2023 Spring Provider Symposium

Artificial Intelligence in Healthcare: Improving Health Outcomes and Advancing Equity with New Tools

Friday, May 19, 2023

Virtual Conference

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Clinical Stratification with Machine Learning

Sule Baptiste

May 19th, 2023

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Maternal-fetal Health: "What are we trying to solve for?"

"Healthier Mothers"

Supporting women from **pre to post pregnancy** journey **to reach full term via Clinical and Social Support**

Goals for Healthfirst Cares (Launch)

Identify more pregnancies in first trimester and connect to providers (PCP, OBGYN)

Reduce preterm delivery and low birth weight babies

Increase prenatal visits

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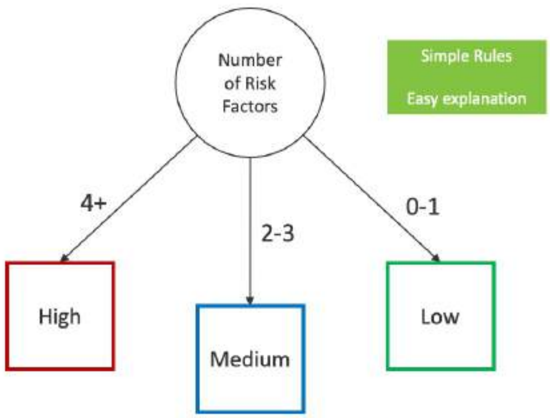
Baseline Approach: Rules Based Classification

Clinical decision trees and healthcare related business rules

- Risk Factors:
  - **Previous preterm labor, shortened cervix, high blood pressure, multiple gestations (or prior),** preeclampsia, fetal development abnormalities, placenta previa, diabetes (T1 or T2), gestational diabetes, blood clotting problems, and substance use
- Maternal Risk Stratification
  - **High:** 4+ Risk Factors [OR] Previous Preterm Labor, Shortened Cervix, High Blood Pressure, Multiple Gestations
  - **Medium:** 2 - 3 Risk Factors
  - **Low:** 1 or less Risk Factors
- Individual **Decision Tree**



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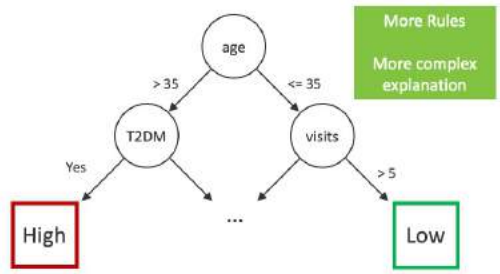
Machine Learning (ML) Approach: Gradient Boosted Trees

- Natural extension of rules-based model
- Aggregates many individual **decision trees**
- Model learns optimal thresholds using algorithm to determine member classification
  - Will member experience pregnancy complication?
- Can accommodate 100's of rules

Individual Decision Tree Example



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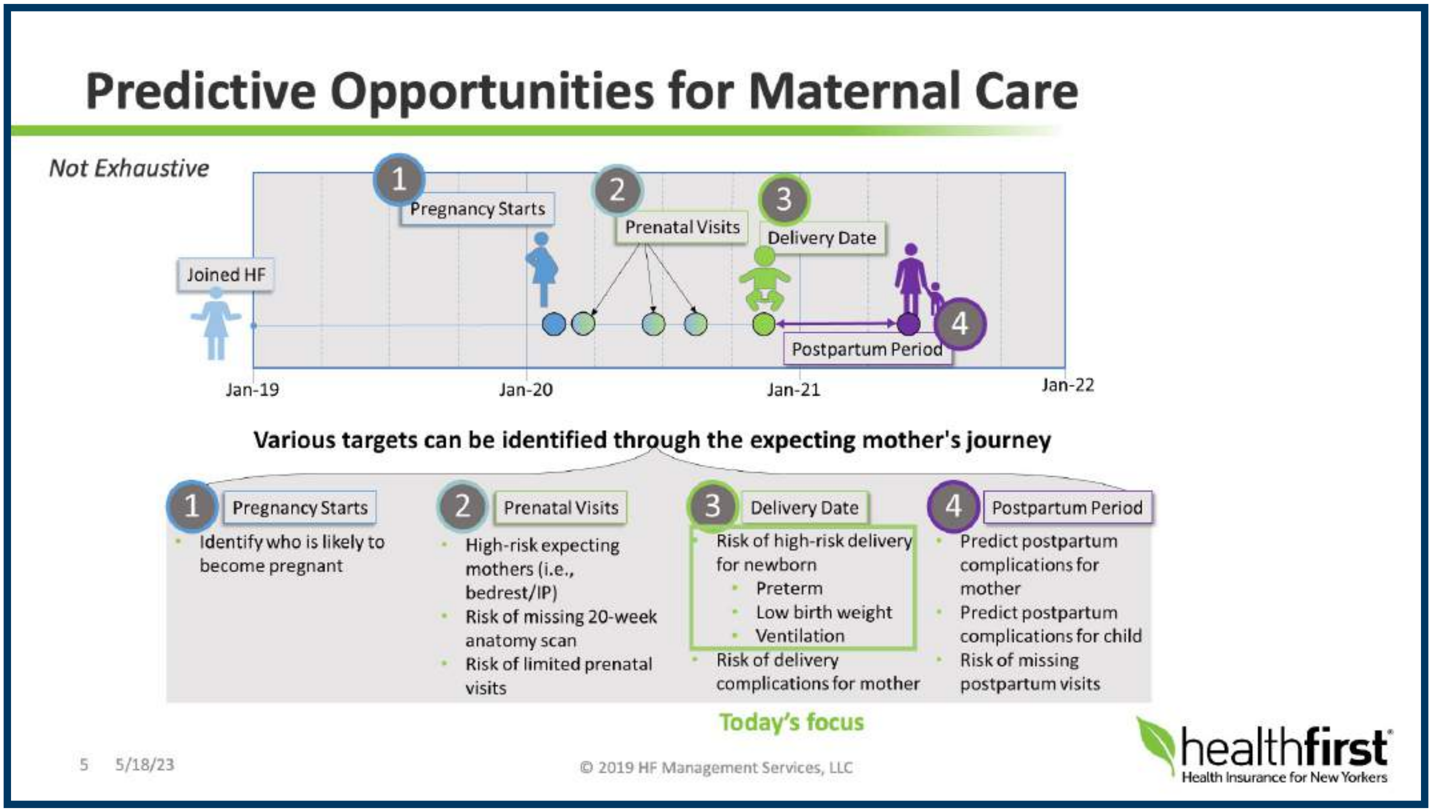
Predictive Opportunities for Maternal Care
Not Exhaustive
1
Pregnancy Starts
2
Prenatal Visits
3
Delivery Date
Joined HF
4
Postpartum Period
Jan-19
Jan-20
Jan-21
Jan-22
Various targets can be identified through the expecting mother's journey
1 Pregnancy Starts
Identify who is likely to become pregnant
2 Prenatal Visits
High-risk expecting mothers (i.e., bedrest/IP)
Risk of missing 20-week anatomy scan
Risk of limited prenatal visits
3 Delivery Date
Risk of high-risk delivery for newborn
Preterm
Low birth weight
Ventilation
Risk of delivery complications for mother
4 Postpartum Period
Predict postpartum complications for mother
Predict postpartum complications for child
Risk of missing postpartum visits
Today's focus
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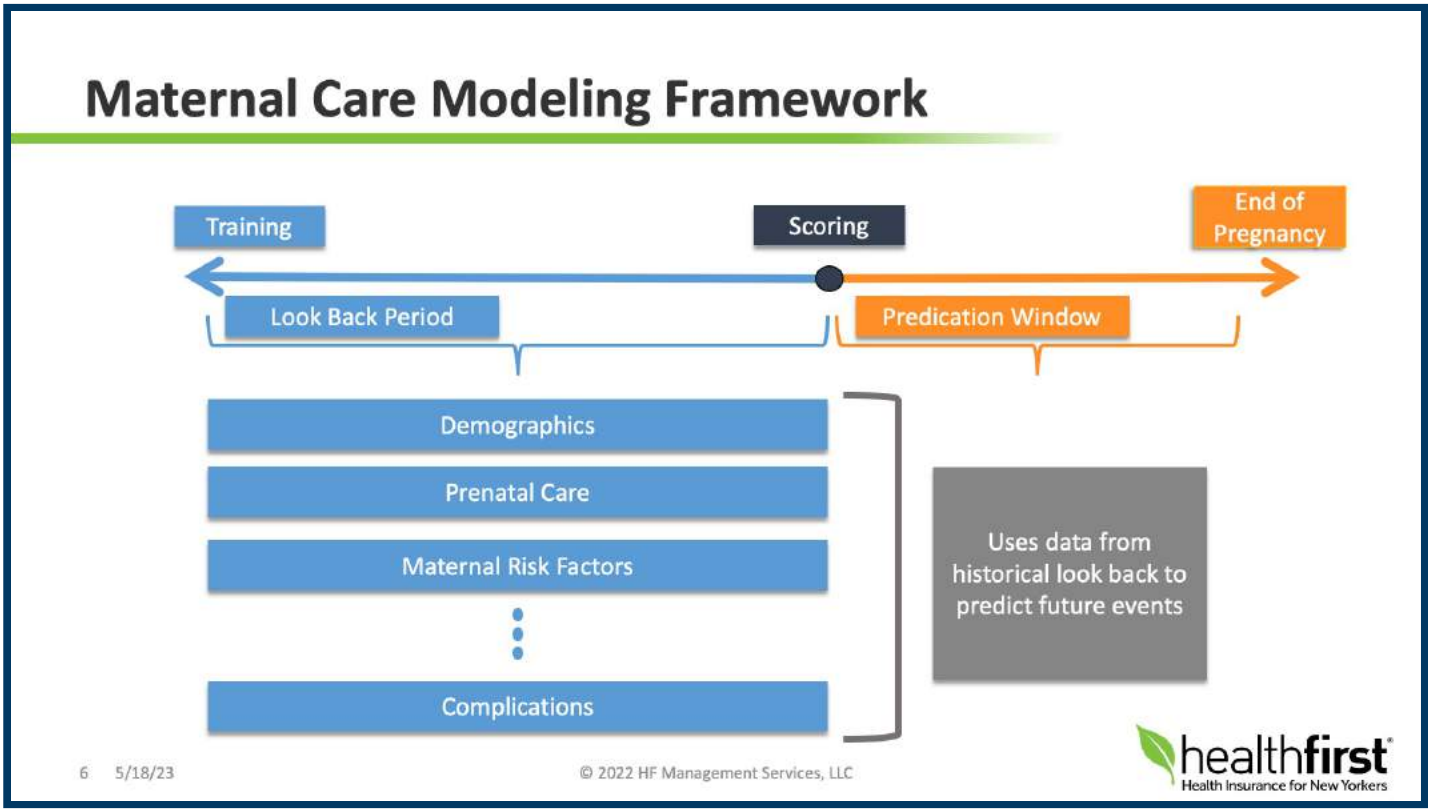
Maternal Care Modeling Framework
Training
Scoring
End of Pregnancy
Look Back Period
Predication Window
Demographics
Prenatal Care
Maternal Risk Factors
Complications
Uses data from historical look back to predict future events
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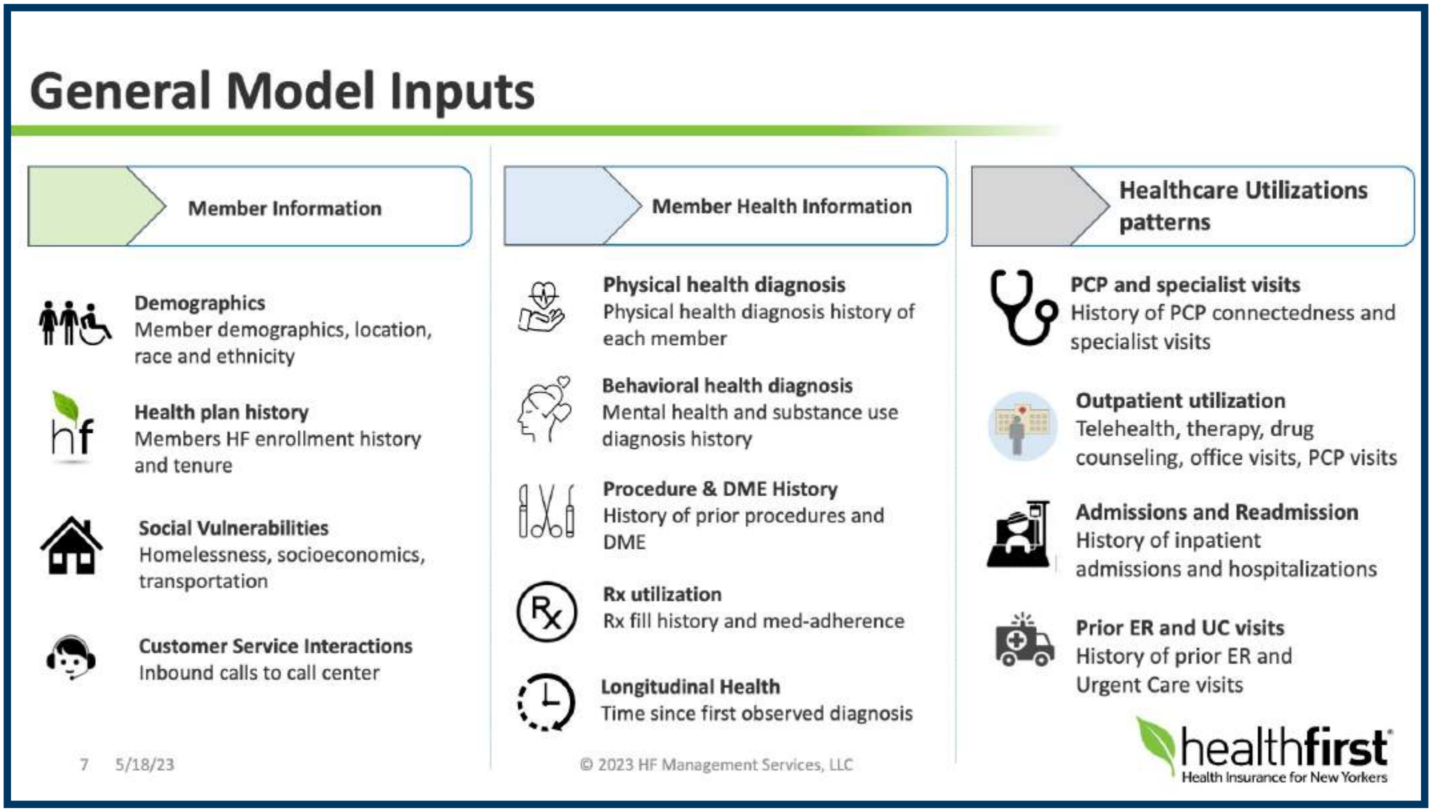
General Model Inputs
Member Information
Demographics
Member demographics, location, race and ethnicity
Health plan history
Members HF enrollment history and tenure
Social Vulnerabilities
Homelessness, socioeconomics, transportation
Customer Service Interactions
Inbound calls to call center
Member Health Information
Physical health diagnosis
Physical health diagnosis history of each member
Behavioral health diagnosis
Mental health and substance use diagnosis history
Procedure & DME History
History of prior procedures and DME
Rx utilization
Rx fill history and med-adherence
Longitudinal Health
Time since first observed diagnosis
Healthcare Utilizations patterns
PCP and specialist visits
History of PCP connectedness and specialist visits
Outpatient utilization
Telehealth, therapy, drug counseling, office visits, PCP visits
Admissions and Readmission
History of inpatient admissions and hospitalizations
Prior ER and UC visits
History of prior ER and Urgent Care visits
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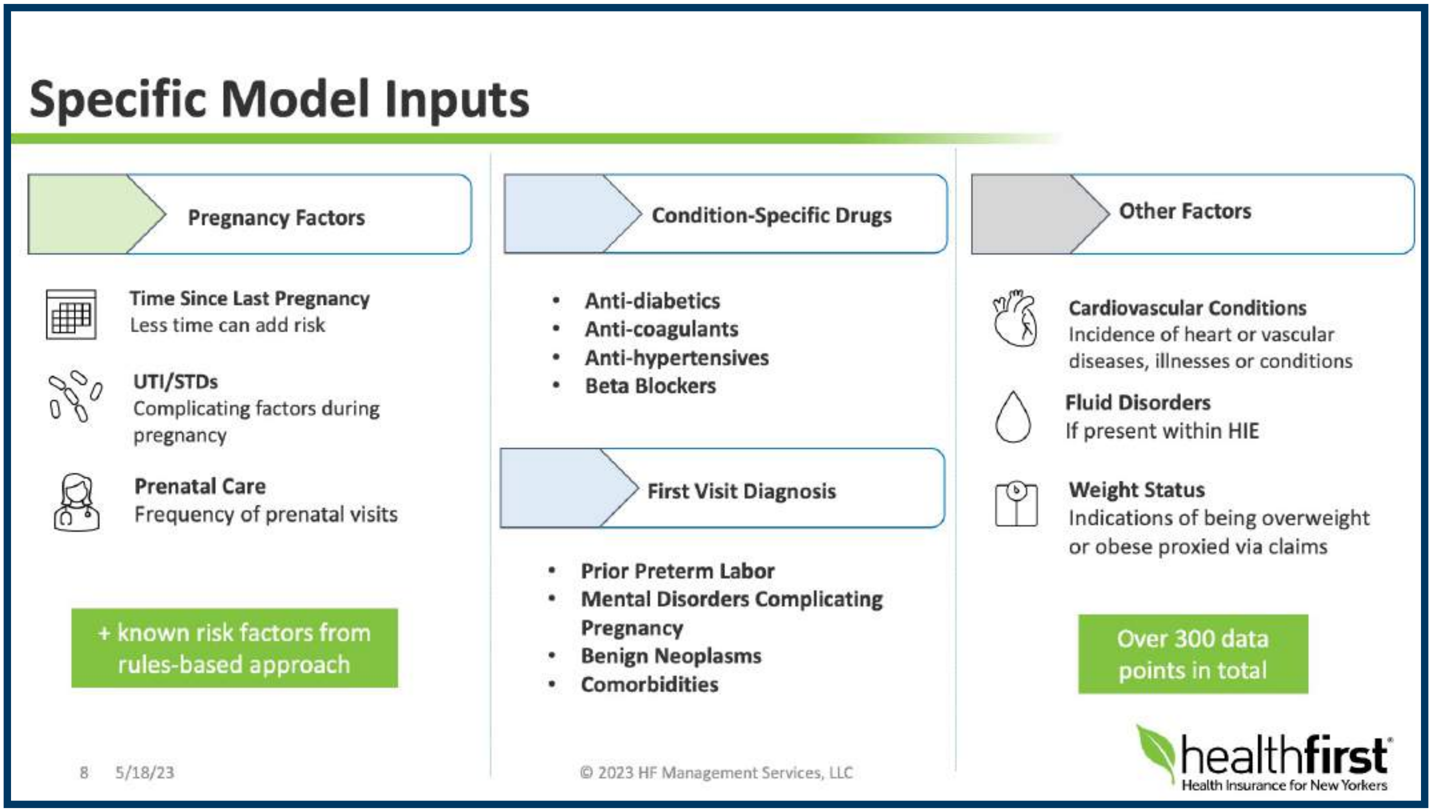
Specific Model Inputs
Pregnancy Factors
Time Since Last Pregnancy
Less time can add risk
UTI/STDs
Complicating factors during pregnancy
Prenatal Care
Frequency of prenatal visits
+ known risk factors from rules-based approach
Condition-Specific Drugs
Anti-diabetics
Anti-coagulants
Anti-hypertensives
Beta Blockers
First Visit Diagnosis
Prior Preterm Labor
Mental Disorders Complicating Pregnancy
Benign Neoplasms
Comorbidities
Other Factors
Cardiovascular Conditions
Incidence of heart or vascular diseases, illnesses or conditions
Fluid Disorders
If present within HIE
Weight Status
Indications of being overweight or obese proxied via claims
Over 300 data points in total
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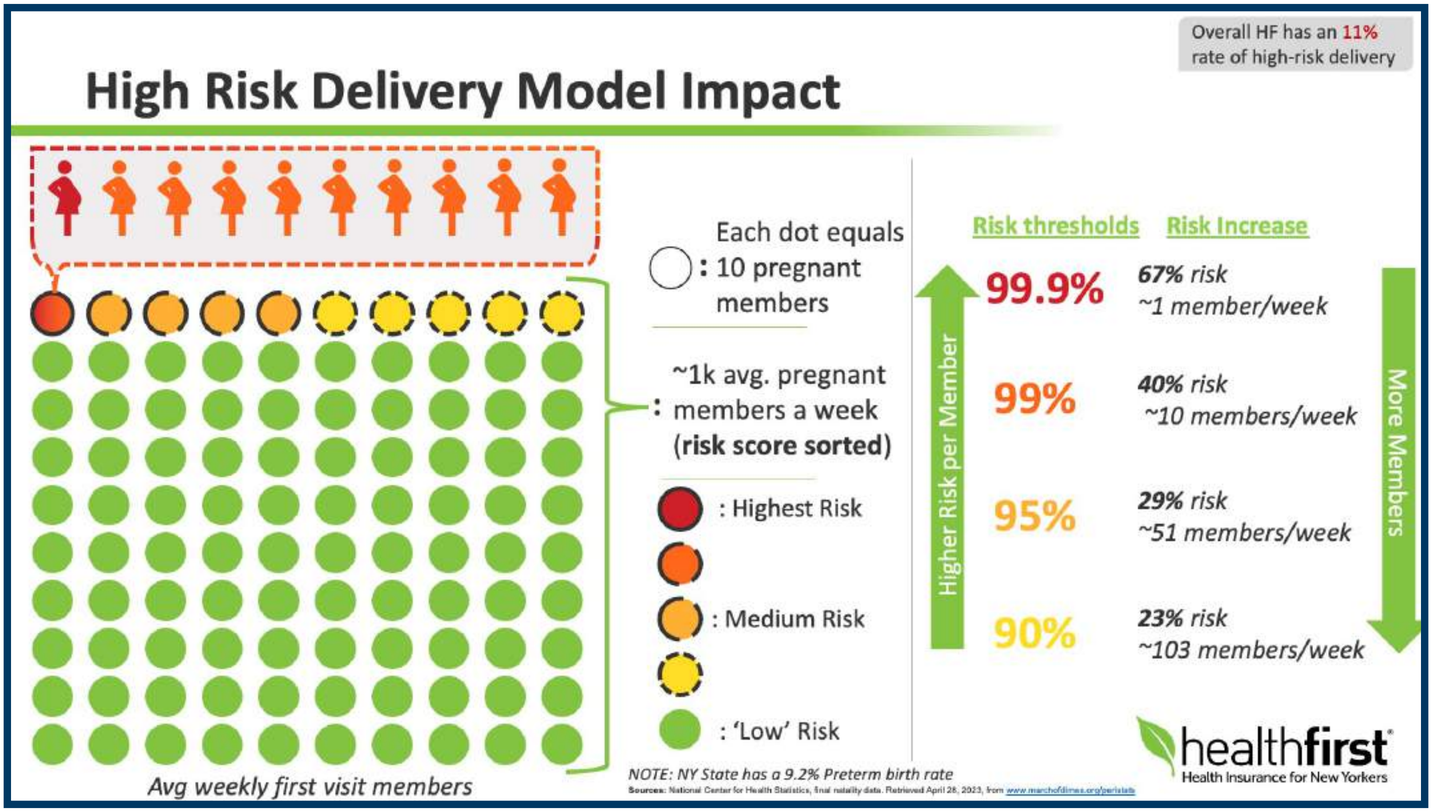
Overall HF has an 11% rate of high-risk delivery
High Risk Delivery Model Impact
Each dot equals
: 10 pregnant members
~1k avg. pregnant
: members a week
(risk score sorted)
: Highest Risk
: Medium Risk
: 'Low' Risk
Avg weekly first visit members
Higher Risk per Member
Risk thresholds
Risk Increase
99.9%
67% risk
~1 member/week
99%
40% risk
~10 members/week
95%
29% risk
~51 members/week
90%
23% risk
~103 members/week
More Members
NOTE: NY State has a 9.2% Preterm birth rate
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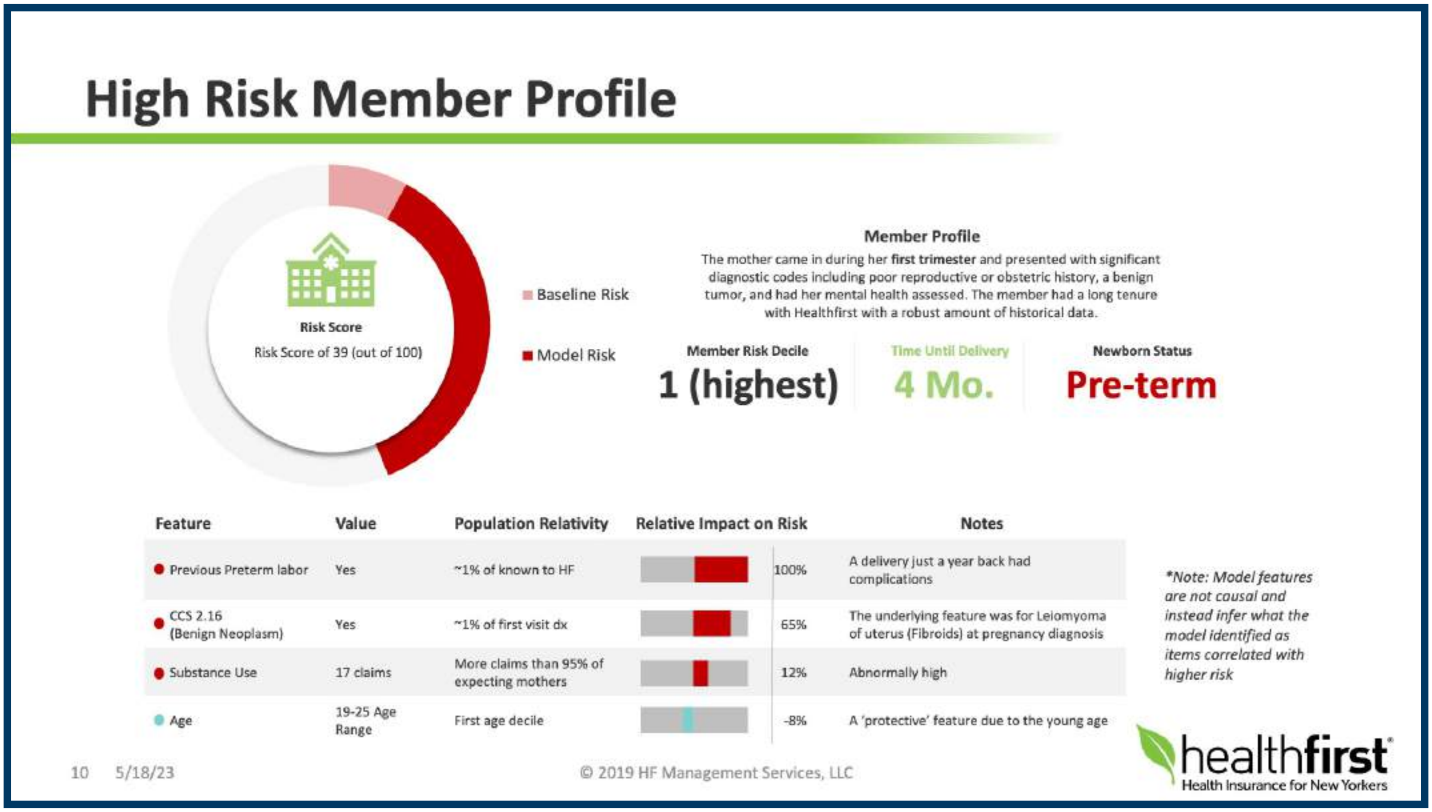
High Risk Member Profile
Risk Score
Risk Score of 39 (out of 100)
Baseline Risk
Model Risk
Member Profile
The mother came in during her first trimester and presented with significant diagnostic codes including poor reproductive or obstetric history, a benign tumor, and had her mental health assessed. The member had a long tenure with Healthfirst with a robust amount of historical data.
Member Risk Decile
1 (highest)
Time Until Delivery
4 Mo.
Newborn Status
Pre-term
Feature
Value
Population Relativity
Relative Impact on Risk
Notes
Previous Preterm labor
Yes
~1% of known to HF
100%
A delivery just a year back had complications
CCS 2.16 (Benign Neoplasm)
Yes
~1% of first visit dx
65%
The underlying feature was for Leiomyoma of uterus (Fibroids) at pregnancy diagnosis
Substance Use
17 claims
More claims than 95% of expecting mothers
12%
Abnormally high
Age
19-25 Age Range
First age decile
-8%
A 'protective' feature due to the young age
*Note: Model features are not causal and instead infer what the model identified as items correlated with higher risk
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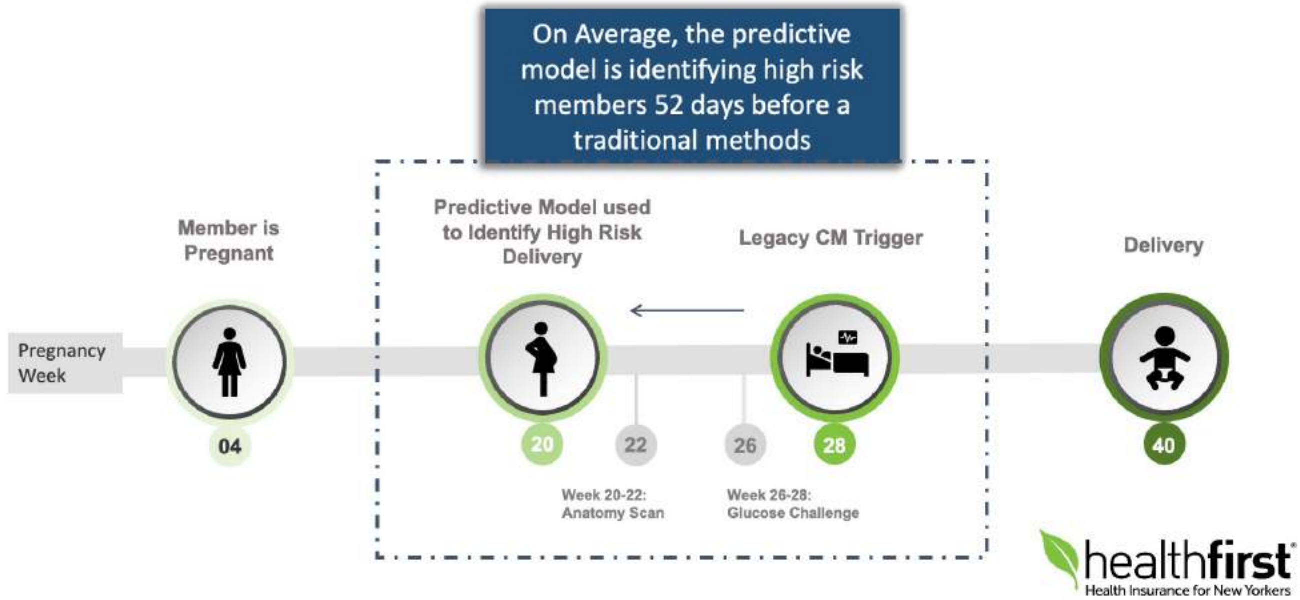
HF Cares Maternity Predictive Model



Member Example

Member Details	• HF Cares identified member during 1st Trimester
Medical Dx	• **Gestational diabetic insulin dependent** • **Morbid obesity** • **Chronic hypertension**
Members issues/concerns	• **Two prior pregnancies** delivered **preterm d/t gestational diabetes & required NICU admissions** • Elevated blood glucose • Husband and two children overweight as advised by medical providers
How did the HF Cares team intervene?	• Educated member on current medications, medical issues, & strategies to have a better overall experience with this pregnancy • Shared the ***statistic 50% of the woman with gestational diabetes will have type 2 Diabetes within 5 years***. After member informed, she stated "I am ***determined not to be part of that group!"*** • Member stated she was very familiar with what to expect and a far as her diet she had ***"heard it all before."*** Even so, continued to collaborated w/ member and advised since ***she does the shopping and cooking, she really could turn things around for the whole family.*** When a diet recall was completed, she did not recognize the volume of carbs • Member was ***offered a consult w/ a HF nutritionist*** and she accepted. She was given information on how her food choices affected her diabetes and HTN • The member really took the info to heart and with ***regular calls and support changed her diet***. • Members ***providers impressed & she was receiving positive reinforcement at each visit*** • She was proud to share her ***improved glucose levels & blood pressure*** during each call • ***This was the first pregnancy she wasn't being told her baby was measuring too big and being shamed because of her poor glucose control***
Outcomes of interventions	• Member ***discontinued insulin prior to delivery*** • Member ***delivered full term w/o NICU*** • Member ***lost 50 lbs***. during the pregnancy due to the healthy choices (with provider approval) • Members husband ***lost 40 lbs***. and ***her children started accepting healthier food choices***

Staff feedback:

*"Receiving the Healthfirst OB members **earlier in the pregnancy** is making a huge impact!"*

*"Having the majority of the pregnancy to work with members allows us to **affect more outcomes for our members and their families**"*

Clinical Stratification

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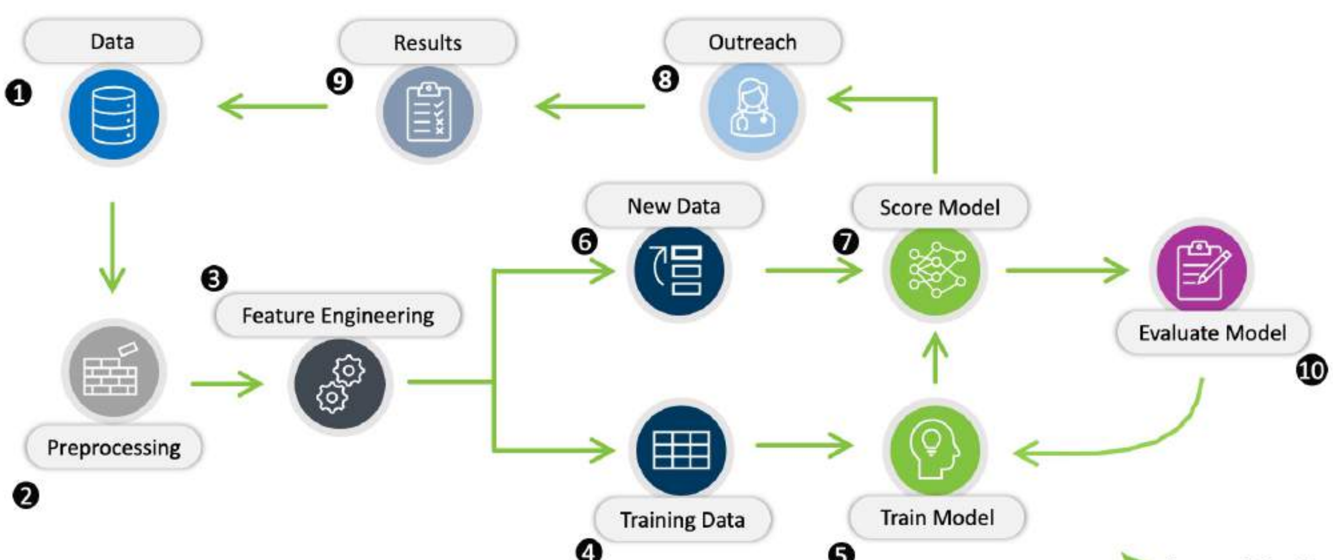
Machine Learning System Overview



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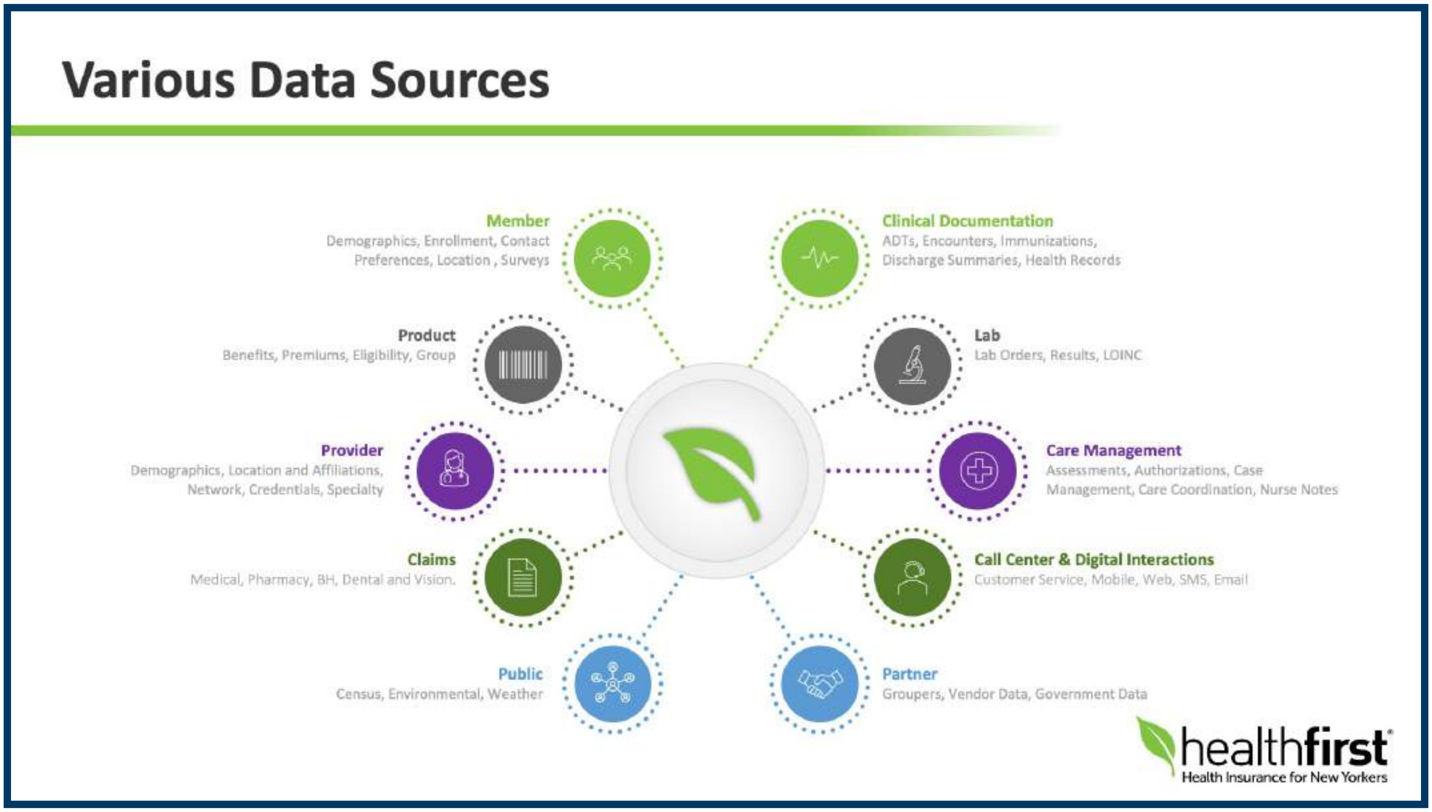
Various Data Sources
Member
Demographics, Enrollment, Contact Preferences, Location , Surveys
Clinical Documentation
ADTs, Encounters, Immunizations, Discharge Summaries, Health Records
Product
Benefits, Premiums, Eligibility, Group
Lab
Lab Orders, Results, LOINC
Provider
Demographics, Location and Affiliations, Network, Credentials, Specialty
Care Management
Assessments, Authorizations, Case Management, Care Coordination, Nurse Notes
Claims
Medical, Pharmacy, BH, Dental and Vision.
Call Center & Digital Interactions
Customer Service, Mobile, Web, SMS, Email
Public
Census, Environmental, Weather
Partner
Groupers, Vendor Data, Government Data
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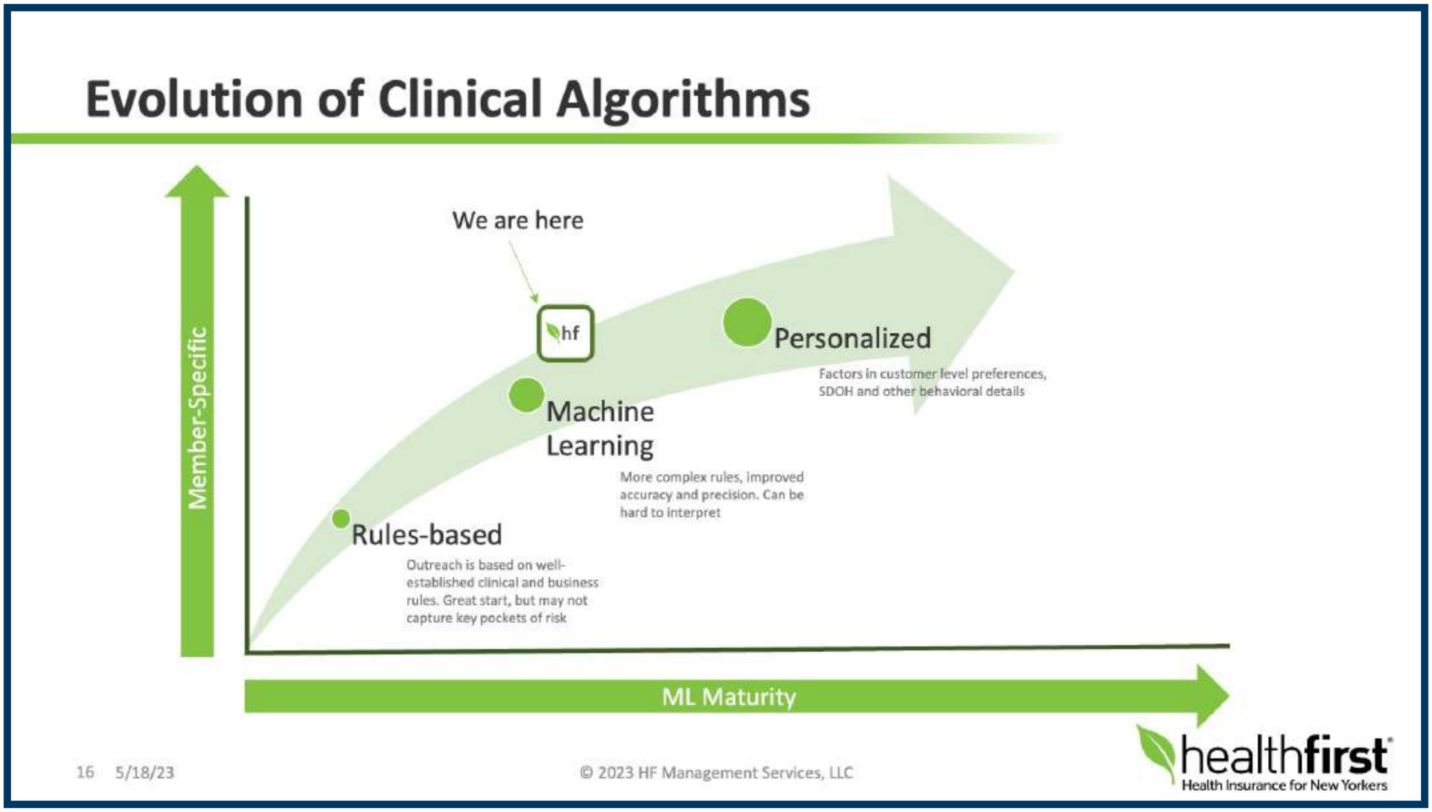
Evolution of Clinical Algorithms
We are here
hf
Personalized
Factors in customer level preferences, SDOH and other behavioral details
Machine Learning
More complex rules, improved accuracy and precision. Can be hard to interpret
Rules-based
Outreach is based on well-established clinical and business rules. Great start, but may not capture key pockets of risk
Member-Specific
ML Maturity
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Possible Predictive Inputs into Clinical Stratification

Clinical stratification framework can vary based on population needs, access to data, and clinical programming

Physical Health
Presence and severity of physical conditions based on claims, authorizations, and assessment data

Behavioral Health
Presence and severity of mental health or substance use related illness on claims, authorizations, and assessment data

Access to Care
Connectedness to PCP and specialists (utilization and access measurements)

Medication Management
Medication adherence and compliance, medication therapy management (MTM), polypharmacy

Social Determinants of Health
Housing instability, lack of transportation, food insecurity, etc

Clinical Cost Trajectory
Changes in medical, pharmacy or total cost of care that may indicate health needs

100s of Predictive Models

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Data-Informed Outreaches

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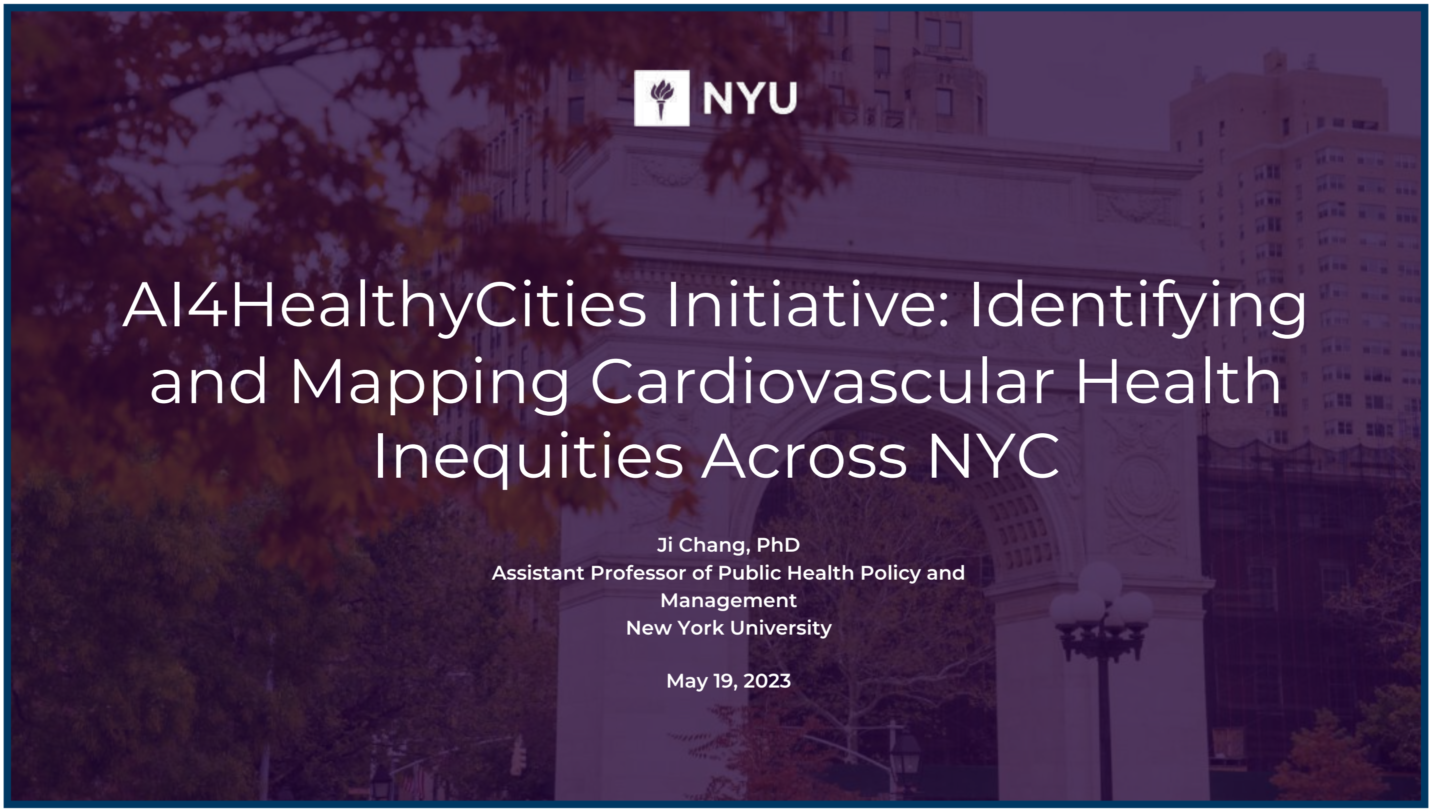
Limitations & Challenges

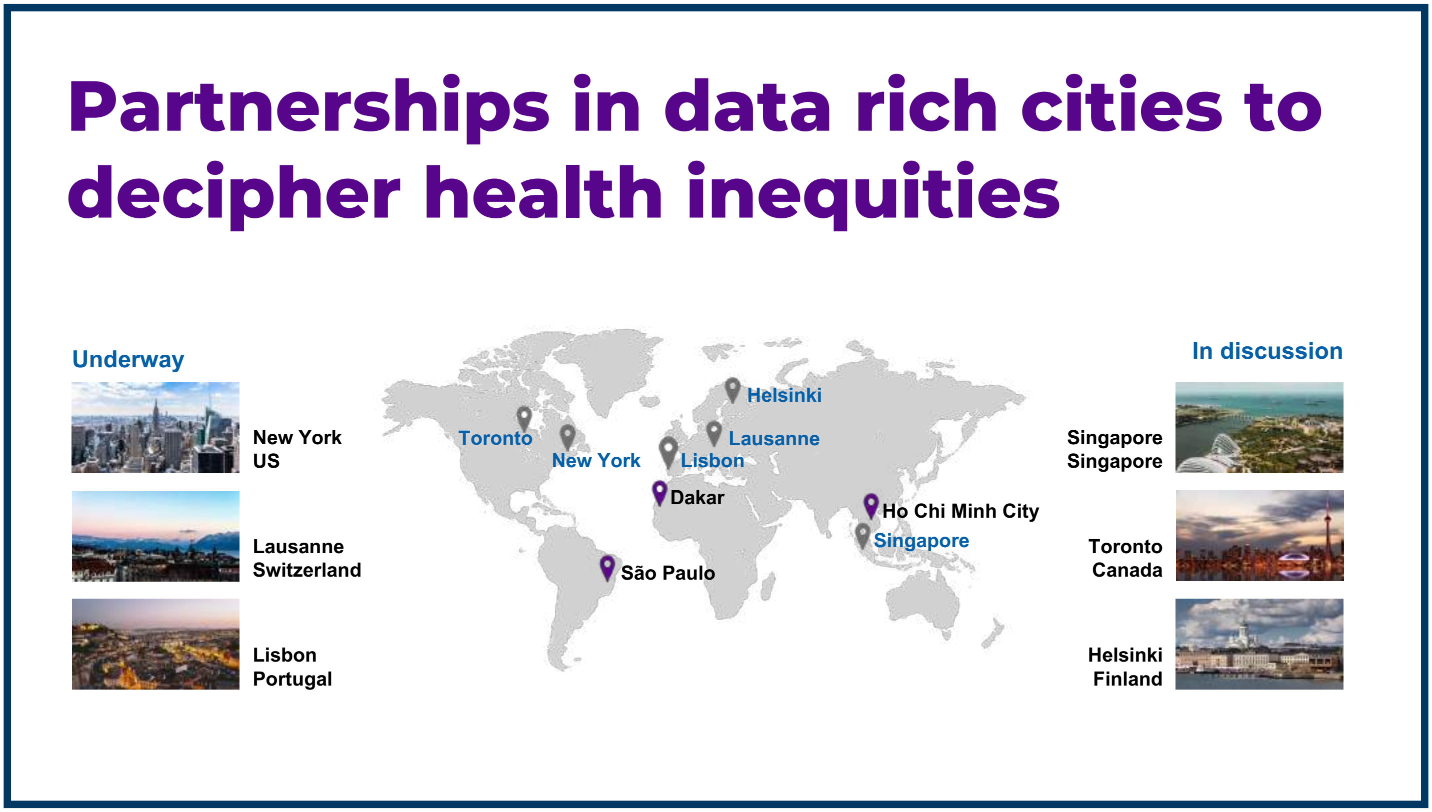
Data

Bias & Fairness

Explainability & Interpretability

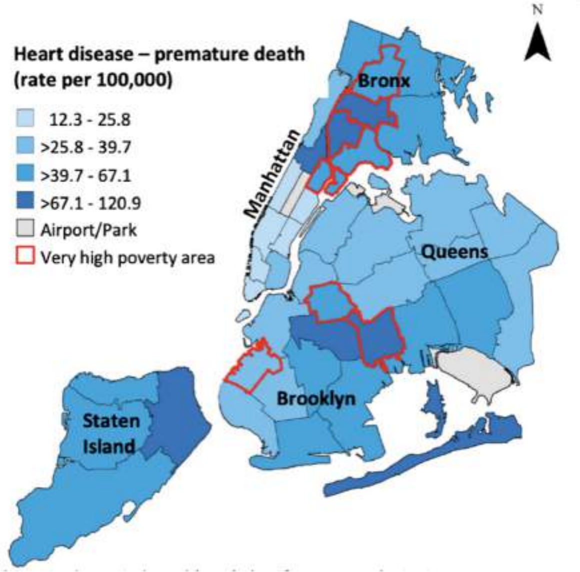
Actionability & Clinical Program Design


NYU
AI4HealthyCities Initiative: Identifying and Mapping Cardiovascular Health Inequities Across NYC
Ji Chang, PhD
Assistant Professor of Public Health Policy and Management
New York University
May 19, 2023


Partnerships in data rich cities to decipher health inequities
Underway
New York US
Lausanne Switzerland
Lisbon Portugal
Helsinki
Toronto
New York
Lausanne
Lisbon
Dakar
Ho Chi Minh City
Singapore
São Paulo
In discussion
Singapore Singapore
Toronto Canada
Helsinki Finland

Health (In)Equity in NYC

- Brownsville, Brooklyn: median income was $32,940 in 2019 vs. Upper East Side, Manhattan: median income was $141,090 in 2019
- A baby born to a family that lives in the Upper East Side will live **11 years longer** than a baby born to a family in Brownsville



Source: NYC Health. Premature Heart Disease and Stroke Deaths among Adults in New York City. Epi Data Brief. 2017.

Key Question

How can we bring together data from health care, public health, and other health-influencing sectors to obtain new insights into factors that influence cardiovascular health and reduce health inequities in New York City

Phase 1: Landscape Analysis

Scoping Review	Data Compendium	Stakeholder Interviews
What has been published in the literature about the use of data to address cardiovascular disease and SDOH?	What data are available about the social determinants of health in NYC and at what geographic level?	How do key public health stakeholders use SDOH data and what data-driven solutions can address health equity?

Scoping Review Results

4,110 abstracts screened, 51 studies included

Most common SDOH domains were healthcare access and quality and neighborhood/built environment

Both electronic health records (patient-level) and neighborhood data (population-level) were commonly used, but not often integrated

Risk scores were commonly used but almost exclusively relied on electronic health records data

Data Compendium

- 57 data sources related to SDOH found through search of peer reviewed and grey literature and databases of federal, state, city agencies.
- Categorized by level (county, zip, neighborhood, census tract, census block) and by social determinant domain
- Identified frequency of updates and geographic availability

Key Findings

Wealth of data available on all SDOH domains

Participants: 11 key stakeholders from across the NYC public health landscape, including current and former executives and senior leaders from city and state health departments, insurance plans, community-based organizations, and hospitals

Topics: How SDOH data are currently being used; what data driven tools are useful to address health equity; challenges to using and developing such tools

Key Findings

- Stakeholders used SDOH data directly collected from patients (ICD-10 z-codes or organization specific screening tools) as well as locally collected data (i.e. NYC Community Health Survey)

However…

- Reliance on patient self-reporting of SDOH was laborious and time consuming, and sometimes error prone.
- Need for integrated data across data systems
- **Area-level measures to account for social-risk is promising, but should be multi-dimensional, updated frequently, and granular to guide decisions**

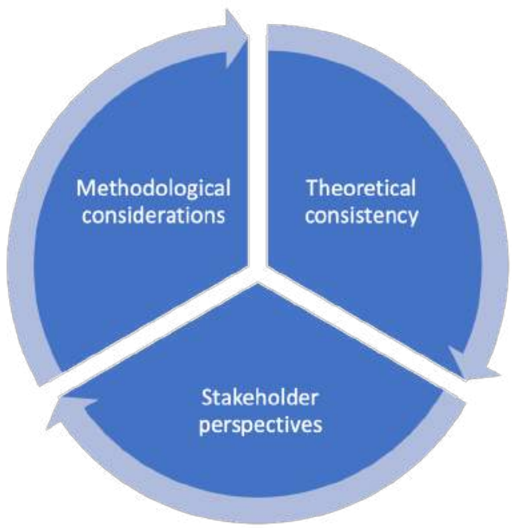
Landscape Analysis Takeaways

- Currently available tools rely on both patient-level or neighborhood-level data, **but are not often integrated.**
- Wealth of data exists on SDOH both within and outside of the health care sector, **but more specific tools needed to meaningfully connect them**.

Phase 2: Mapping and Predicting

Need for tools utilizing neighborhood-level SDOH data at granular level	Develop a multi-dimensional zip-code-level social risk score and tool for CVD health in NYC
Value of combining clinical and non-clinical data for CVD Risk Prediction	Use EHR patient data from NYC H+H to validate and test neighborhood risk-score and predict individual outcomes and needs using AI models

A Balanced Framework for Developing Composite SDOH Risk Scores



Challenges in Creating Area Level Risk Scores

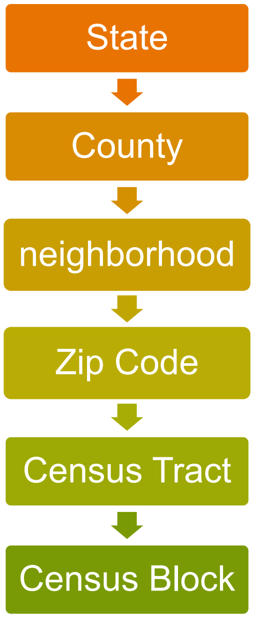
- Data captured at varying geographic levels

  → structured process of linking data
- Variance in data structure, access, availability, completeness

  → data scraping, cleaning and access requests
- Multitude of measures available for similar concepts

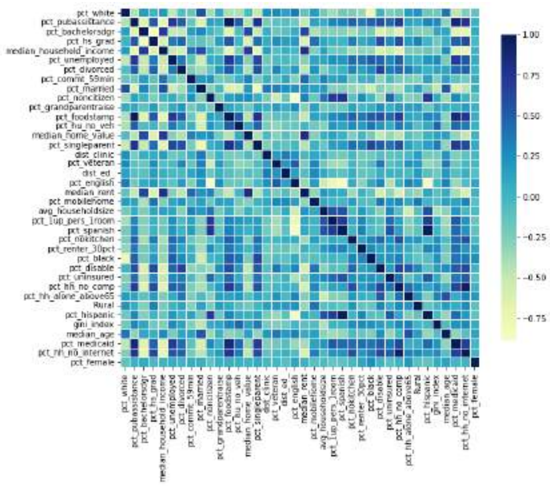
  → dimensionality reduction via statistics and machine learning
- Need for integrating local perspectives and theory

  → stakeholder interviews and literature review



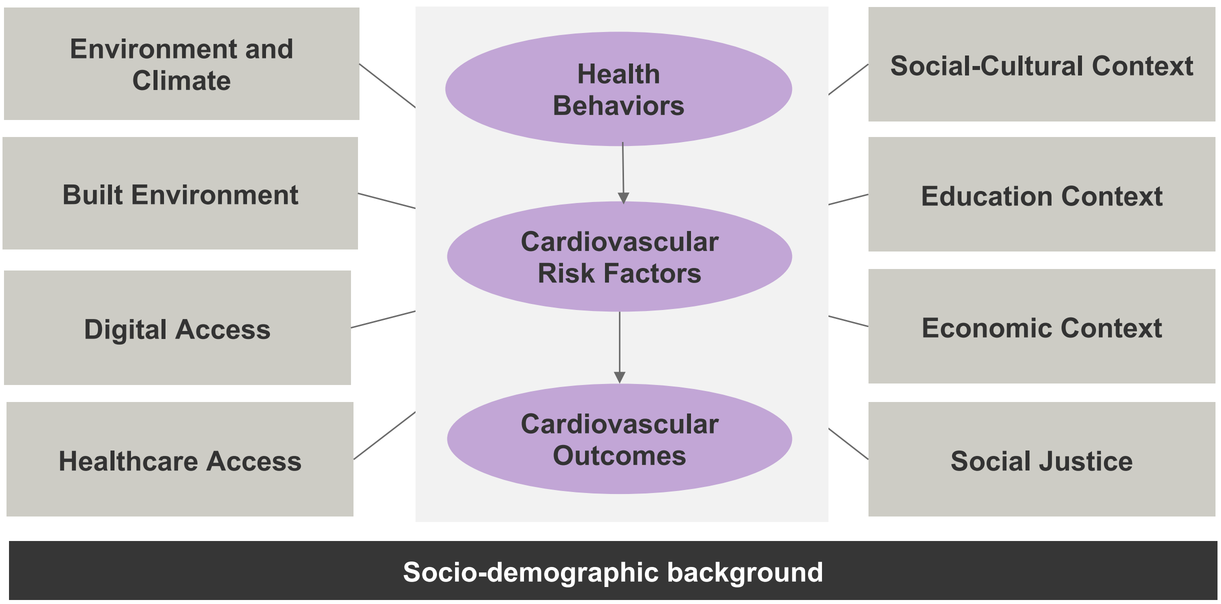
Dimensionality Reduction using National Data

- Generalized Estimating Equations for Longitudinal Analysis
- Cross-Sectional Analysis on change data
- Machine Learning (Random Forest Algorithm) for cross sectional data



NYC Specific Data Sources

Determinants of CVD Health



Localized CVD Risk Index (In Draft)

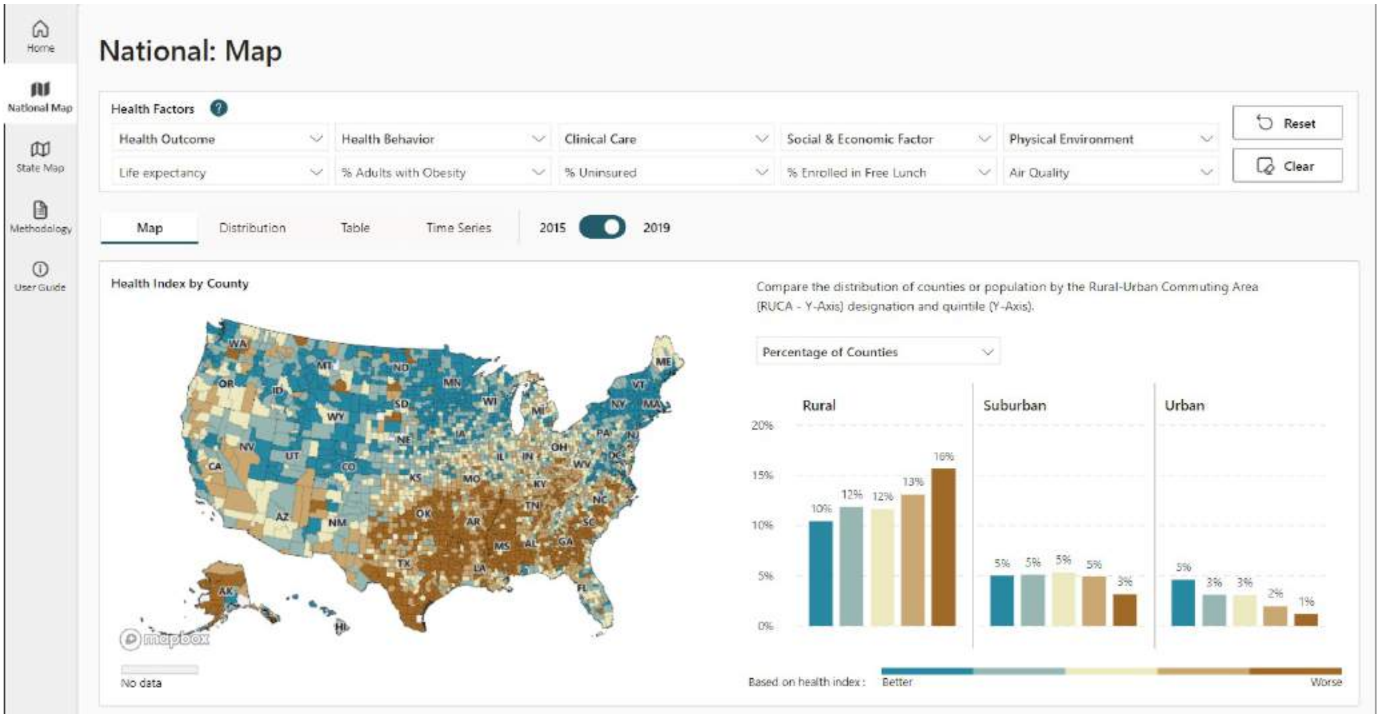
Environment and Climate	Built Environment	Digital Access	Healthcare Access	Socio-cultural context	Education	Economic	Social Justice
Fine particles	Tobacco licenses	% internet	uninsured	Elderly living alone	% bachelor	Household income	redlining
Nitrogen Dioxide	Prop park	% computer	Distance to ED	No English	% high school	unemployed	Gentrification
	% housing w/>1 person					Gini index	Racial segregation
							crime

Demographic population variables

% Hispanic	% Black	% female	% veterans	Median age

NYC data

National data



Phase 2: Mapping and Predicting

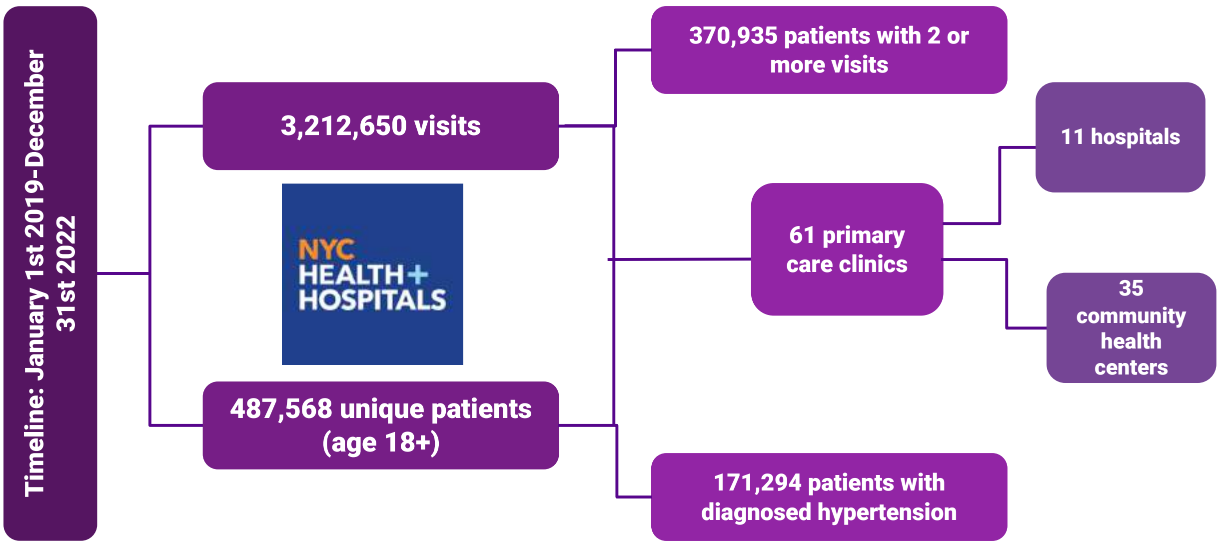
Need for tools utilizing neighborhood-level SDOH data at granular level

Develop a multi-dimensional zip-code-level social risk score and tool for CVD health in NYC

Value of combining clinical and non-clinical data for CVD Risk Prediction

Use EHR patient data from NYC H+H to validate and test neighborhood risk-score and predict individual outcomes and needs using AI models

NYC H+H Data Linkage



Thank you

APPLYING CLINICAL AI TO REDUCE READMISSIONS BY OVER 20%

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Hallie Bleau, ACNP-BC, MBA
VP, Care Management

May 23, 2023

Northwell Health

WELCOME

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Hallie Bleau

VP of Care Management
Health Solutions
Northwell Health

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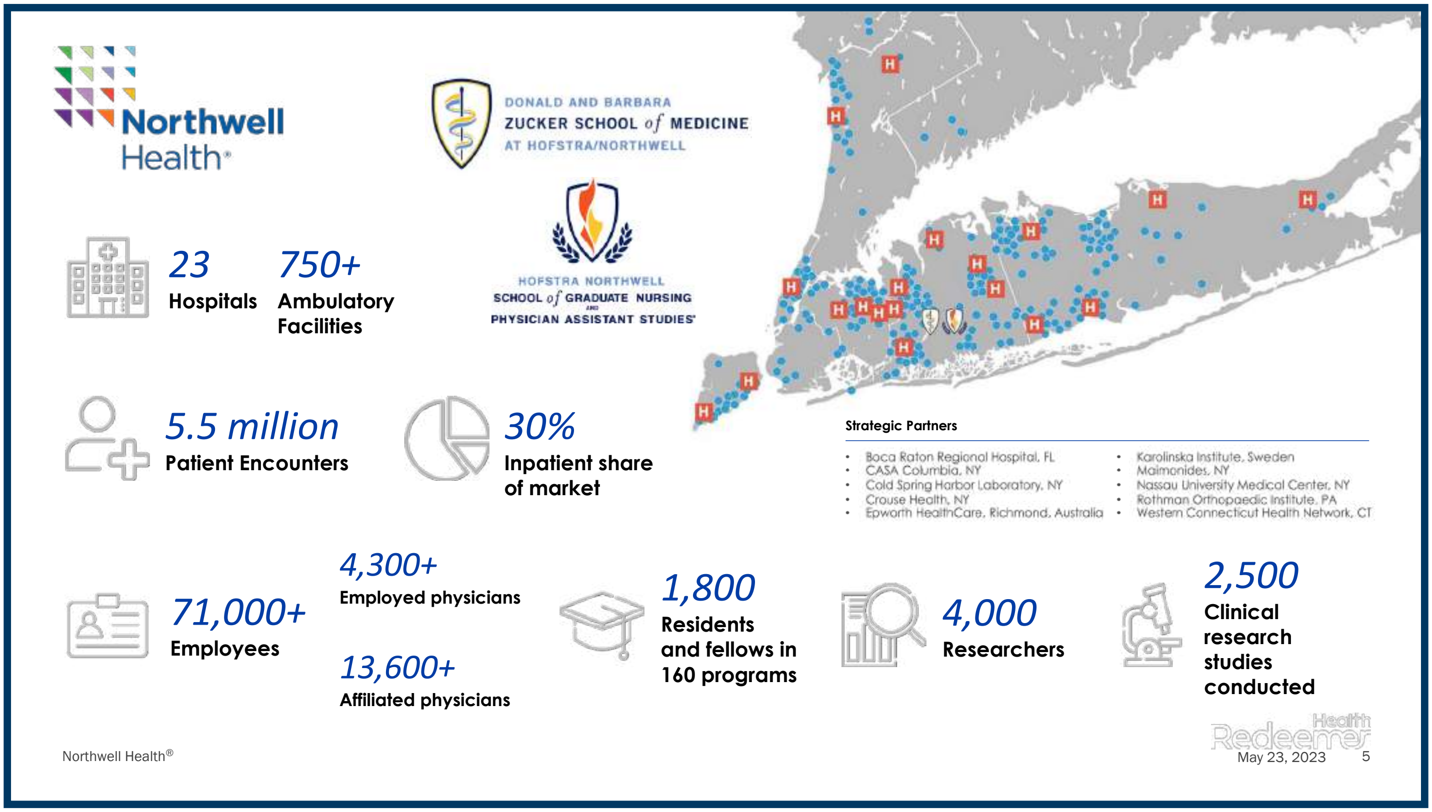
CONFLICT OF INTEREST

Zenobia Brown, MD, MPH

Hallie Bleau, ACNP-BC, MBA

Have no real or apparent conflicts of interest to report.

- NORTHWELL HEALTH OVERVIEW
- A READMISSION PROBLEM TO SOLVE
- ENHANCING CARE MANAGEMENT WITH AI
- DESCRIPTION OF AI TOOL
- METHODOLOGY
  RESULTS



Northwell Health
DONALD AND BARBARA ZUCKER SCHOOL of MEDICINE AT HOFSTRA/NORTHWELL
HOFSTRA NORTHWELL SCHOOL of GRADUATE NURSING AND PHYSICIAN ASSISTANT STUDIES
23 Hospitals
750+ Ambulatory Facilities
5.5 million Patient Encounters
30% Inpatient share of market
Strategic Partners
Boca Raton Regional Hospital, FL
CASA Columbia, NY
Cold Spring Harbor Laboratory, NY
Crouse Health, NY
Epworth HealthCare, Richmond, Australia
Karolinska Institute, Sweden
Maimonides, NY
Nassau University Medical Center, NY
Rothman Orthopaedic Institute, PA
Western Connecticut Health Network, CT
71,000+ Employees
4,300+ Employed physicians
13,600+ Affiliated physicians
1,800 Residents and fellows in 160 programs
4,000 Researchers
2,500 Clinical research studies conducted
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HEALTH SOLUTIONS PROGRAMS
Care Management Organization and Value Based Arm of Northwell Health
24
Transitional Care Management
Clinical Call Center
Complex Care & Behavioral Health
Gaps in Care & Prevention
Health Home
House Calls
Accountable Care Analytics
Research
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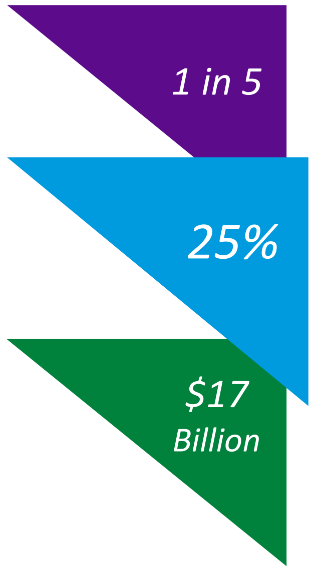
ISSUES IN TODAY'S CARE DELIVERY



1 in 5 patients are readmitted within 30 days of discharge in the United States

25% of all readmissions that occur are preventable

Preventable readmissions have cost Medicare $17 billion annually

Northwell Health®

Agency for Healthcare Research and Quality. Statistical Brief #172, April 2014 Available from: http://www.hcup-us.ahrq.gov/reports/statbriefs/sb172-Conditions-Readmissions-Payer.pdf (Accessed December 9, 2014)

A READMISSION PROBLEM: SOLUTIONS ACROSS MULTIPLE INTERVENTIONS

In 2016, CMS released the Overall Hospital Quality Star Ratings, rating each qualifying acute care hospital with a Star rating from 1 to 5 stars. Readmissions account for 22% of the total Star Rating.

In 2017, of Northwell Health's 11 Hospitals, only 5 met or exceeded the national average of 3 stars with an average Readmission Group Score of -1.39.

In 2022, 11 of Northwell Health's 12 hospitals are meeting or exceeding national average of 3 stars and has moved closer to the national average with an average Readmission Group Score of -0.60.

Hospital	2017 Readmission Group Score (Q3 2012 – Q2 2015)	2017 Quality Star Rating (Q3 2012 – Q2 2015)	2022 Readmission Group Score (Q3 2017– Q4 2019)	2022 Quality Star Rating (Q3 2017 – Q4 2019)
National Average	-0.03	★★★	-0.02	★★★
Site A	-0.93	★★	-0.91 ↑	★★
Site B	-2.49	★	-1.02 ↑	★★★
Site C	-1.18	★★★	- 0.94 ↑	★★★
Site D	-0.67	★★	-0.75 ↓	★★★
Site E	-2.63	★	-1.27 ↑	★★★
Site F	NA	★★★	-0.26	★★★★
Site G	-1.32	★★	-0.29 ↑	★★★★
Site H	-1.19	★★★	-0.75 ↑	★★★★
Site I	-1.72	★★★	-0.12 ↑	★★★★
Site J	-1.19	★★	-0.95 ↑	★★★★
Site K	-1.05	★★	0.82 ↑	★★★★
Site L	-0.94	★★★	-0.48 ↑	★★★★★
All Northwell Average	-1.39	2.3	-0.60 ↑	3.6

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READMISSION REDUCTION STRATEGY ACROSS CARE SETTINGS
The Transitional Care Management Program is integrated in all Northwell Health acute care hospitals and uses a team-based model to support patients' recovery after a hospitalization. The program's goals are to maximize days at home, reduce readmissions and decrease the total cost of care by connecting with patients through follow up phone calls and home visits.
Enrollment in hospital or post discharge
Access to 24/7 Call Center
Enroll in chat bot
Engagement
High Risk patients receive a home visit
Post Acute analytical platform used for SNF LOS management
Community Visits
Real-Time Notification for ED Presentations
Hospital team takes action to meet patient in the ED
ED Action Team
24hr D/C
Every Patient called within 24hrs of discharge 7 days a week
Discharge Instructions Reviewed
Medication Reconciliation Completed
Verify provider f/u appointments
Homecare Coordination
Community Connections
Community Based Care Mgmt
Behavioral Health Care Mgmt
Health Home
Healthy Living
Tobacco Cessation
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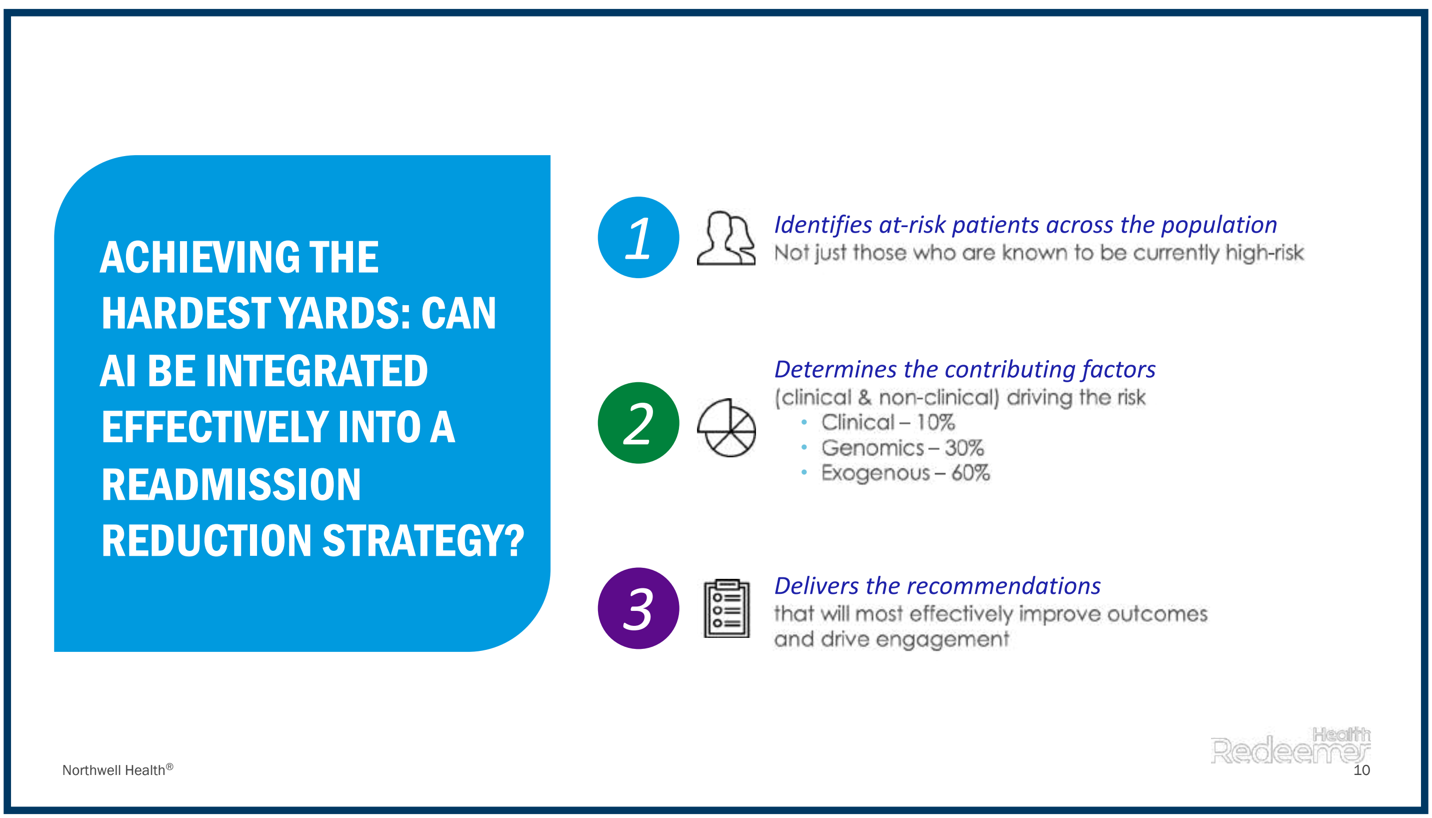
ACHIEVING THE HARDEST YARDS: CAN AI BE INTEGRATED EFFECTIVELY INTO A READMISSION REDUCTION STRATEGY?
1
Identifies at-risk patients across the population
Not just those who are known to be currently high-risk
2
Determines the contributing factors
(clinical & non-clinical) driving the risk
Clinical – 10%
Genomics – 30%
Exogenous – 60%
3
Delivers the recommendations
that will most effectively improve outcomes and drive engagement
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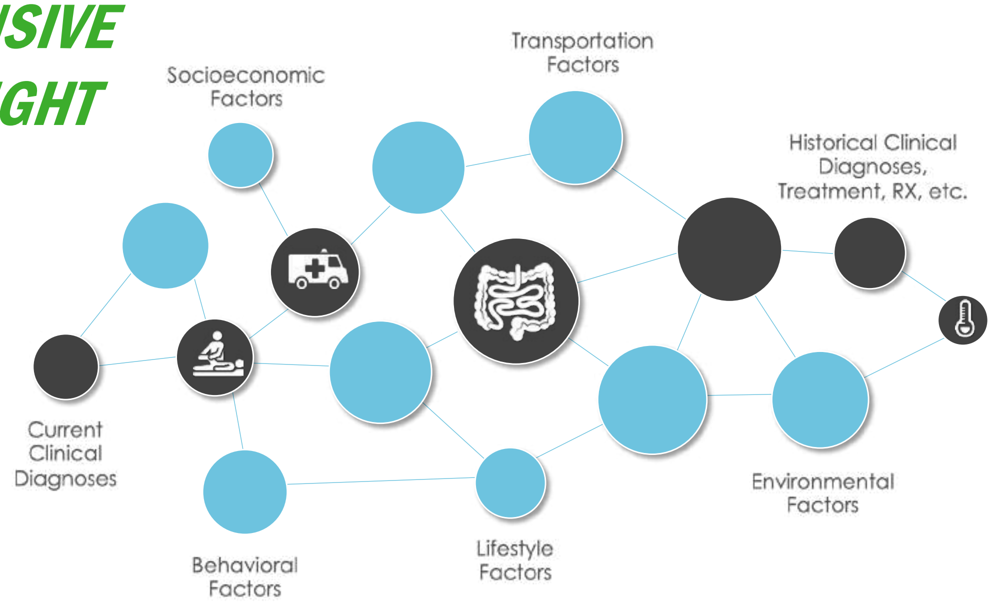
10

COMPREHENSIVE PATIENT INSIGHT

RISK FACTORS

4,500 Clinical & socioeconomic risk factors taken into consideration for every single patient regardless of risk category

Ability to convert multifactorial data into **meaningful clinical action** through evidence-based recommended interventions



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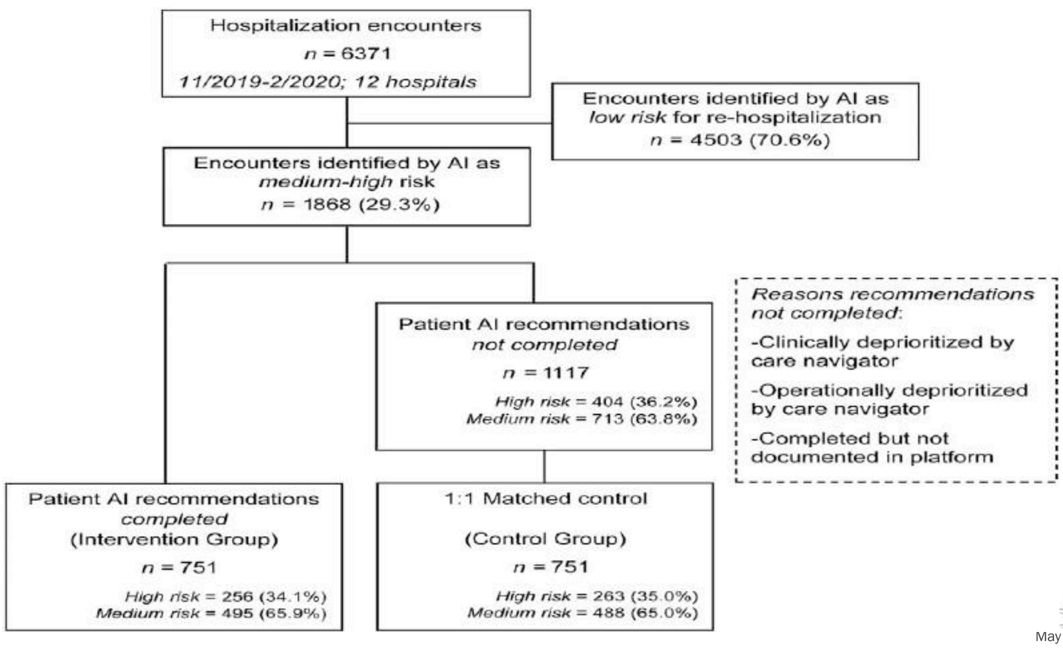
PATIENT POPULATION INCLUDED FOR ANALYSIS

THE STUDY INVESTIGATED THE ABILITY OF MACHINE LEARNING MODELS TO PREDICT RISK FOR AN AVOIDABLE READMISSION AS WELL AS THE EFFICACY OF CLINICAL APPLICATION OF INTERVENTIONS AGAINST THOSE PREDICTIONS



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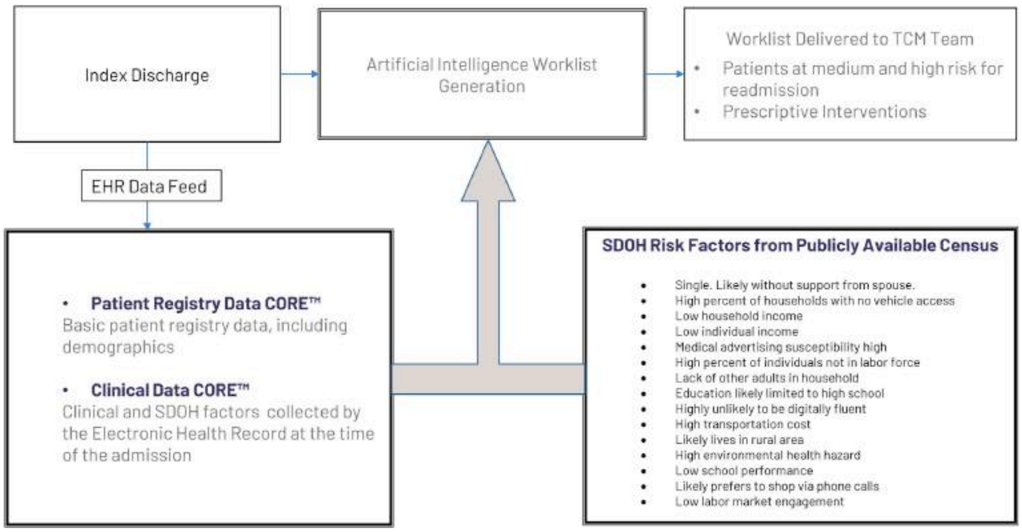
TRANSITIONAL CARE/AI WORKFLOW



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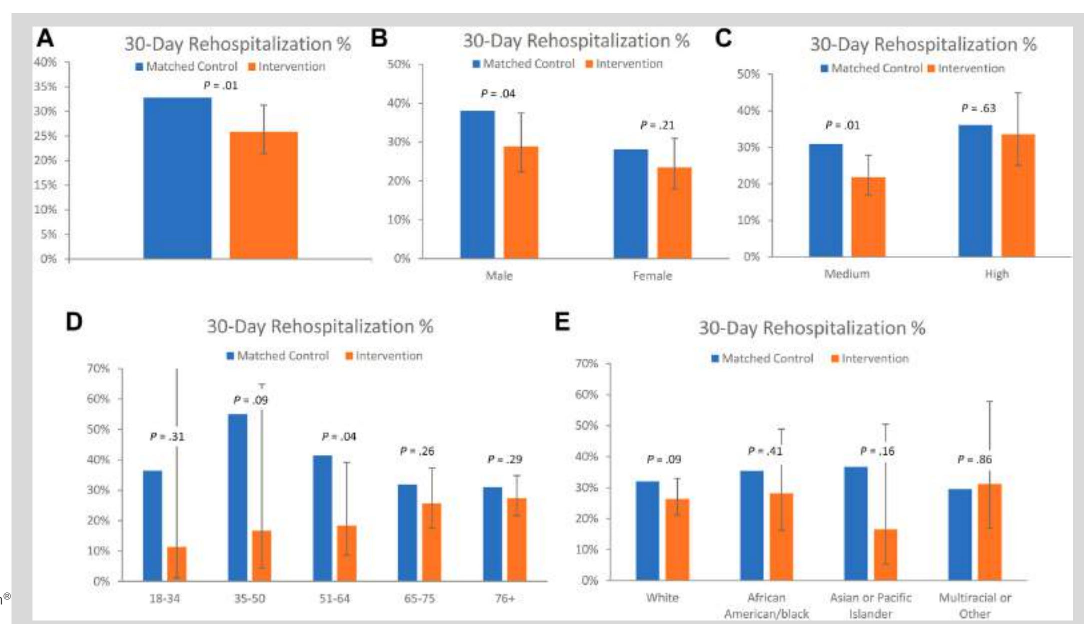
ADJUSTED DIFFERENCES IN 30-DAY REHOSPITALIZATION BETWEEN MATCHED CONTROL AND INTERVENTION GROUPS

BY (A) OVERALL, (B) SEX, (C) REHOSPITALIZATION RISK, (D) AGE, AND (E) RACE.



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RESULTS: IT WORKED

THE RESULTS WERE FOUND TO BE STATISTICALLY SIGNIFICANT WITH FISCHER'S 2X2 EXACT TEST WITH A P-VALUE OF <0.05.

Identification Of High Risk Patients

The AI model is identified correctly patients who are at the highest risk for readmission.

AI identified 29.8% of the population as high risk

Enhanced Readmission Reduction: High and medium Risk

Those patients who were identified as high and medium risk and were intervened on by the care transition team had a lower readmission rate of 25.8% as compared to those patients who were not intervened on with a readmission rate of 32.8%.

The readmission rate was lower by 21% in the patients who had the targeted interventions identified by the AI model implemented.

FUTURE QUESTIONS:

Are there efficiencies to be had with tighter integration?

Are there aspects of our current model/ operations that could be abandoned based on high risk case finding fidelity?

Do we have the right financial and models that fully optimize the ROI?

THANK YOU!

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QUESTIONS

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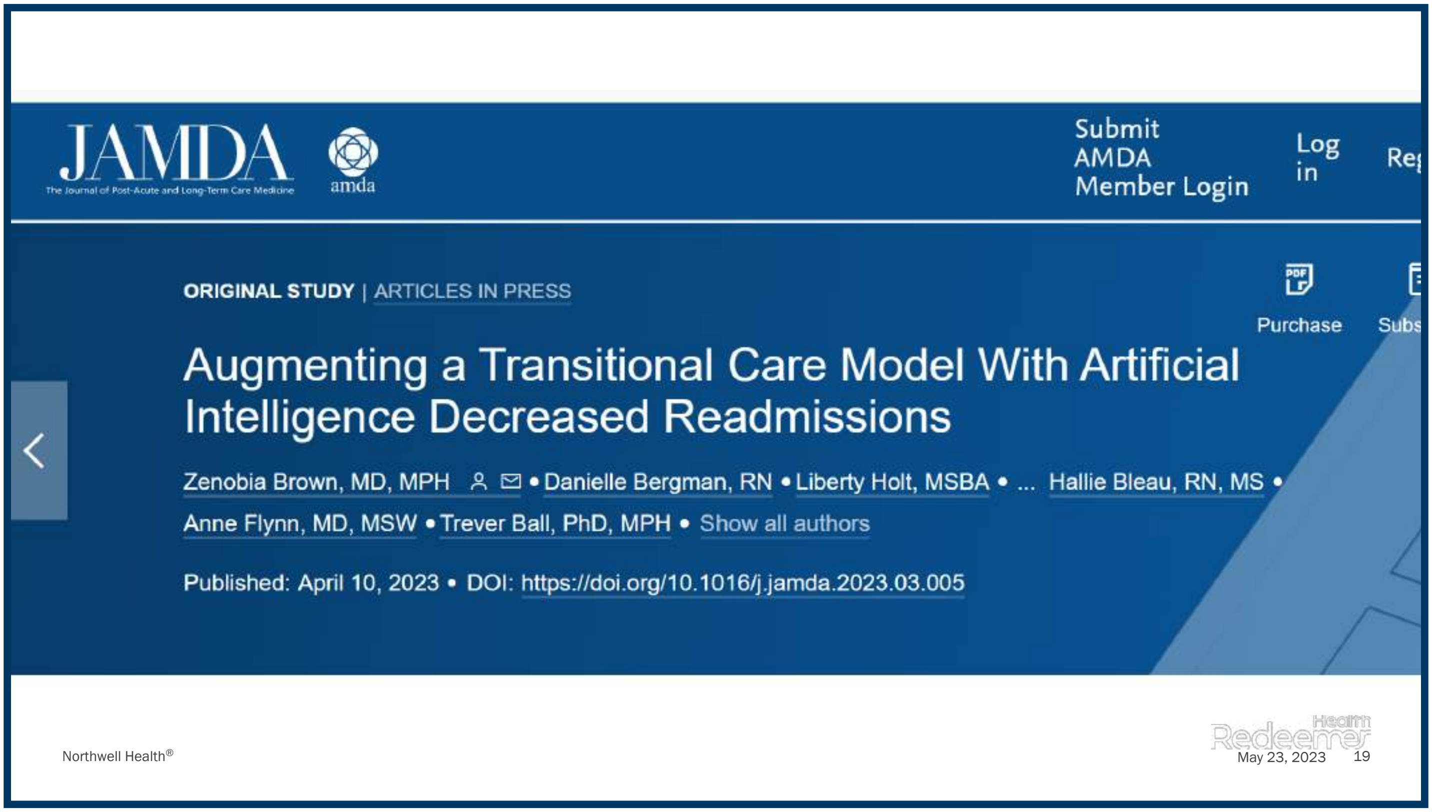
18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19