Empowering Nurses NOW: AI Tools for Better Care and Outcomes

PATRICIA C. DYKES PHD, MA, RN, FAAN, FACMI
BRIGHAM AND WOMEN'S HOSPITAL
HARVARD MEDICAL SCHOOL
BOSTON, MA

Overview

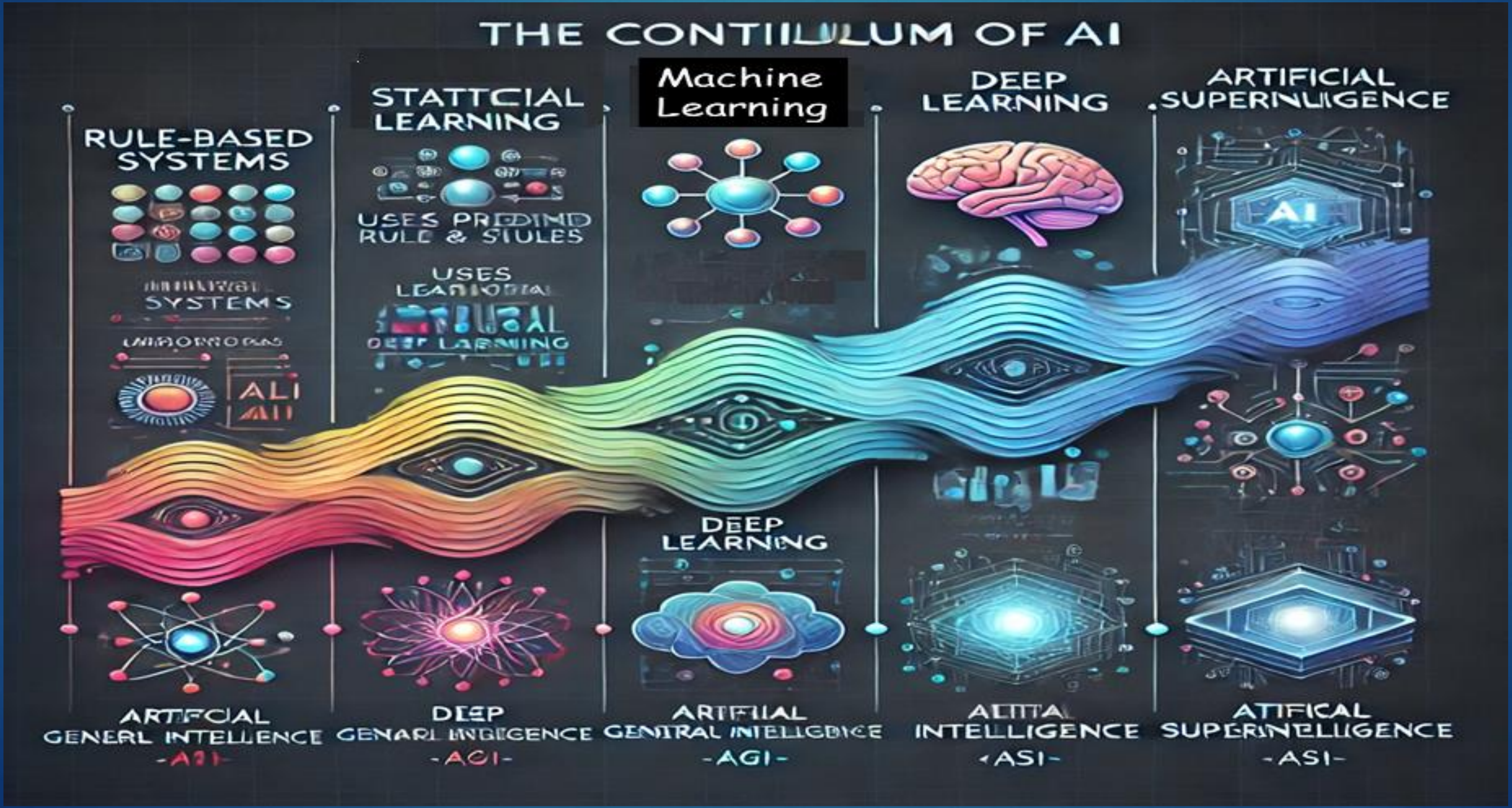
- AI and Healthcare Informatics
- Nursing and the Promise of AI
- Nursing and Healthcare AI Case Examples
- Discussion/Conclusions

Introduction: What is Artificial Intelligence or "AI"

- The science and engineering of making intelligent machines, especially intelligent computer programs' (McCarthy, 1956).

McCarthy, John. "What is Artificial Intelligence?" Computer Science Department, Stanford University, November 12, 2007. Available at: http://www-formal.stanford.edu/jmc/

The Continuum of AI: From Rule-based Systems to Artificial Superintelligence



The Promise of AI and Informatics for Improving Patient Care

Enhanced Decision Making

- ✓ Analyzing vast amounts of data in real time
- ✓ Offering evidence-based recommendations

Predictive Analytics

- ✓ Identify data trends and patterns
- ✓ Early disease detection
- ✓ Predict outcomes

Improved Patient Outcomes

- ✓ Reminders and increased communication
- ✓ Proactive, personalized care
- ✓ Ongoing, real-time identification of safety issues

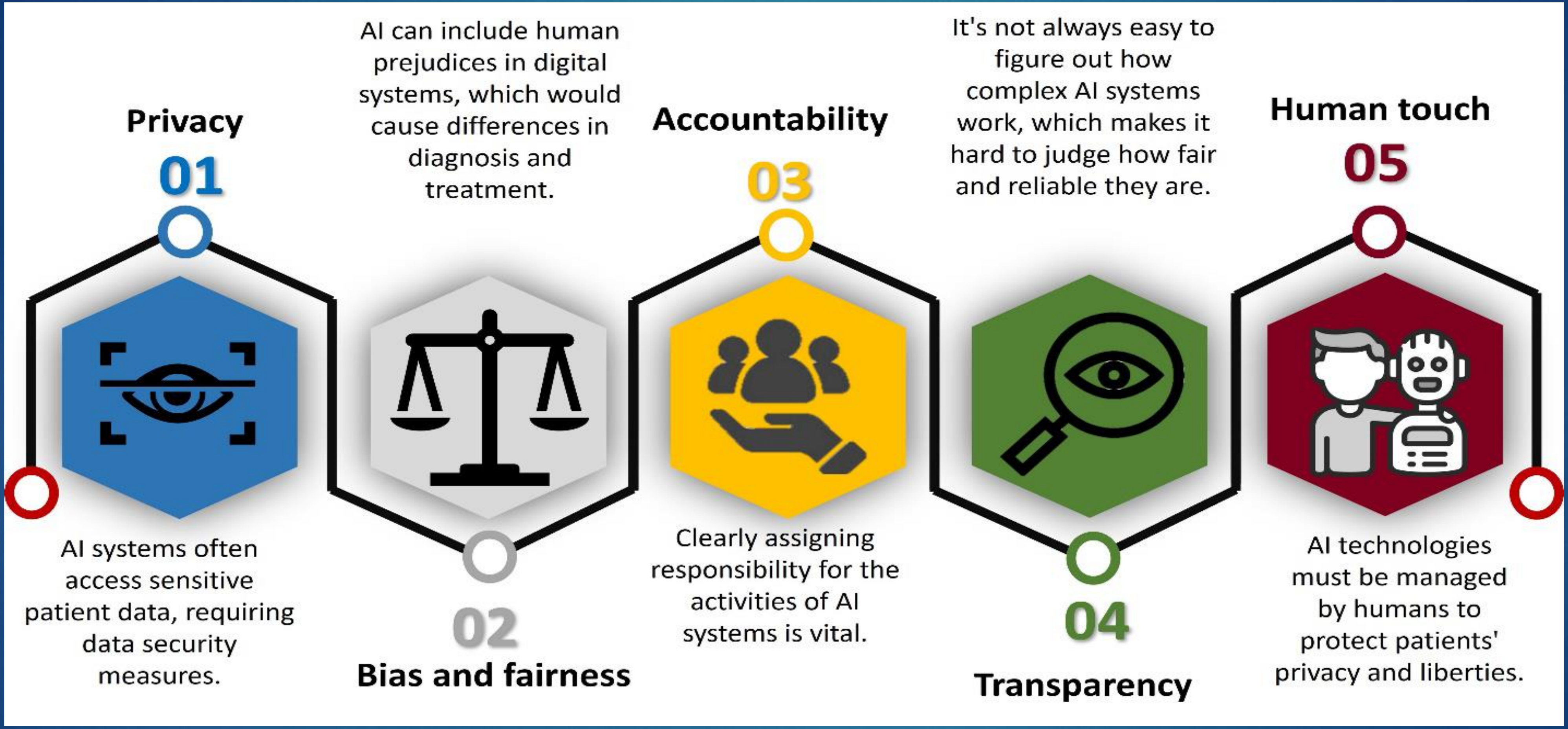
Reduced Administrative Burden

- ✓ Automating repetitive tasks e.g., documentation and scheduling,
- ✓ Allowing nurses to focus on patient care

Optimized Resource Allocation

- ✓ Time savings from more efficient documentation can be reallocated to higher value clinical tasks

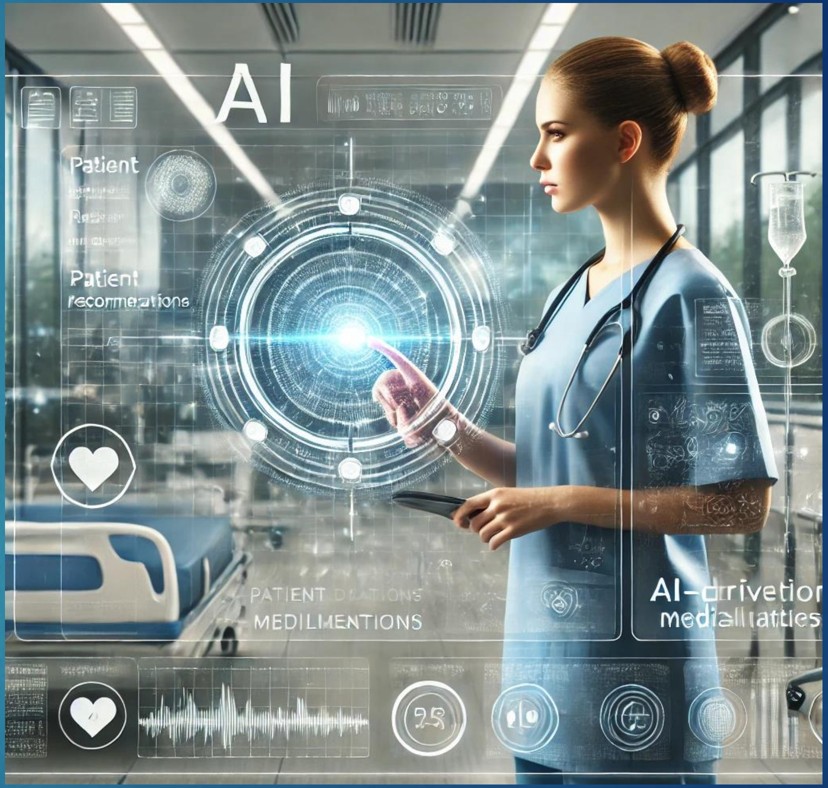
AI Challenges & Ethical Considerations



O'Connor, S., Yan, Y., Thilo, F.J., Felzmann, H., Dowding, D.W., & Lee, J.J. (2022). Artificial intelligence in nursing and midwifery: A systematic review. *Journal of clinical nursing*.

Role of Nurses in AI Integration

- Nurses play a vital role in integrating AI into patient care.
  - Advocate for patient-centered AI solutions.
  - Collaborate in AI tool development and refinement.
  - Ensure ethical AI use and safeguard patient data.



How will you be part of this transformation?

REAL WORLD CASE EXAMPLES

Nursing and AI

- ✓ Early Recognition of Patient Deterioration
- ✓ Pressure injury Prevention
- ✓ Fall Injury Prevention
- ✓ Timely Diagnosis of Venous Thromboembolism

Communicating Narrative Concerns Entered by RNs (CONCERN)

CONCERN

AMERICAN NURSES FOUNDATION

This project is supported by:

American Nurses Foundation (ANF): Reimagining Nursing Initiative

&

NIH NINR

National Institute of Nursing Research (NINR): 1R01NR016941-01

The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health or ANF

COLUMBIA
COLUMBIA UNIVERSITY DEPARTMENT OF BIOMEDICAL INFORMATICS

COLUMBIA UNIVERSITY School of Nursing

NewYork-Presbyterian

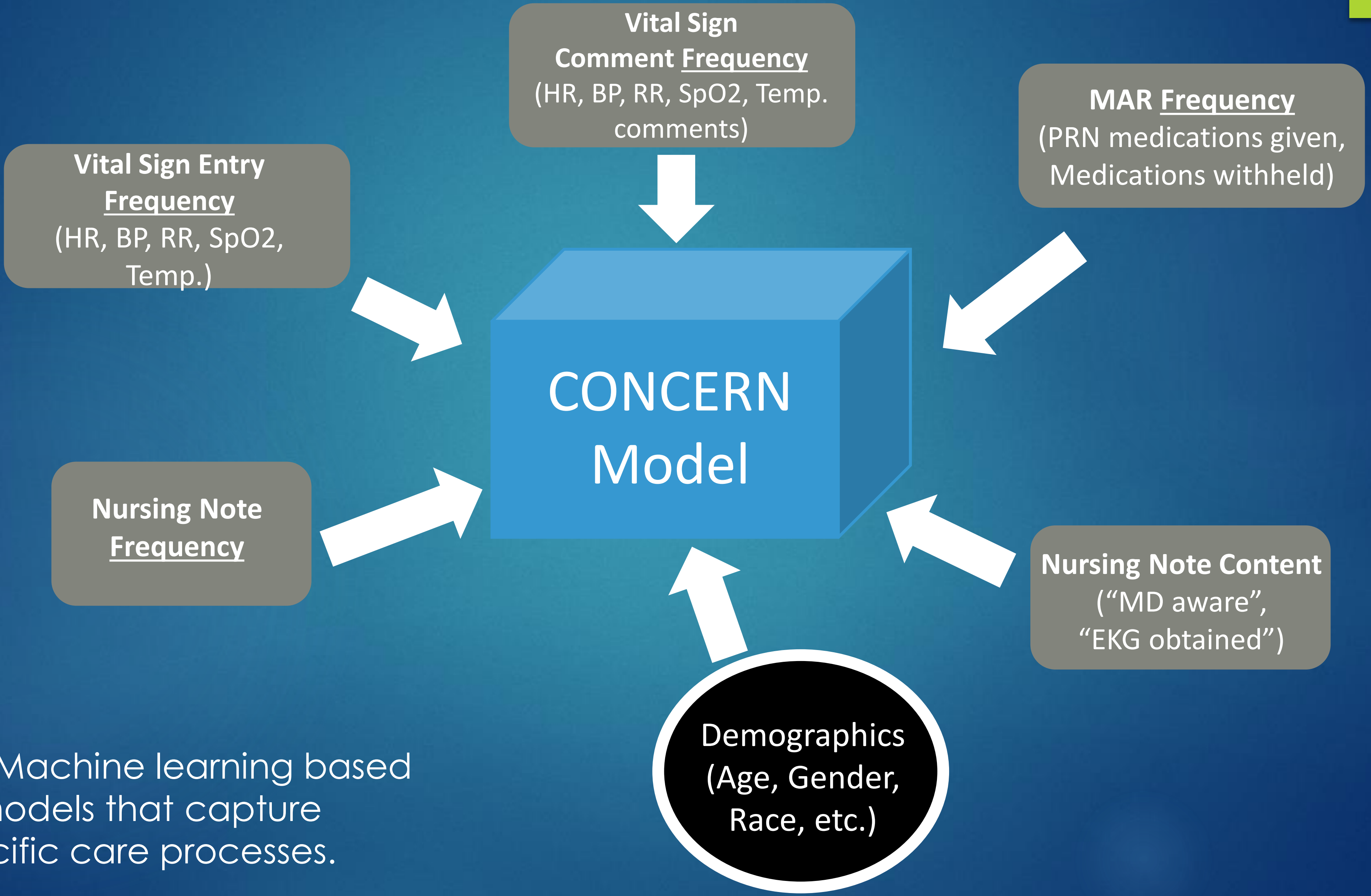
VE RI TAS

What is CONCERN?

- CONCERN is an early warning system (EWS) for patient deterioration based on nursing documentation patterns or "signals"
- CONCERN detects the nurses' expert clinical judgment when it perceives changes in a patient's clinical state
  - Alerts earlier than other EWSs that rely on physiological alterations in the patient
  - Leverages existing documentation

COmmunicating
Narrative
Concerns
Entered by
RNs

CONCERN Predictive Model



CONCERN: Machine learning based ensemble models that capture patient-specific care processes.

CONCERN Study Data Set Used to Develop the EWS

	MGB (Partners)	NYP
Unique Patients	45,309	44,589
Encounter Cohort	61,782	64,842
Flowsheet Data	141,097,242 Rows	76,785,642 rows (Vitals Template) 170,541,580 rows (Assess. Template)
Notes	4,652,682 Rows	4,181,900 rows
Orders	Medication: 9,052,279 Rows Procedures: 5,872,679 Rows	Medication: 3,607,277 Diagnostic: 7,294,739 Other: 4,045,800
MAR(Medication Administration Records)	27,745,906 Rows	16,027,243 Rows

The CONCERN Predictive Model

Validation

- Multinomial Gradient Boosted Machine (GBM) model selected
- Built on random 12-hour time slices to predict (over the next 24 hours) whether a patient is discharged, will still be in the hospital, or has a negative event
- Trained on 70% of the dataset – 30% was used for 10-fold cross validation

Model Performance

Setting	Accuracy	Precision	Recall	Logloss	AUC
ICU	0.970938	0.431373	0.594595	0.073695	0.934683
ACU	0.973341	0.813559	0.643935	0.089369	0.955982

Better lead time than other early warning scores (EWS)

Rossetti SC, Knaplund C, Albers D, Tariq A, Tang K, Vawdrey D, Yip NH, Dykes PC, Klann JG, Kang MJ, Garcia J, Fu LH, Schnock K, Cato K. Leveraging Clinical Expertise as a Feature - not an Outcome - of Predictive Models: Evaluation of an Early Warning System Use Case. AMIA Annu Symp Proc. 2020 Mar 4;2019:323-332. PMID: 32308825; PMCID: PMC7153052.

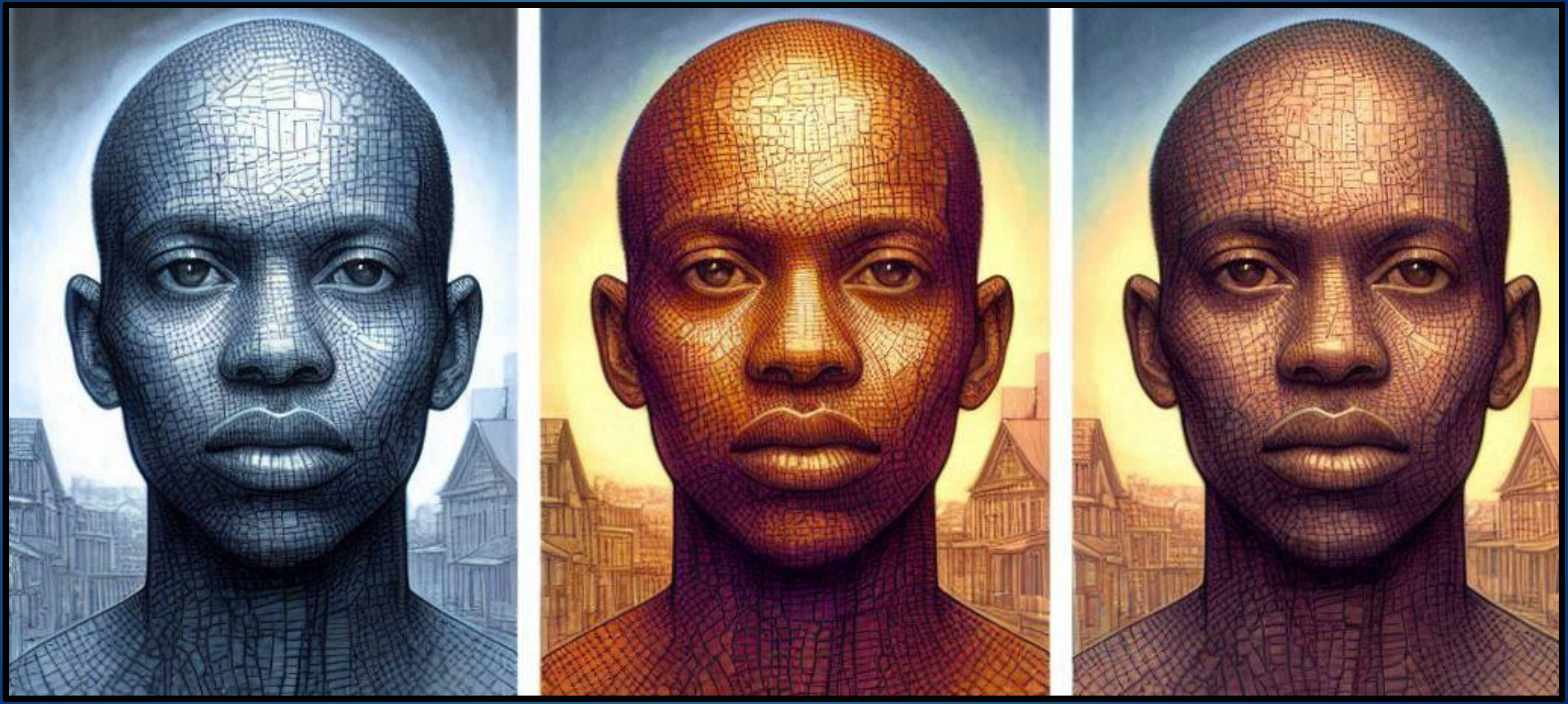
How is CONCERN Different than Other Early Warning Systems (EWS)?

	Patient Deterioration (Early Warning System)	24 Hour Mortality	ICU Readmission	30-Day Readmission
MEWS	x	x		
CONCERN	x	x		
Rothman Index		x	x	x

"Clinically, deteriorating patients in general wards either die or are transferred to ICU. This criterion resulted in exclusion of the Rothman Index, which predicts "death within 24 hours" but not ICU transfer."

Linnen et. al. Statistical Modeling and Aggregate-Weighted Scoring Systems in Prediction of Mortality and ICU Transfer: A Systematic Review. ***J Hosp Med****. 2019 Mar; 14(3): 161–169.*

Racial Bias: 3 Early Warning Systems



CONCERN Early Warning System:

Participatory User- Centered Design

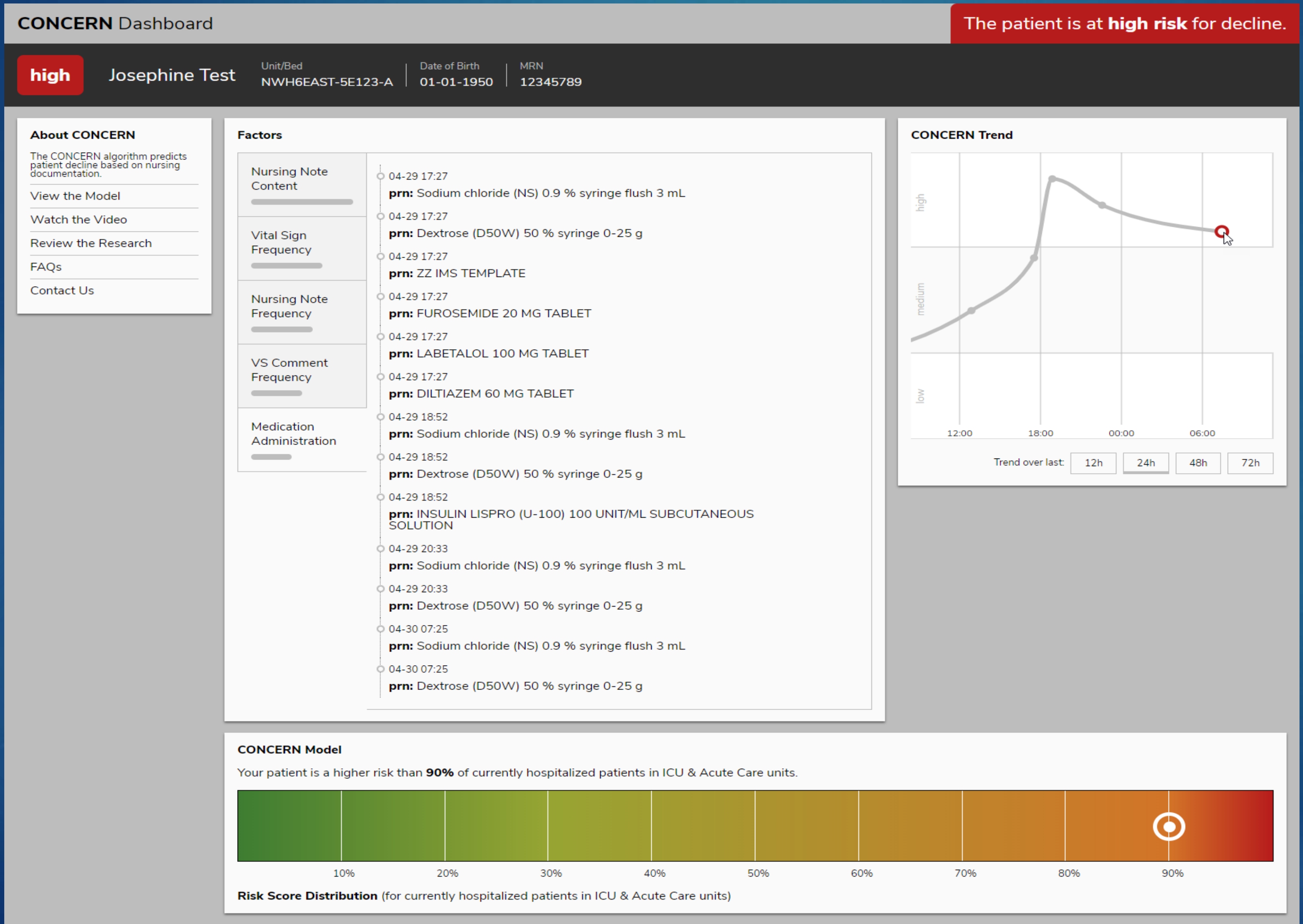
CONCERN Intervention: Configured in EHR Patient List

My patients 5 Patients

Refreshed just now | Search All My Lists

Patient Name / Age / Sex	Unit/Bed	New Messages	Unacknowledged Orders	Med Due	New Rslt Flag	Reassess Pain	CONCERN Score	Admit RN Req Doc	Shift Req Doc	Code Status	Problem	Respondin Clinician	Med Over Pend	Signed/Held
Concern, Martin (91yrs M)	BWH SH 9E 903-1	—				—	*			None on file	None	—		—
Concern, Pal (78yrs M)	BWH 11D 75-1	—		—	—	—	*			None on file	None	—		—
Concern, Sacu (82yrs M)	NWH ICU ICU289 A	—		—		—	*			None on file	None	—	—	—
Concern, Sicu (68yrs M)	NWH 4 USEN 4U457 A	—		—	—	—	*			None on file	None	—	—	—
Concern, Trans (79yrs M)	BWH 14D 75-1	—		—	—	—				None on file	None	—	—	—

CONCERN “App” Intervention



CONCERN Early Warning System:

Pragmatic Clinical Trial

- ✓ *Decreased risk of Mortality*
- ✓ *Decreased Length of Stay*
- ✓ *Decreased risk of Sepsis*
- ✓ *Increased unanticipated transfer to ICU*

nature medicine

Article | Published: 02 April 2025

Real-time surveillance system for patient deterioration: a pragmatic cluster-randomized controlled trial

Sarah C. Rossetti, Patricia C. Dykes, Chris Knaplund, Sandy Cho, Jennifer Withall, Graham Lowenthal, David Albers, Rachel Y. Lee, Haomiao Jia, Suzanne Bakken, Min-Jeoung Kang, Frank Y. Chang, Li Zhou, David W. Bates, Temiloluwa Daramola, Fang Liu, Jessica Schwartz-Dillard, Mai Tran, Syed Mohtashim Abbas Bokhari, Jennifer Thate & Kenrick D. Cato

Nature Medicine (2025) | Cite this article

Abstract

The COmmunicating Narrative Concerns Entered by RNs (CONCERN) early warning system (EWS) uses real-time nursing surveillance documentation patterns in its machine learning algorithm to identify deterioration risk. We conducted a 1-year, multisite, pragmatic trial with cluster-randomization of 74 clinical units (37 intervention; 37 usual care) across 2 health

Discussion/Conclusions

- CONCERN is an EWS that leverages existing EHR data to identify as risk patients.
  - Uses metadata patterns that reflect nurse expert decision making
  - Clinically significant improved lead time for patient deterioration
  - Was developed with user-centered design to optimize workflow integration
- CONCERN enables early identification of at-risk patients
  - Detects clinical deterioration early-- prompting early actions and resulting in better patient outcomes
- CONCERN has been rigorously tested and has demonstrated significant impact on patient outcomes and length of stay.

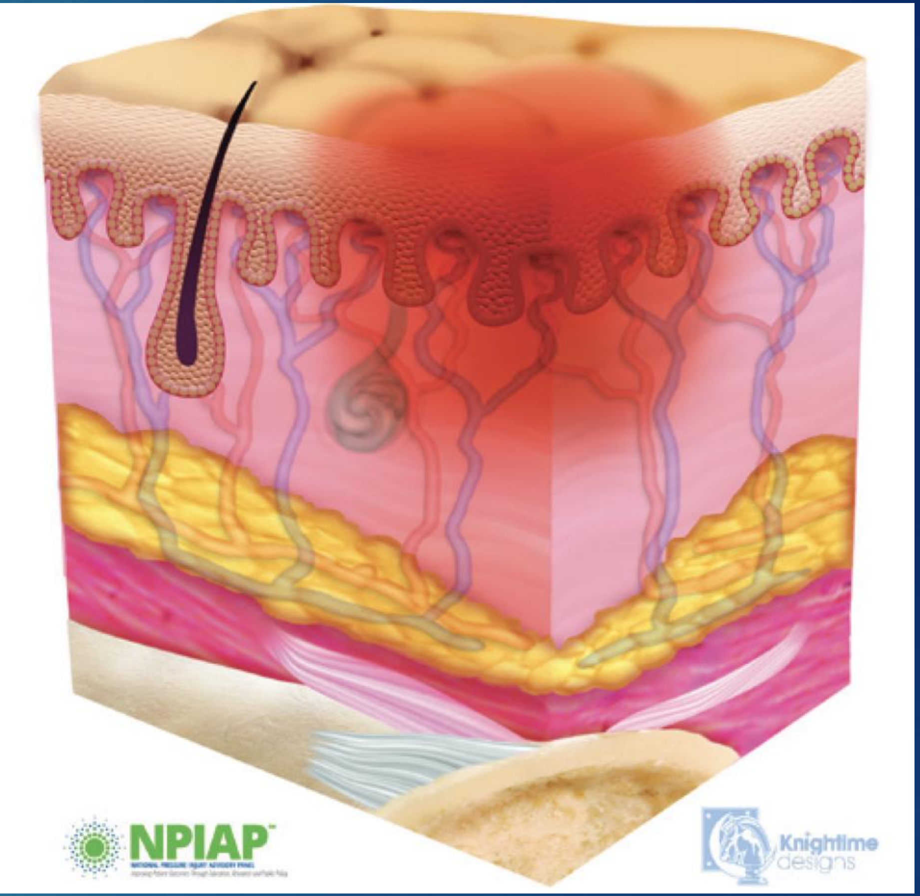
Innovations in Pressure Injury Electronic Health Record (EHR)-Based Phenotyping Pipelines

MULTI-STATE PRESSURE INJURY MODELING

crico

Background: Pressure Injuries and Staging

- National Pressure Injury Advisory Panel Definition: 'Localized damage to the skin and/or underlying tissue due to pressure or pressure in combination with shear'*
  - Painful, expensive, and frequently occurring health problems
  - Associated with increased morbidity and mortality
  - Nurses play a critical role in pressure injury care
- The National Pressure Injury Advisory Panel pressure injury (PrI) categorization:
  - Stage I, II, III, IV, unstageable, suspected deep tissue injury , and mucosal*
- Determining accurate PrI staging information from EHR is a crucial step in developing personalized and generalizable PrI risk assessment tools
  - Accurate PrI staging is a nursing challenge



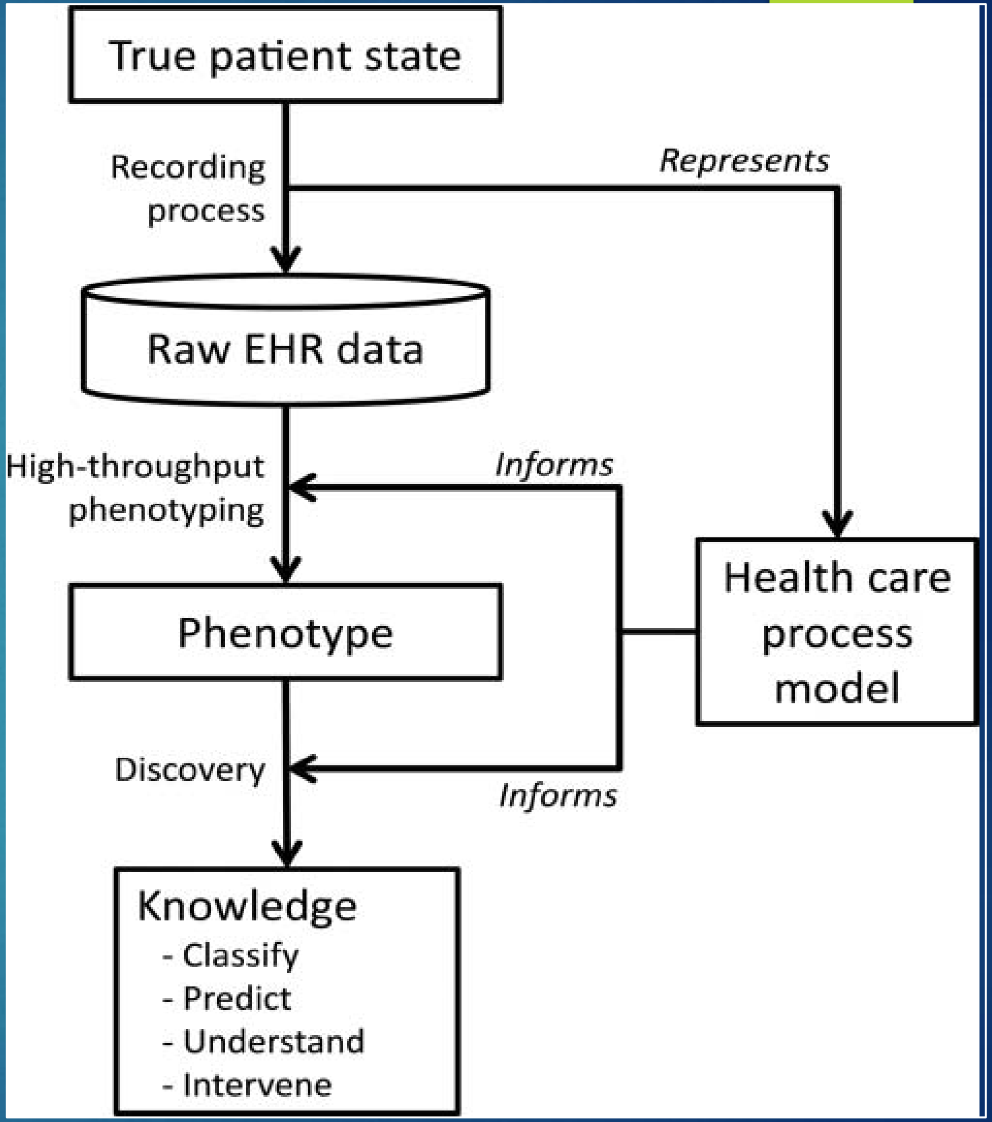
*Kottner J, et al. Journal of tissue viability. 2019;28(2):51-8.

Background: Limitations of Existing Machine Learning Methods for Processing Pressure Injury Data

- Rarely include dynamic changes in daily nursing assessments
  - Missing time-sensitive patterns to improve risk prediction.
- When nursing assessments are included, the data from a single time point missing temporal patterns
  - Single value documented prior to occurrence of PrI in cases and the single value documented prior to discharge in controls.
- Results in loss and bias in patient status information, especially temporal changes

Background: EHR-based Pressure Injury Phenotyping Challenges

- EHR data challenges
  - Accuracy
  - Completeness
  - Complexity
  - Bias
- Health care process models
  - Represents how processes occur and how data are recorded
  - Inform phenotyping
  - Help to identify issues with the recording process that impact data accuracy

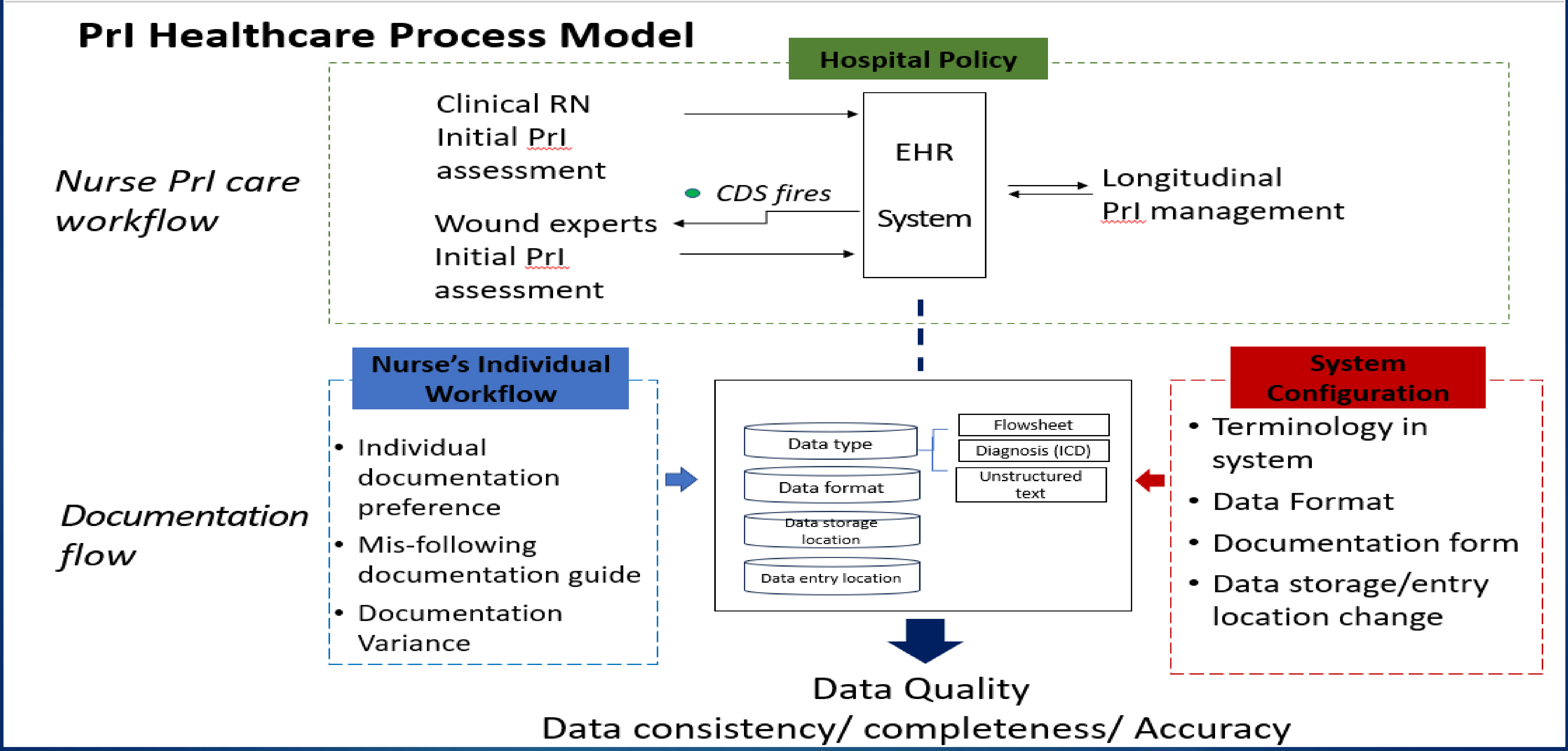


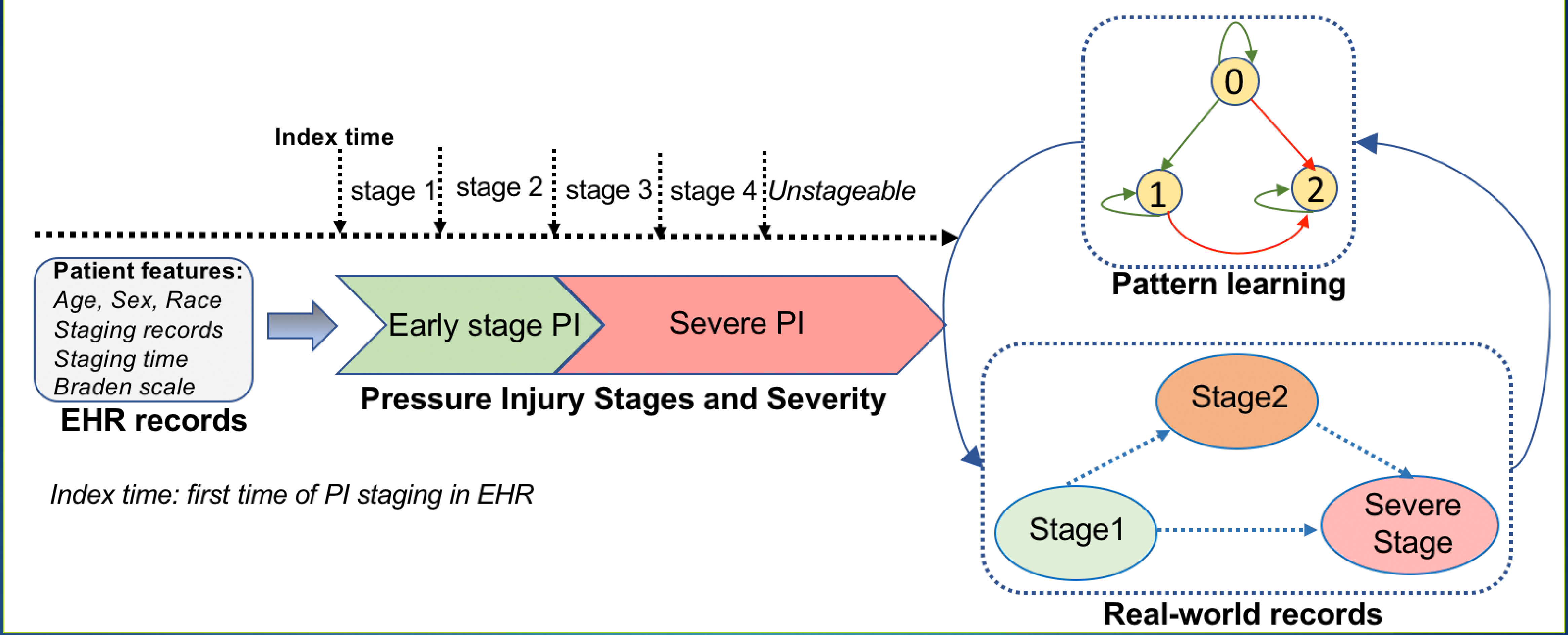
Hripcsak & Albers. Next-generation phenotyping of electronic health records. *J Am Med Inform Assoc* 2013;20:117–121.

Project Goal

- Project Goal: To develop a comprehensive set of EHR data-based severe pressure injury risk factors and compare its prediction accuracy to the Braden Scale.
  - To describe differences in pressure injury detection by age and race
  - To explore the potential value of the Braden Scale and its subcomponents in predicting dynamic pressure injury stage transition patterns.

Pressure Injury Health Care Process Model





- We used **Markov Multi-state Modeling** to evaluate time-sensitive PrI Staging Transition Trajectories.
- Based on expert opinion, stage 1 and stage 2 were defined as early-stage pressure injury and other stages were defined as severe pressure injury.

Study Cohort

- Developed a cohort of 29,475 patients with at least one record of pressure injury documented during 2015 to 2023 from five MGB hospitals.
- Patients were divided into four groups according to pressure injury anatomical locations, including coccyx, buttocks, sacrum and heel.
- Within each pressure injury location group, we further divided patients into 3 staging groups, including stage 1, 2 and severe stage (including stage 3, 4 or unstageable)

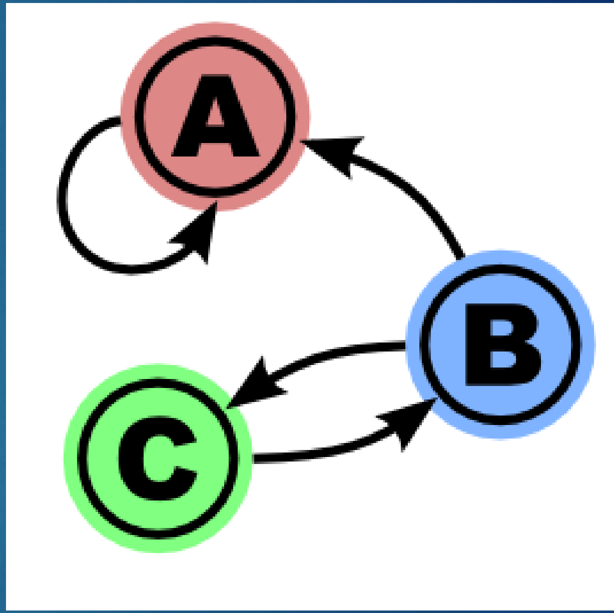
	Patient Feature		**Summary**
Initial study cohort (n=29,475)	Age Mean (SD)		70.7(15.8)
	Female		43.6%
	Race	White	79.5%
		Black or African American	9.0%
		Asian	2.5%

Research Questions

- What is the distribution of PrIs by location?
  - Are there differences in age at the time of PrI diagnosis based on patient demographics.
- What are the transition paths and intensities between PrI states using pressure injury stages derived from rules based on domain knowledge (provided by clinical experts) and NPIAP PrI clinical practice guidelines?
- What is the impact of the Braden Scale and its 6 sub-components as time-varying covariates to all transitions between pressure injury stages?

Methods

1. Comparative analysis among 4 common PrI locations by age, race, and sex.
2. Markov multi-state modeling to evaluate time-sensitive progression trajectory of pressure injury stages
3. Covariate analysis: estimated impact of Braden Scale and its 6 sub-components as time-varying covariates to all transitions between pressure injury stages.



Methods used to minimize challenges

Results: Baseline Characteristics

Number of patients in the dataset (2015-2023): 29,475

- Mean age: 70.7; White 79.5%, Black 9%; Female 43.6%

Total number of pressure injuries after data cleaning/exclusions applied: 3474

Number of pressure injuries per location:

Coccyx
- 1342 (38.6%)

Buttocks
- 1085 (31.2%)

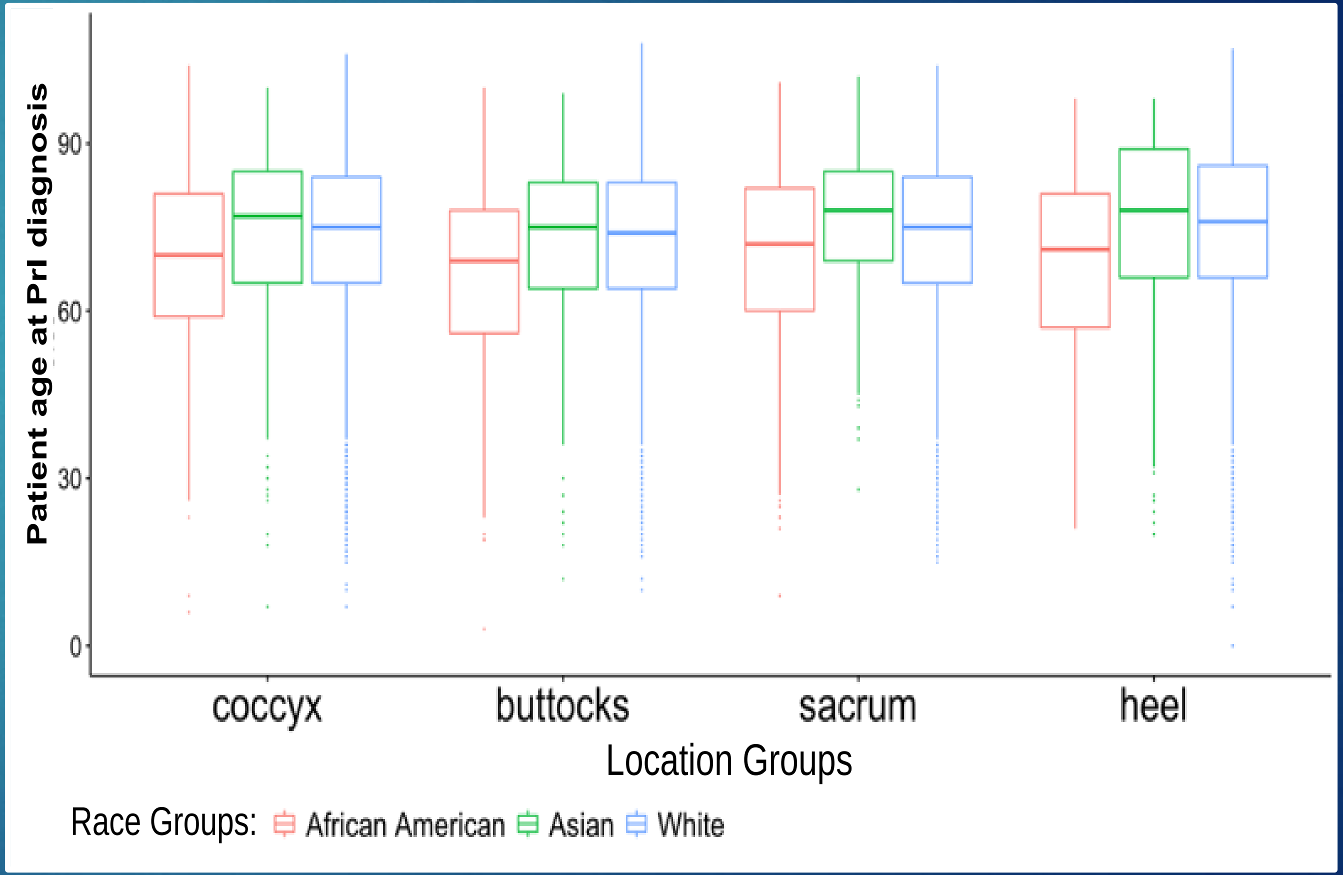
Sacrum

612 (17.6%)

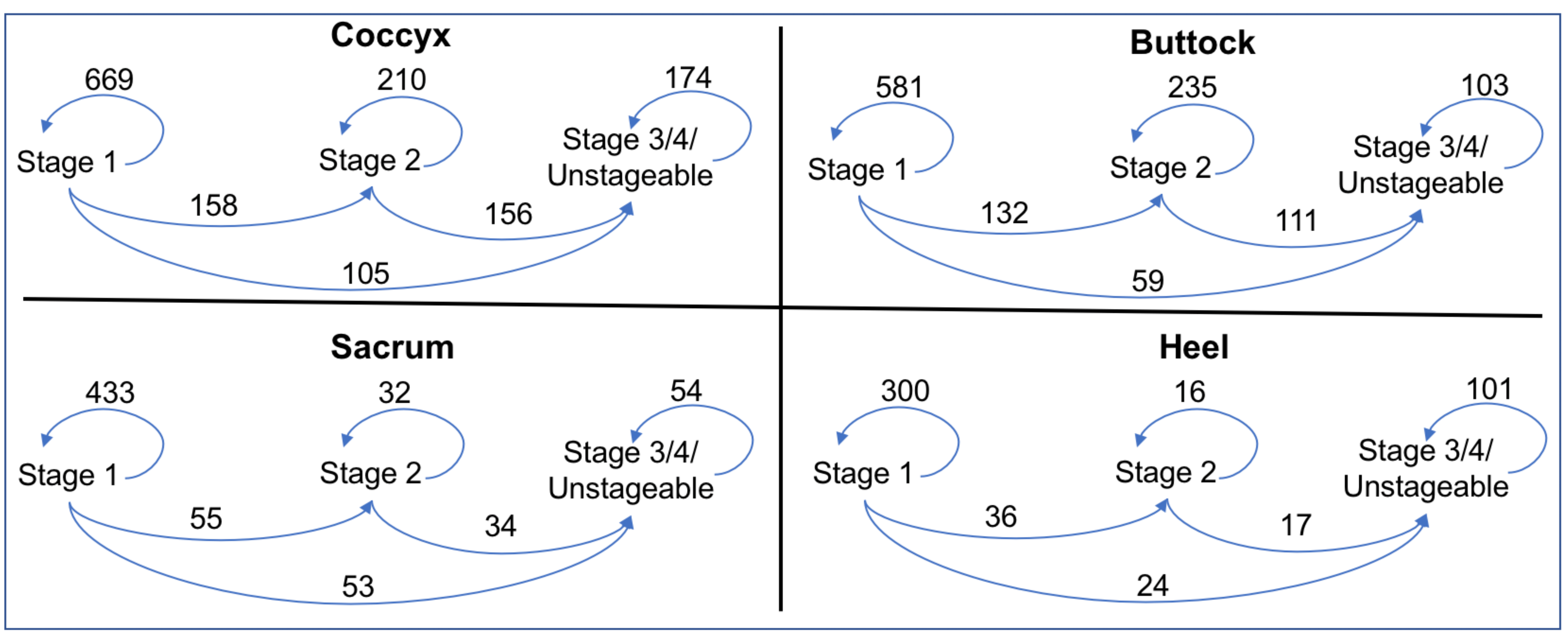
Heel
- 435 (12.5%)

Results: Distribution of Pressure Injury Anatomical Locations and Stages

- Heel pressure injuries had lowest prevalence but highest % of severe pressure injuries (30.5%), as compared with other locations (18.1- to 22.5%)
- Significant difference in median age pressure injury first documented among different injury location groups ($p<0.001$)
    - Median age of Black or African American patients significantly lower than both White and Asian ($p <0.001$)



Observed Transition Frequencies Between Stages



- Transition = A change from one stage to the distinct following stage.
- In **all** locations, patients in stage 2 were more likely to transition to severe stages.

Results: Impact of Braden Scale and Sub-components as Time-varying Covariates

- Low-risk Braden Scale score significantly associated with < likelihood of transitions from stage 2 to severe stages on Buttocks and from stage 1 to severe stages on Sacrum.
- Significant associations identified in Braden sub-components for transition from low to severe stages only.
  - No significant associations found for nutrition, friction and shear in any transitions
  - No significant associations for transitions between stages 1 to 2.
  - No significant associations between age or sex with stage transitions
  - Nonwhite patients more likely to transition from stage 1 to 3 in coccyx and sacrum groups

Discussion/Implications

- We developed a novel multi-state pressure injury trajectory model using real-world clinical data.
- Stage 2 serves as a "gateway state" during the development trajectory to a severe stage pressure injury.
  - Once a patient progresses to stage 2, the likelihood of transiting to severe stages is much greater.
- Observed location-dependent variations, suggesting location-specific interventions and treatments can be important for pressure injury management.

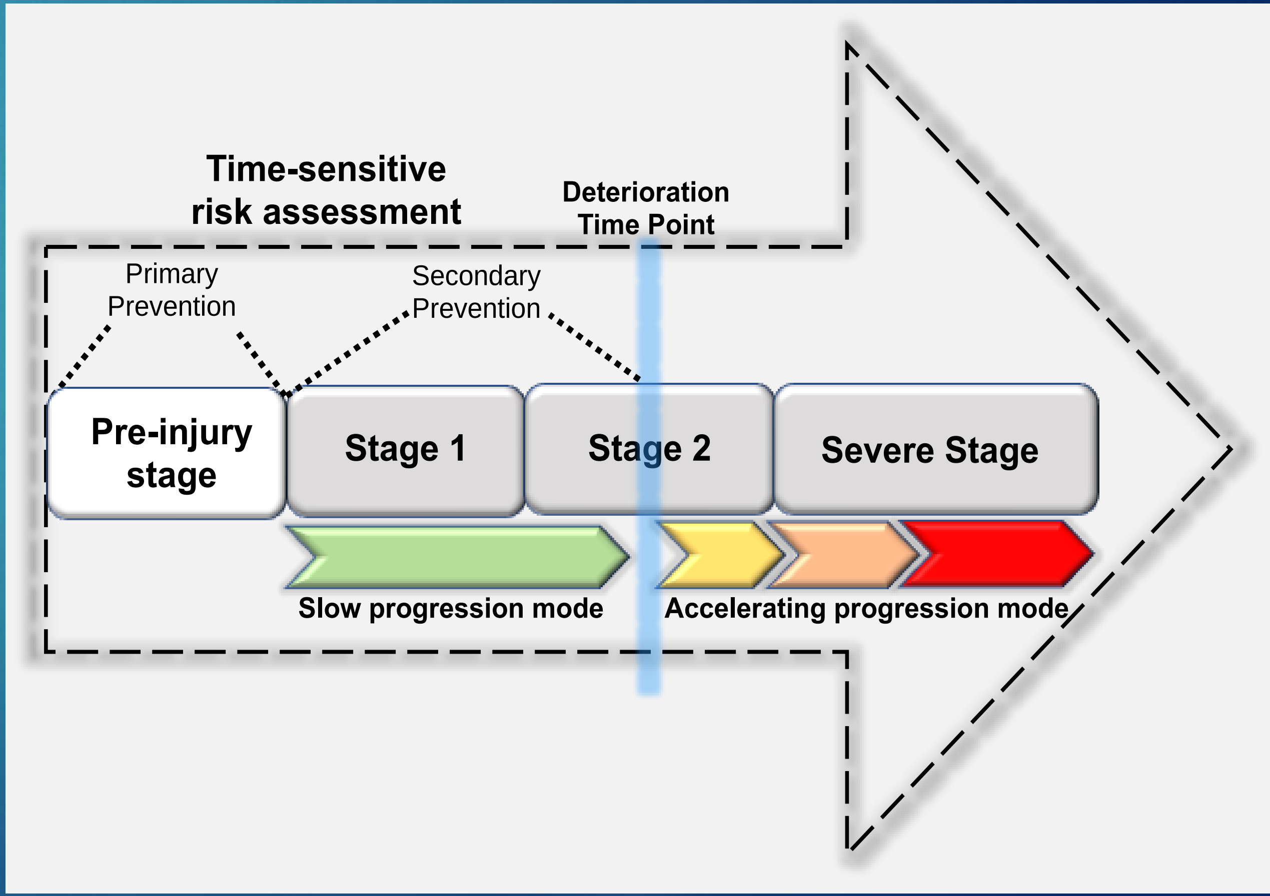
Discussion/Implications

- The Braden Scale and its sub-scales are suboptimal for predicting early stage PrI transitions and may limit its value for supporting early PrI prevention.
  - Highlights the lack of important time-sensitive information in current pressure injury risk assessment tools.
- The trajectory model showed the advantages of capturing time-dependent information among stage transitions and the need for data-driven CDS.
- Dynamic pressure injury risk screening CDS is needed to facilitate personalized and timely prevention.

Future Implications of Next Generation CDS Using Multi-state Modeling

1. **Early and Targeted Intervention**
   - Real-time tracking of patient progression, enabling timely interventions at critical transition points (e.g., prevention of stage 1 and 2).
   - Identify higher risk patients earlier and trigger alerts for preventive care.
2. **Improving Prediction Beyond Traditional Methods**
   - Data-driven, time-dependent risk assessments, improving predictive power beyond traditional cross-sectional tools.
   - Identify patients at risk before they reach the "gateway" Stage 2; preventing severe PrIs more effectively.

Pressure Injury Dynamic Progression And Data-driven Risk Assessment CDS



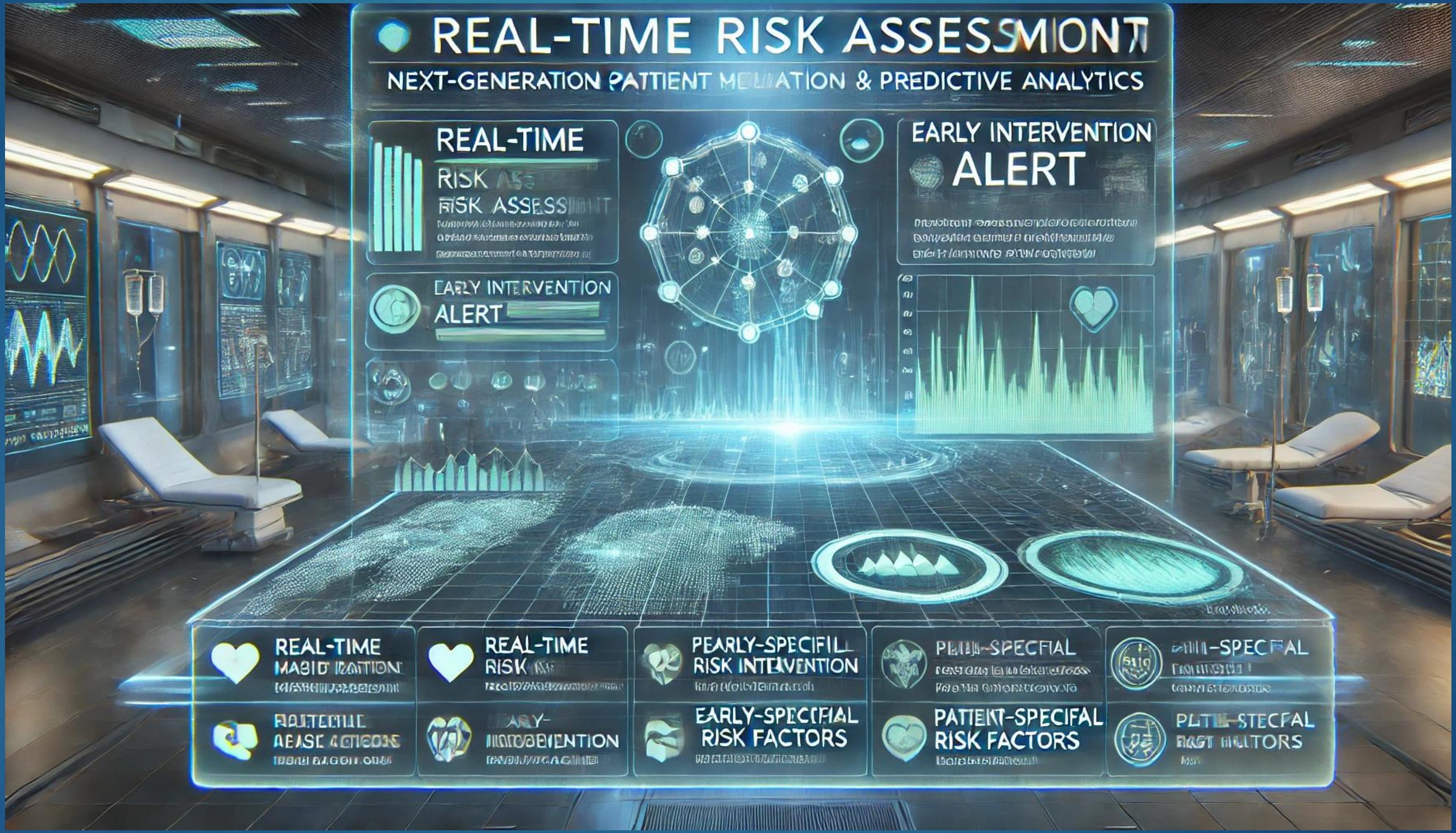
Future Implications of Next Generation CDS Using Multi-state Modeling *(Continued)*

3. **Dynamic Risk Assessment and Real-Time Monitoring**
   - Enables continuous, dynamic assessment of patient condition, allowing CDS to adapt recommendations as risk factors change.
4. **Personalized Risk Stratification**
   - Incorporate demographic, anatomical, and comorbidity data to tailor risk predictions for individual patients or subgroups.
     - Address race-dependent and location-specific variations in PrI progression.
   - Customized prevention strategies based on patient-specific trajectories.

Future Implications of Next Generation CDS Using Multi-state Modeling *(Continued)*

5. **Enhanced Clinical Decision-Making**
   - Provide real-time alerts and predictive analytics.
   - Recommend preventative actions before PrIs progress to severe stages, improving adherence to evidence-based care.
6. **Bridging Gaps in Clinical Practice**
   - Rigorous and objective foundation for risk assessment, potentially replacing or enhancing existing tools.
   - Supports proactive rather than reactive prevention efforts.

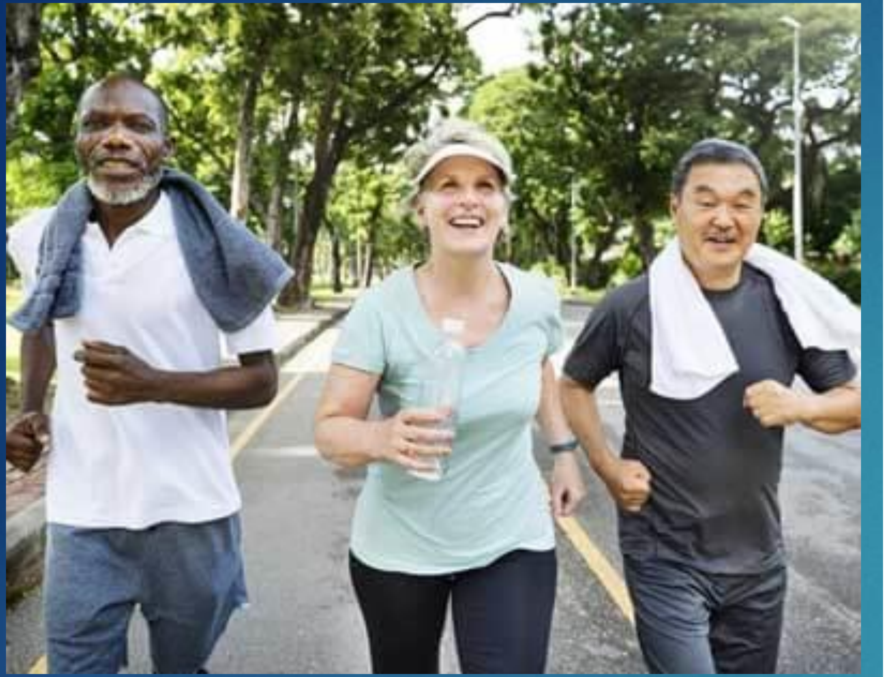
Future Vision: Integration of **Multi-state Modeling for PrI Tracking Into Hospital EHR Systems**



Improving outcomes for community dwelling older adults

PATIENT SAFETY RESEARCH (PRIMARY CARE)

- ✓ eSTEPS
- ✓ DOVE



- Participation in fall-prevention exercise program for an older adult reduces fall risk by 23%
- Guidelines recommend fall-prevention exercise programs for older adults at risk of falls
- Fall prevention is inadequately addressed in primary care and disparities exist.
  - Providers uncomfortable recommending exercise for unsteady patients
  - Providers and patient believe that walking is an acceptable fall prevention exercise
  - Older people in rural areas more likely to fall and experience fall-related injuries and less likely to participate in fall prevention programs

NIH National Institute on Aging
Turning Discovery Into Health

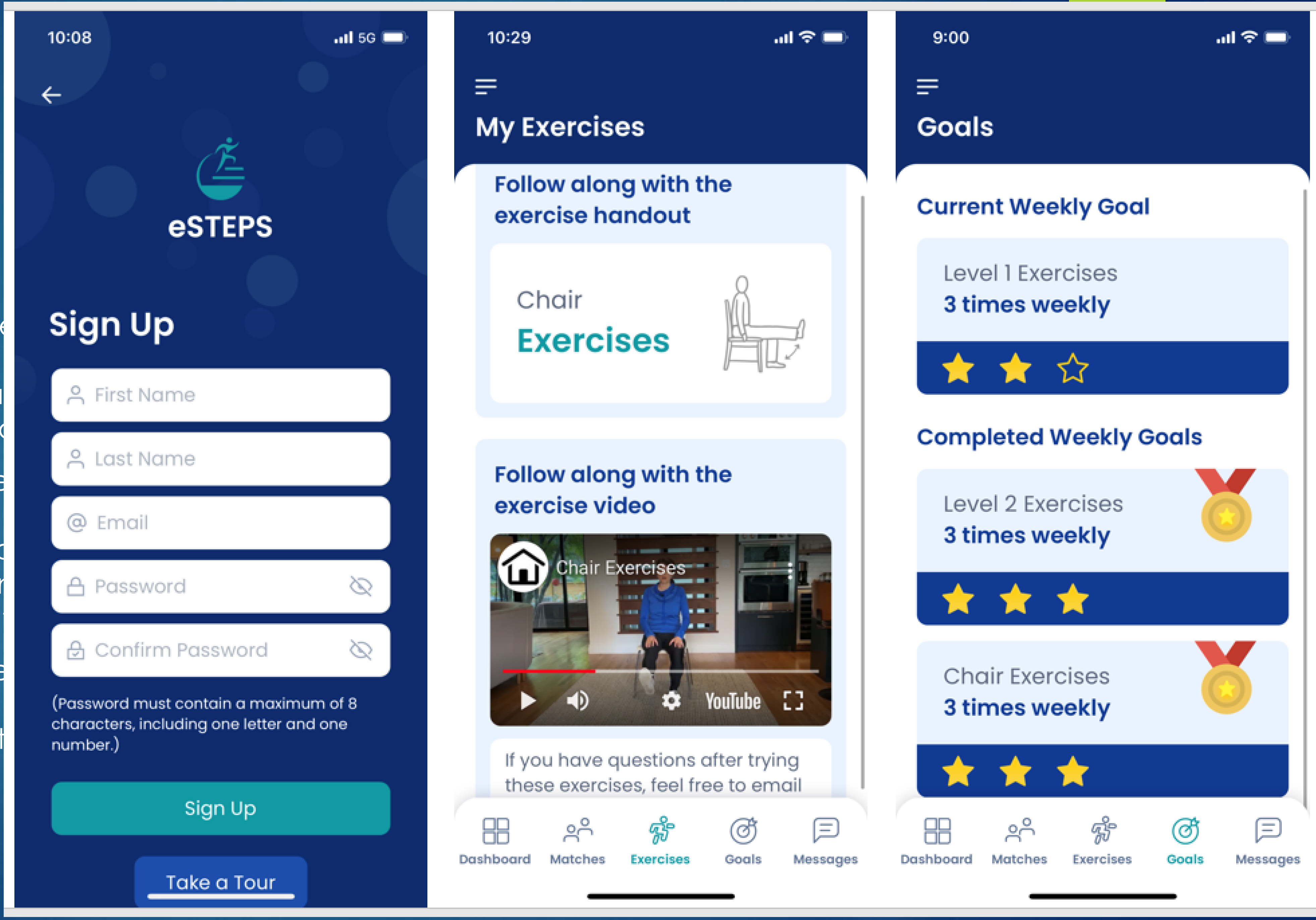
eSTEPS

*ELECTRONIC STRATEGIES FOR TAILORED EXERCISE TO PREVENT FALLS

UTMB
The University of Texas Medical Branch

eSTEPS

- Goals:
  1. To improve
     screening
     learning a
     identify ol
  2. To provide
     that helps
     and staff c
     preventio
     risk patien
  3. To provide
     high tech
     carry out t
     plan.



eSTEPS Clinical Trial

eSTEPS

- Cluster randomized control trial Mass General Brigham (22 practices/>8000 patients)
- Replication trial University of Texas Medical Branch (12 practices/>4000 patients)
- Recruitment 9 months/follow-up 12-21 months
- Outcome measures:
  - Patient falls/injuries
  - Fear of falling/Exercise self-efficacy

Clinical trial ends May 2025– stay tuned!

NIH National Institute on Aging
Turning Discovery Into Health

Diagnostic delay **Of VTE* (DOVE)**

*VENOUS THROMBOEMBOLISM

Background: Venous Thromboembolism (VTE)

- Venous thromboembolic disease (VTED) = Deep Vein Thrombosis (DVT)-- Pulmonary Embolism (PE)
  - Dangerous, preventable public health problem
  - Affects 300,000-600,000 individuals in the U.S. annually
  - Requires timely and adequate treatment
- VTE signs and symptoms are non-specific making timely recognition a challenge
  - Delayed VTE diagnosis in primary care settings is common: ≈ 4 days between symptom onset and diagnosis
  - Previous studies used retrospective record reviews and small sample sizes to estimate time from symptoms presented in primary care to diagnosis

DOVE Project Goals and Data Sources

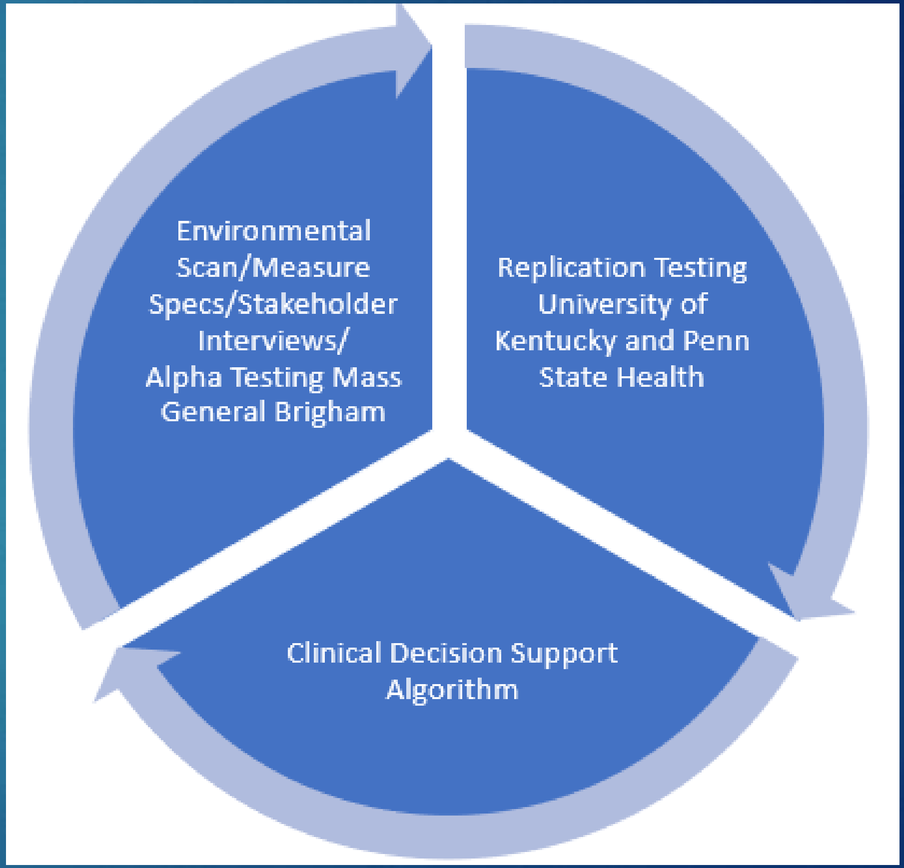
1. Develop DOVE electronic clinical quality measure (eCQM) to Quantify VTE diagnostic delay of adults in primary care at the provider group level.

   - VTE phenotype using commonly captured EHR data.
   - Natural Language Processing (NLP) approach to identify VTE symptoms in unstructured clinical notes.

2. Develop clinical decision support (CDS) using EHR data and machine learning methods Goal: Alert providers of patients at high risk for VTE diagnosis.

Data sources:

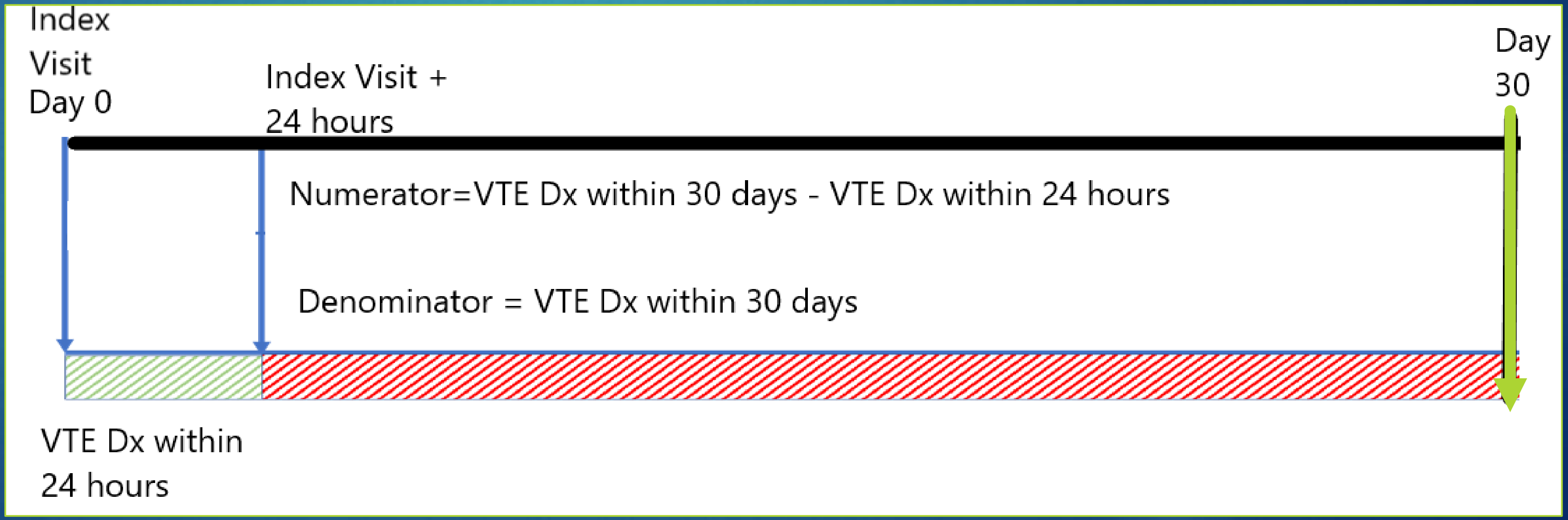
- EHRs: **Site 1** Mass General Brigham, **Site 2** University of Kentucky, **Site 3** Penn State Health



DOVE eCQM Measure Specifications

Denominator: All adult patients (18+) presenting in primary care with VTE-related symptoms (identified by the NLP algorithm) who are subsequently diagnosed with VTE (≤ 30 days of primary care visit).

Numerator: Subset of denominator where VTE diagnosis occurs greater than 24 hours following the index primary care visit.



DOVE VTE Phenotyping Algorithm Accuracy

Traditional method	ICD			PPV* = 64%
Recent studies	ICD +	Imaging		PPV = 75%
BWH method	ICD +	Imaging +	RxNorm	PPV = 95.8%
	Billing	Identification	Treatment	

*PPV=Positive Predictive Value

Natural Language Processing (NLP) in eCQMs

Developed rule-based symptom extractor algorithm to identify classic VTE symptoms in the EHR clinical notes using notes from the MGB system, literature reviews, and expert consensus:

Cough	Hypotension	Lightheadedness	Shortness of breath	Syncope	Tachycardia	Chest pain	Hemoptysis
Calf pain	Leg pain	Foot pain	Calf numbness	Leg numbness	Foot numbness	Calf tingling	Leg tingling
Foot tingling	Calf redness	Leg redness	Foot redness	Calf swelling	Leg swelling	Foot swelling	Calf tenderness
Leg tenderness	Foot tenderness	Calf warmth	Leg warmth	Foot warmth			

- NLP addresses the gap in capturing unstructured data in quality measures

Delayed VTE Diagnosis eCQM Rates:

MGB 2016-2021 Overall (5,514 encounters): 72.6%

- **214 Practice Locations**
  - Range: 0-100% (SD 21.52)
  - Interquartile range 27.03%
- **Sub-analysis of 50 Largest MGB Practices**
  - Number Delayed VTE Diagnosis Events 2016-2021: 425
  - Unadjusted rate: 66.3% (range 0-100%, SD 32.4)

UK 2016-2020 Overall (632 encounters; Organizational level only): 77.14%

Penn State Health 2019-2022 Overall (545 encounters): 81.85%

- **19 Practice Locations**
  - Range 50-100% (SD 15.36)
  - Interquartile range 40%

Delayed VTE Diagnosis eCQM Alpha and Beta Testing

- Frequency of data elements:
  - MGB 1.53% missing (ethnicity)
  - UK: 1.02% missing (ethnicity)
  - PSH: 0% missing
- NLP algorithm easily implemented at organizations with different EHR systems.
- Face validity: 100% agreement among technical expert panel members DOVE eCQM, as specified, can be used to distinguish good from poor quality related to patient safety at the clinician group-level.
- DOVE Benchmark. Based on the ABC method which establishes benchmark performance as the level consistently attained by the top performers accounting for at least 10% of the overall population, the overall benchmark rate for the DOVE eCQM is 49.63%.

*Kiefe CI, Weissman NW, Allison JJ, Farmer R, Weaver M, Williams OD. Identifying achievable benchmarks of care: concepts and methodology. Int J Qual Health Care. 1998;10(5):443-7.

Evidence for Improving Time to Diagnosis to Reduce Morbidity And Mortality

- The relative risk of 30-day mortality following a VTE diagnosis was assessed for patients in Mass General Brigham cohort (2018-2022) with and without a delayed diagnosis (n=3591).

30-day mortality from date of diagnosis by VTE diagnosis type (delayed, not delayed)

*	Death Within 30 Days	No Death Within 30 Days	Total
Delayed Diagnosis	217 (8.3%)	2390 (91.7%)	2607
No Delayed Diagnosis	31 (3.2%)	953 (96.8%)	984
Total	248	3343	*

Summary of Evidence-base for Improving Time to Diagnosis to Reduce Morbidity And Mortality (continued)

- A total of 8.3% of patients with a delayed VTE diagnosis died within 30 days of their primary care provider (PCP) visit where VTE symptoms were reported, compared to 3.2% of patients who died whose VTE diagnosis was not delayed.
  - Individuals with a delayed VTE diagnosis had 2.64 times the risk of death within 30 days (relative risk) compared to individuals whose VTE diagnosis was not delayed.
  - Patient characteristics (demographics, Charlson comorbidity score) in patients with and without delayed diagnosis, were similar, meaning the differences in the death within 30-day of diagnosis between groups was not due to confounding (of observed characteristics).

These results suggest a link between delayed diagnosis and subsequent risk of 30-day death

DOVE eCQM Implementation

- Partnership for Quality Measurement (PQM, formally NQF) 2023: Passed
- CMS Measures Under Consideration List 2023: Rejected with following suggestions:
  - “Refine the 24-hour timeframe to account for weekends/holidays and the testing that would be required to diagnose a VTE”.
  - “Narrow list of symptoms to be more specific to lower limb venous thromboembolism (VTE) or possibly in combination with one of the more broad cardiopulmonary symptoms (syncope, tachycardia, shortness of breath, hemoptysis)”.

DOVE eCQM Implementation

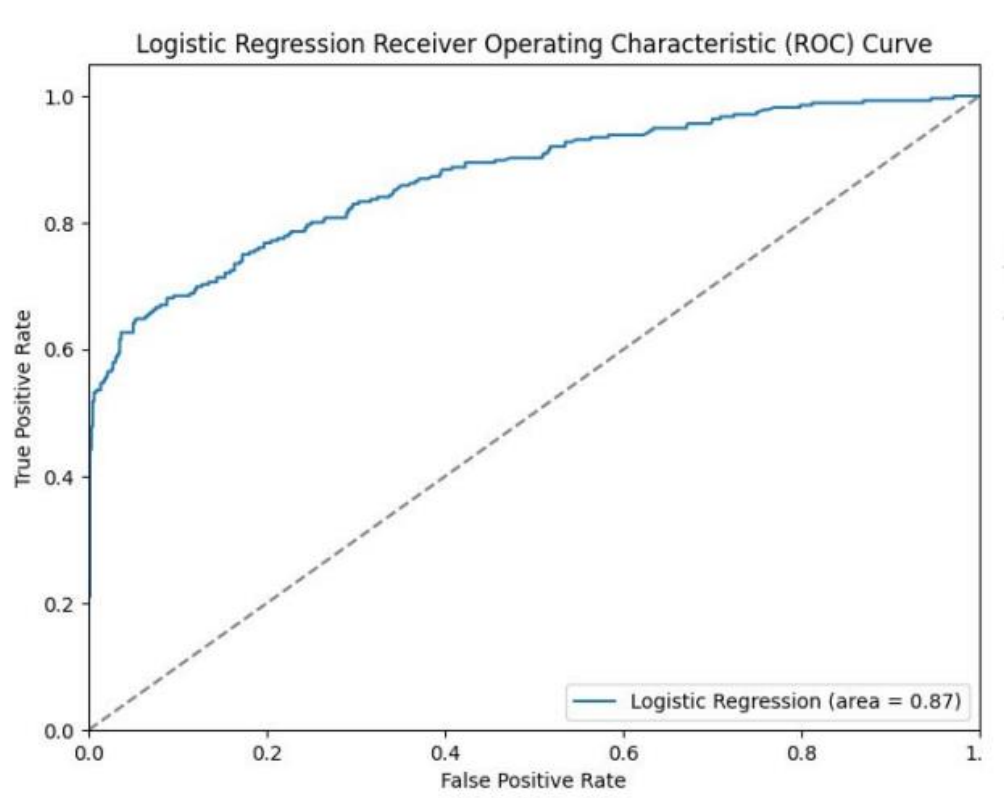
- CMS Measures Under Consideration List Response
  - Calculated DOVE rates using >72-hour time frame
  - Rationale for not narrowing list of symptoms
    - Would lower the ability of the eCQM to detect cases of delayed/missed VTE diagnoses, and artificially lower the rates of delay reported.
  - Consequences of lowered sensitivity:
    - Persistence of the problem of delayed diagnosis.
    - Missed opportunities for education of physicians who may not include VTE in their differential diagnosis.
    - Lowers the index of suspicion for VTE.
- CMS Measures Under Consideration List 2024: Passed

DOVE Rates Using >72 Hours Definition

- MGB: 68%
- Penn State Health: 69.9%

Clinical Decision Support (CDS) Preliminary Development and Model Performance

- VTE CDS Final Study Cohort:
  - Feature selection: Symptoms + Diagnoses (structured)
  - Cases: 1,936 patients confirmed with VTE
  - Controls: 5,050 patients without VTE
  - Data duration: 01/01/2016-12/31/2019
  - Models: Logistic regression, Random Forest, Decision Tree, Gradient Boosting, XGBoost, SVM, Naïve Bayes
  - AUC Range: .76 (Decision tree) - .87 (Logistic regression)



- Top 10 Predictors based on Logistic Regression

• Smoking	• Calf tenderness
• Active cancer	• Calf redness
• Spinal cord injury	• Pacemaker
• Race	• Prothrombin gene mutation
• Leg tingling	• Leg tenderness

DOVE Discussion/Conclusions

- The DOVE eCQM is a tool for primary care provider groups to quantify the rate of avoidable delayed diagnosis events
  - Includes only patients VTE symptoms in the primary care setting
  - Is automated and uses routinely collected EHR data
- Multiple testing sites; geographically distant and different EHR systems
  - Delayed VTE rates similar (>70%) across all three systems.
- Clinical decision support is needed to help identify patients at risk for VTE in the context on a primary care visit to further support VTE diagnostic accuracy and provision of guideline-based care.

Discussion/Conclusions

- AI is here and holds potential to transform healthcare.
- As frontline caregivers, nurses are crucial in leveraging AI for a more efficient and equitable healthcare system.
- Nurses need training to apply AI effectively and ethically in patient care.
- Healthcare informatics and AI projects are challenging but there are many strategies that can be used to overcome challenges:
  - Iterative approaches: Apply lessons learned
  - Engaging stakeholders: Clinicians, patients and family
  - Optimizing workflows
  - Leveraging both high and low-tech interventions
- Educating and engaging nurses in building AI innovations is essential for overcoming challenges
  - Processing & analyzing clinical data
  - Translating predictive models for CDS design
  - CDS implementation
  - Ethical and patient-centered approaches

AI will not replace nurses, BUT nurses who use AI will provide better care than nurses who do not use AI!

Project Teams

CONCERN

Columbia University:

- Sarah Rossetti, PhD, RN
- Kenrick Cato, PhD, RN
- Haomiao Jia, PhD
- Mohtashim Bokhari, PhD, Jennifer Withall, PhD, RN
- Mollie Hobensack, BSN, RN
- Temmi Daramola

MassGeneral Brigham:

- Patricia Dykes PhD, MA, RN
- Sandy Cho MPH, RN
- Graham Lowenthal BA
- Jeff Klann PhD
- Li Zhou MD PhD
- Min Jeoung Kang, RN, PhD
- Frank Chang, MSE

Pressure Injury Prevention Research Team

- Patricia C Dykes PhD, MA, RN
- Wenyu Song PhD
- Min-Jeoung Kang PhD
- David W Bates MD, MSc
- Veysel Baris PhD
- Luwei Liu MS
- Graham Lowenthal BA
- Stuart Lipsitz ScD

MGB Site Pis/Informaticists

- Paula Wolski MSN, RN
- Sandy Cho MPH, RN
- Debra Furlong RN
- Lisa Herlihy RN
- Diane Carroll PhD, RN

Skin and Wound Experts

- Tanya Martel DNP, RN
- Wadia Gilles-Fowler RN
- Jacqueline Massaro MSN, RN
- Beth Melanson RN
- Lori Morrow RN

eSTEPS

MassGeneral Brigham:

- Patricia C. Dykes, PhD, RN
- Nancy Latham, PhD, PT
- Pam Garabedian
- Stuart Lipsitz
- Hannah Rice
- Michael Sainlaire
- David Bates
- Tien Thai
- Lipika Samal
- Wenyu Song
- Min Kang

University of Texas MB

- Erin Hommel
- Biai Digbeu

DOVE

BWH

- Patricia C. Dykes, PhD, RN
- Lipika Samal MD, MPH
- David Bates MD, MSc
- Wenyu Song PhD
- Avery Pullman
- Li Zhou MD, PhD
- John Laurentiev
- Frank Chang
- Michael Sainlaire MS
- Ann Hurley
- Alexandra Frost

University of Kentucky:

- Jin Chen PhD ,
- Krissy Gray,
- Purushottam Panta,

Penn State Health:

- Shadi Hijjawi MD,
- Khalid Nawab MD, Christopher Heron MD,
- Tim Nye,
- Richard Schreiber MD,

Thank You!

PDYKES@BWH.HARVARD.EDU