



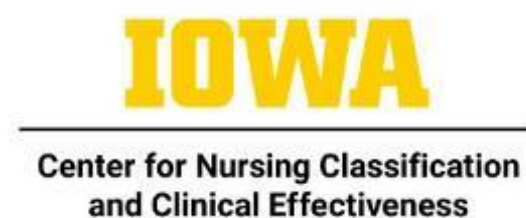
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OF MEDICINE**

Unleashing the Power of Nursing Terminology with Artificial Intelligence

A VIRTUAL WEBINAR

Wednesday, December 4, 2024
1:00pm – 5:00pm Eastern Time

Proudly sponsored by



Welcome

Barbara Redman
Chair of the FNLM Board

NLM Strategic Goals 2017-2027

- 1) Accelerate discovery and advance health through data-driven research
- 2) Reach more people in more ways through enhanced dissemination and engagement
- 3) Build a workforce for data-driven research and health

FNLM support the NLM mission through fora; webinars; celebration of extraordinary leaders in: Distinguished Medical Science, Public Service, Health Communications, Library Outreach and Nursing Informatics

Individual and Organizational Members; become a member and join a forum and work with us in support of the NLM's goals

CNE Credit Disclosures

Accreditation Status

- Emory Nursing Professional Development Center (ENPDC) is accredited as a provider of nursing continuing professional development by the American Nurses Credentialing Center's (ANCC) Commission on Accreditation.

Relevant Financial Relationships

- ENPDC has evaluated everyone who has the ability to control content of this activity (planning committee members, subject matter experts, presenters) and found no relevant financial relationships

Disclosure to Learners: Awarding Contact Hours

- To obtain contact hours participants must
 - Participate in the entire activity
 - Complete the evaluation at the end
- Scan the QR code at the end of the webinar to complete the evaluation
- Certificates will be distributed at the end of the evaluation

Part I

Nursing Terminology

Suzanne Bakken | Moderator
PhD, MS, BSN, FAAN, FACMI, FIAHSI

Presentation

Sarah Rossetti

RN, PhD, FAAN, FACMI, FAMIA, FIAHSI

Clinical Care Classification System + AI

FNLM Workshop

December 4, 2024

Sarah Rossetti, RN, PhD, FAAN, FACMI, FAMIA, FIAHSI
Associate Professor of Biomedical Informatics and Nursing
Columbia University Irving Medical Center

Noise

Signal





Motivation for using CCC

- Developed using nursing documentation
- Framework & Terminology
 - Framework
 - Organize nursing clinical documentation (e.g., the CCC care components)
 - Enable capture of subjective descriptors under the higher level CCC concepts
 - Terminology
 - Represents nursing practice and documentation of that practice
 - Can be linked with other terminology standards, making it easy to map concepts as needed

Clinical Care Classification (CCC) System as framework for understanding structure and content of EHR nursing documentation to support analyses

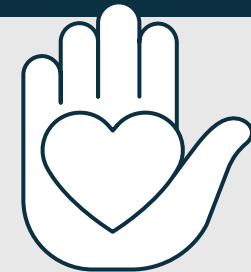
CONCERN is an Early Warning System (EWS)

KEEP PATIENTS SAFE



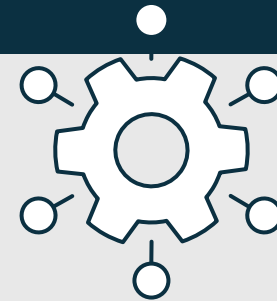
CONCERN early warning system (EWS) helps the care team keep patients safe

NURSING DOCUMENTATION MATTERS



When nurses are worried about a patient, surveillance increases and is reflected in their documentation

AI CHANGE DETECTION



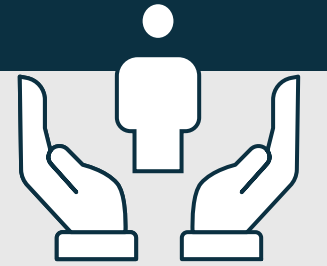
CONCERN uses artificial intelligence to detect documentation changes to generate a risk score

RIGOROUSLY STUDIED AND TESTED



RCT results show that raising care team awareness leads to earlier intervention and fewer negative outcomes

MITIGATE BIAS



CONCERN mitigates bias in clinical data using state-of-the-art approaches

CONCERN Early Warning System (EWS)



1. Helps the care team keep hospitalized patients safe

2. Relies on nursing documentation because it matters

- Nursing surveillance increases with increased nursing concern
- CONCERN uses AI to detect nursing surveillance documentation pattern changes and generate a deterioration score for display in real-time

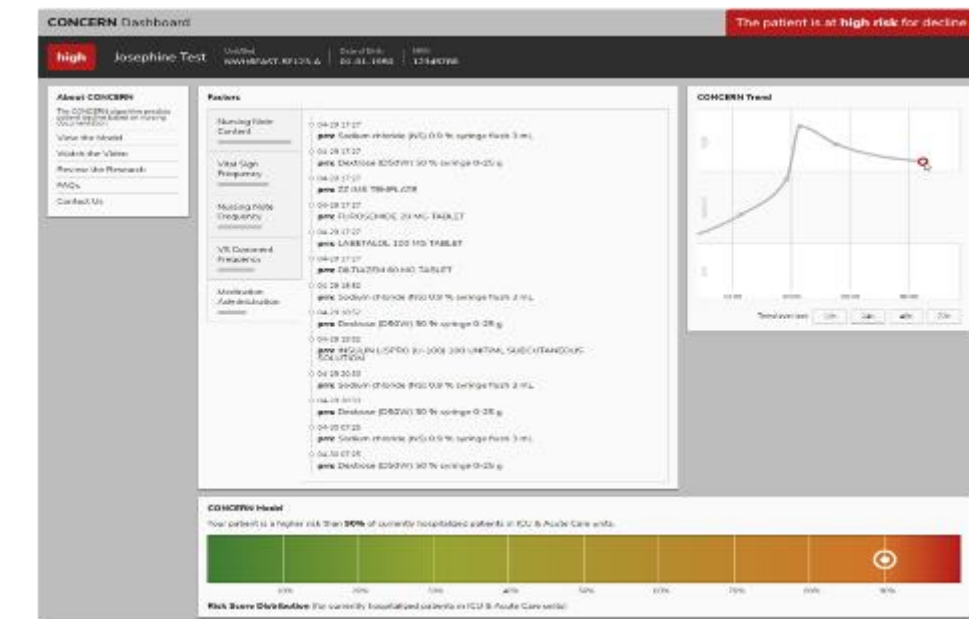
Setting	Accuracy	Precision	Recall	Logloss	AUC
ICU	0.970938	0.431373	0.594595	0.073695	0.934683
ACU	0.973341	0.813559	0.643935	0.089369	0.955982

My patients 5 Patients

Patient Name / Age / Sex	Unit/Bed	New Messages	Unacknowledged Orders	Med Due	New Rslt Flag	Reassess Pain	CONCERN Score
Concern, Martin (91yrs M)	BWH SH 9E 903-1	—	📄	🕒	📄	—	🔴*
Concern, Pal (78yrs M)	BWH 11D 75-1	—	📄	—	—	—	🟢*
Concern, Sacu (82yrs M)	NWH ICU ICU289 A	—	📄	—	📄	—	🟡*
Concern, Sicu (68yrs M)	NWH 4 USEN 4U457 A	—	📄	—	—	—	🟡*
Concern, Trans (79yrs M)	BWH 14D 75-1	—	📄	—	—	—	🟡

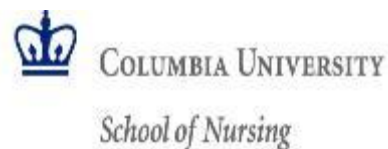
3. Has been rigorously studied and tested

- Multi-site randomized controlled trial (RCT) showed CONCERN intervention patients had:
 - 35.6% decreased risk of death (adjusted HR, 0.644; 95% CI, 0.532-0.778; P<.0001)
 - 7.5% decreased risk of sepsis (adjusted HR, 0.925; 95% CI, 0.861-0.993; P=.0317)
 - 11.2% decreased length of stay (adjusted incidence rate ratio, 0.914; 95% CI, 0.902-0.926; P<.0001)



<https://www.medrxiv.org/content/10.1101/2024.06.04.24308436v1>

4. Mitigates bias in clinical data using state-of-the-art approaches



Institute for Informatics (I²)




VANDERBILT UNIVERSITY MEDICAL CENTER

CENTER FOR COMMUNITY-ENGAGED HEALTH INFORMATICS AND DATA SCIENCE



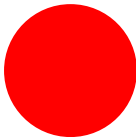
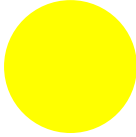
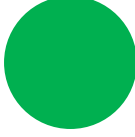
CONCERN Model Purpose

Alerts up to 2 days earlier than other EWSs (subtle patient changes usually occur well before physiological alterations in the patient)

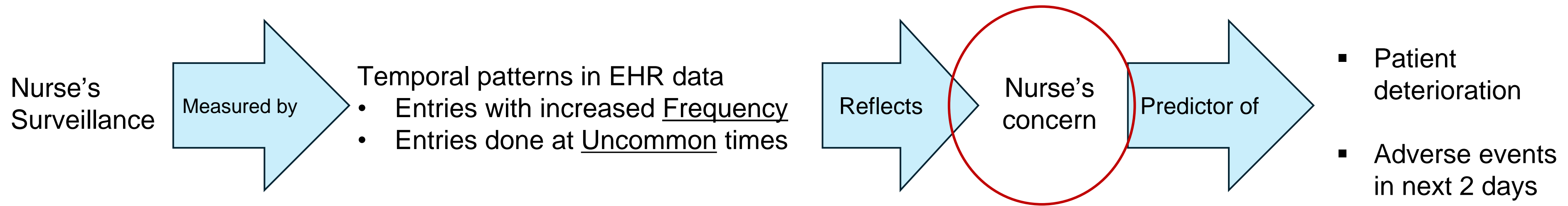
 Patients may be entering
a risky state

 Patients already
in a risky state

CONCERN Levels

-  = High: “Showing signs of deterioration”
-  = Medium: “Increased risk for deterioration”
-  = Low: “Low risk for deterioration”

Nurses' Increased Surveillance Patterns are an Early Predictor of In-hospital Deterioration



> J Am Med Inform Assoc. 2021 Jun 12;28(6):1242-1251. doi: 10.1093/jamia/ocab006.

Healthcare Process Modeling to Phenotype Clinician Behaviors for Exploiting the Signal Gain of Clinical Expertise (HPM-ExpertSignals): Development and evaluation of a conceptual framework

Sarah Collins Rossetti^{1 2}, Chris Knaplund¹, Dave Albers^{1 3}, Patricia C Dykes^{4 5}, Min Jeoung Kang^{4 5}, Tom Z Korach^{4 5}, Li Zhou^{4 5}, Kumiko Schnock^{4 5}, Jose Garcia⁴, Jessica Schwartz², Li-Heng Fu¹, Jeffrey G Klann⁵, Graham Lowenthal⁴, Kenrick Cato²

Affiliations + expand

PMID: 33624765 PMID: PMC8200261 DOI: 10.1093/jamia/ocab006

Am J Crit Care. Author manuscript; available in PMC 2013 Sep 12.

Published in final edited form as:

Am J Crit Care. 2013 Jul; 22(4): 306-313.

doi: 10.4037/ajcc2013426

Relationship Between Nursing Documentation and Patients' Mortality

Sarah A. Collins, RN, PhD, Kenrick Cato, RN, BSN, David Albers, PhD, Karen Scott, MD, MPH, Peter D. Stetson, MD, MA, Suzanne Bakken, RN, PhD, and David K. Vawdrey, PhD

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PMCID: PMC3771321

NIHMSID: NIHMS505735

PMID: 23817819

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Multisite Pragmatic Cluster-Randomized Controlled Trial of the CONCERN Early Warning System

Sarah C. Rossetti, Patricia C. Dykes, Chris Knaplund, Sandy Cho, Jennifer Withall, Graham Lowenthal, David Albers, Rachel 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

doi: https://doi.org/10.1101/2024.06.04.24308436

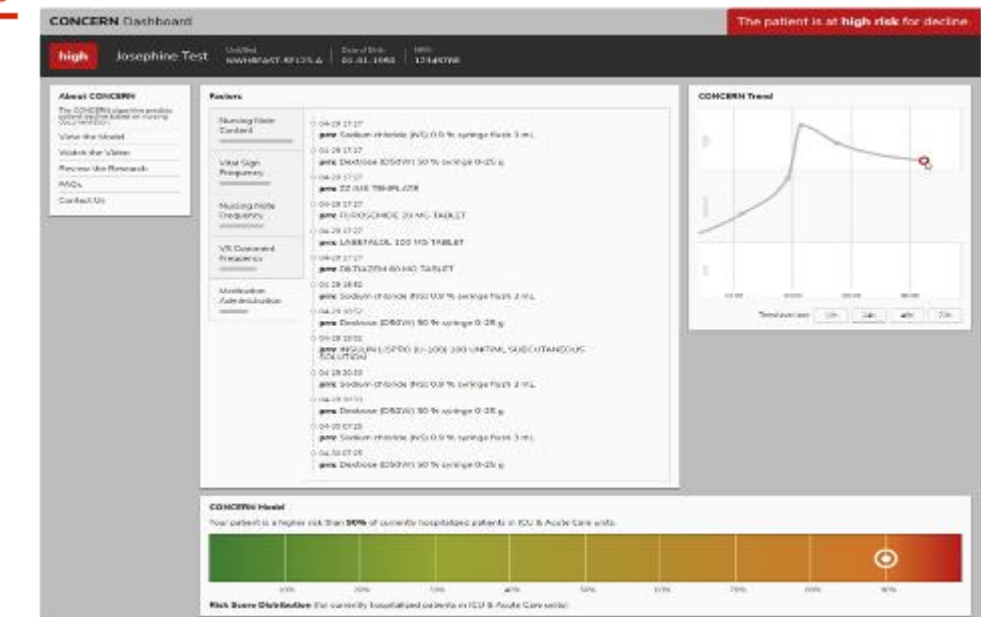


Clinical Care Classification (CCC) System as framework for classifying “nursing concern” concepts



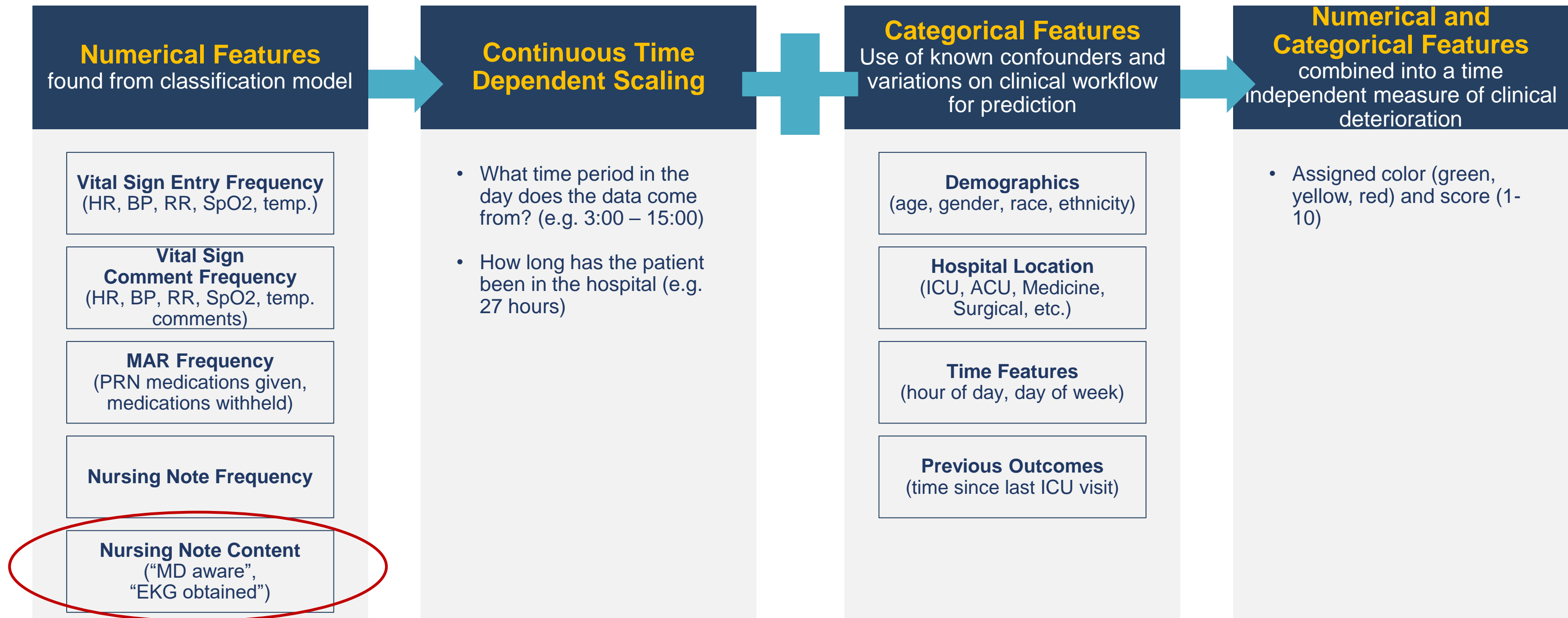
My patients 5 Patients

Patient Name / Age / Sex	Unit/Bed	New Messages	Unacknowledged Orders	Med Due	New Rst Flag	Reassess Pain	CONCERN Score
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Concern, Sacu (82yrs M)	NWH ICU289 A	—	📄	—	🚫	—	🟡*
Concern, Sicu (68yrs M)	NWH 4 USEN 4U457 A	—	📄	—	—	—	🟡*
Concern, Trans (79yrs M)	BWH 14D 75-1	—	📄	—	—	—	🟡*



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CONCERN Back-End Engine (using FHIR)



Methods to extract “nurses concern” from narrative nursing notes

Motivation for using Clinical Care Classification (CCC) System

Int J Med Inform. 2020 January ; 133: 104016. doi:10.1016/j.ijmedinf.2019.104016.

Identifying Nurses’ Concern Concepts about Patient Deterioration Using a Standard Nursing Terminology

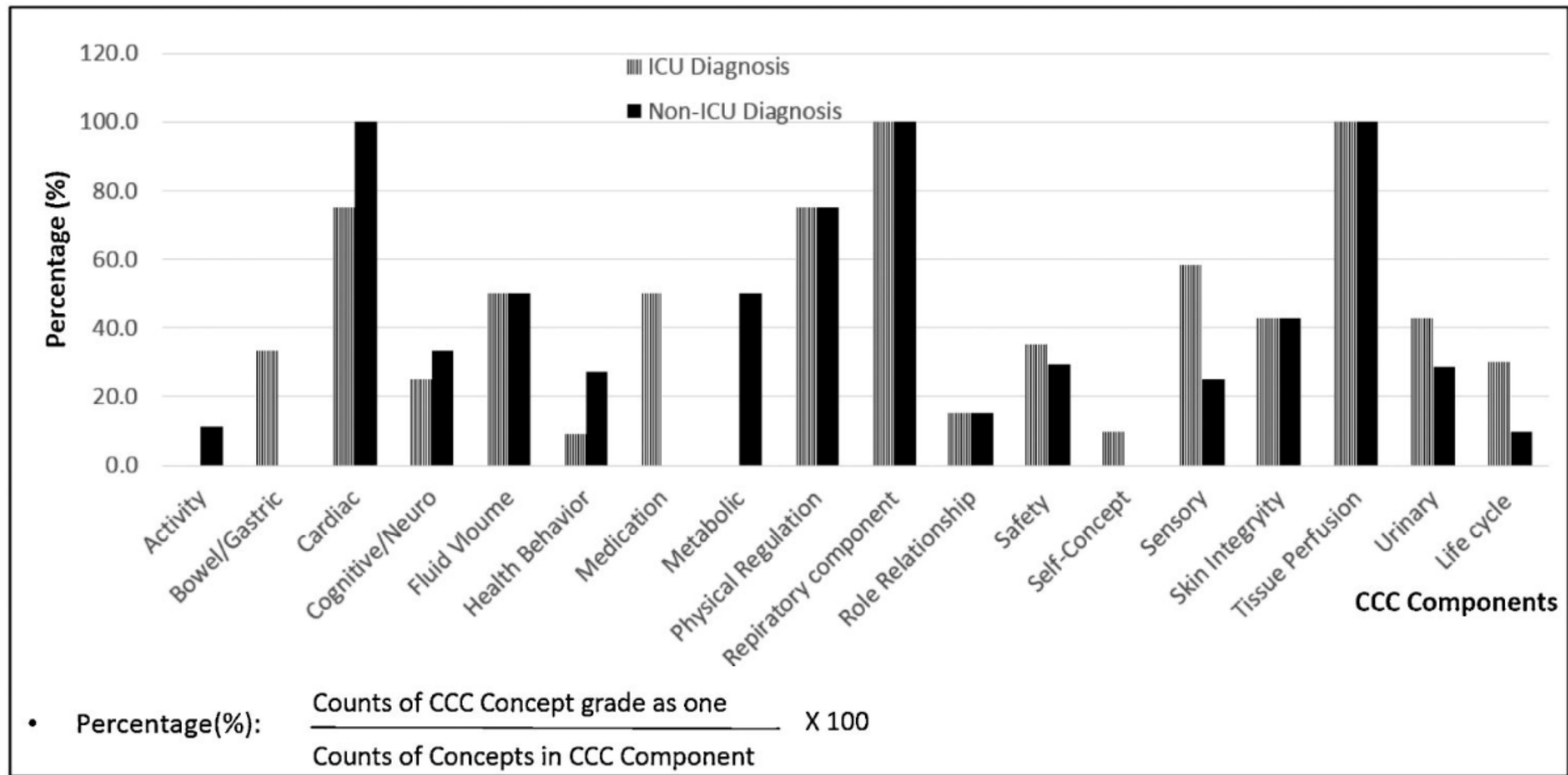
Min-Jeoung Kang, RN, PhD^{a,b}, Patricia C. Dykes, RN, PhD^{a,b}, Tom Z. Korach, MD^{a,b}, Li Zhou, MD, PhD^{a,b}, Kumiko O. Schnock, RN, PhD^{a,b}, Jennifer Thate, RN, PhD^c, Kimberly Whalen, RN, MS^d, Haomiao Jia, PhD^{e,f}, Jessica Schwartz, RN, BSN^f, Jose P. Garcia, BA^{a,b}, Christopher Knaplund, MPhil^f, Kenrick D. Cato, RN, PhD^f, Sarah Collins Rossetti, RN, PhD^{f,g}

^aDivision of General Internal Medicine and Primary Care, Brigham & Women’s Hospital, Boston, USA;

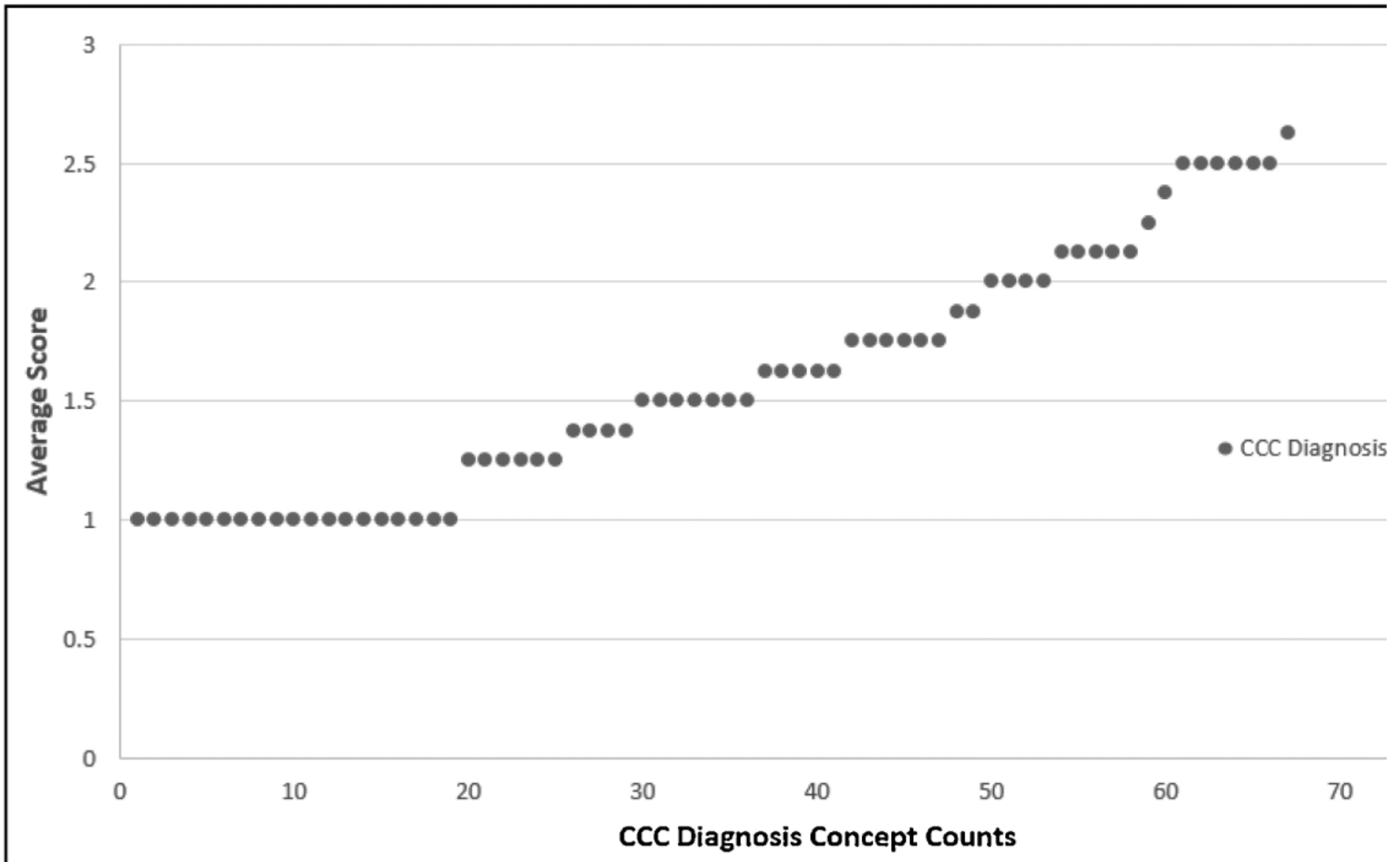
^bHarvard Medical School, Boston, USA;

Methods to extract “nurses concern” from notes

1. Group consensus meetings with nurse SMEs
 - Graded CCC system concepts by level of concern to identify concepts that may indicate “nurse’s concern” in a note
2. Curation of fundamental entities and terms related to nurses’ concerns by SMEs
 - Built fundamental lexicon with selected CCC concepts, entities and seed terms

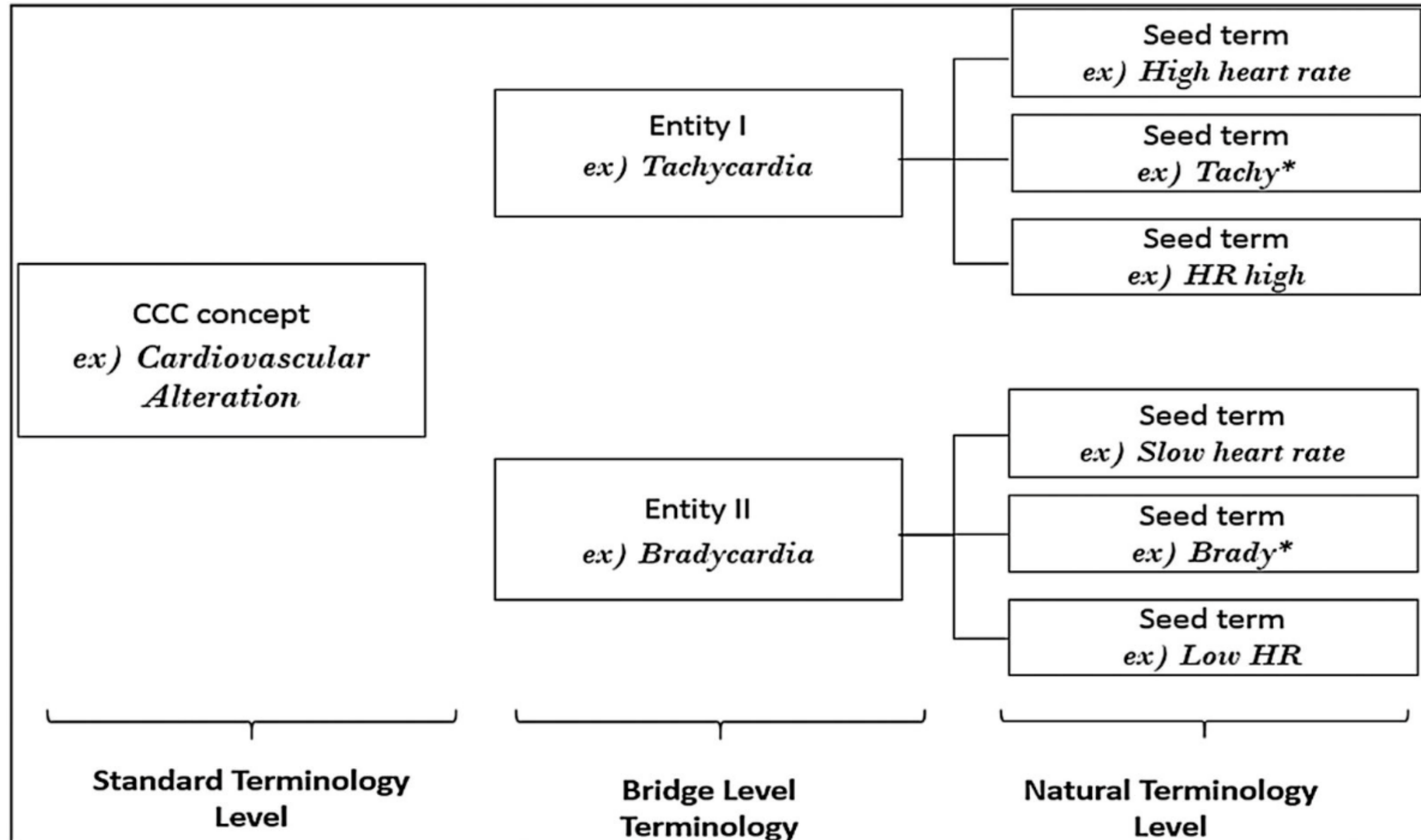


**Expert Nurses
Scoring of CCC
concepts that
may indicate
concerning
patient state
stratified by
setting**



Distribution of CCC concepts on scale of concern (0 no concern to 3 highest concern)

- Average score for 67 CCC diagnosis concept; The 67 concepts were scored as grade c



Example Structure of terminology set for NLP of Nursing Notes

Tool for Expert Nurse Annotations of Nursing Notes for Concerning Concepts

The screenshot displays the WebAnno 2.0 web application interface. At the top, a red header contains the word "Annotation" in white. Below it, a navigation bar includes "WebAnno | Home_" on the left and "User: richard | Log out" on the right. The main toolbar is divided into four sections: "Document" with icons for Open, Prev., Next, Export, and Settings; "Page" with icons for First, Prev., Go to (showing page 1), Next, and Last; "Help" with a "Guidelines" button; and "Workflow" with a "Done" button. The document path "project/sample_romance.txt" is shown, along with the text "showing 1-3 of 3 sentences". The text area contains three sentences with semantic annotations. Sentence 1: "That day, John came to visit us and propose to Mary with a diamond ring." Sentence 2: "When Fred heard of this later in the pub, he was heartbroken." Sentence 3: "He never looked at John again." Annotations include "male | John", "female | Mary", and "male | Fred" in blue boxes. Red arrows labeled "love" connect John to Mary and Fred to John. Red arrows labeled "hate" connect Mary to Fred and Fred to Mary.

(WebAnno 2.0 Tutorial Screen Shot YouTube, <https://youtu.be/72aaYFmKWM4?feature=shared>, 2024)

Hemodynamic and respiratory section of the entity and seed term matrix

Group Type	Entities	Seed Terms (Terms for searching Term Expansion)	CCC Core Concepts		
			Blood Pressure Alteration	Cardiovascular Alteration	Cardiac Output Alteration
Hemodynamic and Respiratory	Abnormal Blood Pressure	abnormal bp; abnormal blood pressure; labile bp; labile blood pressure	Y	Y	Y
	Hypertension	high blood pressure; HTN; high BP; HTN, HT	Y	Y	Y
	Hypotension	low blood pressure; hypo; low BP; HoTN, low bp, low blood pressure	Y	Y	Y
	Abnormal CVP	low CVP, high CVP, abnormal CVP	Y	Y	Y
	Abnormal Arterial line pressure	abnormal arterial pressures, abnormal abp, abnormal aline, high aline pre, aline pressure, high abp, high arterial blood pressure	Y	Y	Y
	Abnormal pulse rate and rhythm	palpate pulse pressure; +1 pedal pulses; +2 pedal pulses; +3 pedal pulses; +1 pulses; +2 pulses; +3 pulses; +0 pulses; diminished pulses; afib, irregular af, irregular a. fib, irregular a. fib, irregular a-fib, hr irregular afib	Y	Y	Y
	arrhythmias	abnormal heart rate; abnormal heart rhythm, rhythm disturbance; dysrhythmia	Y	Y	Y
	Tachycardia	high heart rate; rapid heart rate; tachy; tachycardic; tachy, high heart rate, HR high, tachycardic; PSVT; SVT	Y	Y	Y
	Bradycardia	slow heart rate; brady; low HR; Sinus brady	Y	Y	Y


Seed terms

- The natural language terms written by nurses in notes.
- The children of entities

	ICU		Non- ICU	
CCC Component	Medicine (MICU)	Surgery (SICU, Trauma ICU)	Medicine	Surgery
Bowel/ Gastric	<ul style="list-style-type: none"> • Diarrhea 	<ul style="list-style-type: none"> • Diarrhea • Fecal Impaction • Gastrointestinal Alteration 	–	–
Physical Regulation	<ul style="list-style-type: none"> • Autonomic Dysreflexia • Hyperthermia • Hypothermia • Thermoregulation Impairment • Intracranial Adaptive Capacity Impairment 	<ul style="list-style-type: none"> • Autonomic Dysreflexia • Hyperthermia • Hypothermia • Thermoregulation Impairment • Intracranial Adaptive Capacity Impairment • Infection 	–	–
Skin Integrity	<ul style="list-style-type: none"> • Latex Allergy Response • Peripheral Alteration 	<ul style="list-style-type: none"> • Latex Allergy Response • Peripheral Alteration • Skin Incision 	<ul style="list-style-type: none"> • Skin Integrity Impairment • Latex Allergy Response 	<ul style="list-style-type: none"> • Skin Integrity Impairment • Latex Allergy Response • Peripheral Alteration
Urinary Elimination	<ul style="list-style-type: none"> • Urinary Elimination Alteration • Renal Alteration 	<ul style="list-style-type: none"> • Urinary Elimination Alteration • Renal Alteration • Urinary Retention 	<ul style="list-style-type: none"> • Urinary Elimination Alteration 	<ul style="list-style-type: none"> • Urinary Elimination Alteration • Urinary Retention

Nursing concern CCC concepts by Medicine and Surgery Units

Average Score	CCC Component (Counts)	CCC Concepts
1.00	Cardiac(3)	Blood Pressure Alteration
		Cardiac Output Alteration
		Cardiovascular Alteration
	Cognitive/Neuro(2)	Confusion
		Cerebral Alteration
	Respiratory(3)	Breathing Pattern Impairment
		Gas Exchange Impairment
		Respiration Alteration
	Role Relationship(2)	Communication Impairment
		Verbal Impairment
	Sensory(2)	Acute Pain
		Visual Alteration
	Safety(2)	Suicide Risk
		Violence Risk
	Fluid Volume(1)	Fluid Volume Deficit
Tissue Perfusion(1)	Tissue Perfusion Alteration	
Physical Regulation(3)	Hyperthermia	
	Hypothermia	
	Intracranial Adaptive Capacity Impairment	
1.25	Coping(1)	Airway Clearance Impairment
	Physical Regulation(1)	Autonomic Dysreflexia
	Safety(2)	Injury Risk
		Self-mutilation Risk
	Fluid Volume(1)	Fluid Volume Excess
	Urinary Elimination(1)	Urinary Elimination Alteration
1.37	Fluid Volume(1)	Fluid Volume Alteration
	Physical Regulation(1)	Infection
	Skin Integrity(1)	Peripheral Alteration
	Cognitive/Neuro (1)	Thought Processes Alteration



Nursing Concern Core Concepts organized within CCC Framework

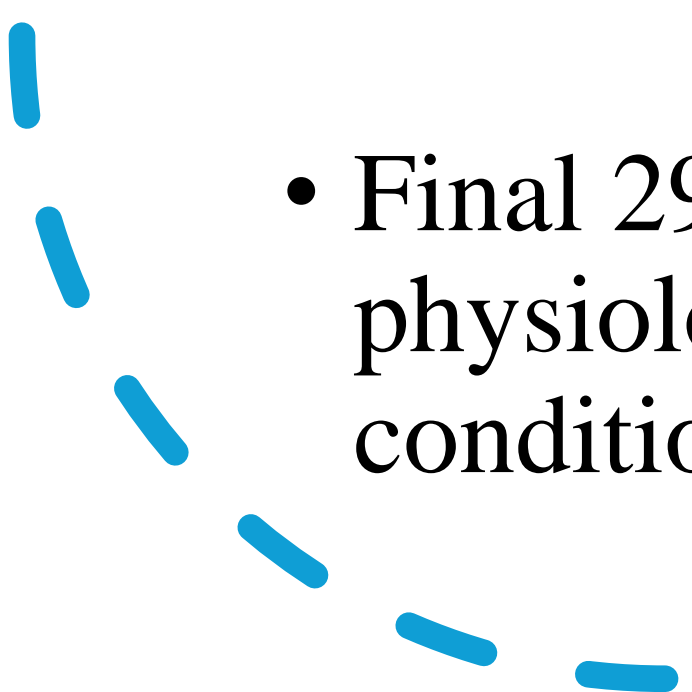
- CCC Concepts, Entities and Seed terms organized into 5 group categories

- Total of 111 unique entities and 586 unique seed terms generated

Group Type	CCC core concepts	Counts of Entities	Counts of Seed Terms
Hemodynamic and Respiratory	Blood Pressure Alteration	46	201
	Cardiovascular Alteration		
	Cardiac Output Alteration		
	Fluid Volume Deficit		
	Fluid Volume Excess		
	Fluid Volume Alteration		
	Breathing Pattern Impairment		
	Respiration Alteration		
	Gas Exchange Impairment tissue Perfusion Alteration		
	Hypothermia		
	Hyperthermia		
Neurology	Cerebral Alteration	15	111
	Confusion		
	Thought Processes Alteration		
	Autonomic Dysreflexia		
	Intracranial Adaptive Capacity		
	Impairment		
Safety Precaution	Violence Risk	12	96
	Suicide Risk		
	Self-mutilation Risk		
	Injury Risk		
Communication	Verbal Impairment	5	25
	Communication Impairment		
Not Otherwise Grouped	Infection	3	12
	Acute Pain	17	79
	Visual Alteration	1	10
	Peripheral Alteration	6	18
	Urinary Elimination iteration	5	30
	Airway Clearance Impairment	1	4



Summary: CCC for Mapping Nurses Concern

- Identified entities used in NLP process as part of our real-time CONCERN Early Warning Score
 - Differences in CCC mapped nursing concern concepts between clinical settings and unit types (surgical vs medicine)
 - Final 29 CCC core concepts were closely related to patient physiological status and are common indicators of inpatient condition across settings and unit types
- 

Current & Future Work

- Use the CCC mapped nursing concern concepts as framework to conduct chart reviews for explainability of CONCERN EWS



Identifying Excess Documentation Burden using CCC and AI

EndBurden Study, Agency for Healthcare Research and Quality (AHRQ): R01HS028454



Special acknowledgment: Hao Fan, PhD Student, Washington University St Louis for leading development of Automated for Concept Mapping from Hierarchical Flowsheet Field Names to Clinical Care Classification Terminology System as part of EndBurden Study

- Health System A
 - 3,230 flowsheet measures
 - 641 flowsheet groups
 - 282 flowsheet templates



- Health System B
 - 9,499 flowsheet measures
 - 1,836 flowsheet groups
 - 727 flowsheet templates

Nursing Flowsheets - The 5 V's of Big Data

- Volume
- Velocity
- Variety
- Veracity
- Value

Cohort of ~160,000 patients
>170 million Flowsheet Observations!

Test, Cristina - Sunrise Clinical Manager

98765 43 21 / 00077777 777
MBS-8327-01
Isom, Robert
DOB: 04/10/1980
28y (10-Apr-1980) Female
Admit Date: 09-Oct-2007

1) Vital Signs Flowsheet (ICU), From 20-Jan-2009 to 21-Jan-2009

Chart Selection:	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009	21-Jan-2009
WEIGHT															
Weight	kg	76.3													
Dry Weight (kg)	kg														
Height	cm														
BMI (Metric Calculation)	kg/m ²														
TEMPERATURE															
Temperature	degrees F		99.7										99.1		
Device Temp	degrees C														
HEART RATE															
Heart Rate	Rate	80	82	79	111		113		90				88	82	86
RESPIRATORY															
Resp Rate, patient	min														
SpO2 (Pulse Ox)	%	100	100	100	100	98	100	100	100	99	100	100	100	100	98
NON INVASIVE BLOOD PRESSURE															
Noninvasive BP	NBP Systolic NBP Diastolic NBP Mean	111/70 83	128/78 94	108/68 81	85/36* 52	97/56 69	96/50 65	100/63 75	98/58 71	105/66 79	100/62 74	112/64 80	102/58 72	99/52 67	98/50 66

	Admission (Current) from 3/19/2017 in BWH 3B		
	6/20/17	7/24/17	1/10/18
	1400	1500	0900
Pressure Ulcer Right Coccyx Suspected deep tissue injury			
Pressure Ulcer Properties	Date First Assessed/Time First Assessed: 05/15/17 0841 Is this a		
Dressing Status	Old drainage	Clean, Dry, Intact	
Dressing Change			
Dressing Type			
Wound Bed Assessment			
Periwound Assessment			
Drainage Amount			
Drainage Description			
Cleansing			
Skin Barrier			
Treatments			
Packing Description			
Packing Amount			
State of Healing			
Red granulation tissue %			
Yellow fibrinous tissue/slough %			
Black Eschar Tissue %			
Shape			
Wound Length (cm)			
Wound Width (cm)			

Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	SpO2
Value	95
<i>*Also called flowsheet field or flowsheet data element</i>	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	SpO2
Value	95
<i>*Also called flowsheet field or flowsheet data element</i>	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs Simple Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	SpO2
Value	90
<i>*Also called flowsheet field or flowsheet data element</i>	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
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Structure Hierarchy	Example
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Value	90
<i>*Also called flowsheet field or flowsheet data element</i>	

FlowsheetMeasure	Template	Frequency	Encounter
PULSE	IP VITALS SIMPLE	1,843,640	106,846
	IP VITALS ICU	1,629,805	27,220
	IP SIMPLE ASSESSMENT	306,243	42,473
	IP COMPLEX ASSESSMENT	45,754	9,715
	INTRA OP SEDATION DOCUMENTATION	688	315
R PAIN ASSESSMENT	IP VITALS SIMPLE	2,507,263	109,320
	IP VITALS ICU	646,157	24,998
R PAIN SCORE	IP VITALS SIMPLE	2,008,193	103034
	IP VITALS ICU	457,195	21680
	INTRA OP SEDATION DOCUMENTATION	50	29
TEMPERATURE	IP VITALS SIMPLE	785,403	92500
	IP VITALS ICU	531,713	20218
	INTRA OP SEDATION DOCUMENTATION	44	40

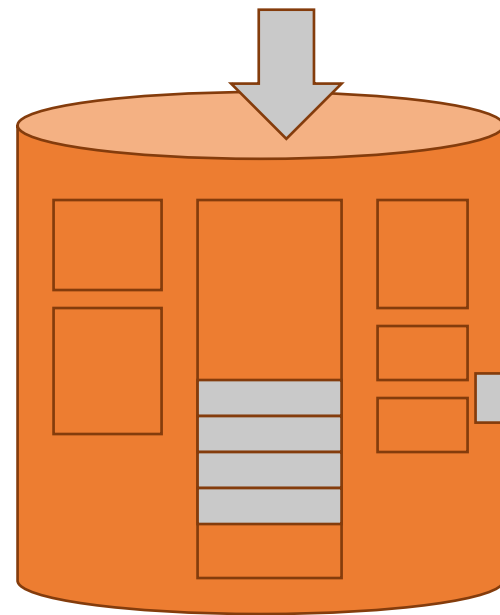
2 years of work

Manual Harmonization of Flowsheets Data Concepts Across 2 Sites

BUCKET 1	BUCKET 2-SubBucket	PHS_Group Display Name	PHS_Row Display Names	PHS_Template Full Name	NYP_FSNAME	NYP_ITEM_NAME	NYP_ITEM_DESCRIPTION
Cardiac	Cardiac	Cardiac	Ectopy	IP SIMPLE ASSESSMENT	1) Vital Signs Flowsheet	vs_hr_ectopy	vs_hr_ectopy
Cardiac	Cardiac	Cardiac	Ectopy Frequency	IP SIMPLE ASSESSMENT	1) Vital Signs Flowsheet	vs_hr_ectopy_freq	Ectopy freq
Cardiac	Cardiac	Cardiac	Pulse	IP SIMPLE ASSESSMENT	1) Vital Signs Flowsheet	vs_vasc_pulse	Pulses
Cardiac	Cardiac	Cardiac	Clinical Monitor Alarms	IP SIMPLE ASSESSMENT	3) Respiratory Flowsheet	resp_check_alaramon	Alarms On
Cardiac	Cardiac	Cardiac	PR Interval	IP SIMPLE ASSESSMENT	5) Treatment Flowsheet	fs_tx_bedside_procs_12lead	12 Lead EKG
Cardiac	Cardiac	Cardiac	QRS Interval	IP SIMPLE ASSESSMENT	5) Treatment Flowsheet	fs_tx_bedside_procs_12lead	12 Lead EKG
Cardiac	Cardiac	Cardiac	QT Interval	IP SIMPLE ASSESSMENT	5) Treatment Flowsheet	fs_tx_bedside_procs_12lead	12 Lead EKG
Cardiac	Cardiac	Cardiac	QTc Interval	IP SIMPLE ASSESSMENT	5) Treatment Flowsheet	fs_tx_bedside_procs_12lead	12 Lead EKG
Cardiac	Cardiac	Cardiac	Cardiac Additional Assessments	IP SIMPLE ASSESSMENT	5) Treatment Flowsheet	fs_tx_cardiac_monitor	Cardiac Monitoring
Cardiac	Cardiac	Cardiac	Heart Sounds	IP SIMPLE ASSESSMENT	6) ICU Assessments	as_icu_cv_heart_sounds	Heart Sounds
Cardiac	Cardiac	Cardiac	Cardiac Rhythm	IP SIMPLE ASSESSMENT	6) ICU Assessments	as_icu_cv_rhythm	Rhythm
Cardiac	Cardiac	Cardiac	Cardiac Signs/Symptoms	IP SIMPLE ASSESSMENT	6) M/S Assessment	as_icu_cv_chest_pain	Chest Pain
Cardiac	Cardiac	Cardiac	Anginal Symptoms	IP SIMPLE ASSESSMENT	6) M/S Assessment	as_icu_cv_chest_pain	Chest Pain

2+ years of work to harmonize data and build CONCERN database across 2 sites...
...manual harmonization is not scalable process for large multi-site work

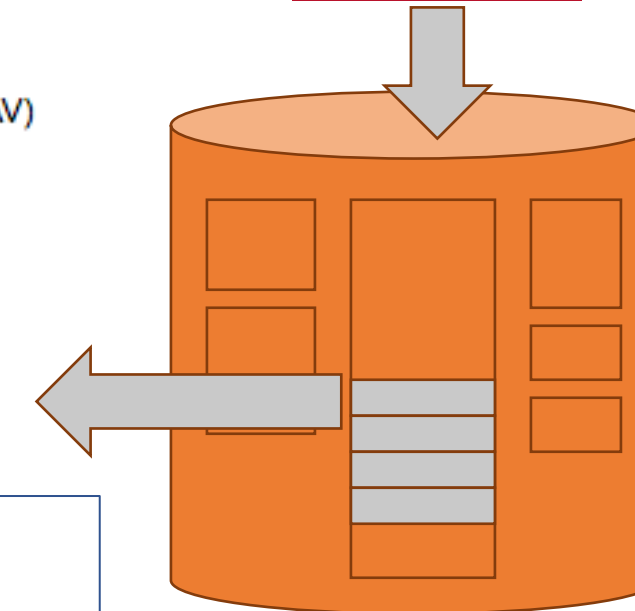
NewYork Presbyterian Health System Data



i2b2 Data Model

- CONCERN Flowsheets v2
 - Assessment (IP SIMPLE ASSESSMENT)
 - Audit C/Tobacco (PHS AUDIT C NAV)
 - Braden Scale Assessment (PHS IP BRADEN SCORE/SKIN NAV)
 - Complex Assessment (IP COMPLEX ASSESSMENT)
 - Daily Cares/Safety (IP DAILY CARES/SAFETY)
 - Intake/Output (IP INTAKE/OUTPUT)
 - Intra Procedure Sedation (INTRA OP SEDATION DOCUMENTATION)
 - IV Line Assessment (IP IV ASSESSMENT)
 - Occupational Performance (T PHS IP OT OCCUPATIONAL PERFORMANCE NAV)
 - Psycho/Social/Spiritual (PHS PSYCHOSOCIAL INA NAV)
 - PT Ranking (PHS IP PT RANKING)
 - QIDS-C (QUICK INVENTORY OF DEPRESSIVE SYMPTOMATOLOGY)
 - Screenings (SCREENINGS)
 - Vital Signs (IP VITALS SIMPLE)
 - Vital Signs Complex (IP VITALS ICU)
- CONCERN Notes
 - Assessment & Plan Note
 - Family Meeting
 - H&P
 - Nursing Note
 - Nursing Summary
 - Plan of Care
 - Procedures
 - Progress Notes
 - Rapid Response Documentation
 - Significant Event
 - Transfer / Sign Off Note
 - Transfer of Care

Mass General Brigham Data

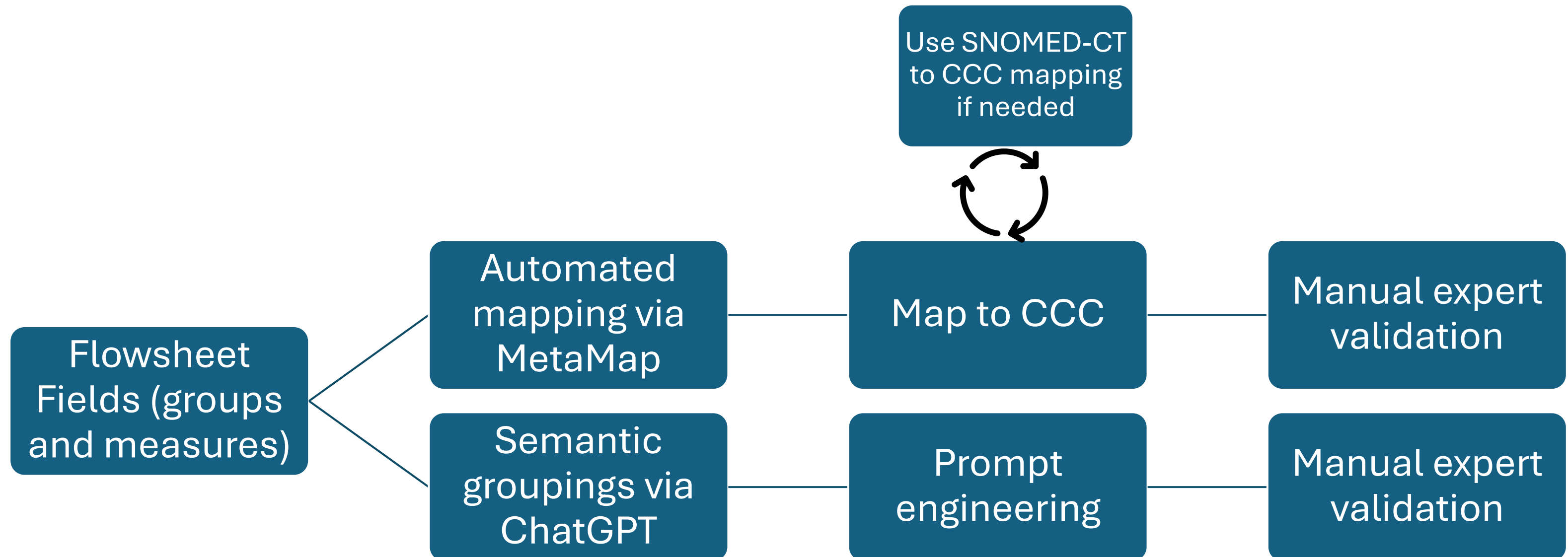


i2b2 Data Model

15 templates
277 groups
85 LDAs
1893 rows
1212 value sets
...30,207 database rows!

Automated Concept Mapping Pipeline

- Motivation:
 - To better understand the EHR data structure via the CCC framework
 - To speed up data element mapping and data harmonization in multi-site studies



Core Documentation Was Grouped Per Clinical Scenarios

Using ChatGPT for Grouping

>>>

Iterative Rounds (Examples)

(Measure names)

This is a list of EHR measures.

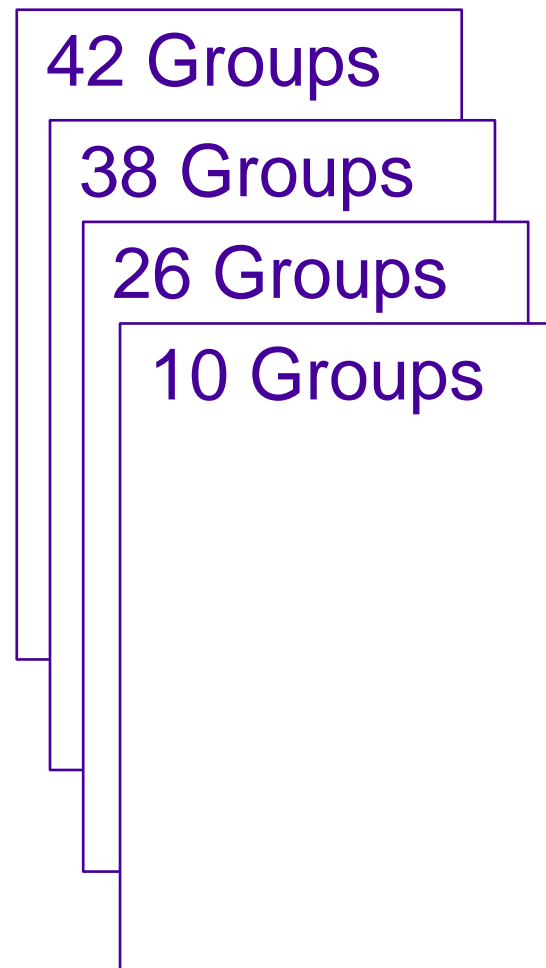
Can you group them based on their clinical semantics?

(1) Give me the number of groups in total and the group names first.

(2) I want at most 10 groups. Give me the group names first.

Do not include any specific measures.

Feel free to expand abbreviations if any.



26 Groups

Volume and Fluids
Assessment and Monitoring
Interventions and Treatments
Vital Signs
Dressings and Wound Care
Oxygenation and Respiration
Urine and Bowel
Pain Assessment
Tube Feeding and Nutrition
Cardiac Function
Drainage and Secretions
Neurological Assessment
Patient Activity and Positioning
Medication and Intake
Skin Assessment and Integrity

Tube and Line Status
Gastrointestinal Assessment
Behavioral and Psychological
Assessment
Safety and Precautions
Fall Risk Assessment
Comfort and Pain
Management
Mobility and Ambulation
Diabetes Management
Seizure Precautions
Comfort Rounds and
Environmental Interventions
Neurological Monitoring

10 Groups

Vital Signs
Fluid Management
Wound Care
Cardiac Function
Respiratory Function

Pain Assessment
Neurological Assessment
GI/GU Assessment
Activity and Mobility
Surgical and Procedural

CCC Mapping Results to Flowsheets from 1 Hospital

80% of the flowsheet
group-measure pairs were
mapped to CCC

When mapping flowsheet
measures only coverage
was much lower (~10%)

Mapping coverage scores
can differentiate readily
mapped concepts from
those in need of manual
mappings for data
harmonization across sites

Specific take-aways from CCC Mapping



CCC concepts have judgments that relate to nursing diagnoses and interventions while flowsheet measures may be neutral

'Noncompliance of Medication Regimen (Medication Nonadherence {CCC}) [Finding]'

Flowsheet group name: 'patient medications'



Pros/Cons to specific-purpose terminology systems (CCC) vs general-purpose systems (SNOMED-CT US version)

Mismatches vs ambiguity/irrelevance

- Flowsheet group names have information about structure and context of flowsheets but in automated mapping can introduce too much ambiguity or irrelevance
- Flowsheet measures if mapped at too high level of granularity lose details of action E.g., 'incision intact staples removed' vs 'Incision Care (Incision care {CCC}) [Therapeutic or Preventive Procedure]



CCC latest 2.5 version from 2004

Flowsheets have newer treatments that are not included such as 'therapeutic hypothermia' and 're-warming phase'



Mapping from SNOMED-CT back to CCC not very efficient

Mapping was originally developed to align CCC to SNOMED-CT
Low rates of SNOMED-CT concepts included overall in the CCC to SNOMED-CT mapping

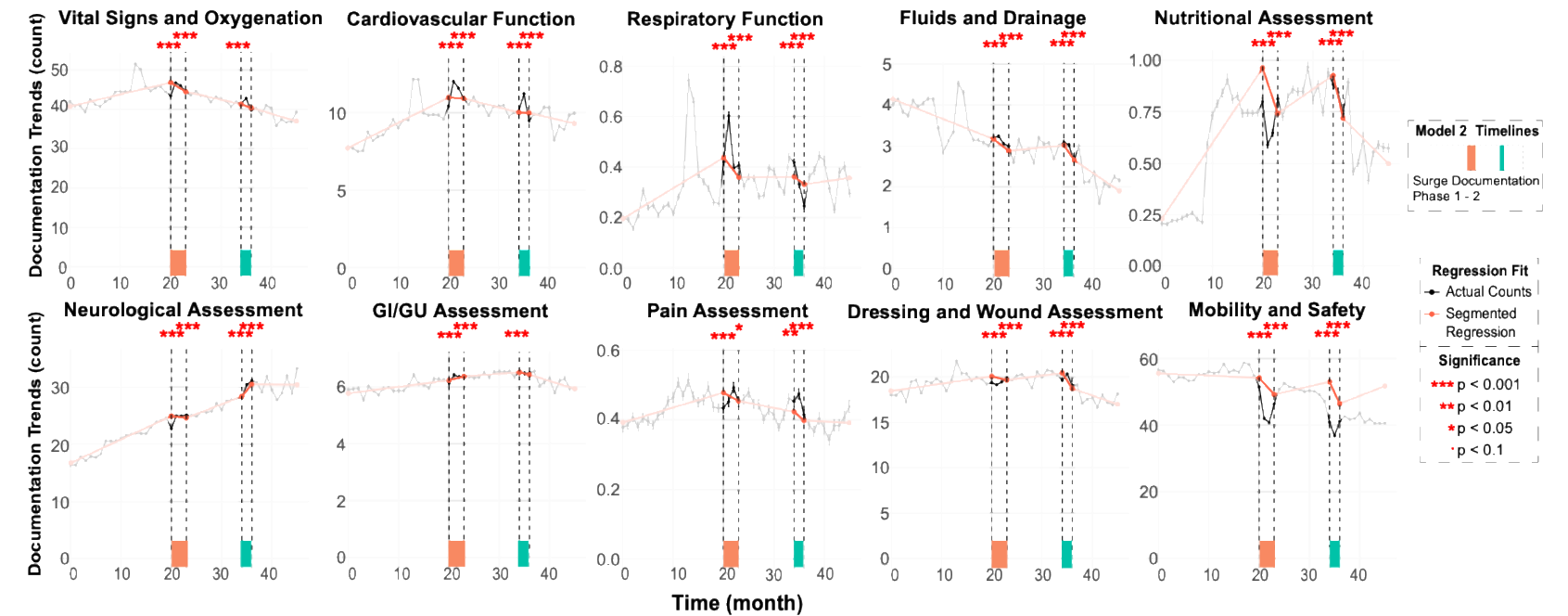
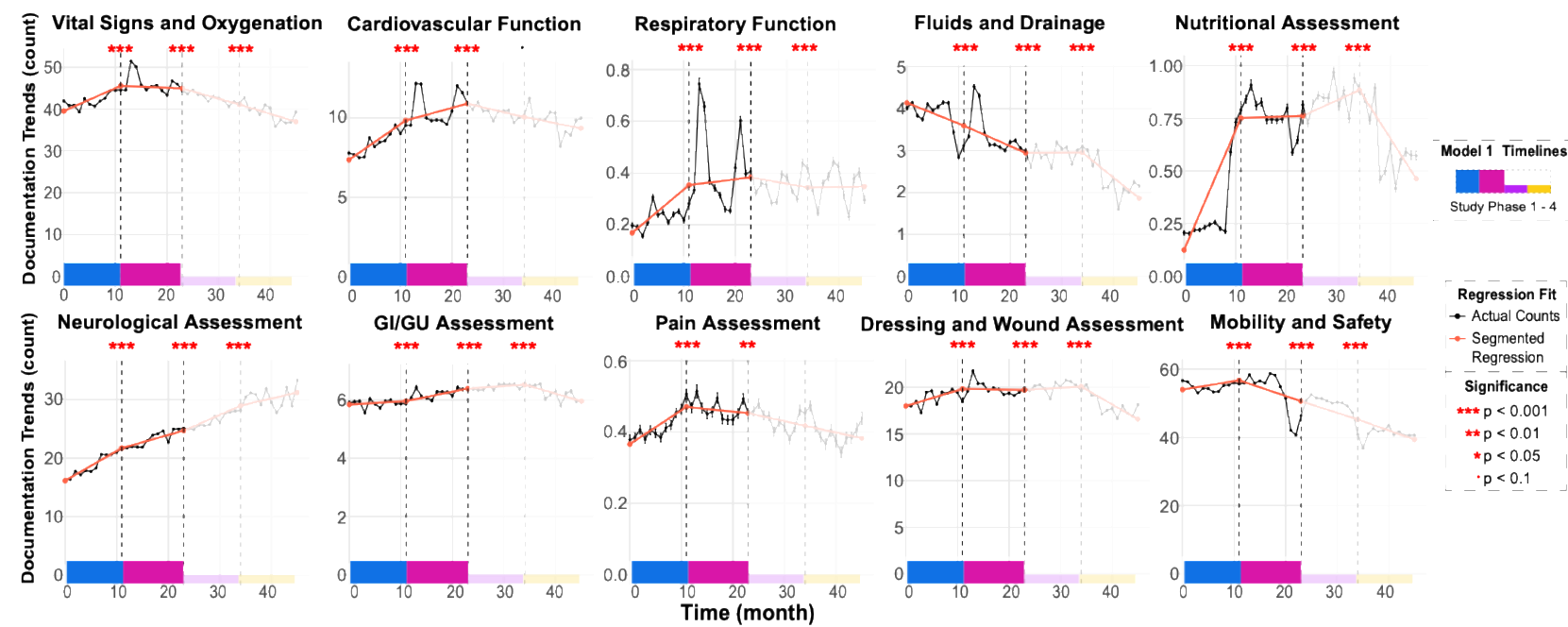
Illuminated disorganized flowsheet structure

- CCC helped better understand
 - Complex structure of EHR flowsheets
 - Convoluted combinations to facilitate nurse EHR workflow
 - Process large volume of flowsheet data

Nurses prioritize “essential documentation” when complexity and acuity is high, such as during COVID-19 pandemic

Most Documentation Frequencies **Increased ↗** During the Pandemic

Most Documentation Frequencies **Decreased ↘** with Relaxation Policies



Essential Documentation

Non-Essential Documentation

Vital Signs and Oxygenation

Cardiovascular Function

Respiratory Function

Fluids and Drainage

Nutritional Assessment

Mobility and Safety

Neurological Assessment

GI/GU Assessment

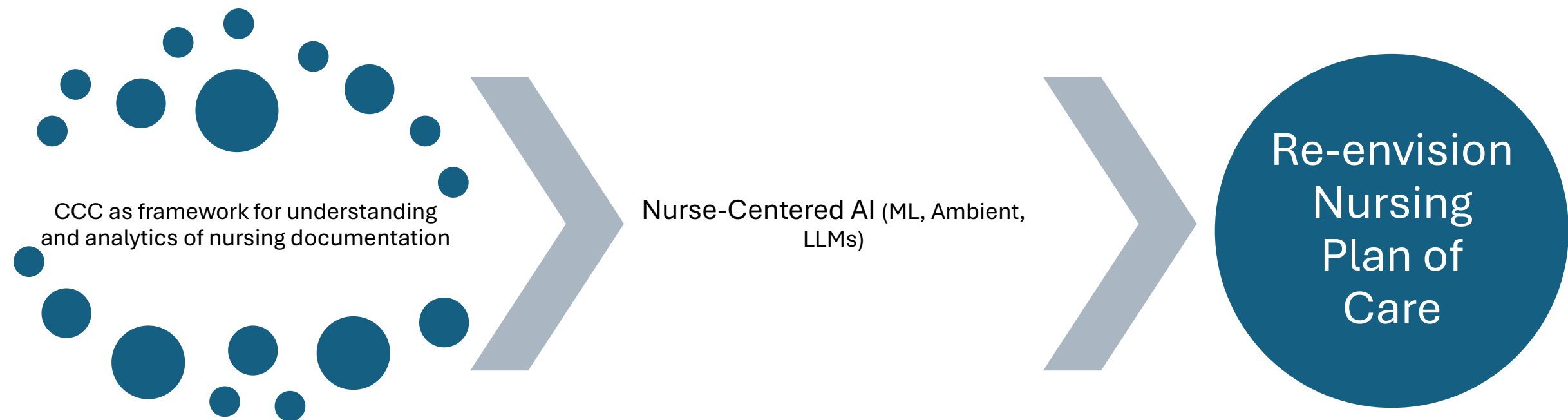
Pain Assessment

Dressing and Wound Assessment

Data-driven methods to re-envision new clinician-driven documentation paradigms

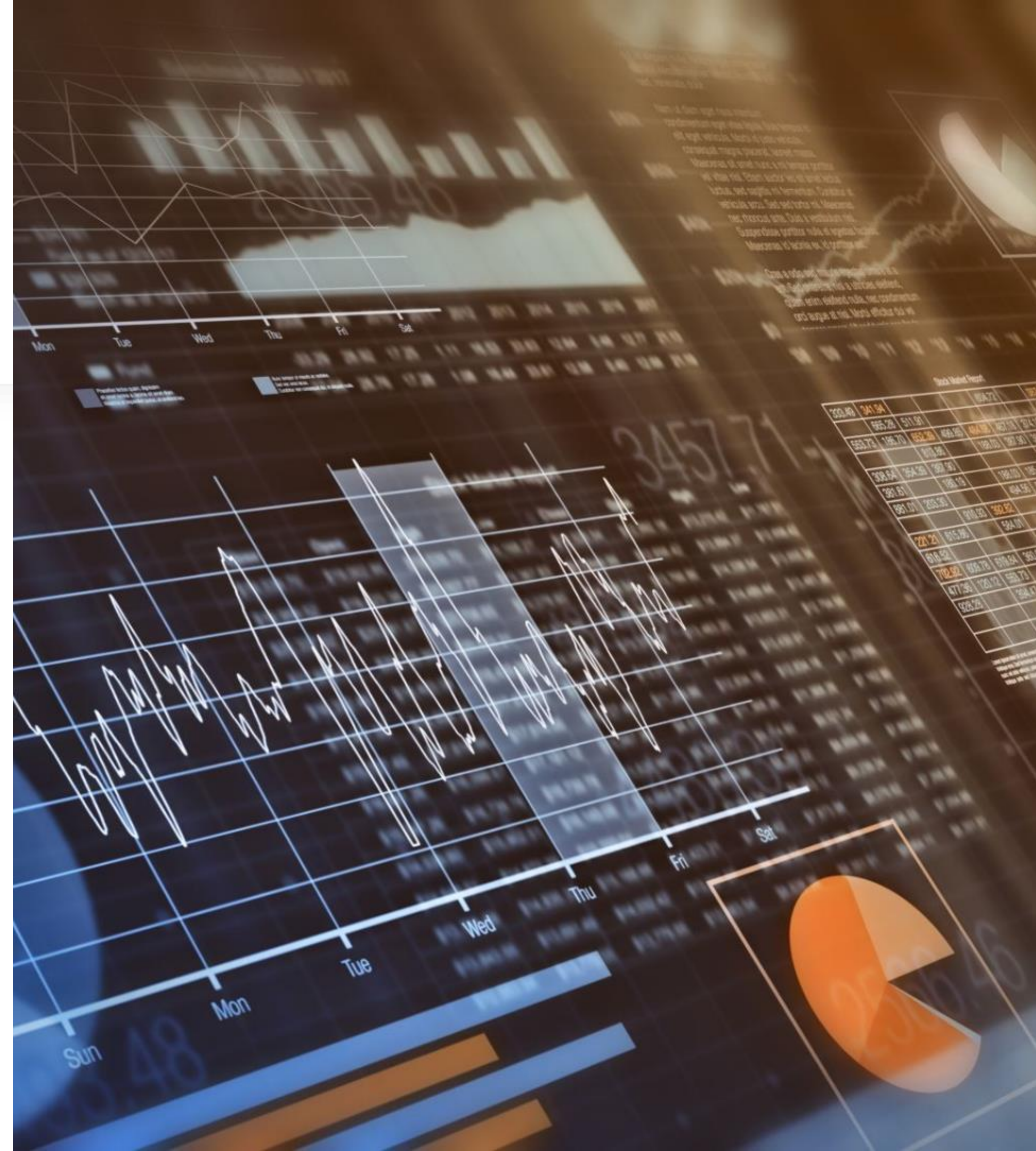
Future work – Innovative Solutions to Decrease Documentation Burden

- Nurses engage in continuous and effective care planning
 - CONCERN EWS provides evidence of how nursing surveillance – a core nurse care planning activity – saves lives
- Yet, nurses perceive current version of EHR-based Nursing Plan of Care lacks value and is highly burdensome
 - Excessive manual structured data entry
 - Lacks variability across patients



Summary

- CCC to identify nurses' concerning concepts
 - Generate seed terms and entities for NLP in CONCERN EWS
- CCC as framework to better understand the structure and enormous amount of flowsheet data
 - More efficient harmonization (with manual validation) in multi-site analytics studies
- CCC as framework + nurse-centered AI
 - Opportunity to innovate and explore tools to support burden reduction and nurse care planning



Essential Nurse

Documentation: Studying EHR Burden during COVID-19 (ENDBurden)

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Communicating Narrative Concerns Entered by RNs (**CONCERN**)

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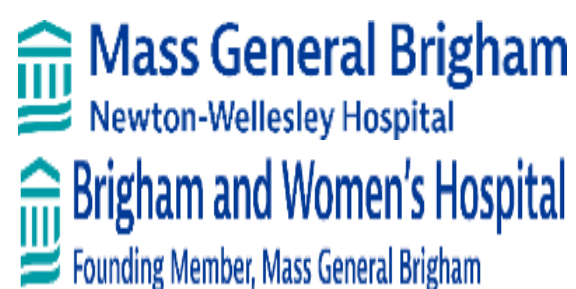
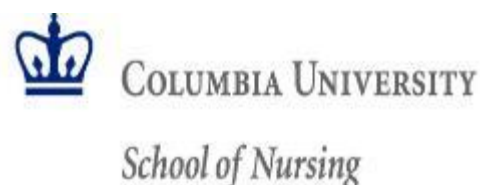
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VANDERBILT UNIVERSITY MEDICAL CENTER

CENTER FOR COMMUNITY-ENGAGED HEALTH INFORMATICS AND DATA SCIENCE

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Thank you!



MPIs: Sarah Rossetti & Kenrick Cato

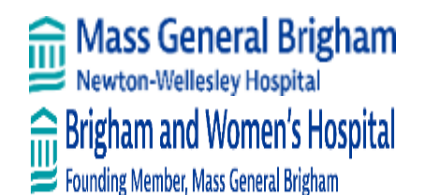


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CENTER FOR COMMUNITY-ENGAGED
HEALTH INFORMATICS AND DATA SCIENCE



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- American Nurses Foundation Reimagining Nursing Initiative
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Q&A

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Presentation

Kathryn Bowles
RN, PhD

Using the Omaha System to Identify Factors Associated with Patient's Risk for Hospitalization or Emergency Department Visits in Home Health Care

**Principal Investigator: Jiyoun Song, RN, PhD Lecturer
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**Presenter and Co-I: Kathryn Bowles, RN, PhD Professor
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#R01HS027742 (PI. Maxim Topaz)
"Building risk models for preventable hospitalizations and emergency department visits in
homecare (Homecare-CONCERN)"

"Building risk models for preventable hospitalizations and emergency department visits in
homecare (Homecare-CONCERN)"

Background

- **Home Health Care (HHC) in the United States**
 - **Approximately 12 million adults receive HHC**
- **One in five HHC patients experience unplanned hospitalizations or emergency department (ED) visits during HHC service**



Background

- Up to 40% of readmissions from HHC are classified as preventable**
- Risk for negative outcomes can be reduced via early patient risk detection and notification**



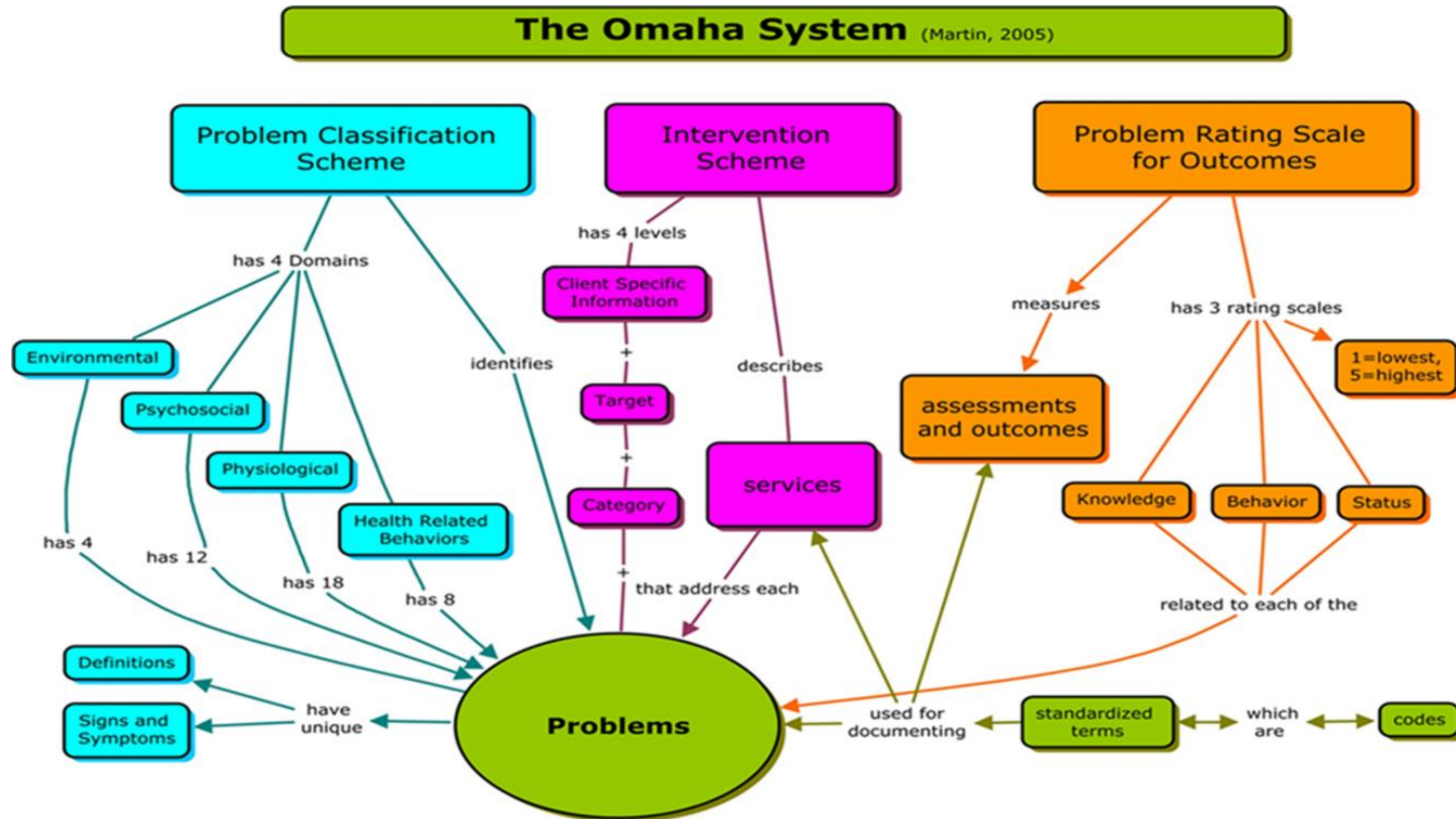
Aim

- **Create an early warning system from narrative clinical notes indicative of home health care patient risk of hospitalizations or emergency department (ED) visits using Omaha System signs and symptoms.**



The Omaha System

A research-based, comprehensive and standardized taxonomy designed to enhance practice, documentation, and information management for community-based care.



The Omaha system (continued)

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL
Environmental	Income	low/no income
		uninsured medical expenses
		difficulty with money management
		able to buy only necessity
		difficulty buying necessities
Psychosocial	Social contact	limited social contact
		uses health care provider for social contact
		minimal outside stimulation/leisure time activities
Physiological	Pain	expresses discomfort/pain
		elevated pulse/respirations/blood pressure
		compensated movement/guarding
		restless behavior
		facial grimaces
		pallor/perspiration
Health-related Behaviors	Health care supervision	fails to obtain routine/preventive health care
		fails to seek care for symptoms requiring evaluation/treatment
		fails to return as requested to health care provider
		inability to coordinate multiple appointments/treatment plans
		inconsistent source of health care
		inadequate source of health care
		inadequate treatment plan

Methods

- ❑ **Expert’s review for the signs/symptoms of the Omaha system**
 - All except one expert (with Masters degree) had a PhD in nursing,
 - four experts had clinical experience in HHC
 - all experts had experience in HHC research.

- ❑ **Question: “Which signs/symptoms, if documented in the patient records, would cause concern for risk of unplanned hospitalizations or ED visits for a HHC patient 65 years of age or older?”**

[Score]
1 - usually not concerning
2 - occasionally concerning
3 - usually concerning



□ Example of reviewed signs/symptoms

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL	Expert_1	Expert_2	Expert_3	Expert_4	Expert_5	Decision
Psychosocial	Neglect	lacks adequate physical care	3	3	3	3	3	CONCERN
	Neglect	lacks emotional nurturance/support	1	1	2	3	2	NOT CONCERN
	Neglect	lacks appropriate stimulation/cognitive experiences	1	1	1	2	1	NOT CONCERN
	Neglect	inappropriately left alone	3	3	3	3	3	CONCERN
	Neglect	lacks necessary supervision	3	3	3	3	3	CONCERN
	Neglect	inadequate/delayed medical care	3	3	3	3	3	CONCERN
Physiological	Pain	expresses discomfort/pain	3	3	3	3	3	CONCERN
	Pain	elevated pulse/respirations/blood pressure	3	3	3	3	3	CONCERN
	Pain	compensated movement/guarding	3	3	3	3	3	CONCERN
	Pain	restless behavior	3	3	3	3	3	CONCERN
	Pain	facial grimaces	3	3	2	2	3	CONCERN
	Pain	pallor/perspiration	3	2	3	3	3	CONCERN

* Score = 1 - usually not concerning; 2 - occasionally concerning; 3 - usually concerning

Results

- A total of 131 signs/symptoms were initially identified as ‘concerning’**
- 29 signs/symptoms added after reviewing the ‘occasionally concerning’ category.**
- Total list of 160/335 (47.8%) signs/symptoms identified as “concerning” for unplanned hospitalizations or ED visits in HHC.**
- These signs/symptoms belong to 31/42 (73.8%) of available Omaha System problems.**

Results: All signs/symptoms were nursing concern concepts (1)

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL
Psychosocial Domain	Abuse (8 / 8 = 100%)	harsh/excessive discipline
		welts/bruises/burns/other injuries
		questionable explanation of injury
		attacked verbally
		fearful/hypervigilant behavior
		violent environment
		consistent negative messages
		assaulted sexually
Physiological Domain	Communicable/infectious condition (7 / 7 = 100%)	infestation
		fever
		biological hazards
		positive screening/culture/laboratory result
		inadequate supplies/equipment/policies to prevent transmission
		does not follow infection control regimen
		inadequate immunity
	Consciousness (4 / 4 = 100%)	lethargic
		stuporous
		unresponsive
		comatose

Results: All signs/symptoms were nursing concern concepts (2)

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL
Physiological Domain	Pain (6 / 6 = 100%)	expresses discomfort/pain
		elevated pulse/respirations/blood pressure
		compensated movement/guarding
		restless behavior
		facial grimaces
		pallor/perspiration
Health-related Behaviors Domain	Health care supervision (7 / 7 = 100%)	fails to obtain routine/preventive health care
		fails to seek care for symptoms requiring evaluation/treatment
		fails to return as requested to health care provider
		inability to coordinate multiple appointments/treatment plans
		inconsistent source of health care
	Medication regimen (6 / 6 = 100%)	inadequate source of health care
		inadequate treatment plan
		does not follow recommended dosage/schedule
		evidence of side effects/adverse reactions
		inadequate system for taking medication
		improper storage of medication
		fails to obtain refills appropriately
		fails to obtain immunizations

Results: Partial signs/symptoms were nursing concern concepts

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL	
Physiological Domain	Circulation (15 / 16 = 93.8%)	abnormal blood pressure reading	edema
		abnormal cardiac laboratory results	excessively rapid heart rate
		abnormal clotting	excessively slow heart rate
		abnormal heart sounds/murmurs	irregular heart rate
		anginal pain	pulse deficit
		cramping/pain of extremities	syncopal episodes /dizziness
		decreased pulses	temperature change in affected area
		discoloration of skin/cyanosis	varicosities
	Skin (7 / 10 = 70%)	lesion/pressure ulcer	
		delayed incisional healing	
		rash	
		excessively dry	
		excessively oily	
		inflammation	
		pruritus	
drainage			
bruising			
		hypertrophy of nails	

Results: Partial or no signs/symptoms were nursing concern concepts

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL
Environmental Domain	Income (2./ 5 = 40%)	low/no income uninsured medical expenses difficulty with money management able to buy only necessity difficulty buying necessities
Health-related Behaviors Domain	Sleep and rest patterns (1 / 7 = 14.3%)	sleep/rest pattern disrupts family frequently wakes during night sleepwalking insomnia nightmares insufficient sleep/rest for age/physical condition sleep apnea snoring
Psychosocial Domain	Growth and development (0 / 4 = 0%)	abnormal results of development screening tests abnormal weight/height/head circumference in relation to growth curve/age age-inappropriate behavior inadequate achievement/maintenance of developmental tasks

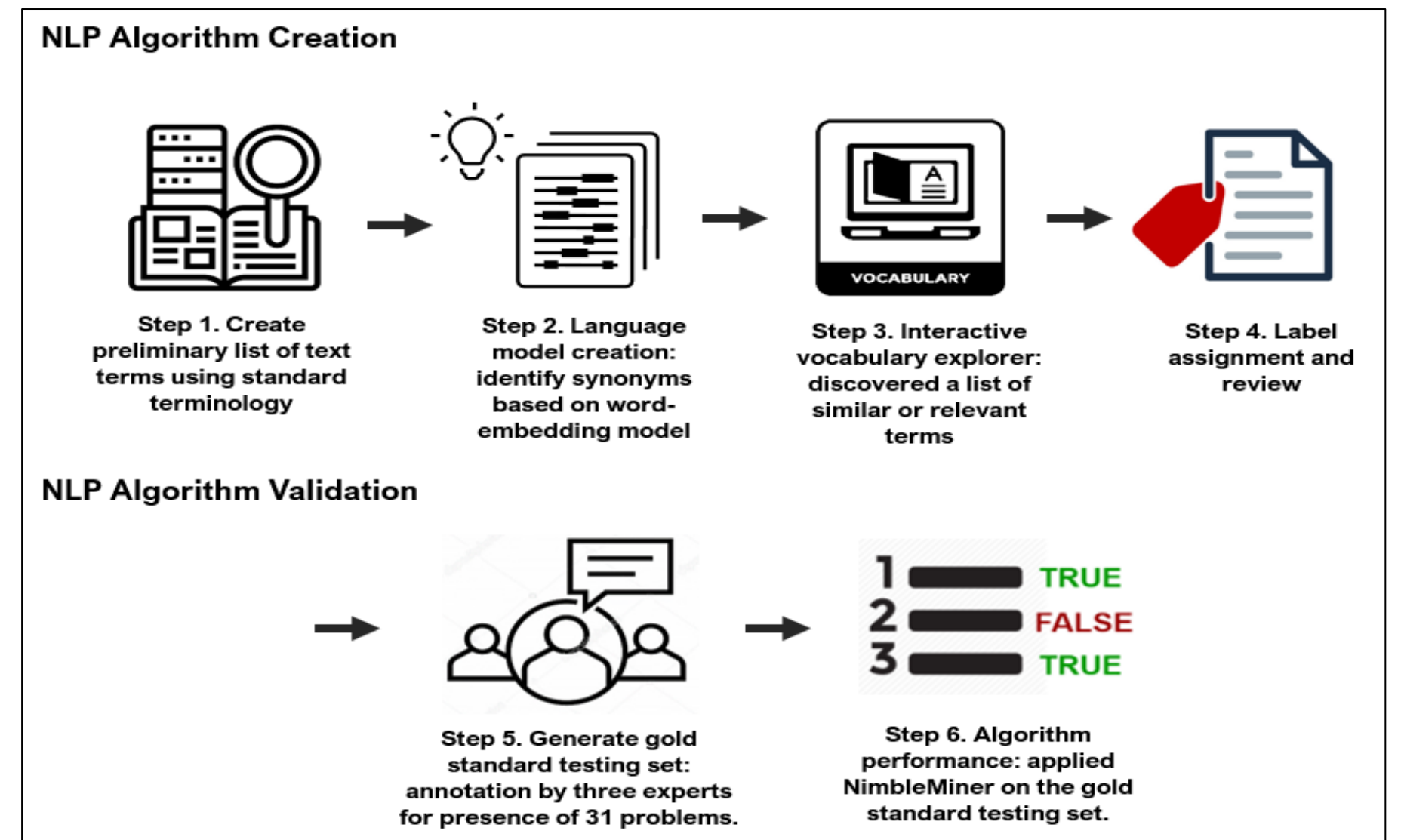
Study #1



#1. Identify risk factors for hospitalization or ED visits using standard nursing terminology through Delphi method

Domain	Problem Classification Scheme	SIGNS/SYMPTOMS OF ACTUAL
Psychosocial Domain	Abuse (8 / 8 = 100%)	harsh/excessive discipline
		welts/bruises/burns/other injuries
		questionable explanation of injury
		attacked verbally
		fearful/hypervigilant behavior
		violent environment
		consistent negative messages
		assaulted sexually
Physiological Domain	Communicable/infectious condition (7 / 7 = 100%)	infecstation
		fever
		biological hazards
		positive screening/culture/laboratory result
		inadequate supplies/equipment/policies to prevent transmission
		does not follow infection control regimen
		inadequate immunity
	Consciousness (4 / 4 = 100%)	lethargic
		stuporous
		unresponsive
		comatose
Physiological Domain	Pain (6 / 6 = 100%)	expresses discomfort/pain
		elevated pulse/respirations/blood pressure
		compensated movement/guarding
		restless behavior
		facial grimaces
		pallor/perspiration
Health-related Behaviors Domain	Health care supervision (7 / 7 = 100%)	fails to obtain routine/preventive health care
		fails to seek care for symptoms requiring evaluation/treatment
		fails to return as requested to health care provider
		inability to coordinate multiple appointments/treatment plans
		inconsistent source of health care
		inadequate source of health care
		inadequate treatment plan
	Medication regimen (6 / 6 = 100%)	does not follow recommended dosage/schedule
		evidence of side effects/adverse reactions
		inadequate system for taking medication
		improper storage of medication
		fails to obtain refills appropriately
		fails to obtain immunizations

#2. Develop NLP algorithm and apply to 2.3 million clinical notes



Study #1



Result and Discussion

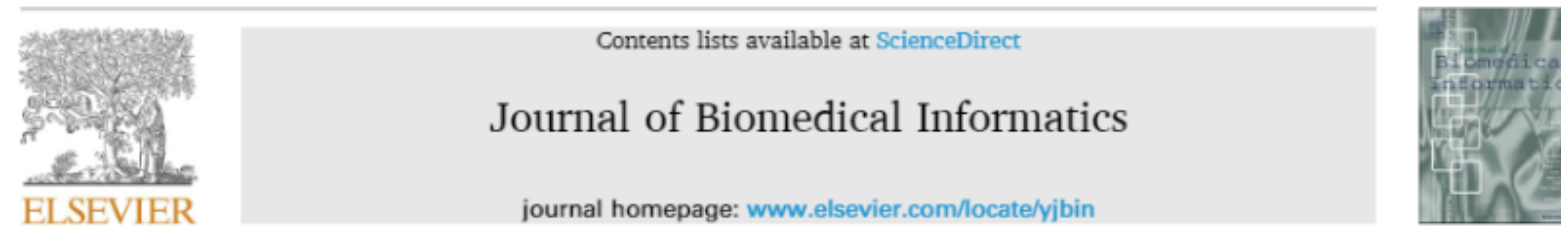


- > 18% of clinical notes were detected as having at least one concerning concept
- >90% of HHC episodes included at least one Omaha System problem
- The most frequently documented concerning concepts were pain, neuromusculoskeletal function, circulation, mental health, and communicable/infectious conditions.
- **Our findings suggest that concerning symptoms or problems are frequently documented in narrative clinical notes.**
- **NLP can automatically extract information from narrative clinical notes to improve our understanding of care needs in HHC.**

Study #2



Objective: To compare the predictive performance of four risk models built with various data sources for hospitalization and ED visits in HHC



Special Communication

Clinical notes: An untapped opportunity for improving risk prediction for hospitalization and emergency department visit during home health care

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Risk assessment
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Nursing informatics

ABSTRACT

Background/Objective: Between 10 and 25% patients are hospitalized or visit emergency department (ED) during home healthcare (HHC). Given that up to 40% of these negative clinical outcomes are preventable, early and accurate prediction of hospitalization risk can be one strategy to prevent them. In recent years, machine learning-based predictive modeling has become widely used for building risk models. This study aimed to compare the predictive performance of four risk models built with various data sources for hospitalization and ED visits in HHC.

Methods: Four risk models were built using different variables from two data sources: structured data (i.e., Outcome and Assessment Information Set (OASIS) and other assessment items from the electronic health record (EHR)) and unstructured narrative-free text clinical notes for patients who received HHC services from the largest non-profit HHC organization in New York between 2015 and 2017. Then, five machine learning algorithms (logistic regression, Random Forest, Bayesian network, support vector machine (SVM), and Naive Bayes) were used on each risk model. Risk model performance was evaluated using the F-score and Precision-Recall Curve (PRC) area metrics.

Results: During the study period, 8373/86,823 (9.6%) HHC episodes resulted in hospitalization or ED visits. Among five machine learning algorithms on each model, the SVM showed the highest F-score (0.82), while the Random Forest showed the highest PRC area (0.864). Adding information extracted from clinical notes significantly improved the risk prediction ability by up to 16.6% in F-score and 17.8% in PRC.

Conclusion: All models showed relatively good hospitalization or ED visit risk predictive performance in HHC. Information from clinical notes integrated with the structured data improved the ability to identify patients at risk for these emergent care events.

Song, J., Hobensack, M., Bowles, K. H., McDonald, M.V., Cato, K., Rossetti, S., Chae, S., Kennedy E., Barron, Y., Sridharan, S., & Topaz, M. (2022) Clinical Notes: An Untapped Opportunity for Improving Risk Prediction for Hospitalization and Emergency Department Visit during Home Health Care (Journal of Biomedical Informatics). DOI:

<https://doi.org/10.1016/j.jbi.2022.104039>

Study #2



Setting



Patients from the largest home health care (HHC) organization in New York between 2015 and 2017

Dataset



Structured dataset:
OASIS and EHR

Unstructured dataset:
Clinical notes



Machine learning-based
NLP approach #1:
“concerning” clinical notes

Rule-based NLP approach
#2: risk factors with the
Omaha System

Risk modeling



- *Risk Model 1*: structured dataset
- *Risk Model 2*: structured dataset + clinical notes (NLP approach #1)
- *Risk Model 3*: structured dataset + clinical notes (NLP approach #2)
- *Risk Model 4*: structured dataset + clinical notes (NLP approach #1 and 2)



Each of the four risk models was trained using five machine learning algorithms (Logistic Regression, Random Forest, Bayesian network, SVM, and Naive Bayes)

Findings



Risk Model 4 shows an increase in the PRC area of 17.8% over *Risk Model 1*

In *Risk Model 3*, which incorporates the detailed risk factors of the Omaha System, the PRC area increased by 5% over *Risk Model 2*



Random Forest had the highest PRC area of 86.4% among the five machine learning algorithms

Conclusion



Clinical notes combined with structured assessment data can improve predictive ability for hospitalization and ED visits in HHC

Research #2



Examine Whether Clinical Notes Contribute to Risk Models for Hospitalization and ED Visit during HHC

- Created Risk Models with Different Combination of Datasets
 - *Risk Model 1*: structured dataset (58 variables)
 - *Risk Model 2*: structured dataset + clinical notes with NLP approach (75 variables)

	F-Measure	PRC Area (Precision-Recall Curve Area)
Logistic regression		
<i>Risk Model 1</i>	0.71	0.74
<i>Risk Model 2</i>	0.76	0.81
Random Forest	7% ↑	10% ↑
<i>Risk Model 1</i>	0.78	0.82
<i>Risk Model 2</i>	0.81	0.86
Bayes Network	3.8% ↑	5.6% ↑
<i>Risk Model 1</i>	0.68	0.71
<i>Risk Model 2</i>	0.79	0.84
SVM (Support Vector Machine)	16.1% ↑	17.8% ↑
<i>Risk Model 1</i>	0.73	0.77
<i>Risk Model 2</i>	0.82	0.82
Naïve Bayes	11.2% ↑	7.3% ↑
<i>Risk Model 1</i>	0.68	0.68
<i>Risk Model 2</i>	0.69	0.68

Song, J., Hobensack, M., Bowles, K. H., McDonald, M.V., Cato, K., Rossetti, S., Chae, S., Kennedy E., Barron, Y., Sridharan, S., & Topaz, M. (2022) Clinical Notes: An Untapped Opportunity for Improving Risk Prediction for Hospitalization and Emergency Department Visit during Home Health Care (Journal of Biomedical Informatics). DOI: <https://doi.org/10.1016/j.jbi.2022.104039>

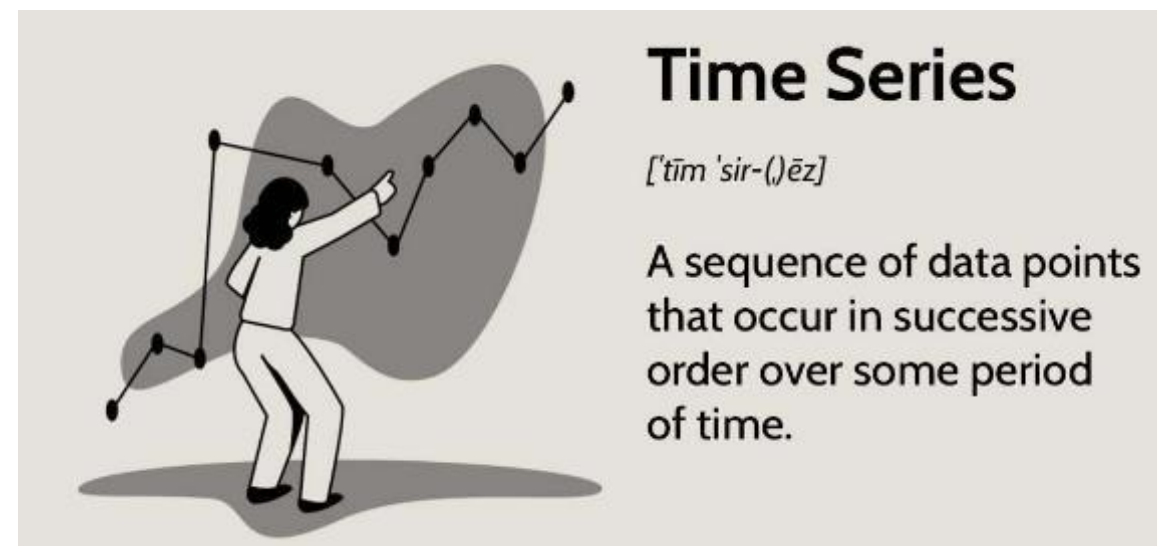
Study #3



Identifying Time Trajectories in Risk Factors Documented in Clinical Notes and Predicting Hospitalizations and Emergency Department Visits during Home Health Care

■ Rationale:

- ✓ In HHC, multiple home visits collect longitudinal data, offering insights into a patient's condition over time
- ✓ Past HHC studies aggregated NLP-extracted risk factors at the episode level, missing changes over time

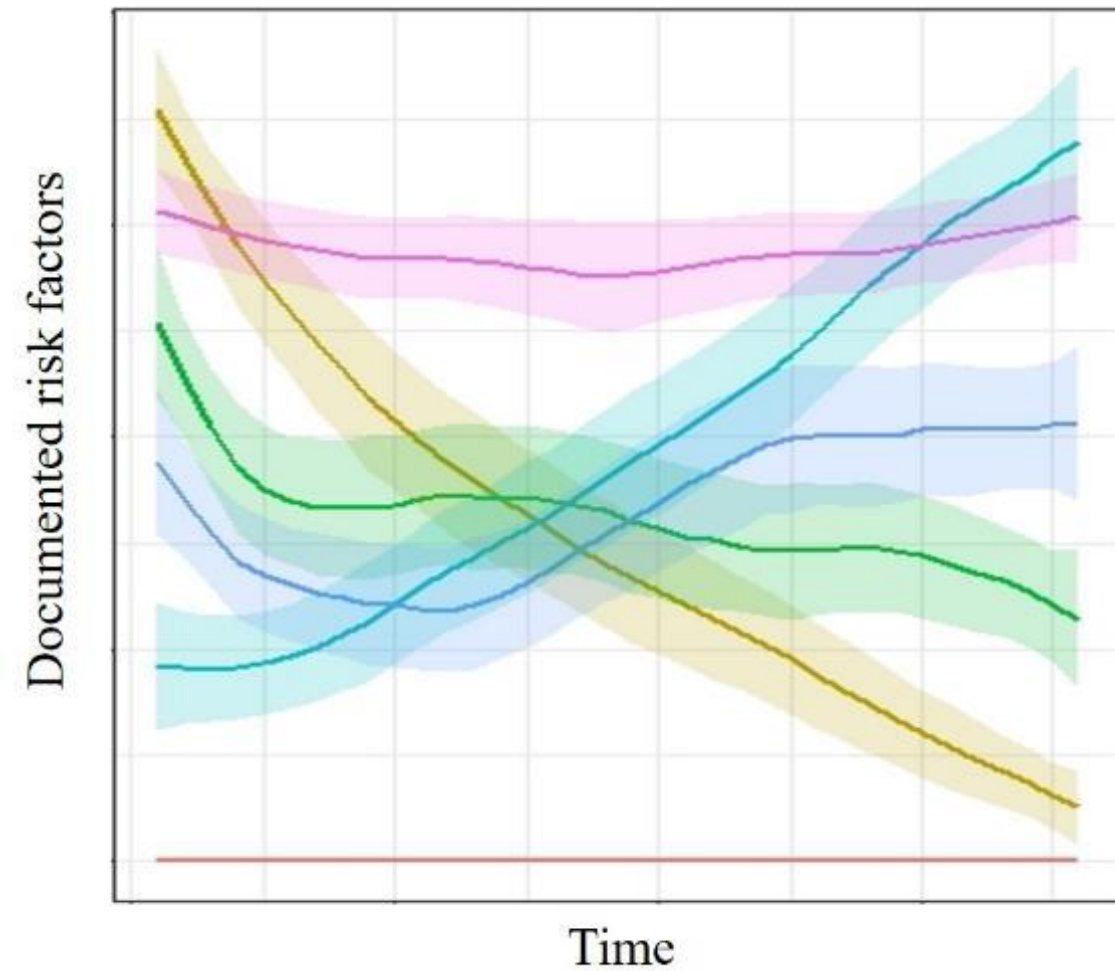


Study #3



Methods:

2. Generating temporal patterns of risk factors via unsupervised hierarchical cluster analysis



Risk factor documented

Cluster 1: No Risk Factors	5,413 (7.38%)
Cluster 2: Steeply Decreased	35,193 (48%)
Cluster 3: Decreased	14,537 (19.8%)
Cluster 4: Steeply Increased	5,608 (7.65%)
Cluster 5: Decreased and Rebound Increased	7,747 (10.56%)
Cluster 6: Steadily Present	4,852 (6.61%)

← Cluster 1: No Risk Factors

Research #3



Methods:

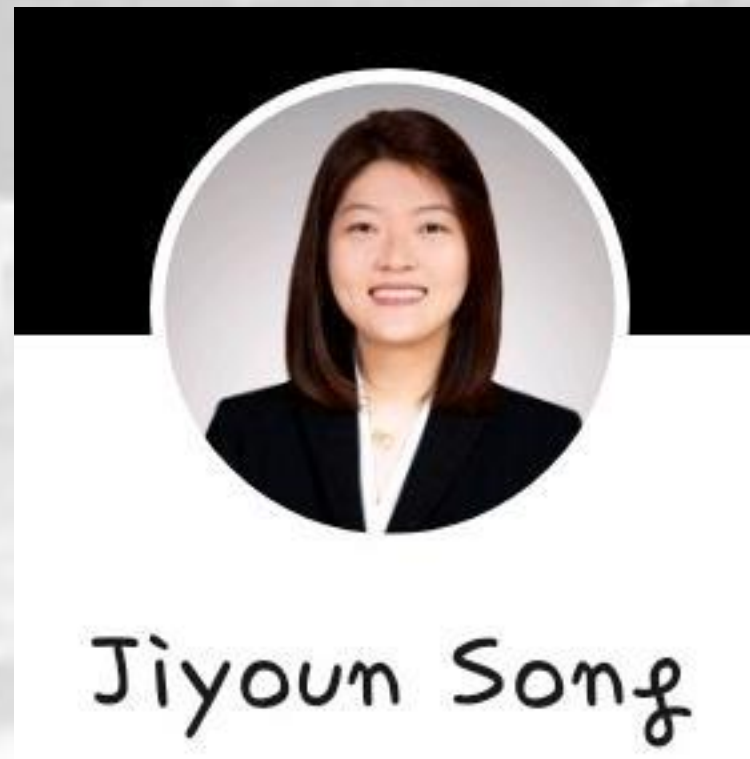
3. A multivariate logistic regression analysis to examine the association between the clusters of temporal risk patterns and hospitalizations and ED visits while adjusting for sociodemographic characteristics, comorbidities, and ADL/IADL function (all $P < .001$)

Predictors	Frequency [n, (%)]	Adjusted Odds Ratio (95% CI)
Cluster 1: No Risk Factors	5,413 (7.38%)	Reference
Cluster 2: Steeply Decreased	35,193 (48%)	1.27 (1.14 - 1.42)
Cluster 3: Decreased	14,537 (19.8%)	1.89 (1.68 - 2.12)
Cluster 4: Steeply Increased	5,608 (7.65%)	2.95 (2.60 - 3.34)
Cluster 5: Decreased and Rebound Increased	7,747 (10.56%)	2.47 (2.19 - 2.79)
Cluster 6: Steadily Present	4,852 (6.61%)	2.27 (1.99 - 2.60)

Thank you!

Questions or comments?

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Q&A

Kathryn Bowles
RN, PhD

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Machine Learning Methods to Discover Hidden Patterns in Well-being and Resilience for Healthy Aging

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Acknowledgements

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Artificial Intelligence and
Technology Collaboratory
for Healthy Aging

Background



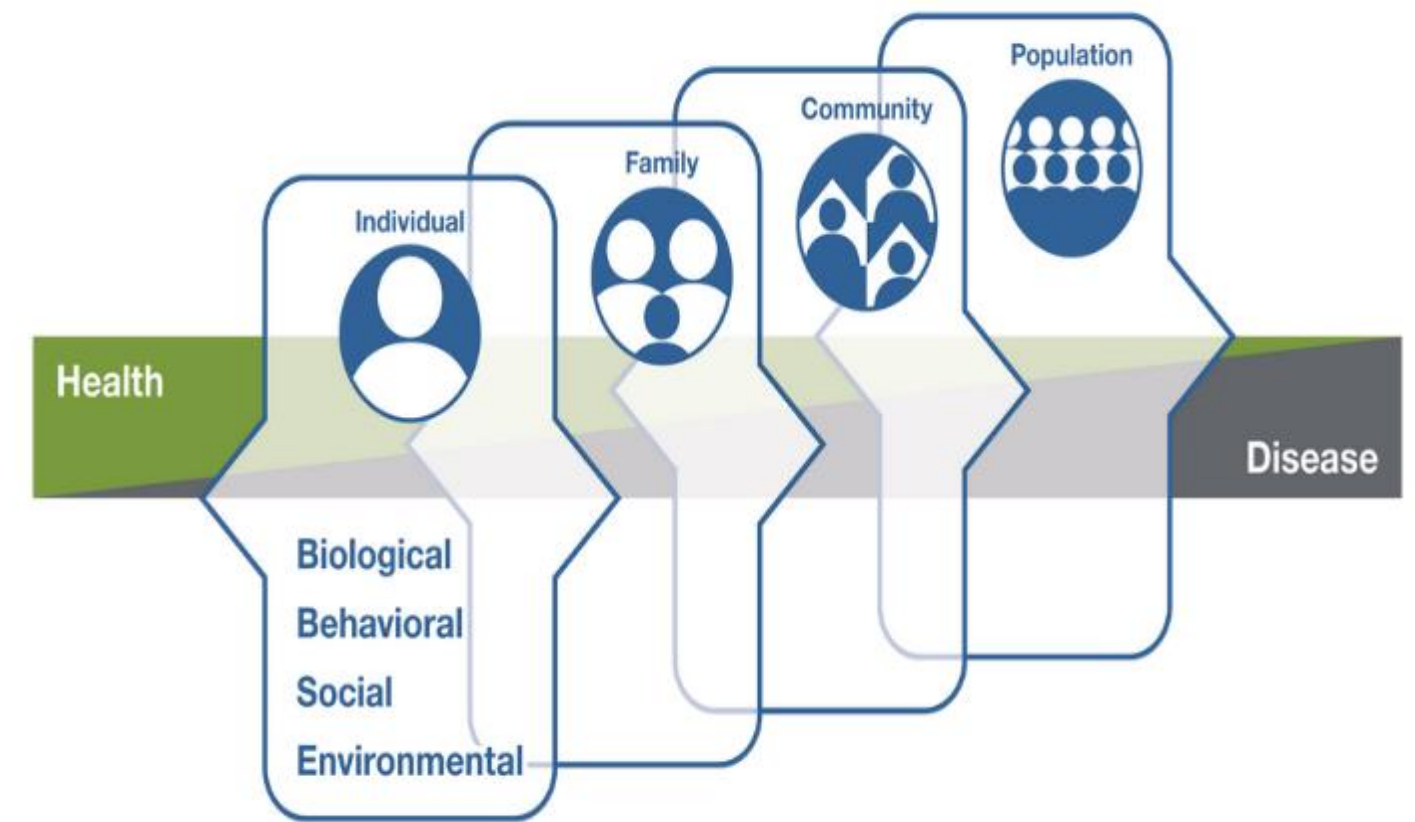
- Healthy aging is essential for maintaining the overall quality of life for a growing global older adult population.¹
- Recommendations support whole person approach that includes a person's strengths in addition to their challenges.^{2,3}
- Whole person health also includes strengths (or resilience).²
- Person-generated health data (PGHD) can offer valuable insights into personalized healthy aging interventions.
- Machine learning methods + PGHD = Hidden patterns and new approaches

Whole-person health framework

Whole-person health takes into account a person's environment, physical and psychosocial aspects, and health-related behaviors, biopsychosocial (BPS) approach.

Empowering individuals, to improve their health in multiple interconnected biological, behavioral, social, and environmental areas.²

Strengths/Resilience: are defined as assets, skills, abilities of individuals, families, and communities to maintain and improve their well-being in the face of short and long-term stressors.^{4,5}



MyStrengths+MyHealth (MSMH) App



- Developed (2017) to enable consumer-self report strengths, health challenges, and needs
- Based on the Omaha System, a multi-disciplinary health terminology⁶
- Translated into Simplified Omaha System Terms (SOST)
- Expert and community-validated at the 5th grade reading level
- Web-based, easy to use on a phone, tablet, or computer
- Multiple world languages
 - Spanish, Dutch, Mandarin, Korean, Thai, Somali, Karen, and Portuguese
- Encoded in SNOMED CT

My Strengths + My Health

About MSMH

Self-identify health strengths, challenges and needs.

MyStrengths MyHealth™ (MSMH) is a whole-person strengths-based consumer-facing mobile enhanced application designed for individuals, families, and communities to self-identify strengths, challenges, and needs.

Change Language

English

English

繁體中文

Español

Nederlands

Turkish

Portuguese

Thai

Hmong

Somali

한국인

Karen

ENTER REPORT CODE

My Strengths



My Health



My Living	My Mind & Networks	My Body		My Self-care
Income	Connecting	Hearing	Breathing	Nutrition
Cleaning	Socializing	Vision	Circulation	Sleeping
Home	Role change	Speech and language	Digestion	Exercising
Safe at home and work	Relationships	Oral health	Bowel function	Personal care
	Spirituality or faith	Thinking	Kidneys or bladder	Substance use
	Emotions	Pain	Reproductive health	Family planning
	Sexuality	Consciousness	Pregnancy	Health care
	Caretaking	Skin	Postpartum	Medications
	Neglect	Moving	Infections	
	Abuse			
	Growth and development			

My Strengths + My Health

Challenges: 335 Challenges select any, all or none apply that concept

Strengths: 'Very Good' or 'Good' are considered a "strength"

Needs: Select any, all or none apply for all concepts

Thinking

Do any of these challenges apply to you?

- hard to figure out the right thing to do
- hard to recall people, places, time
- hard to remember recent things
- hard to remember long ago things
- hard to remember what order to do things in
- hard to concentrate
- hard to talk about my thoughts
- hard to stop my self from doing what pops into my mind
- hard to stop repeating words or actions
- hard to focus my mind
- none apply

Thinking

How would you rate your thinking?

Okay

Very Good

Good

Okay

Bad

Very Bad

No Rating

Thinking

Please select your needs for Thinking.

- Check-ins
- Hands-on Care
- Info / Guidance
- Care Coordination
- No Needs

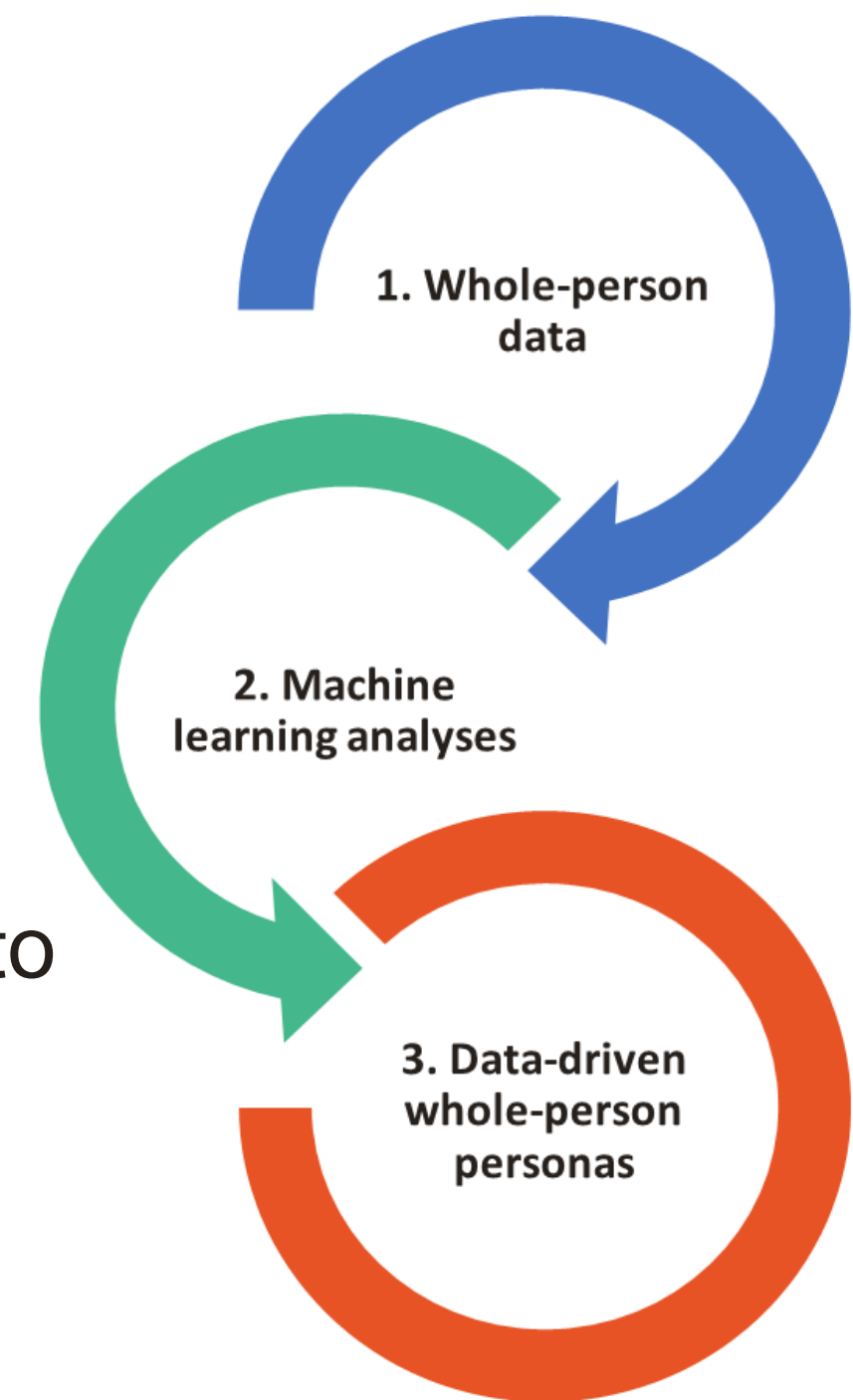
Purpose

The purpose of this research is to use machine learning methods to **examine whole-person health** of adults using consumer-generated health data.

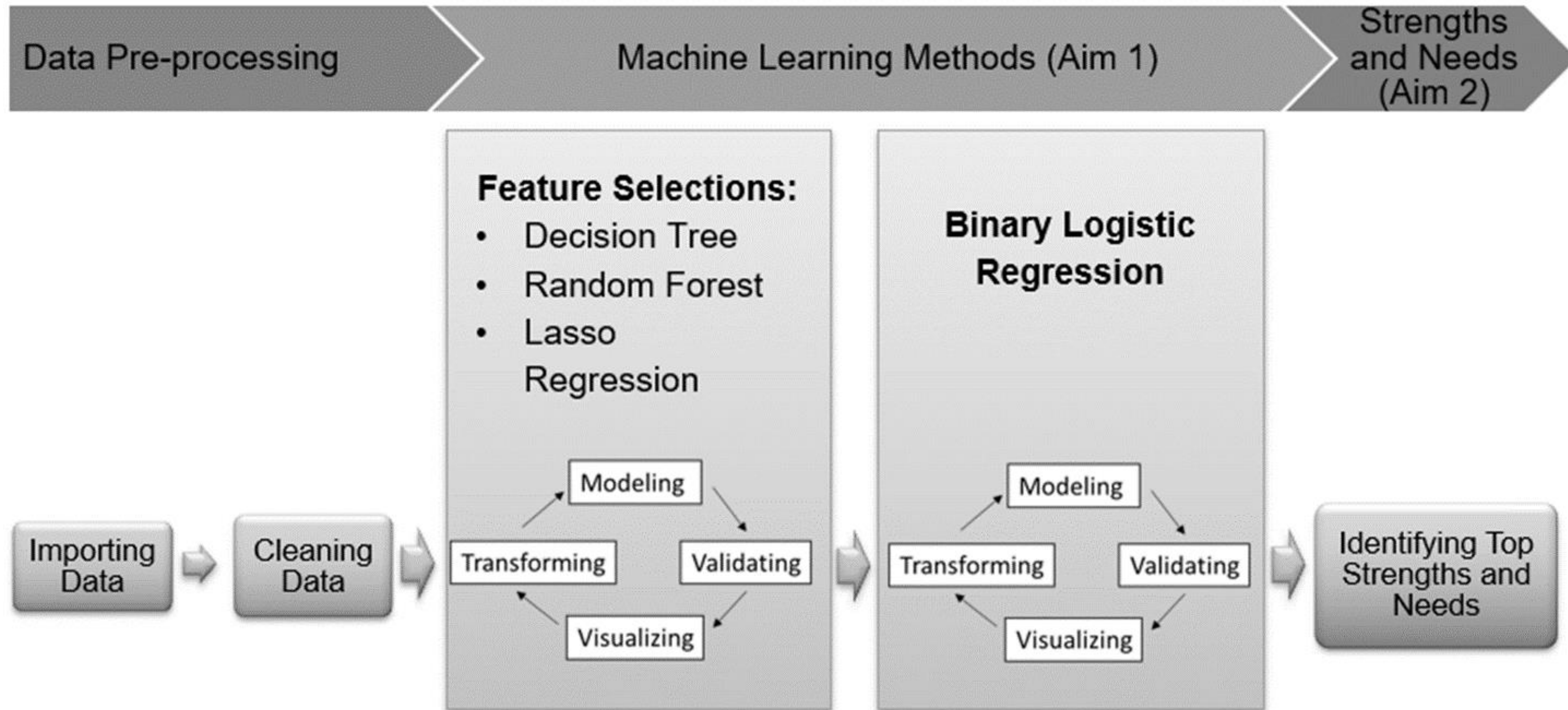
Aim 1: Using an exploratory data-driven approach to generate insights into what aspects of whole person health are related to healthy aging.

Aim 2: Examine differences in self-reported whole person health data (Strengths and Needs) for adults 45 and older.

Aim 3: Create data-driven user personas based on the machine learning data analysis to guide future work and the design of novel technologies to support a diverse range of older adults.



Methods: Data Analysis Process (n=988)



Methods: Data Cleaning, Transforming, and Pre-Processing

Data cleaning (missing values and eliminating irrelevant data) - 9% missing values were deleted.

Transforming the data: Converting Strengths data from ordinal to nominal data

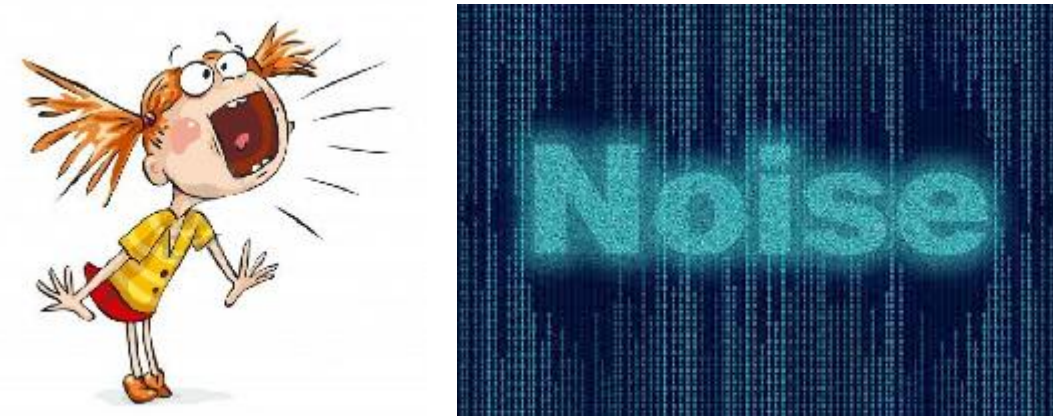
- Strengths data (5-point Likert scale), ranging from 1 (very bad) to 5 (very good)
- Rating of 4 (good) or 5 (very good) was considered a strength.
- Binary form a 4 or 5 as "Yes" (1), and <4 were a "No (0)

The final dataset include 988 respondents and 488 variables [Demographics (5), Strengths (36), Challenges (303), and Needs (144)].

Methods: Machine Learning Methods (Aim 1)

Exploratory data analysis (EDA):

- Principal Component Analysis (PCA)
- Multiple Correspondence Analysis (MCA)
- Decision Tree Analysis
- Entire data and subsets of the data (e.g. Challenges only or Strengths only).



To reduce the dimensionality of the data:

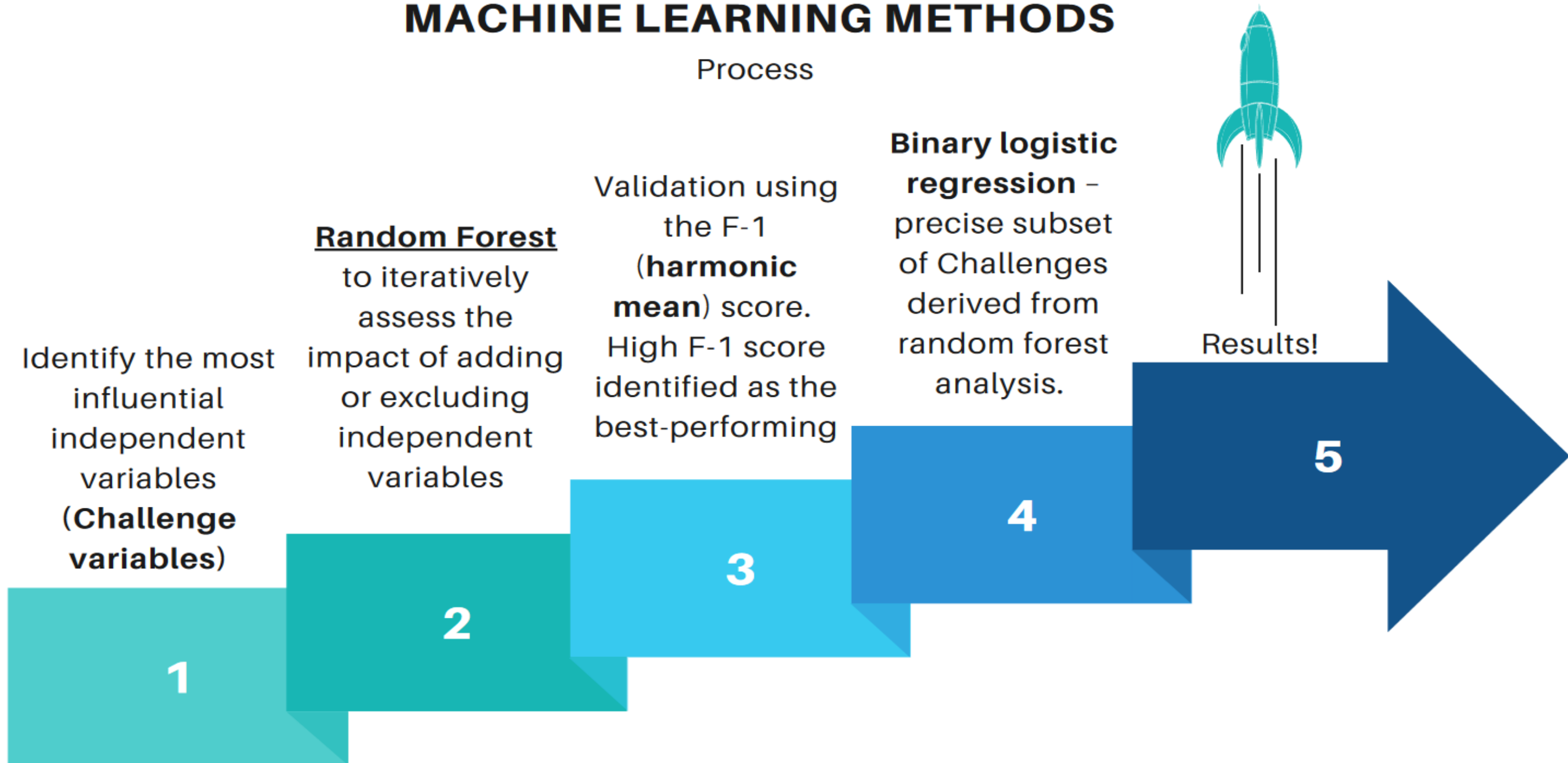
Challenges & Four MSMH challenges

- 1. *Thinking*** (Omaha System term: Cognition)
- 2. *Moving*** (Omaha System term: Neuro-musculo-skeletal function)
- 3. *Emotions*** (Omaha System term: Mental health)
- 4. *Sleeping*** (Omaha System term: Sleep and rest patterns)

Methods: Machine Learning Methods (Aim 1)

MACHINE LEARNING METHODS

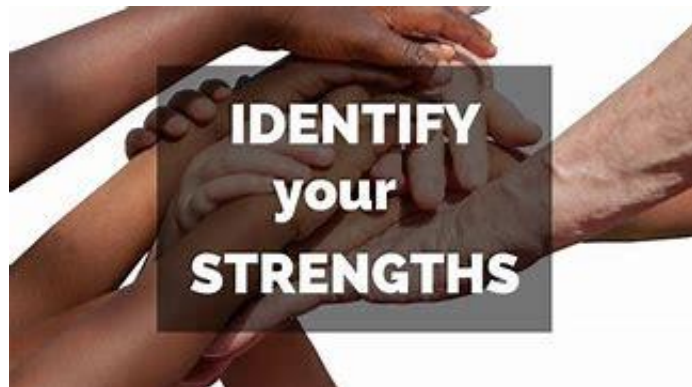
Process



Methods: Examine differences Strengths and Needs (Aim 2) & Create Data-driven User Personas (Aim 3)

Aim 2: Examined prevalent Strengths and Needs for *each* group using descriptive statistics.

Aim 3: Using all data for each group created data-drive user personas.



Overall Results (N=988)

Overall most participants were:

- Ages 45-64 (64.2%)
- Female (57.5%)
- White (68.3%)
- Non-Hispanic/Non-Latino (79.3%)
- Married (55.3%)

Top Strengths – Challenges – Needs:

- Top Strength: *Speech and Language* (76.1%)
- Top Challenge: *Vision* (83.1%)
- Top Need: Hands-on care in *Oral health* (65.8%)

Average:

- Strength 66.1% (SD=5.1)
- Challenges 66.5% (SD=7.5)
- Needs 60.06% (SD=3.1)

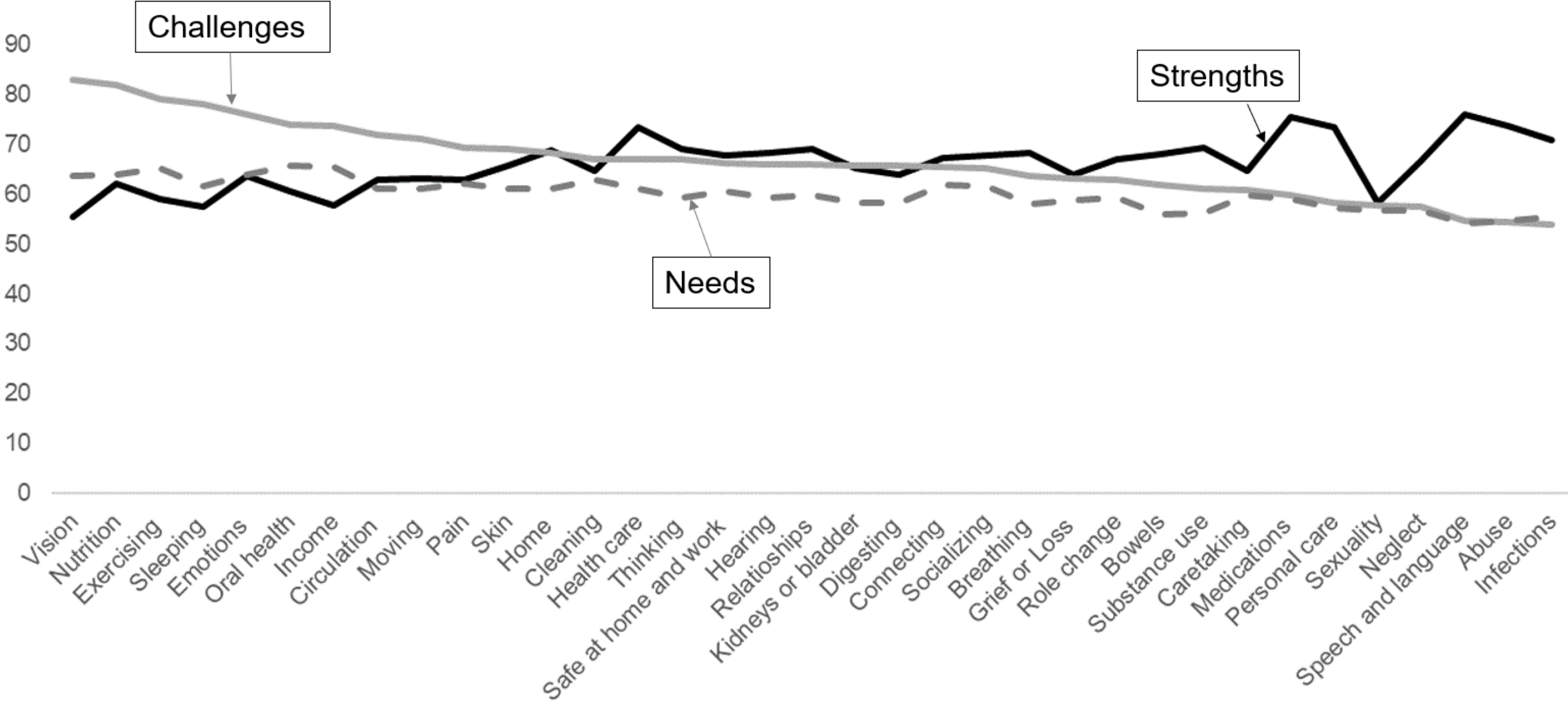
Significant difference:

Strengths and Needs ($p < 0.001$)

Challenges and Needs ($p < 0.001$)

No significant differences Strengths and Challenges.

All Participants (n=988)



All Groups

DataSet (n=988)

Concept Grouped by (had at least 1 Challenge in that concept)	n=for each group	Method	# Challenges from Feature Selection yielded the highest F1-Score	F1-Score	Method	Statistically significant Challenges	Most Common Strength %	Most Common Need %	Most Frequent Need
Thinking	633	Random Forest Feature Selection	63	0.917	Binary Logistic Regression	11	Cleaning 73.1%	Income 56.2%	Hands-on Care
Moving	683	Random Forest Feature Selection	70	0.905	Binary Logistic Regression	9	Speech and Language 74.2%	Income 53.2%	Hands-on Care
Emotions	557	Random Forest Feature Selection	50	0.921	Binary Logistic Regression	4	Cleaning 63.8%	Income 47.0%	Hands-on Care
Sleeping	544	Random Forest Feature Selection	33	0.9	Binary Logistic Regression	4	Speech and Language 71.0%	Oral health 47.2%	Hands-on Care

Aim 1: Data Description and Machine Learning Methods (by Group)

Random Forest: 63 challenges were identified as most relevant to *Thinking* Challenges (F1-score = 0.917)

Binary Regression: 11 Challenges were statistically significant

Odds ratio: 35 times more likely to have *Respiratory* Challenge

Thinking Concept Group (n=633)

Domain	Concepts	Challenges	p-value	OR
My Body	<i>Breathing</i>	need help to cough and spit out mucus	0.01	35.9
My Self-care	<i>Medications</i>	need better system for taking meds	0.002	27.6
My Body	<i>Moving</i>	not coordinated	0.047	13.2
My Body	<i>Circulation</i>	hard to find or weak pulses	0.025	10.7
My Living	<i>Home</i>	unsafe or too steep stairs	0.026	4.8
My Body	<i>Kidneys or bladder</i>	hard to get to the bathroom in time	0.035	4.5
My Mind & Networks	<i>Emotions</i>	hard to manage my stress	0.007	4
My Body	<i>Hearing</i>	hard to hear in crowds	0.0004	3.7
My Living	<i>Cleaning</i>	bugs, rats, mice, squirrels, pests	0.024	3.6
My Body	<i>Moving</i>	weak muscles	0.043	2.8
My Mind & Networks	<i>Socializing</i>	no hobbies or clubs	0.029	2.7

Aim 2: Examine differences Strengths and Needs by Group

Thinking Concept Group (n=633)


Strengths (Top 10)

Domain	Concept	%
My Living	Cleaning	73.1
My Mind & Networks	Role change	72.8
My Mind & Networks	Socializing	72.5
My Mind & Networks	Speech and language	72.5
My Mind & Networks	Relationships	70.8
My Self-care	Health care	70.6
My Self-care	Medications	70.6
My Mind & Networks	Abuse	70.3
My Self-care	Personal care	70.3
My Living	Home	69.0

Needs (Top 10)

Domain	Concept	Need	%
My Living	Income	Hands-on Care	56.2
My Living	Cleaning	Hands-on Care	53.2
My Body	Oral health	Hands-on Care	52.6
My Mind & Networks	Socializing	Hands-on Care	50.1
My Body	Pain	Hands-on Care	49.8
My Mind & Networks	Emotions	Hands-on Care	49.6
My Self-care	Exercising	Hands-on Care	49.3
My Mind & Networks	Connecting	Hands-on Care	48.5
My Mind & Networks	Personal care	Hands-on Care	48.5
My Body	Thinking	Hands-on Care	48.0

Aim 3: Whole-person User Persona for Thinking Challenges



Akio Kobayashi

Because I live alone, seeing friends is important to me.

MARITAL STATUS
Widowed with 1 son and 2 grandchildren


EDUCATION
High School Degree

AGE
85

Living Situation










Akio's spouse passed away five years ago and he lives in an affordable housing complex in a large city.


Main Challenge

Thinking 


Akio's son has noticed that Akio is having a hard time remembering recent events, and is repeating stories. Akio has also been forgetting the names of his close friends. His son wishes he lived closer, and is relying on Akio's friends and a personal care assistant to check in on him and help him with tasks like cleaning.

Additional Challenges

-  He feels uncoordinated and his muscles are getting weak
-  He is finding it hard to hear in crowds
-  He sometimes finds it hard to get to the bathroom in time
-  If he gets mucus in his lungs, he struggles to cough and spit it out
-  His pulse is weak and difficult to find
-  He needs a better system to manage his medications
-  His building has steep stairs and he often sees mice and bugs
-  He wishes he had more hobbies
-  He finds it hard to manage stress



Main Challenge

Thinking 

My Living	Strengths Cleaning Home	Needs Income Cleaning
My Mind and Networks	Role Change Socializing Relationships Speech and Language No Abuse	Socializing Connecting Emotions
My Body	None Reported	Pain Oral Health Thinking
My Self-Care	Health Care Medications Personal Care Substance Abuse	Exercising Personal Care

Aim 1: Data Description and Machine Learning Methods (by Group)

Random Forest: 70 challenges were identified as most relevant to *Moving Challenges* (F1-score = 0.905)

Binary Regression: 9 Challenges were statistically significant

Odds ratio: 27.7 times more likely to have *Respiratory Challenge*

Moving Concept Group (n=683)

Domain	Concepts	Challenges	p-value	OR
My Body	<i>Pain</i>	heart is racing and breathing is fast because of pain	0.013	27.7
My Body	<i>Pain</i>	hard to keep my face from showing I have pain	0.017	24.8
My Body	<i>Circulation</i>	swelling	0	9.2
My Body	<i>Pain</i>	hard to move because of pain	0.012	6
My Body	<i>Pain</i>	restless because of pain	0.021	5.6
My Body	<i>Breathing</i>	stuffed up nose or sinuses	0.004	3.6
My Self-care	<i>Exercising</i>	do not like my exercise plan	0.004	2.6
My Body	<i>Pain</i>	having pain	0.013	2.4
My Body	<i>Vision</i>	hard to see things up close	0.039	0.4

Aim 2: Examine differences Strengths and Needs by Group

Moving Concept Group (n=683)

Strengths (Top 10)

Domain	Concept	%
My Mind & Networks	Speech and language	74.2
My Mind & Networks	Socializing	72.5
My Self-Care	Medications	72.5
My Mind & Networks	Abuse	71.7
My Self-Care	Health care	71.2
My Living	Cleaning	71.0
My Mind & Networks	Role change	70.9
My Mind & Networks	Relationships	70.9
My Self-Care	Personal care	70.6
My Body	Hearing	69.4

Needs (Top 10)

Domain	Concept	Need	%
My Living	Income	Hands-on Care	53.2
My Living	Cleaning	Hands-on Care	51.7
My Body	Oral health	Hands-on Care	50.2
My Body	Pain	Hands-on Care	47.7
My Self-care	Exercising	Hands-on Care	47.1
My Mind & Networks	Socializing	Hands-on Care	46.6
My Mind & Networks	Emotions	Hands-on Care	46.4
My Self-care	Personal care	Hands-on Care	46.4
My Mind & Networks	Connecting	Hands-on Care	46.1
My Self-care	Health care	Hands-on Care	45.5

Aim 3: Whole-person User Persona for Moving Challenges



Gloria Matthews

“ I want to be able to make decisions on my own and do everyday activities. ”

MARITAL STATUS
Married with 3 children and 5 grandchildren.

EDUCATION
Masters Degree

AGE
75

Living Situation

Gloria is a retired school teacher who lives with her husband and often takes care of her grandchildren.

Main Challenge

Moving 

Gloria is noticing that her muscles are getting weaker. It is becoming harder to carry her young grandchildren and go on walks to the park with them. She is also noticing that sometimes her back and leg muscles are tight, making it more difficult to get out of bed or bend over to pick things up.

Additional Challenges

-  She likes to be active, but is not satisfied with her exercise plan
-  She is having a harder time seeing text and objects up close
-  She is noticing some swelling in her legs
-  She often is stuffed up and has trouble with her sinuses

Her pain is challenging

-  Pain makes it hard for her to move
-  Pain makes her restless
-  Her heart is racing and breathing is fast because of her pain
-  It is hard to keep her face from showing her pain



Gloria Matthews

Main Challenge

Moving 

	Strengths	Needs
My Living	Cleaning Home	Cleaning Income
My Mind and Networks	Role Change Socializing Relationships Speech and Language No Abuse	Socializing Connecting Emotions
My Body	None Reported	Pain Oral Health
My Self-Care	Health Care Medications Personal Care	Health Care Exercising Personal Care

Conclusions/Next Steps

Applying Methods

Connect ML methods with patient-generated data using nursing terminology



Strengths!
Adults 45 and older had many Strengths despite numerous Challenges and Needs

Thinking Group
Highest Strengths, Challenges, and Needs compared to other groups



Unique Insights
ML applied patient data to identify unique insights applicable to specific conditions (e.g. oral health) and healthy aging

Nursing Terminologies

Powerful clinical insights with caveats



Next Steps
User personas to design personalized interventions - **MORE RESEARCH!**

Our Team



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*Health informatics,
Standard terminology design
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My Strengths + My Health



Artificial Intelligence and
Technology Collaboratory
for Healthy Aging

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Q&A

Robin Austin

PhD, DNP, DC, NI-BC, FAMIA, FAAN

Suzanne Bakken | Moderator

PhD, MS, BSN, FAAN, FACMI, FIAHSI

Presentation (slides not available)

Tamara Macieira
PhD, RN

Q&A

Tamara Macieira
PhD, RN

Suzanne Bakken | Moderator
PhD, MS, BSN, FAAN, FACMI, FIAHSI

Part II

AI Technology

Kathleen McGrow | Moderator
DNP, MS, RN, PMP, FHIMSS, FAAN



Clinical Coding Generative AI

Kathleen McGrow DNP, MS, RN, PMP, FHIMSS, FAAN
Global Chief Nursing Information Officer

Microsoft



Responsible AI at Microsoft

In 2016: Led the industry in creating a set of human centered principles to guide the ethical creation & use of AI

Established its AI and Ethics in Engineering and Research (AETHER) Committee to ensure that its AI products & services are designed & used responsibly

- **Privacy & Security**
- **Reliability & Safety**
- **Accountability**
- **Fairness**
- **Inclusiveness**
- **Transparency**

Satya Nadella
CEO, Microsoft



AI Opportunities in Healthcare

84%

healthcare executives believe AI will revolutionize the way they obtain information ¹

global pharmaceutical market estimated to reach by 2024 ⁴

\$1.8T

14M

providers will suffer from a projected shortage of workers worldwide by 2030 ²

patients unsatisfied with their current healthcare experience ⁵

81%

150B

projected savings for healthcare providers by 2026 with AI helping to prevent medication dosing errors ³

providers say data and analytics challenges are preventing them from succeeding in value-based care models ⁶

41%

Definition and Purpose

- Definition of Clinical Coding
 - Translates detailed medical information into standardized codes
 - Includes diagnoses, procedures, and treatments
- Purpose of Clinical Coding
 - Ensures uniformity in medical records
 - Facilitates accurate billing and insurance claims

Applications of Clinical Coding

- Billing and Reimbursement
 - Ensures accurate compensation for healthcare services
- Statistical Analysis and Research
 - Aggregates health data for research, public health monitoring, and policy-making
- Quality Measurement
 - Tracks outcomes and adherence to clinical guidelines
 - Calculates HEDIS performance measures
- Standardize Assessments
 - Calculates HCC risk score to estimate healthcare costs
- Regulatory Compliance
 - Meets legal and administrative requirements in healthcare documentation
- Consistent Documentation

Clinical Coding Systems

- ICD (International Classification of Diseases)
 - Created by WHO
 - Used globally for coding diagnoses and health conditions
 - ICD-10 is the most used version
 - In the US, ICD-10-CM for diagnosis and ICD-10-PCS for inpatient procedures
- CPT (Current Procedural Terminology)
 - Developed by AMA
- SNOMED CT (Systematized Nomenclature of Medicine Clinical Terms)
- RxNorm
- LOINC (Logical Observation Identifiers Names and Codes)
- RadLex
- UMLS (Unified Medical Language System)

GenAI use for Clinical Coding

- Use with caution
- Recognize complexities of healthcare language, medical intent, and the clinical guidelines
- Human experts needs to apply judgement
- Double check and validate
- Require special models trained specifically for the task
- Clinical coding validation in the clinical safeguard

Complexity in Clinical Coding

- Clinical Coding Requires Subtle Judgments
 - Involves understanding medical context and clinician's thinking
 - Not just translating terms into codes
- Examples of Complex Coding Scenarios
 - Diabetes mellitus coding varies based on conditions
 - Different codes for pregnancy-induced diabetes, treatment methods, and secondary conditions
 - Family history of diabetes has a different code than patient diagnosis
- Multiple Terms for Same Condition
 - Example: 'myocardial infarction' and 'heart attack'
- Challenges for Generative AI
 - Struggles with proper clinical coding

Why Generative AI Struggles with Clinical Coding

- Language ambiguity
- Lack of contextual understanding
- Constantly changing guidelines
- Hallucinations especially when data is ambiguous

Language Ambiguity

- Language Ambiguity in Clinical Notes
 - Shorthand and abbreviations are common
 - Incomplete sentences are frequently used
- Need for Context and Pragmatism
 - Understanding requires clinician experience
 - Generative AI struggles without context
- Example of Ambiguity
 - "PT" could mean "physical therapy"
 - "PT" could also mean "prothrombin time"

Lack of Contextual Understanding

- Lack of Contextual Understanding
 - Generative AI learns from language patterns
 - Struggles with deciding specific code based on mixed information
 - Often guesses or uses frequent patterns
- Human Coders' Approach
 - Take a holistic view
 - Consider lab results and medication lists
 - Do not rely solely on raw text

Constantly Changing Guidelines

Constantly Changing Guidelines

- Clinical coding has strict guidelines that are frequently updated
- Coders must understand billable items and compliance
- Guidelines vary based on payer requirements

Difficulty for Human Coders

- Even experienced human coders struggle to keep up

Challenges for Generative AI

- AI trained on static internet data finds it harder to adapt

Hallucinations

- AI Tools' Design to Please Users
 - Provide answers regardless of accuracy
 - Overconfidence in responses
- Impact of Ambiguous Input Data
 - Complex guidelines lead to inaccuracies
 - Incorrect code due to pattern recognition
- Creation of New, Inaccurate Code
 - AI generates plausible but incorrect code

Avoid Using Raw ChatGPT

-
- Generative AI and Clinical Coding
 - AI is improving daily
 - Complexities of healthcare language and medical intent
 - Importance of Human Experts
 - AI might simplify coding
 - Human judgment is crucial

Validation of AI-Suggested Codes

- Generative AI in Clinical Coding
 - AI models can suggest clinical codes
 - Suggested codes need verification
- Need for Double-Checking
 - Ensures accuracy and reliability
 - Prevents potential errors
- Clinical Safeguards
 - Recently announced measures
 - Include validation processes

Need for Special-Purpose Models

Responsible AI Safeguards

- Clinical fabrications and omissions detection, helping detect them in generative answers compared to grounding data
- Clinical anchoring, providing clinical context and concept identification to clinical elements within prompts, making them more prominent to the AI system
- Clinical provenance, helping identify the source of claims against the grounding data
- Clinical coding verification, helping verify that clinical codes provided by generative AI actually exist and are relevant to context
- Clinical semantic validation, helping verify that responses conform to known valid clinical semantic structures

Recommendations

- Generative AI and Clinical Coding
 - Generative AI is improving but not yet reliable for clinical coding
 - Complexities of healthcare language and medical intent require human judgment
- Need for Special-Purpose Models
 - AI for clinical coding needs models trained specifically for this task
 - Raw ChatGPT is not suitable for clinical coding
- Importance of Validation
 - AI-suggested clinical coding must be double-checked and validated
 - Clinical coding validation included in recent clinical safeguards



By 2027, 70% of healthcare organizations will use generative AI to address data fragmentation and improve patient care.

By 2027, 60% of healthcare organizations will prioritize partnerships that focus on "techquity," aiming to reduce the digital divide and address social determinants of health.

By 2027, a doubling of hospital-at-home patients will propel a 55% growth in investments in tech-enabled integrated care initiatives to address patient safety, workforce, and care access concerns.

References

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- [Introducing healthcare agent service in Microsoft Copilot Studio - Microsoft Industry Blogs](#)



Presentation

Cathy Turner
BSN, MBA, RN-BC



Nursing and AI: Unleashing the Power of Nursing Terminology with Artificial Intelligence

Cathy Turner, BSN, MBA, RN-BC

Chief Marketing and Nurse Executive, MEDITECH
Director, Nursing Informatics, MEDITECH
Adjunct Faculty, Northeastern University

Agenda

- Current Landscape
- Foundational Imperatives
- Innovations



Federal and State Regulations



BLUEPRINT FOR AN AI BILL OF RIGHTS

MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE



OSTP

Office of Science and
Technology Policy



Safe and Effective
Systems



Algorithmic
Discrimination
Protections



Data Privacy



Notice and
Explanation



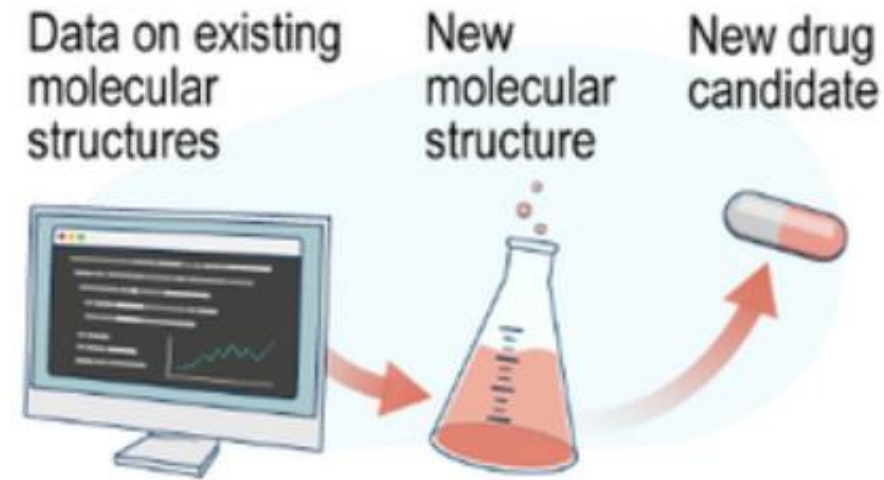
Human
Alternatives,
Consideration, and
Fallback

Science & Tech Spotlight:

Generative AI in Health Care

GAO-24-107634
Published and Publicly
Released: 09/09/2024

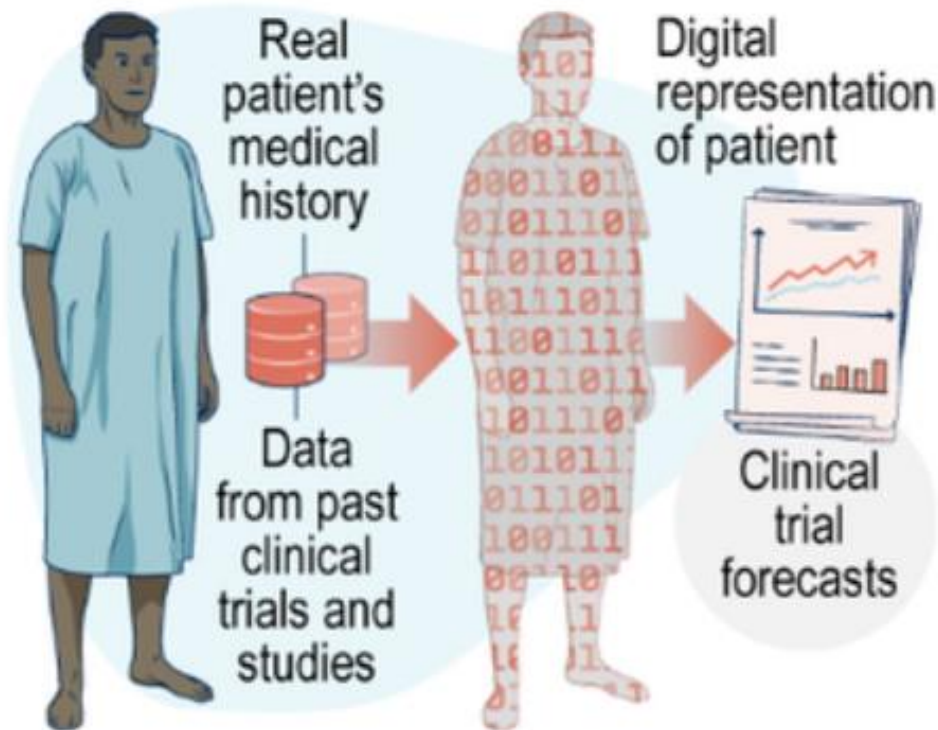
Developing drugs



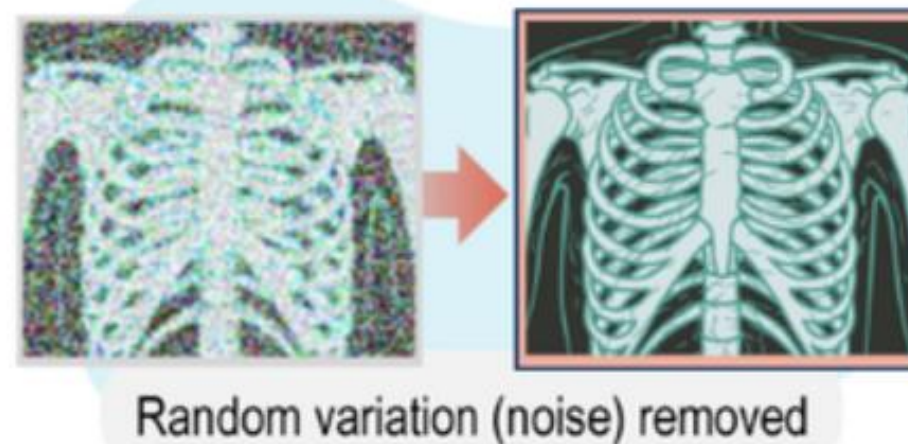
Clinical documentation



Clinical trials



Medical imaging



Source: GAO (analysis and illustration). | GAO-24-107634

Challenges:
False Information, Data Privacy, Data Availability, Bias



**U.S. Department of
Health and Human Services**

Enhancing the health and well-being of all Americans

HHS shares its Plan for Promoting Responsible Use of Artificial Intelligence in Automated and Algorithmic Systems by State, Local, Tribal, and Territorial Governments in the Administration of Public Benefits



FEDERAL REGISTER

The Daily Journal of the United States Government



- Common framework to identify and capture clinical errors
- Central tracking repository for associated incidents that cause harm, including bias or discrimination, to patients and caregivers,
- Analyze data; create and disseminate best practices to stakeholders, including healthcare providers.

Artificial Intelligence in Healthcare Safety

the Agency for Healthcare Research and Quality on 10/31/2024

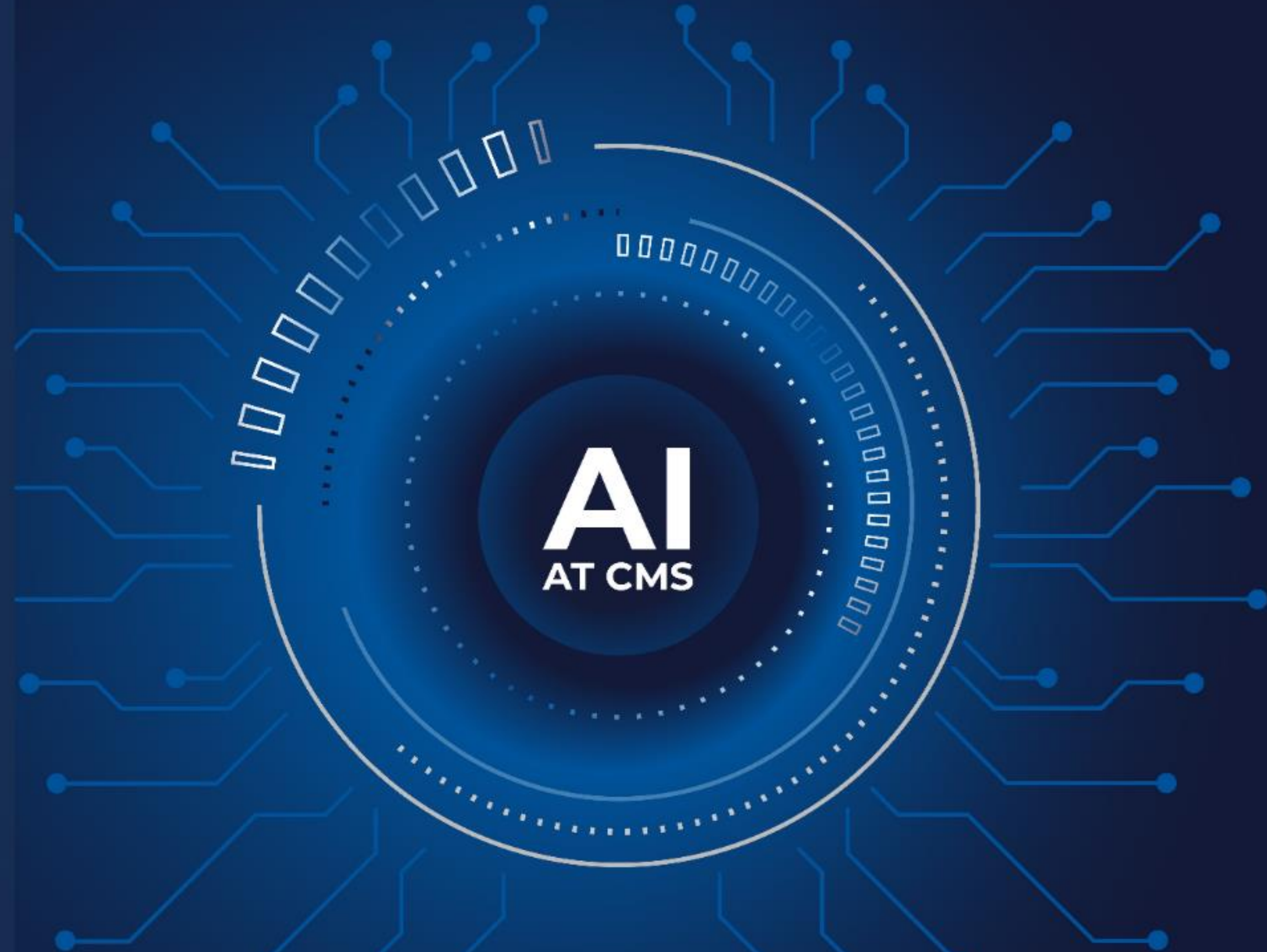
AI Safety Program in Partnership
with Patient Safety Organizations



Artificial Intelligence at CMS

At CMS, Artificial Intelligence (AI) has the power to reshape the way we use data to make decisions. In fact, because CMS is such a data-rich agency, there is no better place to implement AI technology. To do so responsibly, we must educate our workforce, share knowledge with our partners, follow ethical standards, and experiment with new methodologies.

That is why we have created this website. It offers a starting point for stakeholders interested in any aspect of AI at CMS.



Leveraging the power of AI to serve America's healthcare needs

MEDITECH /Tri Agency Meeting

October 21, 2024

Boston, Massachusetts



CMS Nurse Burden Reduction



U.S. CENTERS FOR DISEASE
CONTROL AND PREVENTION

MEDITECH
EXPANSE

What are Nurses Saying about AI?

1. Trust in accuracy: 61%
2. Lack of human interaction: 49%
3. Lack of knowledge on how to use: 36%
4. Increase patient safety risk: 34%
5. Data privacy: 30%
6. Information overload: 20%
7. Poor usability: 20%
8. Job elimination due to automation: 19%
9. Bias and fairness: 19%
10. Lack of time: 6%

Sentiments

- Untested, Unregulated
- Degradation and devaluation of nursing practice
- No nurse should be replaced by a robot
- Chatbot vs. nurse discussion when in crisis
- Lacks empathy and connection
- Fear replacement as opposed to adjunct

Patients Are Not Algorithms

NEWS

Nurses Warn Patient Safety at Risk as AI Use Spreads in Health Care



LISTEN



Jhabvala Romero Apr 22 Save Article



Claire Siegel rallies alongside fellow nurses from across California at Kaiser Permanente on Geary Boulevard in San Francisco on April 22, 2024, to advocate for patient safety in the face of artificial intelligence technology. (Beth LaBerge/KQED)

As the use of artificial intelligence proliferates in the health care industry, Bay Area unionized nurses call for greater transparency and say in how the technologies are deployed to minimize risks to patients.

At a protest on Monday outside of Kaiser Permanente's San Francisco Medical Center, many in the

NEW JERSEY MONITOR

GOV + LEGISLATURE CRIMINAL JUSTICE COURTS SCHOOLS HOUSING SOCIAL JUSTICE ELECTION 2024

HEALTH

Absence of AI hospital rules worries nurses

BY: MADYSON FITZGERALD - MARCH 6, 2024 6:43 AM



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LOCAL NEWS

AI technology no substitute for human touch when caring for patients, rallying nurses say

by Aly Brown, Bay City News April 26, 2024



Patients Are Not Algorithms

nurse.org

CAREERS ▾ PROGRAMS ▾ DEGREES ▾ SALARIES ▾ JOBS ▾ RESOURCES ▾

NEWS

These AI Nurse Like “Agents” Cost \$9 Per Hour - Threat or Help To Human Nurses?

Written By: [Angelina Walker](#)

4 MIN READ Published March 21, 2024

POLITICO

A nurse's take on AI

By DANIEL PAYNE, EVAN PENG, RUTH READER and ERIN SCHUMAKER | 11/14/2023 02:00 PM EST

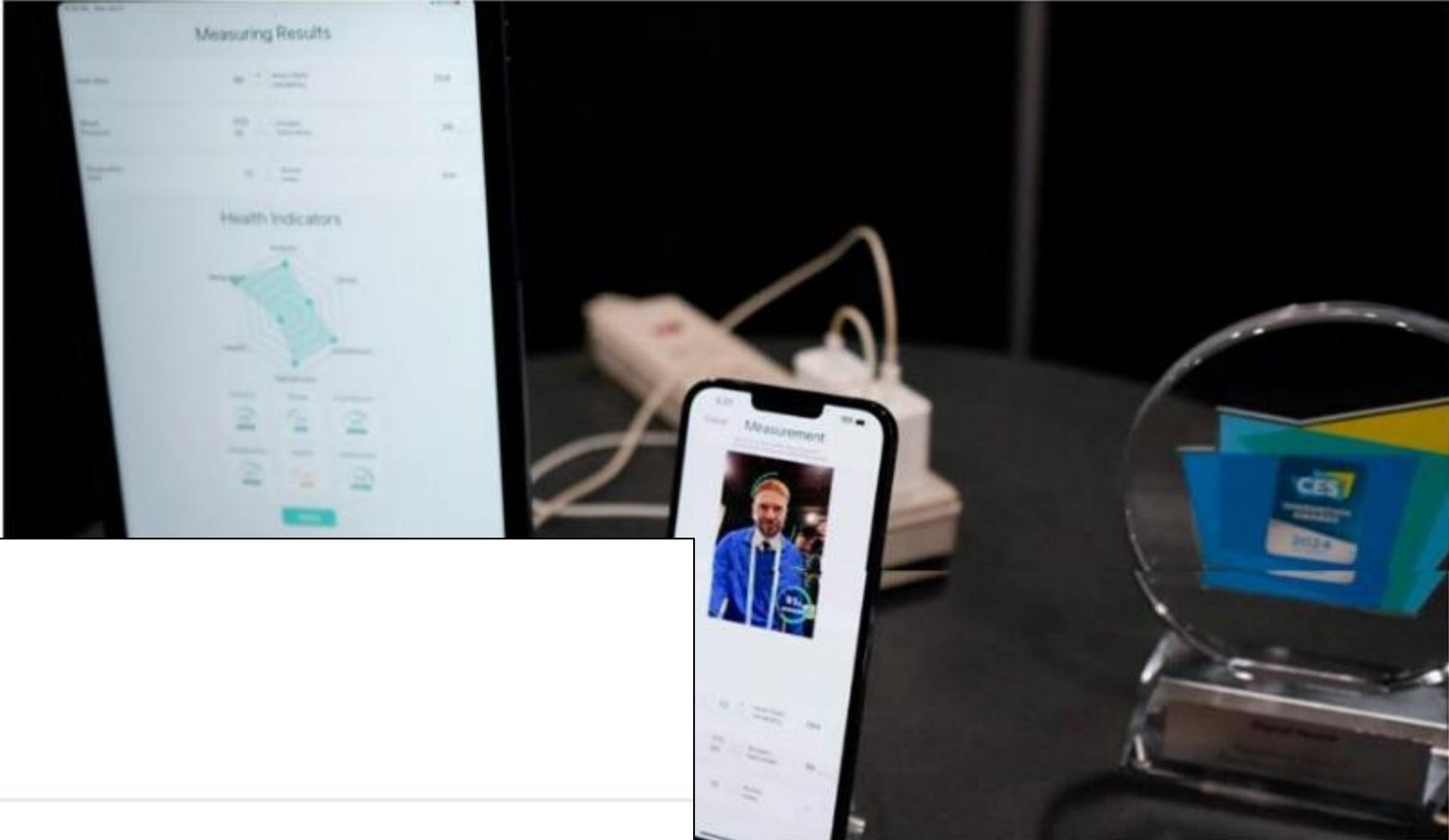
NEW JERSEY MONITOR

GOV + LEGISLATURE CRIMINAL JUSTICE COURTS SCHOOLS HOUSING SOCIAL JUSTICE ELECTION 2024

HEALTH

Absence of AI hospital rules worries nurses

BY: MADYSON FITZGERALD - MARCH 6, 2024 6:43 AM



the start of the CES tech show Sunday, Jan. 7, 2024, in Las Vegas. FaceHeart is a health monitoring (in Sun)

oked up to critical patients at the Community Medical
al part of the whirlwind of activity in the intensive

Schmidt said she realizes those machines were using
yze and track the patients' health.

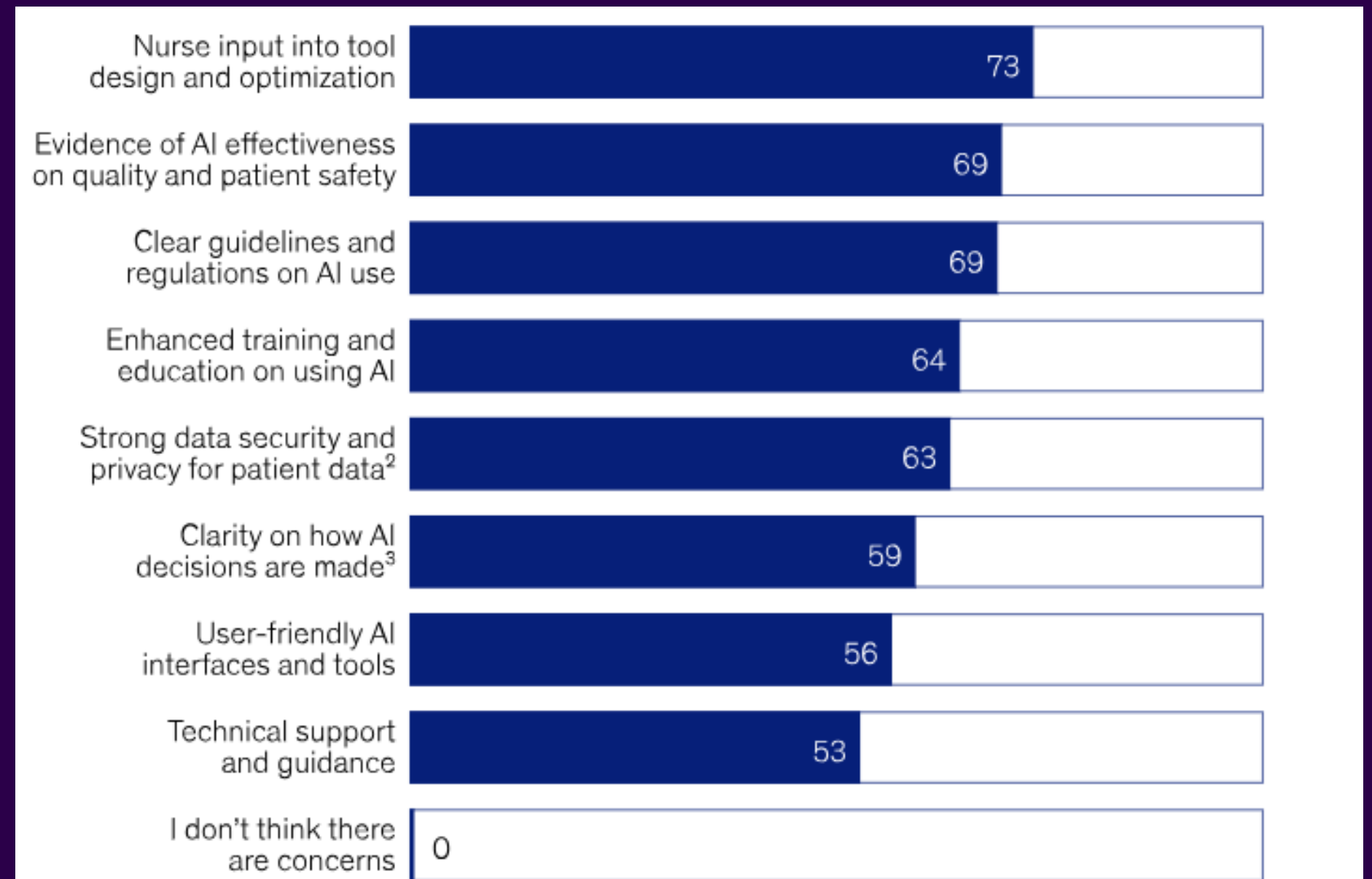
Artificial intelligence has been used in health care settings for years, even before the public became familiar with the technology, said Schmidt, CEO of the New Jersey State Nurses Association, a professional organization.

Allaying Fears

Be Clear About Intention

- Meeting staffing challenges
 - Adjunct, not replacement
- Time consuming events
 - Admission assessments
 - Discharge planning
 - Patient education
- Tasks that don't require RN level of practice
 - Supply delivery
 - Meal delivery
- Leveraging time consuming translation/dictation/notes

US Nurses on the Best Methods to Manage AI Concerns



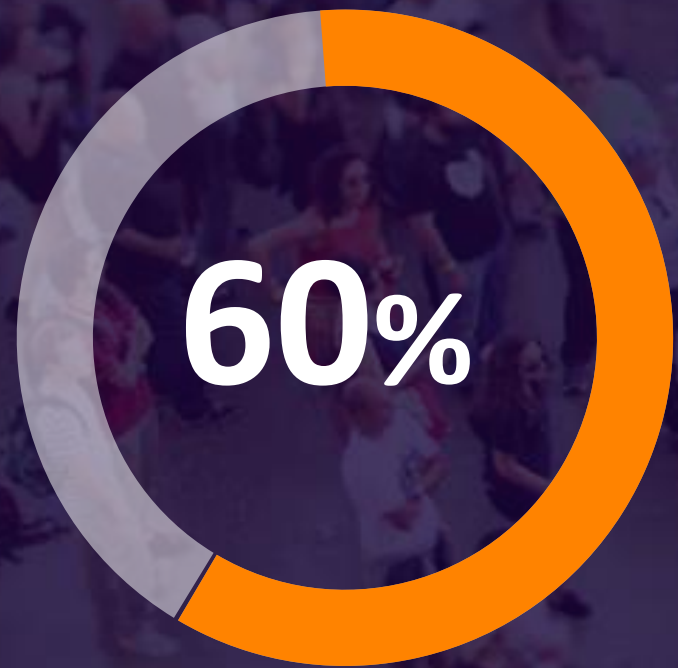
Question: What do you think is needed most to alleviate concerns about using AI technology in healthcare? (Select all that apply.)

²Eg, minimal risks of data leaks or hacks.

³Eg, algorithmic transparency.

Source: American Nurses Foundation Nurses Survey, Mar 2024

Patient Perspectives



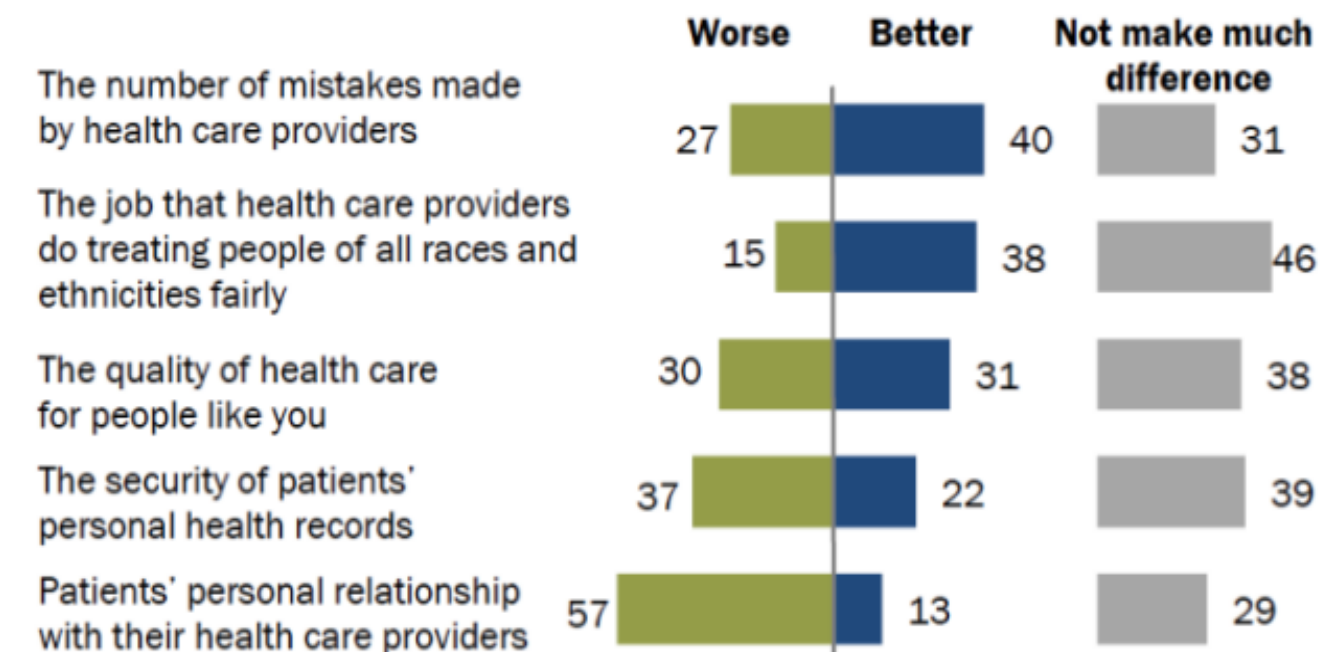
of Americans Would Be **Uncomfortable** With Provider Relying on AI in Their Own Health Care

But.....

They recognize the potential in reducing medical errors

Americans tilt positive on AI's ability to reduce medical errors; greater concern around data security, patient-provider relationships

% of U.S. adults who say the use of artificial intelligence in health and medicine to do things like diagnose diseases and recommend treatments would make each of the following ...



Note: Respondents who did not give an answer are not shown.

Source: Survey conducted Dec. 12-18, 2022.

"60% of Americans Would Be Uncomfortable With Provider Relying on AI in Their Own Health Care"

PEW RESEARCH CENTER

MEDITECH and AI: Our Mission



MEDITECH's mission is to provide technology that enables healthcare organizations to deliver **safe, efficient, and impactful care**; our approach to incorporating AI into EHR solutions is thoughtful, deliberate, and driven by an understanding that it should safely **enhance the experience** for **patients, care teams, and healthcare organizations.**

AI

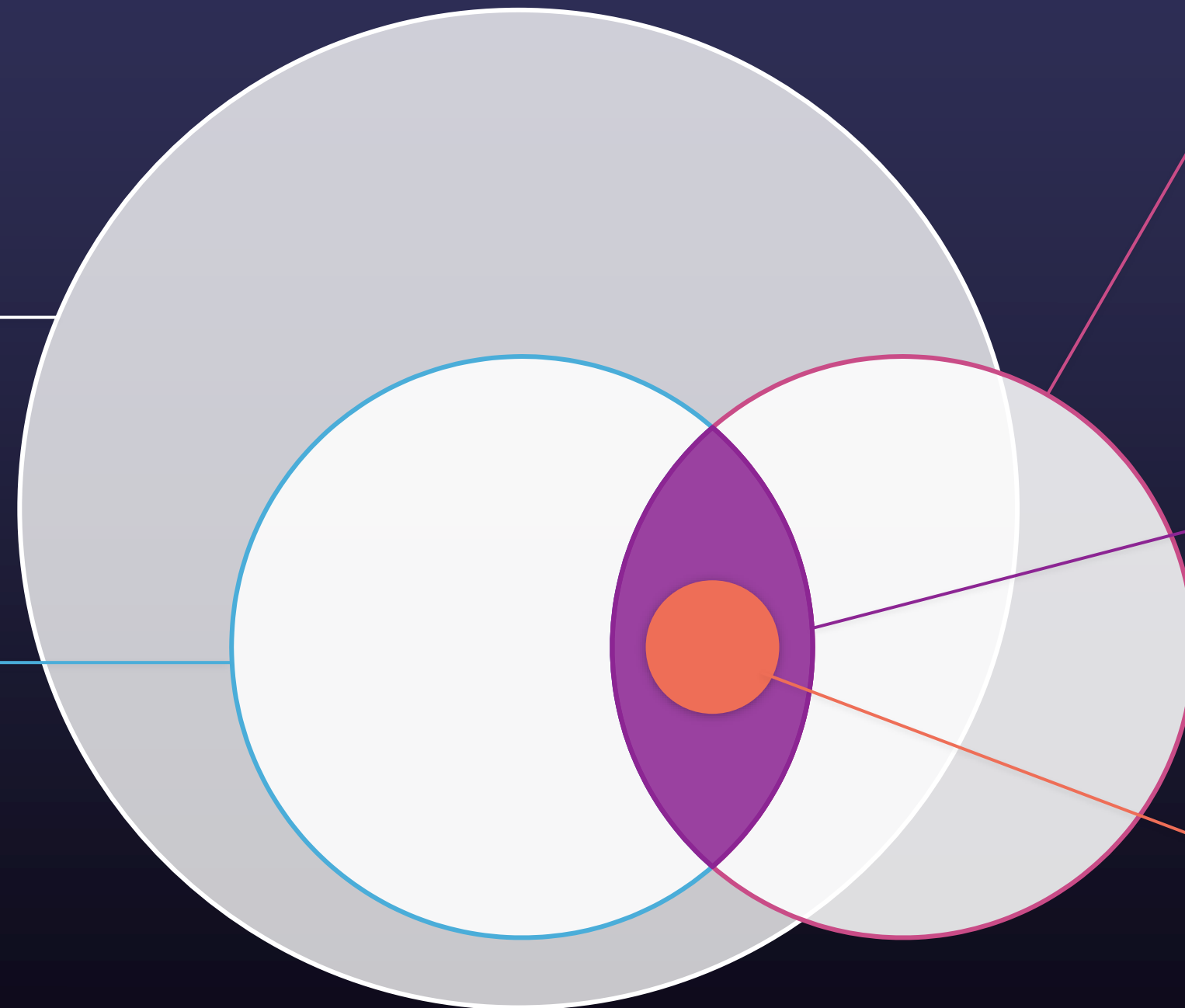
Overarching term for teaching computers to think and act in a *human-like* way

Machine Learning

Type of AI that uses large datasets to train models to identify patterns, make predictions

Deep Learning

Type of Machine Learning, defined by artificial neural networks used for internal processing and pattern extraction; requires very large volumes of data



Natural Language Processing

Field of AI that involves training computers to understand (Natural Language Understanding) and generate (Natural Language Generation) spoken and written word

Generative AI

AI models that identify and use patterns and relationships in data to create new content

LLM

A type of model that uses an understanding of language to generate content

Nursing Terminology and AI

Nursing Terminologies
NIC/NOC/NANDA,
CCC, OMAHA, PNDS

Allied Health, Behavioral
Health, Therapy
Nomenclature

LOINC, Snomed-CT
CPT, DSM, ICD

- **Central Data Repository**
- **Data Mapping**
- **Real-time Generative AI**

30% of the world's data volume is attributed to the healthcare industry

Projected to grow to 36% by 2025



Data Sources

All Disciplines

Data Mapping

Data Mapping
Templates

Data Integration

Data Mapping to Data
Source

MEDITECH: The Practical Integration of AI

- Decrease clinician burden
- Enhance the patient experience
- Improve organizational efficiency
- Empower health systems to develop an AI strategy that is sustainable and safe





Achieving AI's Promise Requires Thoughtful Navigation of Challenges

Promise

- Reduce cognitive burden
- Put focus back on direct care
- Augment human decision-making
- Facilitate top-of-license practice
- Expand our knowledge base by generating insights

Challenges

- Complex interplay of data and human behavior
- Introduction or replication of bias
- Data security
- Lack of legal precedent
- Regulations still in development
- Change management and optimal incorporation into workflows

From Data to NLP and Gen AI: **Key Challenges**



Accessible

- Affordable to All
 - Cost and Slow ROI
- Meets Diverse User needs
- Interpretable, Explainable



Fair & Appropriate

- Ethical Concerns and Biases
- Training the Model
- False Positives



Transparent

- Handling Ambiguity
- Context in Language
- Dialects and Speech Patterns
- Colloquialisms



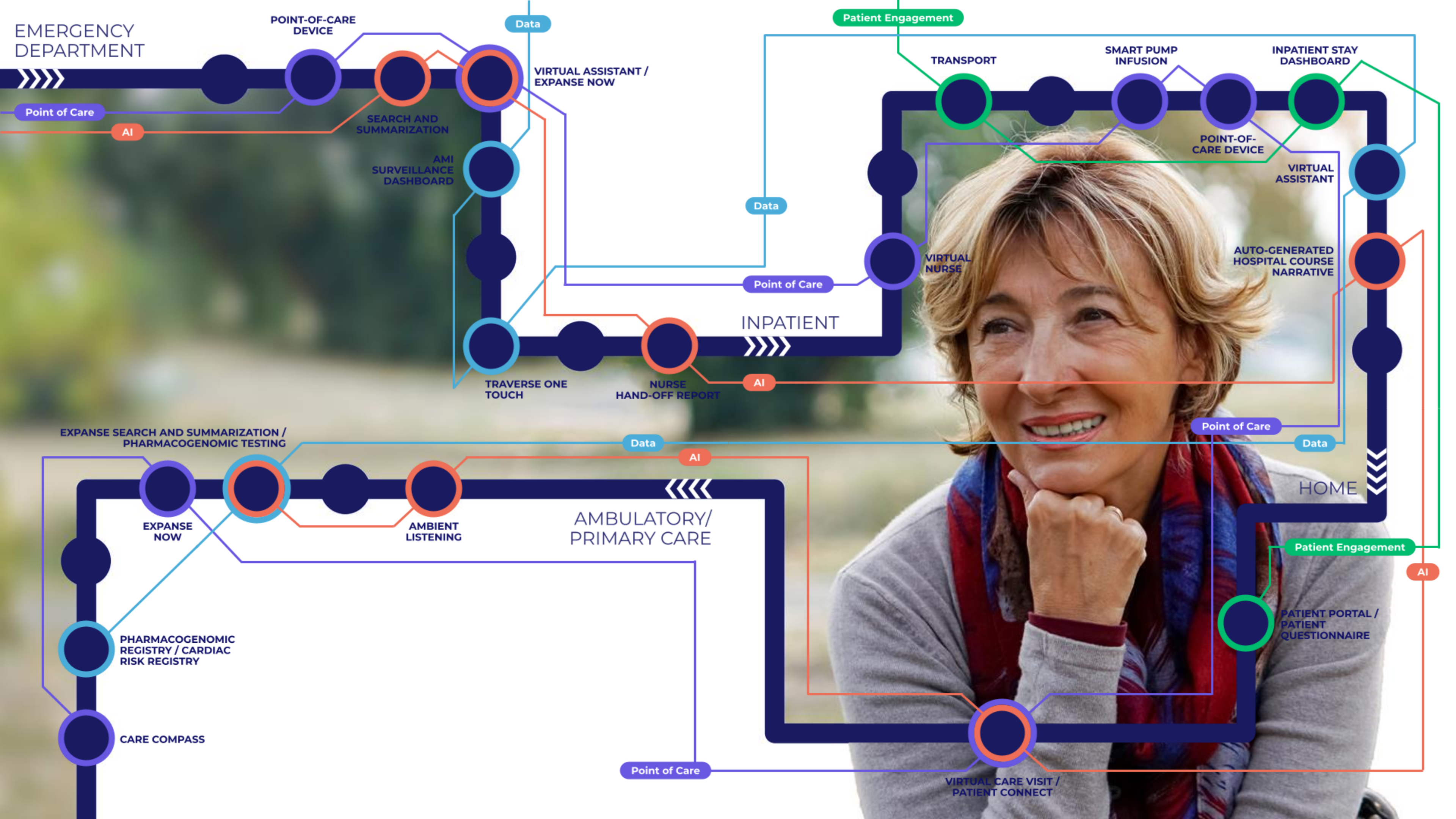
Safe & Effective

- Achieves stated Purpose
- Measurable and Positive Impact on Outcomes



Privacy-Protective & Secure

- Data Quality
- Data Availability
- Data Security
- Evolving Regulations



TYPE

NURSING BENEFIT

Generative AI

- › Time-savings
- › Improved note quality and standardization
- › Reduced cognitive burden – utilize human-in-the-loop as high-level editor

- › Auto-generation of Nurse Handoff Summary for clinician review
- › Discharge Summary

Advanced Natural Language Understanding & Processing

- › Keep patient/clinician interaction at the forefront of the encounter; enable patient convenience
- › Quickly develop an understanding of patient's history and baseline, ensure care decisions do not conflict with past/ongoing treatment plans
- › Longitudinal view of patient's progress, better prioritize care planning and patient educational needs

- › Expanse search and summarization, powered by Google Health
- › Patient Connect
- › Ambient Listening

Machine Learning

- › Proactively respond to patients' needs
- › Move beyond data access to better data operationalization and dynamic use
- › Use prediction outcomes to identify and assess opportunity for workflow/process improvement

- › Tool for predicting patient risk of missing an appointment
- › Genomics and Clinical Trials

MEDITECH SOLUTIONS *powered by AI*

Auto-generating Clinical Documentation



Hospital Course Narrative

- Open within discharge, transfer or referral workflow
- Automate the generation of a draft narrative of patient's hospital course
- Final review and editing by clinician



Nurse Handoff

- Manage transitions of care between clinicians
- Automate the generation of clinical notes for nurse to nurse communication
- Final review and editing by clinician

Deliver or Empower with Generative AI

Auto Generating Clinical Documentation:

| Hospital Course Narrative

Problem Statement

Transitions of care are highly vulnerable points in the care process for patients. Care transitions should be facilitated through comprehensive and concise communication of pertinent information necessary to maintain a high-quality of care and treatment for patients.

Benefits

Automate the generation of a hospital course narrative within the discharge summary. Potential benefits include

1. Time-savings
2. Enhanced note quality through more concise narratives and a reduction in errors or accidental omissions of information
3. Timely transfer of discharge documentation in real time

Ambient Listening Experience

The screenshot displays a medical application interface. At the top, there is a navigation bar with icons for 'Return To', 'Home', 'Workload', 'Chart', 'Document', 'Orders', 'Sign', and 'Compose'. Below this, the main content area shows a patient visit summary for 'AMB Office Visit' by 'Principal Michael Coelho Contributors'. The summary includes sections for 'Intake', 'Vital Signs', 'HPI', and 'Low Back Pain'. A 'Suki' AI-generated note is overlaid on the right side of the screen, titled 'History of Present Illness'. The note contains a suggestion: 'A 47-year-old female patient presents with sudden onset mid back pain that began a few days ago. She originally noticed a dull ache when going to sleep, which has progressively'.



Access 3rd party ambient solution via mobile or desktop application



Record the conversation between the patient and provider



View AI generated provider note in the app



Edit the note in the app using dictation, typing, or macros



Narrative summary or population of discrete flowsheet data

Ambient Listening Experience

[Demo](#)

The screenshot displays a medical software interface with a top navigation bar containing icons for 'Return To', 'Home', 'Workload', 'Chart', 'Document', 'Orders', 'Sign', and 'Compose'. The main content area is titled 'AMB Office Visit' and includes buttons for 'Preview' and 'Rapid Entry'. Below this, the patient's name 'Principal Michael Coelho Contributors' is shown, along with a 'Last Saved' timestamp. A horizontal menu lists various chart sections: 'Intake', 'HPI', 'Review of Systems', 'Exam', 'Procedures', 'Assessment and Plan', and 'Coding'. The 'HPI' section is expanded, showing sub-sections for 'HPI' and 'Low Back Pain'. A 'Details' section is visible with a text input field. Below this, several labels are listed: 'Onset', 'Location', 'Duration', 'Characteristics of symptom or complaint', 'Aggravating or associated factors', 'Relieving factors', and 'Treatment'. On the right side, a 'Suki' AI-generated text window is open, displaying a 'Suggestion' for the 'History of Present Illness'. The suggestion text reads: 'A 47-year-old female patient presents with sudden onset mid back pain that began a few days ago. She originally noticed a dull ache when going to sleep, which has progressively worsened. The pain is described as sharp and radiates down towards the patient's groin, and comes in waves. The patient rates the pain as 7-8 out of 10 in severity. She has tried using a heating pad and taking Tylenol, but neither has provided relief. The patient reports no weakness or numbness in her legs but has noted increased urinary frequency and pink-tinged'. A checkmark icon is visible in the bottom right corner of the Suki window.

Hospital Course/Discharge Summary

E
Return To

Home

Chart
Document
Orders
Discharge

Sign
Workload
Menu
More
Help
RW User
Close

☰
Rachel Wilkes, MD





Find Patient

Rounds Patients
4

MEDITECH General H...

Rounding

Sign Out

	Patient Name	Diagnosis	Notes
	Bourne, Lawrence 70 M 1S1/1S16-4 Inpatient	Left Leg Deep Vein Thromb...	Lawrence has improved significantly with reduced leg pain, swelling, and tenderness, stable vital signs, and cellulitis improvement. He's responded well to meds and antibiotics, regained mobility, and can independently perform activities. Patient is ready to be discharged
	Mahoney, Lillian 24 F 2N/2N14-5 Inpatient	Acute Appendicitis	Lillian is recovering well from the procedure. Incision site is well approximated and healing as desired. Her ability to main her pain appears to be improving. May need to consider moving her over to oral pain medications in advance of discharge
	Porter, Harold 58 M 1S1/1S100-130 Inpatient	Systolic Congestive Heart F...	New admit with hx of CHF and PAD. Will need observation and monitoring
	Wolmack, Amanda 53 F 1S1/1S100-126 Inpatient	Pneumonia	Amanda presented to the ED with fever and dyspnea and found to have right lower lobe pneumonia. COVID+ initial pulse oximetry 82%on room air. Patient admitted to Med/Surg for IV Antibiotics, O2 Therapy.

My Workload

Recently Accessed

Name (Preferred)	Visit Date	Close Chart
Bourne, Lawrence	09/12/2023	
Moxley, Stephen	09/14/2023	
Dannon, Richard A	09/14/2023	
Wolmack, Amanda		
Franklin, David		
Mahoney, Lillian		
Manning, Kevin		
Bradford, John		
Keller, Marcus		

Empower with Generative AI

Auto Generating Clinical Documentation:

| Nurse's Handoff

Problem Statement

Transitions of care are highly vulnerable points in the care process for patients. Shift changes and transitions of care within the acute setting allow nursing staff to exchange necessary patient information to ensure continuity of care and patient safety.

Benefits

Automate the generation of a nurse note within Expanses' Nurse Handoff routine.

Potential benefits include

1. Time-savings
2. Enhanced note quality through more concise narratives and a reduction in errors or accidental omissions of information
3. Real-time documentation
4. Real-time transfer of information

Narrative to Flowsheet

The screenshot displays a clinical information system interface. On the left, a staff list for Rachel Wilkes, RN, shows several staff members, including Clancy, Joshua, with a pop-up window for 'AI-Generated Hand Off Please Wait...'. The main area shows a patient's flowsheet for Fisher, Amy, with a table of vital signs and ventilator settings over time. The table includes columns for time intervals from 03:00 to 12:00. The flowsheet shows data for Pulse, Respirations, Blood Pressure, and Ventilator Settings. A pop-up window for 'Prednisone' is also visible, showing details like 'Prednisone 5 Mg/ 5 MI Solution'.

Staff List:

- Rachel Wilkes, RN** (Staff Nurse 3, 2 North 18)
- Clancy, Joshua** (2E-11, 53 M)
- Carbone, John** (2E-27, 76 M)
- Mahoney, Hillary** (2E-19, 65 F)

AI-Generated Hand Off:

AI-Generated Hand Off
Please Wait...

Preferred Language:

Generic Name
Trade Name
Prednisone
Prednisone 5 Mg/
5 MI Solution

Flowsheet Data (Fisher, Amy):

Time	Pulse Rate (60-90 bpm)	Respiratory Rate (12-20)	Blood Pressure (mmHg)
Tue Mar 3 03:00	95 H	25 H	140/84 H
Tue Mar 3 04:00	95 H	20	
Tue Mar 3 05:00	82 H	21	
Tue Mar 3 06:00	90	25 H	
Tue Mar 3 07:00	85	26 H	
Tue Mar 3 08:00	96 H	27 H	
Tue Mar 3 09:00	95 H	25 H	
Tue Mar 3 10:00	91	24	
Tue Mar 3 11:00	93 H	23	
Tue Mar 3 12:00	95 H	25 H	

Narrative to Flowsheet

The screenshot displays a medical software interface with a top navigation bar containing icons for Return To, Home, Chart, Document, Orders, Discharge, Sign, Workload, Menu, More, Help, User, and Close. The main interface is divided into several sections:

- Staff List:** A list of staff members including Rachel Wilkes, RN (Staff Nurse 3, 2 North 18), John Carbone (2E-27, 76 M), Joshua Clancy (2E-11, 53 M), and Hillary Mahoney (2E-19, 65 F). A search bar is present.
- AI-Generated Health Summary:** A box with the text "AI-Generated Health Summary Please Wait..."
- Vital Signs Table:**

Vital Sign	Value
Temperature	98.3 F
Pulse Rate	55 L
O2 Sat by Pulse Oximetry	98
Blood Pressure	120/80
Blood Pressure Position	
Blood pressure location	
- Social History Table:**

Smoking Status	Never smoker
physical activity	walking
- Diabetic Care Table:**

Right foot	normal
Left foot	abnormal
- Medication Table:**

BP	01/03/2024 09:21	140/84 H
----	------------------	----------
- Flowsheet View:** A detailed view of vital signs for a patient with Diabetes, showing data for All Visits - Most Recent. It includes fields for Height, Weight, Body Mass Index (BMI), Temperature, and Pulse Rate across multiple visits.

Developing an AI Strategy



Promote Data and AI Literacy

- Facilitate an understanding of available data sources, purposes
- Develop common understanding of AI types, purposes

Identify Pain Points

- Determine areas of strategic priority
- Identify relevant workflows, pain points, and stakeholders

Align Expectations

- Evaluate opportunities for AI to address pain points
- Determine aspects of workflow that will need to change to accommodate
- Assess readiness

Establish AI Governance

- Establish guidelines, policies for optimal AI use* (ethics, education, human-in-the-loop, risk management framework)
**These may vary based on AI use case*
- Identify metrics for measuring outcomes and comparative effectiveness, and who is responsible for monitoring

Establish Overarching Data Governance and Strategy

Successful AI Organizations



Policies and Principles

- Safe
 - ◆ Evaluation of Risk
 - ◆ Enhances Care
- Accountable and Transparent
 - ◆ Disclose Model Capabilities and Limitations
 - ◆ Measure Impact (pre and post)
- Fair and Accessible
 - ◆ Equitable Care Delivery
 - ◆ Minimize/Avoid Bias
 - ◆ Techquity
- Efficient and Impactful
 - ◆ Seamless to Workflow
 - ◆ Meets the Nurses' Needs
- Privacy-Protective
 - ◆ Ensure Informed Consent
 - ◆ Data Protections

Data-ready organization

Data science resources

Processes amenable to AI/ML

Optimal workflow integration

Interventional capacity

Explainability

End-use willingness to adopt

End-user training

AI Ethics/Governance Board

Model Customization, MLOps

Regulatory Compliance

A smart, strategic approach to **Artificial Intelligence**

What it is:

- Assistive technology
- A new way of thinking
- An opportunity to put the focus back on care
- Data optimization / tapping into the next-level potential of data
- The potential to explore new methods of care deliver

.... And is Not:

- Autonomous
- A replacement for:
 - Human caring and compassion
 - Professional experience
 - Judgement and clinical reasoning
- Infallibly/Fully mature
- Fully adaptable and context-driven



ACCELERATING YOUR INNOVATION



Thank You

MEDITECH
EXPANSE

Presentation

Karina Rohrer-Meck
MS, BSN, RN

Empowering Nurses with AI Technology



Karina Rohrer-Meck, MS, BSN, RN
Clinical Informatics, Epic

Agenda & Objectives



Background on Nursing Terminology in the EHR



Overview of Artificial Intelligence



Generative AI in Epic



Case Study



Wrap up and What's Next

Agenda & Objectives



Background on Nursing Terminology in the EHR



Overview of Artificial Intelligence



Generative AI in Epic



Case Study



Wrap up and What's Next

Background on Nursing Terminology in the EHR



History & Significance

- Improve communication and coordination of care
 - Demonstrate value of nursing
 - Nursing research
 - Education and training tool
 - Interoperability

Use Cases: [Advancing Nursing Terminology](#)



Terminology in the EHR

- Why are adoption rates so low in Epic community?
- Variation by care setting increases install and maintenance expense
 - Perception that term sets are not interdisciplinary
 - No aligned incentives among authors-health systems-industry-nurses delivering care

Case Study: [Implementation of Standardized Nomenclature in the Electronic Medical Record - Klehr - 2009 - International Journal of Nursing Terminologies and Classifications - Wiley Online Library](#)

Agenda & Objectives



Background on Nursing Terminology in the EHR



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Case Study



Wrap up and What's Next

The Spectrum of Artificial Intelligence



Rule-Based Logic

Expert-defined and explicitly coded



Predictive Analytics

Statistically-derived to predict a pre-defined event



Generative AI (Large Language Models)

Generally-trained to generate novel content



Deterministic

Targeted

Probabilistic

More generalized

Understanding *the* Difference



Predictive Models

Outcome Prediction
Specific Datasets
Specific Variables & Patterns
Specific Outcomes (ex: Score)
Deterministic

Use Cases: Risk Predictions, Forecasting
Demand, Etc.



Large Language Models

Word Prediction
Large Datasets (Text)
Word Patterns & Relationships
Generate Novel Text
Probabilistic

Use Cases: Draft Notes & Responses,
Ambient, Summarizations, Etc.

Epic Generative AI Rollout

November 30, 2022

ChatGPT released



January 19

Azure OpenAI service available

April

First customers live with In Basket draft replies



HIMSS23: Epic taps Microsoft to integrate generative AI into EHRs

August

Announced 15+ use cases at UGM

Ambient integration went live (prod), summarization went live (non-prod)

SideKick live on Cosmos



Today

297 customers using generative AI!

Late 2022

March 10

Epic integrates GPT

May

Epic supports GPT-4

June 15

First customer live on GPT-4

January

Inpatient Summaries and Draft Nursing Care Plans live (non-prod)

May

Two Dutch customers live with outpatient summarizations

Today

Considerations for Responsible Use of AI



Accuracy



User Experience



Ethics

Trust-Centered AI

Personalization

Combatting
Automation
Bias

Transparency

Confidence
Measures

Decreasing
Verification
Complexity

Citations

Explainable AI

Tone &
Semantics

Immersion
trips

Reducing
Cognitive
Load

Workflow
Integration

Usability &
Accessibility

Reflective
Design

Predictive
Assistance

Feedback
Loops

Trauma-
Informed
Care

Onboarding &
Learnability

Multi-modal
Interactions

User Control &
Freedom

Generative AI Adoption

297 Organizations live
as of November 15

36k+ Users with Gen
AI features

2M/month
Notes drafted using
Ambient voice

1M/month
Replies drafted
using Art

“It has improved our patient experience and quality of care. **Our patients feel better connected** with us; we are there for that moment.”

“I have found having a draft to start from **helpful**, and **I’m glad I could provide feedback** on improvements and features to ensure this can be a good tool for nurses and have a **positive impact on our patients.**”

“By **leveraging Gen AI**, we are setting new standards for clinical documentation and efficiency, ultimately leading to **better patient care** and more **empowered nursing professionals.**”

Measurable Impact

JAMA Network

March 2024

Artificial Intelligence–Generated Draft Replies to Patient Inbox Messages

There were statistically significant reductions in burden and burnout scores

LLM usage was associated with an improvement in clinician well-being

SSRN

May 2024

Completeness, Correctness and Conciseness of Physician-Written Versus Large Language Model Generated Patient Summaries Integrated in Electronic Health Records

LLM summaries were as complete & correct as physician summaries

There was a preference for LLM summaries (57% to 43%)

Trust in both the physician and LLM summaries was similar

EpicShare

March 2024

Gen AI Saves Nurses Time by Drafting Responses to Patient Messages

3.9 million
draft responses generated

30 sec/message
saved using draft responses

1,500 hours
predicted to be saved

Agenda & Objectives



Background on Nursing Terminology in the EHR



Overview of Artificial Intelligence



Generative AI in Epic



Case Study



Wrap up and What's Next

Generative AI & Epic

Draft Text



Generate Summaries



Translate Content



Task Automation





Nurses



AVAILABLE NOW

In Basket Art – generate draft response to patient messages [improve coordination of care]

AI Text Assistant – adjust writing for brevity and reading level [improve communication]

Inpatient Summaries – review recent events, assessments, notes, etc. [capture the value of nursing]

End of Shift Notes – draft end-of-shift note based on the chart [improve communication and coordination of care, demonstrate the value of nursing]

Ambient Flowsheets – document flowsheets with a conversation [demonstrate the value of nursing]

Enhance Nursing Experience



Catch Up *in the* Hospital

Epic | Chart | Encounter | SlicerDicer | Search Epic (Ctrl + Space) | Print | Log Out | EpicCare

Glen Anderson
Male, 50 y.o., 6/14
MRN: 29580
Room: 310
Code: FULL (has AC)

Recent Events Past 24 Hours (AI)

- Condition has worsened, requiring increased oxygen flow rates
- Blood pressure has dropped, possibly due to sepsis, and sodium chloride 0.9% infusion has been started
- Blood culture shows growth of *S. pneumoniae*
- Levofloxacin (LEVAQUIN) IVPB 750 mg has been ordered for antibiotic coverage
- Chest X-ray shows right lower lobe pneumonia with effusion
- Renal function has worsened.

Recent Notes Past 3 Days (AI)

- Internal Medicine**
The patient presented with symptoms of fever, chills, cough with rust-colored sputum, and shortness of breath, indicative of community-acquired pneumonia with possible para-pneumonic effusion. 1 Physical examination revealed tachycardia, rhonchi, and rales. 1 Laboratory studies revealed an elevated WBC. 1 The patient is being treated with broad-spectrum antibiotics pending cultures. 2 The patient's oxygen saturation remains low despite O2 by nasal cannula. 2
- 1. H&P by Pat Cooper, MD on Aug 17 at 14:16 | 2. Progress Notes by Pat Cooper, MD on Aug 18 at 18:38
- Infectious Disease**
Infectious disease consult was requested due to pneumococcal pneumonia and history of penicillin allergy. 3 CT chest revealed loculated parapneumonic effusion suspicious for empyema. 3 Recommend treating with levofloxacin empirically and consulting IR for chest tube placement. 3 We will adjust antibiotics based on susceptibilities. 3
- 3. Consult by Kavita Singh, MD on Aug 18 at 22:00

Progress Notes (Handoff)
Subjective
Summary of the Last 24 Hours:
The last 24 hours have been eventful. Patient has required increased oxygen flow rate.

Objective
Last vitals
BP 90/57 | Pulse 106 | Temp(Src) 101.2 °F | Resp 20 | Ht 5' 8" (1.727 m) | Wt 78.926 kg | BMI 26.46 kg/m² | SpO2 94%

Physical Exam
Constitutional: alert, oriented x4
HEENT: PERRLA, MMM
Neck: No lymphadenopathy or JVD
Cardiovascular: Tachycardia. No murmurs, rubs, or gallops.
Lungs: Tachypnea with increased work of breathing w nasal cannula. Decreased breath sounds in the right lower lobe with crackles diffusely.
Abdominal: Soft, nontender, nondistended. Normal bowel sounds. No organomegaly.
Skin: Intact. No rashes.

Assessment and Plan
Community Acquired Pneumonia

simvastatin (ZOCOR) tablet 40 mg 08/19 18:00 Given: Dose 40 mg, Oral
Continuous
ICI 1,000 mL infusion 08/19 21:00 New Bag: 125 mL/hr Intravenous

Accept Cancel | SIGN ORDERS



FEB 2023

Quickly Catch Up on Your Patients

End of Shift Note Draft

Drafted Care Plan Note



Shift Summary

Overall, the patient's condition appears to be stable with some improvement in pain and oxygenation levels. 📊 🩺

Achieves optimal ventilation and oxygenation:

Patient's SpO2 levels improved from 93% to 98% over the shift, and respiratory rate remained stable. BP increased gradually but remained within normal range. 📊

Displays adequate comfort level or baseline comfort level:

Patient's pain score decreased from 5 to 2 after morphine administration. Patient was initially restless but became comfortably by the end of the shift. 📊 🩺

Administrations of morphine injection

Administration	Action Time	Recorded Time	Documented By
Given : 1 mg : Intravenous	04/25/24 1723	04/25/24 1723	Stuht, Andrew, RN Dual Signoff By: Rauwerdink, Brian, RN

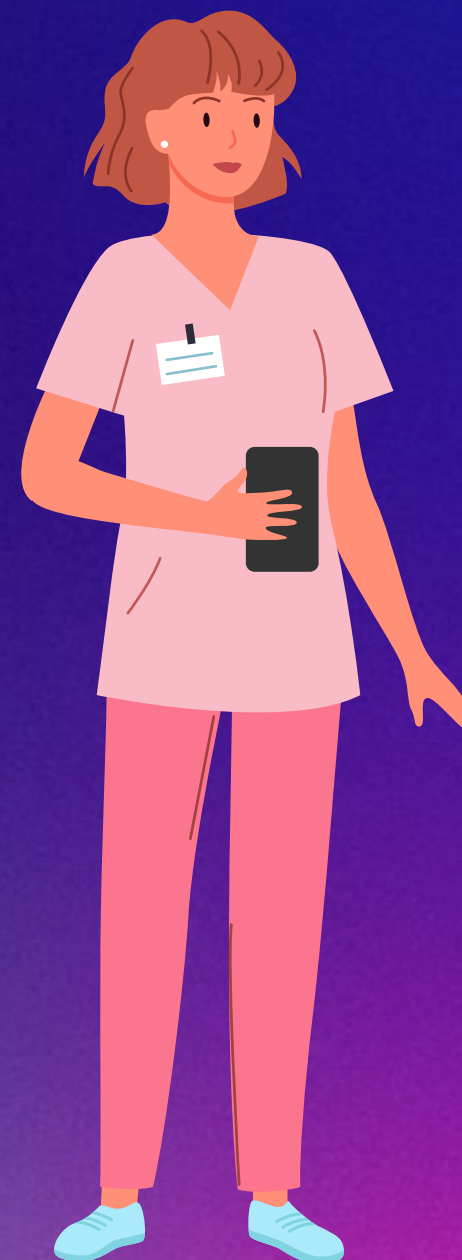
👍 👎 ⓘ Learn More

Start with

“This is so **exciting!** End of Shift notes have been accurate and helps pull together the **picture** of how the day went.”



“It **saves time** with making notes.
I love it. It summarizes all the tasks done for the whole day or night shift.”



MAY 2024

Behind the Scenes



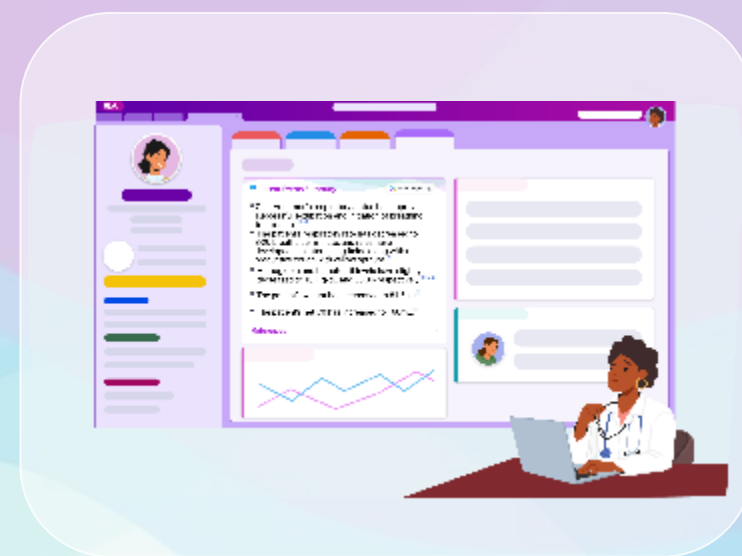
Data Collection

Assemble goals, flowsheets, medication information



Categorization

Associate goals with related flowsheets and medications



Summarize!

Brain

4 Patients Shift: Today 0700 - 1500 Show: My Discipline All Disciplines Meds Labs Assessments To Do [Hide All](#) Sign In Sign Out

Prior	2/20/24 0600	0700	0800	0900	1000	1100	1200	1300	1400	1500
-------	-----------------	------	------	------	------	------	------	------	------	------

Personal Tasks

Atwood, Glen 340
50 y.o. / M
Code: Full Code
Diet: Diet - NPO

Attending Pat Cooper, MD
Primary Problem: Infection
Community acquired pneu...
Deterioration Index: 33

Notifications:

PRN
Orders
Labs

Adams, Kim 365-2
63 y.o. / F
Code: Full Code
Diet: Diet - general

Attending Pat Cooper, MD
Primary Problem: Infection
Community acquired pneu...
Deterioration Index: 25

Notifications:

PRN
Orders
Labs

Roberts, John 387
72 y.o. / M
Code: Full Code
Diet: Diet - general

Attending Stan Lapidus, MD
Primary Problem: Infection
Community acquired pneu...
Deterioration Index: 27

Notifications:

PRN
Orders
Labs

Davidson, Todd OR
51 y.o. / M
Code: Full Code
Diet: —

Attending Sean Armstrong, MD
Primary Problem: Infection
Osteoarthritis of right knee...
Deterioration Index: 33

Notifications:

PRN
Orders
Labs

Summary and Note

Group by: Problem Outcome ▼ Add to note

Shift Focus

Respiration
Vital sign status
Today at 0807 - by Kim Harker, RN

Achieves optimal ventilation and oxygenation
Today at 0807 - by Kim Harker, RN

Infection
Absence of infection during hospitalization
Today at 0807 - by Kim Harker, RN

Draft Note AI

Shift Summary

- NS bolus was administered twice to manage low blood pressure.
- Acetaminophen was administered three times to manage fever.
- Morphine was administered four times to manage pain.
- Despite ongoing signs of infection and respiratory issues, vital signs stabilized and pain is managed.

Vital signs status: Blood pressure was initially low but stabilized with administration. Pulse rate decreased over the shift. Temperature peaked at 38.9 °C, managed with acetaminophen. Respiratory rate and SpO2 remained relatively stable.

Achieves optimal ventilation and oxygenation: Breath sounds showed persistent rhonchi on the right and crackles on the left. Despite this, chest expansion remained symmetrical and respiratory pattern regular throughout the shift.

Absence of infection during hospitalization: Temperature spikes suggest ongoing infection, managed with acetaminophen. No new signs of infection observed.

[Start with Draft](#) [Start Blank Note](#)

Administrations of morphine injection

Administration	Action Time	Recorded Time	Documented By
Given : 1 mg : Intravenous	04/25/24 1723	04/25/24 1723	Stuht, Andrew, RN Dual Signoff By: Rauwerdink, Brianna RN

Ambient Flowsheets



AUGUST 2024

8:30

Peters, Dev
M 74 yo (12/26/1949) MRN: 13264
541-349-2982 (H)
Penicillins

Epic

< 8:30 today Pain

Pain Screening

Currently in Pain Yes

Pain Assessment 0-10

Pain Score 4

Pain Type Tap to enter data

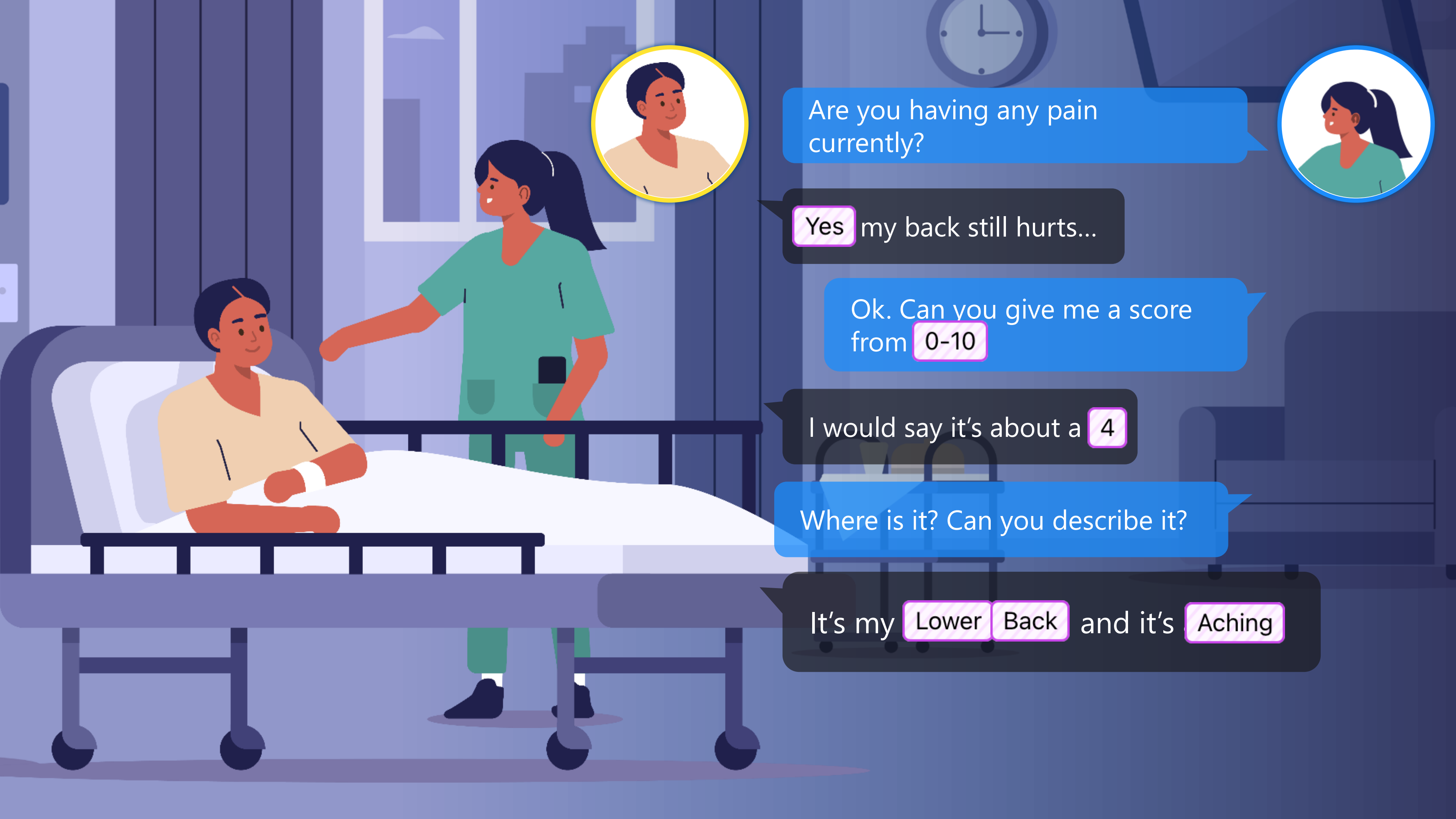
Pain Location Back

Pain Orientation Lower

Pain Radiating Towards Tap to enter data

Pain Descriptors Aching

✓ File



Are you having any pain currently?

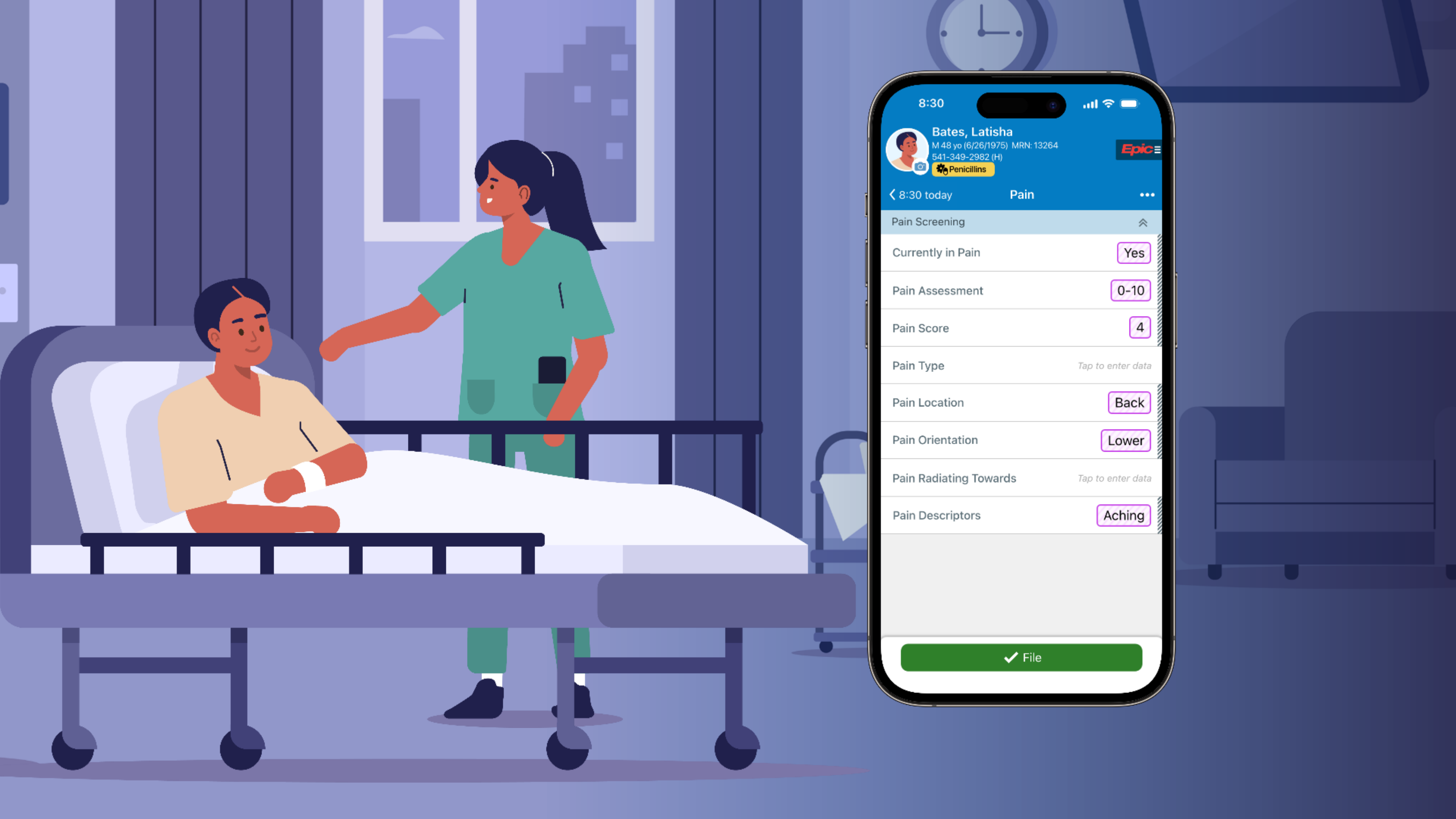
Yes my back still hurts...

Ok. Can you give me a score from 0-10

I would say it's about a 4

Where is it? Can you describe it?

It's my Lower Back and it's Aching



8:30



Bates, Latisha
M 48 yo (6/26/1975) MRN: 13264
541-349-2982 (H)



Penicillins

< 8:30 today Pain

Pain Screening

Currently in Pain **Yes**

Pain Assessment **0-10**

Pain Score **4**

Pain Type *Tap to enter data*

Pain Location **Back**



Pain Orientation **Lower**

Pain Radiating Towards *Tap to enter data*

Pain Descriptors **Aching**

✓ File




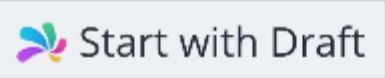

Drafted In Basket Responses


 **Draft by Art**
Generated at: 6/18/2024 9:56 AM.  AI

Hi George,

You've got it right. Jessica's lab test is now scheduled at the health center on 11/2 before her allergy appointment. The video visit is set for 11/5. No worries at all, it's understandable that things can get a bit hectic. If you have any more questions or need further clarification, feel free to ask.


Best,
Dr. Walker

   Learn More  Start with Draft  Start Blank Reply

 **Lab test dates?** (Newest Message First)

George Adams (Proxy for Jessica Adams) → supporting Drew Walker, MD Just now (4:55 PM)

Hi Dr. Walker,
just confirming... instead of the previous plan to do the lab test on 10/24 at the hospital, and then a video visit with you on 10/25, we'd do the lab at the health center on 11/2 before her allergy appointment? Then we're doing the video visit on 11/5? Did I get all that right? Forgive me... it's been a crazy week.
-George



AVAILABLE NOW

Reporting

for understanding time saved

Include conversation history

for more tailored responses

Proxy support

for expanded use cases

Drafts for result notes

for expanded use cases

Updated default prompts

for easier prompt engineering



CURRENT

Nurses Using Gen AI (In Basket Art)

UWHealth

June 2024

"This has been a fascinating process, and one **I've been glad to be part of**," said Amanda Weber, registered nurse clinic supervisor, UW Health. "I have found having a draft to start from helpful, and **I'm glad I could provide feedback** on improvements and features to ensure this can be a good tool for nurses and have a positive impact on our patients."

Every message drafted using LLMs is reviewed and edited, if needed, **by a person**, and the user is responsible for the accuracy and appropriateness of the contents. Patient information is kept private and secure within the electronic health records system.

[UW Health: Nurses piloting generative AI \(weau.com\)](https://weau.com)

Nurses are part of the process.

Human in the loop



Gen AI Saves Nurses Time by Drafting Responses to Patient Messages

Mayo Clinic uses generative AI to draft responses to patient messages. Initial pilots showed that it **saves nurses around 30 seconds per** message and drafts more empathetic responses. Mayo Clinic plans to expand access to all LPNs and RNs by mid-2024, which could save **1,500 hours per month**.

[Epic Share: Gen AI Saves Nurses Time by Drafting Responses to Patient Messages](#)

Quickly Catch Up *on a Patient*

The screenshot displays the Epic EMR interface for a patient named Flora Hussain. The main window shows a 'Notes Summary' generated on 6/3/2024 at 2:50 PM, focused on CHF. The summary lists several key points: her history of congestive heart failure due to hypertension, her current treatment regimen (dietary sodium restriction, regular aerobic exercise, and daily weight measurement), her heart failure reassessment schedule (3 months), her stable diabetes management, her current medications, her exercise routine (5 days a week), and a pre-visit phone call on 5/22/2024. The summary also includes a 'References' section and a 'Learn More' link. A secondary window, titled 'Evidence of Treatment Regimen', provides a detailed view of the patient's progress note on 6/2/24, highlighting specific treatment recommendations such as continuing the current regimen, dietary sodium restriction, regular aerobic exercise, and daily weight measurement. The background shows the patient's medical history, including conditions like Essential Hypertension, Diabetes Mellitus, Hypercholesterolemia, and Hypothyroidism, and a list of medications.

Notes Summary AI
Generated at: 6/3/2024 2:50 PM. Focused on: CHF

- Hussain, Flora, 52, has a history of congestive heart failure due to hypertension, which is currently stable. 1
- She is on a treatment regimen that includes dietary sodium restriction, regular aerobic exercise, and daily weight measurement. 2
- Her heart failure is to be reassessed in 3 months. 2
- She is also managing diabetes, which is stable and will also be reassessed in 3 months. 1
- Her current medications are well-tolerated without significant side effects.
- She is exercising 5 days a week and is compliant with her hypertension treatment.
- A pre-visit phone call was completed on 5/22/2024, during which she was advised to continue her current treatment regimen and to reassess her heart failure in 3 months. 4

Evidence of Treatment Regimen AI
Progress Note on 6/2/24

Congestive heart failure due to hypertension. Heart failure is stable. Continue current treatment regimen. Dietary sodium restriction. Recommend regular aerobic exercise as tolerated. Recommend daily weight measurement. Heart failure should be reassessed in 3 months.

👍 👎 ⓘ Learn More

References
👍 👎 ⓘ Learn More

Medical History: Essential Hypertension (High), Diabetes Mellitus (Medium), Hypercholesterolemia (High), Hypothyroidism (Medium)

Medications: [Listed in background]

Communications: Patient Handout, Send Notes (To: PCP + 2, Provider Notes)

Buttons: Add Order, Add Dx (0), Level of Service, Print AVS, Sign Visit, Accept, Cancel



Agenda & Objectives



Background on Nursing Terminology in the EHR



Overview of Artificial Intelligence



Generative AI in Epic



Case Study



Wrap up and What's Next

Mark's Story

Case Study: Use AI to Extract Social Drivers from Notes



Mark **needs help** with making sure he has enough **food** to eat



Based on the nurse's note, **AI suggests** that she update Mark's **social isolation** screening

Mark Anderson
Male, 40 y.o., 3/9/1984
MRN: 29580
Scheduled
Code: Not on file (no ACP docs)

Chelsa Murray, MD
PCP - General
Coverage: Epic Healthcare...
Allergies: Clear Eyes Seasonal

SOCIAL WORKER
Kyle Hart, DCSW

SOCIAL DRIVERS OF HEALTH

Recent concerns: 1
Assistance Requested: 2

CARE GAPS

- Influenza Immunization
- Lipid Panel
- Blood Pressure
- Complete Blood Count
- Comprehensive Metabolic P...

PROBLEM LIST

- Hypertension
- Hyperlipidemia
- Seasonal Allergies
- Mild Anxiety

Chart Review

Allergies

- Clear Eyes Seasonal (Mild - Hives)

Problems

- Mood Disorder (Noted 3 months ago)
- Essential Hypertension (6 months ago)

Goals

Goal	Result	Noted
Blood Pressure < 120/75	122/78	6 months ago
Consume under 2 grams of sodium per day	-	-

Medication Management

Name	Dose, Frequency	Adh
lisinopril (PRINVIL, ZESTRIL) 10 MG tab...	1 tablet, once daily	

Social Drivers of Health

Care Gaps

- Overdue: Influenza Immunization, Lipid Panel, Blood Pressure

Notes

My Note

Subjective

Mark presents for his routine annual check-up. During the visit, he shares that his wife recently passed away, which has been difficult for him. He expresses feelings of loneliness and notes that he has been struggling with motivation to engage in social activities. He denies any significant changes in appetite or sleep but acknowledges feeling...

Social Drivers Insights

Patient may be experiencing social isolation, due to the recent passing of his wife.

Assess: Social Isolation | **Dismiss**

Follow-Up:

- Follow-up visit in 6 months to monitor BP, lipid levels, and mental well-being.
- Patient advised to reach out earlier if symptoms of depression, anxiety, or other concerns arise.

Mark's Story

Case Study: Use AI to Extract Social Drivers from Notes



Mark **needs help** with making sure he has enough **food** to eat



Based on the nurse's note, **AI suggests** that she update Mark's **social isolation** screening

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CARE GAPS

- Influenza Immunization
- Lipid Panel
- Blood Pressure
- Complete Blood Count
- Comprehensive Metabolic P...

PROBLEM LIST

- Hypertension
- Hyperlipidemia
- Seasonal Allergies
- Mild Anxiety

Chart Review

Allergies

- Clear Eyes Seasonal (Mild - Hives)

Problems

- Enable clinical decision support by reconciling outside information (Noted)
- Mood Disorder (3 months ago)
- Essential Hypertension (6 months ago)

Goals

Goal	Result	Noted
Blood Pressure < 120/75	122/78	6 months ago
Consume under 2 grams of sodium per day	-	-

Medication Management

Name	Dose, Frequency	Adh
lisinopril (PRINVIL, ZESTRIL) 10 MG tab...	1 tablet, once daily	

Care Gaps

- Overdue
- Never done: Influenza Immunization
- Never done: Lipid Panel
- Never done: Blood Pressure
- +2 More Care Gaps

Social Drivers of Health

Update community resources

Social Isolation
Not on file

Social Drivers Insights
Generated at 6/1/2024 1:11 PM

Patient may be experiencing **social isolation**:

Progress Note by Chelsa Murray on 6/1/2024

"...his wife recently passed away which has been difficult for him. He expresses feelings of loneliness and notes that he has been struggling with motivation to engage in social activities."

Learn More

Assess: Social Isolation

Epic Cosmos Community Collaboration

270 health systems working together to create new medical knowledge



1,500
Hospitals

63 Academic Medical Centers

44 Pediatric Hospitals

140 Critical Access Hospitals



35,000
Clinics

1 Billion Specialty Visits

6 Billion Face-to-Face Visits

1 in 5 FQHC Visits

277 Million

Unique Patient Records

124 Million with visit in last year



17 Million
Cancer Cases



9 Million
Rare Disease Patients

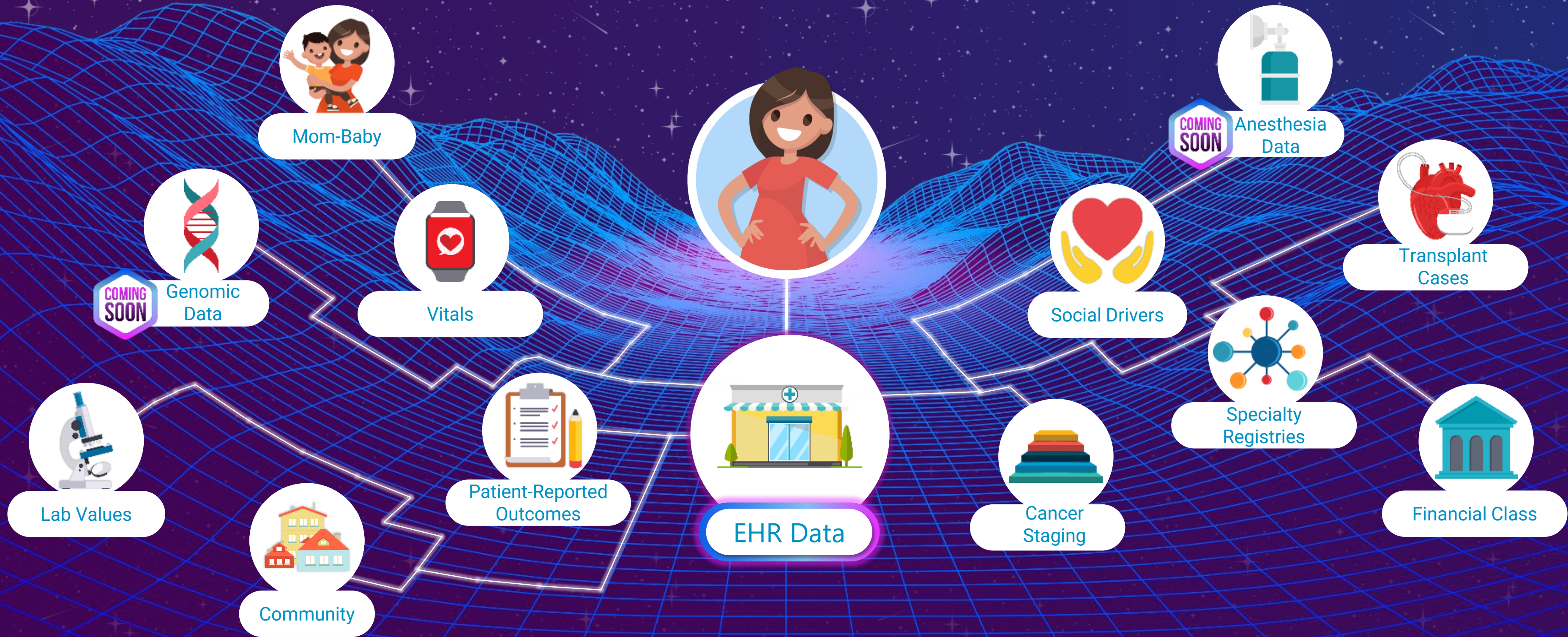


+ Canada, Lebanon, &
Saudi Arabia



13 Billion
Encounters

Many data sources, one integrated patient record



Inform SDoH *from* Outside Sources



Most Exchanged Domains

 **Depression**
38M Exchanges

 **Food Insecurity**
20M Exchanges

 **Alcohol Use**
15M Exchanges

 **Transportation**
19M Exchanges

OCHIN

42 Million SDoH Exchanges

MAYO CLINIC


12 Million SDoH Exchanges

 **Providence**

12 Million SDoH Exchanges

NOVANT HEALTH

10 Million SDoH Exchanges

SDoH Regulatory Requirements

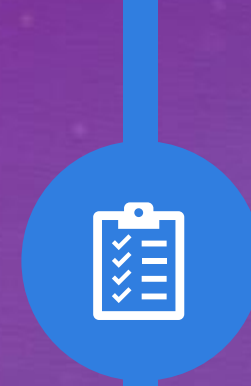
January 2023

January 2024



The Joint Commission

Screen hospital patients for health-related social needs & provide information about resources & support services.



HEDIS

Members screened for food, housing, transportation, & received a corresponding intervention.



Medicare Advantage SNPs

SNP HRAs must include one or more questions about food, housing, & transportation.



CMS IQR

Patients admitted to the hospital screened for food, housing, transportation, utilities, & interpersonal violence.



CMS ACO REACH

Patients screened for any 5 health-related social needs (HRSN).

Mark's Story

Case Study: Use AI to Extract Social Drivers from Notes



Mark **needs help** with making sure he has enough **food** to eat



Based on the nurse's note, **AI suggests** that she update Mark's **social isolation** screening

Mark Anderson
Male, 40 y.o., 3/9/1984
MRN: 29580
Scheduled
Code: Not on file (no ACP docs)

Chelsa Murray, MD
PCP - General
Coverage: Epic Healthcare...
Allergies: Clear Eyes Seasonal

SOCIAL WORKER
Kyle Hart, DCSW

SOCIAL DRIVERS OF HEALTH

Recent concerns: 1
Assistance Requested: 2

CARE GAPS

- Influenza Immunization
- Lipid Panel
- Blood Pressure
- Complete Blood Count
- Comprehensive Metabolic P...

PROBLEM LIST

- Hypertension
- Hyperlipidemia
- Seasonal Allergies
- Mild Anxiety

Chart Review

Allergies

- Clear Eyes Seasonal (Mild - Hives)

Problems

- Enable clinical decision support by reconciling outside information (Noted)
- Mood Disorder (3 months ago)
- Essential Hypertension (6 months ago)

Goals

Goal	Result	Noted
Blood Pressure < 120/75	122/78	6 months ago
Consume under 2 grams of sodium per day	-	-

Medication Management

Name	Dose, Frequency	Adh
lisinopril (PRINVIL, ZESTRIL) 10 MG tab...	1 tablet, once daily	

Care Gaps

- Overdue
- Never done: Influenza Immunization
- Never done: Lipid Panel
- Never done: Blood Pressure
- +2 More Care Gaps

Social Drivers of Health

Update community resources

Social Isolation
Not on file

Social Drivers Insights
Generated at 6/1/2024 1:11 PM

Patient may be experiencing **social isolation**:

Progress Note by Chelsa Murray on 6/1/2024

"...his wife recently passed away which has been difficult for him. He expresses feelings of loneliness and notes that he has been struggling with motivation to engage in social activities."

Learn More

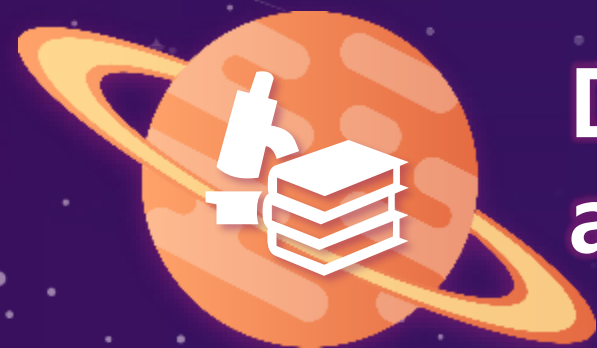
Assess: Social Isolation

DATA SCIENCE AND RESEARCH TOOLS

Powered by **Epic** Cosmos



EXPANDING KNOWLEDGE



**Data Science
and Publication Tools**



**Epic Research
and Data Trackers**



**Clinical Trial Feasibility
and Recruitment**

IMPROVING CARE



Look-Alikes



Best Care Choices



Embedded Insights



Epic Research

GETTING GOOD DATA OUT QUICKLY



The New England Journal of Medicine

Mpox Vaccination Can Prevent Two-Thirds of New Infections.

2 of 3 cases prevented in fully vaccinated individuals.

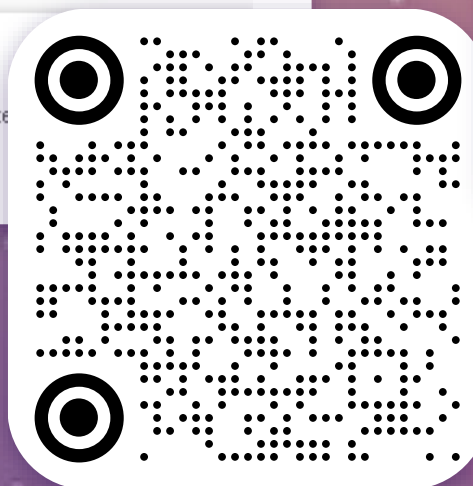


Even **one dose** provides **some protection** against Mpox infection.



May 18, 2023

<https://epicresearch.org/articles/nejm-vaccine-effectiveness-of-jynneos-against-mpox-disease-in-the-united-state>



Babies with Withdrawal Symptoms 68% More Likely to Have Developmental Disorders Than Those without

Rates of Developmental Disorders and Autism in Children by Prior NAS Diagnosis

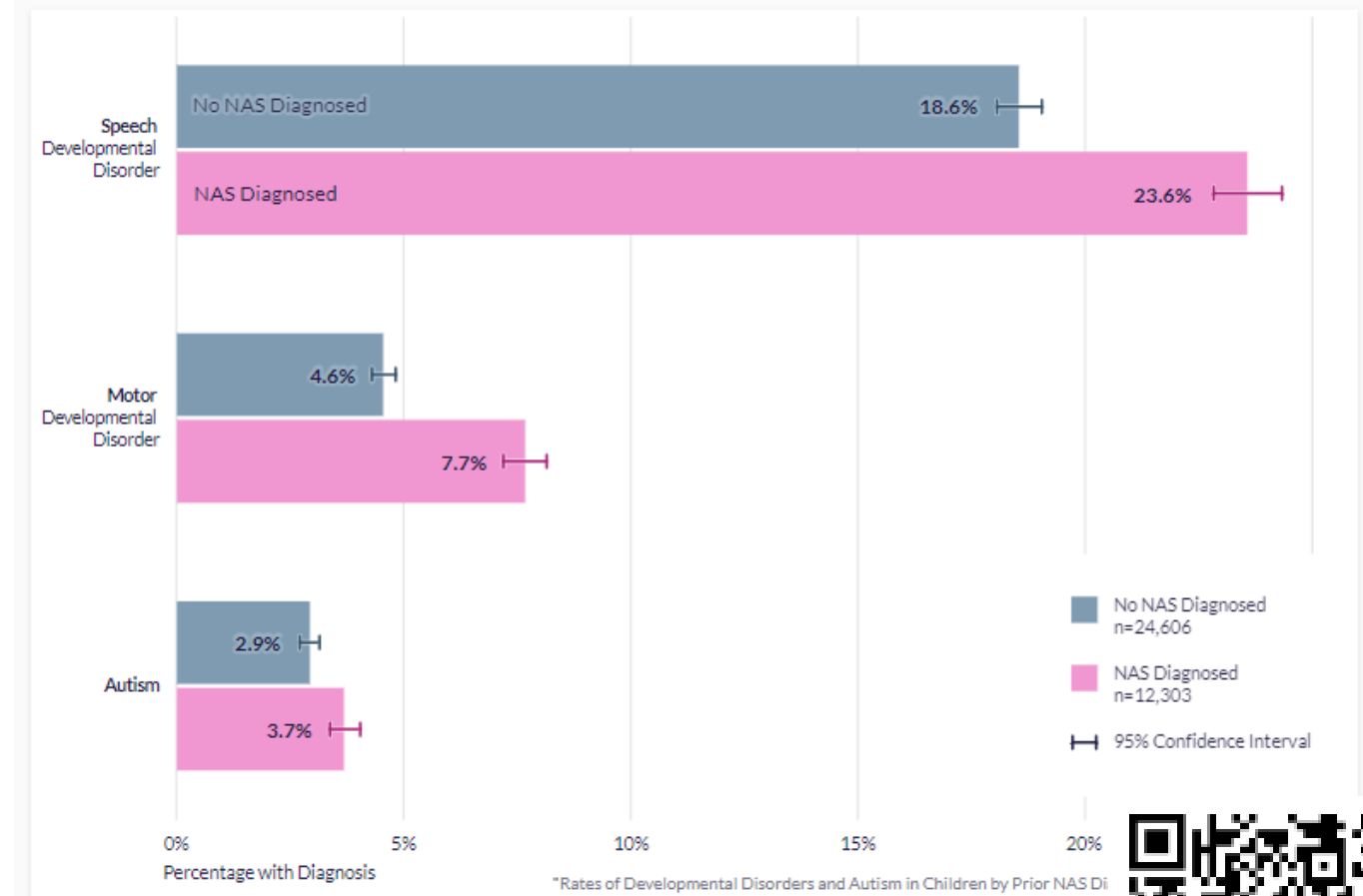


Figure 1. Rates of autism, speech developmental disorders, and motor developmental disorders in and without NAS.



Expected Length of Stay

Patient Lists

Edit List | Open Chart | Add Patient | Remove Patient | Wrap Text

MedSurg Discharges 41 Patients

Curr Loca	Patient	Readm Risk	Med Ready?	Exp DC Date	PT Sign-Off	OT Sign-Off	Case Mgt Sign-Off	Days to GMLOS	Attending	RN	DC Comm
523-1	Kozak, Melissa 60 y.o. / F	7%	11/23	02/22 0.6 before CMLOS	—	—	—	4	Chris Eddison, MD	Arellano, Sidney E, RN	
523-2	Bloom, Margaret 70 y.o. / F	8%	11/22	02/21 0.8 before CMLOS	—	—	—	5.8	Terry Clemmer, MD	Banks, Tarena, RN	
524-1	Adkins, John 63 y.o. / M	7%	Yes	01/17 0.3 after CMLOS	—	—	—	0.8	Paul Hart, MD Walt Vanders...	Thomas, Sam, RN	
524-2	Robbins, John C 71 y.o. / M	5%	Yes	01/16 0.4 before CMLOS	×	×	—	11.1	Stephen S Yu, MD	Raynolds, Kelly, RN	
525-1	Best, Steven Robert 64 y.o. / M	9%	5+ ...	02/21 0.6 before CMLOS	—	—	—	4.3	Terry Clemmer, MD	Thomas, Sam, RN	

Cosmos Median Length of Stay
Calculated with data from similar patients across the Epic community

0.6 Days Before Median

Cosmos median LOS: 3.6 days
Exp disch date: 2/22/24
LOS from EDD: 3 days

1,992 similar patients
Age 50-64
Pneumonia, unspecified organism
Admitted from ED
No time spent in ICU

Distribution for Similar Patients

Length of Stay (Days)

Typical Length of Stay

Refreshed 2 minutes ago | Search All Admitted P...

Kozak, Melissa DOB: 9/4/1963 Unit: MedSrg2 Room: 523 Bed: 523-1

Discharge Progress | Nurse Snapshot (Rev'd) | MAR 3 Days | MAR 7 Days

Click to Update Discharge Info

Discharge Milestones

Expected date/time: 2/22/2024
Anticipated: 11/23/2023

Discharge Planning

Discharge Planning Flowsheet

Expected SNF
Discharge Disposition

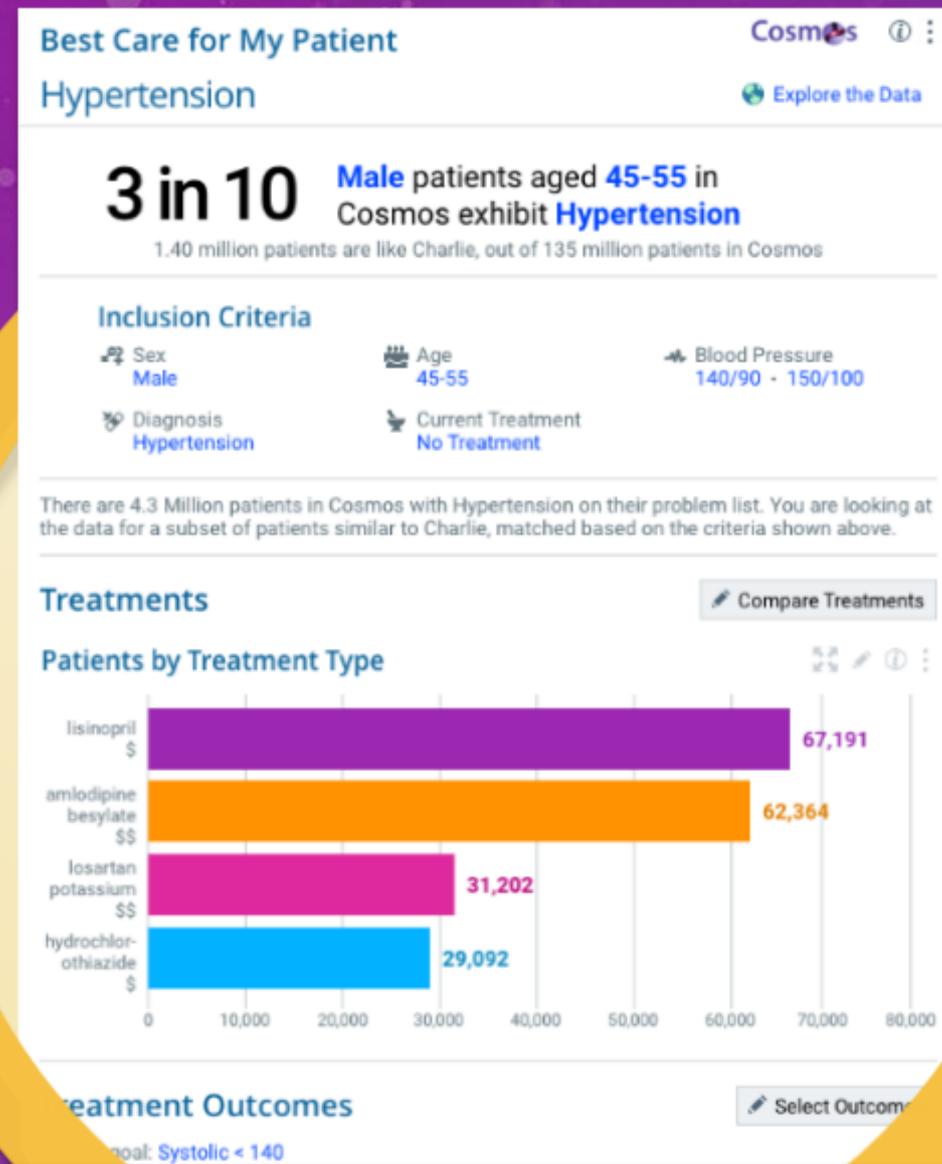
DME and Supply Orders
(From admission, onward)
None

PT/OT Orders
(48h ago, onward)

Comment

Feb 24 for Early Adopters

Embedded Insights *from* Cosmos



BEST CARE

For My Patient

Compare treatments from **millions** of similar patients



LOOK-ALIKES

Connect with clinicians treating patients with similar **rare** conditions



Best Care Choices *for* My Patient

The screenshot displays the Epic EMR interface for Jackie Gerhart, showing the 'Best Care Choices for My Patient' tool for patient Darryl Black. The patient's profile includes demographic information (Male, 60 y.o., 7/15/1964, MRN: 37431) and clinical data (BP: 155/95, Stage 4 chronic kidney disease). The tool allows defining comparison patients based on criteria such as Systolic BP (140-160), Diastolic BP, Comorbidities (CKD stage 4, 5, or ESRD), Pertinent Negatives (Diabetes, Myocardial Infarction), BMI, and Has ever smoked?. It also allows selecting comparison demographics (Age 50-70 years, Sex Male, Race, Ethnicity) and Labs (Potassium 3.4-4.9 mmol/L). The tool compares treatments by % at Goal BP (Blood Pressure < 130/80) and Mean BP, with options for Stroke and Myocardial Infarction. The interface includes a search bar, navigation tabs (Current Visit, Chart Review, Best Care Choices for My Patient), and a Notes panel on the right.

May 24 for Early Adopters

Best Care Choices *for* My Patient

Best Care Choices for My Patient

2,868 patients like Darryl out of 274 million patients in Cosmos

Define Patients Like Darryl with **Hypertension**

- Systolic BP 140 - 160
- Diastolic BP
- Comorbidities CKD stage 4, 5, or ESRD
- Pertinent Negatives Diabetes
Myocardial Infarction
- BMI
- Has ever smoked?
- Currently Taking Calcium Channel Blockers
- Currently Not Taking ACE Inhibitors
Alpha-blockers
+6 more...

Comparison Demographics

- Age 50 - 70 years
- Sex Male
- Race
- Ethnicity
- Labs Potassium 3.4 - 4.9 mmol/L

Reported **Hypertension** Treatment Outcomes

Find Treatments By: % at Goal BP, Mean BP, Stroke, Myocardial Infarction

Detail Level: Class, Drug, Dose

Goal: Blood Pressure < 130/80

	Short-Term (1 month)		Long-Term (3 years)	
	% at Goal BP	Mean BP	Stroke	Myocardial Infarction
ACE Inhibitors + CCBs	23.5%	140/81	5.5%	10.1%
Beta-blockers + CCBs	20.2%	139/79	5.3%	6.7%
CCBs + Diuretics	20.1%	139/79	4.0%	3.5%
CCBs + Vasodilators	16.0%	142/81	15.7%	7.8%
ARBs + CCBs	8.3%	141/82	4.9%	4.9%

5 of 58 treatments shown

Find More Treatments

Notes: My Note, Progress Notes • 8/29/2024 10:35 AM

SmartLinks: Sign when Signing Visit, Accept, Cancel

LEVEL OF SERVICE, PRINT AVS, SIGN VISIT

May 24 for Early Adopters

Agenda & Objectives



Background on Nursing Terminology in the EHR



Overview of Artificial Intelligence



Generative AI in Epic



Case Study



Wrap up and What's Next

Up Next...

Generative AI Features in Development

100+

In development

Cheers Live Chat with intent detection

SlicerDicer SideKick

Ambient voice documentation for tool charting

Level of service suggestions

AI insights in synopsis

Generative AI-powered conversational search

Conversational search training tips

Emergency Department Summarization

AI to improve FCC accuracy

Ambient for ProcDoc-based injections

Generate patient instructions from notes

Extract sensitive information in notes

Generate summaries for health plan auth review

Inpatient insights summarization

Post-visit CDI coding for risk adjustment

Generated draft utilization review

Parse free text sigs to discrete with AI

AI Text Assistant in In Basket

Suggest encounter actions for patient messages

Conversational SMS scheduling for tickets

...with more on the way

Nursing Focused Webinar

The Nursing Network: Pioneering AI for Nursing



Friday, June 28, 2024 12:00 PM - 1:00 PM *Displayed in your computer's local time zone*

Epic for the Clinical Informaticist, EpicCare Inpatient, Generative AI, Nursing, Nursing Steering Committees, The Nursing Note

 This webinar is part of a series

Contact: Kara Wynkoop Hirz

Join us to hear how AI can be used to support nursing workflows.

UNC Health and Mercy are implementing the AI generated draft end of shift care plan note for inpatient nursing. They will share how they governed the implementation and use of AI and what the experience has been like for IT, informatics, and end users.

Epic developers will also share how this and other AI tools are evolving to support nursing workflows.

[The Nursing Network: Pioneering AI for Nursing \(epic.com\)](https://www.epic.com)

Preparing *for* AI

Establishing Governance for AI



With the rapid development of AI-powered tools that aim to improve workflows and user experience, organizations need to carefully consider the processes and governance needed to evaluate the potential of new AI-assisted workflows, roll them out to users, and track ongoing performance metrics. Even if you plan to take a wait-and-see approach to AI, you should prepare now so you can move quickly when these features advance from cutting edge to mainstream use.

This document outlines key considerations for integrating AI into your workflows. It provides insights and example strategies that Epic community members using AI today have established at their organizations and guides your initial conversations about responsibly and effectively using AI at your organization.

In addition to reading this document, you can also prepare by networking with other organizations on the [Generative AI forum on the UserWeb](#) and participating in webinars. The UserWeb forum includes both details on upcoming webinars and recordings and slides of past webinars. For information about upcoming AI features, check out the [Generative AI section of the Cognitive Computing Roadmap](#) and talk to your BFF.

Promote general AI literacy: You can't govern what you don't understand

To foster thoughtful discussions and support decision making for how to incorporate AI to assist in clinical and other workflows, stakeholders, decision makers, and users throughout your organization need to develop a shared understanding of how AI works and its potential capabilities.

To improve organizational AI literacy, groups like the University of Wisconsin, UNC, and McLeod Health have developed AI overview training, websites, and videos. They also present roadshows at existing department and unit meetings to share their knowledge and answer questions. As part of their roadshows and leadership education, University of Wisconsin focuses on four literacy principles: ownership, compliance, performance/prompting, and third-party apps. Franciscan Missionaries of Our Lady Health System includes key information about generative AI in their annual employee training.

Other organizations publish high-level guidelines or offer specific training but are not yet focusing on organization-wide training. Keith Morse, MD, Medical Director of Informatics at Stanford Children's Health says, "We recognize that GenAI is new for everyone, from our organizational leadership to frontline providers and staff. We're designing our educational tools to meet people where they are—introductory material for those just getting started and deeper prompting workshops for more advanced users. We also believe that experience is the best teacher, so

Promote
You can't govern

Establish Go
Assess, Test, M

Communication
users

en
gility
ing fast

Resources Available Now

Executive Overview

Planning & Adoption

Governance

Webinars

Sample Health System | Peers: All Epic

Artificial Intelligence

AI is built into Epic and already in use. Multiple AI-assisted workflows are now available and new AI-assisted workflows are being added frequently. If your organization is interested in exploring the use cases below, please contact your BFF.

► Dates represent current plans for initial production. Information in this document should be shared only with those who need to know.

Simplify Documentation

Reduce time spent at the keyboard

- Generate In Basket responses to patient messages
- Write visit notes based on the cc visits with ambient voice technology
- Adjust notes, correspondence, and factors like brevity and reading level
- Generate care plan notes for nurses
- Generate utilization review summaries
- Generate hospitalists' course summaries. ^{Q2 2025}
- Generate MyChart result comments
- Help cardiologists write case narratives
- Draft refill coordination notes for physicians
- Nudge physicians with opportunity documentation. ²⁰²⁵

Generated documentation is reviewed by clinical staff.

Tailor Communication

Communicate better by having the right information at the right time

- Help translate clinical and scheduled into additional languages.
- Revise letters, patient instruction responses to use less technical language
- Transform questions into reportable queries
- Simplify note text to patient-friendly
- Answer patients' billing questions
- Write patient instructions, including based on clinical notes.

Ready to Start? We can help. Contact your BFF.

Notes represent current plans for initial production. Information in this document should be shared only with those who need to know.

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Epic & Generative AI

AI is built into Epic and already in use in the US, Europe, and Canada. New AI-assisted workflows are being added frequently. If your organization is interested in exploring the use cases below, please contact your BFF.

► Dates represent current plans for initial production. Information in this document should be shared only with those who need to know.

Planning Generative AI Adoption

AI is built into Epic and continually improving. This table provides a plan to allow staged adoption for product areas you want to begin using these workflows. If you need additional detail for an AI-assisted workflow, please contact your BFF.

AI-assisted workflow	Current Status
Generate draft responses to patient messages	Current
Review the previous shift	Current
Prompt engineering testbed ¹	Current
Summarize recent notes before a visit	Current
Analyze dashboard for key takeaways	Current
Extract follow-ups from imaging reports	Current
Transform questions into reporting queries	Current
Translate questionnaires into additional languages ²	Current
Recommend codes from clinical details	Current
Adjust writing for brevity and reading level	Current
Draft denial appeal letters	Current
Generate utilization review summaries	Current
Answer patient questions with a custom service agent via website	Current
Generate clinical summary for health plan authorization review	Current
Summarize the patient journey for care transition planning	Current
Patients can schedule visits with an agent	Current
Generate care plan notes for nurses	Current
Generate draft hospital course summaries	Current
Summarize recent events for call centers	Current
Generate campaign content	Current
Recommend level of service	Current
Explain patient bills with an agent	Current
Suggest discrete sigs for refill requests	Current
Automatically document synoptic forms	Current
Suggested answers for prescription prior authorization questions	Current

¹ This column indicates the date when we expect to begin testing this workflow.

² This column indicates the Epic versions in which we expect to begin testing this workflow. Additional SUs might be required before you can begin testing.

³ These features are available only for build or test environments.

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Establishing Governance for AI

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This document outlines key considerations for integrating AI into your workflows. It provides insights and example strategies that Epic community members using AI today have established at their organizations and guides your initial conversations about responsibly and effectively using AI at your organization.

In addition to reading this document, you can also prepare by networking with other organizations on the [Generative AI forum on the UserWeb](#) and participating in upcoming webinars and recordings and slides of presentations. For more information, see the [Generative AI section of the Cognitive Computing Strategy](#).

Generative AI

Predictive models, machine learning, generative AI, and how they all work together in Epic workflows.

All Discussion | Announcements

Past Webinars

Webinar Title	Date	Time
Following Your North Star Through Epic AI in In Basket with Baylor Scott and White • Webinar Recording • Webinar Slides	8/2/2024	12:00 PM - 1:00 PM
Generative AI & Epic: In the Hospital	7/15/2024	3:00 PM - 4:00 PM
The Nursing Network: Pioneering AI for Nursing • Slides • Q&A • Transcript • Recording	6/28/2024	12:00 PM - 1:00 PM
Automating Your In Basket: Art at Ochsner • Webinar Recording • Webinar Slides • Smartlists in Your Responses • Smartlists in Your Responses (v 2.0)	6/18/2024	1:00 PM - 2:00 PM
Generative AI & Epic: Coding	6/10/2024	1:00 PM - 2:00 PM

Show upcoming webinars +

Show more...

Keith Morse describes Stanford Children's Health's strategy as, "We want very much to be cutting edge, but we have zero tolerance for additional risk for our patients. We have a couple of rules of thumb we go by: a human in the loop for everything we do, and, for Generative AI, we are not going to touch patient care in any way."



Contact Info: Karina@epic.com

Q&A

Karina Rohrer-Meck
MS, BSN, RN

Kathleen McGrow | Moderator
DNP, MS, RN, PMP, FHIMSS, FAAN

Wrap up of the day

Barbara Redman
Chair of the FNLM Board

THANK YOU FOR ATTENDING

Please scan the QR code
using your smartphone
camera to complete the
evaluation and receive your
CNE certificate



Join us at an upcoming webinar by registering at
fnlm.org