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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

Columbia School of Nursing

University of Maryland School of Nursing

Iowa Center for Nursing Classification and Clinical Effectiveness

National League for Nursing

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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

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Part I
Nursing Terminology

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

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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

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

Motivation for using CCC

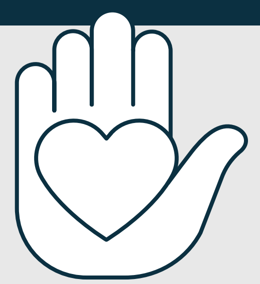
- Developed using nursing documentation
- Framework & Terminology
  - Framework
    - Organize nursing clinical documentation (e.g., the CCC care components)
    - Enable capture of subjective descriptors under the higher level CCC concepts
  - Terminology
    - Represents nursing practice and documentation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

CONCERN is an Early Warning System (EWS)

KEEP PATIENTS SAFE

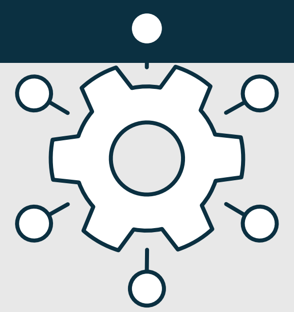
CONCERN early warning system (EWS) helps the care team keep patients safe

NURSING DOCUMENTATION MATTERS



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

AI CHANGE DETECTION

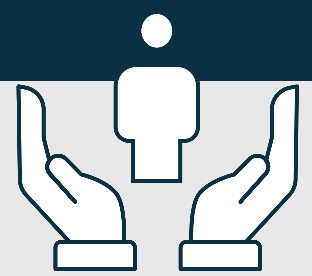


CONCERN uses artificial intelligence to detect documentation changes to generate a risk score

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

MPIs: Sarah Rossetti & Kenrick Cato

CONCERN Early Warning System (EWS)

1. Helps the care team keep hospitalized patients safe

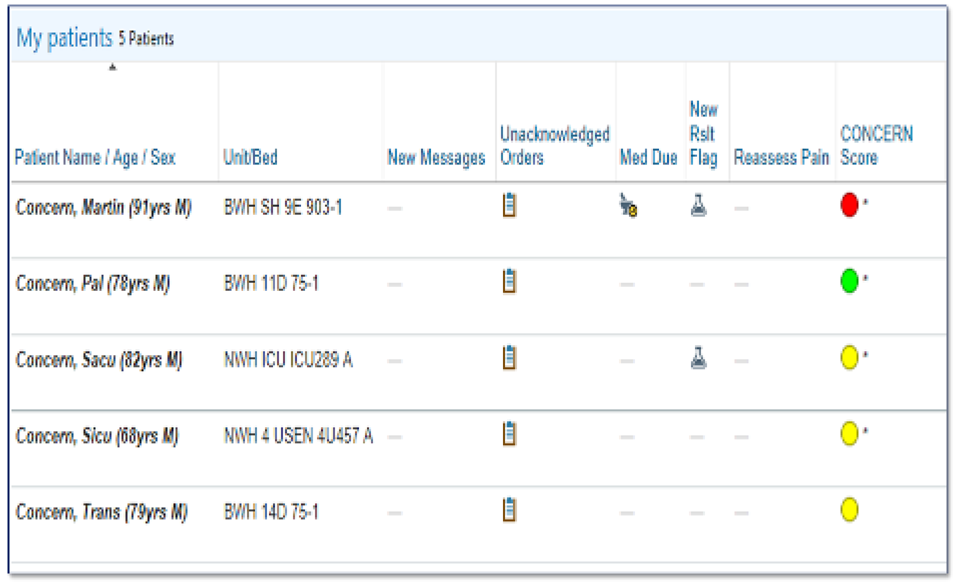
2. Relies on nursing documentation because it matters
   - Nursing surveillance increases with increased nursing concern
   - CONCERN uses AI to detect nursing surveillance documentation pattern changes and generate a deterioration score for display in real-time

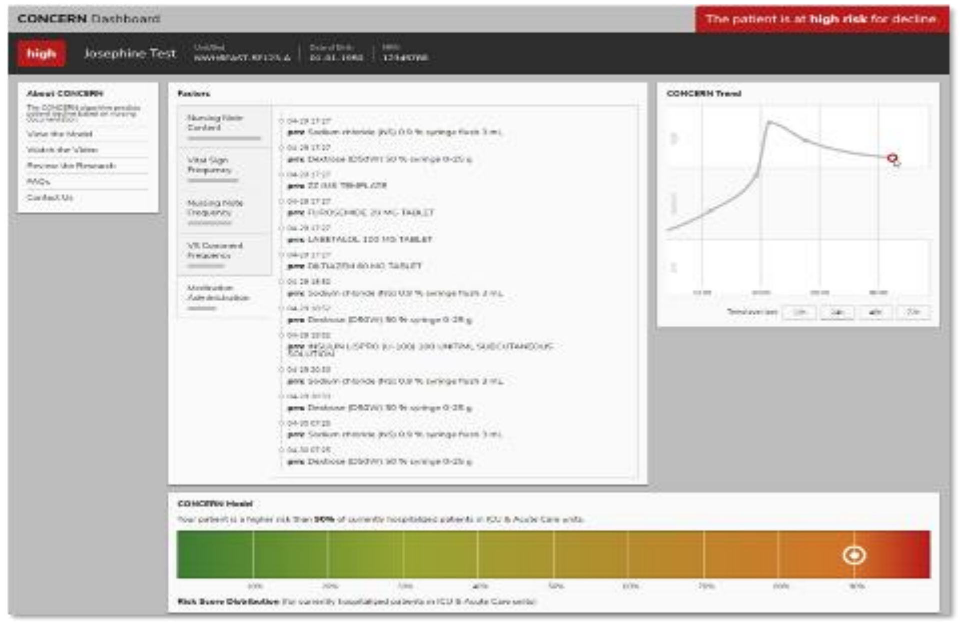
Setting	Accuracy	Precision	Recall	Logloss	AUC
ICU	0.970938	0.431373	0.594595	0.073695	0.934683
ACU	0.973341	0.813559	0.643935	0.089369	0.955982

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





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The COmmunicating Narrative Concerns Entered by RNs (CONCERN) study is supported by: American Nurses Foundation (ANF): Reimagining Nursing Initiative & National Institute of Nursing Research (NINR): 1R01NR016941-01 *The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH or ANF*

American Nurses Foundation · Reimagining Nursing · NIH NINR

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

Nurse's Surveillance → Measured by → Temporal patterns in EHR data

- Entries with increased Frequency
- Entries done at Uncommon times

→ Reflects → Nurse's concern → Predictor of →

- Patient deterioration
- Adverse events in next 2 days

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 Knaplund [1], 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 Garcia [4], Jessica Schwartz [2], Li-Heng Fu [1], Jeffrey G Klann [5], Graham Lowenthal [4], Kenrick Cato [2]

Affiliations + expand

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

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PMCID: PMC3771321
NIHMSID: NIHMS505735
PMID: 23817819

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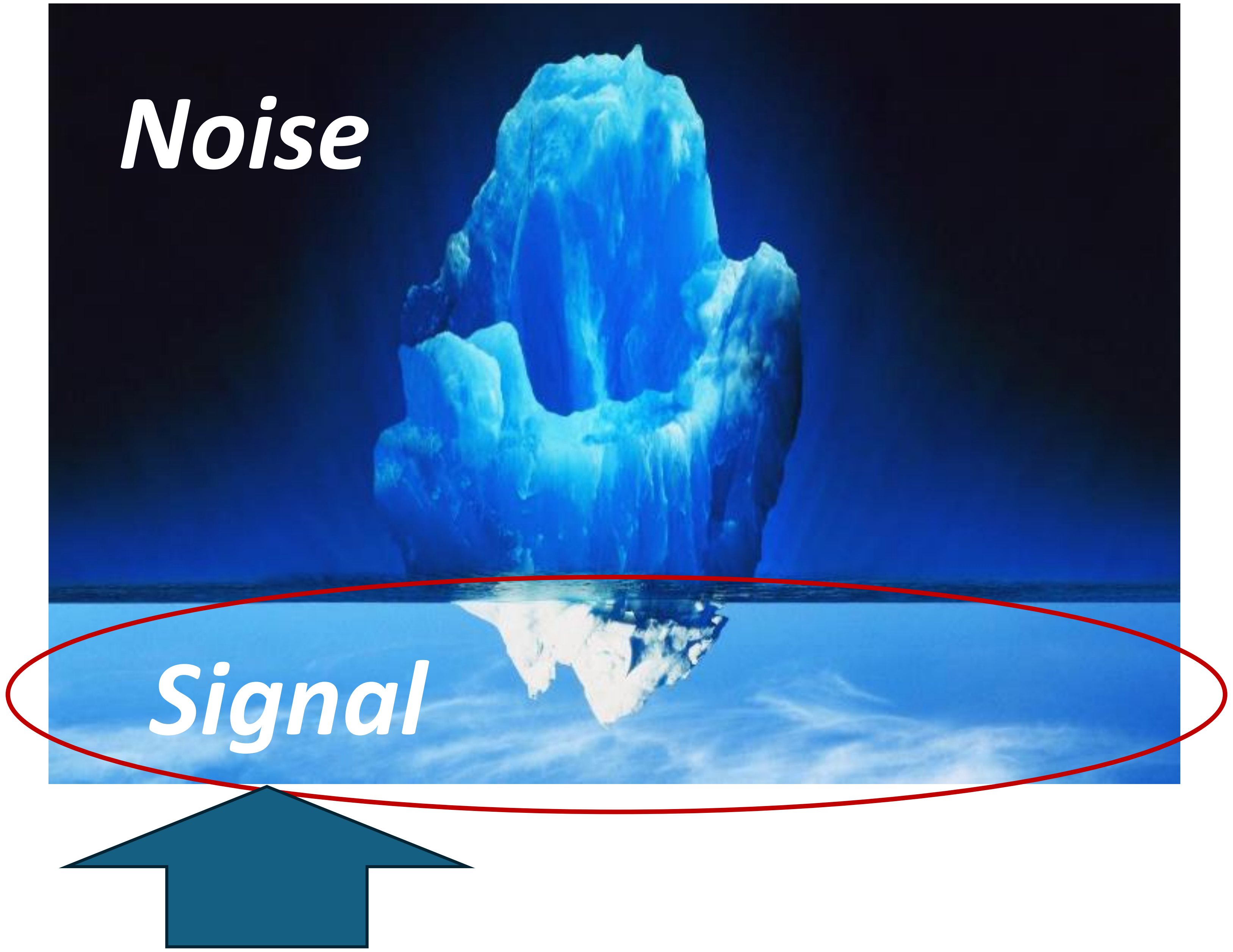
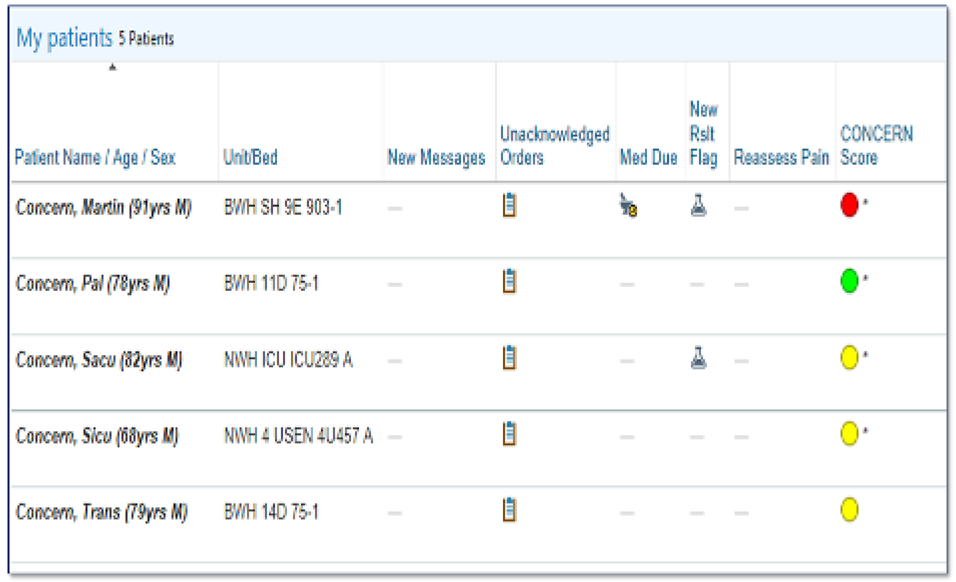
Multisite Pragmatic Cluster-Randomized Controlled Trial of the CONCERN Early Warning System

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

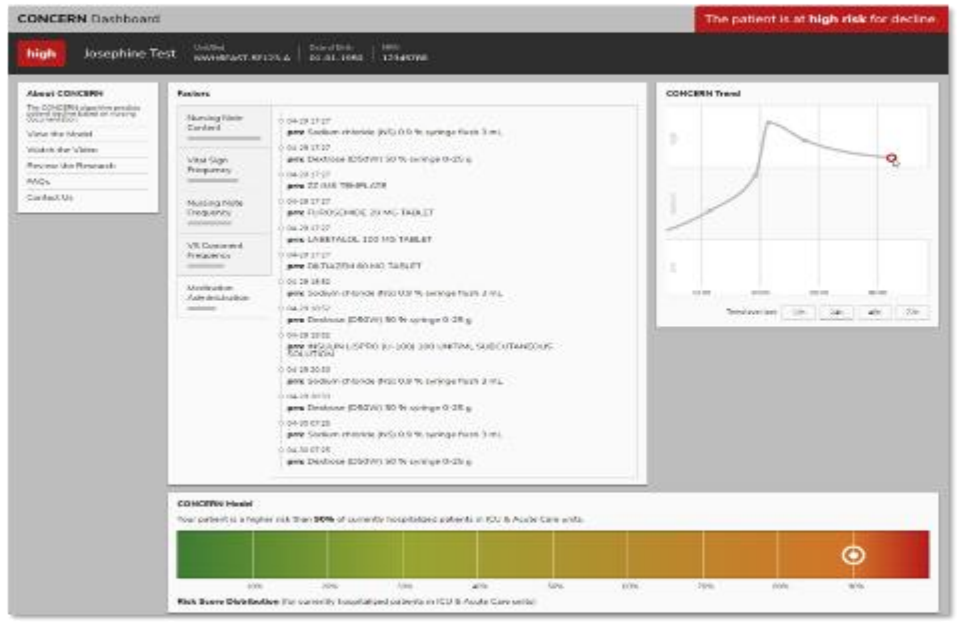


Clinical Care Classification (CCC) System as framework for classifying "nursing concern" concepts



My patients 5 Patients

Patient Name / Age / Sex	Unit/Bed	New Messages	Unacknowledged Orders	Med Due	New 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	—		—	—	—	



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CONCERN Back-End Engine (using FHIR)

Numerical Features
found from classification model

- **Vital Sign Entry Frequency** (HR, BP, RR, SpO2, temp.)
- **Vital Sign Comment Frequency** (HR, BP, RR, SpO2, temp. comments)
- **MAR Frequency** (PRN medications given, medications withheld)
- **Nursing Note Frequency**
- **Nursing Note Content** ("MD aware", "EKG obtained")

Continuous Time Dependent Scaling

- What time period in the day does the data come from? (e.g. 3:00 – 15:00)
- How long has the patient been in the hospital (e.g. 27 hours)

Categorical Features
Use of known confounders and variations on clinical workflow for prediction

- **Demographics** (age, gender, race, ethnicity)
- **Hospital Location** (ICU, ACU, Medicine, Surgical, etc.)
- **Time Features** (hour of day, day of week)
- **Previous Outcomes** (time since last ICU visit)

Numerical and Categorical Features
combined into a time independent measure of clinical deterioration

- Assigned color (green, yellow, red) and score (1-10)

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]

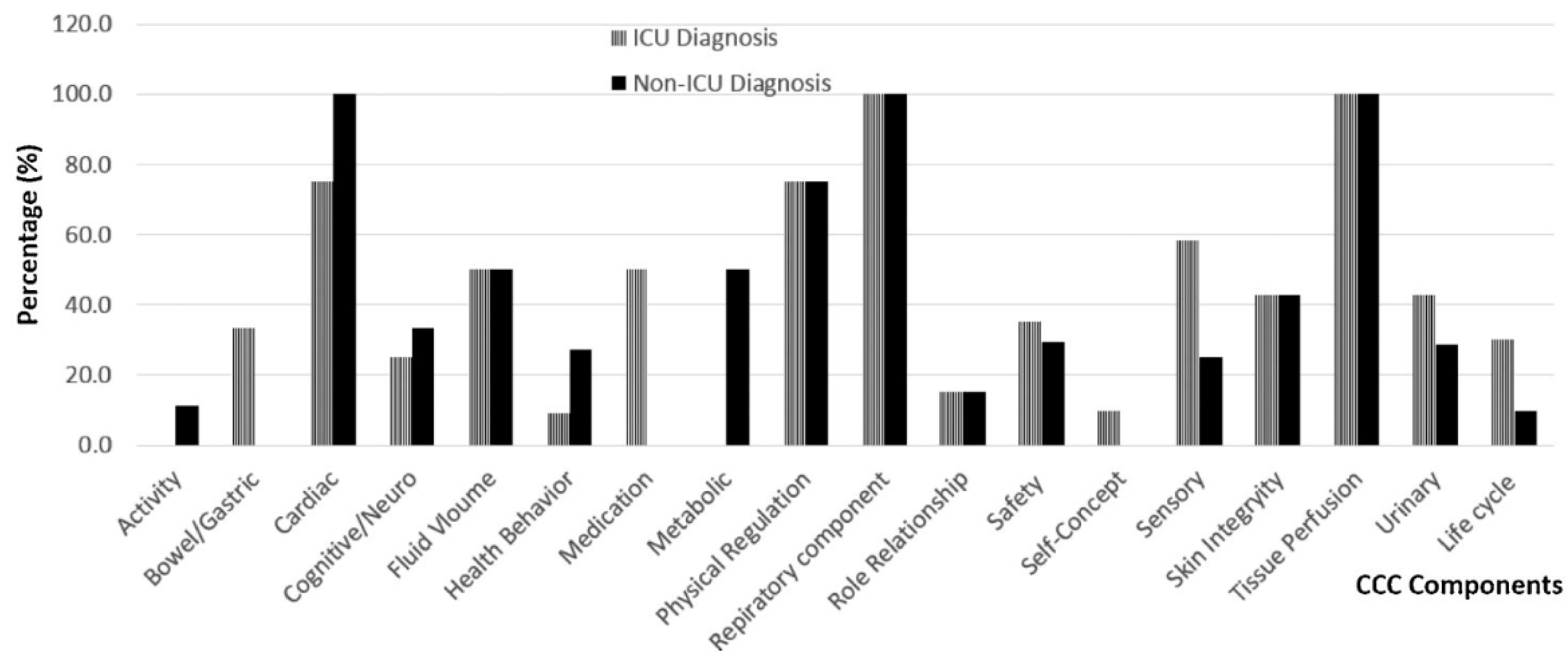
[a]Division of General Internal Medicine and Primary Care, Brigham & Women's Hospital, Boston, USA;

[b]Harvard Medical School, Boston, USA;

Methods to extract “nurses concern” from notes

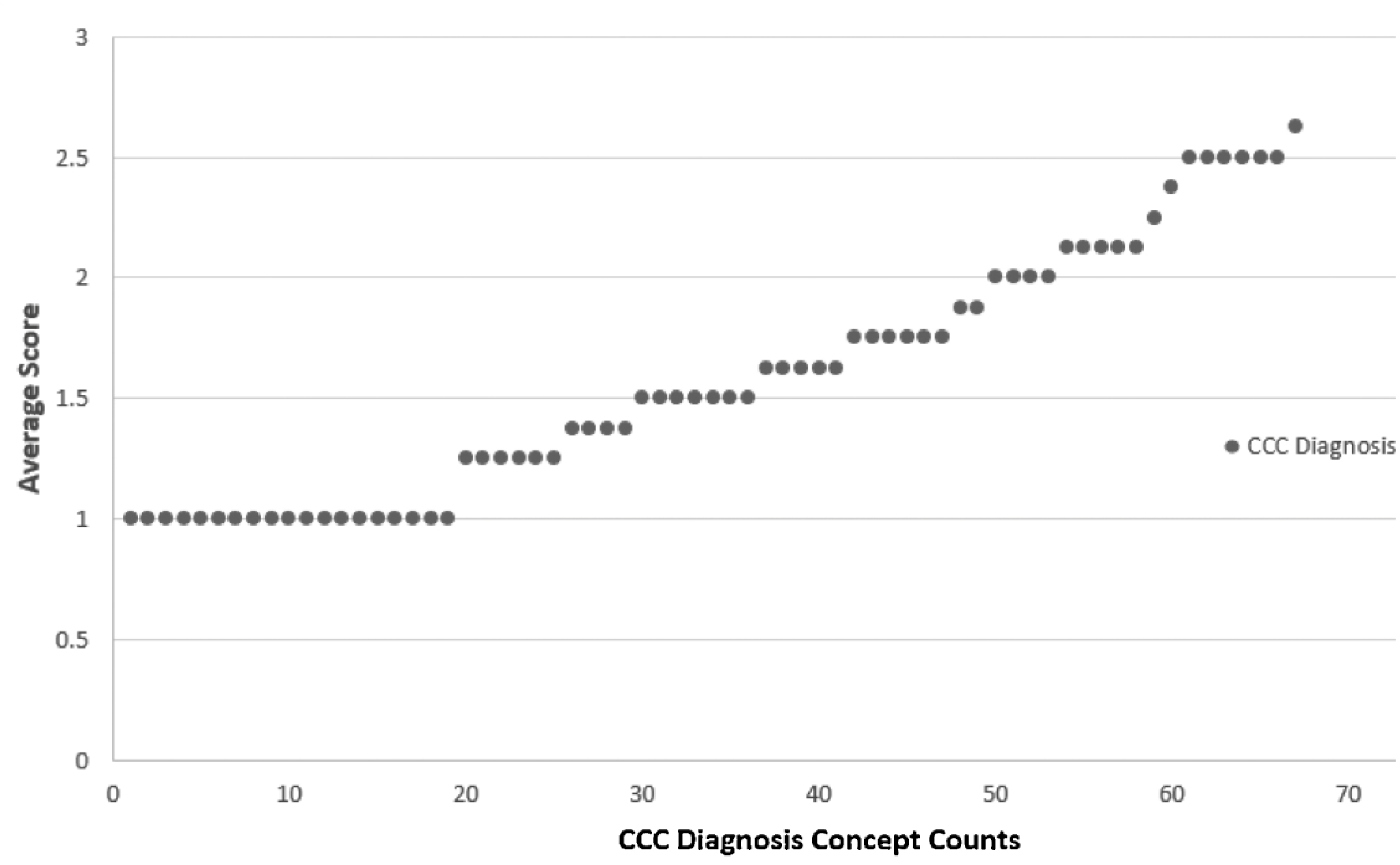
1. Group consensus meetings with nurse SMEs
   - Graded CCC system concepts by level of concern to identify concepts that may indicate “nurse’s concern” in a note

2. Curation of fundamental entities and terms related to nurses’ concerns by SMEs
   - Built fundamental lexicon with selected CCC concepts, entities and seed terms



- Percentage(%): $\frac{\text{Counts of CCC Concept grade as one}}{\text{Counts of Concepts in CCC Component}} \times 100$

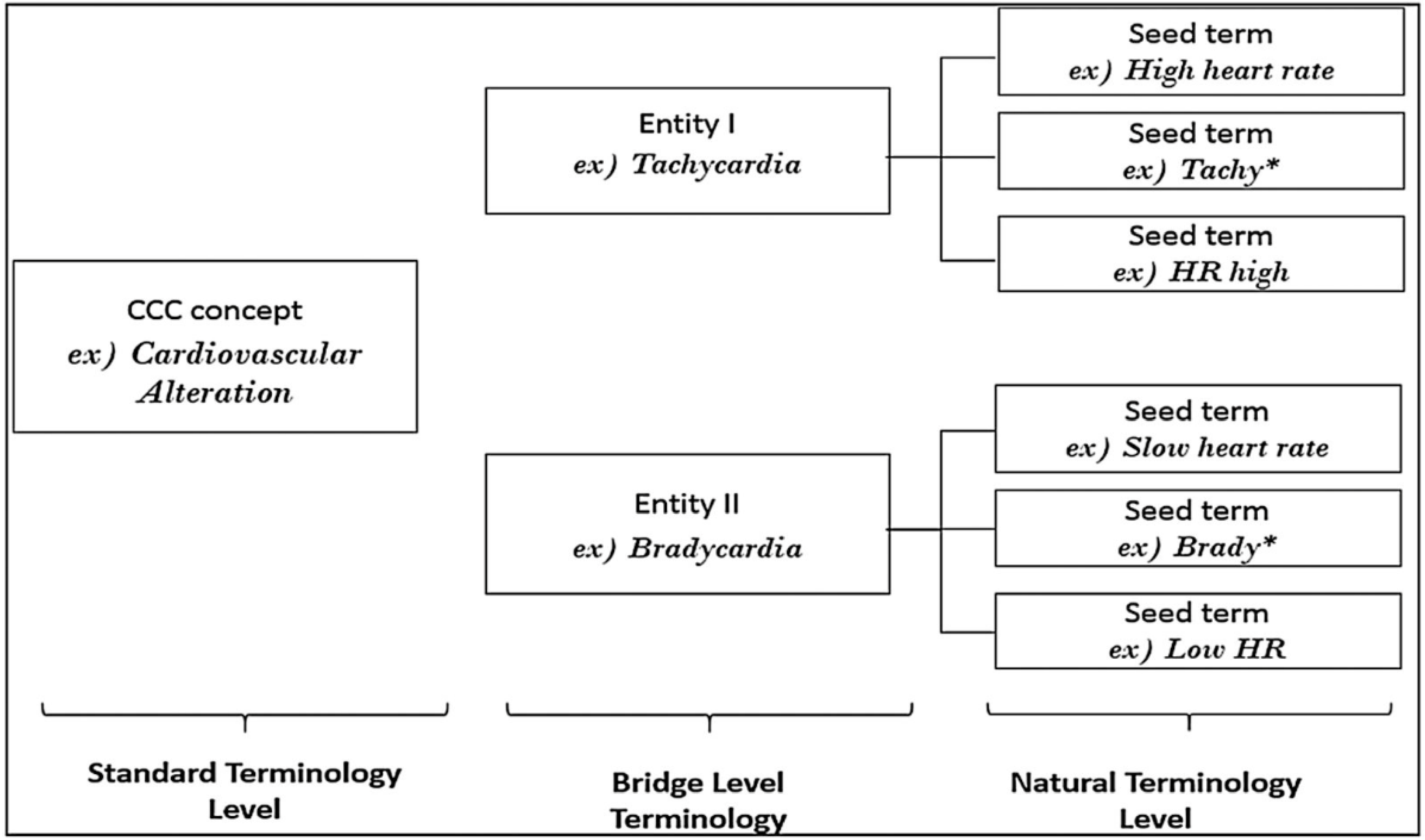
Expert Nurses Scoring of CCC concepts that may indicate concerning patient state stratified by setting



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

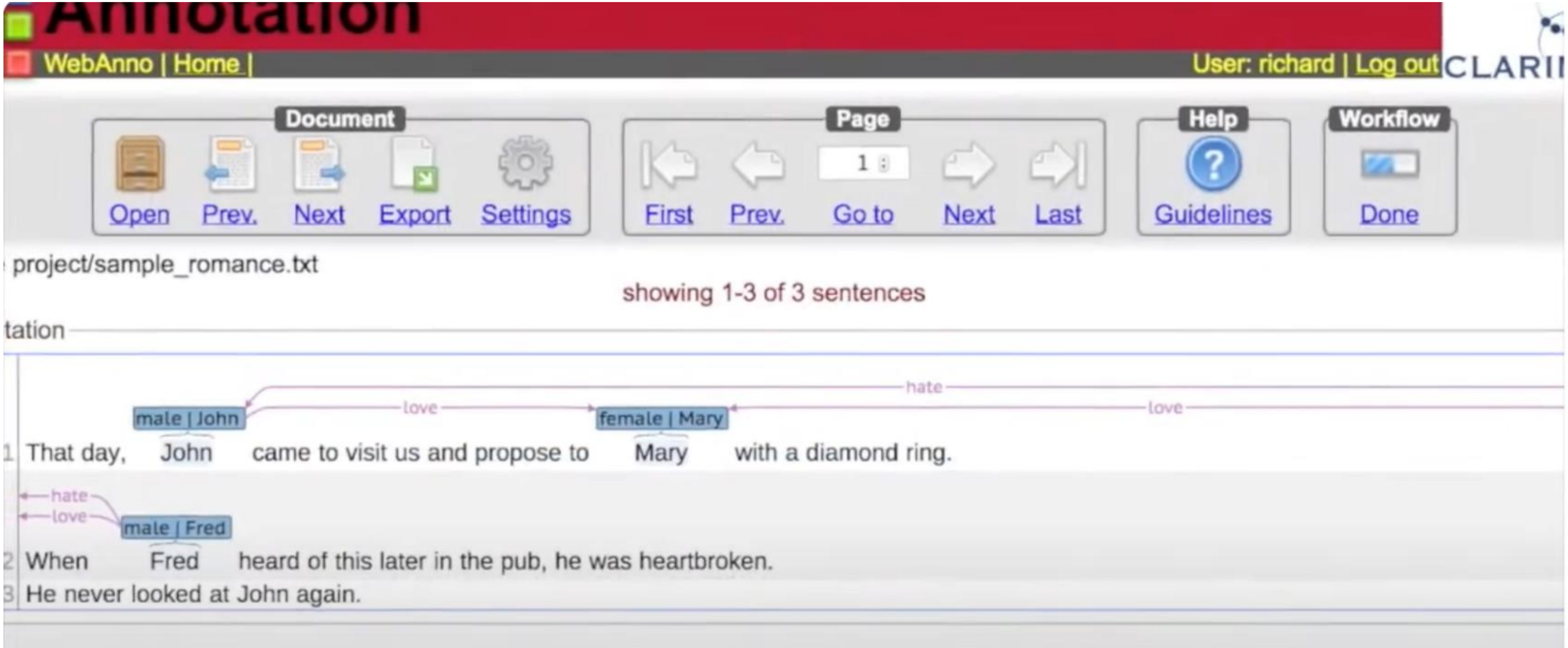
Distribution of CCC concepts on scale of concern

(0 no concern to 3 highest concern)



Example Structure of terminology set for NLP of Nursing Notes

Tool for Expert Nurse Annotations of Nursing Notes for Concerning Concepts



(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 bood 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 blod 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

Nursing concern CCC concepts by Medicine and Surgery Units

	ICU		Non- ICU	
CCC Component	**Medicine (MICU)**	**Surgery (SICU, Trauma ICU)**	**Medicine**	**Surgery**
Bowel/ Gastric	• Diarrhea	• Diarrhea • Fecal Impaction • Gastrointestinal Alteration	–	–
Physical Regulation	• Autonomic Dysreflexia • Hyperthermia • Hypothermia • Thermoregulation Impairment • Intracranial Adaptive Capacity Impairment	• Autonomic Dysreflexia • Hyperthermia • Hypothermia • Thermoregulation Impairment • Intracranial Adaptive Capacity Impairment • Infection	–	–
Skin Integrity	• Latex Allergy Response • Peripheral Alteration	• Latex Allergy Response • Peripheral Alteration • Skin Incision	• Skin Integrity Impairment • Latex Allergy Response	• Skin Integrity Impairment • Latex Allergy Response • Peripheral Alteration
Urinary Elimination	• Urinary Elimination Alteration • Renal Alteration	• Urinary Elimination Alteration • Renal Alteration • Urinary Retention	• Urinary Elimination Alteration	• Urinary Elimination Alteration • Urinary Retention

Abbreviations: MICU: Medical Intensive Care Unit; SICU: Surgical Intensive Care Unit: Trauma ICU, Trauma Intensive Care Unit

Nursing Concern Core Concepts organized within CCC Framework

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

- 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

AHRQ Agency for Healthcare Research and Quality
COLUMBIA
Columbia University Department of Biomedical Informatics
Washington University in St. Louis School of Medicine
Institute for Informatics (I²)

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

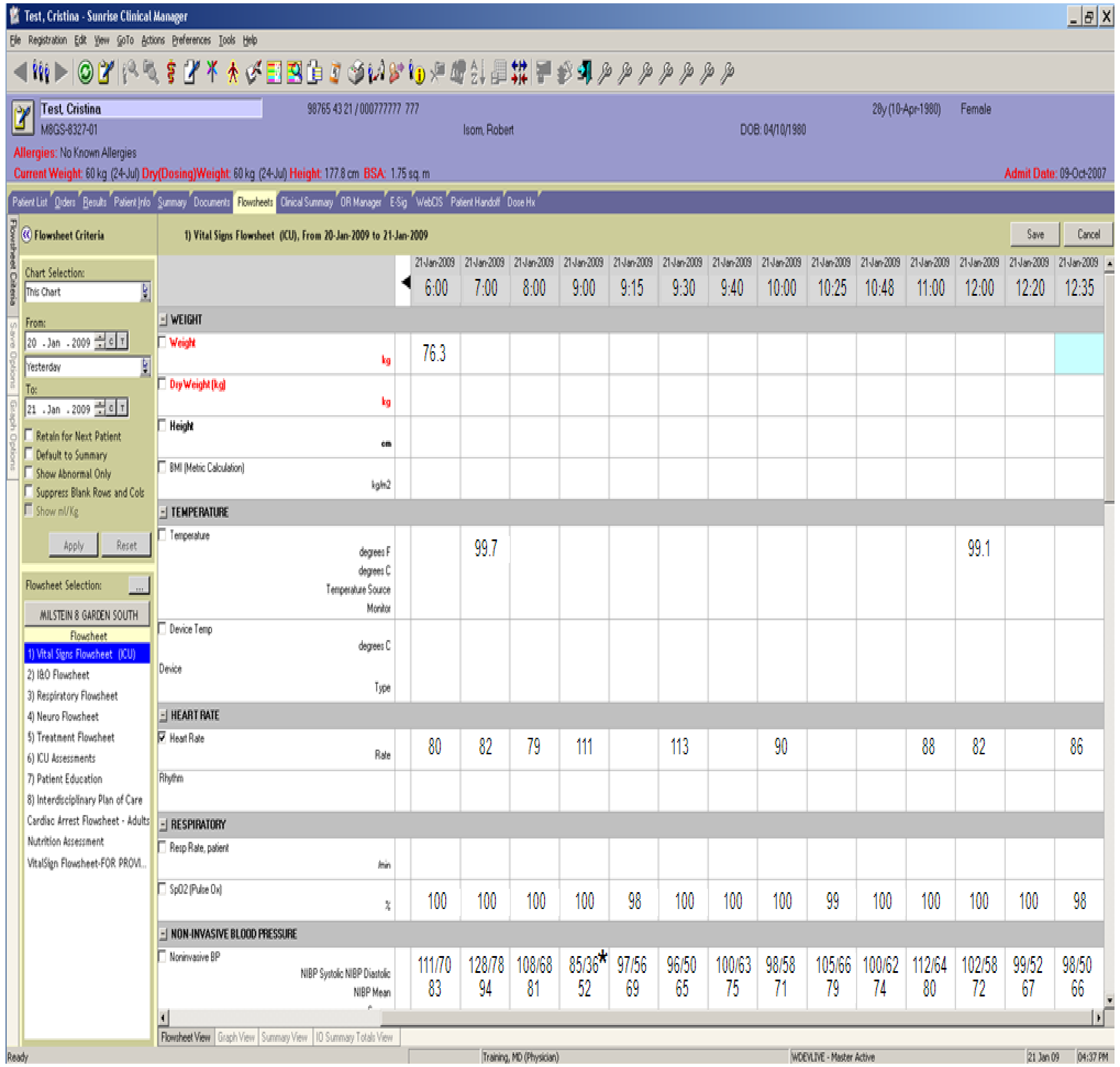
- Health System A
    - 3,230 flowsheet measures
    - 641 flowsheet groups
    - 282 flowsheet templates

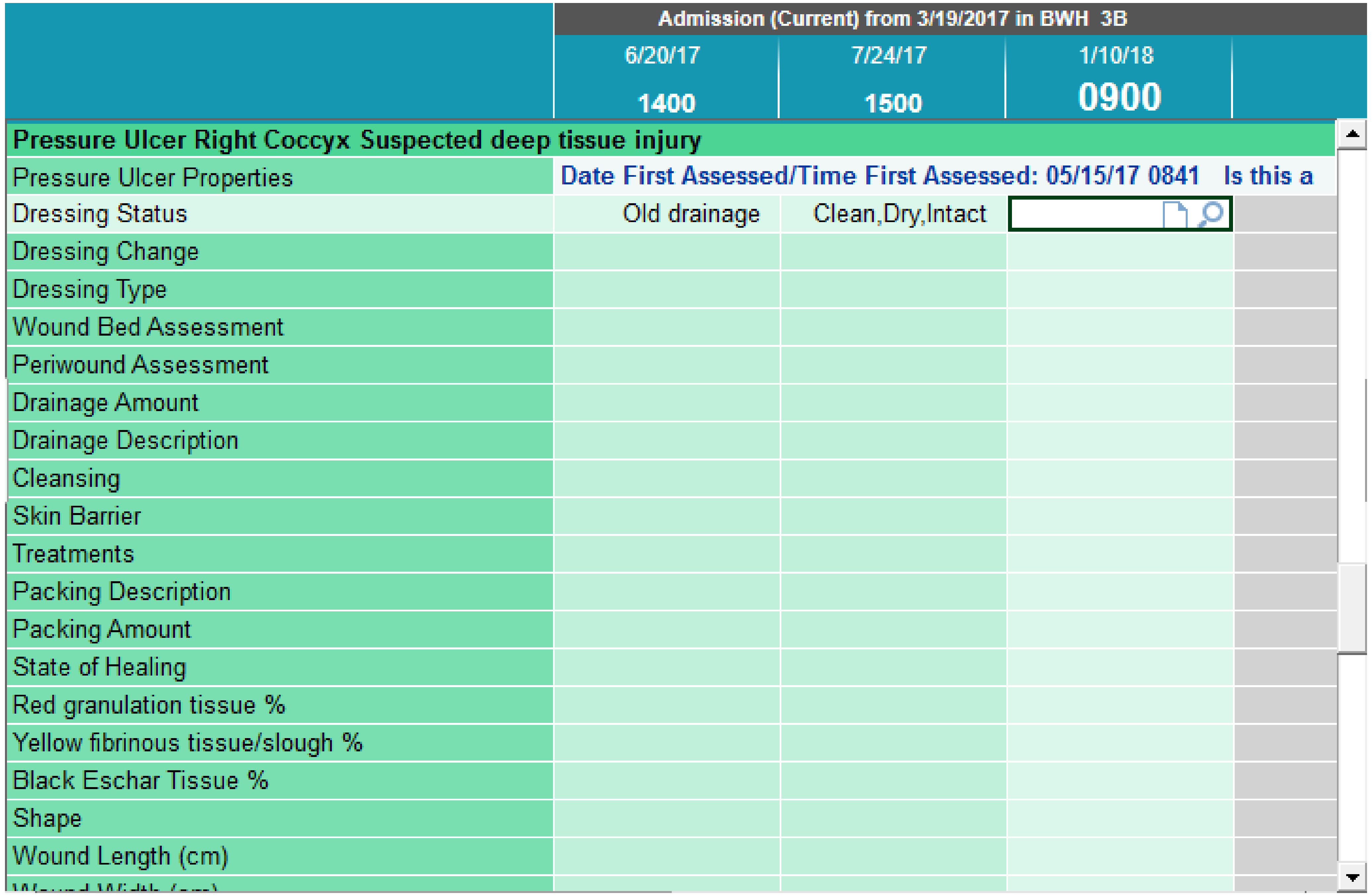
- Health System B
    - 9,499 flowsheet measures
    - 1,836 flowsheet groups
    - 727 flowsheet templates

Nursing Flowsheets - The 5 V's of Big Data

- Volume
- Velocity
- Variety
- Veracity
- Value

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





Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	Sp02
Value	95
**Also called flowsheet field or flowsheet data element*	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	Sp02
Value	95
Also called flowsheet field or flowsheet data element	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs Simple Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	Sp02
Value	90
Also called flowsheet field or flowsheet data element	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs ICU Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	Sp02
Value	95
**Also called flowsheet field or flowsheet data element*	

Structure Hierarchy	Example
Flowsheet Template	Vital Signs Simple Flowsheet
Flowsheet Group	Oxygen Therapy
Flowsheet Measure*	Sp02
Value	90
**Also called flowsheet field or flowsheet data element*	

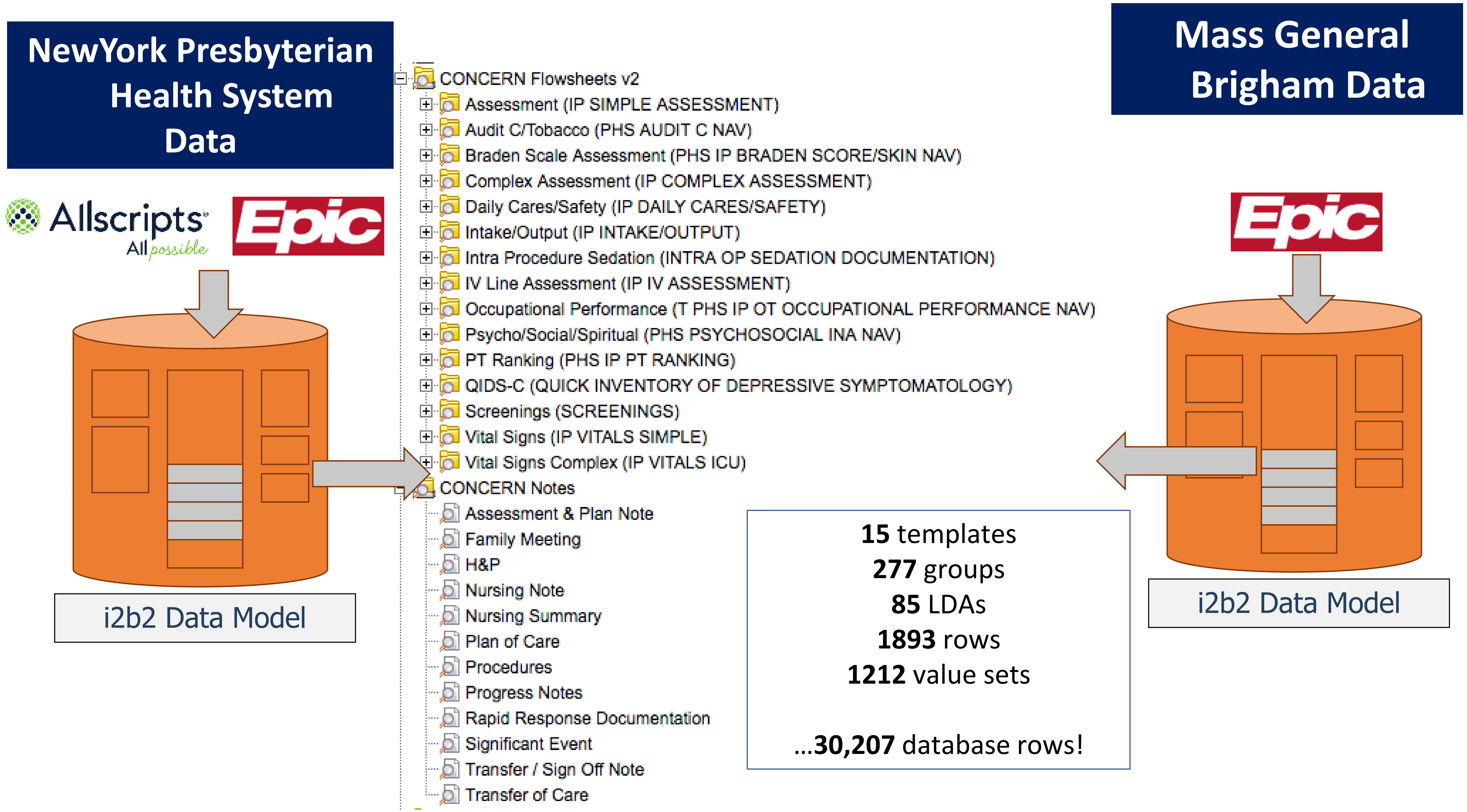
FlowsheetMeasure	Template	Frequency	Encounter
PULSE	IP VITALS SIMPLE	1,843,640	106,846
	IP VITALS ICU	1,629,805	27,220
	IP SIMPLE ASSESSMENT	306,243	42,473
	IP COMPLEX ASSESSMENT	45,754	9,715
	INTRA OP SEDATION DOCUMENTATION	688	315
R PAIN ASSESSMENT	IP VITALS SIMPLE	2,507,263	109,320
	IP VITALS ICU	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

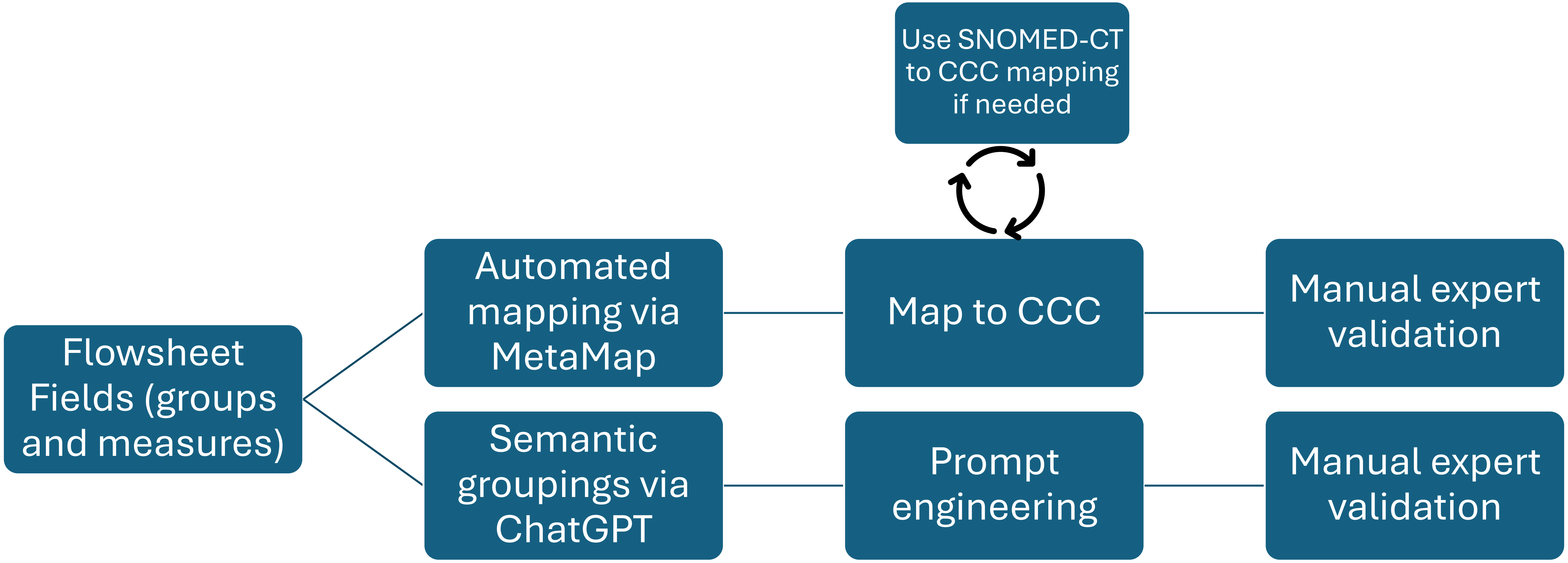
BUCKET 1	BUCKET 2-SubBucket	PHS_Group Display Name	PHS_Row Display Names	PHS_Template Full Name	NYP_FSNAME	NYP_ITEM_NAME	NYP_ITEM_DESCRIPTION
Cardiac	Cardiac	Cardiac	Ectopy	IP SIMPLE ASSESSMENT	1) Vital Signs Flowsheet	vs_hr_ectopy	vs_hr_ectopy
Cardiac	Cardiac	Cardiac	Ectopy Frequency	IP SIMPLE ASSESSMENT	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



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



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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.

- 42 Groups
- 38 Groups
- 26 Groups
- 10 Groups

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

(Hao Fan, AMIA 2024)

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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

(Hao Fan, AMIA 2024)

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

(Hao Fan, AMIA 2024)

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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

(Hao Fan, AMIA 2024)

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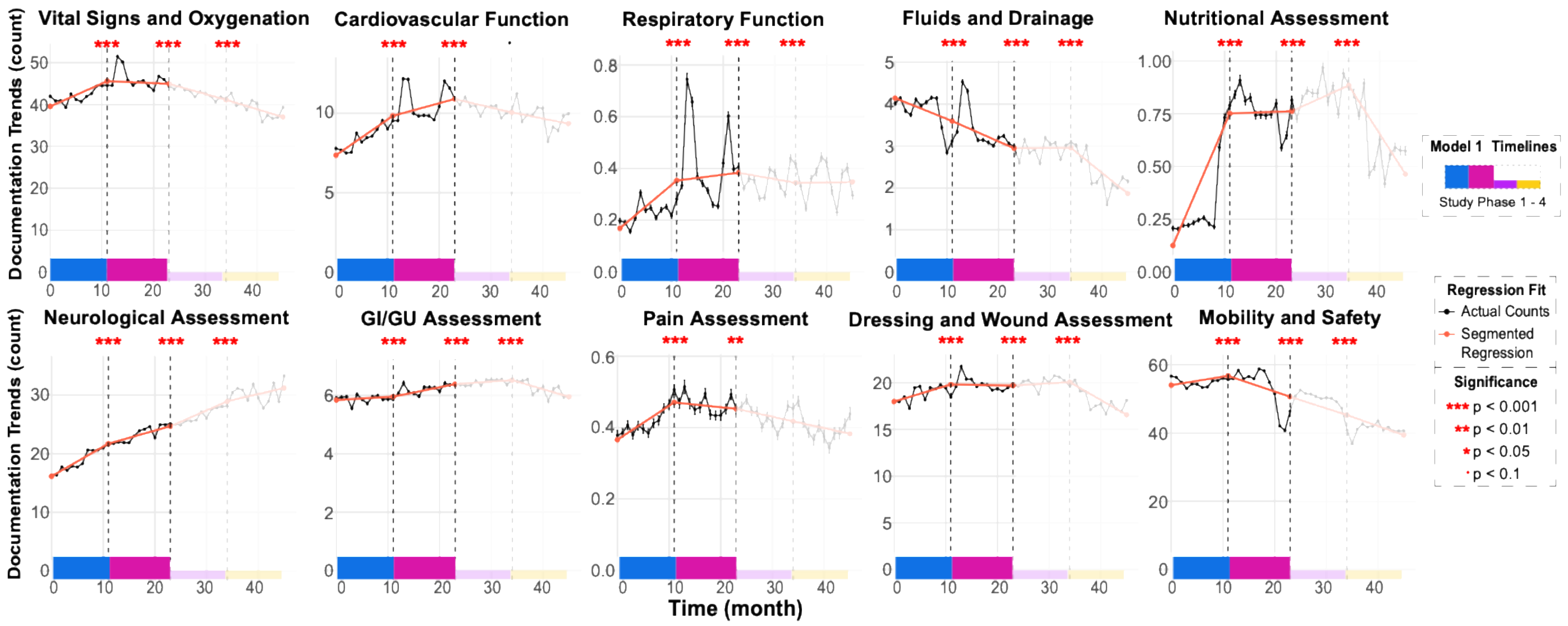
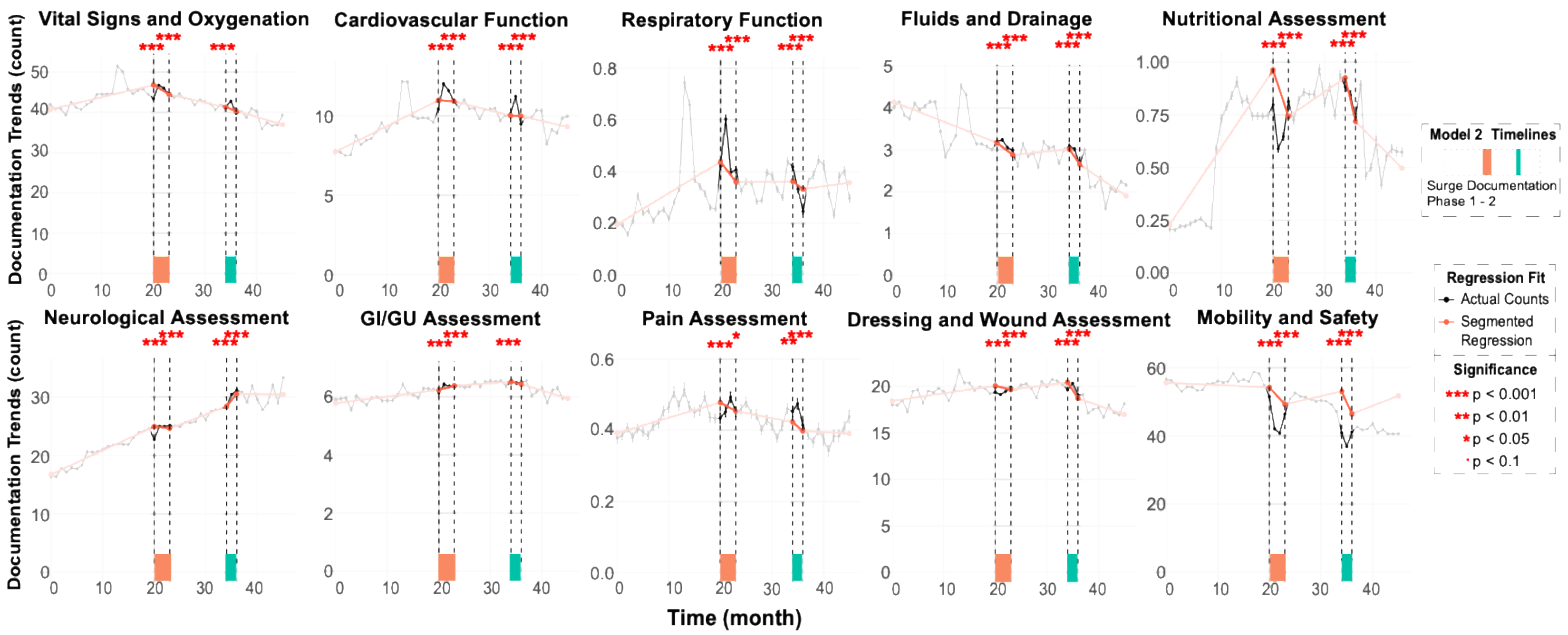
Nurses prioritize “essential documentation” when complexity and acuity is high, such as during COVID-19 pandemic

Most Documentation Frequencies Increased ↗ During the Pandemic



Most Documentation Frequencies Decreased ↘ with Relaxation Policies



Essential Documentation

Vital Signs and Oxygenation

Cardiovascular Function

Respiratory Function

Fluids and Drainage

Neurological Assessment

GI/GU Assessment

Pain Assessment

Dressing and Wound Assessment

Non-Essential Documentation

Nutritional Assessment

Mobility and Safety

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

(Hao Fan, AMIA 2024)

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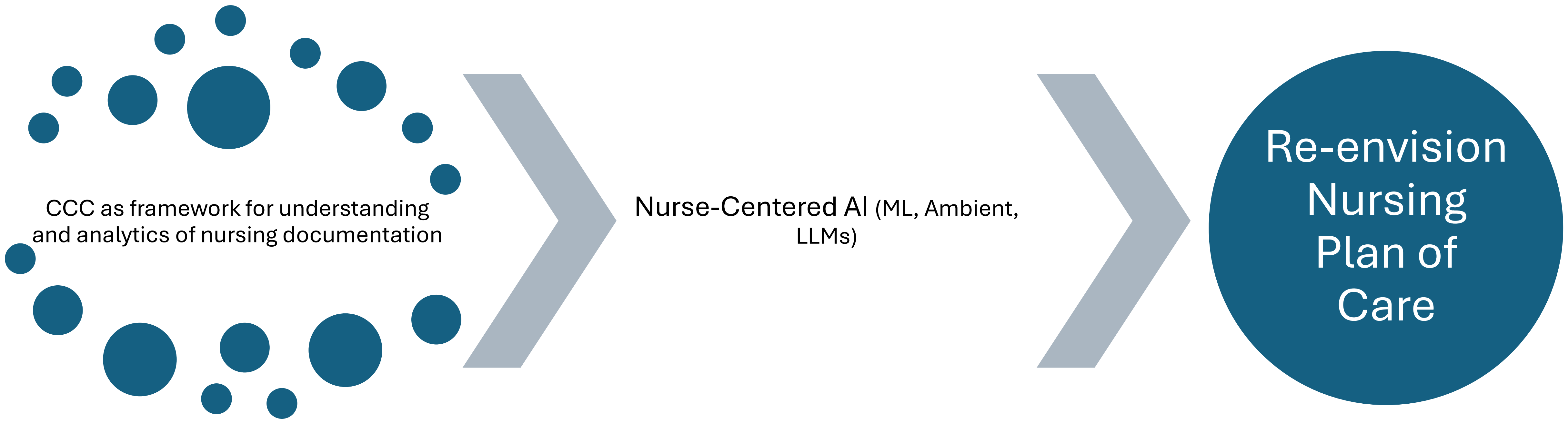
Future work – Innovative Solutions to Decrease Documentation Burden

- 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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AHRQ Agency for Healthcare Research and Quality

CONCERN

Communicating **N**arrative **C**oncerns **E**ntered by **RN**s (CONCERN)

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American Nurses Foundation

Reimagining Nursing

NIH NINR

Thank you!

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EndBurden

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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)"

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

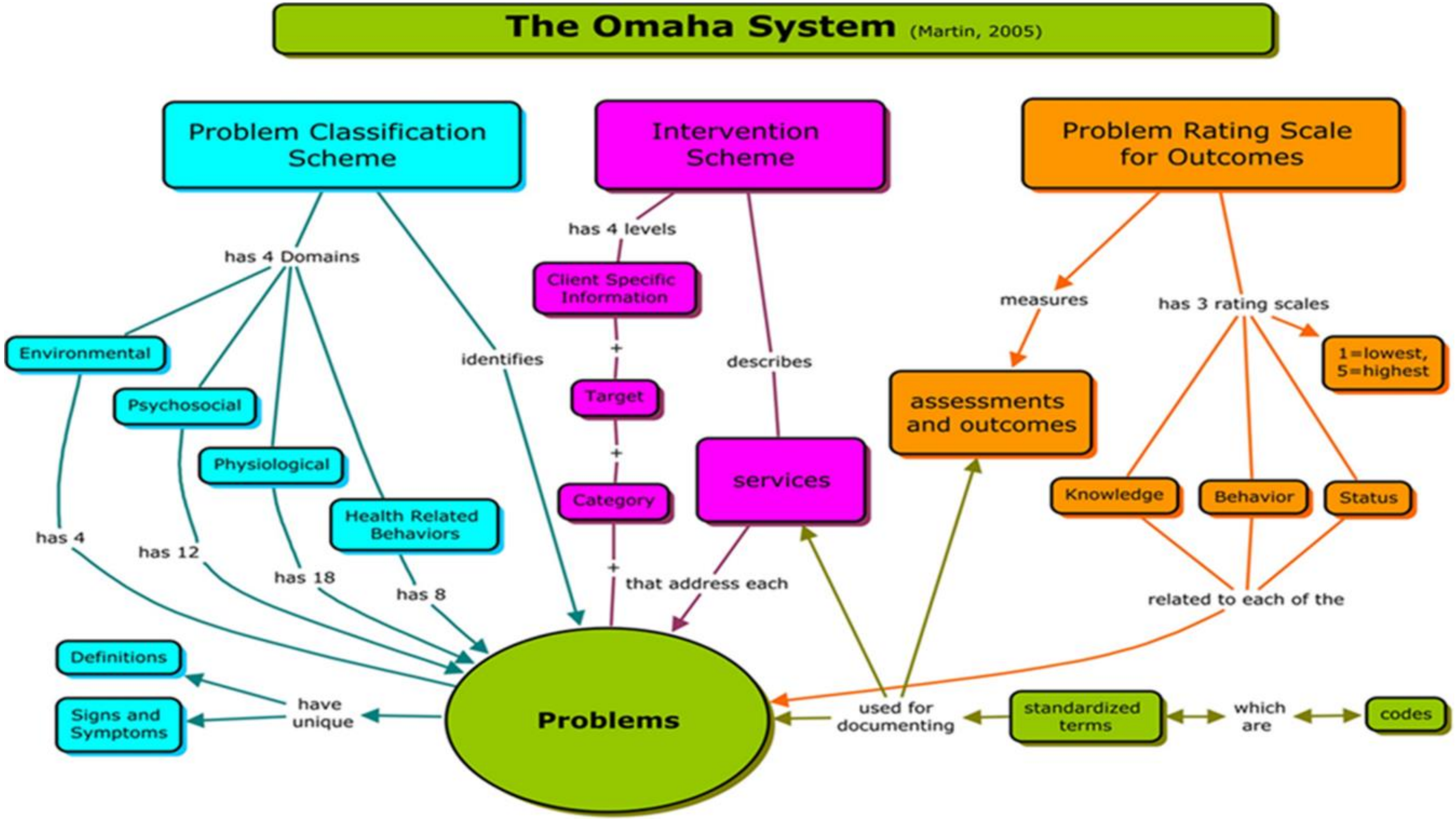
- Up to 40% of readmissions from HHC are classified as preventable
- Risk for negative outcomes can be reduced via early patient risk detection and notification

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	inadeqaute/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
		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

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
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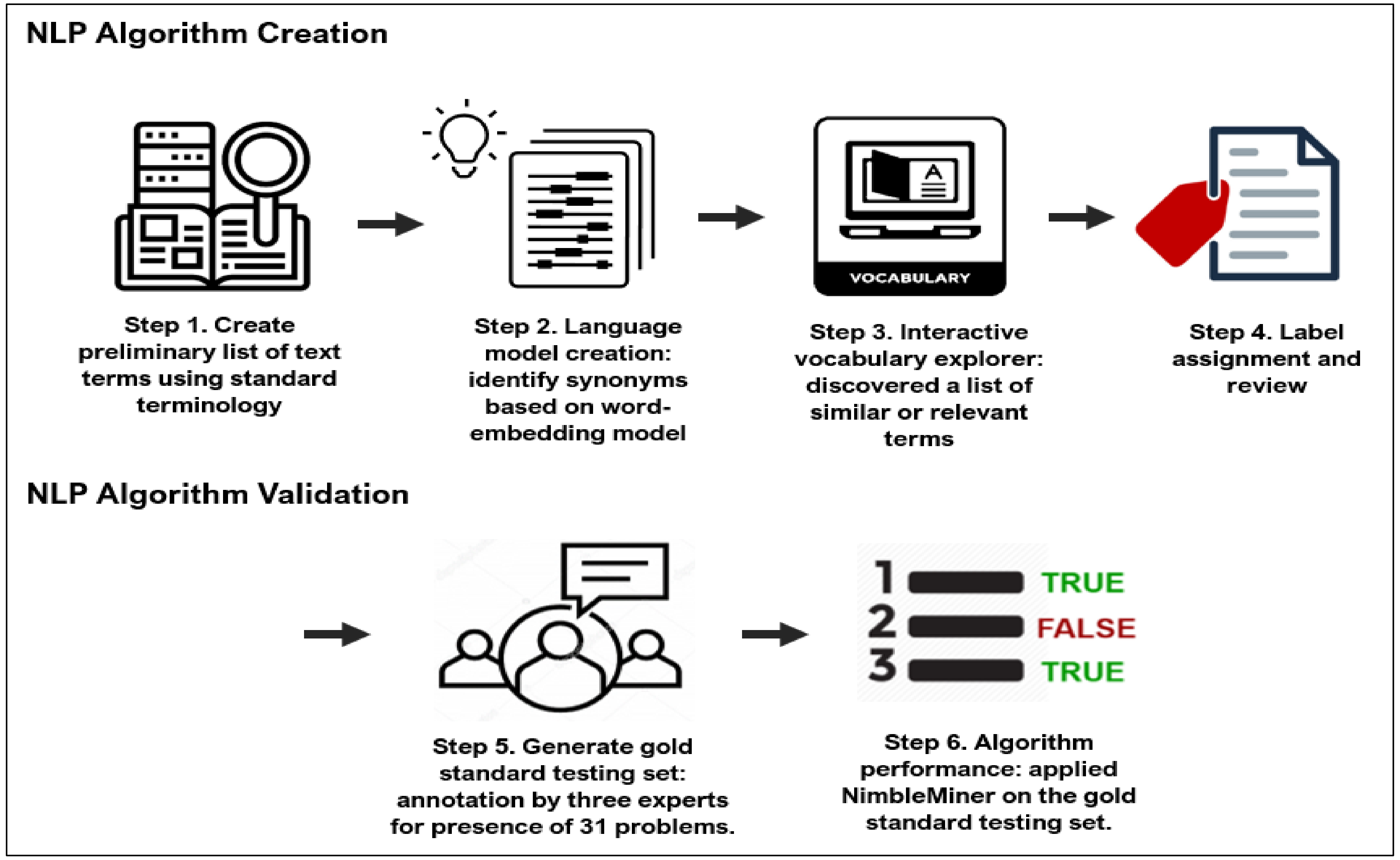
	Medication regimen (6./ 6 = 100%)	does not follow recommended dosage/schedule
		evidence of side effects/adverse reactions
		inadequate system for taking medication
		improper storage of medication
		fails to obtain refills appropriately
		fails to obtain immunizations

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



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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

Contents lists available at ScienceDirect

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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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A R T I C L E I N F O

Keywords
Home health care
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Risk assessment
Clinical deterioration
Nursing informatics

A B S T R A C T

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 Naïve 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.

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

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

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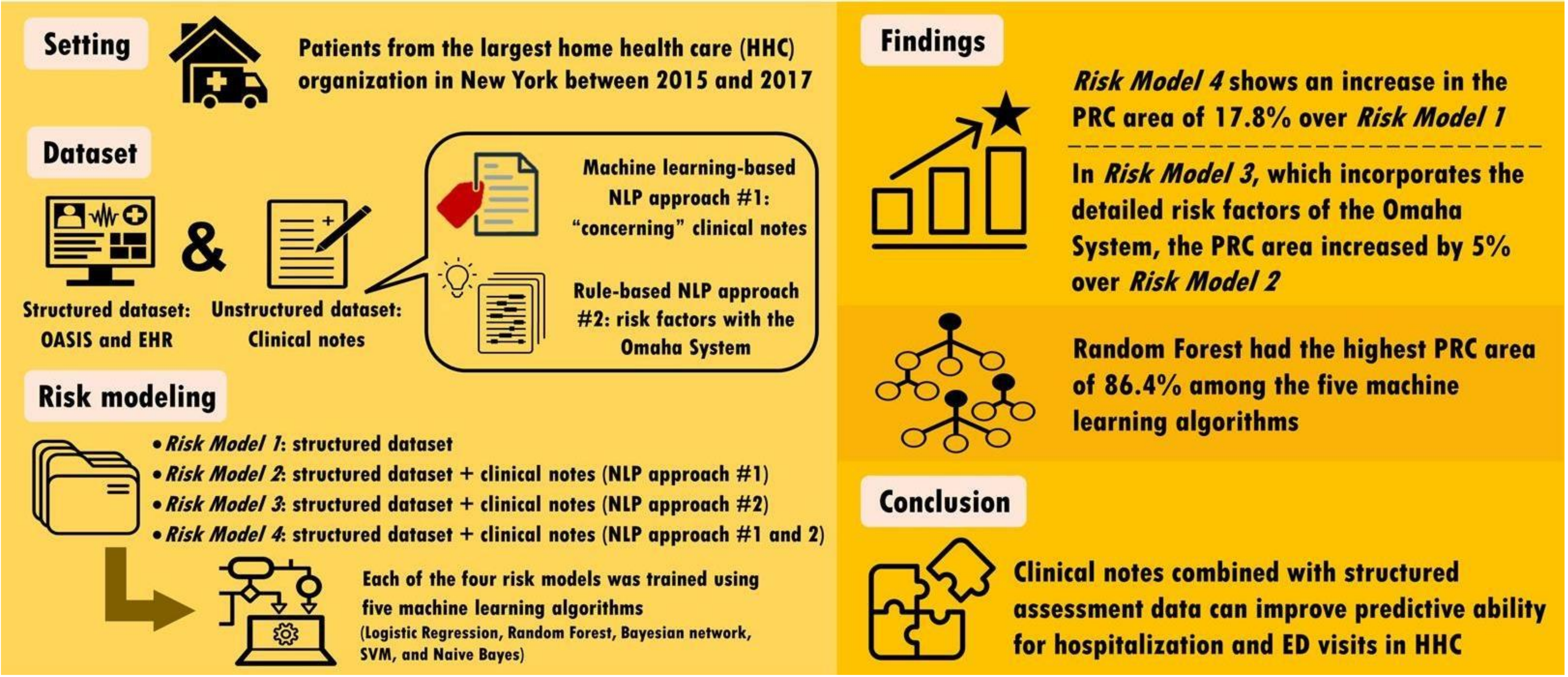
Study #2



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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		
Risk Model 1	0.71	0.74
Risk Model 2	**0.76**	**0.81**
Random Forest	**7% ↑**	**10% ↑**
Risk Model 1	0.78	0.82
Risk Model 2	**0.81**	**0.86**
Bayes Network	**3.8% ↑**	**5.6% ↑**
Risk Model 1	0.68	0.71
Risk Model 2	**0.79**	**0.84**
SVM (Support Vector Machine)	**16.1% ↑**	**17.8% ↑**
Risk Model 1	0.73	0.77
Risk Model 2	**0.82**	**0.82**
Naïve Bayes	**11.2% ↑**	**7.3% ↑**
Risk Model 1	0.68	0.68
Risk Model 2	**0.69**	**0.68**

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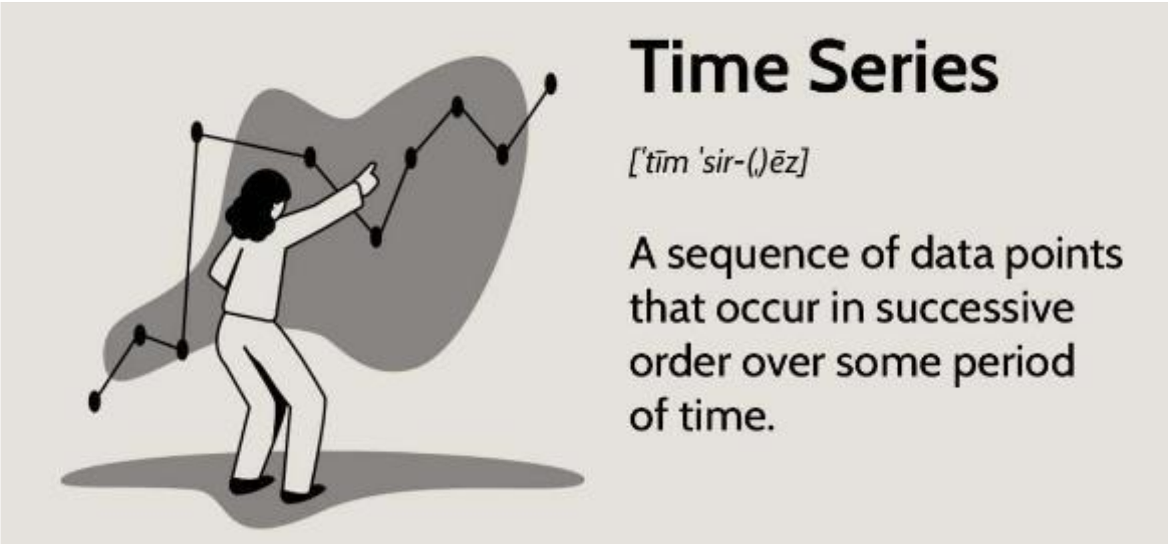
Study #3

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



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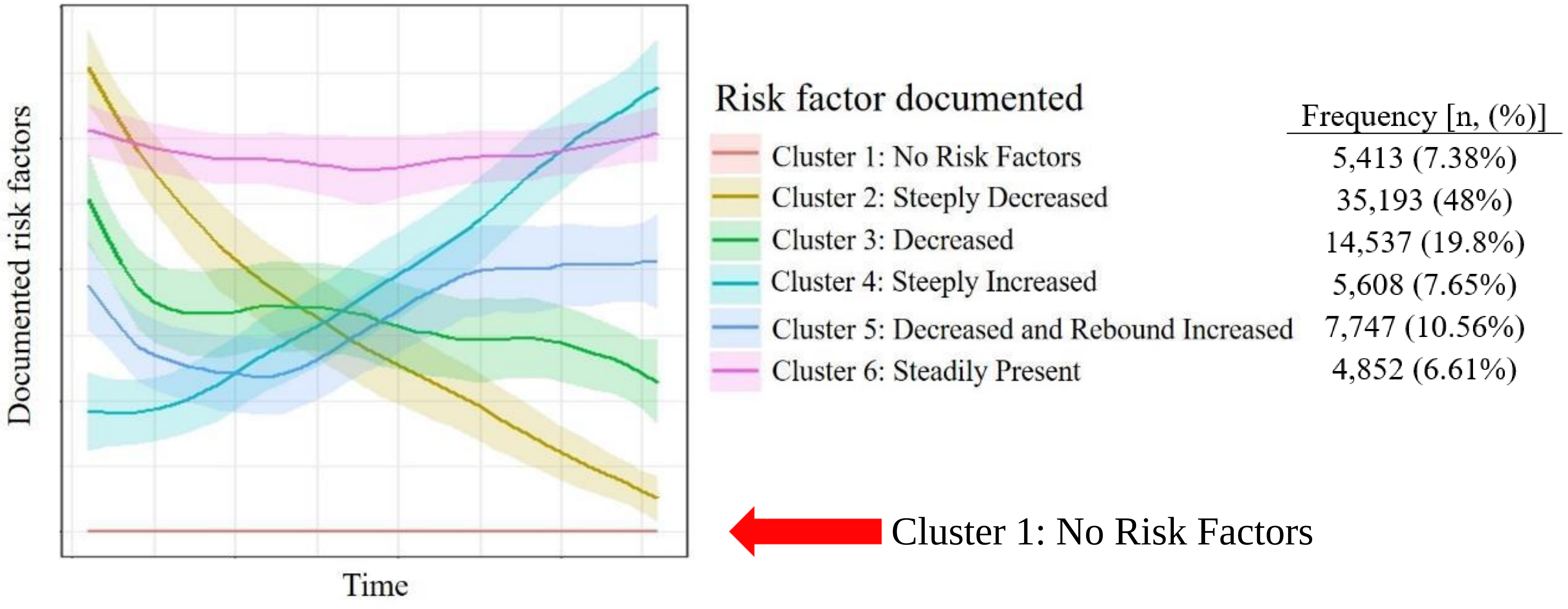
Song, J., Min, SH., Chae, S., Bowles, K. H., McDonald, M.V., Hobensack, M., Barron, Y., Sridharan, S., Davoudi, A., Oh, S., Evans, L., & Topaz, M. (2023) Uncovering Hidden Trends: Identifying Time Trajectories in Risk Factors Documented in Clinical Notes and Predicting Hospitalizations and Emergency Department Visits during Home Health Care (Journal of the American Medical Informatics Association (JAMIA)). DOI: https://doi.org/10.1093/jamia/ocad101

Study #3

- **Methods:**
  2. Generating temporal patterns of risk factors via unsupervised hierarchical cluster analysis



Cluster 1: No Risk Factors

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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)

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VNS Health

Thank you!

Questions or comments?

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Q&A

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Presentation

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

Robin R. Austin, PhD, DNP, DC, NI-BC, FAMIA, FAAN,

Ratchada Jantraporn, PhD, MS, RN, Martin Michalowski, PhD, FAMIA, FIAHSI and

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Acknowledgements

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Penn UNIVERSITY of PENNSYLVANIA | Artificial Intelligence and Technology Collaboratory for Healthy Aging

Background

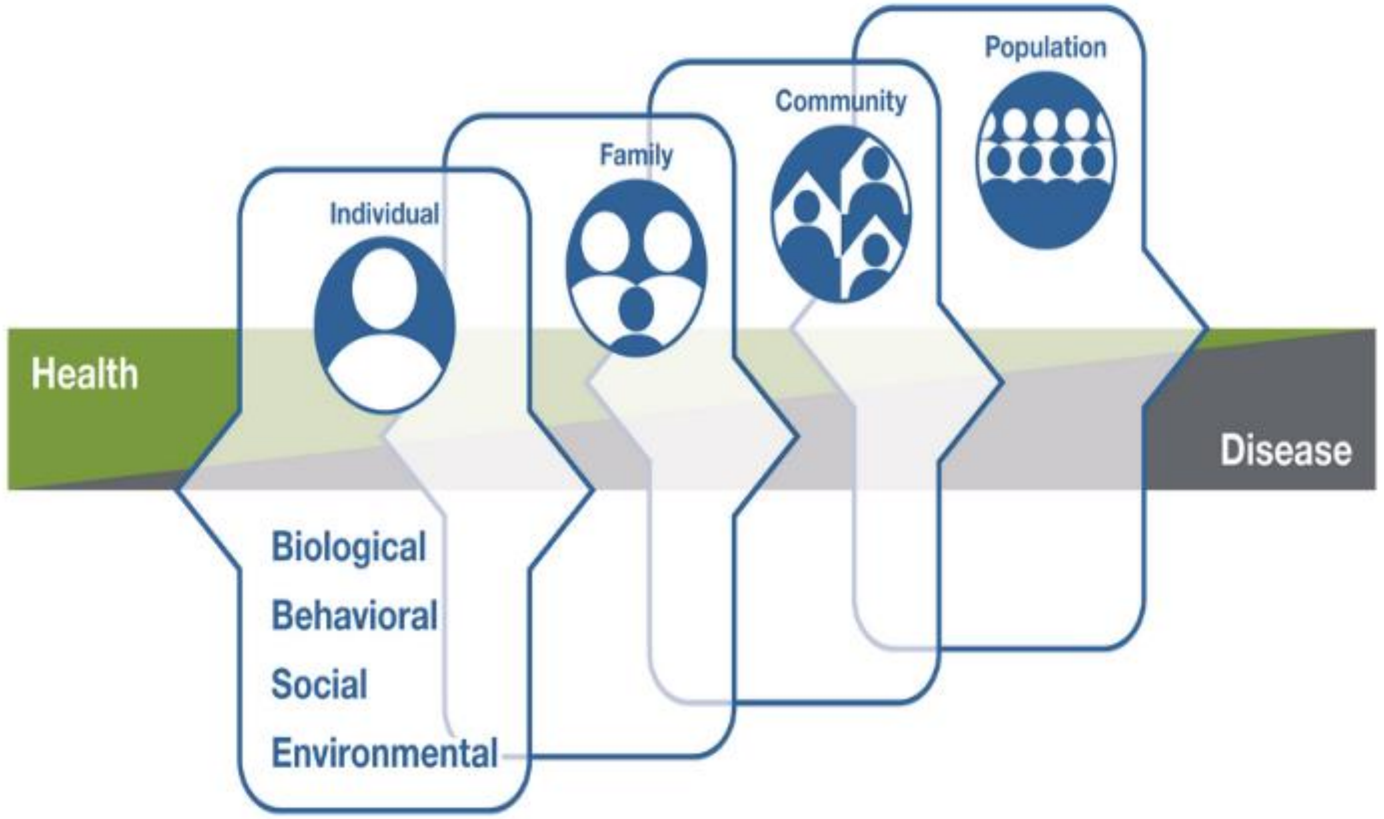
- Healthy aging is essential for maintaining the overall quality of life for a growing global older adult population.[1]
- Recommendations support whole person approach that includes a person's strengths in addition to their challenges.[2,3]
- Whole person health also includes strengths (or resilience).[2]
- 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.

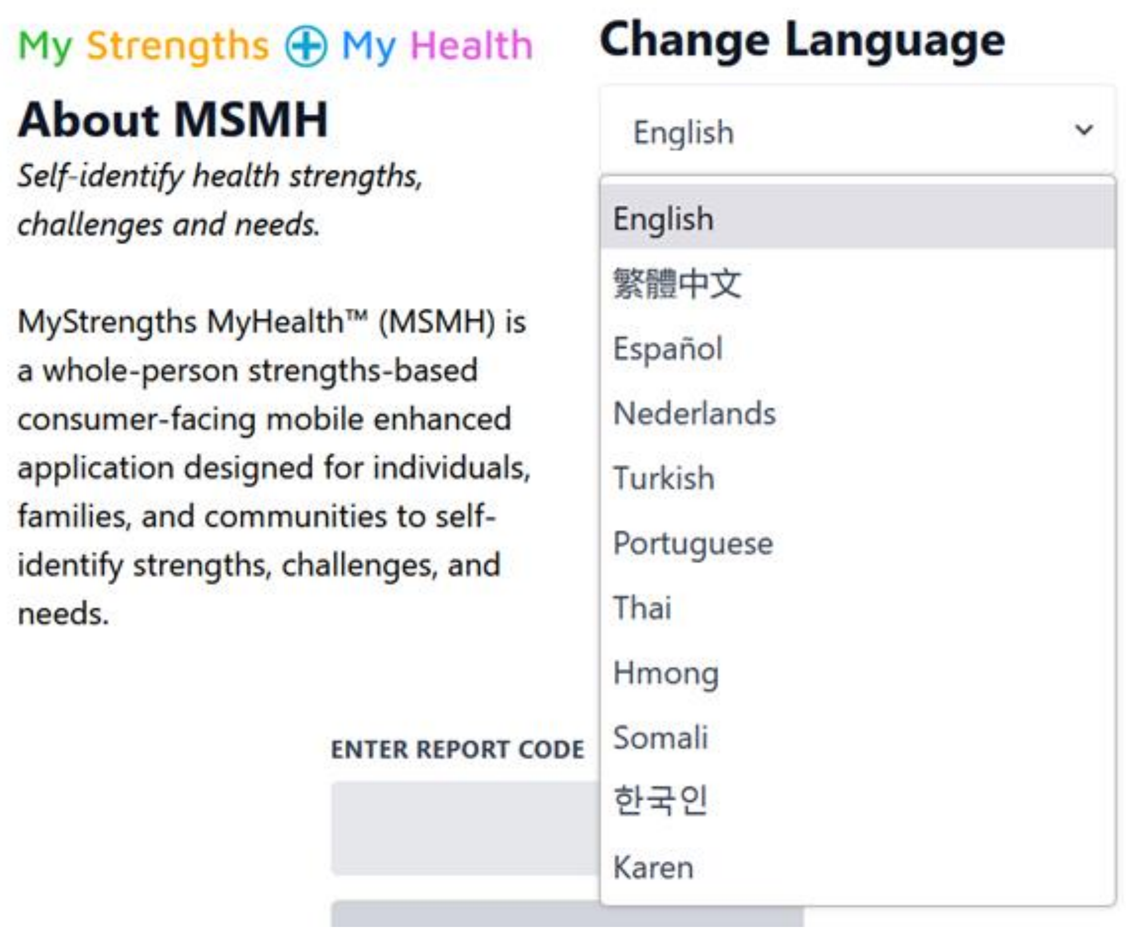
Empowering individuals, to improve their health in multiple interconnected biological, behavioral, social, and environmental areas.[2]

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 terminology[6]
- 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

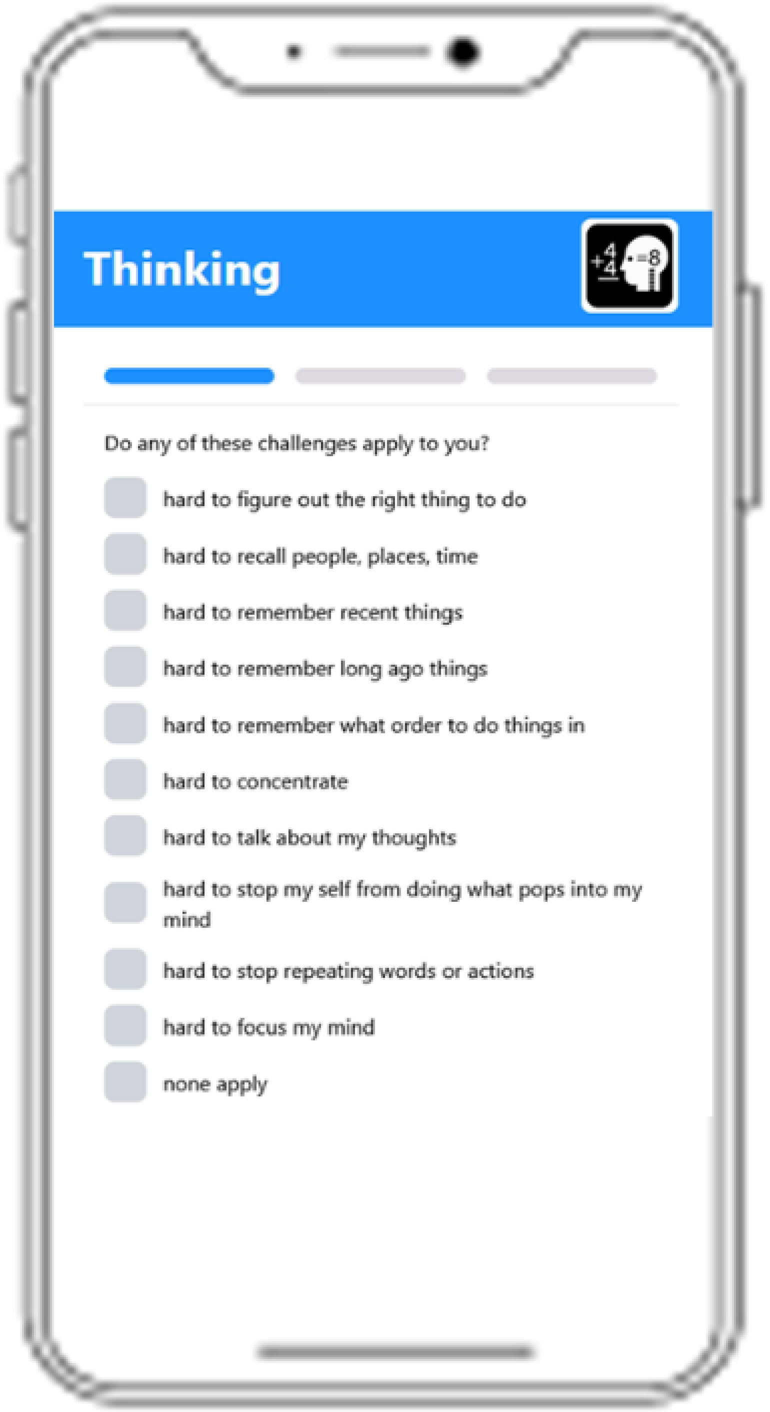
My Living	My Mind & Networks	My Body		My Self-care
Income	Connecting	Hearing	Breathing	Nutrition
Cleaning	Socializing	Vision	Circulation	Sleeping
Home	Role change	Speech and language	Digestion	Exercising
Safe at home and work	Relationships	Oral health	Bowel function	Personal care
	Spirituality or faith	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			

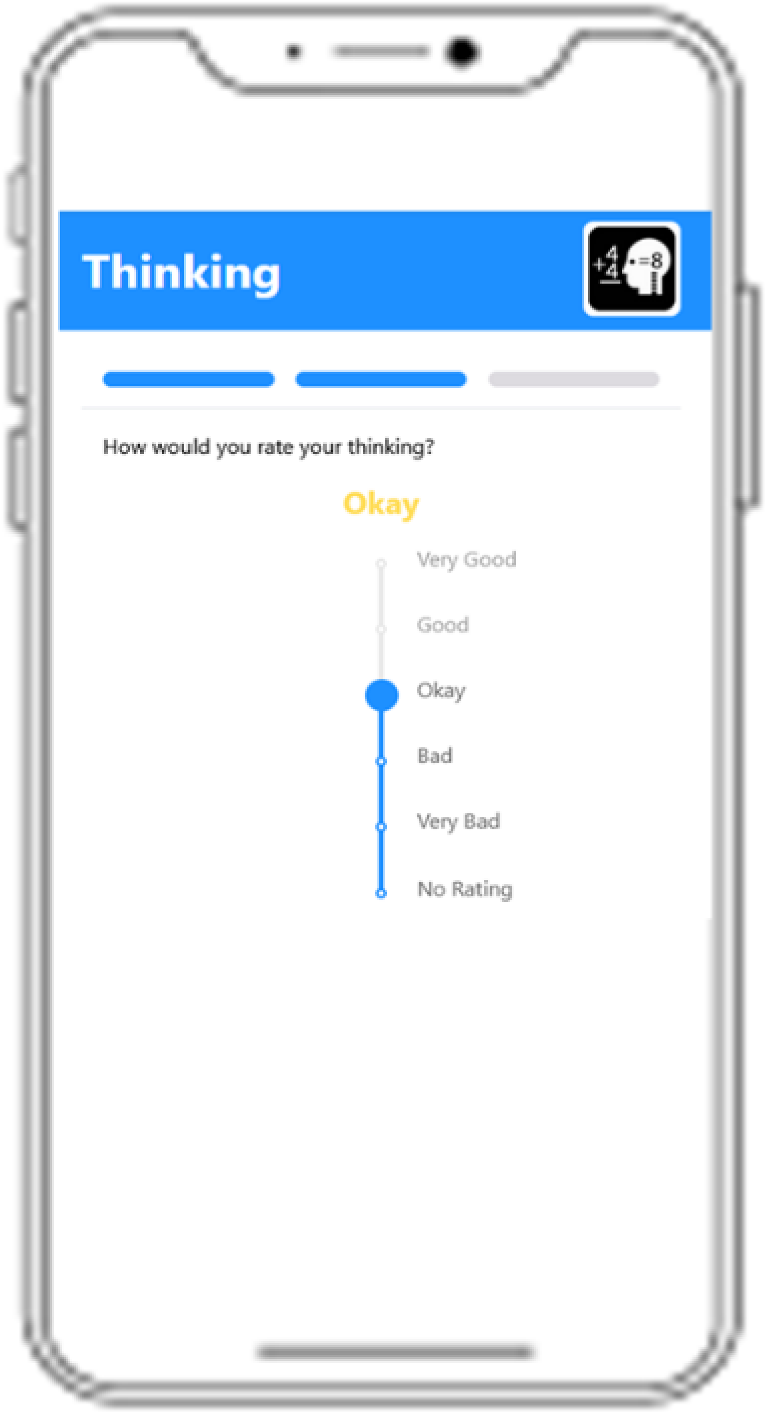
My Strengths + My Health

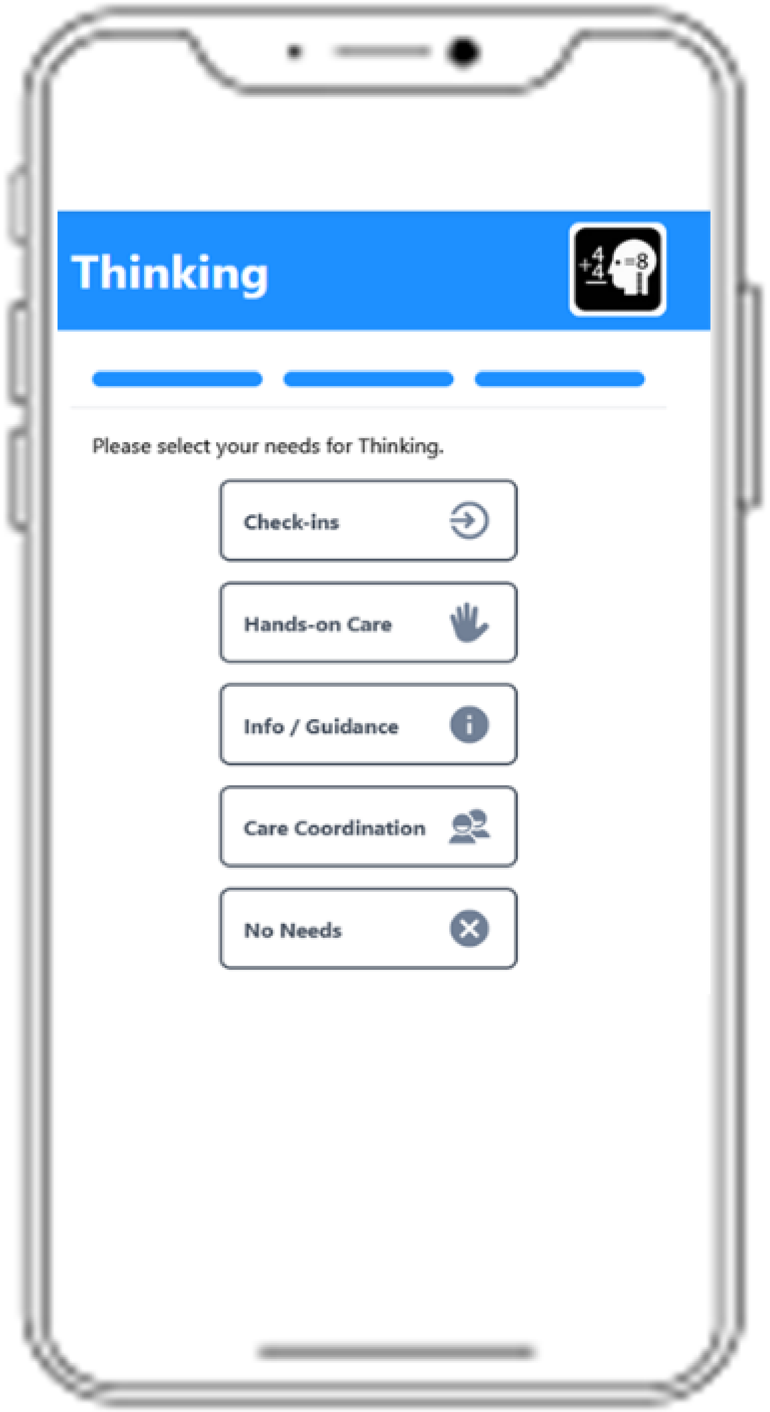
Challenges: 335 Challenges select any, all or none apply that concept

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

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







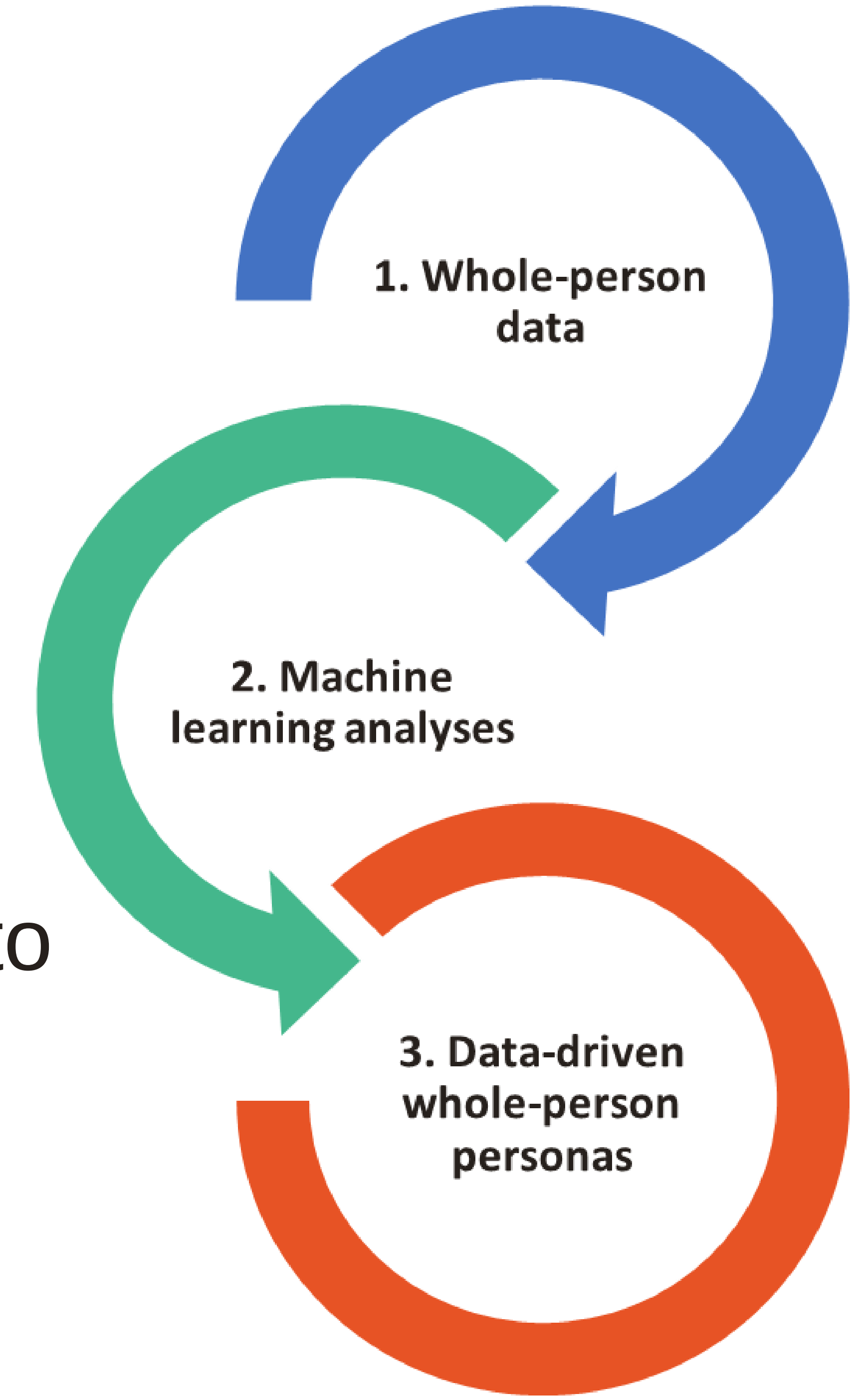
Purpose

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

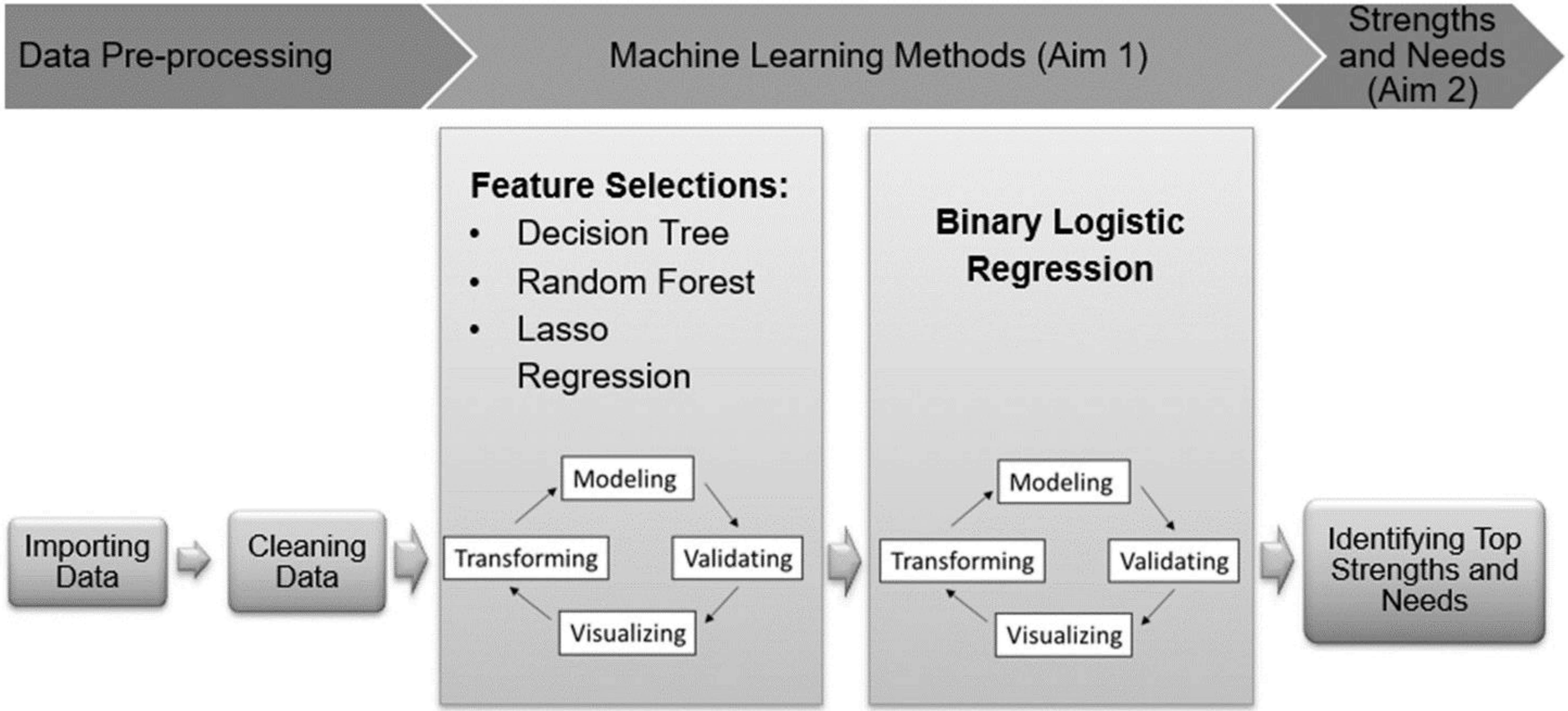
Aim 1: Using an exploratory data-driven approach to generate insights into what aspects of whole person health are related to healthy aging.

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):

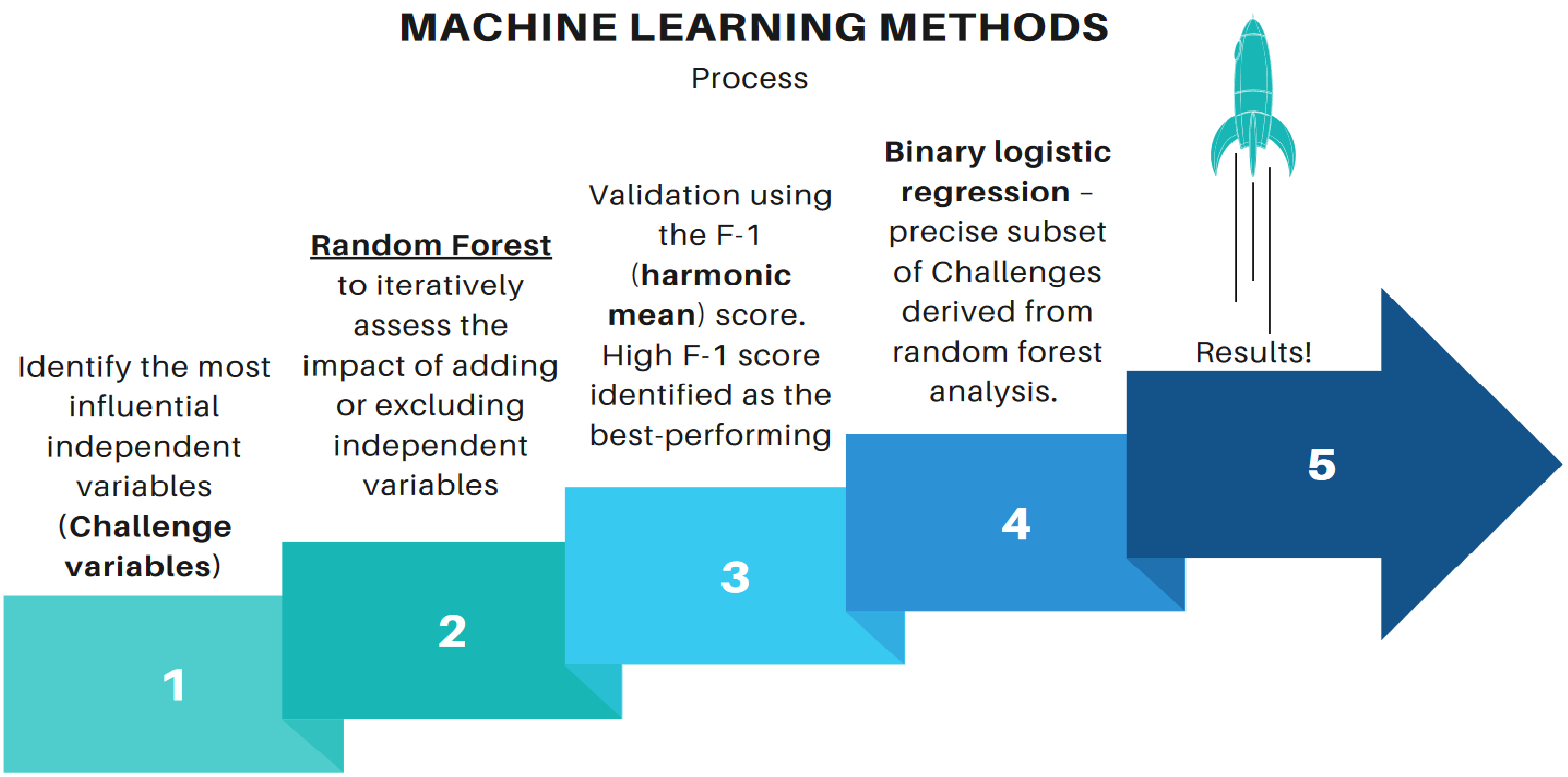
- Principal Component Analysis (PCA)
- Multiple Correspondence Analysis (MCA)
- Decision Tree Analysis
- Entire data and subsets of the data (e.g. Challenges only or Strengths only).

To reduce the dimensionality of the data:

<u>**Challenges**</u> & <u>**Four MSMH challenges**</u>

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)



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)

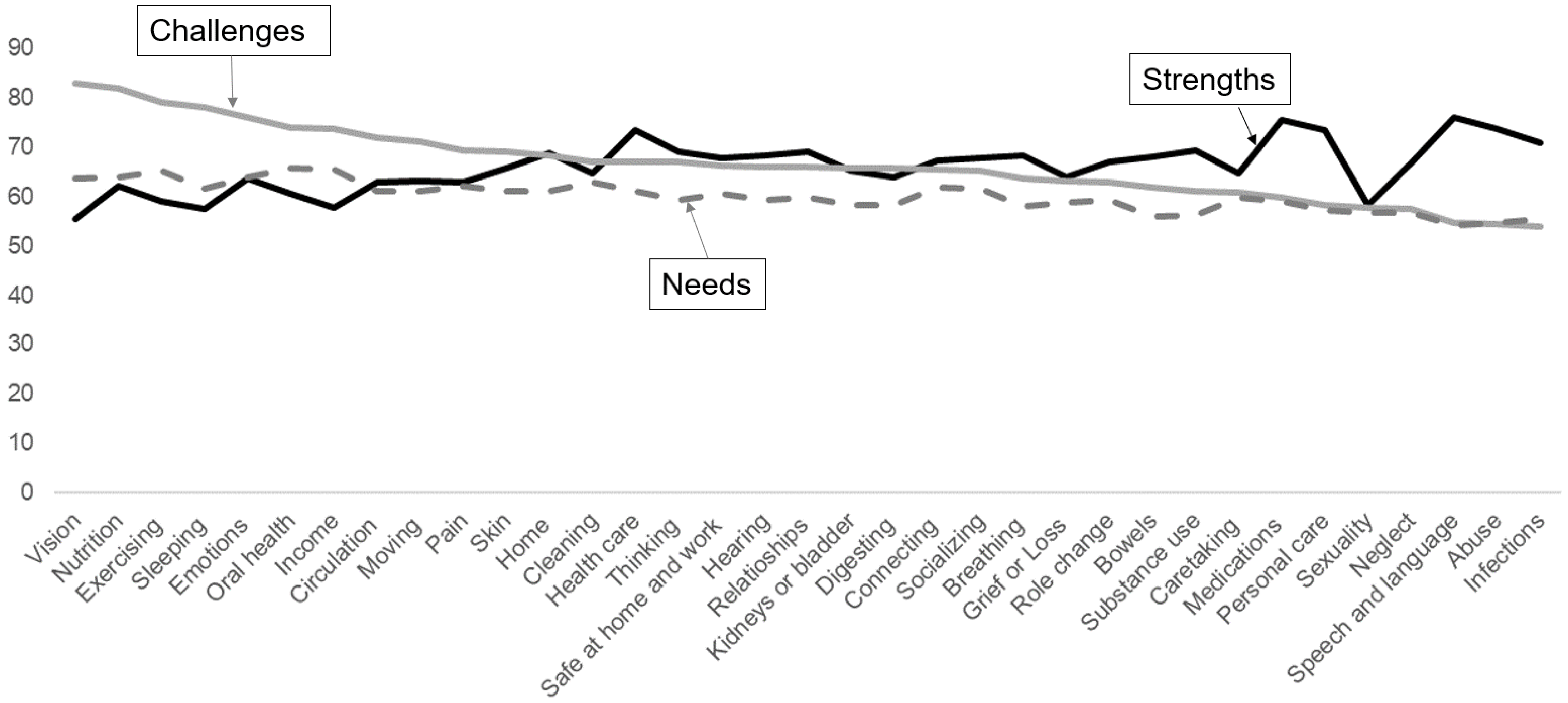
Significant difference:

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

Aim 2: Examine differences Strengths and Needs by Group

Thinking Concept Group (n=633)

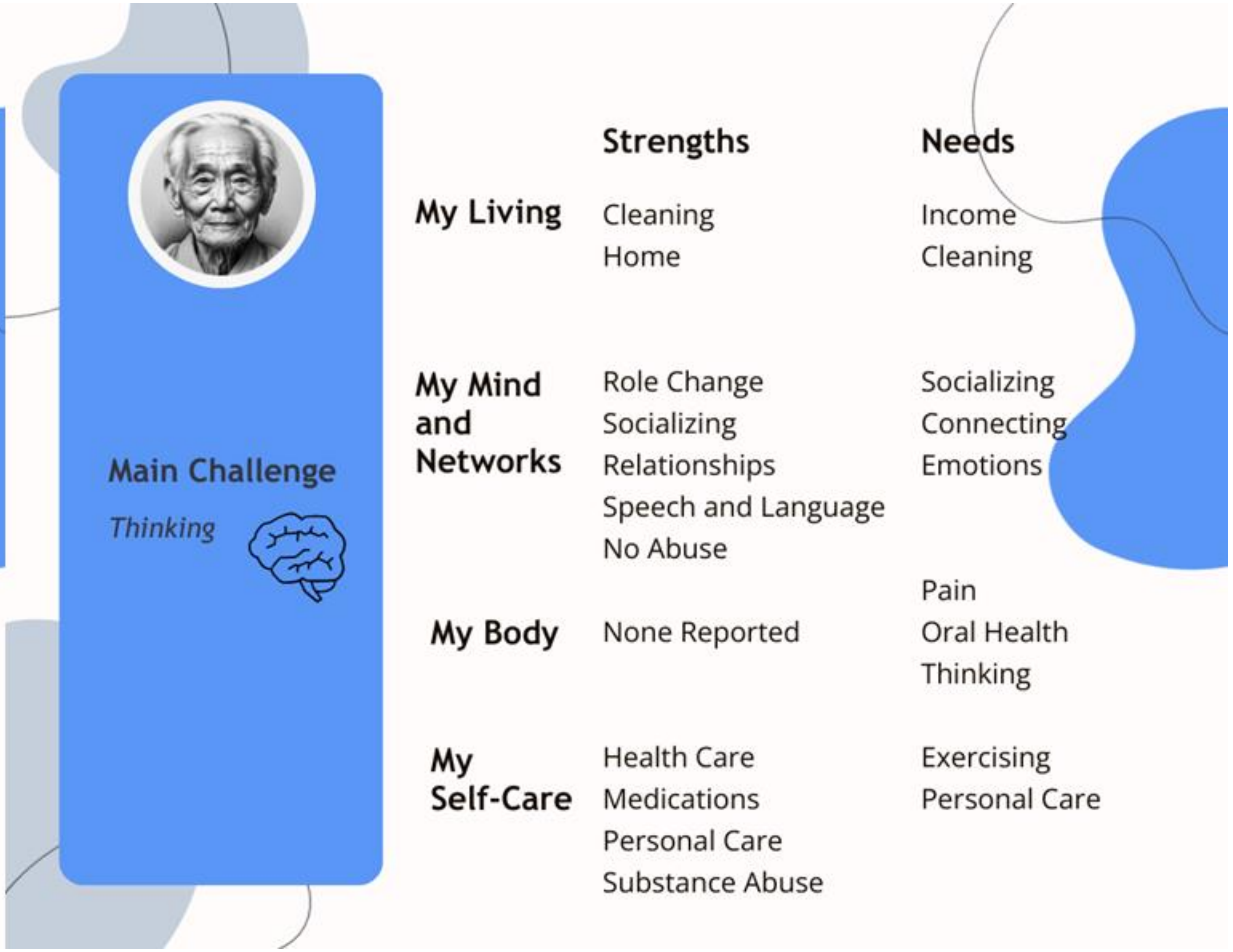
Strengths (Top 10)

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	Relatioships	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



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	*Pain*	heart is racing and breathing is fast because of pain	0.013	27.7
My Body	*Pain*	hard to keep my face from showing I have pain	0.017	24.8
My Body	*Circulation*	swelling	0	9.2
My Body	*Pain*	hard to move because of pain	0.012	6
My Body	*Pain*	restless because of pain	0.021	5.6
My Body	*Breathing*	stuffed up nose or sinuses	0.004	3.6
My Self-care	*Exercising*	do not like my exercise plan	0.004	2.6
My Body	*Pain*	having pain	0.013	2.4
My Body	*Vision*	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	Relatioships	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

Conclusions/Next Steps

1 Applying Methods

Connect ML methods with patient-generated data using nursing terminology

2 Strengths!

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

3 Thinking Group

Highest Strengths, Challenges, and Needs compared to other groups

4 Unique Insights

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

5 Nursing Terminologies

Powerful clinical insights with caveats

6 Next Steps

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

Our Team

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Thank you!

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My Strengths ⊕ My Health

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Artificial Intelligence and Technology Collaboratory for Healthy Aging

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Q&A

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Presentation (slides not available)

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Q&A

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Microsoft

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]

14M providers will suffer from a projected shortage of workers worldwide by 2030 [2]

150B projected savings for healthcare providers by 2026 with AI helping to prevent medication dosing errors [3]

$1.8T global pharmaceutical market estimated to reach by 2024 [4]

81% patients unsatisfied with their current healthcare experience [5]

41% providers say data and analytics challenges are preventing them from succeeding in value-based care models [6]

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

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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

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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

- Generative AI and Clinical Coding - by Hadas Bitran
- Introducing healthcare agent service in Microsoft Copilot Studio - Microsoft Industry Blogs

Microsoft

FRIENDS OF THE
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OF MEDICINE

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

BLUEPRINT FOR AN AI BILL OF RIGHTS

MAKING AUTOMATED SYSTEMS WORK FOR THE AMERICAN PEOPLE

OSTP

Office of Science and Technology Policy

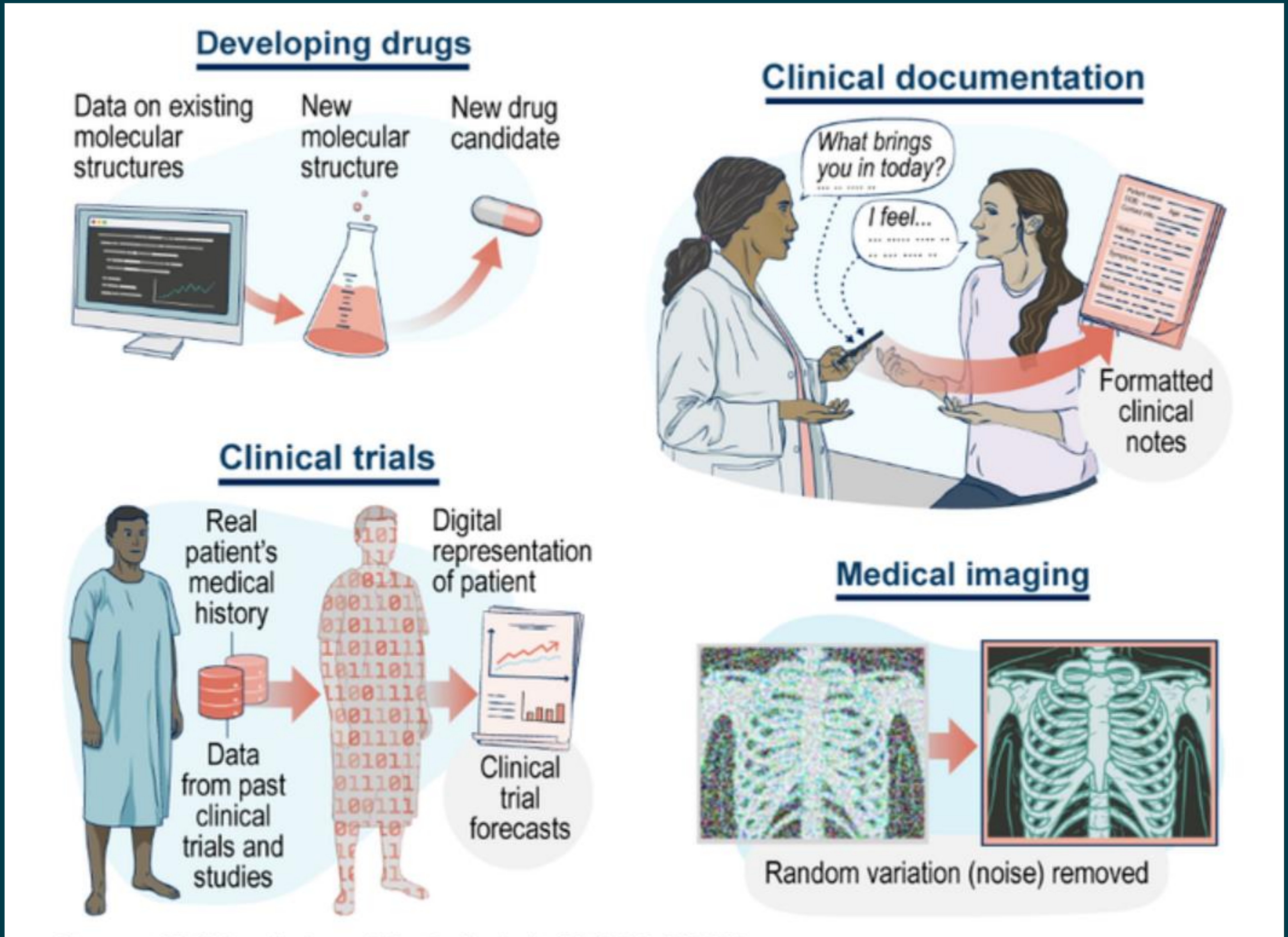
Safe and Effective Systems

Algorithmic Discrimination Protections

Data Privacy

Notice and Explanation

Human Alternatives, Consideration, and Fallback



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

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

U.S. Government Accountability Office

Science & Tech Spotlight:

Generative AI in Health Care

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

https://www.gao.gov/products/gao-24-107634

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

- 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.

NATIONAL ARCHIVES

FEDERAL REGISTER

The Daily Journal of the United States Government

Artificial Intelligence in Healthcare Safety

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

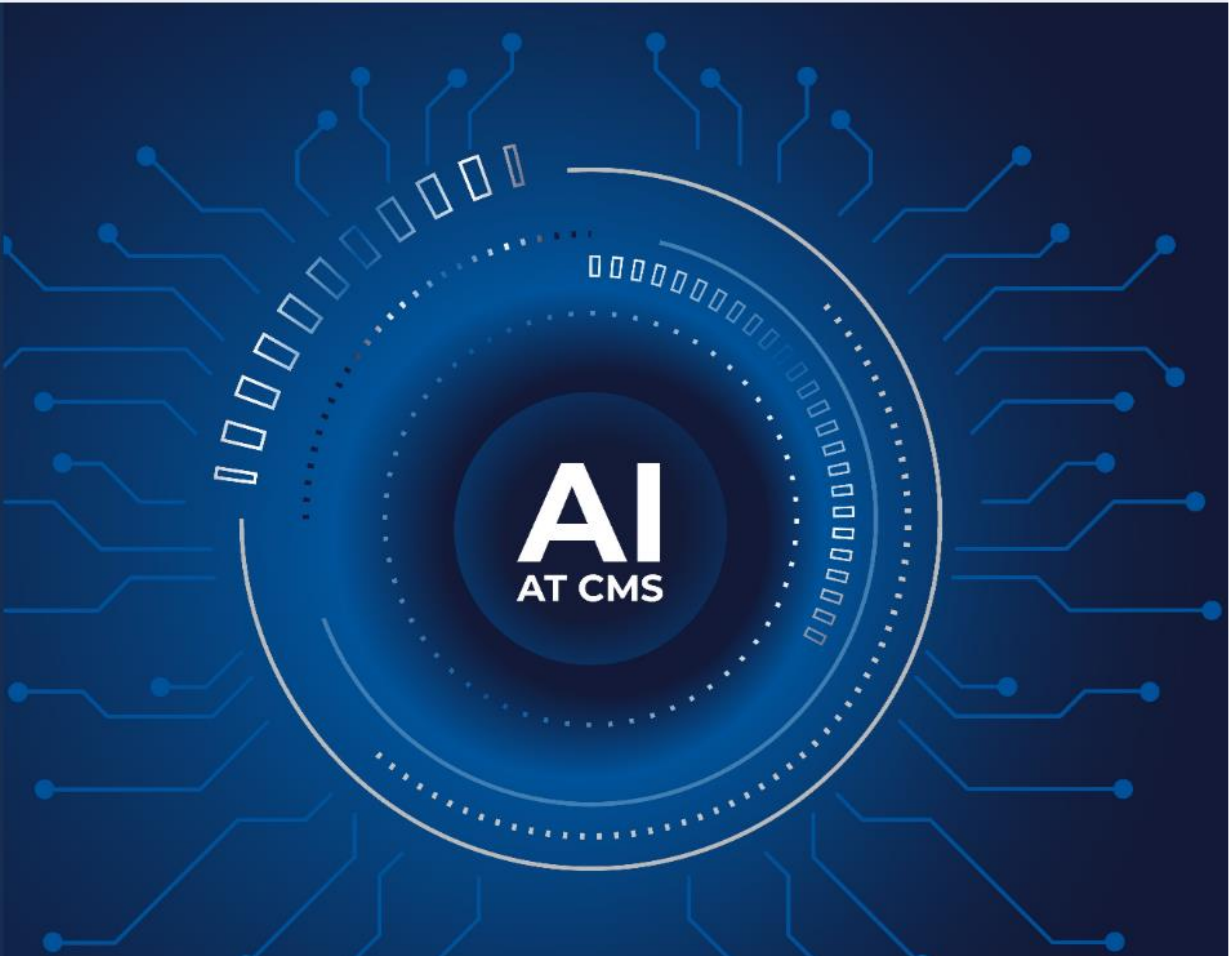
AI Safety Program in Partnership with Patient Safety Organizations

AHRQ Agency for Healthcare Research and Quality

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

ASTP | ONC

CMS.gov
CMS Nurse Burden Reduction

CDC 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%

McKinsey report Oct. 2024

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

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

NEWS

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

LISTEN

a 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

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

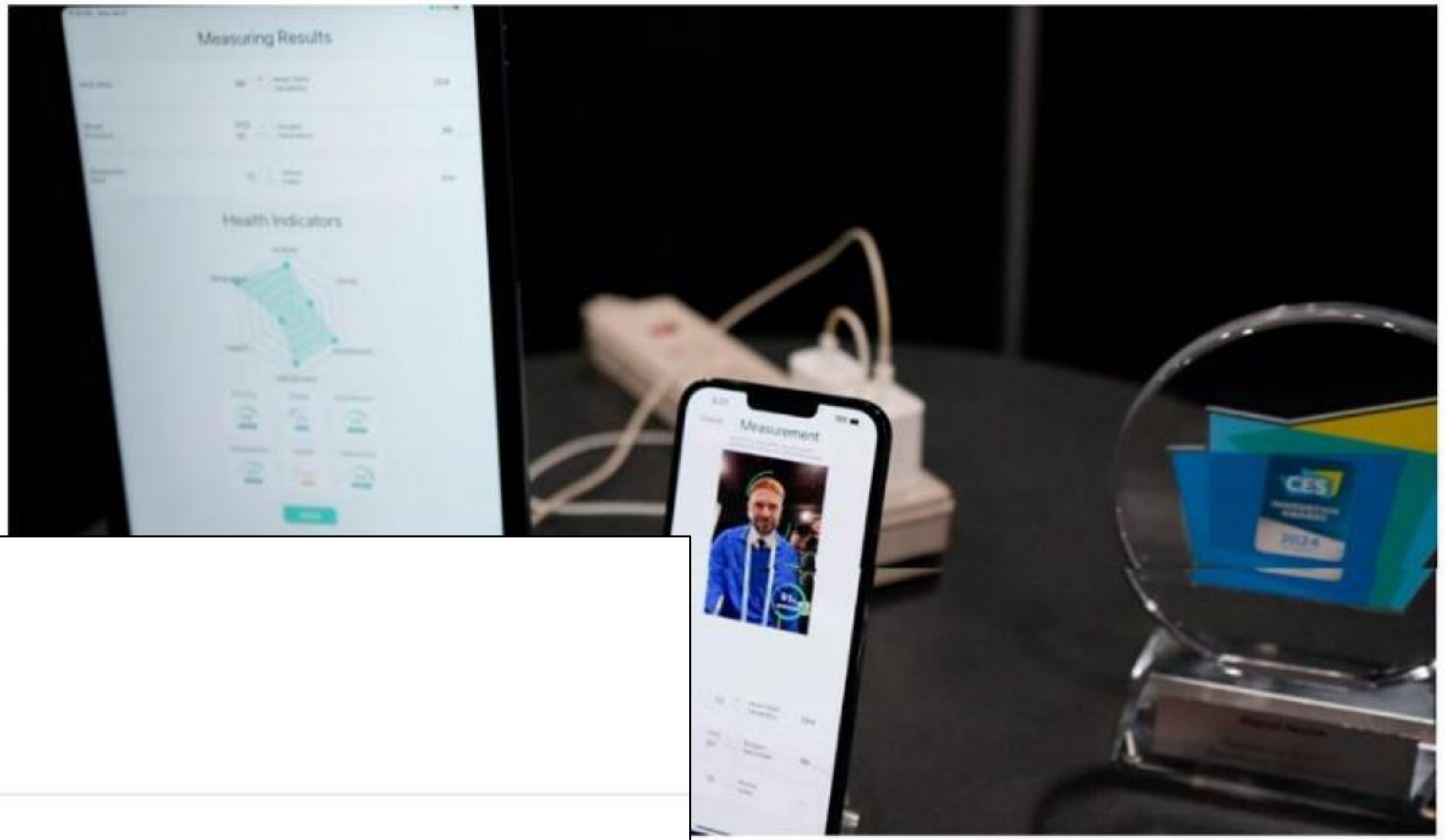
NEW JERSEY MONITOR

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
n Sun)

ked 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
ze and track the patients’ health.

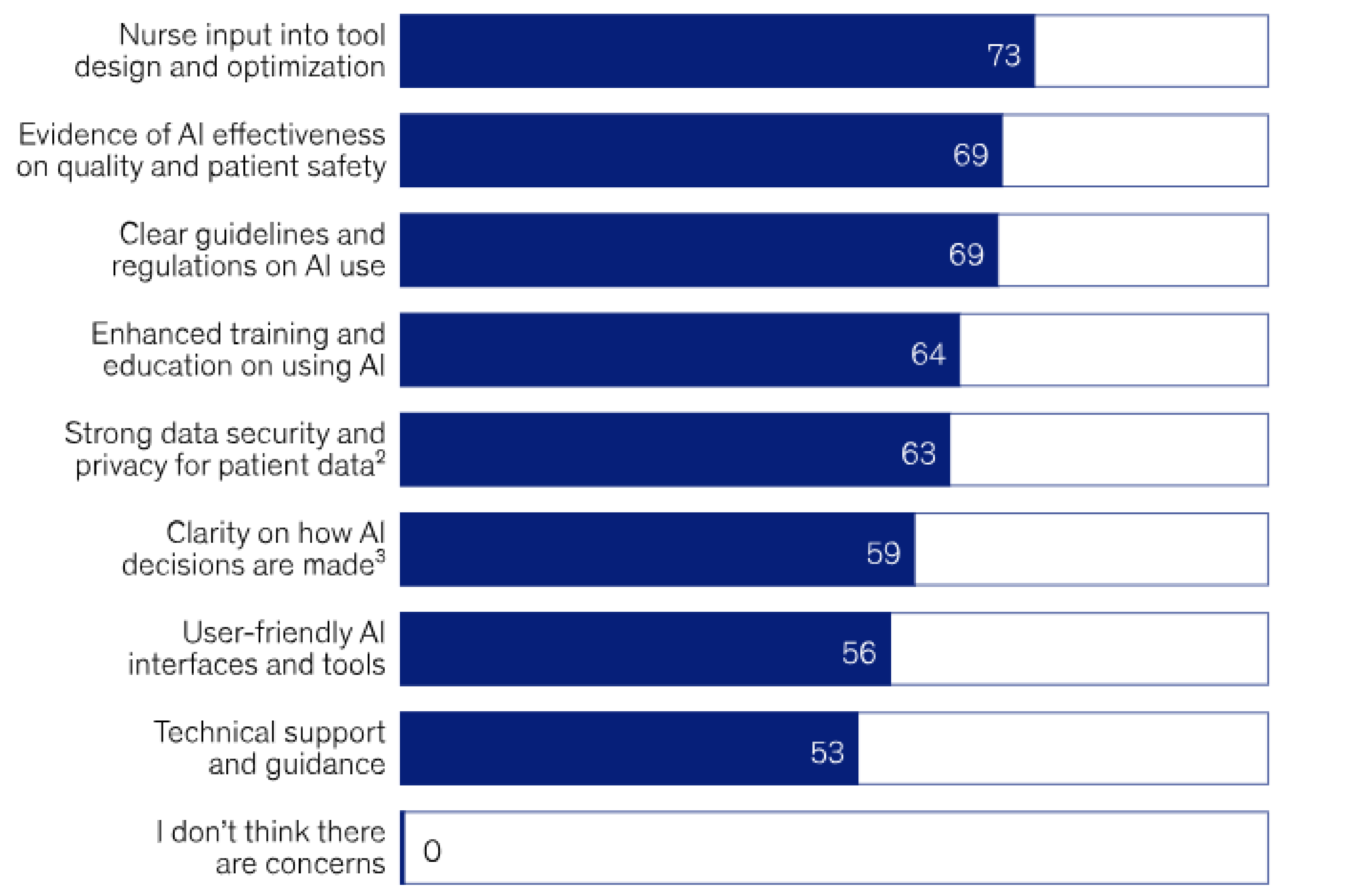
settings for years, even before the public became familiar with the technology, said Schmidt, CEO of the New Jersey State Nurses Association, a professional organization.

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

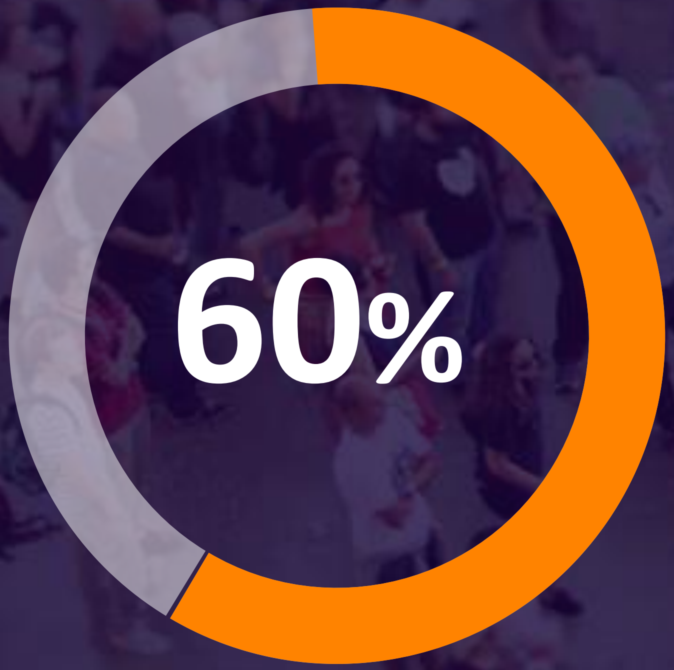
US Nurses on the Best Methods to Manage AI Concerns



[1]Question: What do you think is needed most to alleviate concerns about using AI technology in healthcare? (Select all that apply.)
[2]Eg, minimal risks of data leaks or hacks.
[3]Eg, algorithmic transparency.
Source: American Nurses Foundation Nurses Survey, Mar 2024

McKinsey & Company

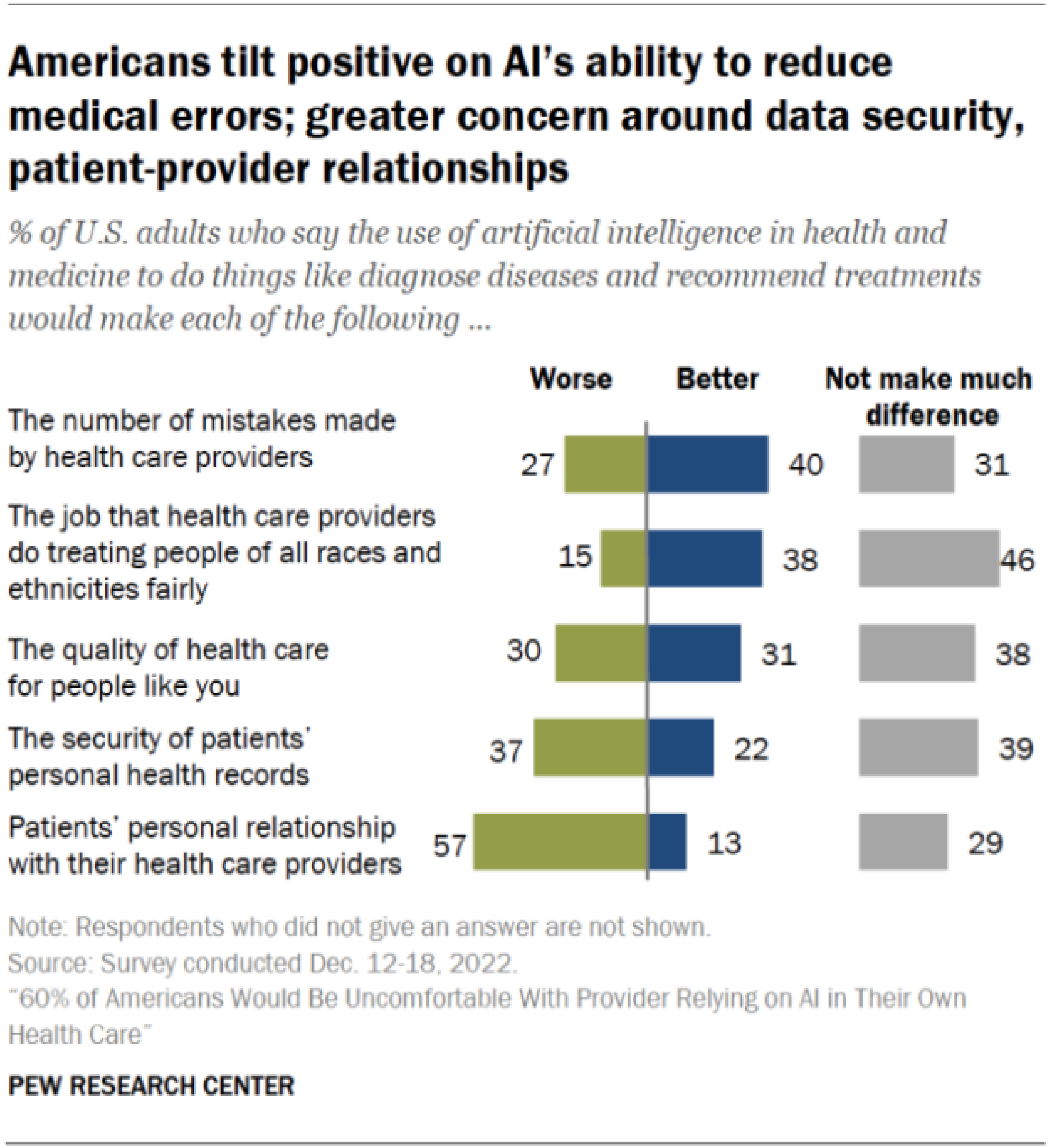
Patient Perspectives



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

But.....

They recognize the potential in reducing medical errors



Pew Research Center, 2022 Survey

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

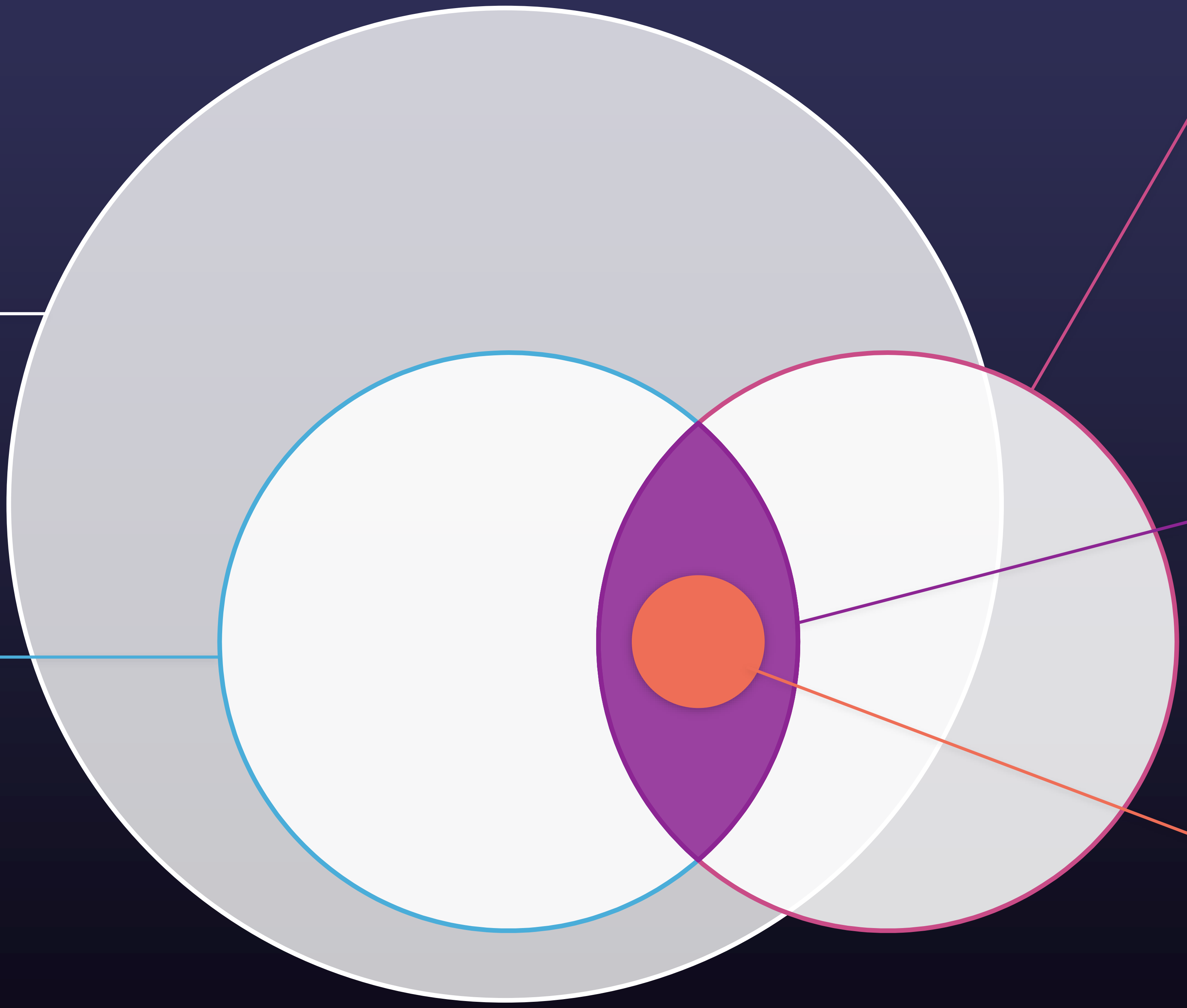
Overarching term for teaching computers to think and act in a ***human-like*** way

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

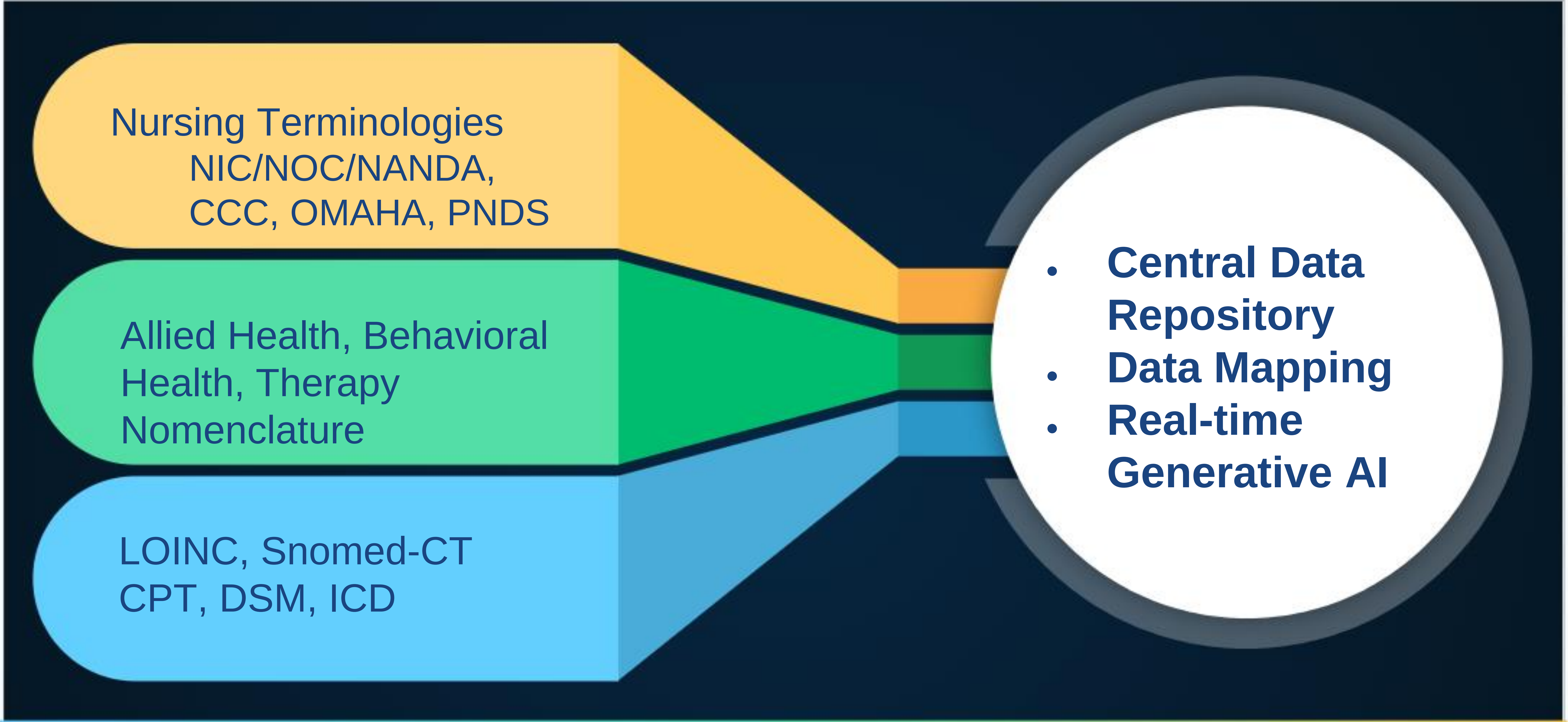
Generative AI

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



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

Projected to grow to 36% by 2025

Data Normalization

+

Structured and Unstructured Data

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

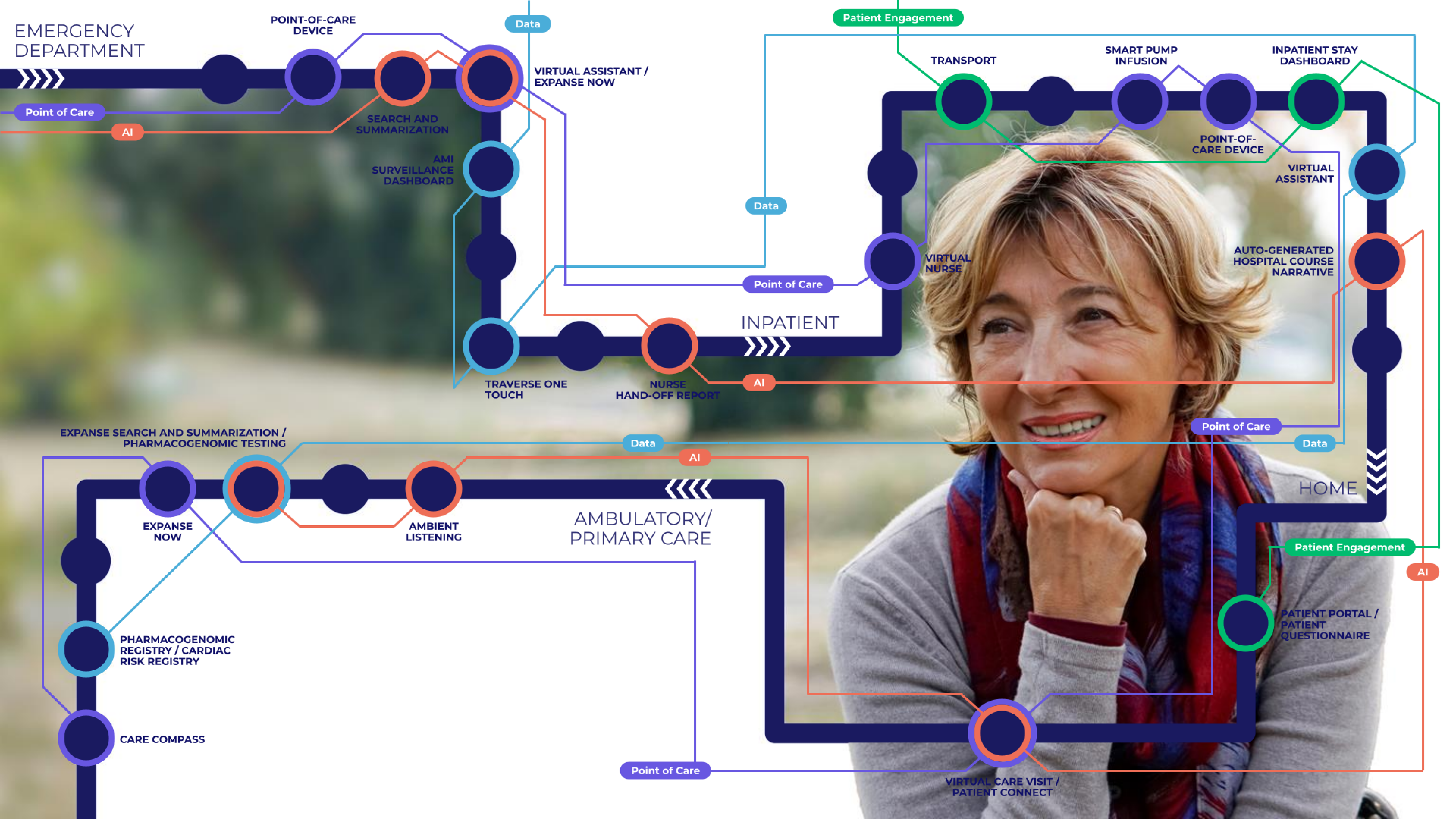
- Handling Ambiguity
- Context in Language
- Dialects and Speech Patterns
- Colloquialisms

Safe & Effective

- Achieves stated Purpose
- Measurable and Positive Impact on Outcomes

Privacy-Protective & Secure

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



EMERGENCY DEPARTMENT
POINT-OF-CARE DEVICE
Data
VIRTUAL ASSISTANT / EXPANSE NOW
Point of Care
AI
SEARCH AND SUMMARIZATION
AMI SURVEILLANCE DASHBOARD
TRAVERSE ONE TOUCH
NURSE HAND-OFF REPORT
INPATIENT
Patient Engagement
TRANSPORT
SMART PUMP INFUSION
INPATIENT STAY DASHBOARD
POINT-OF-CARE DEVICE
VIRTUAL ASSISTANT
Data
VIRTUAL NURSE
Point of Care
AUTO-GENERATED HOSPITAL COURSE NARRATIVE
AI
Point of Care
Data
HOME
EXPANSE SEARCH AND SUMMARIZATION / PHARMACOGENOMIC TESTING
Data
AI
EXPANSE NOW
AMBIENT LISTENING
AMBULATORY/ PRIMARY CARE
Patient Engagement
AI
PATIENT PORTAL / PATIENT QUESTIONNAIRE
PHARMACOGENOMIC REGISTRY / CARDIAC RISK REGISTRY
CARE COMPASS
Point of Care
VIRTUAL CARE VISIT / PATIENT CONNECT

TYPE	NURSING BENEFIT	MEDITECH
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

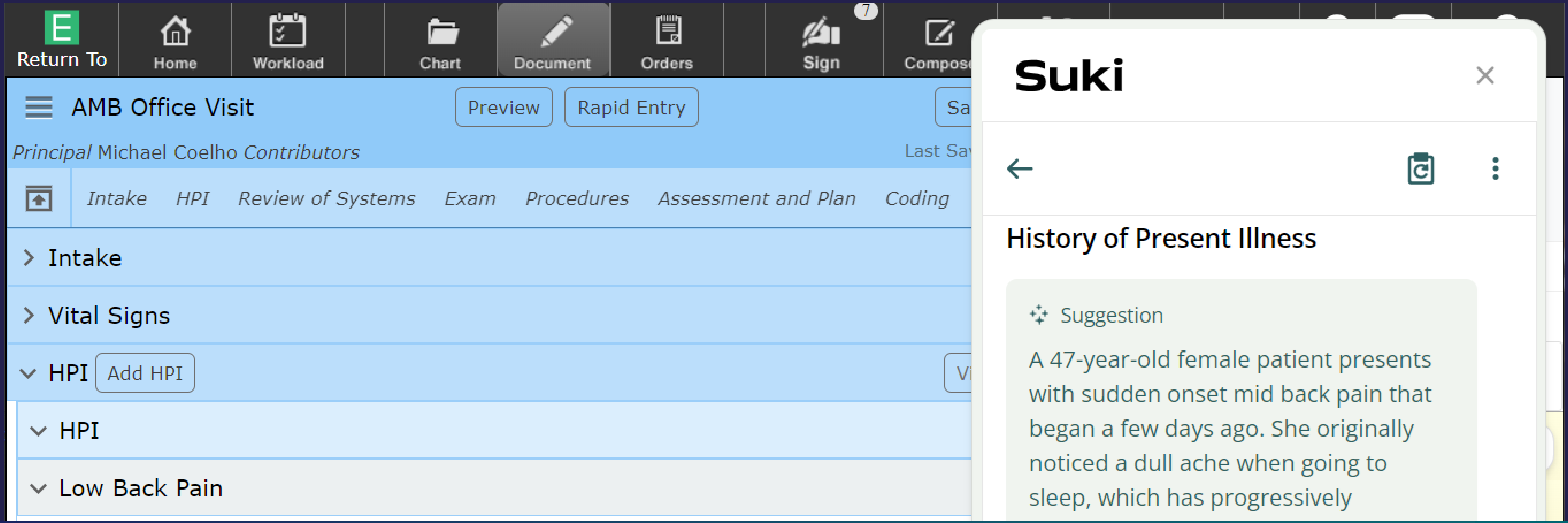
Transitions of care are highly vulnerable points in the care process for patients. Care transitions should be facilitated through comprehensive and concise communication of pertinent information necessary to maintain a high-quality of care and treatment for patients.

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



Access 3rd party ambient solution via mobile or desktop application

Record the conversation between the patient and provider

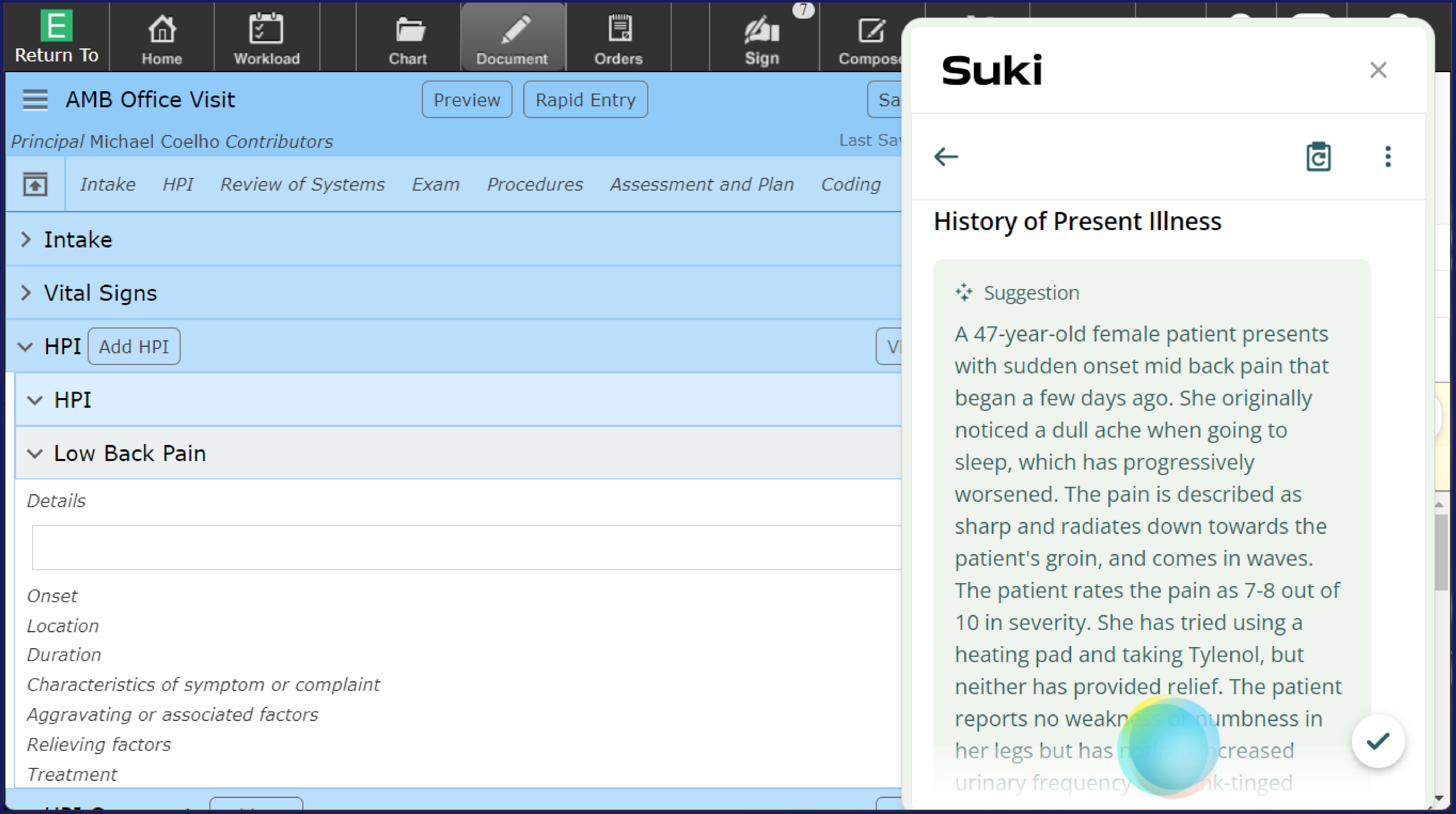
View AI generated provider note in the app

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

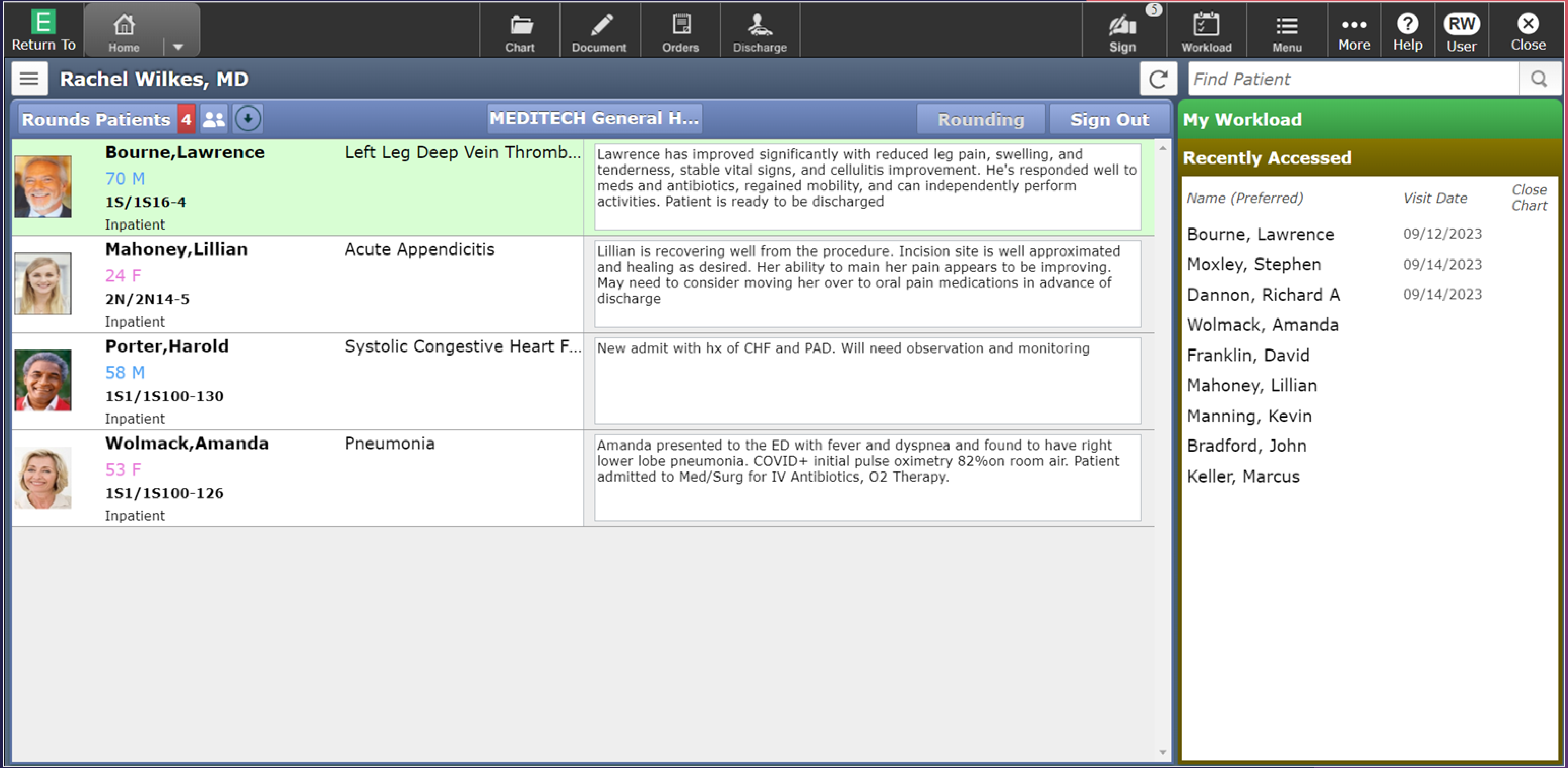
Narrative summary or population of discrete flowsheet data

Ambient Listening Experience

Demo



Hospital Course/Discharge Summary



Demo

Empower with Generative AI
Auto Generating Clinical Documentation:

| Nurse's Handoff

Problem Statement

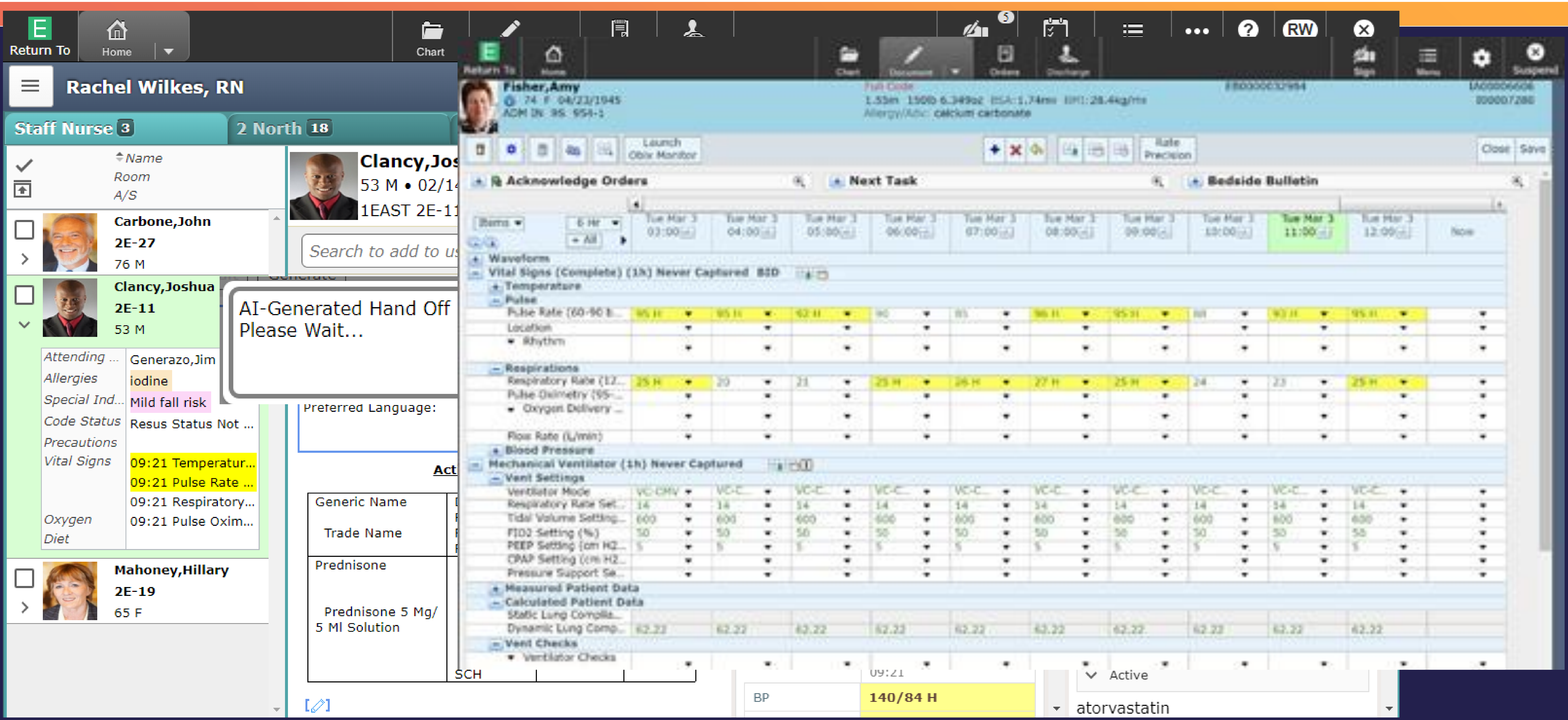
Transitions of care are highly vulnerable points in the care process for patients. Shift changes and transitions of care within the acute setting allow nursing staff to exchange necessary patient information to ensure continuity of care and patient safety.

Benefits

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

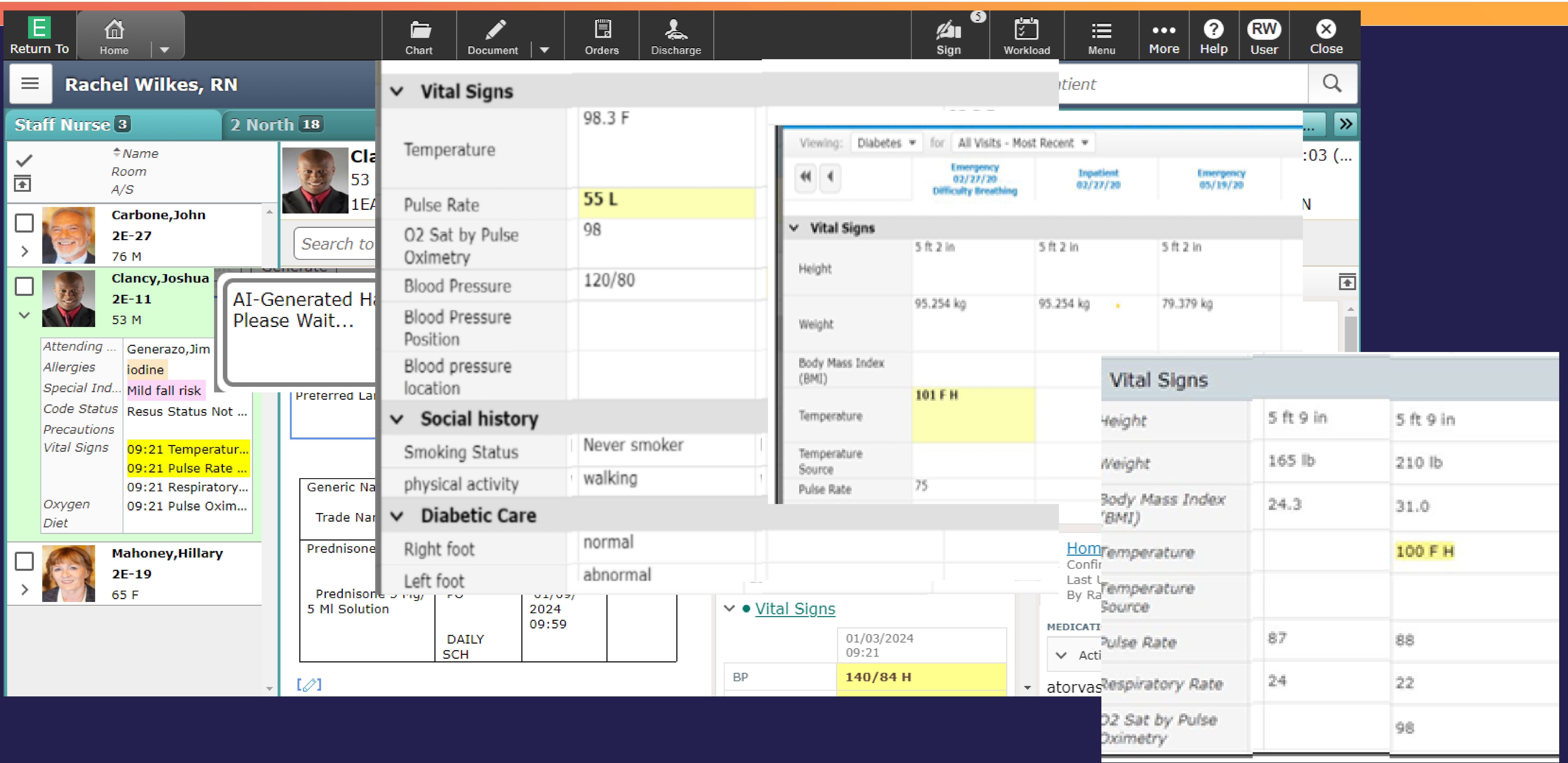
1. Time-savings
2. Enhanced note quality through more concise narratives and a reduction in errors or accidental omissions of information
3. Real-time documentation
4. Real-time transfer of information

Narrative to Flowsheet



[Demo]

Narrative to Flowsheet



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

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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
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- 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
- **Overview of Artificial Intelligence**
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- 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

Late 2022

November 30, 2022
ChatGPT released

January 19
Azure OpenAI service available

March 10
Epic integrates GPT

April
First customers live with In Basket draft replies

FIERCE Healthcare

HIMSS23: Epic taps Microsoft to integrate generative AI into EHRs

May
Epic supports GPT-4

June 15
First customer live on GPT-4

August
Announced 15+ use cases at UGM

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

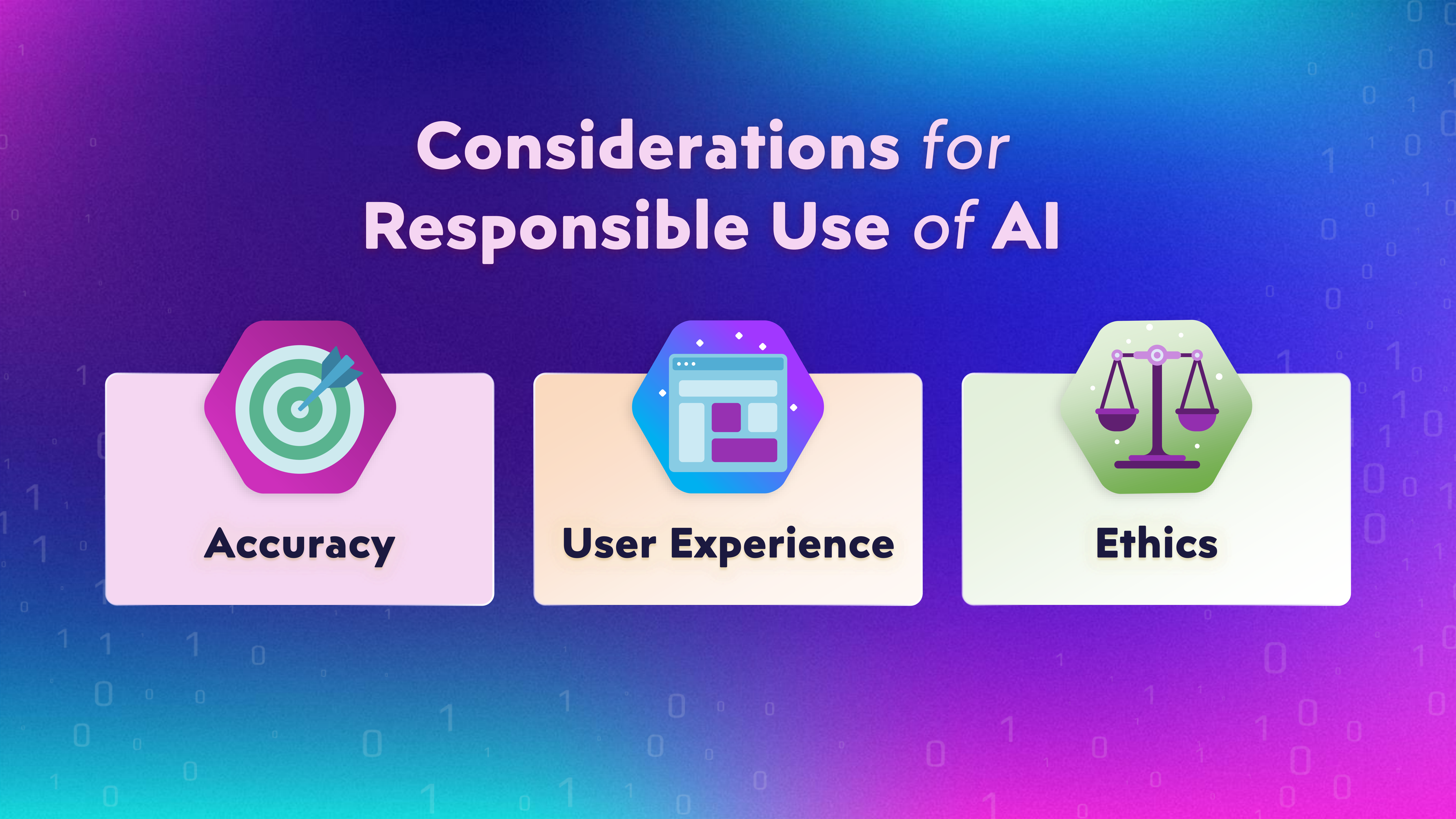
SideKick live on Cosmos

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

May
Two Dutch customers live with outpatient summarizations

Today
297 customers using generative AI!

Today


Considerations for
Responsible Use of AI
Accuracy
User Experience
Ethics

Trust-Centered AI

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

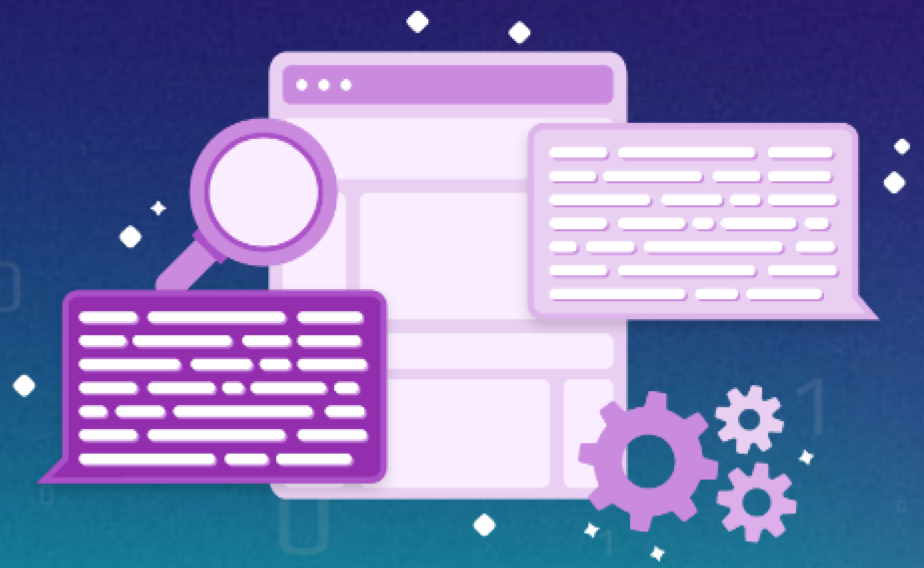
- Background on Nursing Terminology in the EHR
- Overview of Artificial Intelligence
- **Generative AI in Epic**
- Case Study
- Wrap up and What's Next

Generative AI & Epic

Draft Text

Generate Summaries

Translate Content



Task Automation

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]*

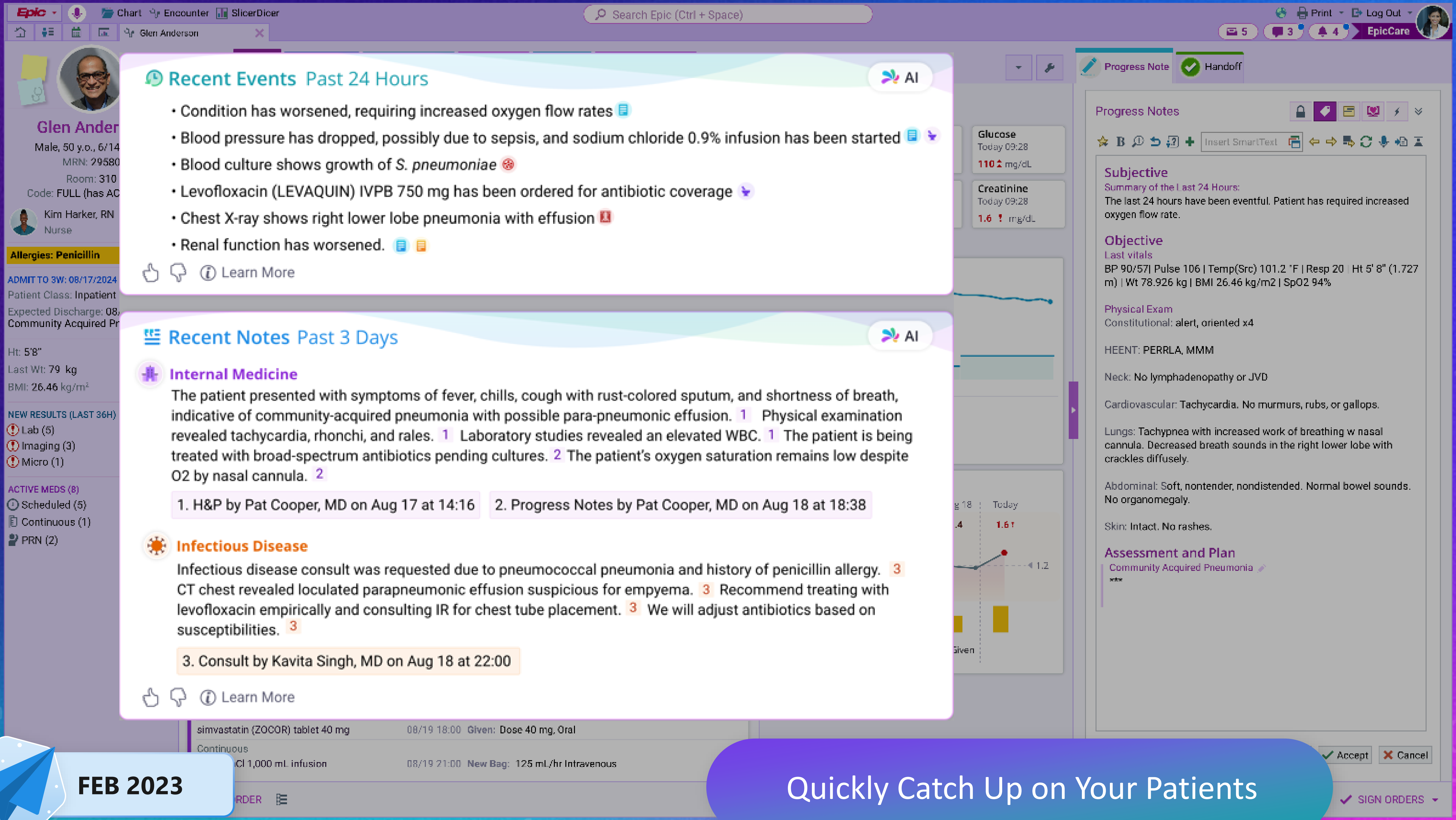
End of Shift Notes – *draft end-of-shift note based on the chart [improve communication and coordination of care, demonstrate the value of nursing]*

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

Nurses

Enhance Nursing Experience

Catch Up *in the* **Hospital**



FEB 2023

Quickly Catch Up on Your Patients

End of Shift Note Draft

Drafted Care Plan Note

AI

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.

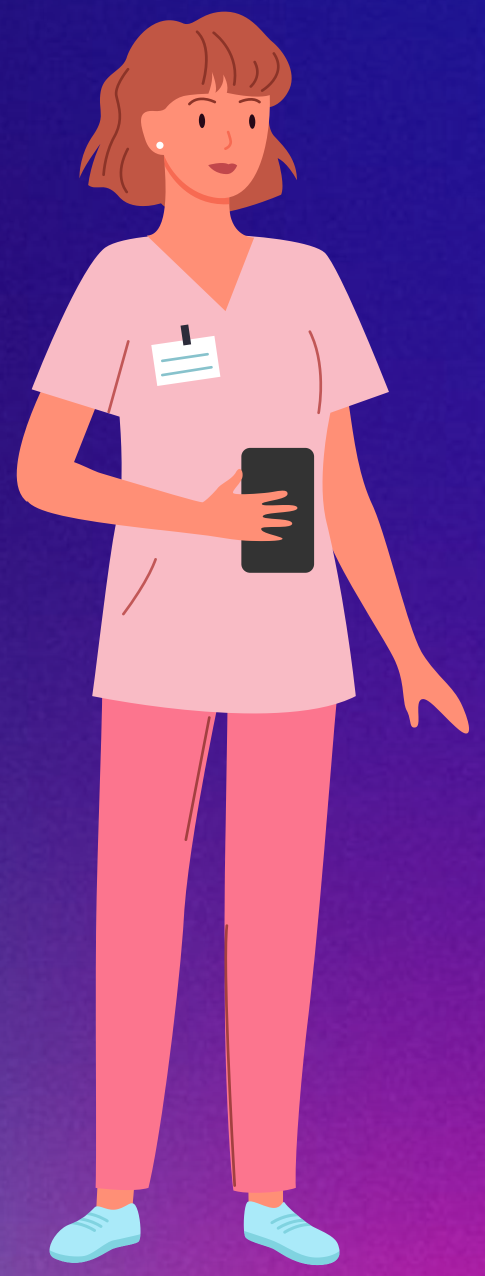
Displays adequate comfort level or baseline comfort level:
Patient's pain score decreased from 5 to 2 after morphine administration. Patient was initially restless
comfortably by the end of the shift.

Learn More

Start wit

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



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

Mercy

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

UNC HEALTH

MAY 2024

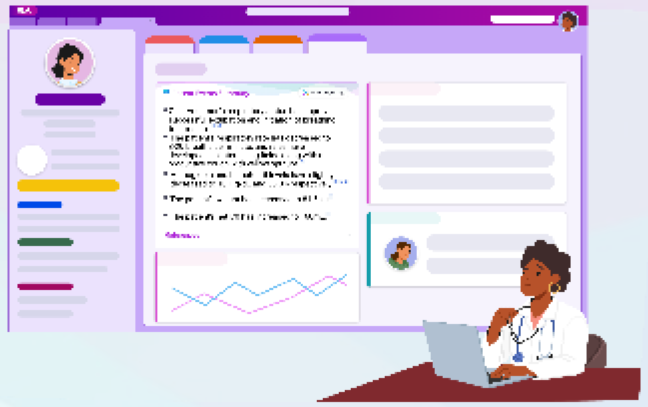
Behind the Scenes

Data Collection

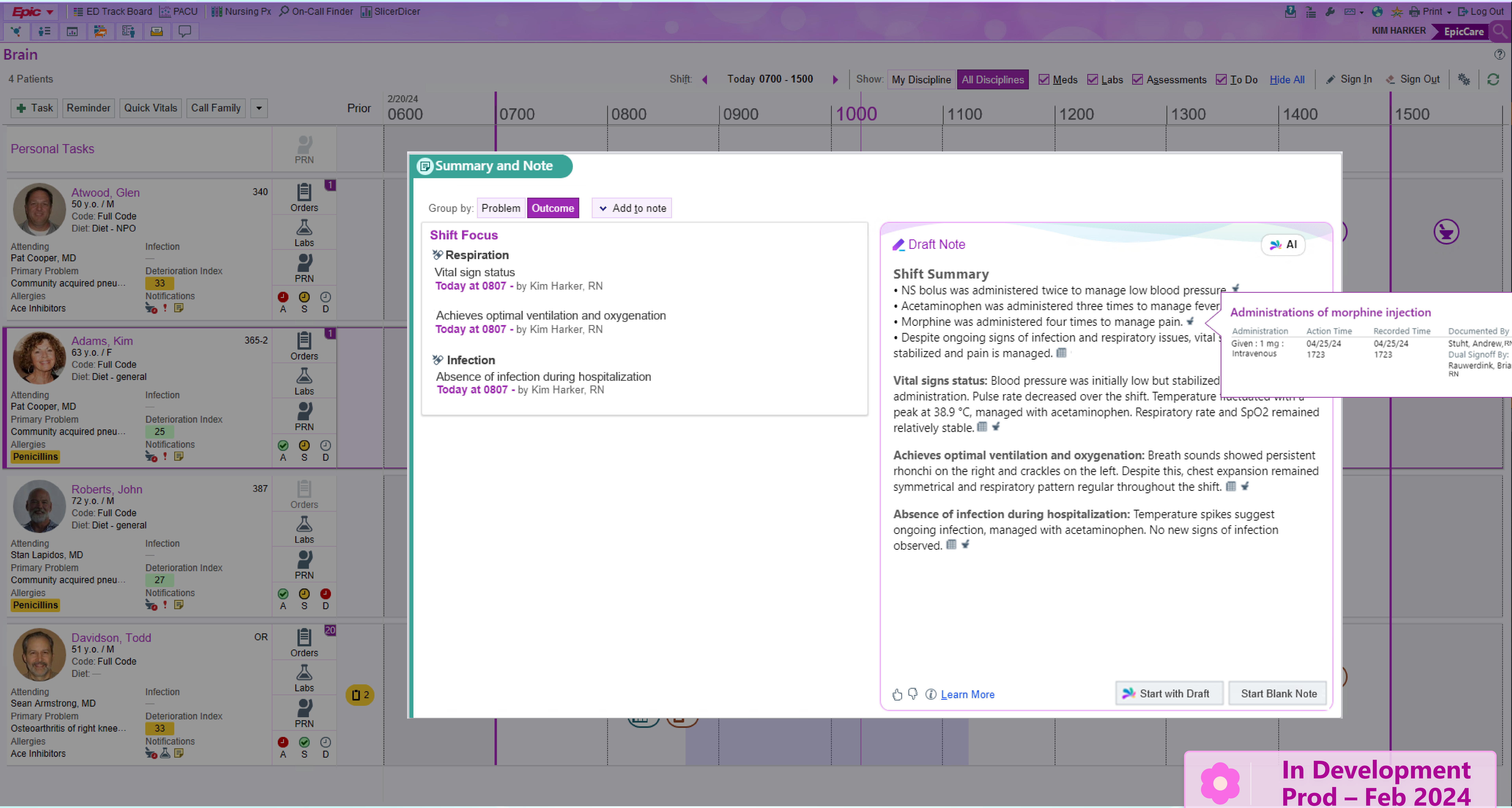
Assemble goals, flowsheets, medication information

Categorization

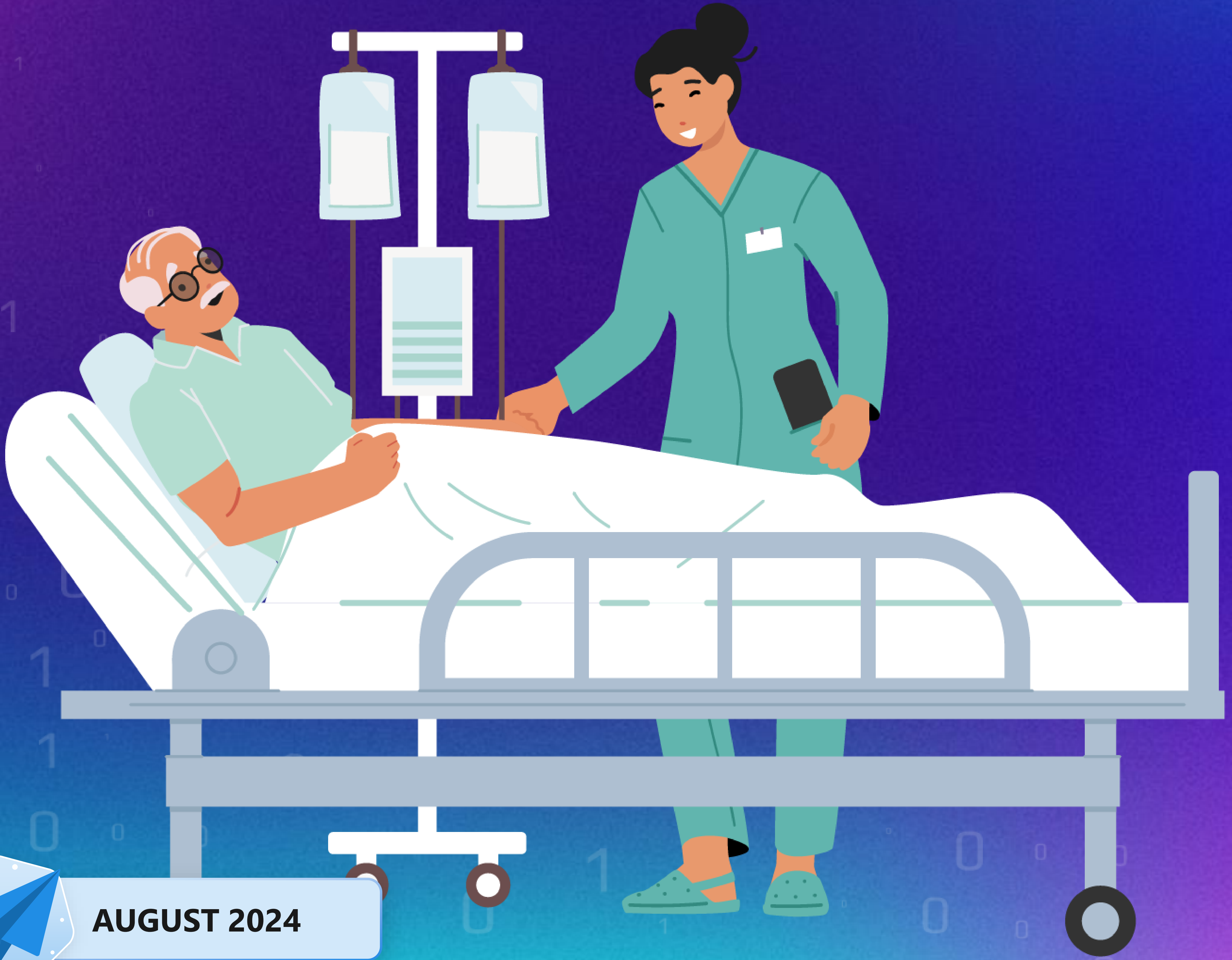
Associate goals with related flowsheets and medications

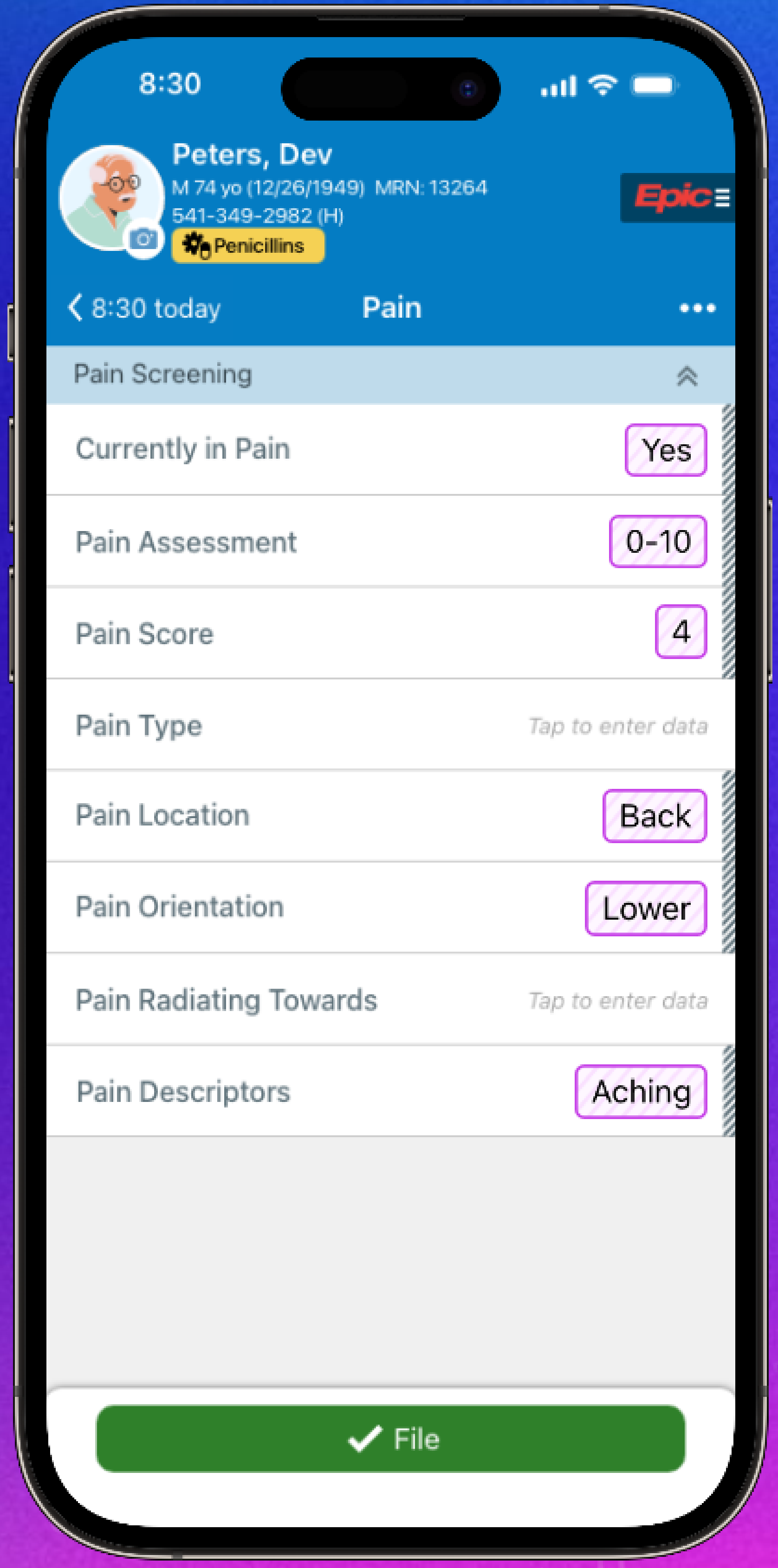


Summarize!

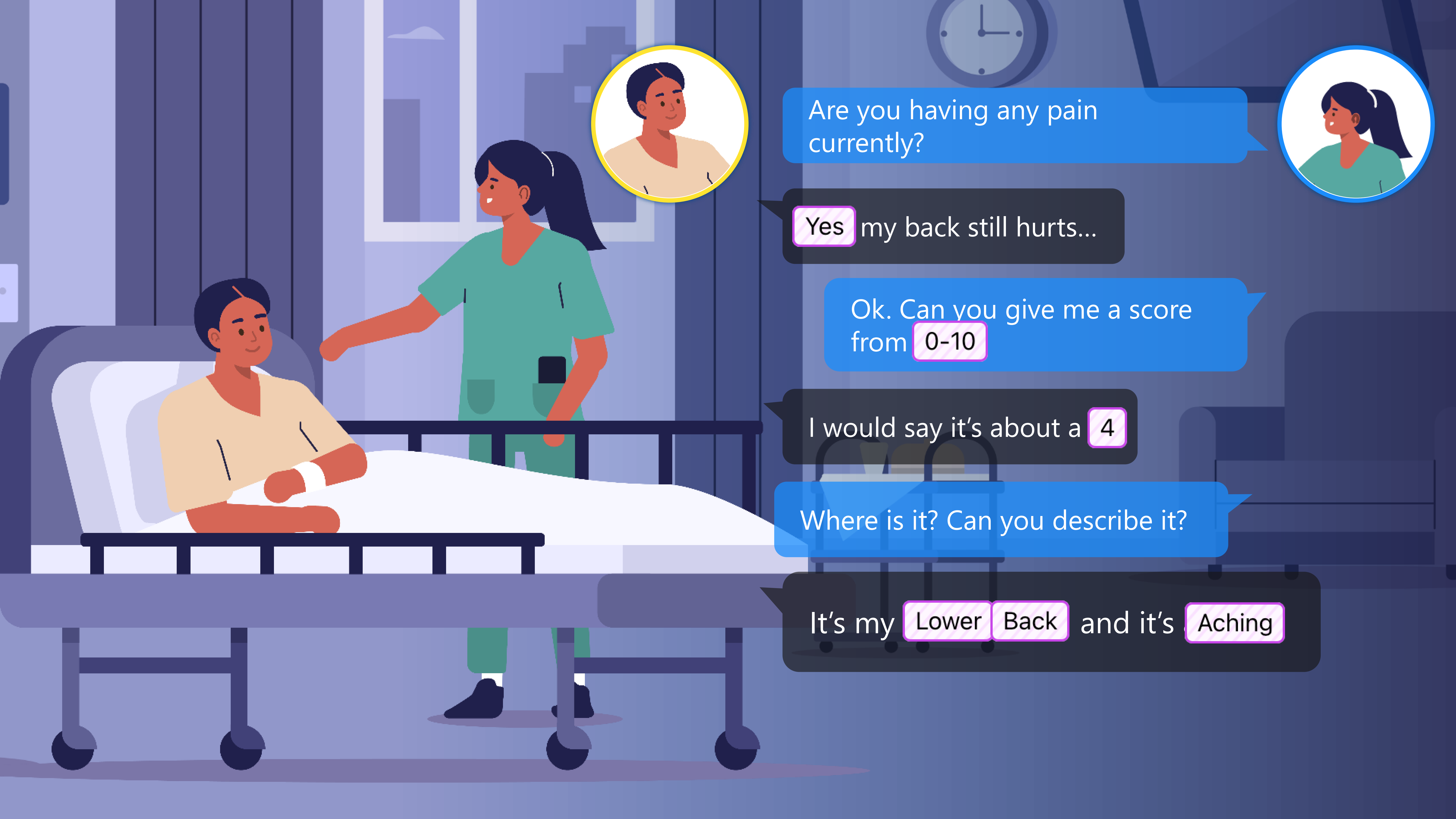

Epic
ED Track Board
PACU
Nursing Px
On-Call Finder
SlicerDicer
Print
Log Out
KIM HARKER
EpicCare
Brain
4 Patients
Shift:
Today 0700 - 1500
Show:
My Discipline
All Disciplines
Meds
Labs
Assessments
To Do
Hide All
Sign In
Sign Out
Task
Reminder
Quick Vitals
Call Family
Prior
2/20/24
0600
0700
0800
0900
1000
1100
1200
1300
1400
1500
Personal Tasks
PRN
Atwood, Glen
340
50 y.o. / M
Code: Full Code
Diet: Diet - NPO
Attending
Pat Cooper, MD
Infection
Primary Problem
Community acquired pneu...
Deterioration Index
33
Allergies
Ace Inhibitors
Notifications
Orders
Labs
PRN
A S D
Adams, Kim
365-2
63 y.o. / F
Code: Full Code
Diet: Diet - general
Attending
Pat Cooper, MD
Infection
Primary Problem
Community acquired pneu...
Deterioration Index
25
Allergies
Penicillins
Notifications
Roberts, John
387
72 y.o. / M
Code: Full Code
Diet: Diet - general
Attending
Stan Lapidos, MD
Infection
Primary Problem
Community acquired pneu...
Deterioration Index
27
Allergies
Penicillins
Notifications
Davidson, Todd
OR
51 y.o. / M
Code: Full Code
Diet: —
Attending
Sean Armstrong, MD
Infection
Primary Problem
Osteoarthritis of right knee...
Deterioration Index
33
Allergies
Ace Inhibitors
Notifications
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 s... stabilized and pain is managed.
Vital signs status: Blood pressure was initially low but stabilized ... administration. Pulse rate decreased over the shift. Temperature fluctuated with a peak 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.
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, Bria RN
Learn More
Start with Draft
Start Blank Note
In Development
Prod – Feb 2024

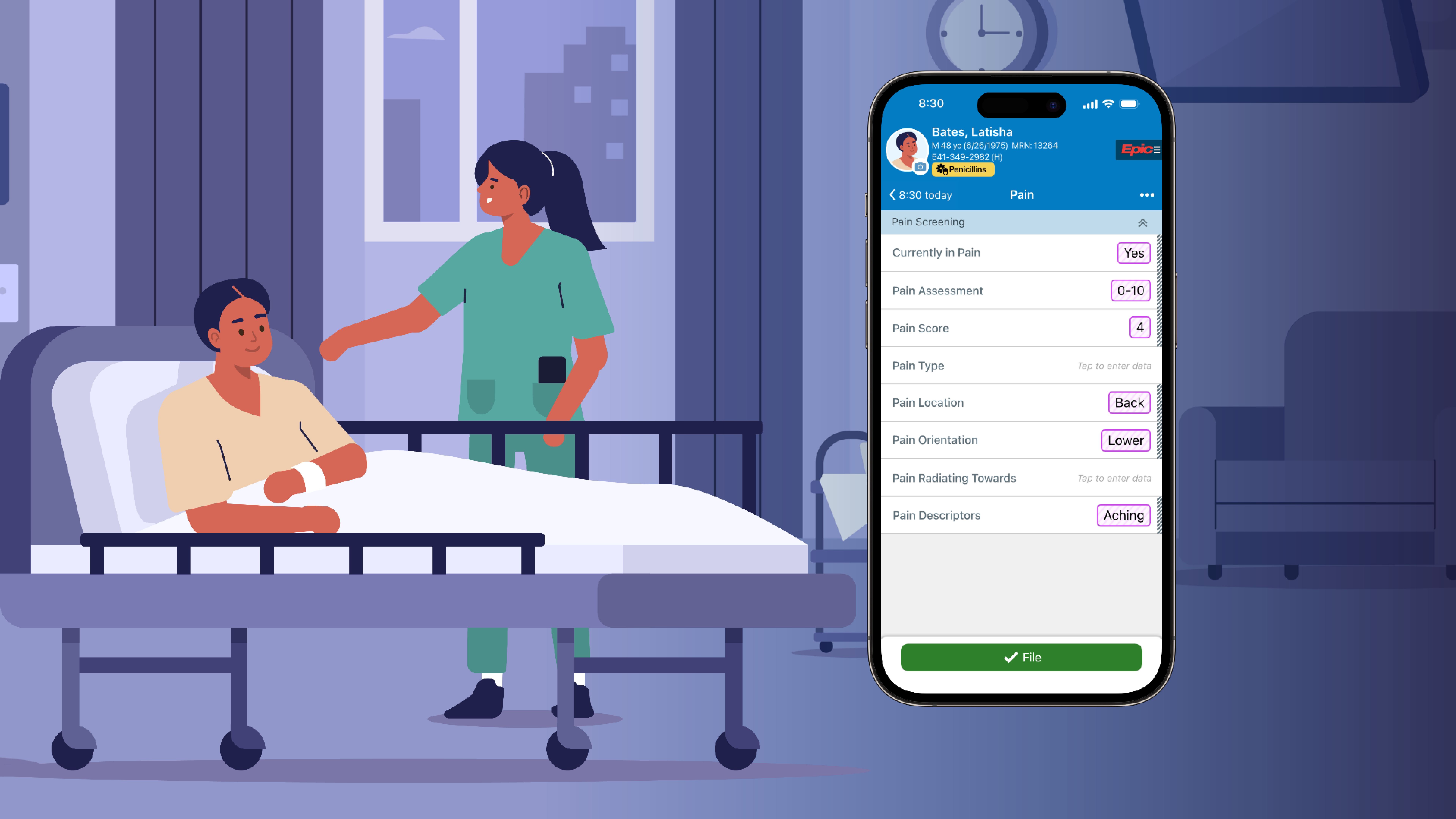
Ambient Flowsheets



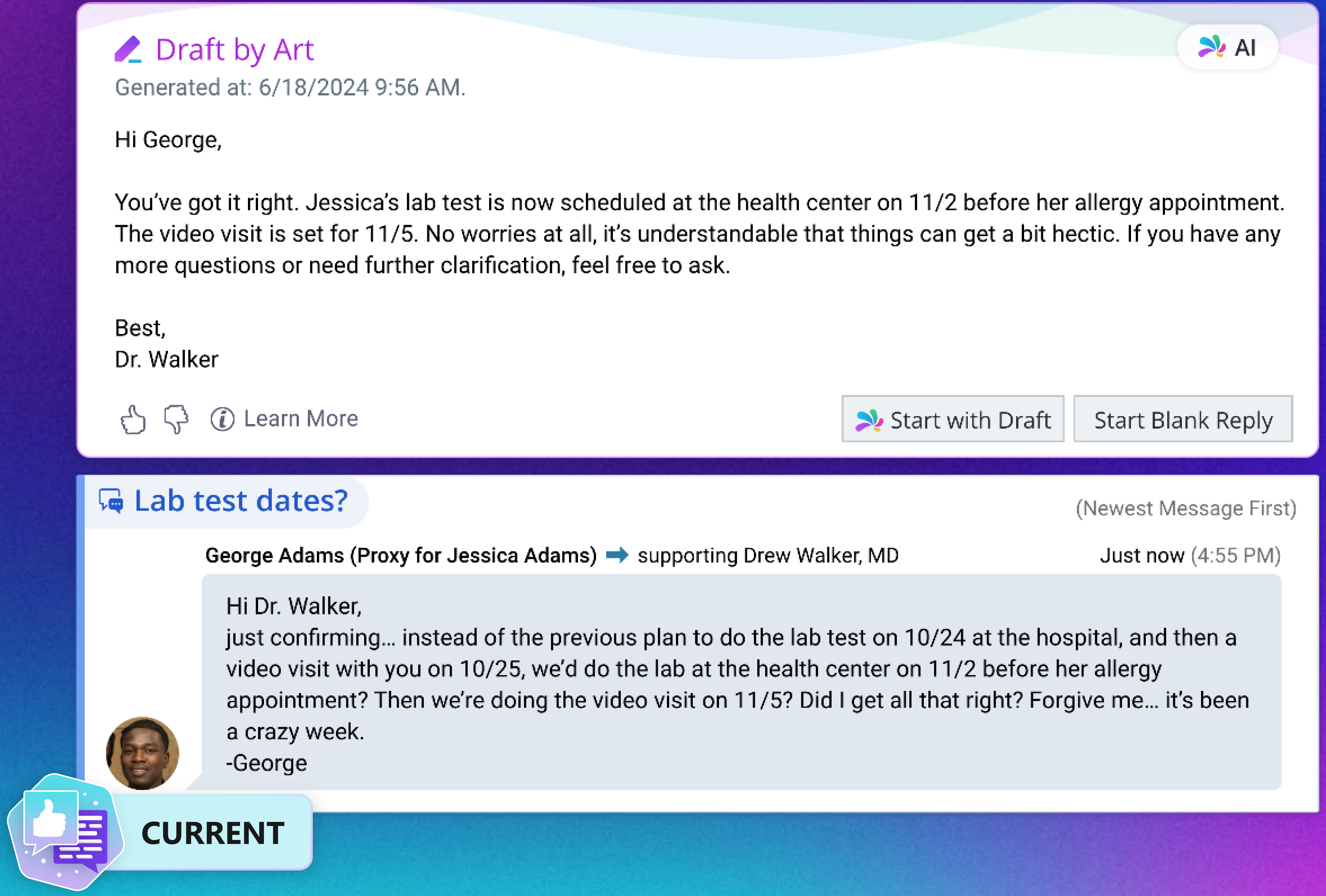


AUGUST 2024


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



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

Nurses Using Gen AI (In Basket Art)

UW Health

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.

Nurses are part of the process.

Human in the loop

UW Health: Nurses piloting generative AI (weau.com)

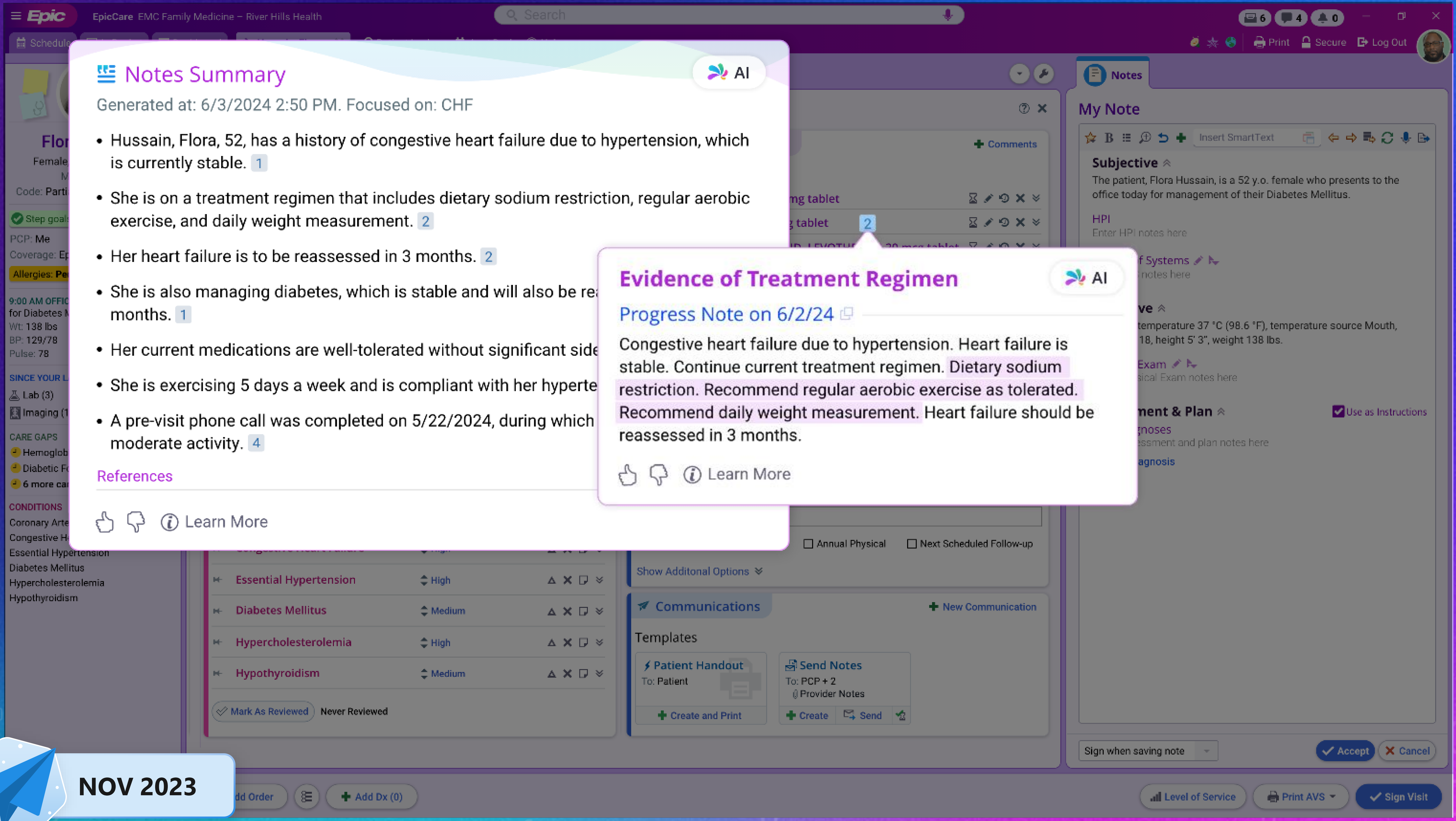
MAYO CLINIC

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



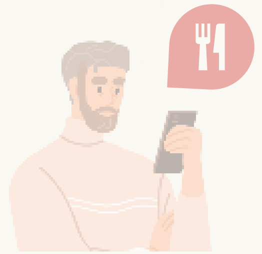
NOV 2023

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

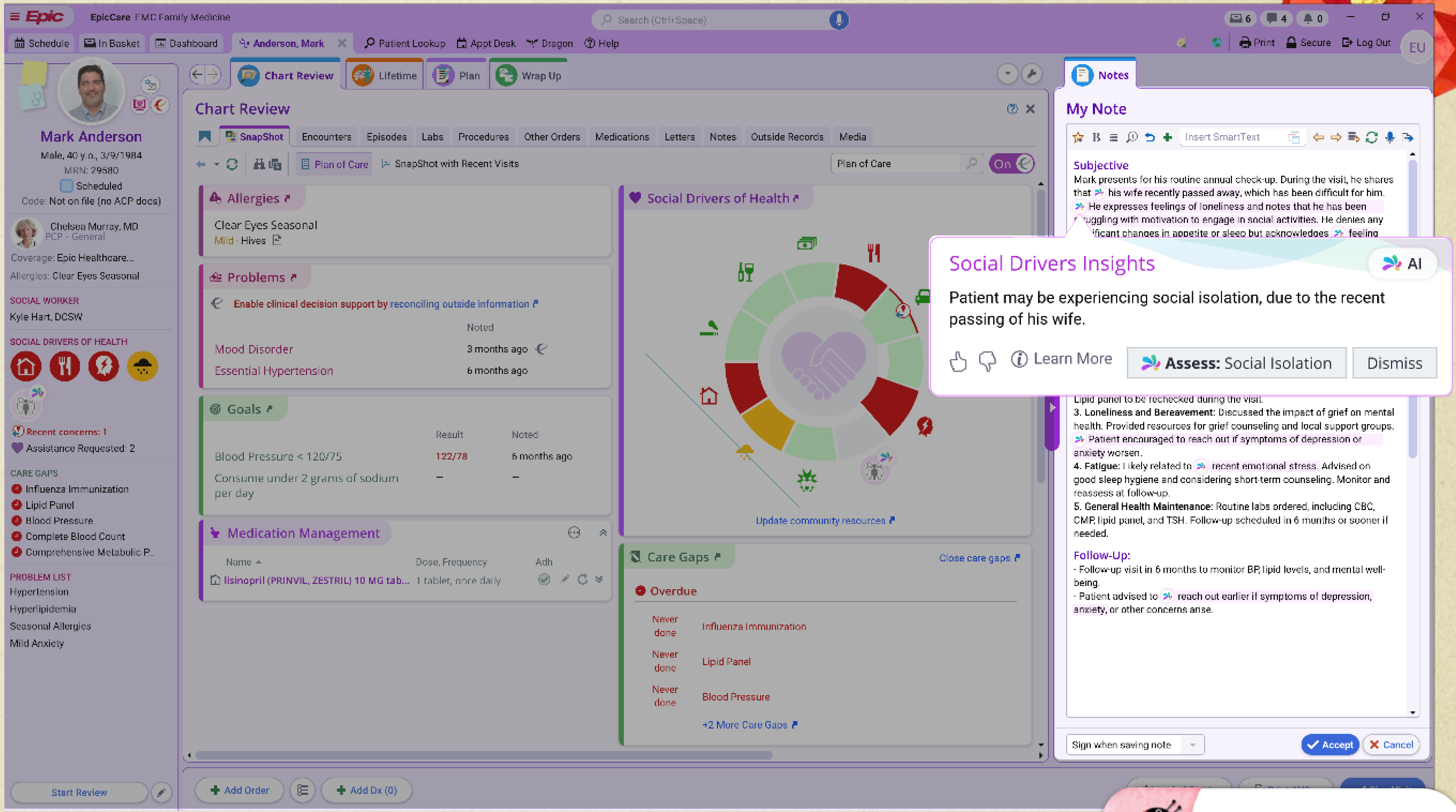
Case Study: Use AI to Extract Social Drivers from Notes

Mark's Story



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



Coming **2025**

Case Study: Use AI to Extract Social Drivers from Notes

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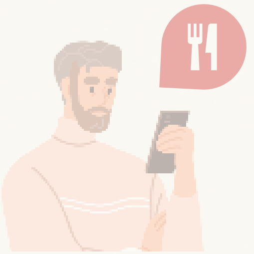

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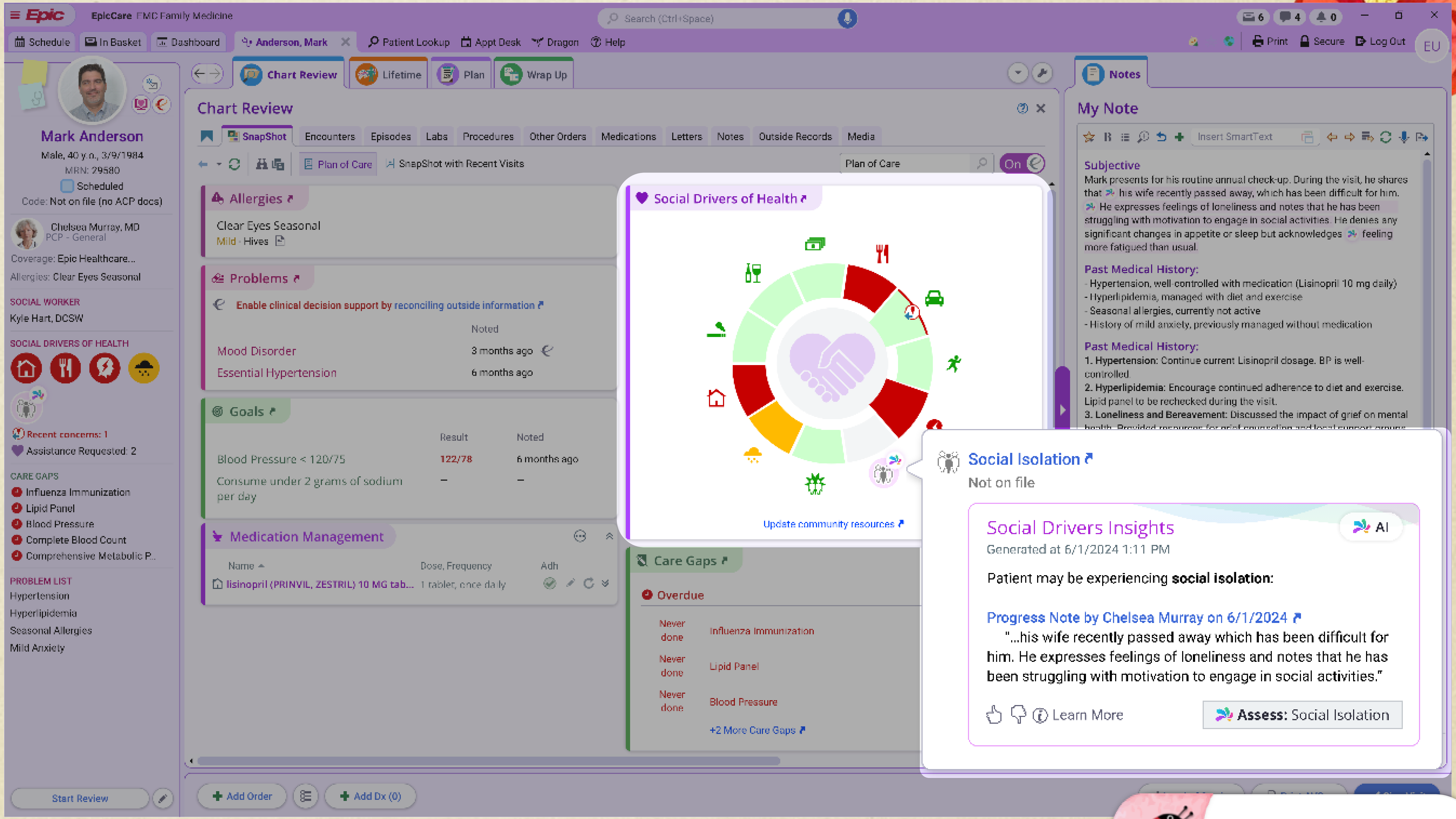


Coming **2025**

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

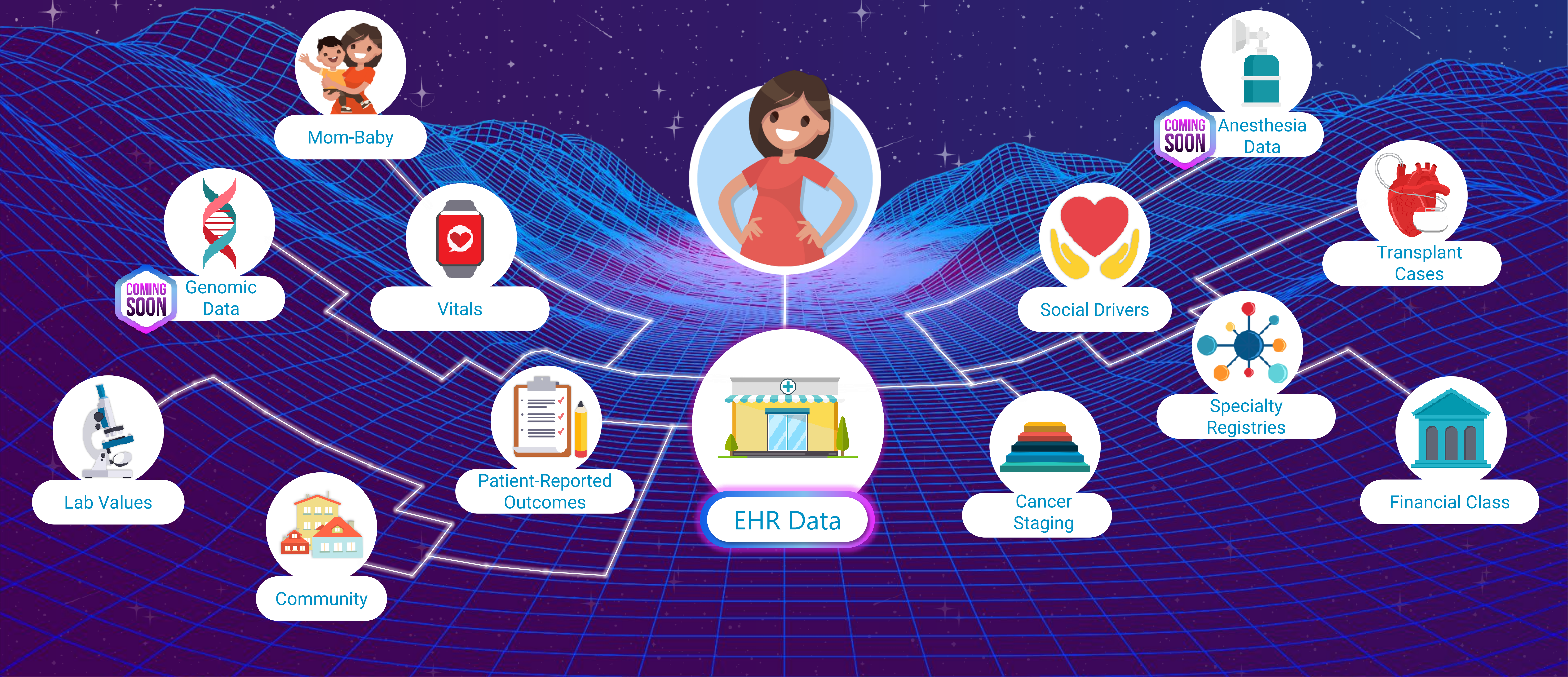
9 Million
Rare Disease Patients

Representing
50 States

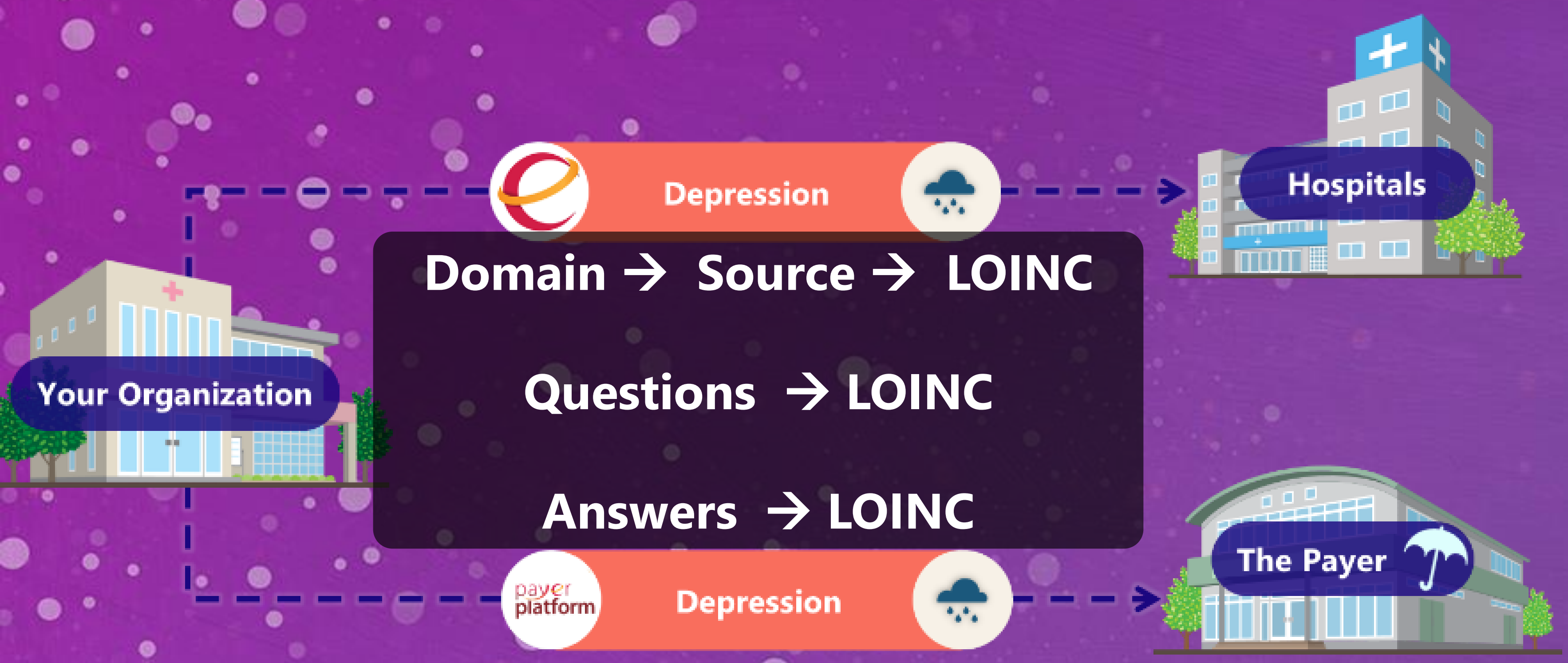
+ Canada, Lebanon, & Saudi Arabia

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	MAYO CLINIC	Providence	NOVANT HEALTH
42 Million SDoH Exchanges	12 Million SDoH Exchanges	12 Million SDoH Exchanges	10 Million SDoH Exchanges

Epic

SDoH Regulatory Requirements

January 2023

The Joint Commission

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

January 2024

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

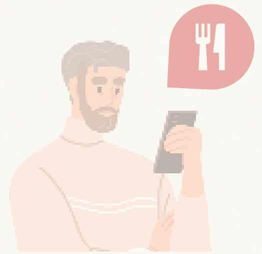
Patients admitted to the hospital screened for food, housing, transportation, utilities, & interpersonal violence.

CMS ACO REACH

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

Case Study: Use AI to Extract Social Drivers from Notes

Mark's Story



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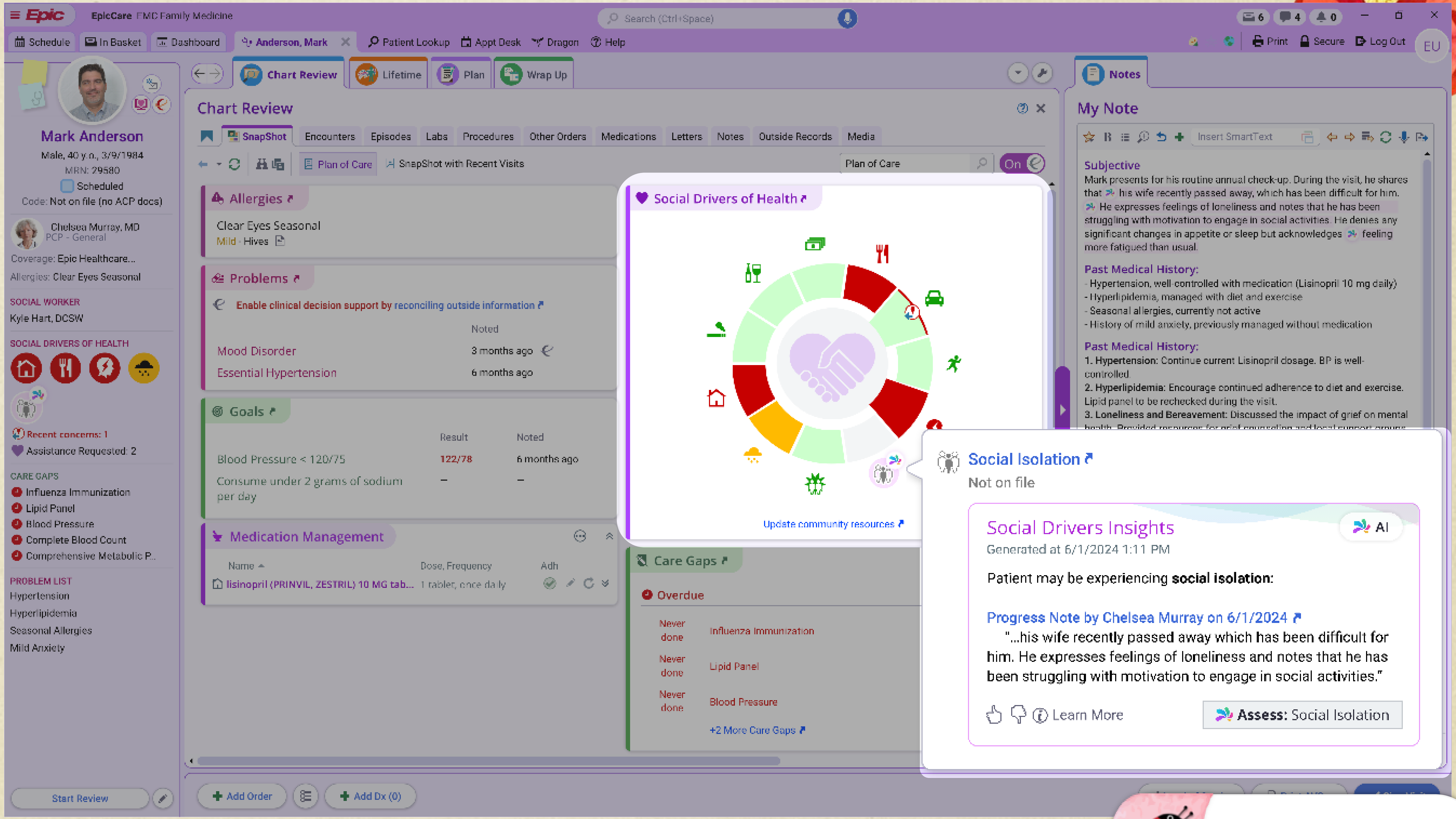


Coming 2025

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

Powered by Epic Cosmos

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.

Epic Research

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

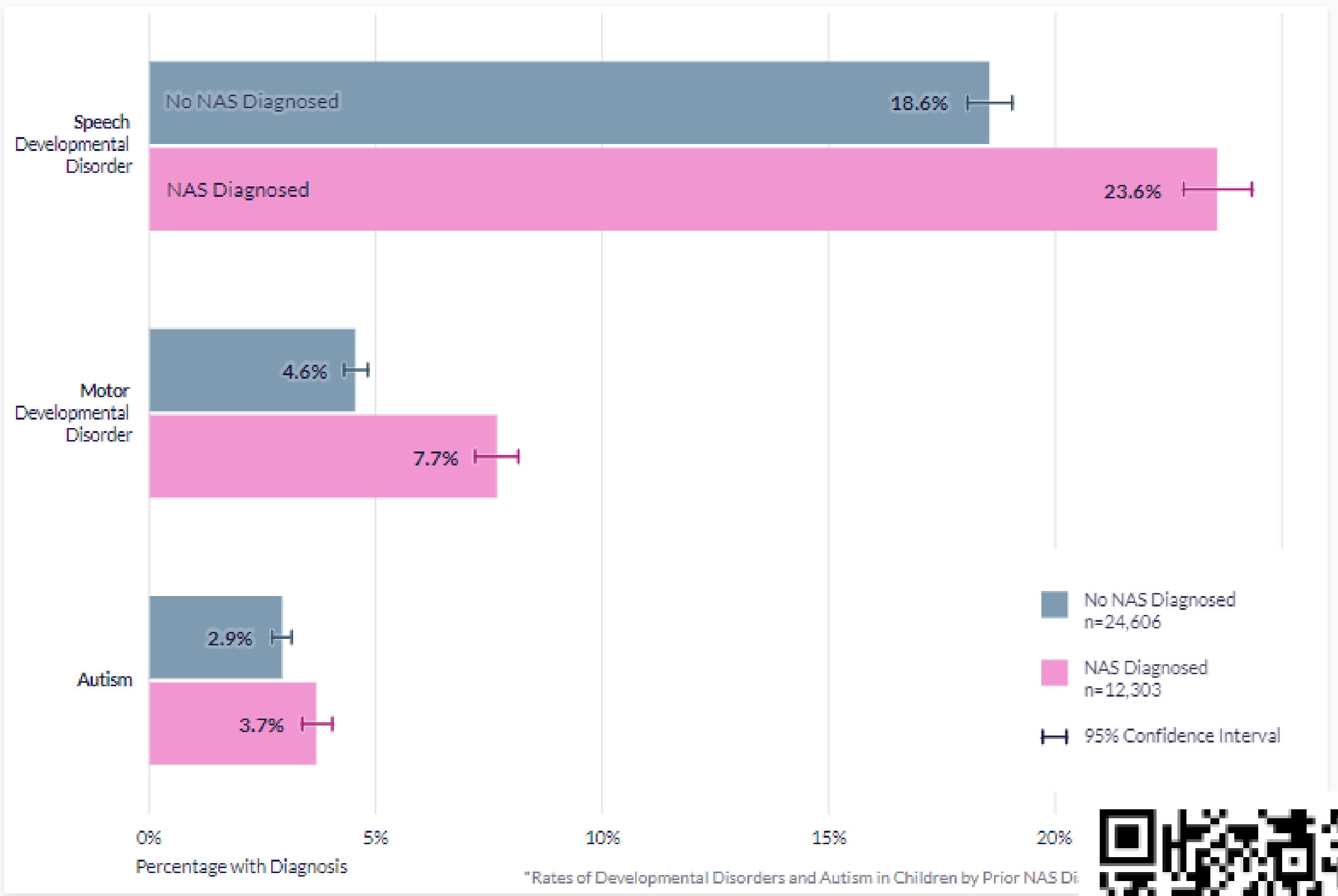
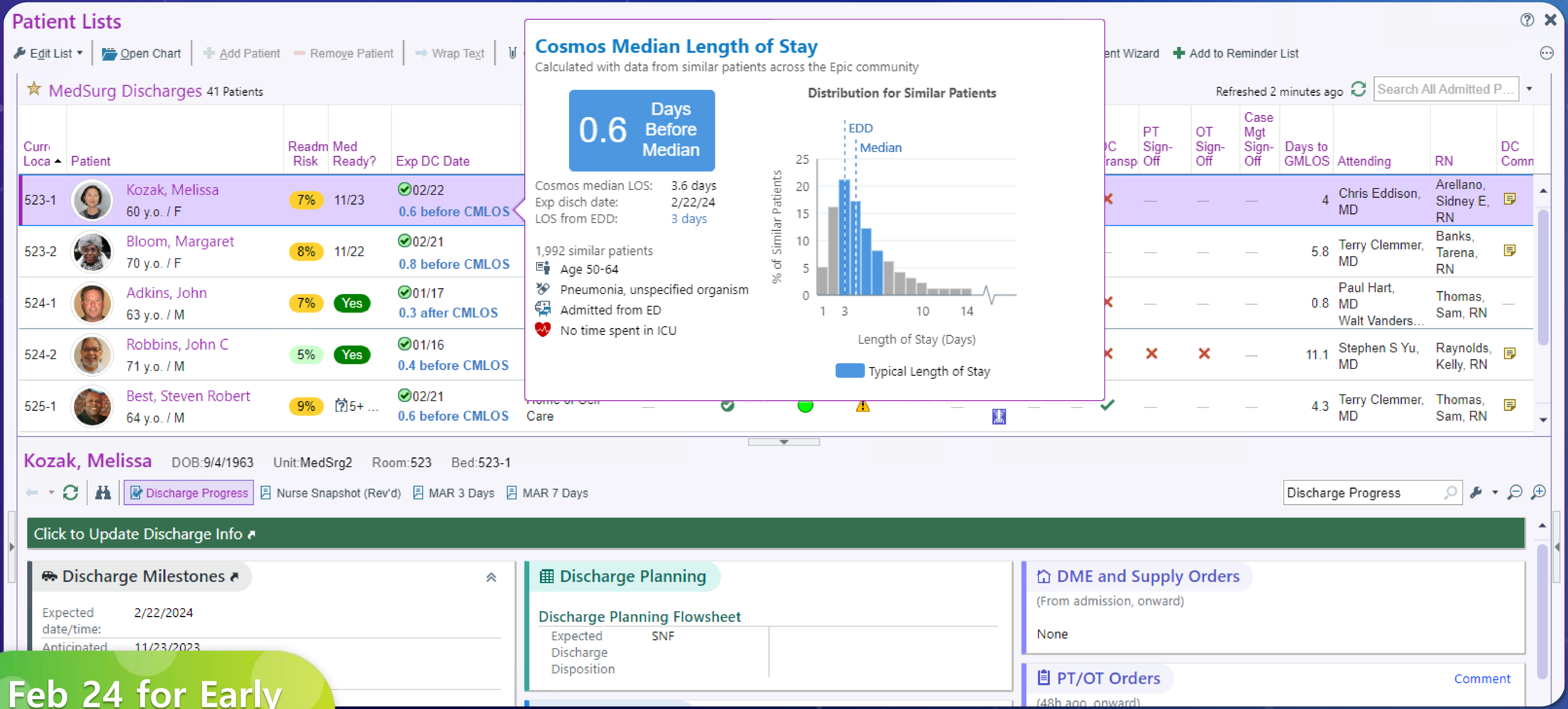


Figure 1. Rates of autism, speech developmental disorders, and motor developmental disorders in and without NAS.

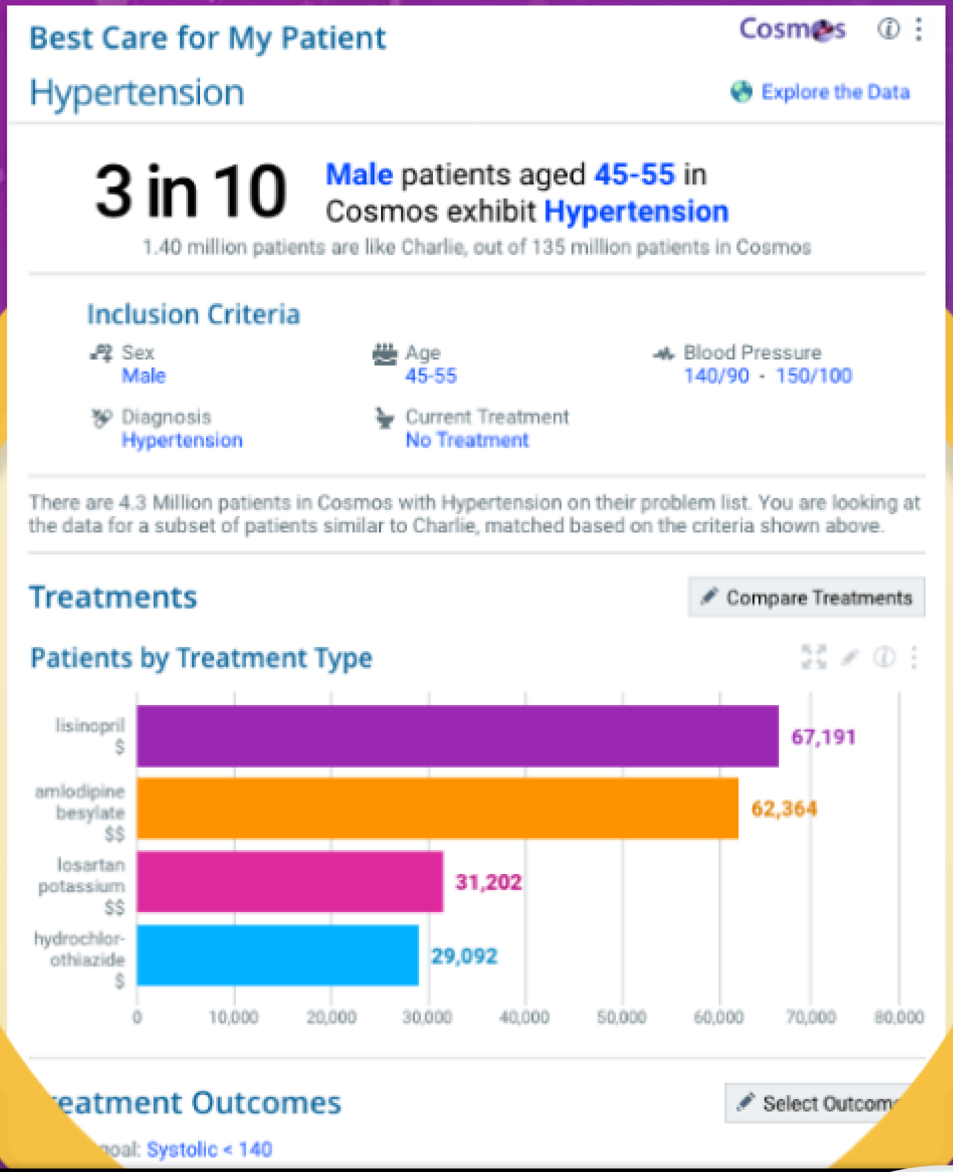
Expected Length of Stay

Powered by Cosmos



Feb 24 for Early Adopters

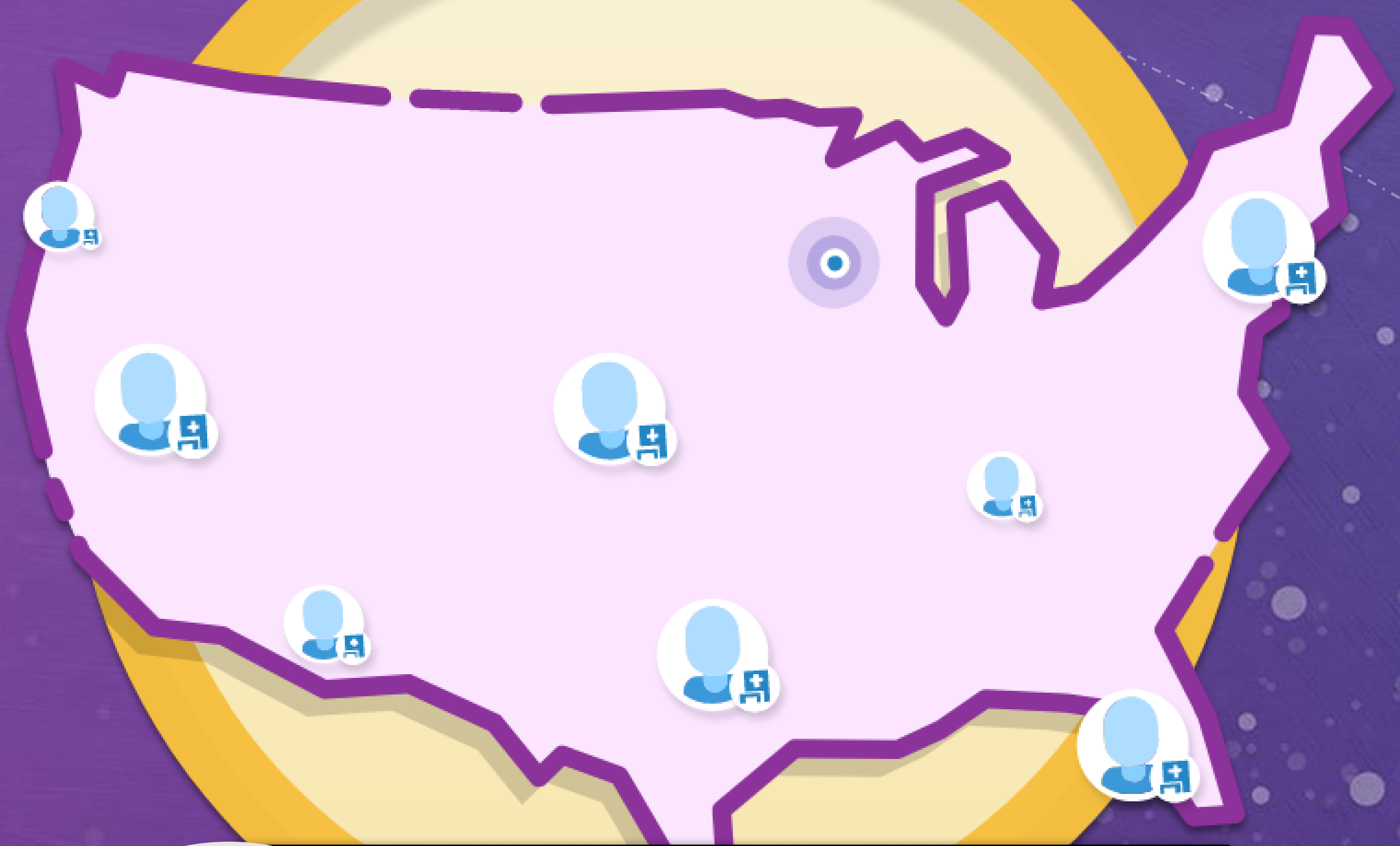
Embedded Insights *from* Cosmos



BEST CARE

For My Patient

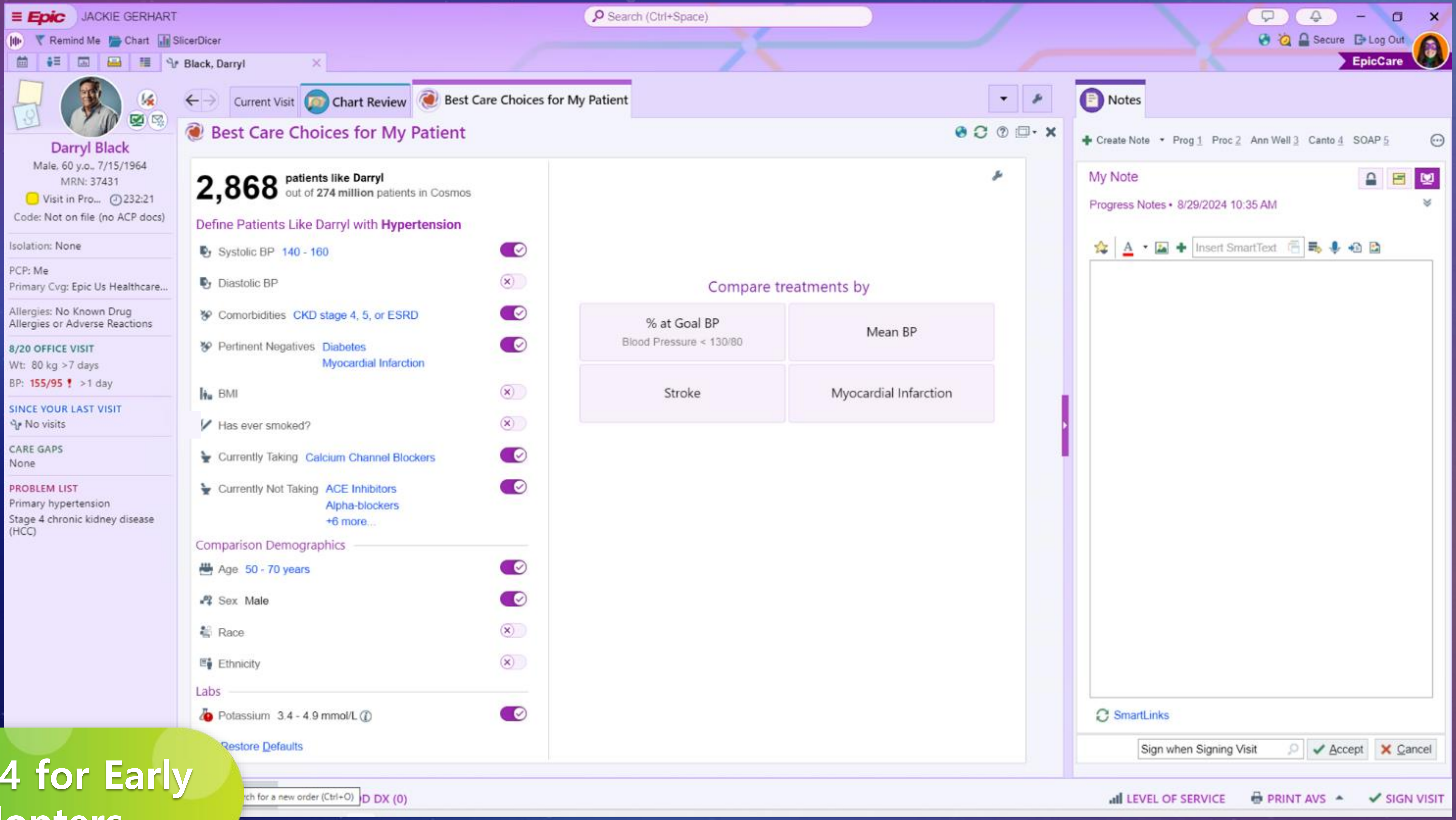
Compare treatments from **millions** of similar patients



LOOK-ALIKES

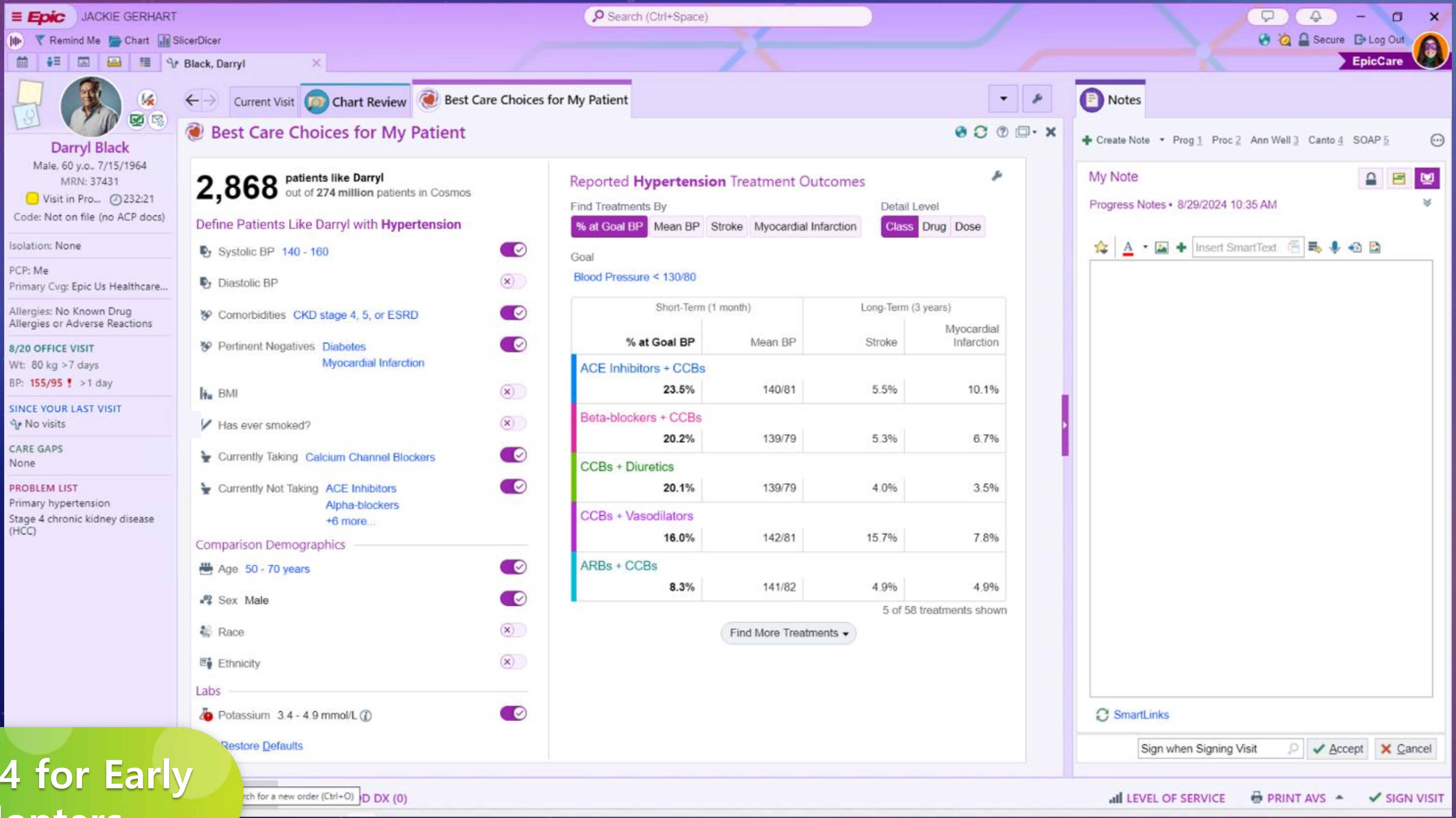
Connect with clinicians treating patients with similar **rare** conditions

Best Care Choices *for* My Patient



May 24 for Early Adopters

Best Care Choices *for* My Patient



May 24 for Early Adopters

Agenda & Objectives

- Background on Nursing Terminology in the EHR
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- 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 dete
- SlicerDicer SideKick
- Ambient voice documentation for to charti
- 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
- G era patient instructions from notes
- tect s sitiv in notes
- G summari for health plan auth review
- Inpatient insights summarization
- Post- isit 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)]

Preparing *for* AI

Prom
You can't govern

unication
users

Establish Go
S
Assess, Test, I

en
gility
ing fast

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.

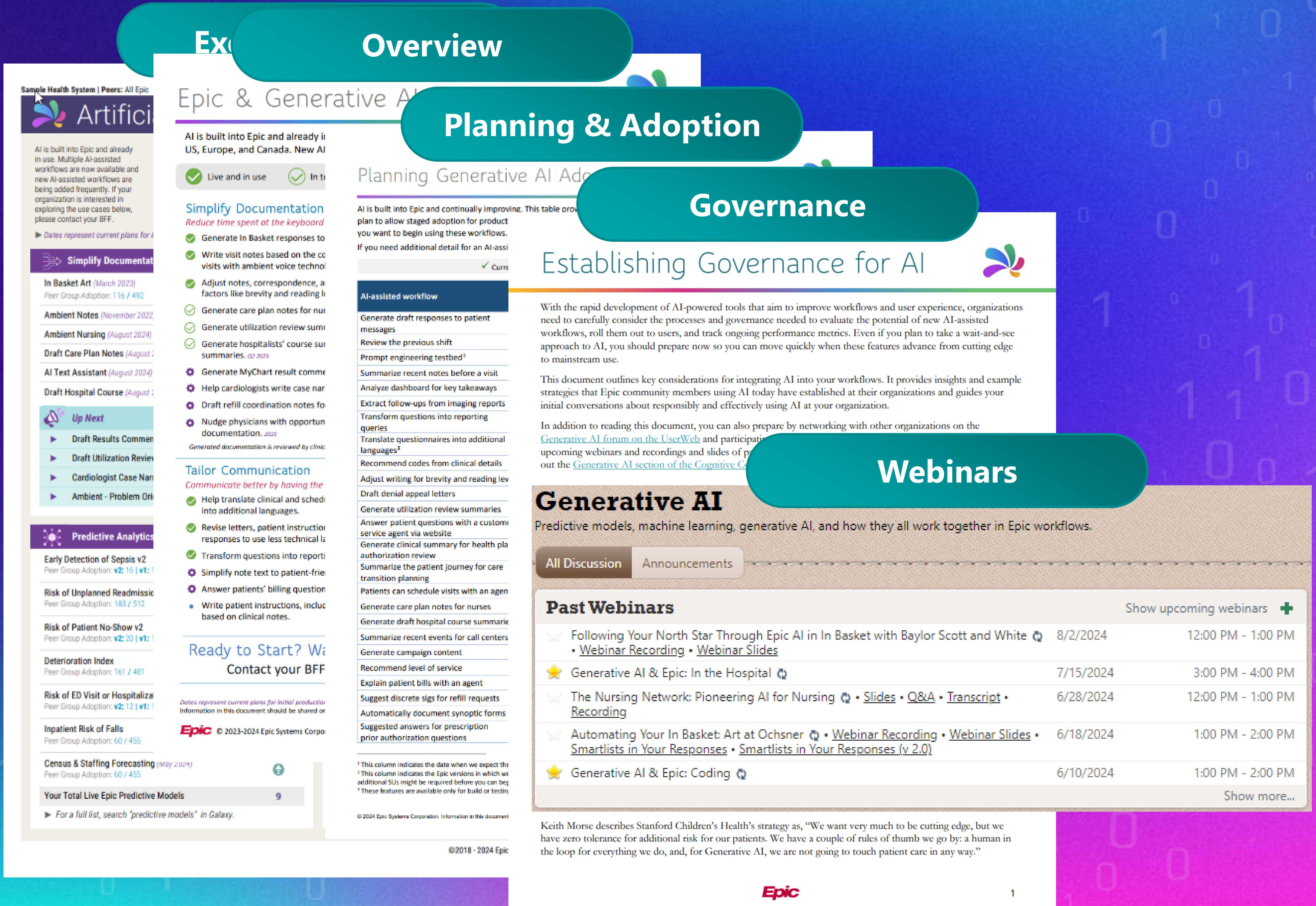
Promote general AI literacy: You can't govern what you don't understand

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

Resources *Available Now*



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

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