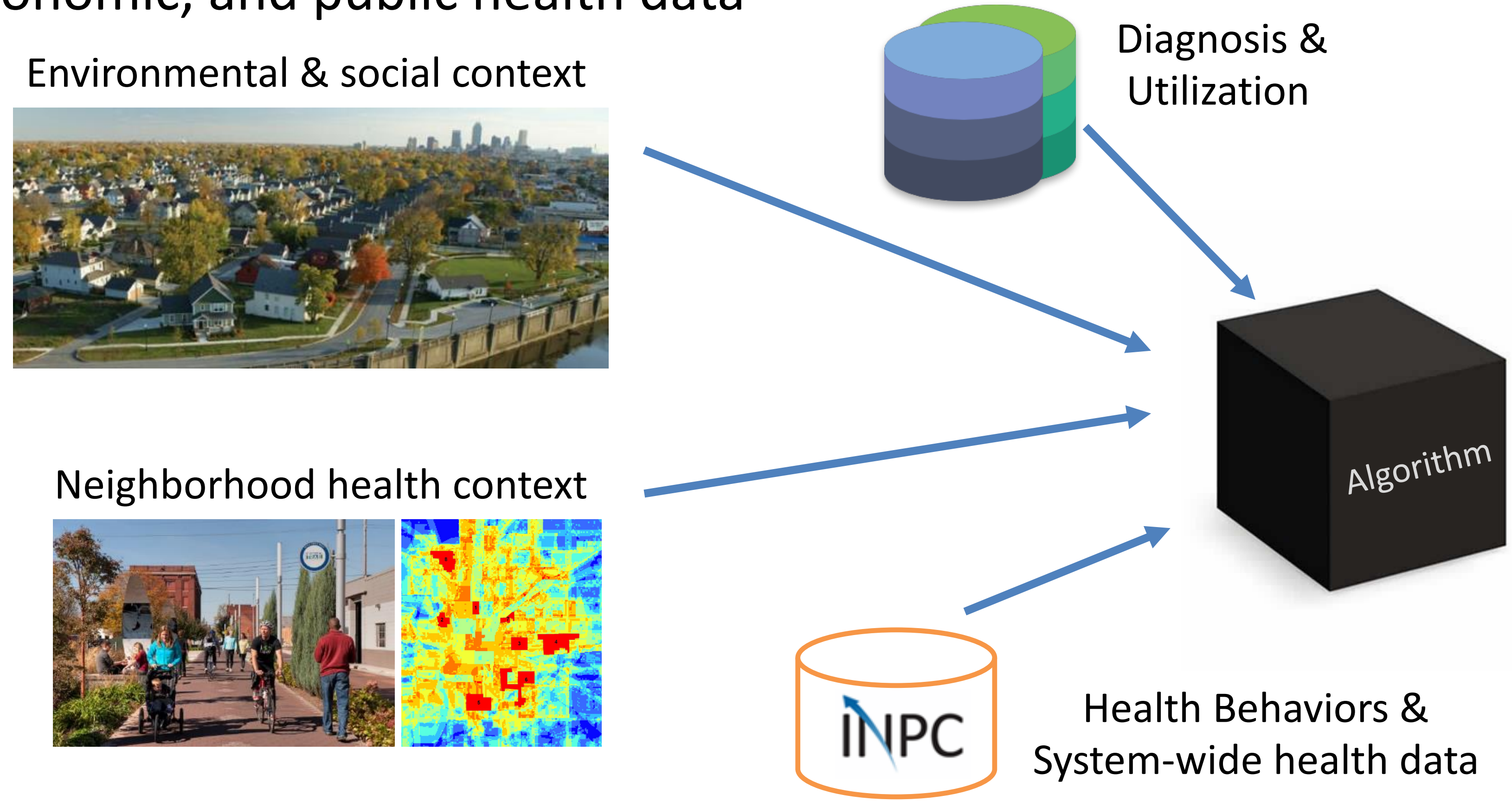
Limitations of current predictive modeling

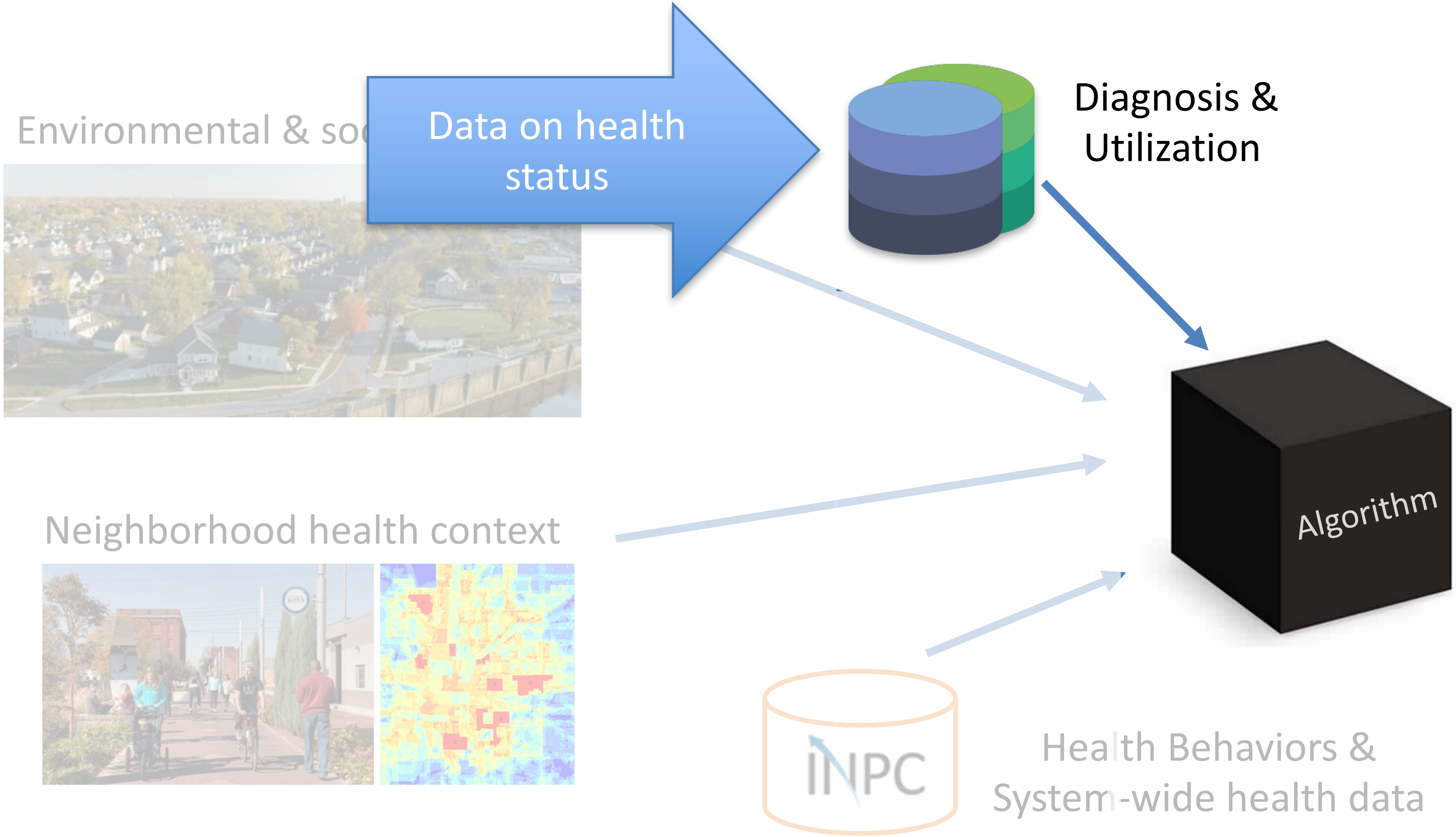


- Limited to EHR or claims data
- Social determinants often absent
- Often single-site data

- Focus on “too late” outcomes (reactive not proactive)
- Don’t provide insights into what services patients should get

Objective 1: Evaluate predictive models that use combinations of clinical, socioeconomic, and public health data

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Data on health
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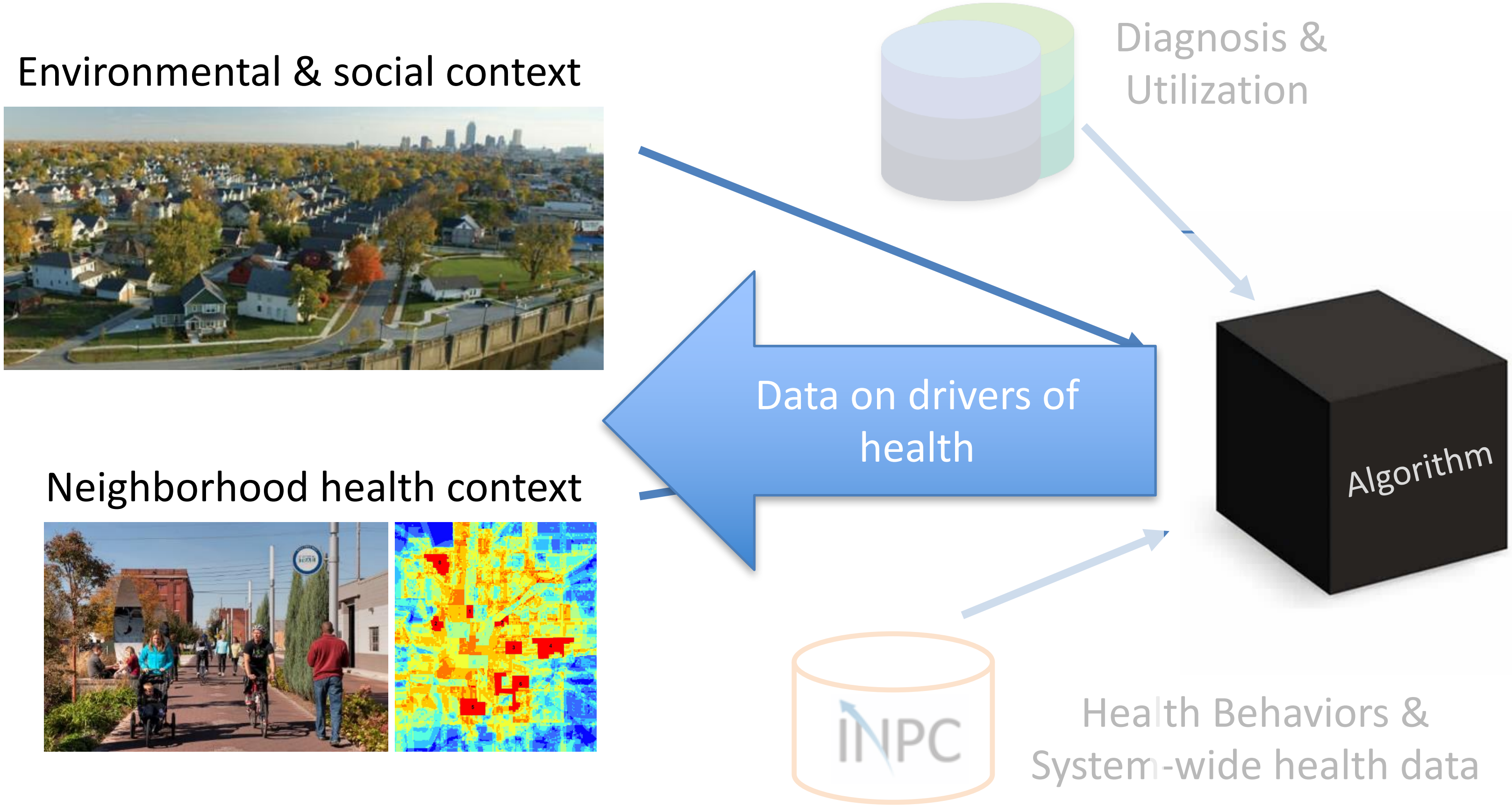
Diagnosis &
Utilization
Algorithm
Neighborhood health context
INPC
Health Behaviors &
System-wide health data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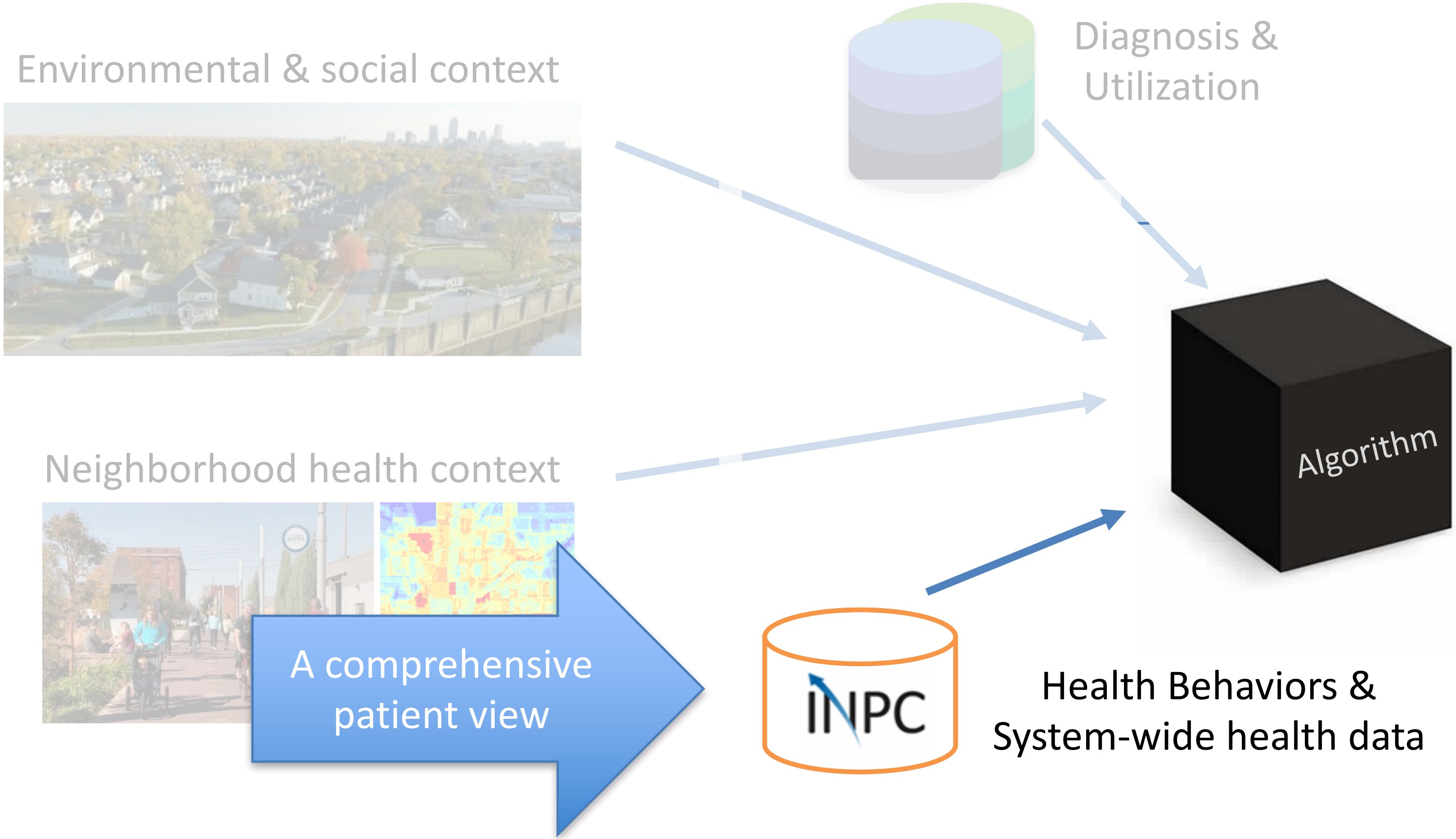
Health Behaviors & System-wide health data


Environmental & social context
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A comprehensive
patient view
INPC
Health Behaviors &
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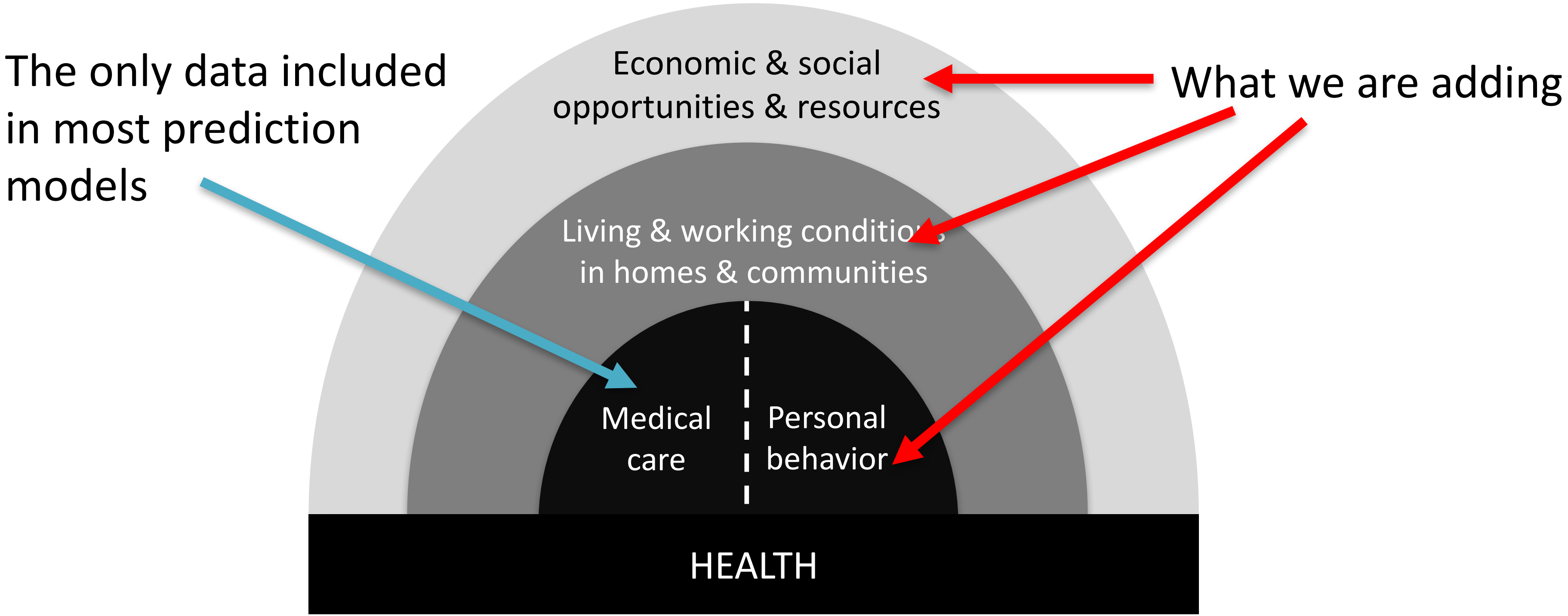
Framework for organizing the factors included in risk identification tool



“Social Determinants of Health Model” by Braveman et al (2011) Annu. Rev. Public Health, 32:381-398

Objective 2: Contribution of these data on the novel outcome of referrals to social services

To be responsive to new payment strategies, health care organizations in the US are beginning to offer these non-medical services.

www.chelseajewish.org/celebrating-social-work-month-senior-care/

http://cchci.org/_services/behavioral-health/

Fitday.com

usf.edu

dmkelite.com

Pplay.google.com

guide.berkeley.edu/undergraduate

Objective 1:
Evaluate predictive models that use combinations of clinical, socioeconomic, and public health data.

Objective 2:
Contribution of these data on the novel outcome of referrals to social services.

Approach

Compare the performance of risk prediction models with:

1) clinical data only

2) clinical data with community-level socioeconomic & public health indicators

Setting & sample

- Eskenazi Health outpatient clinics
  - Indianapolis safety-net provider (for medical indigent)
  - urban population
  - all social services offered on a co-located basis (no referrals to other organizations)
- 84,317 adult patients
  - at least 1 outpatient visit between 2011-2016

Sample demographics

Demographics	
Age (mean, sd)	43.9 (15.6)
Male gender	35.1
Race / ethnicity	
White, non-Hispanic	25.2
African American, non-Hispanic	37.2
Hispanic	19.5
Diagnoses	
Hypertension	38.7
Asthma	7.9
Cancer	7.6
COPD	9.5
Depression	19.0
Diabetes	20.3
Substance abuse	15.1
Tobacco use	21.3

Data & measures (outcome)

Referral to social services

- Social work
- Dietitian
- Mental health
- All other services (due to low frequency)

Data sources

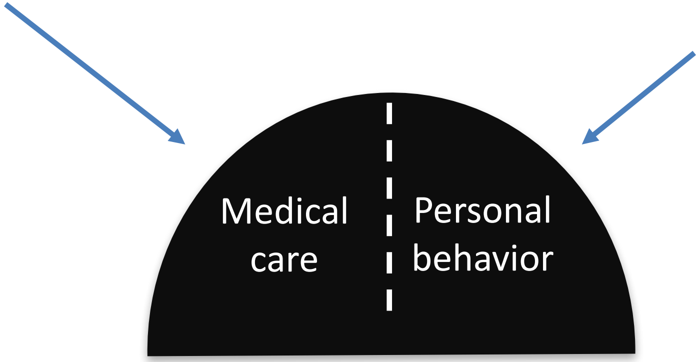
- Eskenazi EHR billing and encounter data
- scheduling system data (including kept, missed, & cancelled appointments)
- unstructured EHR orders and notes

Data & measures (predictors)

“Social Determinants of Health Model” by Braveman et al (2011) Annu. Rev. Public Health, 32:381-398

Data & measures (predictors)

- Diagnoses
  - Asthma
  - Coronary artery disease
  - Chronic kidney disease
  - Congestive heart failure
  - COPD
  - Stroke / cerebrovascular accident
  - Depression
  - Diabetes
  - Hypertension
  - Ischemic vascular disease
  - Obesity
  - Pregnancy
  - ....
- ED visits (number)
- Inpatient admissions
- PCP visits
- Mental illness

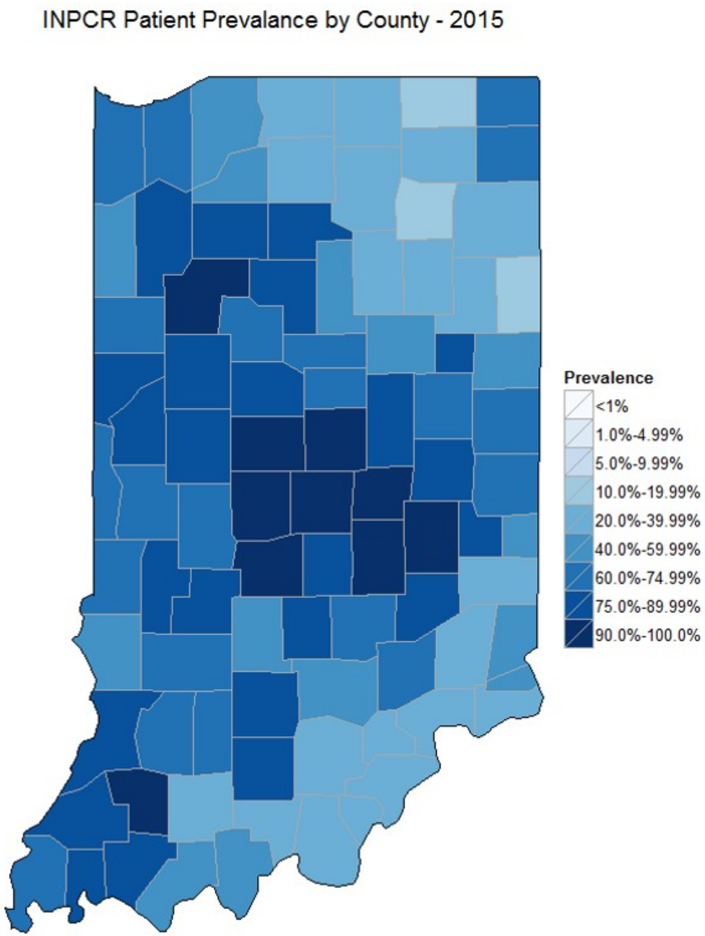


- Smoking
- Substance abuse

"Social Determinants of Health Model" by Braveman et al (2011) Annu. Rev. Public Health, 32:381-398

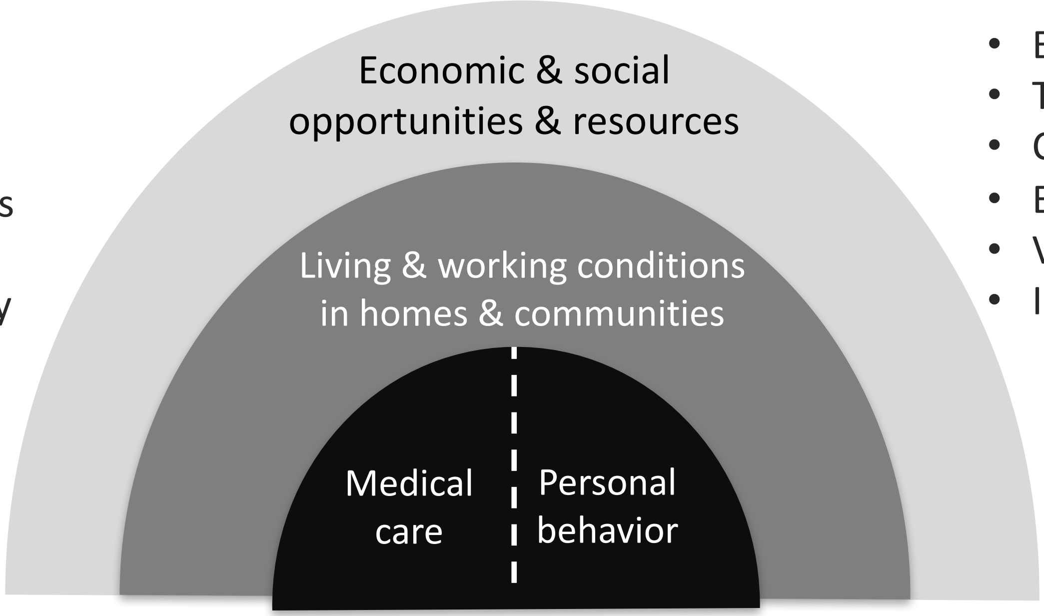
INPC

- **I**ndiana **N**etwork for **P**atient **C**are
- US' oldest HIE
  - Started at Regenstrief Institute in 1995
- One of the nation's largest
  - > 80 hospitals' medical records
  - 17.2 million individual patients
  - 4.6 billion clinical observations
  - 165 million text reports
  - Over 68% of Indiana population captured in 2014
- Data include:
  - admission and discharge
  - lab reports
  - Microbiology
  - Pathology
  - Radiology
  - Cardiology
  - EKG data



Data & measures (predictors)

- Smoking prevalence
- Perceived safety
- Mortality rates
- Infant mortality rates
- Maternal smoking
- Overweight / obesity prevalence
- Walkability



- Employment rates
- Tax delinquent properties
- Crime indices
- Education rates
- Voter participation
- Income

From survey or census data and linked by geolocation.

"Social Determinants of Health Model" by Braveman et al (2011) Annu. Rev. Public Health, 32:381-398

Framework for organizing the factors

Social Determinants of Health

Economic Stability	Neighborhood and Physical Environment	Education	Food	Community and Social Context	Health Care System
Employment Income Expenses Debt Medical bills Support	Housing Transportation Safety Parks Playgrounds Walkability	Literacy Language Early childhood education Vocational training Higher education	Hunger Access to healthy options	Social integration Support systems Community engagement Discrimination	Health coverage Provider availability Provider linguistic and cultural competency Quality of care

Health Outcomes

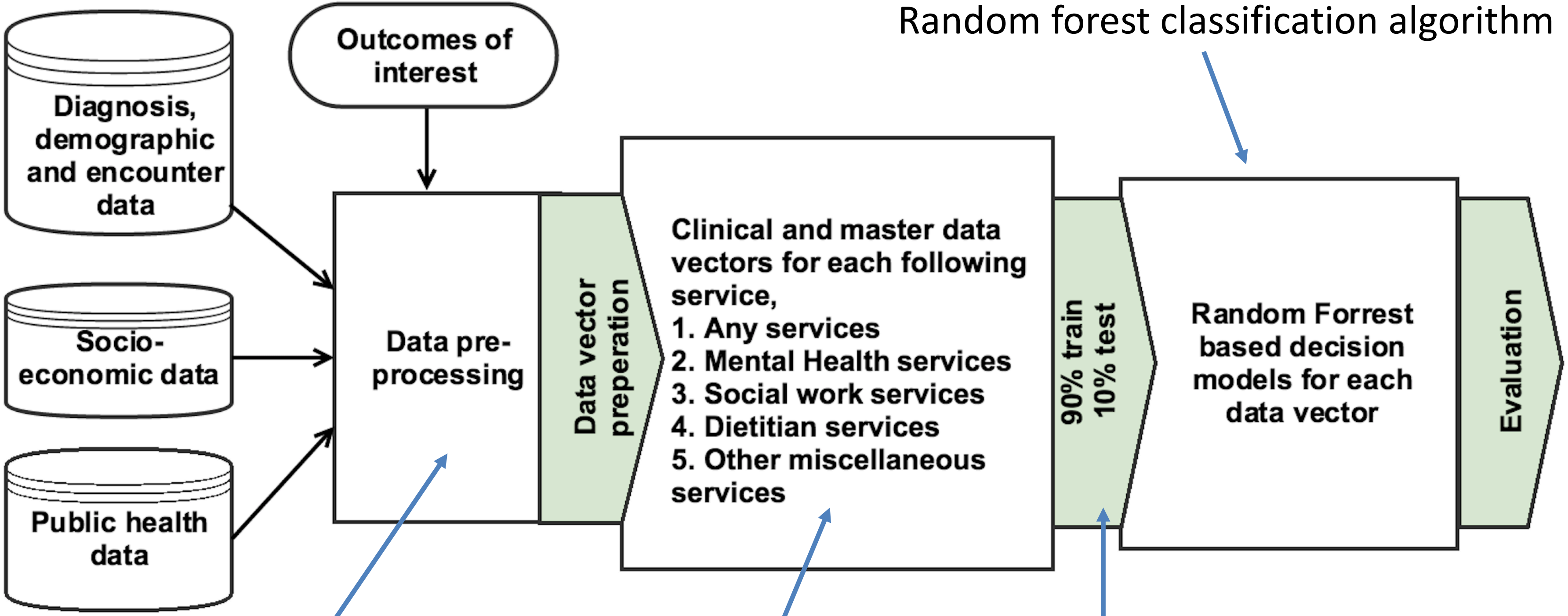
Mortality, Morbidity, Life Expectancy, Health Care Expenditures, Health Status, Functional Limitations

THE HENRY J. KAISER FAMILY FOUNDATION

kff.org/disparities-policy/issue-brief/beyond-health-care-the-role-of-social-determinants-in-promoting-health-and-health-equity/

Analytic approach: performance of prediction models with novel data

Random forest classification algorithm



Model each outcome twice.

1) Clinical data only (41 variables)
2) Clinical plus socioeconomic & public health (48 variables)

Split samples for training & testing

Prevalence of social service referral need

Type of service	%
Any service	53.0
Mental health	18.5
Social work	8.7
Dietitian	32.6
Other services	20.0

Prediction for social services referrals was in the “useful” range.

Area under the ROC curve values for each decision model

	Clinical data
Any referral	0.745
Mental health	0.785
Social work	0.731
Dietitian	0.743
Other referral	0.711

Consistent with performance of models on:

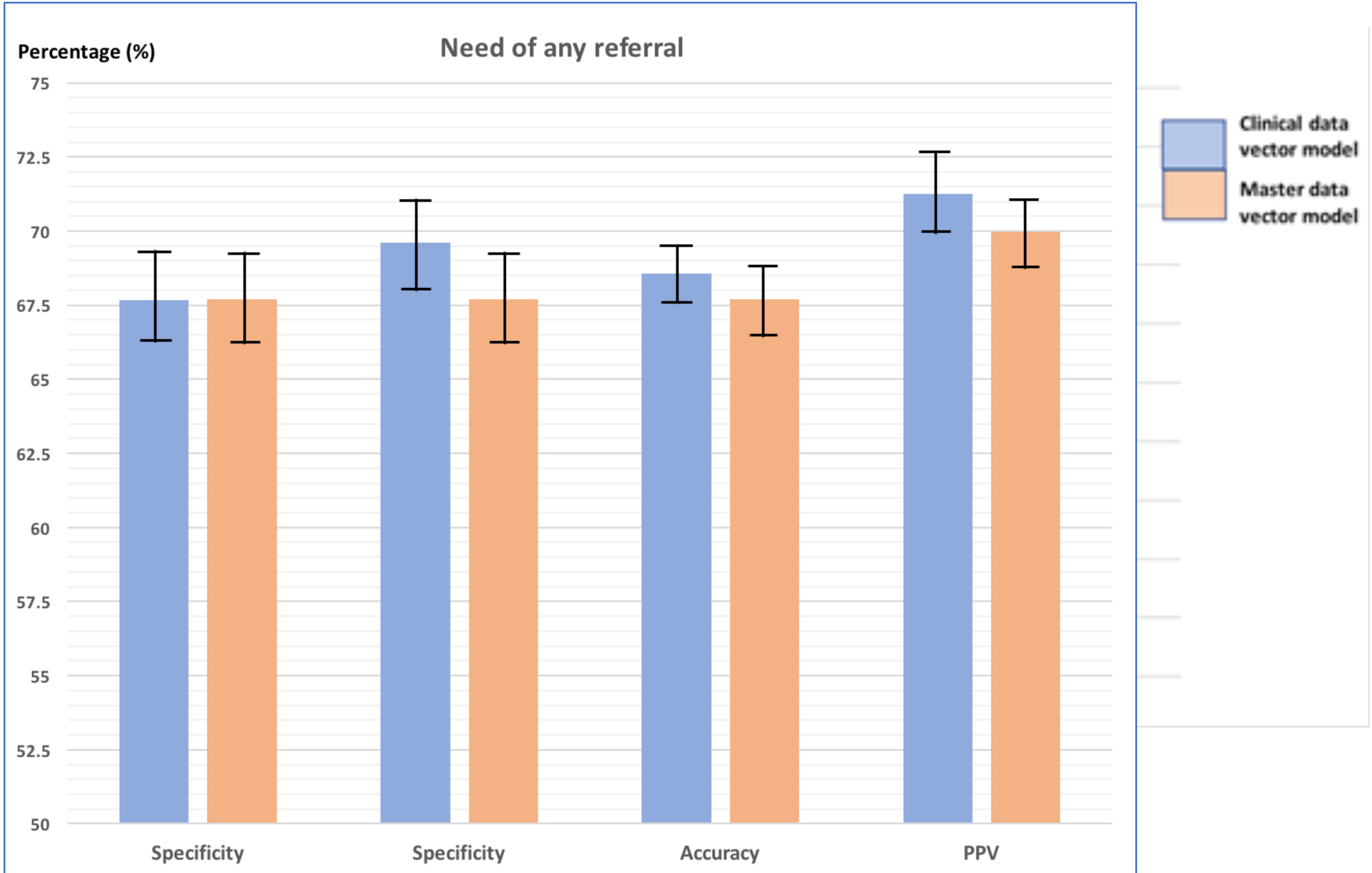
- Mortality
- Readmissions
- Disease development
- Care coordination need

Socioeconomic & public health data did not contribute significantly.

Area under the ROC curve values for each decision model

	Clinical data	Clinical + socioeconomic & public health
Any referral	0.745	0.741
Mental health	0.785	0.778
Social work	0.731	0.714
Dietitian	0.743	0.730
Other referral	0.711	0.708

Socioeconomic & public health data did not contribute significantly.



Limitations

- Socioeconomic measures at aggregate level
  - small geographic area, but still aggregate
  - limited geographic variation because only within a single urban area
  - individual level measures generally unavailable from EHRs
- High need, vulnerable population
  - limited generalizability
  - probably lots of unmet need
- All services were co-located with primary care
  - May not apply to referrals to outside services / other organizations
- No assessment whether or not the referral was appropriate or appointment was kept

Predictive models for referrals to social services are currently live.

Before clinics open

ESKENAZI HEALTH

SharePoint

5:00 AM

The Polis Center

MARION COUNTY PUBLIC HEALTH DEPARTMENT

Prevent. Promote. Protect.

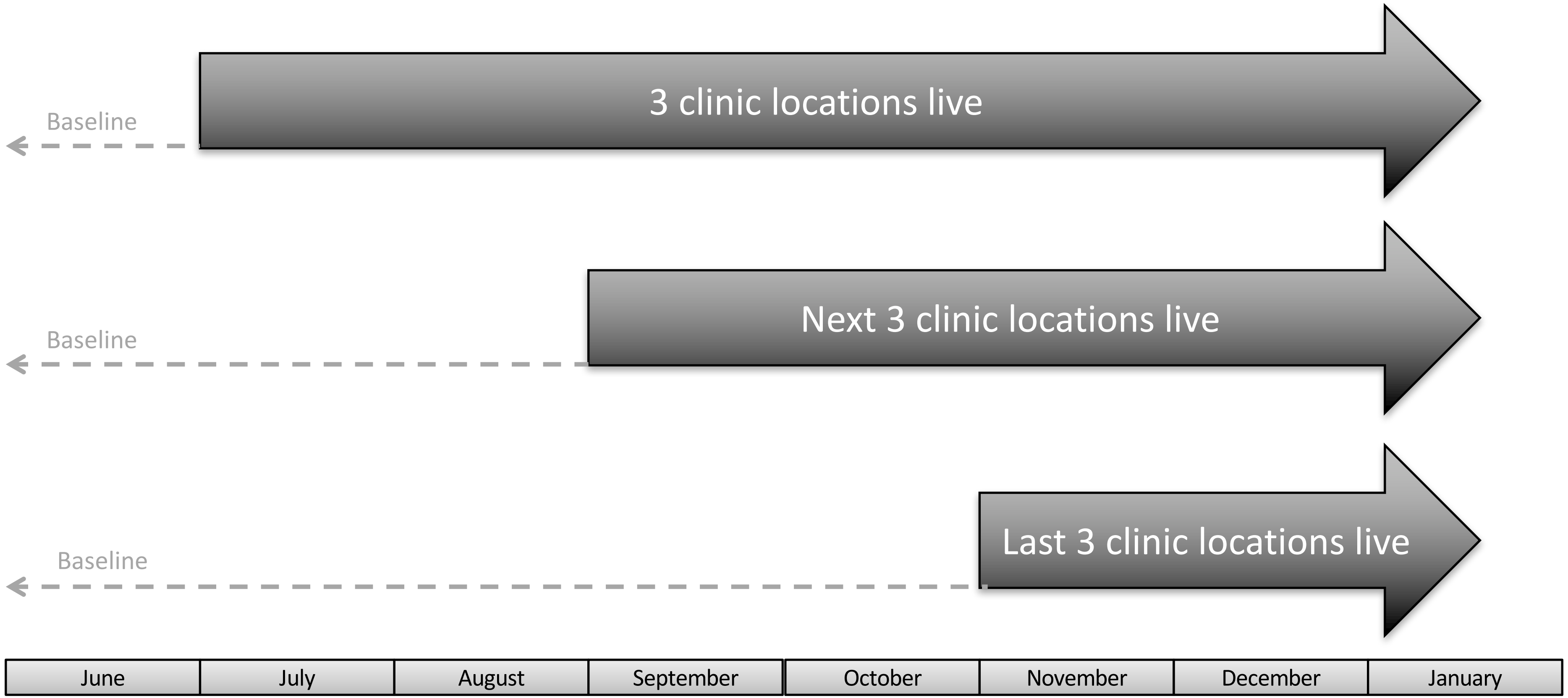
INPC

MRN	Name	provider	DOB	Any referral - need category	Any referral - probability	Mental health - need category	Mental health - probability	Dietitian - need category	Dietitian - probability	Social Work - need category	Social Work - probability
1	A	B	C	Low risk	0.70	Rising risk	0.50	Low risk	0.40	Rising risk	0.30
2	A	B	C	Low risk	0.60	Rising risk	0.40	Low risk	0.20	Low risk	0.10
3	A	B	C	Rising risk	0.90	Low risk	0.20	Low risk	0.50	Rising risk	0.40
4	A	B	C	Low risk	0.60	Low risk	0.20	Low risk	0.40	Rising risk	0.20
5	A	B	C	Low risk	0.50	Low risk	0.27	Low risk	0.30	Low risk	0.00
6	A	B	C	Rising risk	0.90	Low risk	0.20	Low risk	0.40	High risk	0.70
7	A	B	C	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	A	B	C	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	A	B	C	Low risk	0.60	Low risk	0.30	Low risk	0.10	Low risk	0.00
10	A	B	C	Low risk	0.40	Rising risk	0.67	Low risk	0.50	Rising risk	0.20

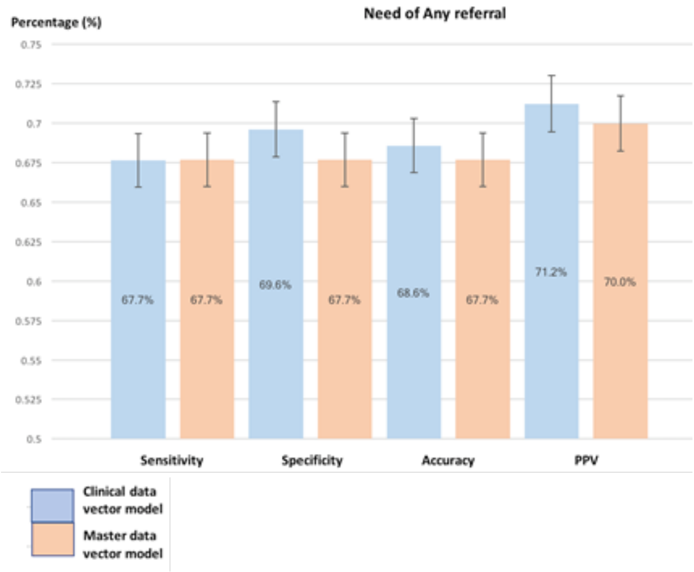
The predicted probably the patient is in need of mental health services.

Identifiers

Impact of predicted models on referral rates currently being evaluated.



Using predictive modeling to identify patients who need social services.



- Indications that predictive modeling for social services may be useful
  - models leveraged EHR and HIE data
  - performance could be improved, but consistent with literature
- Socioeconomic & public health measures (at the aggregate level) did not improve model performance

Regenstrief Institute

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