Nurse-Driven, Human-Centered AI: Opportunities to Improve Patient Outcomes and Decrease Burden

Sarah Rossetti, RN, PhD, FACMI, FAMIA, FAAN
Associate Professor, Biomedical Informatics and Nursing
Columbia University

2026

COLUMBIA
COLUMBIA UNIVERSITY
DEPARTMENT OF
BIOMEDICAL INFORMATICS

Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data (SC2K)

SC2K Team

Columbia University

- Sarah Rossetti, PhD, RN, FAAN, FACMI, FAMIA, FIAHSI
- Shalmali Joshi, PhD
- Varsha Varkhedi, BS

University of Pennsylvania

- Kenrick Cato, PhD, RN, CPHIMS, FAAN, FACMI

University of Colorado

- David Albers, PhD

University of Utah

- Vicky Tiase, PHD, RN-BC, FAMIA, FNAP, FAAN

Consultant

- Amy Finnegan, PhD

Advisory Board

- Noemie Elhadad, PhD, *Columbia University*
- Hojjat Salmasian, MD, MPH, PhD, *Children's Hospital of Philadelphia*
- Anna Schoenbaum, DNP, MS, RN, NI-BC, FHIMSS, *University of Pennsylvania*
- Amanda Hessels, PhD, MPH, RN, CIC, FAPIC, FAAN, *Columbia University*

Columbia | Columbia University Irving Medical Center
Columbia | School of Nursing
Columbia | Columbia University Department of Biomedical Informatics
University of Colorado Anschutz Medical Campus
Penn Nursing
Health University of Utah

This project is supported by the Assistant Secretary for Technology Policy (ASTP) of the U.S. Department of Health and Human Services (HHS) under 90AX0042/01-02, Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data, $998,903. This information or content and conclusions are those of the author and should not be construed as the official position or policy of, nor should any endorsements be inferred by ASTP, HHS, or the U.S. Government. PI Contact: Sarah Rossetti, RN, PhD

ASTP Assistant Secretary for Technology Policy

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

Team Members

Columbia University

- **Sarah Rossetti, PhD, RN**
- **Kenrick Cato, PhD, RN**
- **Haomiao Jia, PhD**
- **Jennifer Thate, PhD, RN, CNE**
- **Temmi Daramola**
- **Amy Finnegan, PhD**
- **Pinyue Vicky Wang**

Washington University

- **Po-Yin Yen, PhD, RN**
- **Albert Lai, BS, MA, MS, PhD**
- **Rosemary Mugoya, BSN, Nursing**
- **Hao Fan, MBBS**
- **Jay Rodriguez**

Columbia
Columbia University Department of Biomedical Informatics
Washington University in St. Louis School of Medicine
Institute for Informatics (I²)

This work is funded by the Agency for Healthcare Research and Quality (AHRQ): AHRQ R01HS028454

AHRQ Agency for Healthcare Research and Quality

Thank you to all the nurses who have participated in these research studies to share their expertise!

CONCERN Team

CONCERN

Columbia University

- Sarah Rossetti, PhD, RN, FAAN, FACMI, FAMIA, FIAHSI
- Haomiao Jia, PhD
- Kriste Krstovski, PhD
- Jennifer Withall, PhD, RN
- Rachel Lee, PhD, RN
- Brandon Lau
- Temmi Daramola

University of Pennsylvania

- Kenrick Cato, PhD, RN, CPHIMS, FAAN, FACMI

University of Colorado

- David Albers, PhD

Mass General Brigham

- Patricia Dykes, PhD, RN, FAAN, FACMI
- Sandy Cho, MPH, BSN, RN-BC
- Graham Lowenthal, BA

Vanderbilt University

- Catherine Ivory, PhD, NI-BC, NEA-BC, FAAN
- Brian Douthit, PhD, RN, NI-BC

Washington University

- Po-Yin Yen, PhD, RN
- Albert Lai, PhD, FACMI, FAMIA
- Adam Wilcox, PhD, FACMI
- Lisa Kidin, PhD, RN
- Michele Butkiewicz, MSN, RN
- Marilyn Schallom, PhD, MSN

Advisory Board

Informatics Experts

- Suzanne Bakken, PhD, RN, FAAN, FACMI, *Columbia University*
- David W. Bates, MD, MS, FACMI, *Brigham and Women's Hospital*
- Bonnie L. Westra, PhD, RN, FAAN, FACMI, *University of Minnesota*

Clinical Nursing Subject Matter Experts

NYP Site

- Monika Tukacs, BSN, RN, CCRN
- Robert Schroeder, RN
- Amy Moynihan, RN
- Colleen Schneiderman, RN
- Jennifer Osborne, RN
- Leo Rotter, BSN, RN

MGB Site

- Sarah Beth Thomas, BSN, RN

NWH Site

- Hailey Poole, RN

Columbia | Columbia University Irving Medical Center
Columbia | School of Nursing
Columbia | Columbia University Department of Biomedical Informatics
Center for Community-Engaged Health Informatics and Data Science
Brigham and Women's Hospital Founding Member, Mass General Brigham
Mass General Brigham Newton-Wellesley Hospital
NewYork-Presbyterian
University of Colorado Anschutz Medical Campus
Vanderbilt University Medical Center
Washington University in St. Louis School of Medicine
Penn Nursing

This project 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 National Institutes of Health or ANF

NIH NINR
American Nurses Foundation
Reimagining Nursing

Disclosures

- Named inventor on US non-provisional patent application (U.S. Patent Application No. 18/814,823) related to CONCERN Early Warning Technology

Learning Objectives

- 1. Explain a core component of health care process modeling approach used in the CONCERN Early Warning System (EWS)
- 2. Interpret how earlier escalation of care influenced outcomes in the trial
- 3. Explain an approach that can be used to integrating clinician expertise into an AI-based model

SCI AM

May Issue: Your Heart in Flames. Read Now!

February 17, 2026 | 11 min read | Add Us On Google

AI enters the exam room

When alerts misfire or can't explain themselves, nurses still carry the risk

BY HILKE SCHELLMANN EDITED BY ERIC SULLIVAN

'Nurse Avery'—Google Backed AI Nursing Assistant Launches in 10 Health Systems

Written By: Angelina Walker

4 MIN READ Published June 5, 2025

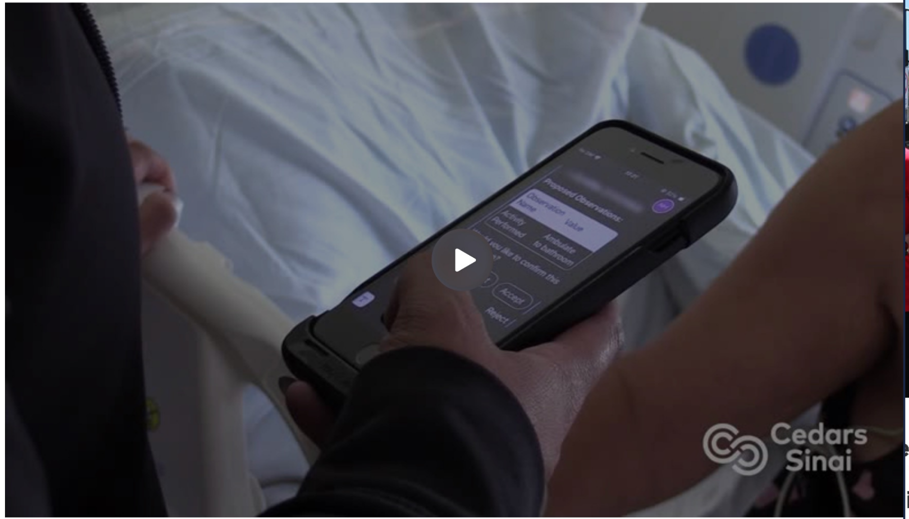
Sorry AI, you can't call yourself a nurse

Washington State Legislature passes bill to restrict nursing titles to licensed human professionals.

The Washington Nurse This story appears in the March 2026 edition of

Los Angeles, Feb 12, 2025

Artificial Intelligence Lightens Administrative Burden on Nurses



Nurses Get an Assist from AI

elligence to replace us, but nursing care. How we're fighting ion.

ECONOMY • JOBS

The most valuable worker in the AI economy is Nurse Dana from 'The Pitt'

By Nick Lichtenberg
Business Editor

Add us on G

April 13, 2026, 12:52 PM ET

Katherine LaNasa plays Nurse Dana on "The Pitt."
MICHAEL TRAN—AFP/GETTY IMAGES

AIMING FOR SUSTAINABLE CHANGE: HOW AN AI TOOL AT UCSF IS STREAMLINING NURSE WORKLOAD

ANALYSIS | BY G HATFIELD | MARCH 13, 2026

UCSF Health implemented an AI tool at the request of the bedside nurses who felt that their assignments were unbalanced, says this nurse leader.

PARTNER WITH US

Nursing bo workforce

A growing number of workers surges and o

April 22, 2026 by Keenan Gibson

THE WALL STREET JOURNAL. SIGN IN SUBSCRIBE

Nursing Is the Surefire New Path to American Prosperity

Plentiful jobs and potential six-figure incomes draw young people as other industries falter; 'modern middle-class jobs engine'

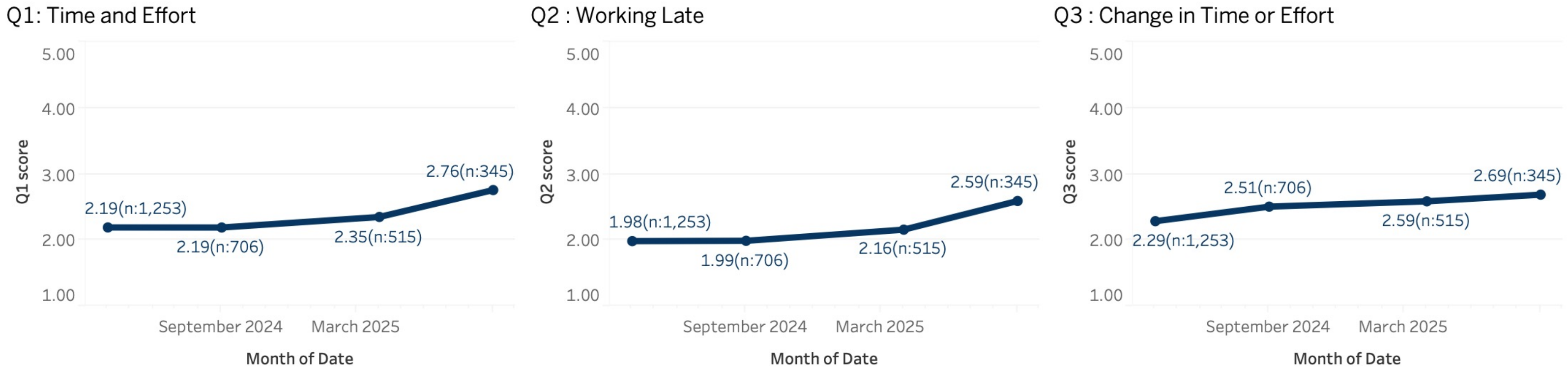
Aa 569 Listen (3 min)

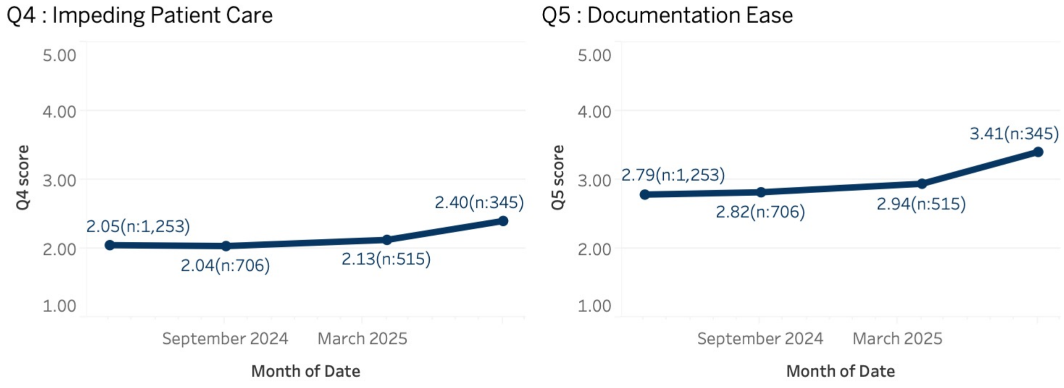
Yet, Documentation Remains Excessively Burdensome

Are we waiting for AI?

Responses to TrendBurden Pulse Survey

1-5 Score range (Higher is better)





Overall Summary

Measure Values 1.000 – 5.000

	April 2024	September 2024	April 2025	September 2025
Q1 score	2.19 (1,253)	2.19 (706)	2.35 (515)	2.76 (345)
Q2 score	1.98 (1,253)	1.99 (706)	2.16 (515)	2.59 (345)
Q3 score	2.29 (1,253)	2.51 (706)	2.59 (515)	2.69 (345)
Q4 score	2.05 (1,253)	2.04 (706)	2.13 (515)	2.40 (345)
Q5 score	2.79 (1,253)	2.82 (706)	2.94 (515)	3.41 (345)

TrendBurden 2026 Survey now live!

(Includes AI question)

Clinical Nurses Perspectives on AI
(national sample via SC2K study*)

"You can't replace nursing judgment and nursing experience. So yes, AI to me is welcomed in this field…but I think it shouldn't be the end all be all. There should be some built-in component for clinical judgment because you're at the bedside, you're laying eyes on the patient, and I think that's paramount."

"The idea of it being fully automated without some human involvement really scares me" ⟷ "I feel cautiously optimistic."

The Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data (SC2K) Study. This project is supported by the Assistant Secretary for Technology Policy (ASTP) of the U.S. Department of Health and Human Services (HHS) under 90AX0042/01-02, Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data, $998,903. This information or content and conclusions are those of the author and should not be construed as the official position or policy of, nor should any endorsements be inferred by ASTP, HHS, or the U.S. Government. PI Contact: Sarah Rossetti, RN, PhD,

Human-Centered AI

Prioritizes well-bring, ethics and values of humans

Aligned with human values and goals

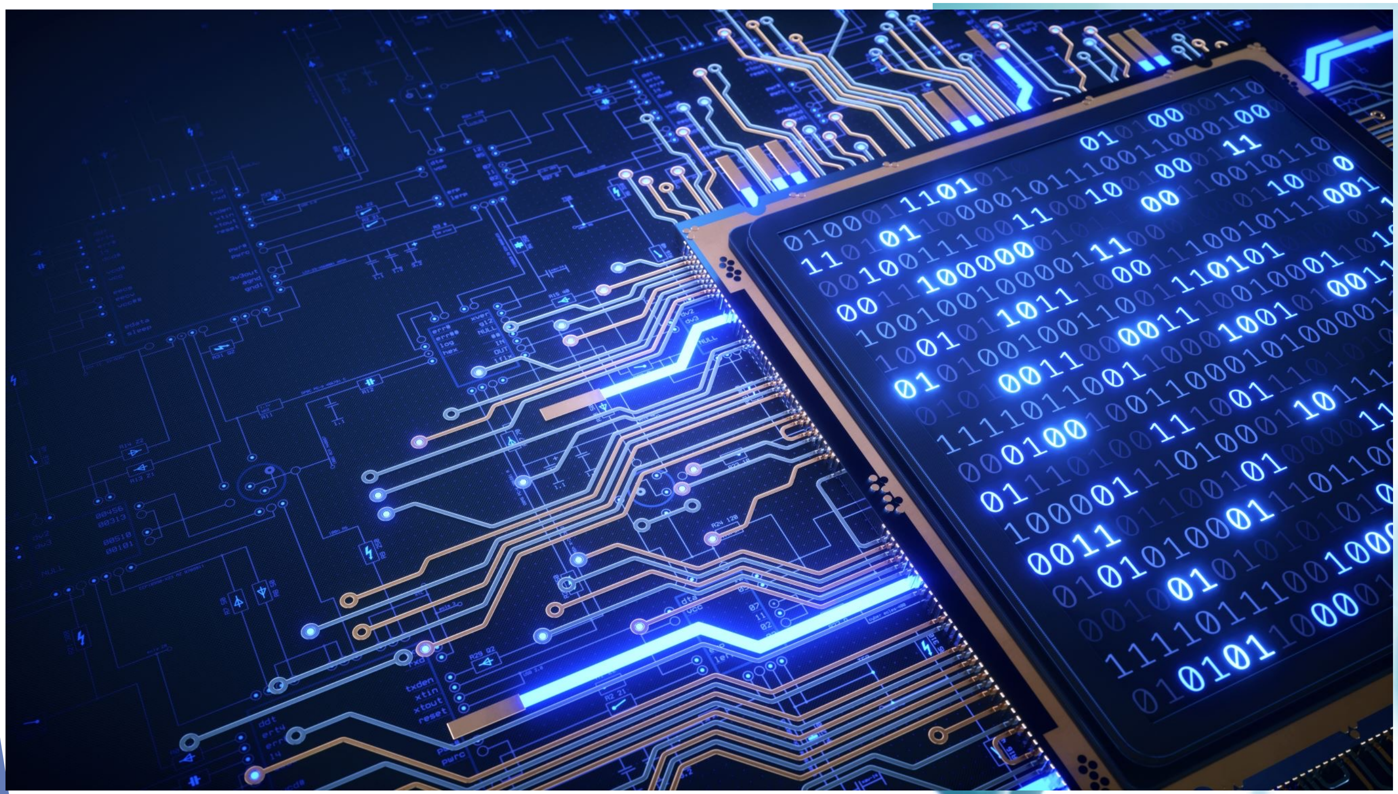
Designed with awareness that it is part of a larger system

Collaborative tool

Focuses on amplifying, augmenting, and enhancing - not replacing - human performance

Time of Blurred Lines

Tools that take over the work vs Tools that work alongside and support people?



THE AI LIFECYCLE

The AI lifecycle is central to understanding and implementing CHAI's Responsible AI Guidance in healthcare. The six-step lifecycle outlines the essential stages and processes involved in developing, deploying, and maintaining AI systems.

By systematically addressing each phase of the lifecycle, the framework ensures that AI systems adhere to the highest standards of safety, efficacy, fairness, transparency, and security. This structured approach supports risk mitigation, managing biases, and promotes accountability and trustworthiness in AI applications.

1

- Engage stakeholders to define the problem & perform root-cause analysis
- Identify solution & plan future state
- Gather business requirements
- Assess feasibility, potential for impact, & prioritization
- Make procure/build/partner decision

2

- Select/understand model task & architecture
- Capture design & technical requirements or determine best solution to meet business requirements
- Design solution application & system workflow according to human-centered design principles
- Design deployment strategy with end users
- Design risk management, monitoring & reporting plan

3

- Access data
- Prepare data
- Develop data management plan
- Train & tune model

4

- Conduct installation qualification (when applicable)
- Validate local system performance (when applicable)
- Execute prospective, silent evaluation
- Establish risk management plan
- Train end users
- Test usefulness
- Ensure compliance with applicable healthcare regulations & standards

5

- Implement small-scale pilot to assess real-world impact
- Execute and update risk management plan
- Educate & train users on AI application reporting
- Assess usefulness and adoption

6

- Deploy at a larger scale on a general population
- Audit AI system to inform whether to maintain, refine or sunset
- Conduct ongoing risk management

CHAI

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

THE CORE PRINCIPLES FOR TRUSTWORTHY HEALTH AI

Usefulness, Usability & Efficacy

AI solutions should be beneficial, reliable, and improve user experience. They must solve specific problems and show clear benefits for patients and healthcare providers, such as better clinical outcomes and patient satisfaction. Usability means the AI should be easy to use and fit well into existing workflows. Efficacy ensures the AI achieves its goals and continues to perform well through ongoing testing and monitoring.

Fairness

AI solutions must be fair and work equally well for all demographic groups. Fairness means the AI's performance should be consistent across different groups, and outcomes should not depend on protected attributes like race or sex. Bias management includes regularly checking and correcting any biases in the data or AI system to promote fairness and improve the balanced allocation of resources, access to care, and outcomes for all.

Safety & Reliability

AI solutions should not harm patients or healthcare providers. This involves thorough testing and risk assessments before implementation, and continuous monitoring to detect and address any safety issues. Clear accountability and governance structures must be in place to ensure the AI system remains safe and reliable throughout its use.

Transparency, Intelligibility & Accountability

Stakeholders need clear and understandable information about AI systems and their outputs. Transparency involves sharing how the AI system works and its limitations. Intelligibility ensures stakeholders can understand the AI's decision-making processes. Accountability means being responsible for minimizing harm and addressing any negative impacts of the AI system.

Security & Privacy

AI systems must protect data confidentiality and integrity with strong security measures. This includes preventing unauthorized access and data breaches, and ensuring personal data is handled in compliance with privacy regulations. Organizations should have protocols for monitoring security and privacy, and for addressing any incidents, to keep data safe and maintain trust.

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 1 - Define Problem & Plan

Usefulness, Usability & Efficacy	Fairness	Safety	Transparency, Intelligibility & Accountability	Security & Privacy
Clearly explain the problem and why the AI solution is necessary	Ensure the AI solution does not disadvantage any groups	Identify potential harms and risks	Ensure there is a clear reason for using AI over non-AI solutions	Maintain complete documentation of AI systems and data
Assess how the AI will fit into existing workflows	Establish how fairness will be evaluated	Establish clear criteria for the patient population	Document the intended use and users of the AI solution	Establish and maintain policies to manage AI privacy and security risks
Evaluate the benefits, risks, and costs of the AI solution	Develop a strategy to monitor and mitigate biases	Ensure both developer and implementer are responsible for safety	Make project and model information accessible to all stakeholders	Clearly define the AI's purpose and ensure it aligns with organizational goals
Determine if end users will trust the AI solution	Identify socio-demographic groups at risk of bias	Ensure compliance with federal and local regulations	Keep thorough documentation of the AI solution	Conduct initial privacy and security risk assessments
Involve clinical experts in the AI's development and validation	Identify potential types and sources of bias	Address ethical and legal challenges	Clearly communicate potential risks to end users and patients	Regularly update risk assessments

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 2: Design the AI System

Usefulness, Usability & Efficacy	Fairness	Safety	Transparency, Intelligibility & Accountability	Security & Privacy
Ensure usability is considered and documented	Ensure real-world outcomes are fair across all groups	Ensure users can control and override AI recommendations	Compare the AI system to the benchmarks and document predictors and validation methods	Trace AI system requirements to privacy and security risks
Document robustness testing and trust-building measures	Identify and document limitations and risks	Establish processes for error disclosure and legal considerations	Define clear and understandable decision thresholds	Implement user access control policies
Assess differences between development and implementation environments	Create easy and effective feedback mechanisms	Plan risk management from conception to deployment	Ensure documentation considers end user knowledge	Use privacy-enhancing technologies (PETs) to mitigate privacy and cybersecurity risks
	Ensure all stakeholders review and approve implementation processes	Determine if deployment constitutes HSR and meet IRB requirements	Assess performance across demographic groups and ensure explainability	Consider privacy preferences and contextual factors in design
		Establish a monitoring process for AEs and SAEs		
		Label AI models with development and limitation information		
		Define procedures for reporting flaws and safety concerns		
		Ensure the AI system allows for human oversight and intervention		
		Include end users in the design process		

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 3 - Engineer the AI Solution

Usefulness, Usability, & Efficacy	Fairness	Safety	Transparency, Intelligibility, & Accountability	Security & Privacy
Assess data quality and integrity	Justify use of protected attributes	Ensure training data represents the deployment population	Plan data security and scalability	Implement controls for privacy and security requirements
Consider bias and fairness during feature extraction	Address disparities between training data and target population	Monitor data quality and dataset drifts	Ensure transparency in data monitoring	Ensure data management policies address privacy and cybersecurity risks
Ensure data availability for model training matches deployment	Define and assess socio-demographic subgroups	Trace complaints, ethical concerns, and safety risks	Include socio-demographic information and diversity details	Protect against unauthorized access and data leaks
	Assess data quality by socio-demographic factors	Apply clear inclusion/exclusion criteria	Document data provenance and limitations	Ensure data inputs and provenance support accuracy and manage bias
	Evaluate proxies and composite scores for bias	Implement proper access controls and audit trails	Document data lineage	Protect development and production environments with secure user access
	Examine robustness of data representation	Ensure stakeholders understand roles in data quality	Implement version control for datasets	
	Ensure local data is representative for model tuning	Establish safety monitoring for adverse events	Assess patient impact and need for consent	
	Document training and test data for fairness and bias	Label AI models with development information	Ensure transparency in data manipulation rationale	

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 4: Assess

Usefulness, Usability, & Efficacy	Fairness	Safety	Transparency, Intelligibility, & Accountability	Security & Privacy
Ensure AI integrates into workflows	Evaluate fairness and bias across subgroups	Evaluate local performance and safety	Report AI effectiveness to users and stakeholders	Train workforce on cybersecurity and privacy roles
Reassess if the AI addresses the problem	Ensure training and test datasets are independent	Implement risk management and assessment methods	Establish goals, standards, terms, and conditions	Assess performance of implemented controls
Reevaluate AI usability	Assess model performance and parity across subgroups	Triage and report risks to the implementer and developer	Define roles to foster trust and transparency	Identify third-party providers and ensure their compliance
Facilitate trust through risk-benefit assessment	Consider broader measures of performance and impact	Conduct verification and validation activities	Plan for data security and scalability	Perform risk assessment on third-party providers
Tailor AI to specific work contexts		Ensure transparency of validation methods and results	Ensure accessibility and explainability	Maintain third-party audit records
			Consider downstream impacts of AI	Ensure documentation of third-party systems
			Incorporate user feedback and documentation	Implement processes for third parties to report vulnerabilities
			Report on performance metrics and fairness audits	
			Test data and generalization contingencies	

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 5: Pilot

Usefulness, Usability, & Efficacy	Fairness	Safety	Transparency, Intelligibility, & Accountability	Security & Privacy
Communicate AI capabilities to end users	Assess real-world outcomes for bias	Implement risk management and mitigation methods	Evaluate system's capacity to handle errors and data volume	Include stakeholder privacy preferences in algorithm design
Compare anticipated and actual benefits, risks, and costs	Ensure representativeness of pilot site and approach	Maintain monitoring for adverse events and serious adverse events	Provide education/training for end users	Implement and review audit log records
Re-assess usability in clinical environment	Evaluate human interaction and workflow impact	Implement a structured, transparent decision-making process	Identify ongoing audit monitoring methods	Establish configuration change control processes
Manage clinician disagreements with AI output		Mitigate automation bias	Assess end user experience	Ensure an incident response plan is in place
Assess user actions after AI interaction		Establish robust reporting and recall procedures	Consider continuous reporting methods	Establish delivery and resilience requirements for critical AI services
		Continue human factors evaluation	Communicate model limitations to users and patients	Examine and document privacy and cybersecurity risks
		Regularly review AI solution's relevance and obsolescence	Ensure transparency in clinical trials	Incorporate contextual factors into AI design

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

IMPLEMENTING BEST PRACTICES FOR TRUSTWORTHY HEALTH AI

Stage 6: Deploy and Monitor

Usefulness, Usability, & Efficacy	Fairness	Safety	Transparency, Intelligibility, & Accountability	Security & Privacy
Re-assess usability in the clinical environment	Monitor data drift impacts on bias	Implement risk management and assessment methods	Report effectiveness to end users and stakeholders	Support incident response plans with impact assessments
Evaluate AI integration in workflow	Identify responsible parties for monitoring bias	Maintain monitoring for adverse events and serious adverse events	Ensure patients are aware of AI use	Notify stakeholders about cybersecurity incidents or privacy events
Monitor AI solution performance over time	Mitigate model drift impacts on fairness	Regularly review AI relevance and obsolescence	Maintain access to project-related and model information	Continuously evaluate privacy risk
Manage clinician disagreements with AI output	Monitor system bias impacts effectively	Establish robust reporting and recall procedures		Assess and communicate compliance with legal requirements
Solicit and use end user feedback	Facilitate feedback from impacted populations	Implement proper access controls and audit trails		
Compare anticipated and actual benefits, risks, and costs	Assess risks of performance drift from pilot to full deployment	Report unintended uses of AI solution		
Assess user actions after AI interaction	Monitor AI system performance and parity	Conduct impact analysis on safety and benefit measures		
Support user trust building	Clarify accountability for data/model breaches	Mitigate automation bias		
Define inclusion/exclusion criteria for patients	Evaluate transition impacts from pilot to full deployment	Ensure AI solutions are labeled with development information		
	Inform affected groups about AI role	Ensure end-of-life (EOL) processes are clear		
	Provide end-user feedback loops	Use assurance techniques for supply chain risk management		
		Ensure updates maintain safety and effectiveness		

CHAI

Prepared by CHAI.

https://assets.ctfassets.net/7s4afyr9pmov/65plMtolcCmZFIgqNpXD00/581204a79e087cae7529db2eba7f30e0/CHAI_Responsible-AI-Guide_Executive-Summary.pdf

Opportunities for AI to Leapfrog Decision Support with Burden Reduction

Fully Automated

AI to fully complete a task

Semi-automated

AI to complete part of a task

Clinician in the Loop

AI to guide clinicians' reasoning and/or subsequent actions.

Opportunities for AI to Leapfrog Decision Support with Burden Reduction

Fully Automated | Semi-automated | Clinician in the Loop

Fully Automated

AI to fully complete a task

Potential Examples:
burdensome/administrative task not a part of professional practice

Opportunities for AI to Leapfrog Decision Support with Burden Reduction

Fully Automated

Semi-automated

Clinician in the Loop

AI to complete part of a task

Potential Examples: documentation of action performed by clinician

Opportunities for AI to Leapfrog Decision Support with Burden Reduction

Fully Automated | Semi-automated | **Clinician in the Loop**

AI to guide clinicians' reasoning and/or subsequent actions.

Potential Examples:

- Interactions that enhance workflows
- Synthesizing structured and unstructured data
- Intelligently filtering patient level information
- Contextualizing information to current situation
- Identifying pertinent data for optimal decision making
- Prioritizing and filtering recommendations to account for clinical complexities

What about the risks?

How could it fail?

Why didn't you use your clinical judgment?

vs

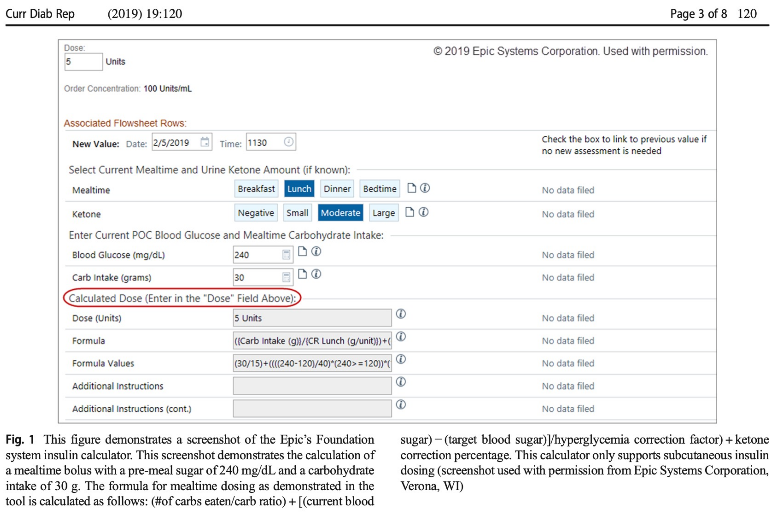
Why didn't you follow the protocol?

Data Quality for AI Inputs – Essential to Confirm Nursing Perspective

- Most nursing processes are embedded within an institutional process or protocol, so why can't we just use processes/protocols to inform AI models' use of nursing data?

- Nurses do follow processes and protocols but actual care and data recorded is conditional on many dependent processes that prevent execution in a linear way

  - Protocols are linear and do not reflect realities of care processes



Curr Diab Rep (2019) 19:120 Page 3 of 8 120

© 2019 Epic Systems Corporation. Used with permission.

Dose: 5 Units

Order Concentration: 100 Units/mL

Associated Flowsheet Rows:

New Value: Date: 2/5/2019 Time: 1130

Check the box to link to previous value if no new assessment is needed

Select Current Mealtime and Urine Ketone Amount (if known):

Mealtime	Breakfast Lunch Dinner Bedtime	No data filed
Ketone	Negative Small Moderate Large	No data filed

Enter Current POC Blood Glucose and Mealtime Carbohydrate Intake:

Blood Glucose (mg/dL)	240	No data filed
Carb Intake (grams)	30	No data filed

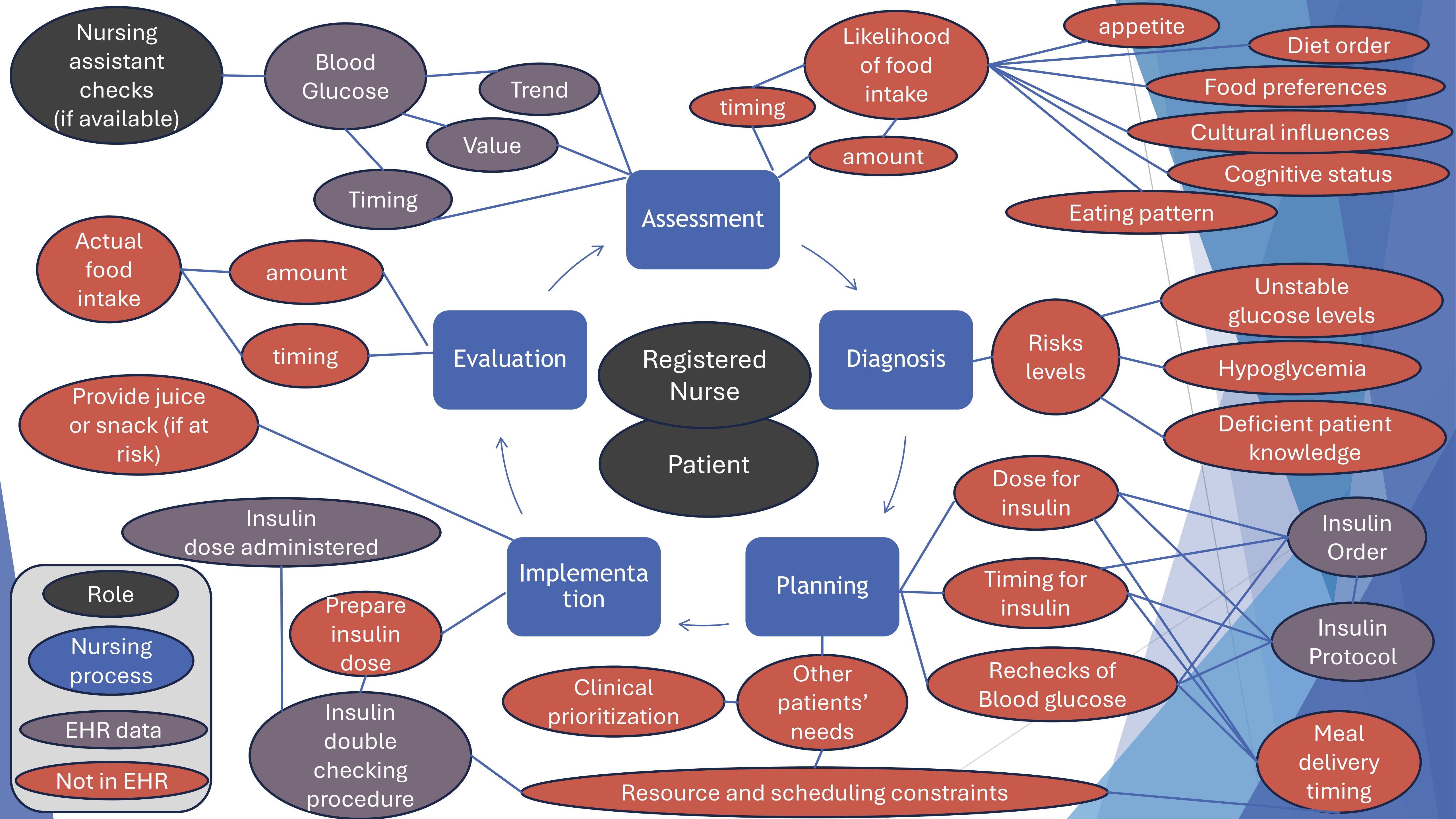
Calculated Dose (Enter in the "Dose" Field Above):

Dose (Units)	5 Units	No data filed
Formula	({Carb Intake (g)}/{CR Lunch (g/unit)})+(	No data filed
Formula Values	(30/15)+((((240-120)/40)*(240>=120))*(	No data filed
Additional Instructions		No data filed
Additional Instructions (cont.)		No data filed

Fig. 1 This figure demonstrates a screenshot of the Epic's Foundation system insulin calculator. This screenshot demonstrates the calculation of a mealtime bolus with a pre-meal sugar of 240 mg/dL and a carbohydrate intake of 30 g. The formula for mealtime dosing as demonstrated in the tool is calculated as follows: (#of carbs eaten/carb ratio) + [(current blood sugar) − (target blood sugar)]/hyperglycemia correction factor) + ketone correction percentage. This calculator only supports subcutaneous insulin dosing (screenshot used with permission from Epic Systems Corporation, Verona, WI)

Ulla et al., Subcutaneous Insulin Dosing Calculators for Inpatient Glucose Control. Current Diabetes Reports (2019) 19:120. https://doi.org/10.1007/s11892-019-1254-y

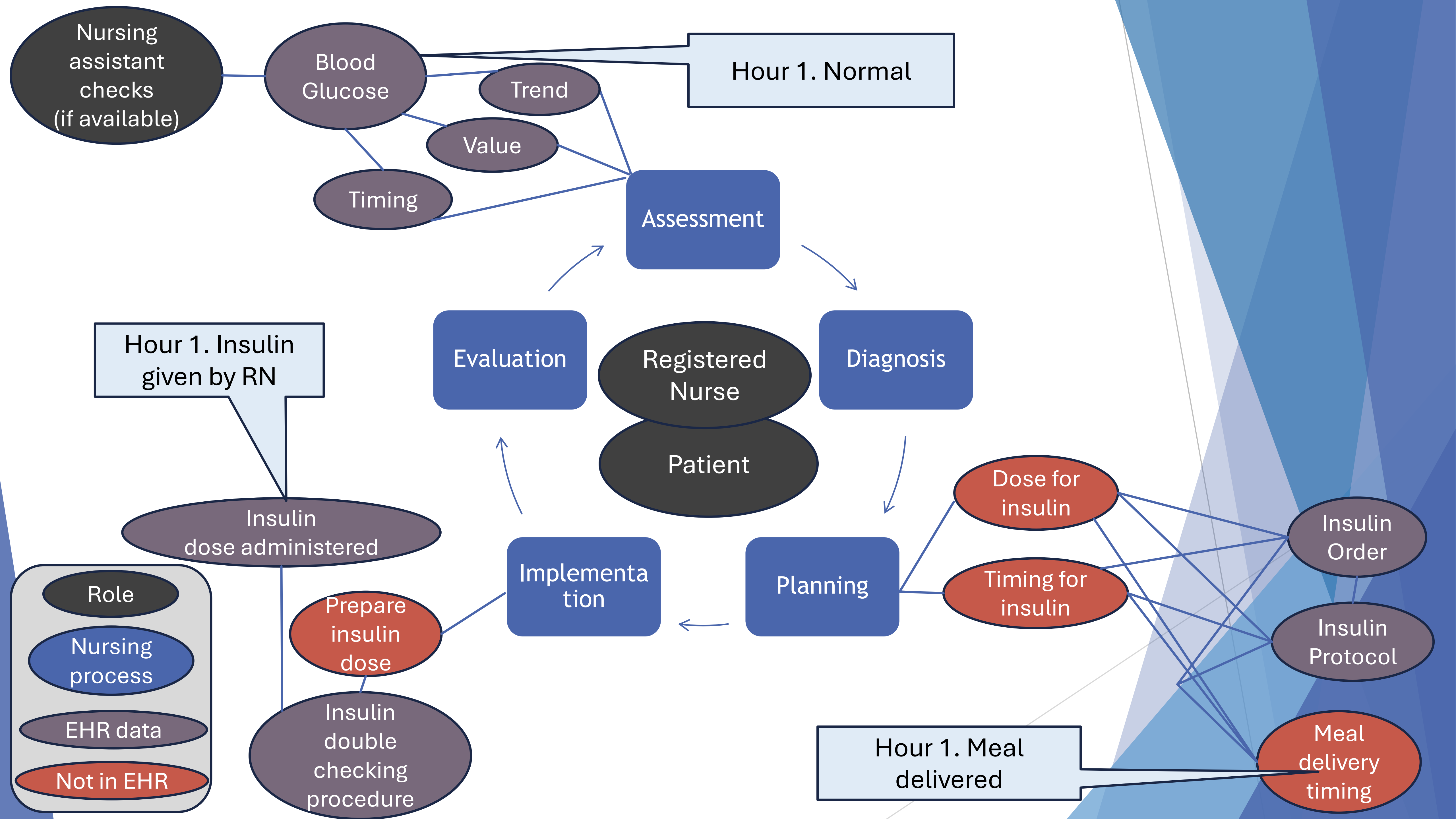
- Missing data may indicate nurse was avoiding harm
  - AI models cannot assume missing data = missed care



Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Assessment
timing
Likelihood of food intake
amount
appetite
Diet order
Food preferences
Cultural influences
Cognitive status
Eating pattern
Actual food intake
amount
timing
Evaluation
Registered Nurse
Patient
Diagnosis
Risks levels
Unstable glucose levels
Hypoglycemia
Deficient patient knowledge
Provide juice or snack (if at risk)
Insulin dose administered
Implementation
Planning
Dose for insulin
Timing for insulin
Rechecks of Blood glucose
Insulin Order
Insulin Protocol
Meal delivery timing
Prepare insulin dose
Insulin double checking procedure
Clinical prioritization
Other patients' needs
Resource and scheduling constraints
Role
Nursing process
EHR data
Not in EHR

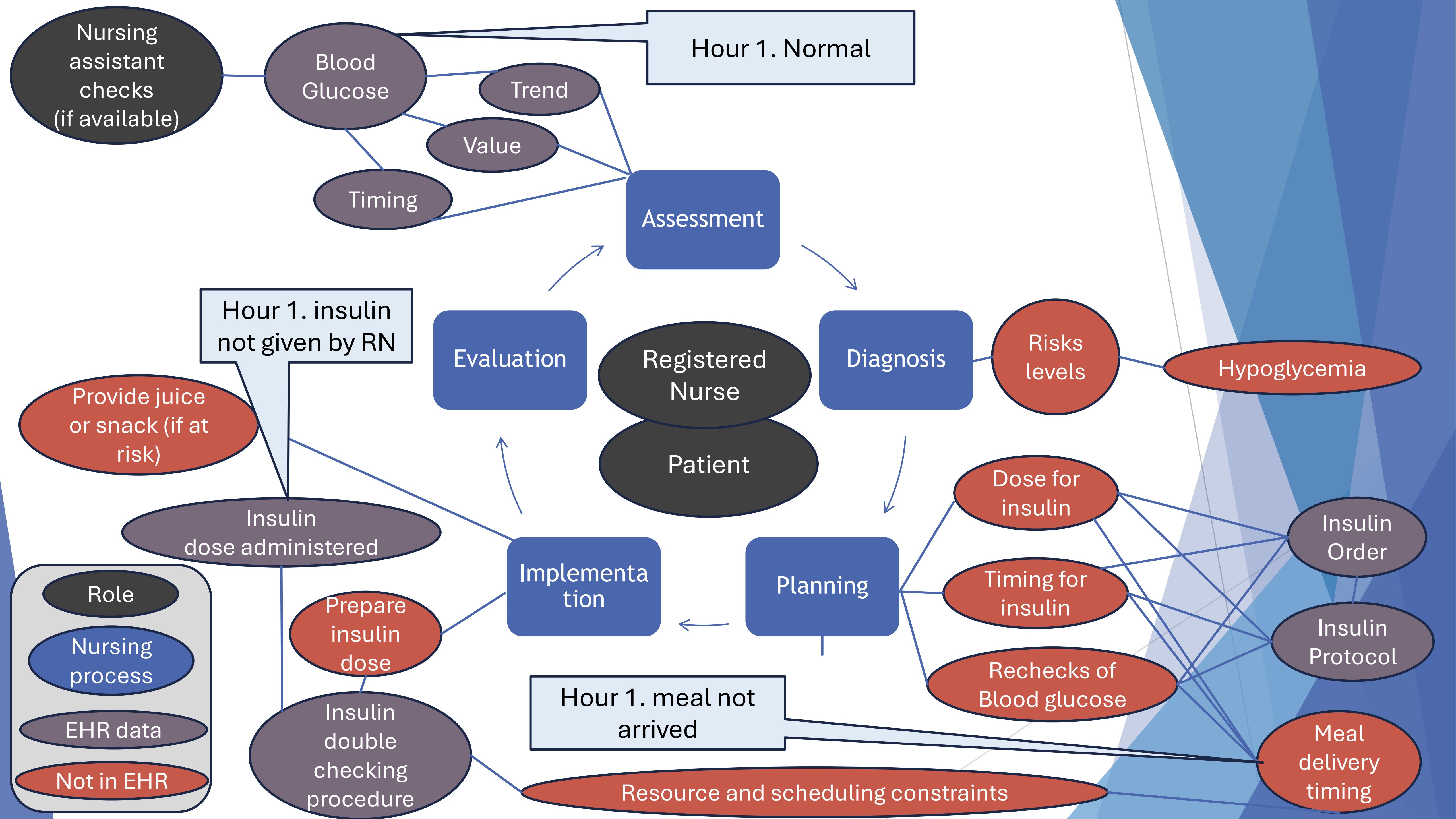
Example 1

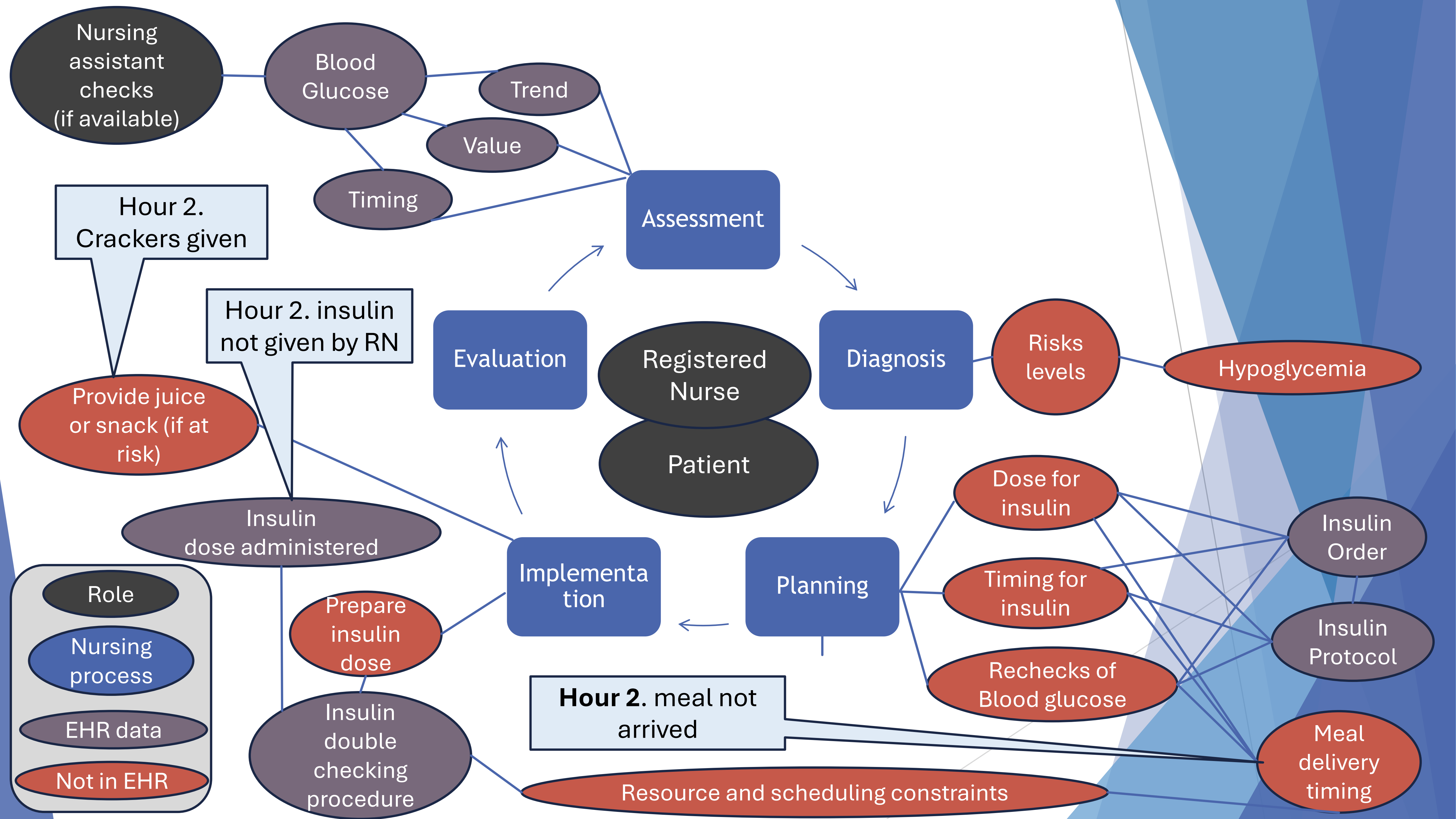
- On schedule & per protocol


Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Hour 1. Normal
Assessment
Diagnosis
Evaluation
Registered Nurse
Patient
Hour 1. Insulin given by RN
Insulin dose administered
Implementation
Planning
Dose for insulin
Timing for insulin
Insulin Order
Insulin Protocol
Prepare insulin dose
Insulin double checking procedure
Hour 1. Meal delivered
Meal delivery timing
Role
Nursing process
EHR data
Not in EHR

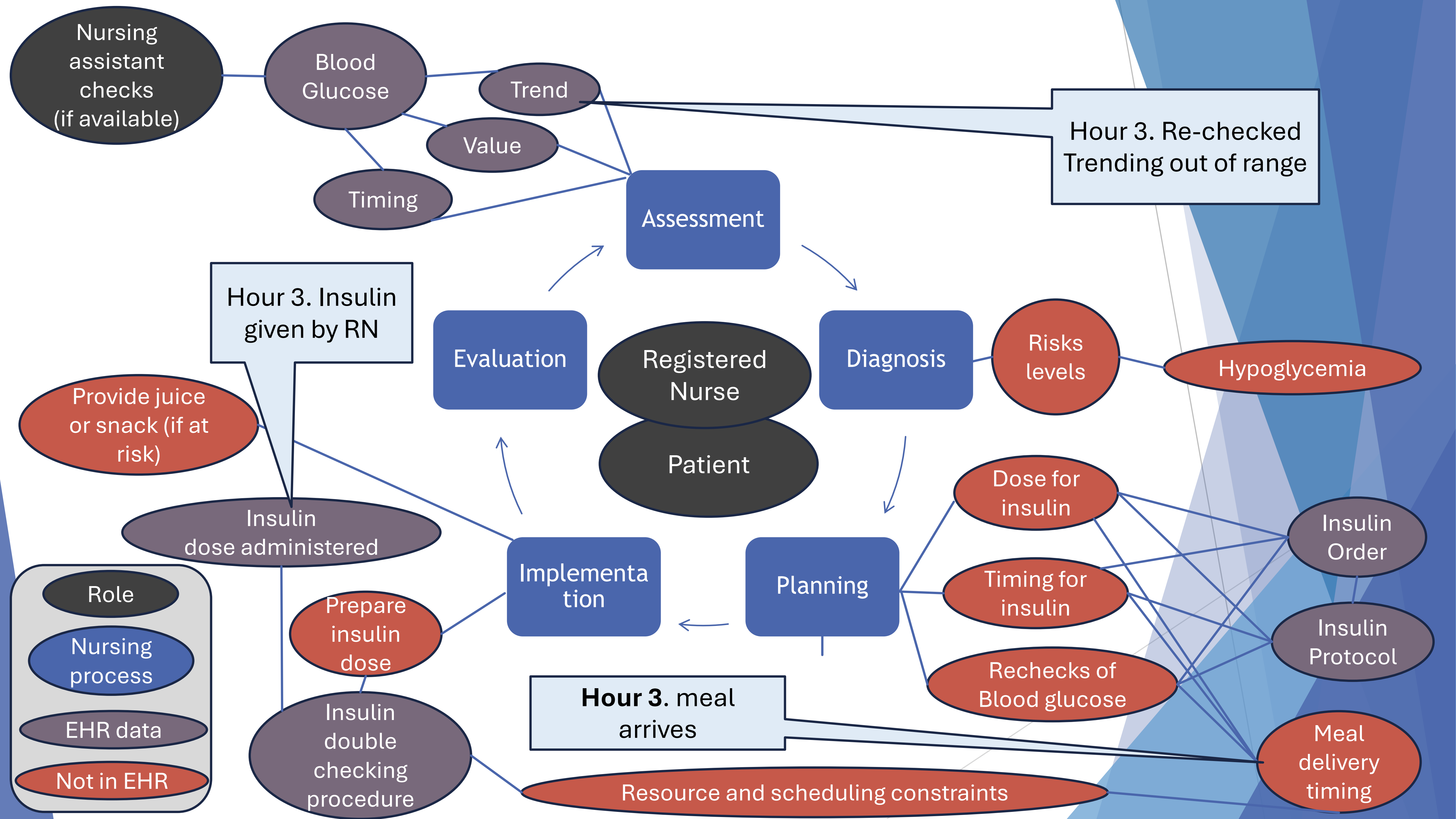
Example 2

- Nurse intervenes


Hour 1. Normal
Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Assessment
Hour 1. insulin not given by RN
Evaluation
Registered Nurse
Patient
Diagnosis
Risks levels
Hypoglycemia
Provide juice or snack (if at risk)
Insulin dose administered
Dose for insulin
Insulin Order
Timing for insulin
Insulin Protocol
Implementation
Planning
Prepare insulin dose
Rechecks of Blood glucose
Role
Nursing process
EHR data
Not in EHR
Insulin double checking procedure
Hour 1. meal not arrived
Meal delivery timing
Resource and scheduling constraints



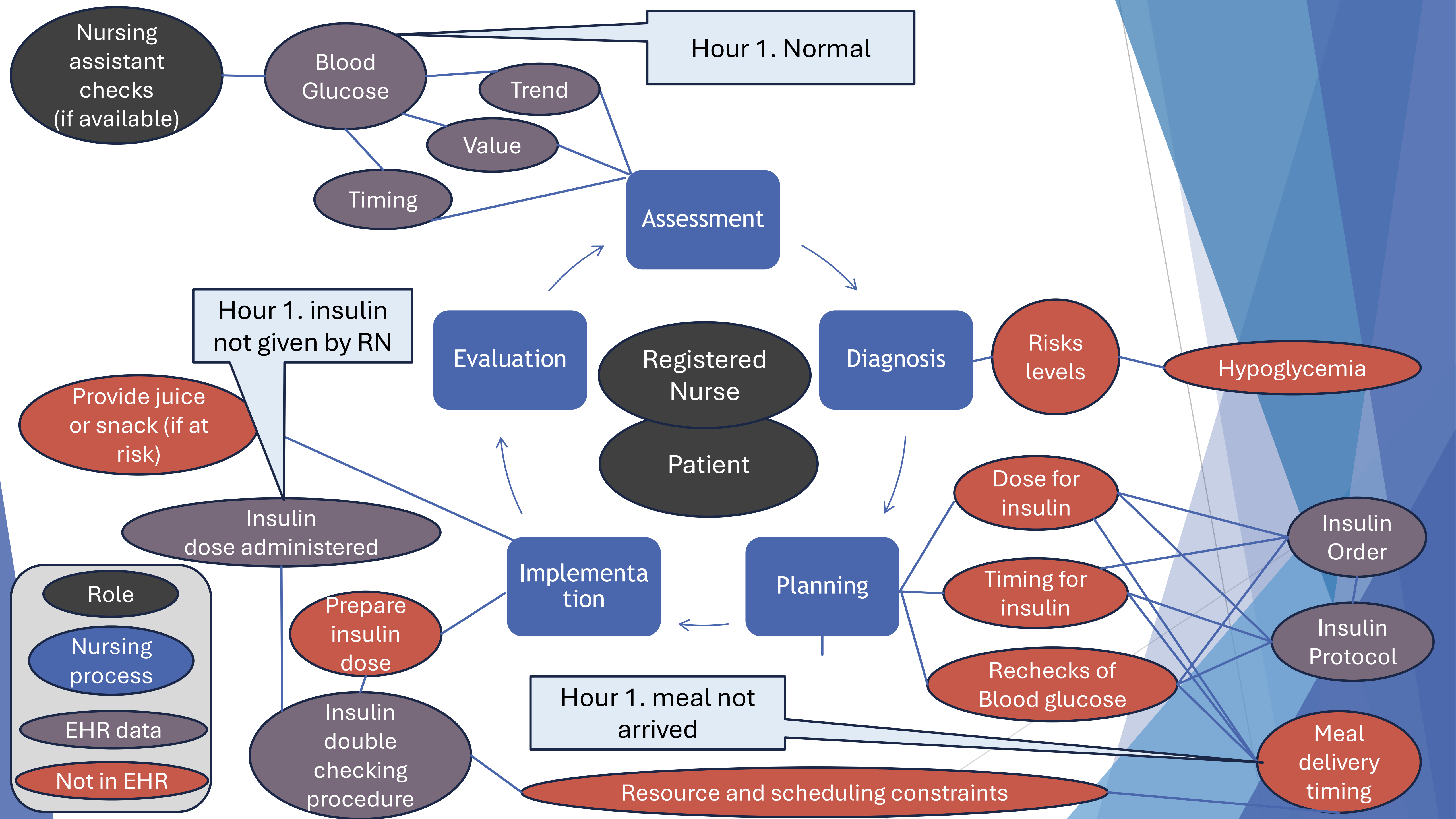
Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Assessment
Hour 2. Crackers given
Hour 2. insulin not given by RN
Evaluation
Registered Nurse
Patient
Diagnosis
Risks levels
Hypoglycemia
Provide juice or snack (if at risk)
Insulin dose administered
Implementation
Planning
Dose for insulin
Timing for insulin
Rechecks of Blood glucose
Insulin Order
Insulin Protocol
Meal delivery timing
Prepare insulin dose
Insulin double checking procedure
Hour 2. meal not arrived
Resource and scheduling constraints
Role
Nursing process
EHR data
Not in EHR

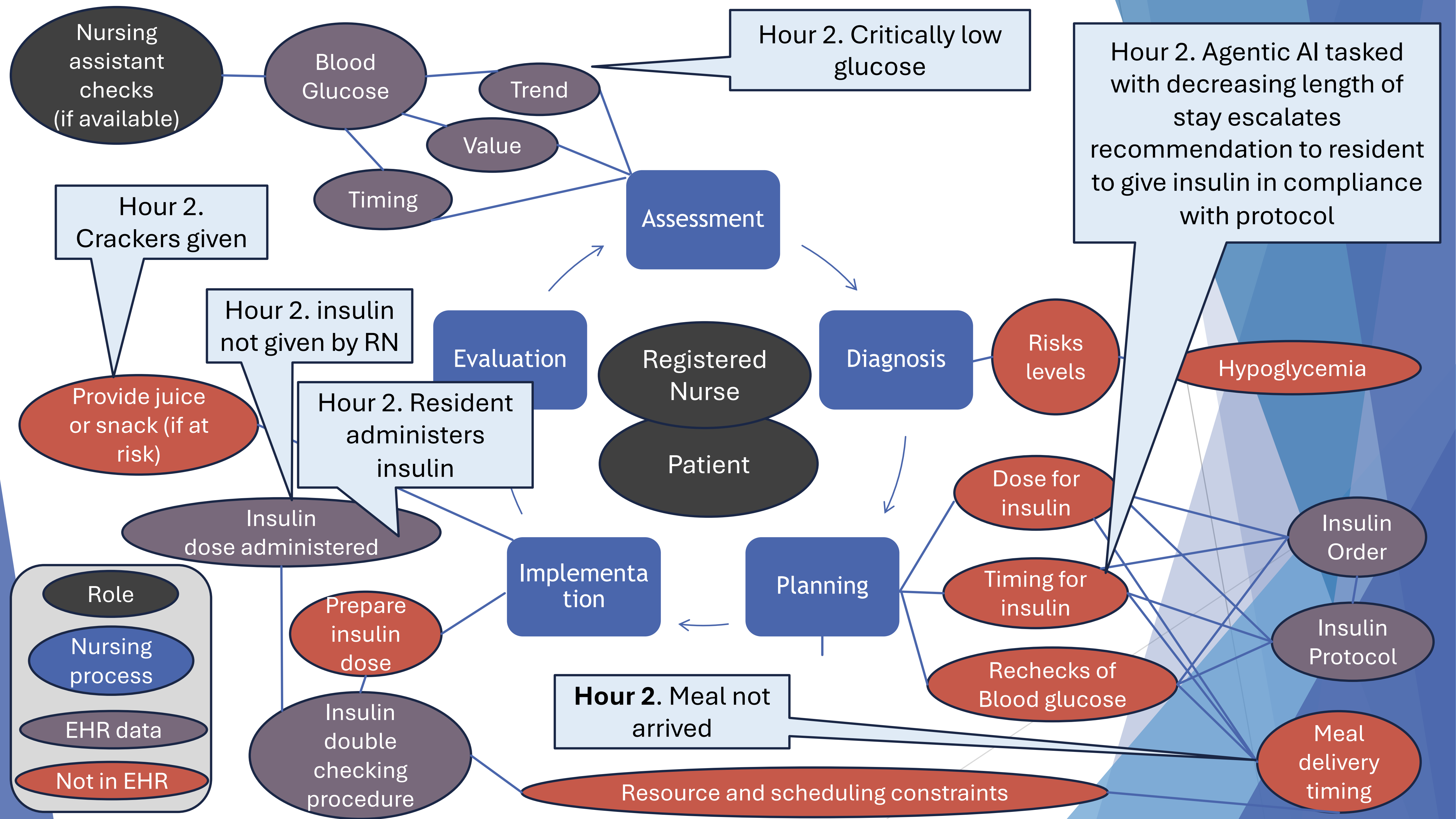


Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Hour 3. Re-checked Trending out of range
Assessment
Hour 3. Insulin given by RN
Evaluation
Registered Nurse
Patient
Diagnosis
Risks levels
Hypoglycemia
Provide juice or snack (if at risk)
Dose for insulin
Insulin dose administered
Insulin Order
Implementation
Planning
Timing for insulin
Prepare insulin dose
Insulin Protocol
Rechecks of Blood glucose
Hour 3. meal arrives
Insulin double checking procedure
Meal delivery timing
Resource and scheduling constraints
Role
Nursing process
EHR data
Not in EHR

Example 3

- Potential Risk with Agentic AI

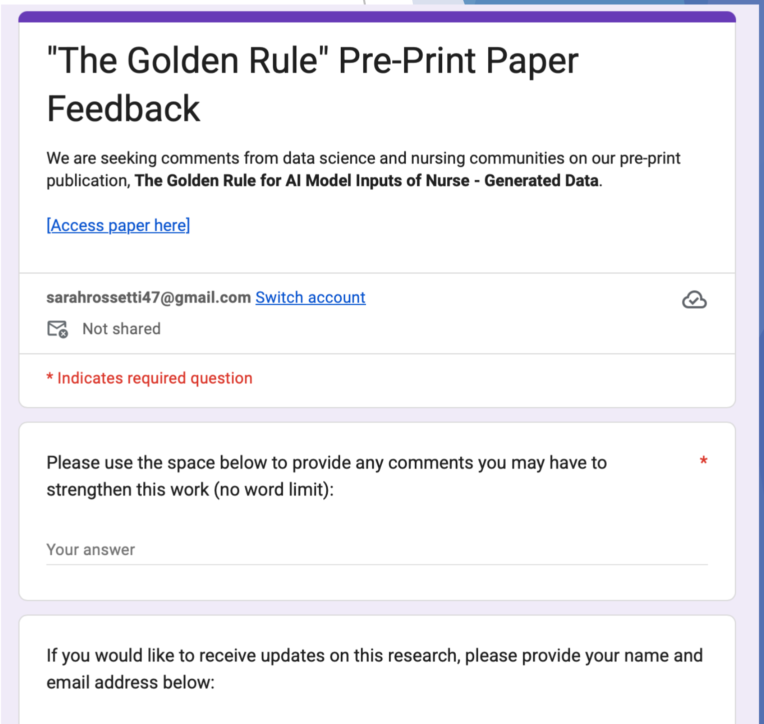

Nursing assistant checks (if available)
Blood Glucose
Hour 1. Normal
Trend
Value
Timing
Assessment
Hour 1. insulin not given by RN
Evaluation
Registered Nurse
Diagnosis
Risks levels
Hypoglycemia
Provide juice or snack (if at risk)
Patient
Dose for insulin
Insulin dose administered
Insulin Order
Role
Implementation
Planning
Timing for insulin
Nursing process
Prepare insulin dose
Insulin Protocol
Rechecks of Blood glucose
EHR data
Hour 1. meal not arrived
Insulin double checking procedure
Meal delivery timing
Not in EHR
Resource and scheduling constraints



Nursing assistant checks (if available)
Blood Glucose
Trend
Value
Timing
Hour 2. Critically low glucose
Hour 2. Agentic AI tasked with decreasing length of stay escalates recommendation to resident to give insulin in compliance with protocol
Assessment
Hour 2. Crackers given
Hour 2. insulin not given by RN
Evaluation
Registered Nurse
Patient
Diagnosis
Risks levels
Hypoglycemia
Provide juice or snack (if at risk)
Hour 2. Resident administers insulin
Insulin dose administered
Dose for insulin
Insulin Order
Timing for insulin
Implementation
Planning
Insulin Protocol
Prepare insulin dose
Rechecks of Blood glucose
Role
Nursing process
EHR data
Not in EHR
Insulin double checking procedure
Hour 2. Meal not arrived
Meal delivery timing
Resource and scheduling constraints

Golden Rule for AI Model Inputs of Nurse-Generated Data: *Do Not Assume*

Table 1. Heuristics when using nurse-generated data for safe and trustworthy AI	
1.	Do Not Assume that missing data equals missed care.
2.	Do Not Assume protocols should be followed exactly as the logic states.
3.	Do Not Assume that all data capture is equal.
4.	Do Not Assume an understanding of the process of data capture nor the temporal sequence of how data capture relates to actual care processes.
5.	Do Not Assume the clinical procedures and protocols that apply to your population.
6.	Do Not Assume that the same EHR has the same configurations and settings.
7.	Do Not Assume that all values are reliable.
8.	Do Not Assume that all structured values make sense clinically or do not vary in time.
9.	Do Not Assume a SQL query retrieved all the values needed for your modeling task.
10.	Do Not Assume the value of narrative data based on its length nor assume that low frequency fields are of low value.
11.	Do Not Assume that information will be reliably captured in the same fields over time.
12.	Do Not Assume that nursing data are statistically consistent over time, across different units, or across different institutions, nor assume that these data were extracted completely, correctly, or consistently.


"The Golden Rule" Pre-Print Paper Feedback

We are seeking comments from data science and nursing communities on our pre-print publication, **The Golden Rule for AI Model Inputs of Nurse - Generated Data**.

[Access paper here]

sarahrossetti47@gmail.com Switch account

Not shared

* Indicates required question

Please use the space below to provide any comments you may have to strengthen this work (no word limit): *

Your answer

If you would like to receive updates on this research, please provide your name and email address below:

CONCERN Early Warning System:

AI-driven Real-Time Early Warning System for Patient Deterioration

www.concernearlywarningscore.org

Lacks Variability

- ***Excessive doc requirements***
- Recording of standard of care
- Lacks a statistical signal

Good variability

- ***Nursing surveillance patterns***
- Personalized care
- Based on clinical state
- Statistical signal

assess → diagnose → plan → implement → evaluate → assess

Nurses' Increased Surveillance Patterns are an Early Predictor of Adverse Events

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

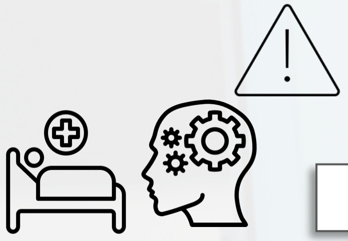
Am J Crit Care. Author manuscript; available in PMC 2013 Sep 12.
PMCID: PMC3771321
Published in final edited form as:
NIHMSID: NIHMS505735
Am J Crit Care. 2013 Jul; 22(4): 306–313.
PMID: 23817819
doi: 10.4037/ajcc2013426

Relationship Between Nursing Documentation and Patients' Mortality

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

What is CONCERN Early Warning System (EWS)?

Tacit Knowledge and Expert Behaviors



Increase in nursing surveillance

Changes in Nursing Documentation Patterns

AI- based prediction model

Multinomial Gradient Boosted Machine (GBM) model
- Prediction accuracy >97% in both acute care units and ICUs

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

Real-time CDS in EHR

CONCERN

CONCERN Levels
- = Red: "Showing signs of deterioration"
- = Yellow: "Increased risk for deterioration"
- = Green: "Low risk for deterioration"

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)	ABC 101-1	—				—	*
Concern, Pal (78yrs M)	ABC 101-2	—		—	—	—	*
Concern, Sacu (82yrs M)	ABC 101-3	—		—		—	*
Concern, Sicu (68yrs M)	ABC 101-4	—		—	—	—	*
Concern, Trans (79yrs M)	ABC 101-5	—		—	—	—	

Alerts up to 2 days earlier than other EWSs[12]

CONCERN Model Purpose - Increase Shared Team Situational Awareness

✓ 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”

Clinical Impact | Clinical Trial

Total N= 60,893 Patients

Multi-site pragmatic cluster-randomized controlled clinical trial (October 2020- October 2022)

COLUMBIA
COLUMBIA UNIVERSITY IRVING MEDICAL CENTER

NewYork-Presbyterian

Brigham and Women's Hospital
Founding Member, Mass General Brigham

Mass General Brigham
Newton-Wellesley Hospital

74 units

- 52 Acute care units (ACUs)
- 21 Intensive care units (ICUs)

Randomization

CONCERN Intervention (n=37 units)

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)	ABC 101-1	—				—	*
Concern, Pal (78yrs M)	ABC 101-2	—		—	—	—	*
Concern, Sacu (82yrs M)	ABC 101-3	—		—		—	*
Concern, Sicu (68yrs M)	ABC 101-4	—		—	—	—	*
Concern, Trans (79yrs M)	ABC 101-5	—		—	—	—	

n=33,024 patients

Usual care (n=37 units)

My patients 5 patients

Patient Name / Age / Sex	Unit/Bed	New Messages	Unacknowledged Orders	Med Due	New Rslt Flag	Reassess Pain
Concern, Martin (91yrs M)	ABC 101-1	—				—
Concern, Pal (78yrs M)	ABC 101-2	—		—	—	—
Concern, Sacu (82yrs M)	ABC 101-3	—		—		—
Concern, Sicu (68yrs M)	ABC 101-4	—		—	—	—
Concern, Trans (79yrs M)	ABC 101-5	—		—	—	—

n=27,869 patients

Included:

- 18 years and older
- Hospitalized for greater than 24 hours
- Admitted to a study unit for more than 12 hours
- Free from any in-hospital event (including discharge) until at least 6 hours after study unit admission

Excluded:

- Hospital and palliative care patients
- Patients with DNR/DNI and comfort care orders

Setting: 4 hospitals in 2 healthcare systems

CONCERN Early Warning System:

Pragmatic Clinical Trial

- ✓ *Decreased risk of Mortality by 35.6%*
- ✓ *Decreased Length of Stay over ½ day*
- ✓ *Decreased risk of Sepsis by 7.5%*
- ✓ *Enabled timely ICU transfer*

nature medicine

Article | Published: 02 April 2025

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

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

Nature Medicine (2025) | Cite this article

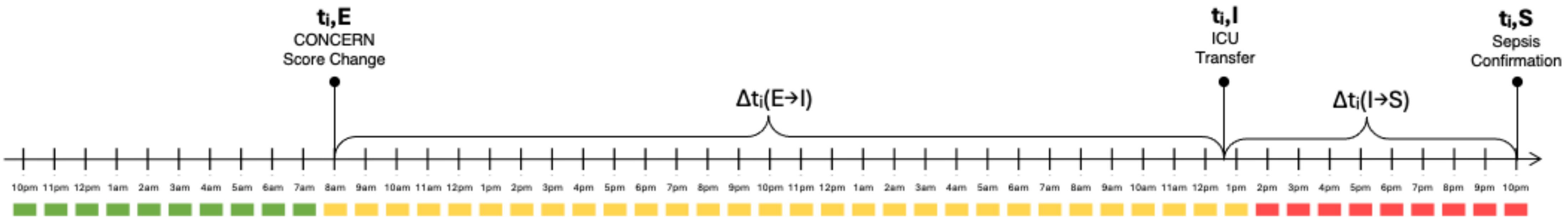
Abstract

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

Early vs Late ICU Transfer via CONCERN EWS Score Changes

- Data from multi-site clinical trial (2020-2022)

CONCERN Intervention (n=33,024) → Patients who had <u>'unanticipated ICU transfer'</u> *before* <u>confirmed sepsis</u> (n=100) → One or more CONCERN score escalation 48 hours prior to ICU transfer (n=54)



Outcome: In-hospital death vs Discharge alive

All patients who died were transferred ≥ 36 hrs. after score change

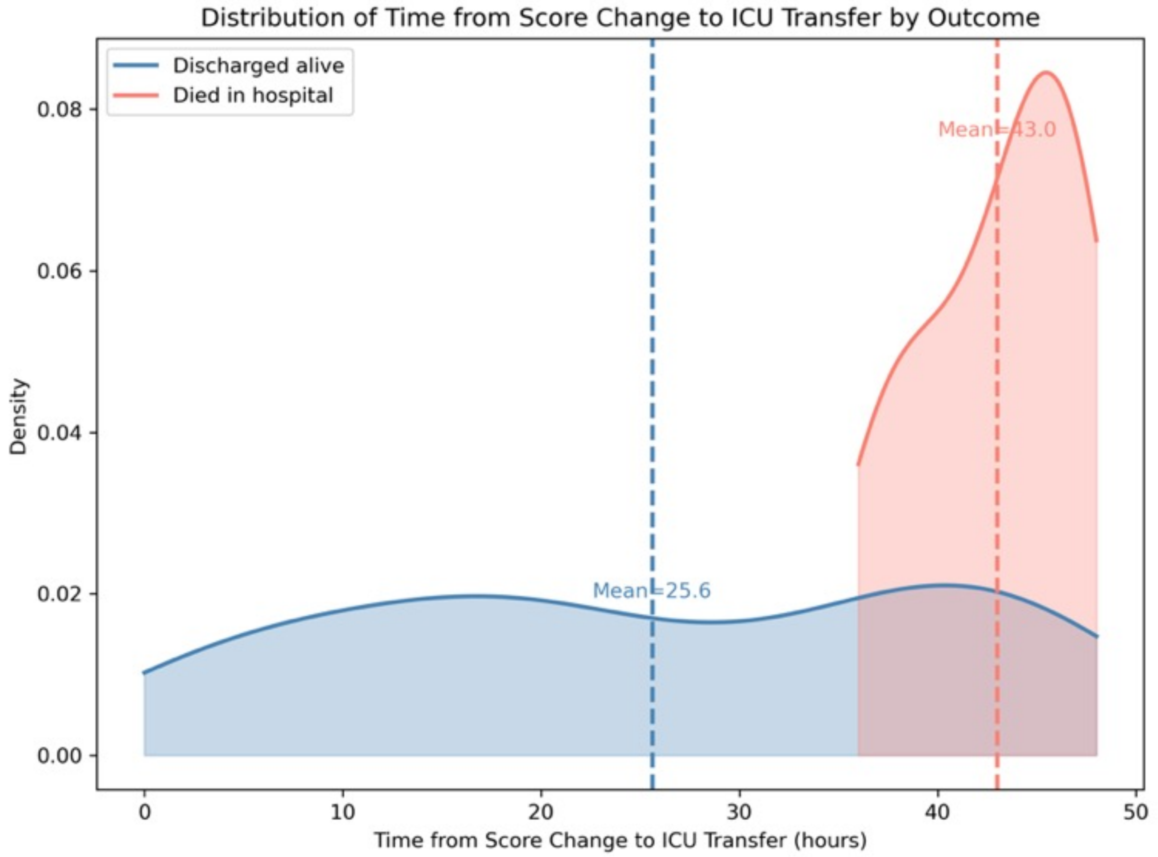


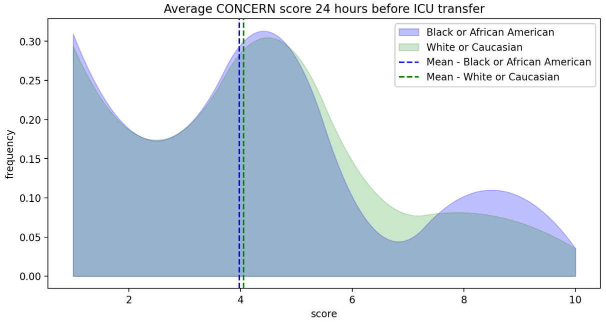
Figure 2. Kernel density estimates of score-change-to-ICU-transfer time interval by in-hospital mortality.

Each 1-hour delay of ICU transfer increased odds of death by 28%
(OR=1.28, p=0.019)

Distribution significantly different (U=371, p=0.0007**)

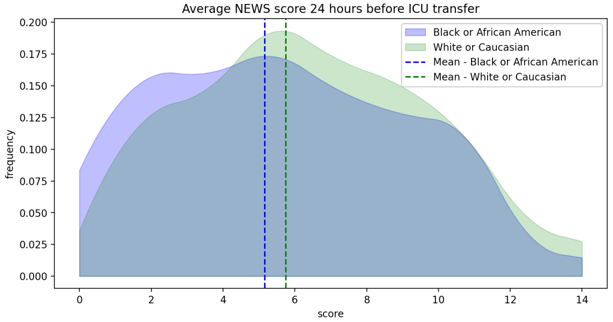
AI Fairness

CONCERN



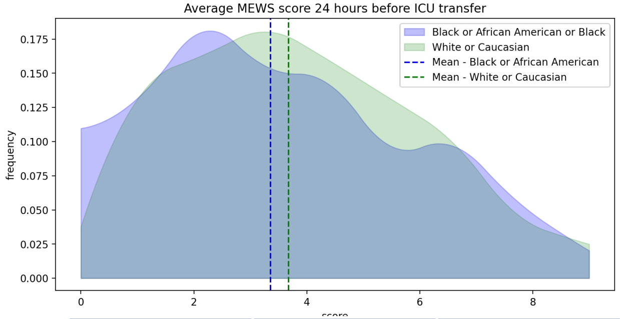
Mean - Black or African American	Mean - White or Caucasian	P-value
3.976190	4.053905	**0.210805**

National Early Warning Score (NEWS)



Mean - Black or African American	Mean - White or Caucasian	P-value
5.161055	5.752857	**0.009656**

Modified Early Warning Score (MEWS)



Mean - Black or African American	Mean - White or Caucasian	P-value
3.355838	3.673857	**0.046306**

	Primary Language		Non-English	
	English	Non-English		
Flowsheet Items	M (SD)	M (SD)	OR [95% CI]	p-value
Heart rate	47.29 (32.42)	51.68 (35.54)	1.01 [1.00-1.02]	1.00
Respiratory rate	44.77 (29.76)	47.70 (31.21)	0.99 [0.97-1.01]	0.43
Temperature	25.23 (26.52)	27.52 (28.00)	1.00 [0.99-1.01]	0.51
Blood pressure	34.82 (21.29)	36.89 (23.44)	0.99 [0.98-1.01]	0.26
SpO2	42.20 (28.46)	45.15 (28.98)	1.00 [0.98-1.03]	0.72
Comments*	**0.76 (1.46)**	**0.74 (1.41)**	**0.81[0.71-0.93]**	**<0.01****
Nursing notes	2.34 (2.81)	1.87 (2.56)	0.93 [0.87-1.00]	0.06
**p < 0.01				

Nurses Agreement with CONCERN

Categories	Total patients	Sample cases selected for chart review	Clinical record review results		
			Agreement case	Disagreement case	Agreements rate
Green Only	128	5 (random selection)	4	1	80%
Yellow Only	4	4	4	0	100%
Red Only	0	NA	NA	NA	NA
Green & Yellow	123	5 (random selection)	5	0	100%
Green & Red	1	1	1	0	100%
Yellow & Red	0	NA	NA	NA	NA
Green, Yellow, & Red	9	9*	9	0	100%
10+ score changes		4* (2 included above)	4	0	100%
Transfer to ICU		2*	2	0	100%
Sepsis		1*	1	0	100%
Transfer to the outside hospitals		6	6	0	100%
Total	265	37	36	1	97%

- * The sample includes Green, Yellow, and Red cases, covering two cases from the 10+ score changes category and three cases related to clinical outcomes (two ICU transfers and one sepsis). The clinical record review involved clinicians % agreement with the CONCERN EWS.

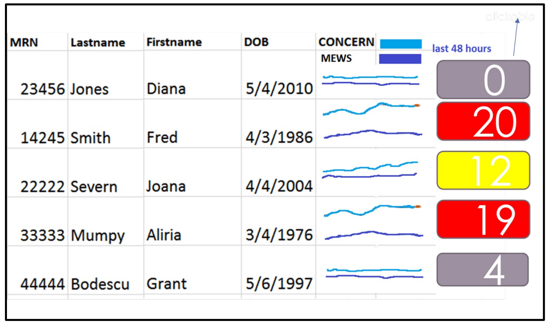
Exploring the Implementation Experience and Use of CONCERN Early Warning System in a Rural Community Hospital: A Mixed Method Convergent Approach

Youngjin Lee, PhD, RN[1,2,3], Min-Jeoung Kang, PhD, RN[1,2], Veysel K. Baris, PhD, RN[1,2], Graham Lowenthal[1], Sarah C. Rossetti, PhD, RN, FAAN, FACMI, FAMIA, FIAHSI[4,5], Kenrick D. Cato, PhD, RN, CPHIMS, FAAN[6], Rachel Y. Lee, PhD, RN[4], Janna Kramer, MS-HIA, RN[7], Richard Huffam, BSN[7], Patricia C. Dykes, PhD, RN, FAAN, FACMI, FIAHSI [1,2]

[1]Brigham and Women's Hospital, Boston, MA; [2]Harvard Medical School, Boston, MA; [3]College of Nursing Research Institute of Nursing Science, Ajou University, Suwon, South Korea; [4]Columbia University, Department of Biomedical Informatics, New York, NY; [5]Columbia University, School of Nursing, New York, NY; [6]University of Pennsylvania, Philadelphia, PA;[7]Martha's Vineyard Hospital

Extensive User-Centered Design & Simulation Studies with RNs and Prescribing Providers

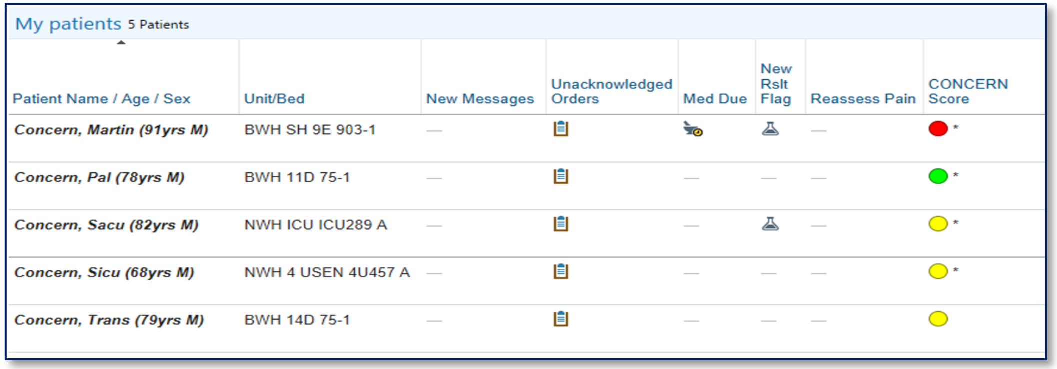
Low Fidelity Prototypes



MRN	Lastname	Firstname	DOB	CONCERN MEWS	last 48 hours
23456	Jones	Diana	5/4/2010		0
14245	Smith	Fred	4/3/1986		20
22222	Severn	Joana	4/4/2004		12
33333	Mumpy	Aliria	3/4/1976		19
44444	Bodescu	Grant	5/6/1997		4

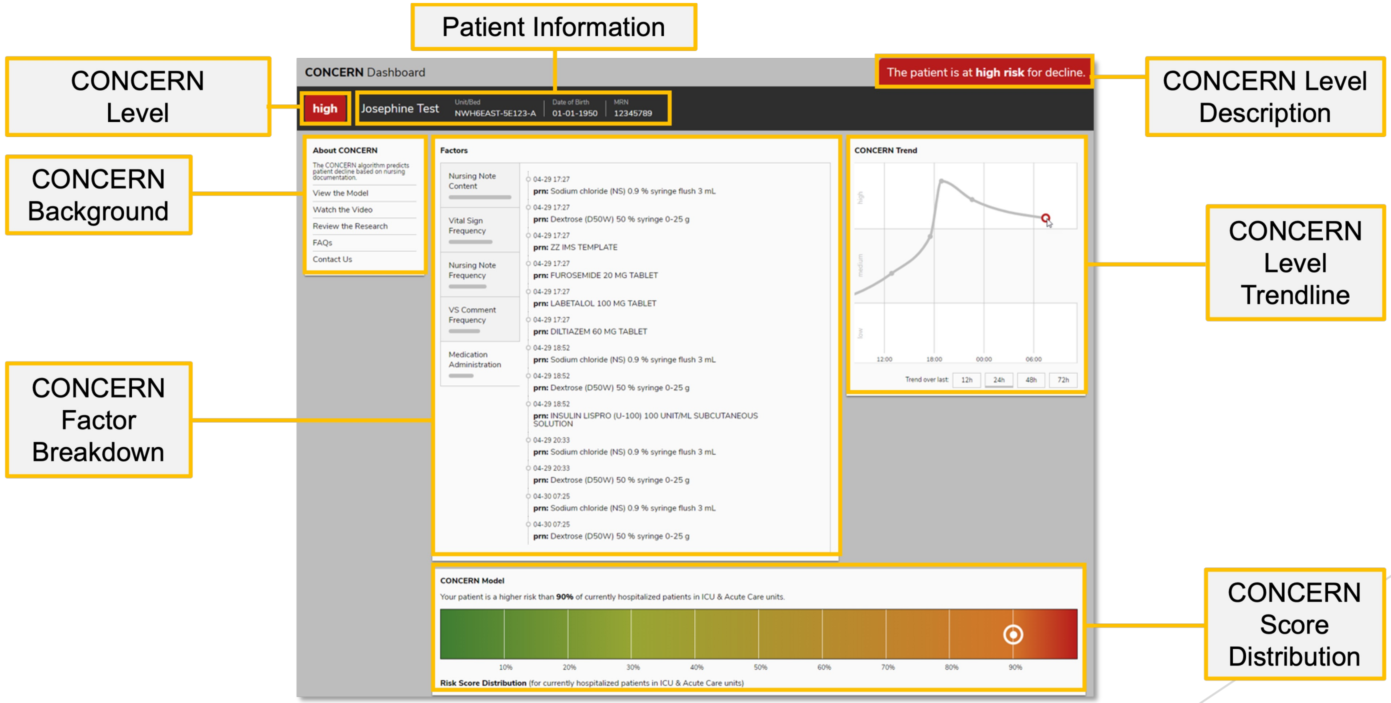
High Fidelity Prototypes

Final Design



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	—		—	—	—	



Scaling & Spreading CONCERN

Funded by American Nurses Foundation

CONCERN EWS Implementation Toolkit

- Home
- Login
- Register
- About CONCERN EWS
- Usage and Licensing
- CONCERN EWS Implementation Toolkit

CONCERN Early Warning System (EWS)

The **CONCERN Early Warning System (EWS)** is a powerful tool that uses Artificial Intelligence (AI) to help doctors and nurses detect when hospitalized patients might be getting worse— **two days earlier** than other warning systems. This early prediction gives healthcare teams **more time to take action**, preventing serious complications. What makes CONCERN special is that it's built on **nurses' expertise and real-life observation patterns** in both regular hospital units and intensive care units. Because of this, it has been widely accepted by doctors, nurses, and other care providers. As part of eight years of funding by the **National Institutes of Health (NIH)**, CONCERN EWS was developed and evaluated at **Columbia University Irving Medical Center (CUIMC) and tested in a large clinical trial at CUIMC and Mass General Brigham**, which found that patients whose care teams used CONCERN had:

✔ **36% lower risk of death**
✔ **11% shorter hospital stays**
✔ **7.5% lower risk of developing sepsis** (a life-threatening infection)
✔ **25% more timely transfers to the ICU when needed**

These improvements are largely due to **CONCERN's ability to predict problems two days in advance**, allowing care teams to step in sooner. Unlike many AI-based healthcare tools, CONCERN has been **successfully tested in real hospitals** and proven to work across multiple locations. An early version of the predictive model was even independently validated by researchers at the **University of Utah**, who found it worked well on data from over **200 hospitals**. Current efforts were expanding the system to **pediatric hospitals and emergency departments**, in collaboration with **several major medical centers**, including the University of Colorado, Mass General Brigham, Washington University in St. Louis, and Vanderbilt University Medical Center. During their **eight years of NIH funding**, the CONCERN research team was able to bring their vision from a novel idea based on nursing practice to a validated AI-based tool in the hospital helping healthcare teams save lives by predicting problems before they become critical.

We encourage interested hospitals to join the **CONCERN Initiative** to receive the toolkit, training, and implementation materials. Please fill out our registration form to receive access to the complete toolkit; there is no charge to join our initiative.

If you have questions, please reach out to the CONCERN team at CONCERN-EWS@cumc.columbia.edu.

Screenshot

COLUMBIA | Columbia University Department of Biomedical Informatics

DBMI Home | News & Events | Research | People | Prospective Students | Academics | Resources

CONCERN Toolkit Resources

Getting Started

- + Getting Started Tools
- + Definitions
- + Readiness Assessment Tools
- + FAQs

Executive Leader Stakeholder Engagement

- + Executive Leadership Engagement Tools
- + Financial Consideration Tools
- + Governance Tools

Technical Stakeholder Engagement

- + Technical Implementation Tools
- + Model Calibration & Bias Tools
- + Evaluation Measure Tools

Clinical End-User Engagement

- + Clinical Practice and Documentation Tools
- + Sustainability & Spread Tools

Scaling & Spreading CONCERN *(adult inpatients)*

Washington University in St. Louis
School of Medicine

Vanderbilt University
Medical Center

CONCERN Models: Reproducible & Generalizable across Adult ICUs from > 200 Hospital

> J Biomed Inform. 2025 Sep:169:104887. doi: 10.1016/j.jbi.2025.104887. Epub 2025 Jul 27.

Conceptual framework for prediction models of patient deterioration based on nursing documentation patterns: reproducibility and generalizability with a large number of hospitals across the United States

Yik-Ki Jacob Wan [1], Samir E Abdelrahman [1], Julio C Facelli [1], Karl Madaras-Kelly [2], Kensaku Kawamoto [1], Deniz Dishman [3], Samuel R Himes [1], Kenrick Cato [4], Sarah C Rossetti [5], Guilherme Del Fiol [6]

Affiliations + expand

PMID: 40730293 PMCID: PMC12321195 DOI: 10.1016/j.jbi.2025.104887

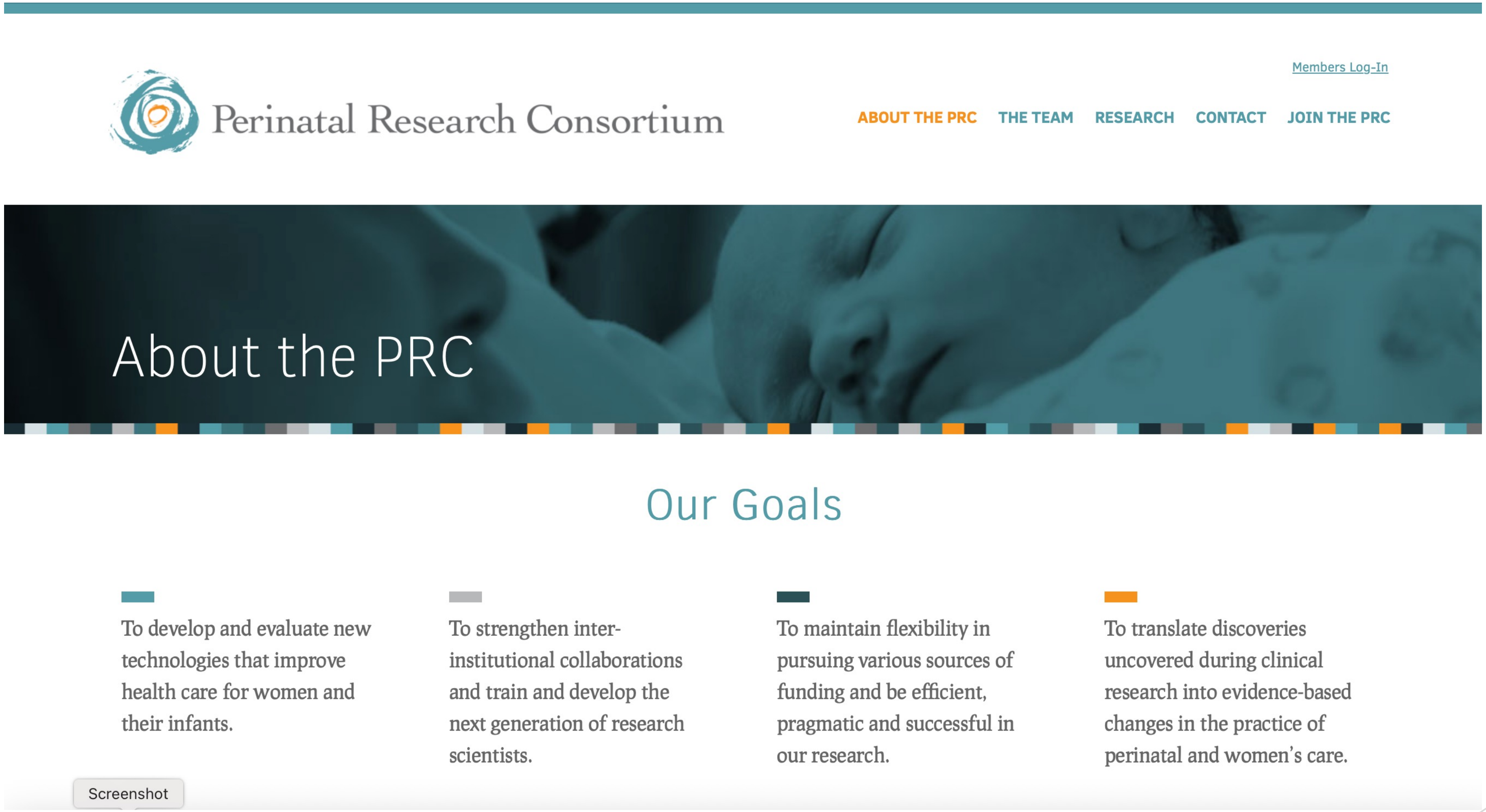
Abstract

Objective: The Health Process Model (HPM)-ExpertSignals Conceptual Framework posits that healthcare professionals' patient care behaviors can be used to predict in-hospital deterioration. Prediction models based on this framework have been validated using data from 4 hospitals within two healthcare systems. As clinician-system interactions may differ across organizations, this study aimed to evaluate the reproducibility and generalizability of the underlying conceptual framework using data from over 200 hospitals across the US.

Methods: This study used eICU-CRD, a publicly accessible dataset with data from 208 US hospitals. A logistic regression model was developed to predict in-hospital deterioration following the HPM-ExpertSignals conceptual framework. To test its reproducibility, patients were randomly split into training and testing datasets. After bootstrap testing of the model, the mean precision-

eICU Collaborative Database

Applying CONCERN Modeling to Labor and Delivery



Funding: *The Eunice Kennedy Shriver* National Institute of Child Health and Human Development (NICHD) (UH3HD111247, R01HD104943).

CONCERN Logic Model for Pediatrics

Patient Stable

At-Risk

Deteriorate

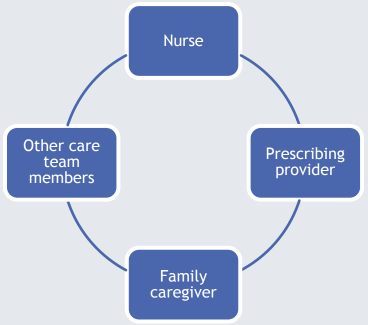
Identification of Patients at Risk

CONCERN

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)	ABC 101-1	—				—	*
Concern, Pal (78yrs M)	ABC 101-2	—		—	—	—	*
Concern, Sacu (82yrs M)	ABC 101-3	—		—		—	*
Concern, Sicu (68yrs M)	ABC 101-4	—		—	—	—	*
Concern, Trans (79yrs M)	ABC 101-5	—		—	—	—	

↑ Care Team Situational Awareness



↑Team communication

Timely Escalation of Care

E.g., early, non-urgent ICU transfer

Improved Outcomes

↓ (Ultra) urgent ICU transfer
↓ Sepsis
↓ Mortality

Adapting CONCERN to Children

- What new or different data points are needed to accurately predict worsening among children?
- Are caregivers or patients being treated differently based on demographic ?
- If nurses' concerns helped make better predictions, would families' concerns help even more?

Nursing Surveillance & AI

Nurses may make it look easy to put patients at ease, but there are costs to unprotected time

DATA, SCIENCE, AND NURSING VALUE

Nursing Surveillance from Invisible to Measurable to Indispensable: The CONCERN Early Warning System Trial

Sarah C. Rossetti, Kenrick Cato

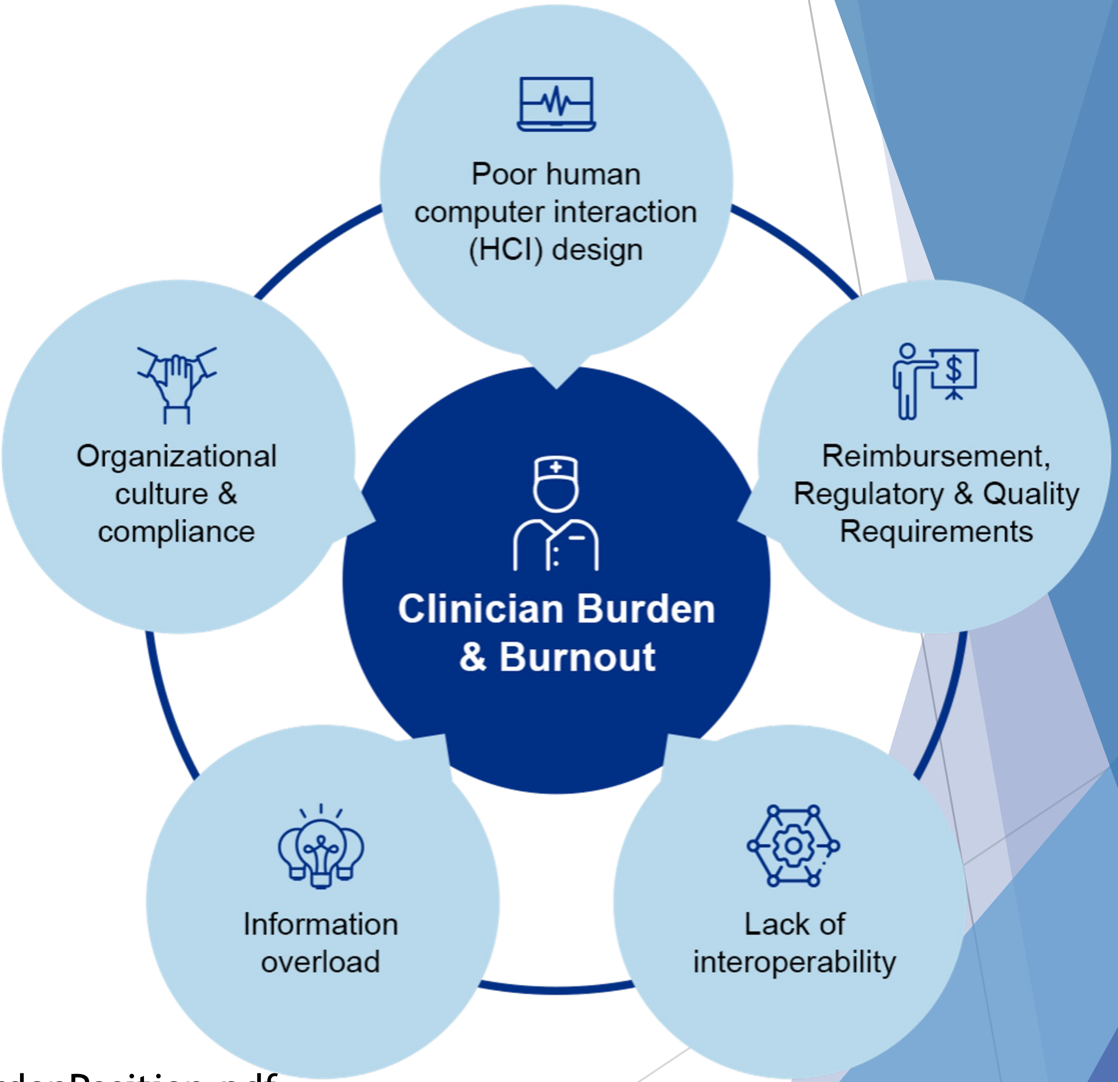
Authors and Affiliations >

Nursing Economic$ 43(5):p 253-258, September-October 2025. | ***DOI:*** 10.62116/NEC.2025.

Abstract

Excessive documentation burdens undermine nurses' ability to effectively perform the valuable and lifesaving skill - expert nursing surveillance. This article discusses the de and implementation of the CONCERN Early Warning System, an artificial intelligence al measures nursing surveillance by predicting deterioration of hospital patients, and the that predictive score to the interdisciplinary care team.

A Wicked Problem



Source: https://www.ania.org/assets/documents/position/ehrBurdenPosition.pdf

Opportunities for AI to Leapfrog Decision Support with Burden Reduction

Fully Automated

AI to fully complete a task

Potential Examples:
burdensome/administrative task not a part of professional practice

Semi-automated

AI to complete part of a task

Potential Examples:
documentation of action performed by clinician

Clinician in the Loop

AI to guide clinicians' reasoning and/or subsequent actions.

Potential Examples:

- Contextualizing information to current situation
- Prioritizing and filtering recommendations to account for clinical complexities

Ambient AI: Passive inputs (audio, sensors) to automate data capture tasks

Potential Game Changer

- *Reducing burnout*
- *Reducing documentation burden*
- *Increasing data completeness*
- *Enhancing care relationships*

Potential Pitfalls

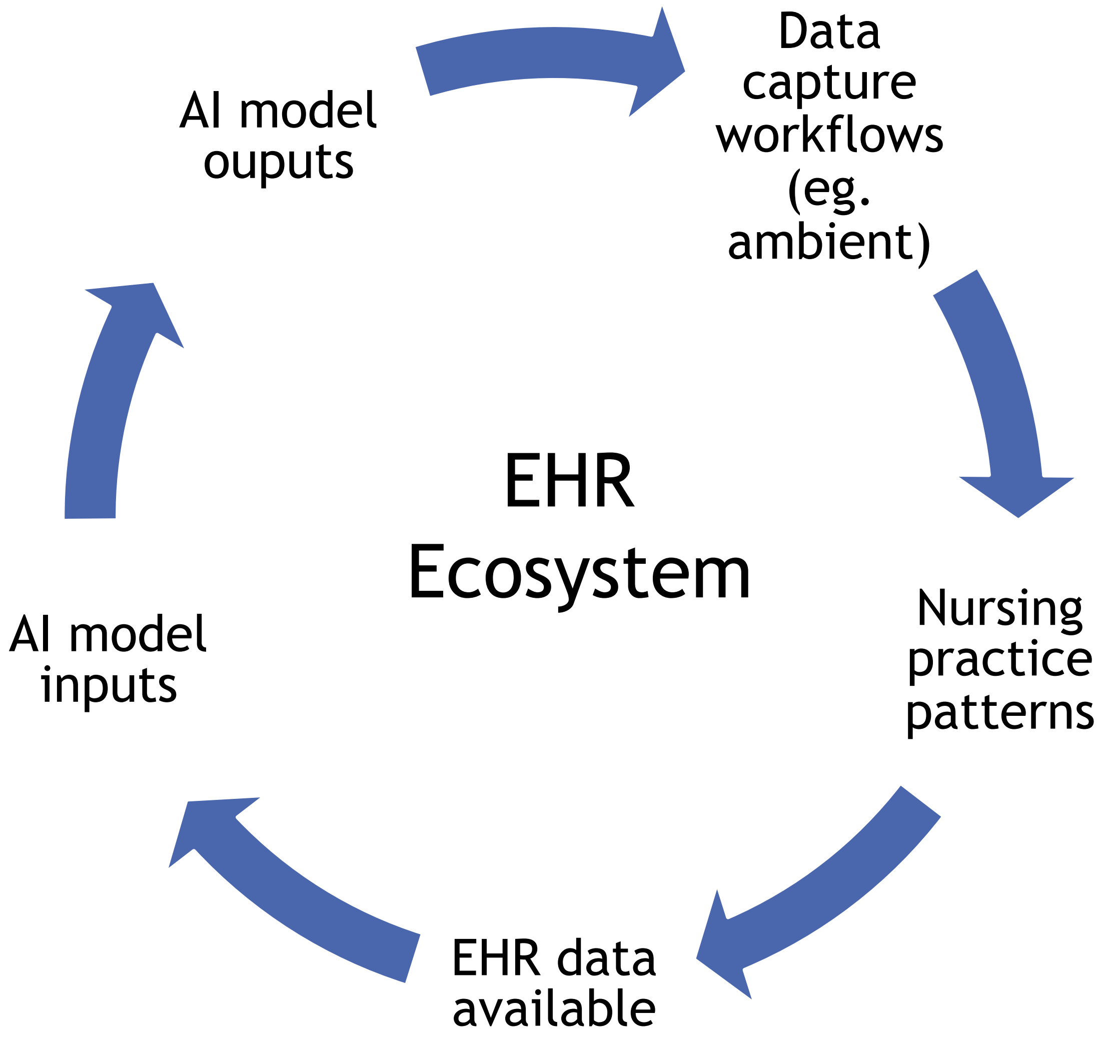
- *Unintended practice changes*
- *Not monitoring for new inefficiencies, errors, and burdens*
- *Overreliance on clinician and patient vigilance*
  - *Ignoring cognitive science principles*
- *Defaulting to labels of "system training issues" and user blame*

Need a Culture of AI Safety

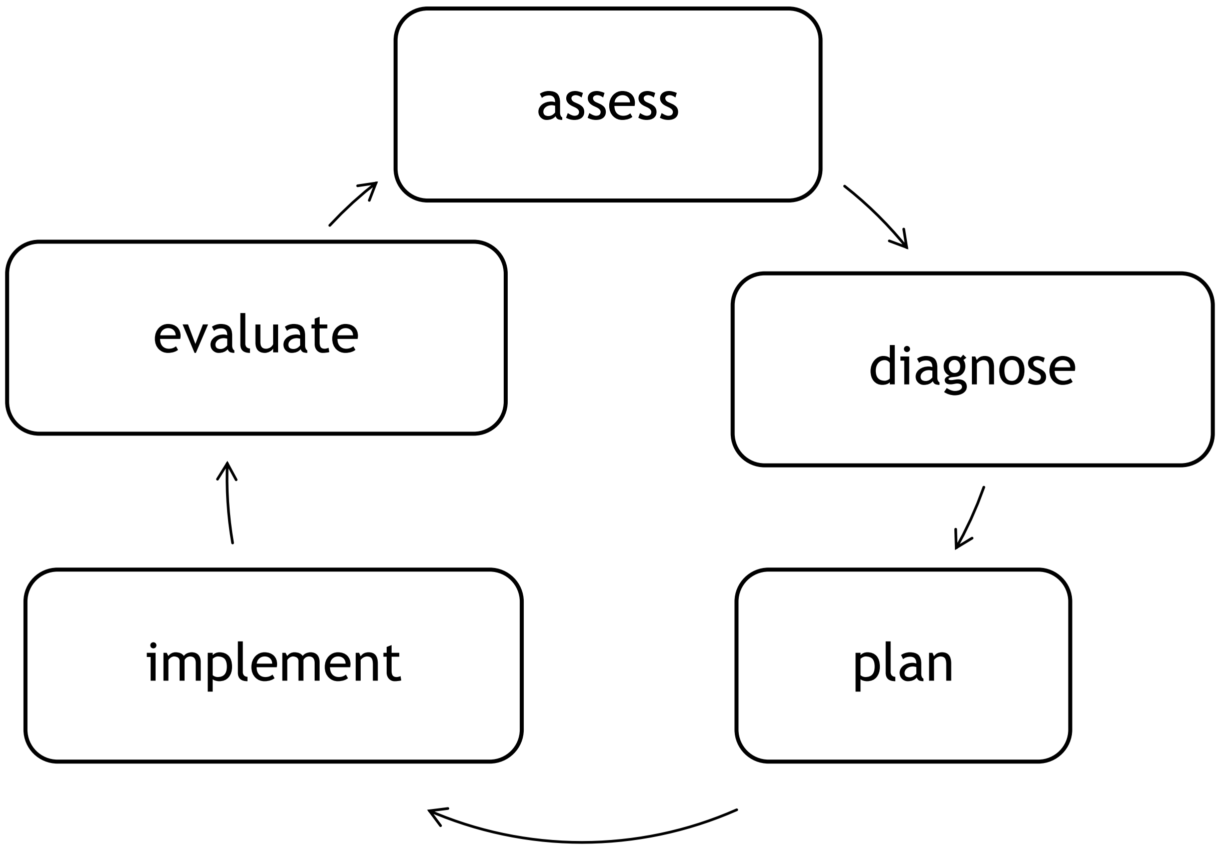
- *Conditions that enable clinician & patient agency to influence AI*
  - *Training simulations*
- *Clinical environment that makes vigilance & feedback easy*
  - *New generation of AI-based feedback tools*
    - *Fast, intuitive, and effortless at the point of care*
    - *Actually used*
    - *Multi-modal*

Adler-Milstein et al., The Limits of Clinician Vigilance as an AI Safety Bulwark JAMA, 2024;331;(14):1173-1174

AI likely will force new documentation & practice patterns



CONCERN EWS models nurses' behavior



EndBurden Study

Natural experiment of nurses' behavior when documentation requirements were relaxed during the COVID-19 pandemic

The hope for the future of nursing practice data

When free to decide and under high workloads nurses streamlined charting to focus on information that drives care decisions and team communication and coordination

e.g., vital signs, respiratory assessment, neurological assessment

Maintained consistent levels of "essential" clinical data capture

Documented less regulatory information that is already standard of care for all patients

e.g., patient re-positioning, safety equipment at bedside, arm band on

Summary

- Nursing perspectives on AI

- Knowing and respecting the arena brings clarity to Human-Centered AI

- Opportunities and risks of AI in nursing
  - burden reduction
  - data quality
  - linear protocols vs complexities of care

- Nursing Surveillance saves lives

- Protect that time
- Great optimism for the future of nursing practice data

"In terms of the safety aspect, there's some reservations, but mostly I feel as if we're [taking] the right steps. ***We need to get the right people involved to make it safe and show the data that it is safe****…it's going to take time for that to happen because within healthcare…we're affecting patients, it can be slow. But I find it very optimistic."*

(RN, 2025)

Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data (SC2K)

SC2K Team

Columbia University

- Sarah Rossetti, PhD, RN, FAAN, FACMI, FAMIA, FIAHSI
- Shalmali Joshi, PhD
- Varsha Varkhedi, BS

University of Pennsylvania

- Kenrick Cato, PhD, RN, CPHIMS, FAAN, FACMI

University of Colorado

- David Albers, PhD

University of Utah

- Vicky Tiase, PHD, RN-BC, FAMIA, FNAP, FAAN

Consultant

- Amy Finnegan, PhD

Advisory Board

- Noemie Elhadad, PhD, *Columbia University*
- Hojjat Salmasian, MD, MPH, PhD, *Children's Hospital of Philadelphia*
- Anna Schoenbaum, DNP, MS, RN, NI-BC, FHIMSS, *University of Pennsylvania*
- Amanda Hessels, PhD, MPH, RN, CIC, FAPIC, FAAN, *Columbia University*

Columbia University Irving Medical Center
Columbia School of Nursing
Columbia University Department of Biomedical Informatics
University of Colorado Anschutz Medical Campus
Penn Nursing
Health University of Utah

This project is supported by the Assistant Secretary for Technology Policy (ASTP) of the U.S. Department of Health and Human Services (HHS) under 90AX0042/01-02, Scalable, Shareable, and Computable Clinical Knowledge for AI-Based Processing of Hospital-Based Nursing Data, $998,903. This information or content and conclusions are those of the author and should not be construed as the official position or policy of, nor should any endorsements be inferred by ASTP, HHS, or the U.S. Government. PI Contact: Sarah Rossetti, RN, PhD

ASTP Assistant Secretary for Technology Policy

Essential **N**urse **D**ocumentation: Studying EHR Burden during COVID-19 (**ENDBurden**)

Team Members

Columbia University

- **Sarah Rossetti, PhD, RN**
- **Kenrick Cato, PhD, RN**
- **Haomiao Jia, PhD**
- **Jennifer Thate, PhD, RN, CNE**
- **Temmi Daramola**
- **Amy Finnegan, PhD**
- **Pinyue Vicky Wang**

Washington University

- **Po-Yin Yen, PhD, RN**
- **Albert Lai, BS, MA, MS, PhD**
- **Rosemary Mugoya, BSN, Nursing**
- **Hao Fan, MBBS**
- **Jay Rodriguez**

Columbia Columbia University Department of Biomedical Informatics
Washington University in St. Louis School of Medicine
Institute for Informatics (I^2)

This work is funded by the Agency for Healthcare Research and Quality (AHRQ): AHRQ R01HS028454

AHRQ Agency for Healthcare Research and Quality

Thank you to all the nurses who have participated in these research studies to share their expertise!

CONCERN Team

CONCERN

Columbia University

- Sarah Rossetti, PhD, RN, FAAN, FACMI, FAMIA, FIAHSI
- Haomiao Jia, PhD
- Kriste Krstovski, PhD
- Jennifer Withall, PhD, RN
- Rachel Lee, PhD, RN
- Brandon Lau
- Temmi Daramola

University of Pennsylvania

- Kenrick Cato, PhD, RN, CPHIMS, FAAN, FACMI

University of Colorado

- David Albers, PhD

Mass General Brigham

- Patricia Dykes, PhD, RN, FAAN, FACMI
- Sandy Cho, MPH, BSN, RN-BC
- Graham Lowenthal, BA

Vanderbilt University

- Catherine Ivory, PhD, NI-BC, NEA-BC, FAAN
- Brian Douthit, PhD, RN, NI-BC

Washington University

- Po-Yin Yen, PhD, RN
- Albert Lai, PhD, FACMI, FAMIA
- Adam Wilcox, PhD, FACMI
- Lisa Kidin, PhD, RN
- Michele Butkiewicz, MSN, RN
- Marilyn Schallom, PhD, MSN

Advisory Board

Informatics Experts

- Suzanne Bakken, PhD, RN, FAAN, FACMI, *Columbia University*
- David W. Bates, MD, MS, FACMI, *Brigham and Women's Hospital*
- Bonnie L. Westra, PhD, RN, FAAN, FACMI, *University of Minnesota*

Clinical Nursing Subject Matter Experts

NYP Site

- Monika Tukacs, BSN, RN, CCRN
- Robert Schroeder, RN
- Amy Moynihan, RN
- Colleen Schneiderman, RN
- Jennifer Osborne, RN
- Leo Rotter, BSN, RN

MGB Site

- Sarah Beth Thomas, BSN, RN

NWH Site

- Hailey Poole, RN

Columbia University Irving Medical Center
Columbia School of Nursing
Columbia University Department of Biomedical Informatics
Center for Community-Engaged Health Informatics and Data Science
Brigham and Women's Hospital Founding Member, Mass General Brigham
Mass General Brigham Newton-Wellesley Hospital
NewYork-Presbyterian
University of Colorado Anschutz Medical Campus
Vanderbilt University Medical Center
Washington University in St. Louis School of Medicine
Penn Nursing

This project 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 National Institutes of Health or ANF

NIH NINR American Nurses Foundation Reimagining Nursing

Thank you!

Sarah Rossetti, RN, PhD, FACMI, FAMIA, FAAN

sac2125@cumc.columbia.edu