Using AI to Advance Nursing & Health: Tools, Pitfalls, and Practical Workflows

Presented by Max Topaz, PhD, RN, MA, FAAN, FIAHSI, FACMI

 by Maxim Topaz

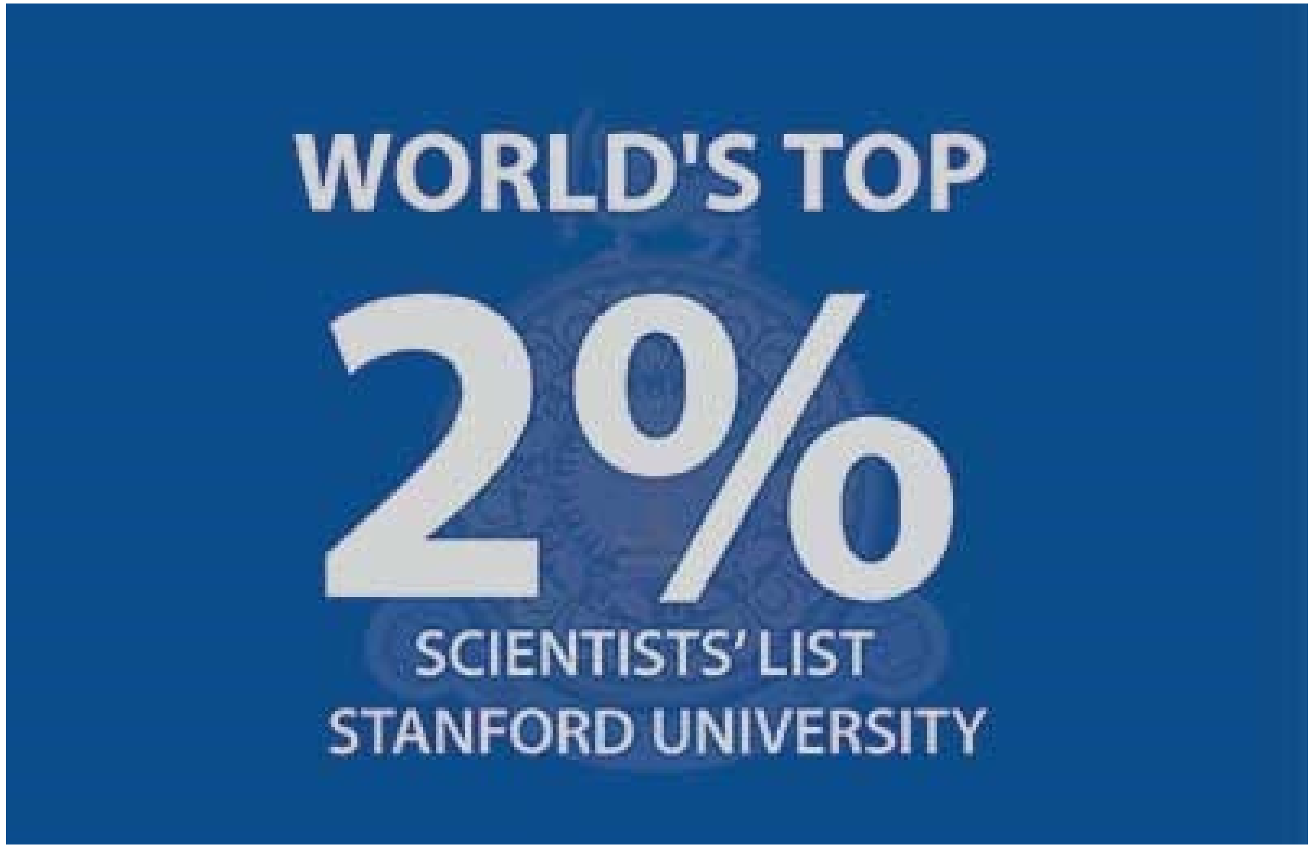
Brief Bio

- **Education:**
  - BA/MA Nursing, University of Haifa, Israel
  - University of Pennsylvania (USA) PhD
  - Harvard Medical School & Brigham Women's Health Hospital (USA) Postdoctoral Fellowship
- **Current Affiliations:**
  - **Elizabeth Standish Gill Associate Professor of Nursing** | Columbia University Medical Center & Columbia University Data Science Institute| Maribor University
  - **Senior Research Scientist** | VNS Health
  - **Co-Director**| Nursing and Artificial Intelligence Leadership (NAIL) Collaborative
  - **Lead**, Health Informatics and Data Science Services| Center for Community Engaged Data Science and Health Informatics

My contributions

~200 published studies

>$25 Million in federal and other funding



A Personal Journey in AI Development

1

PREVENT (2010–2025)

Long-term research initiative (15 years)

2

CONCERN (2015–2023)

Multi-year development project (8 years)

3

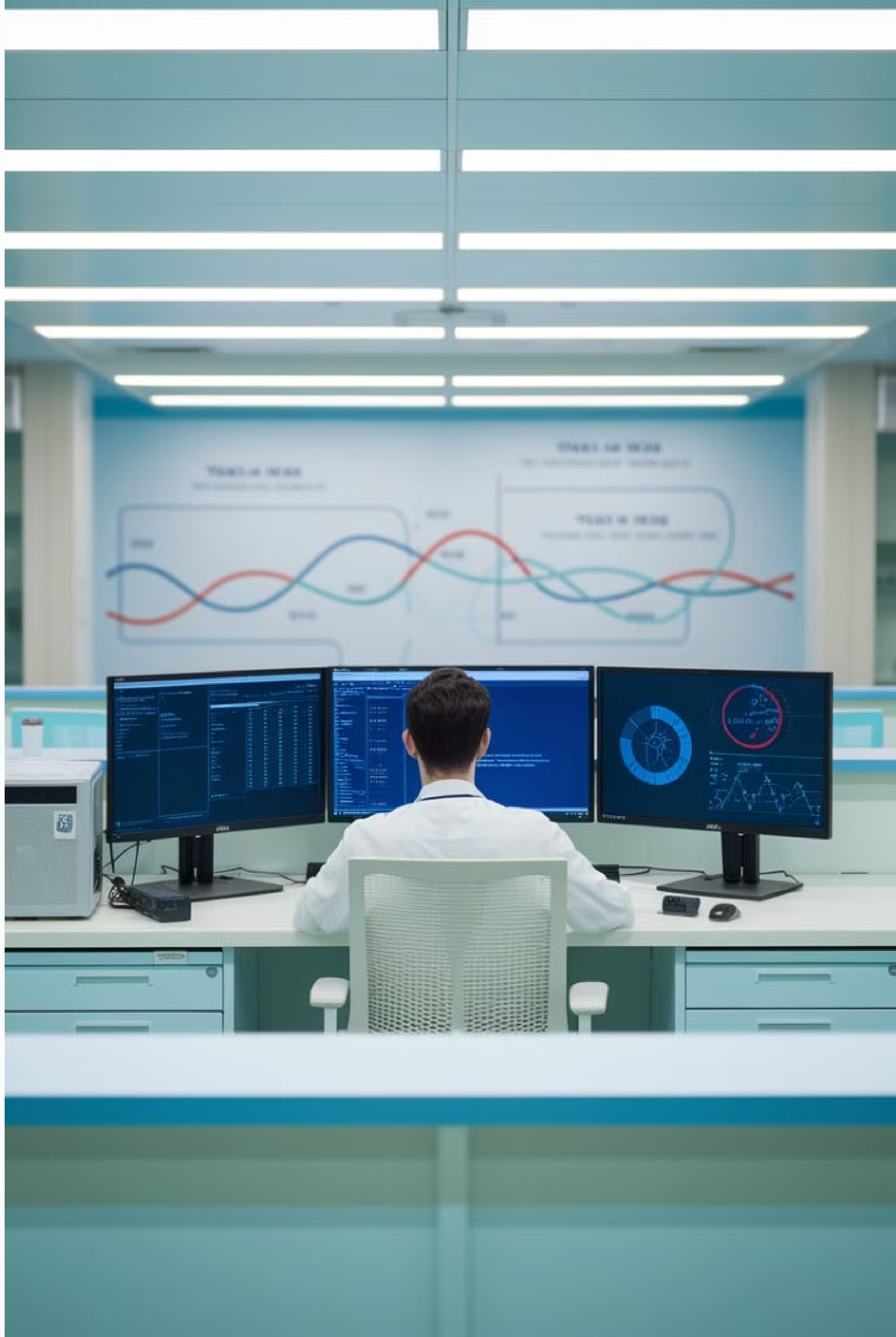
Speech AI (2019–Now)

Ongoing innovation work (4 years)

4

Video AI (2024–Now)

Just started (few months)



But Everything Has Changed!

Then	Now
15 years of careful R&D	GPT/Claude building tools in minutes
Methodical progress	Rapid development cycles
Academic pace	Industry setting the pace

How often do you use generative AI tools like ChatGPT, Gemini, or Perplexity?

A. Never
B. Once a month
C. Weekly
D. Daily
E. Cannot live without it!

Generative AI in Action


ChatGPT
Log out
ChatGPT
Hellof How can I assist you foday?
Good evening, I would like to leam about modem modern techhology
Of course! I'd be happy to help with that. What would you like to know?


ChatGPT

Meet Sarah

Chief Nursing Officer

Sarah faces an urgent staffing crisis at Metro General Hospital

Today 12 more nurses submitted resignations over the weekend.

Hospital turnover now at 40% annually.

The Board's Demand

Evidence-based retention strategy by Friday's emergency meeting

Sarah's Challenge

Find research-based solutions at the speed of crisis

Traditional Research Response: 6-month workforce study while losing more nurses weekly.

Watch what Sarah can accomplish with AI research tools that didn't exist 2 years ago...

What You're About to See

Literature synthesis

on nursing retention strategies

Survey design

for rapid workforce assessment

Predictive modeling

on existing workforce data

Executive action plan

ready for board presentation

The Timeline: Real-time research response **The Tools:** AI platforms available today **The Question:** Is this the future of nursing research?

PROMPT

Gemini

- URGENT: I need comprehensive research synthesis on nursing retention strategies for hospital systems experiencing 40%+ turnover rates. Focus on:
- - Evidence-based retention interventions with measurable outcomes
- - Cost-effectiveness data for retention programs
- - Rapid implementation strategies (30-90 days)
- - Predictive factors for nursing turnover risk
- - Successful case studies from similar crisis periods
- Prioritize 2022-2024 sources. Format for emergency executive briefing.

The New Research Reality

Systematic literature review

Hundreds of studies synthesized

Valid survey instrument

Ready for 1,200 staff deployment

Predictive modeling

Risk stratification and ROI analysis

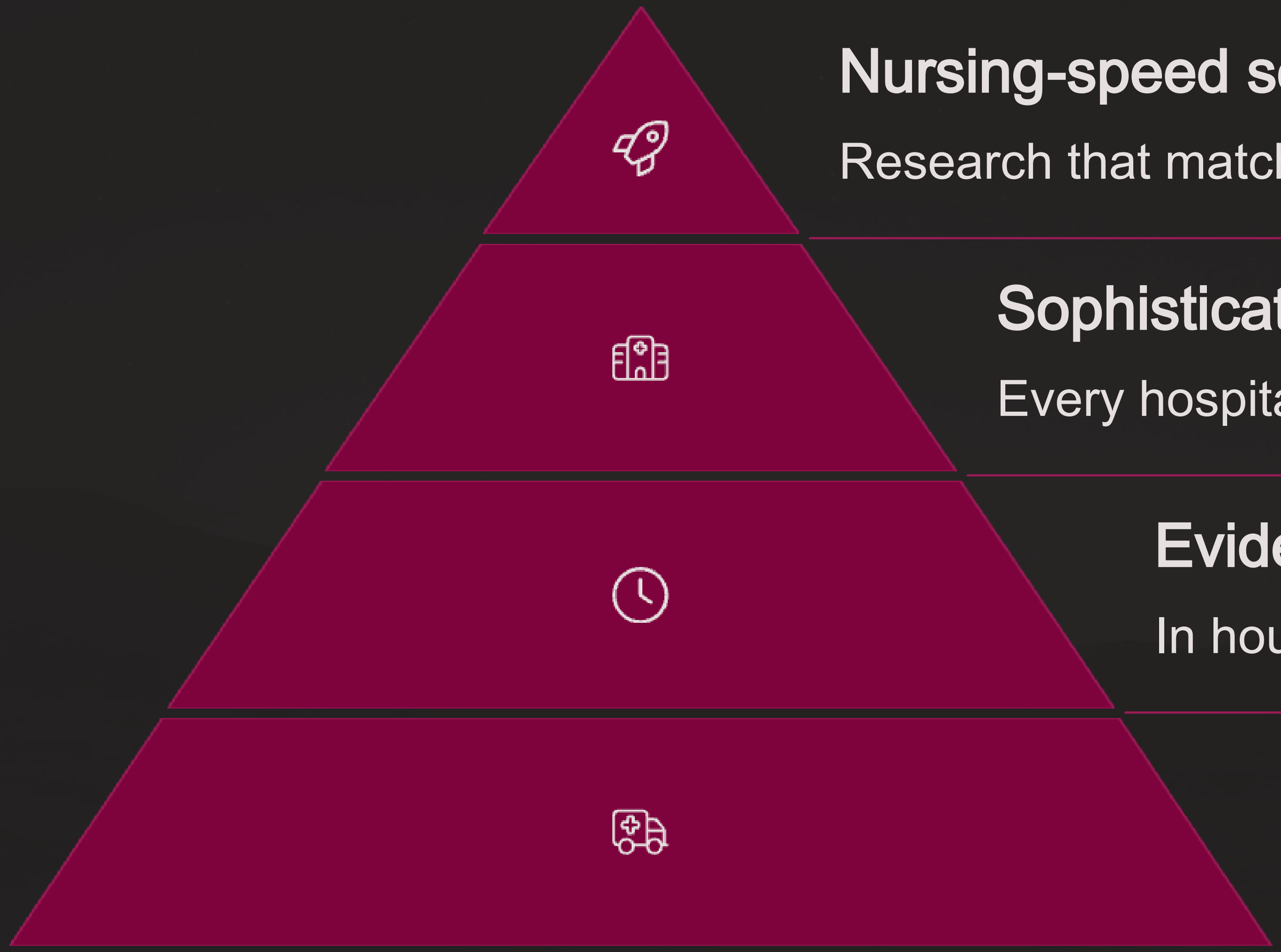
Action plan

Board-ready implementation strategy

Traditional timeline: 6 months → **AI-enhanced:** 6 minutes

In a few minutes, we accomplished what traditionally takes months of research work.

Research Responsiveness Revolution



Nursing-speed solutions

Research that matches care delivery pace

Sophisticated analytics for all

Every hospital can access advanced research tools

Evidence-based decisions

In hours, not months

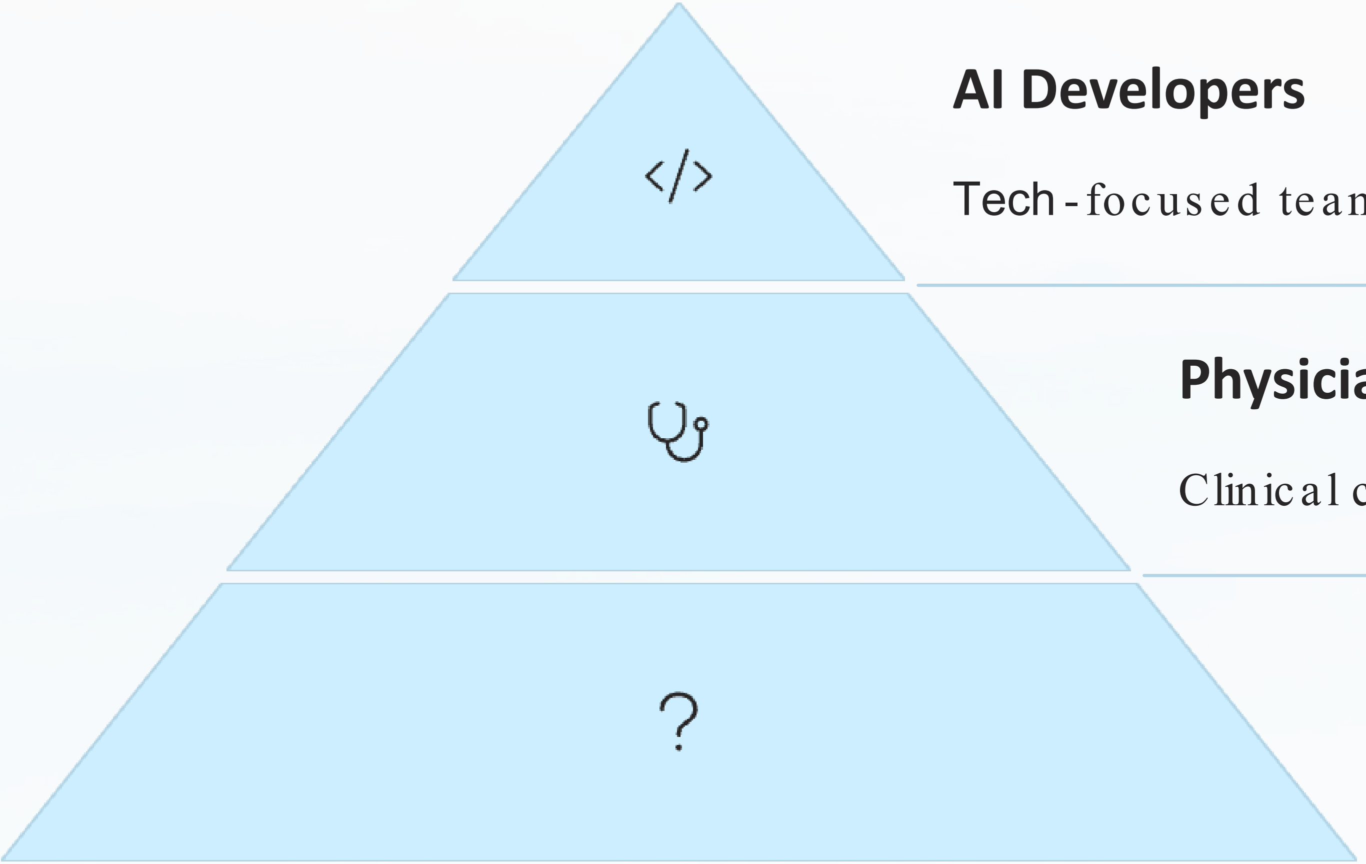
Emergency research

Matching emergency timelines

The Critical Insight:

We can now research at the speed of care delivery

The Risk of Exclusion



AI Developers

Tech-focused teams

Physicians

Clinical consultants

Where are the nurses?

Missing from decision-making

What Happens Without Nursing in the Loop?

Under-documentation

Critical nursing data missed

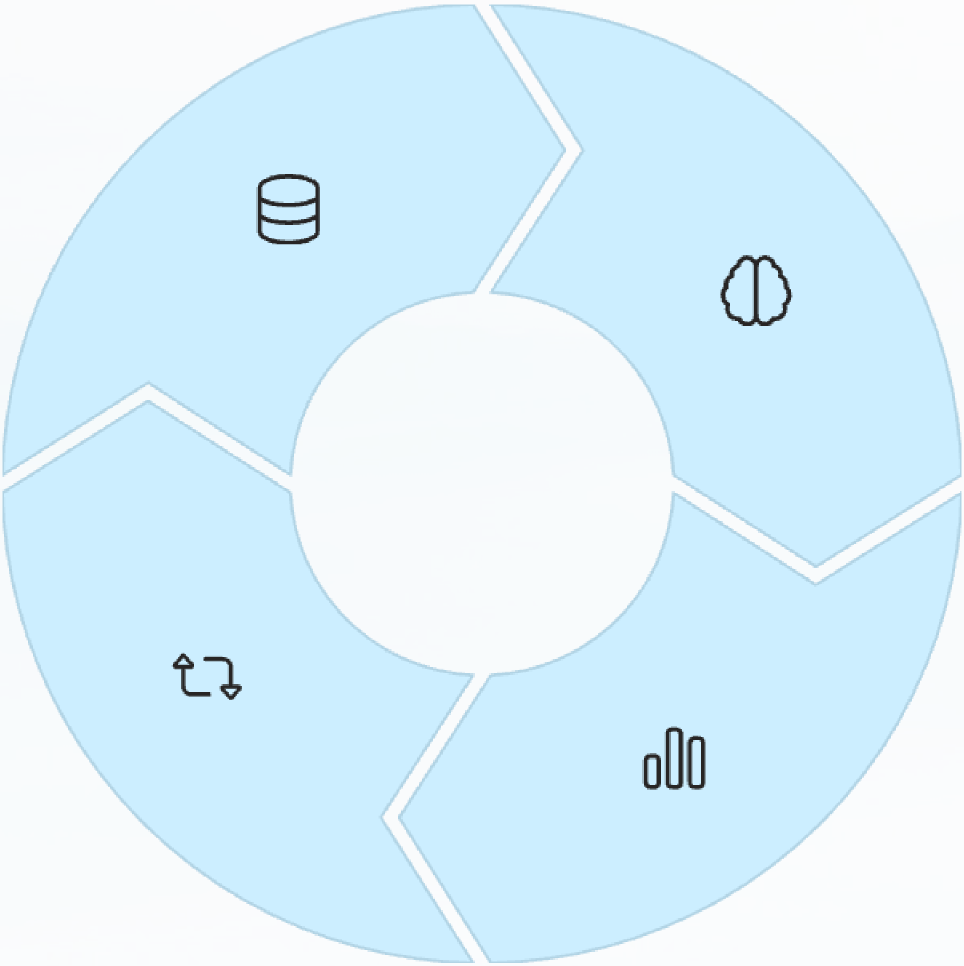
Over-alerting

Alert fatigue compromises safety

Biased AI

50% of concerns undocumented; racial bias

The Path Forward –Nursing + AI



Nursing Input

Nurses guide AI

AI Models

Learning nursing language

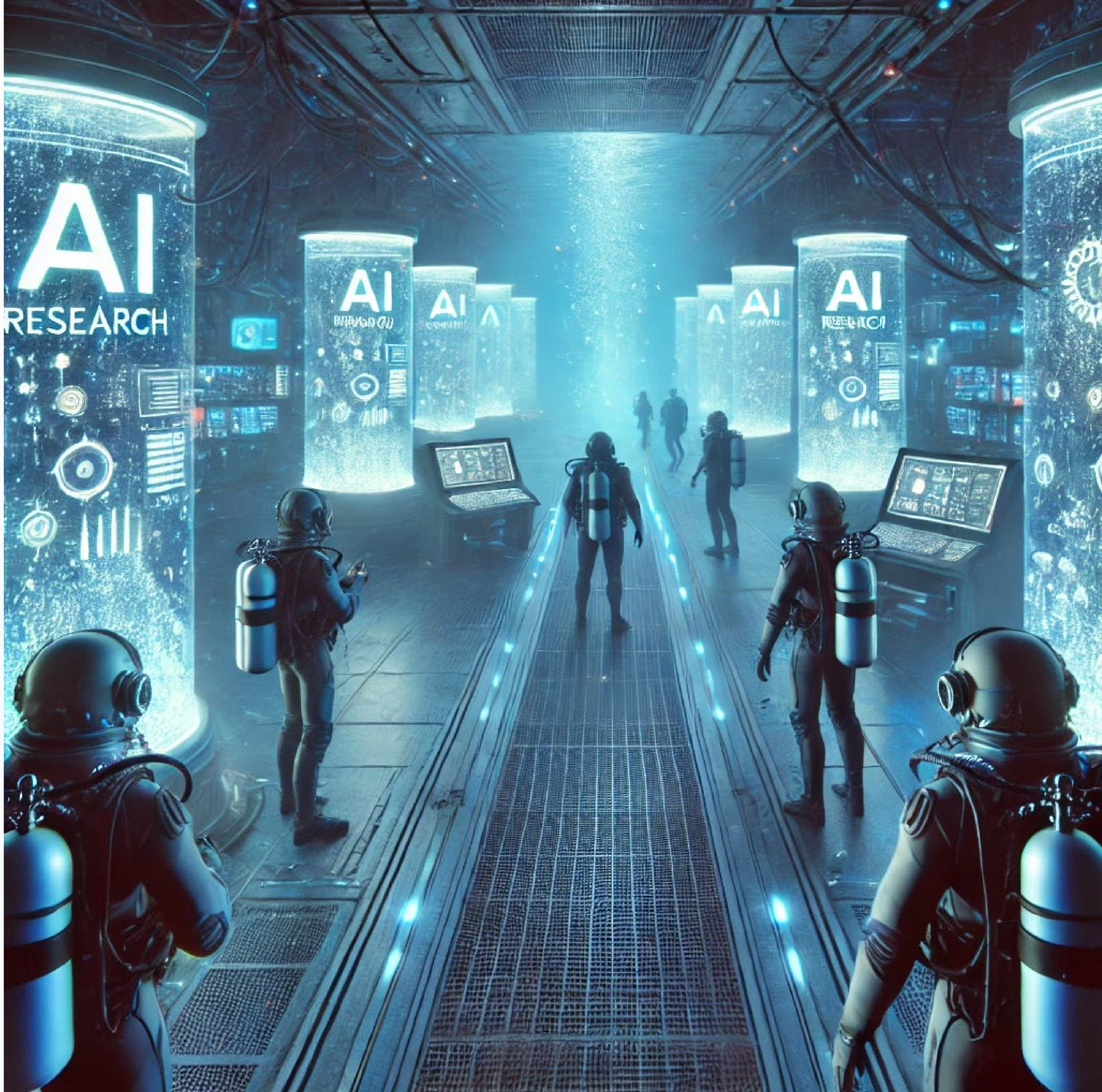
Continuous Improvement

Evolving knowledge base

Better Outcomes

Improved patient care

Deep Dive into AI Research Evolution



Key challenge

Home healthcare goal: promote self-care and decrease negative outcomes

However, 1 in 5 patients are admitted to hospitals or ED

Example 1: PREVENT

Developed an automated tool - PREVENT- to identify high-risk patients during hospital discharge [1].

High-risk patients are prioritized for nursing care - they receive home visits within 48 hours of hospital discharge.

Example 1: PREVENT

Risk factors:

- Presence of wounds
- Depression
- Toileting status
- Number of medications
- Number of comorbid conditions

<u>PREVENT</u>

cy for First Home Health Visit Tool PREVENT© is copyrighted and is used ONLY with permission from Maxim Topaz 267-994-2751, mtopaz80@gmail.com

<u>Rule:</u> Sum scores as follows. Any score >26 would suggest high priority for the first home health visit.

Question: (Response =Score)	Score
Count the <u>NUMBER OF MEDICATIONS</u> prescribed to the patient =	
Count the <u>NUMBER OF COMORBID CONDITIONS</u> patient has =	
Does the patient have a comorbid condition of <u>DEPRESSION</u> (e.g. Depressive disorder, NEC)? NO = 0 YES = 15	
Does the patient have <u>WOUND</u> of any type? NO = 0 YES = 15	
Does the patient have <u>LIMITATION IN TOILETING</u> functional ability requiring use of any assistive equipment, assistive person or both? NO = 0 YES = 20	
Total Score:	

Example 1: PREVENT

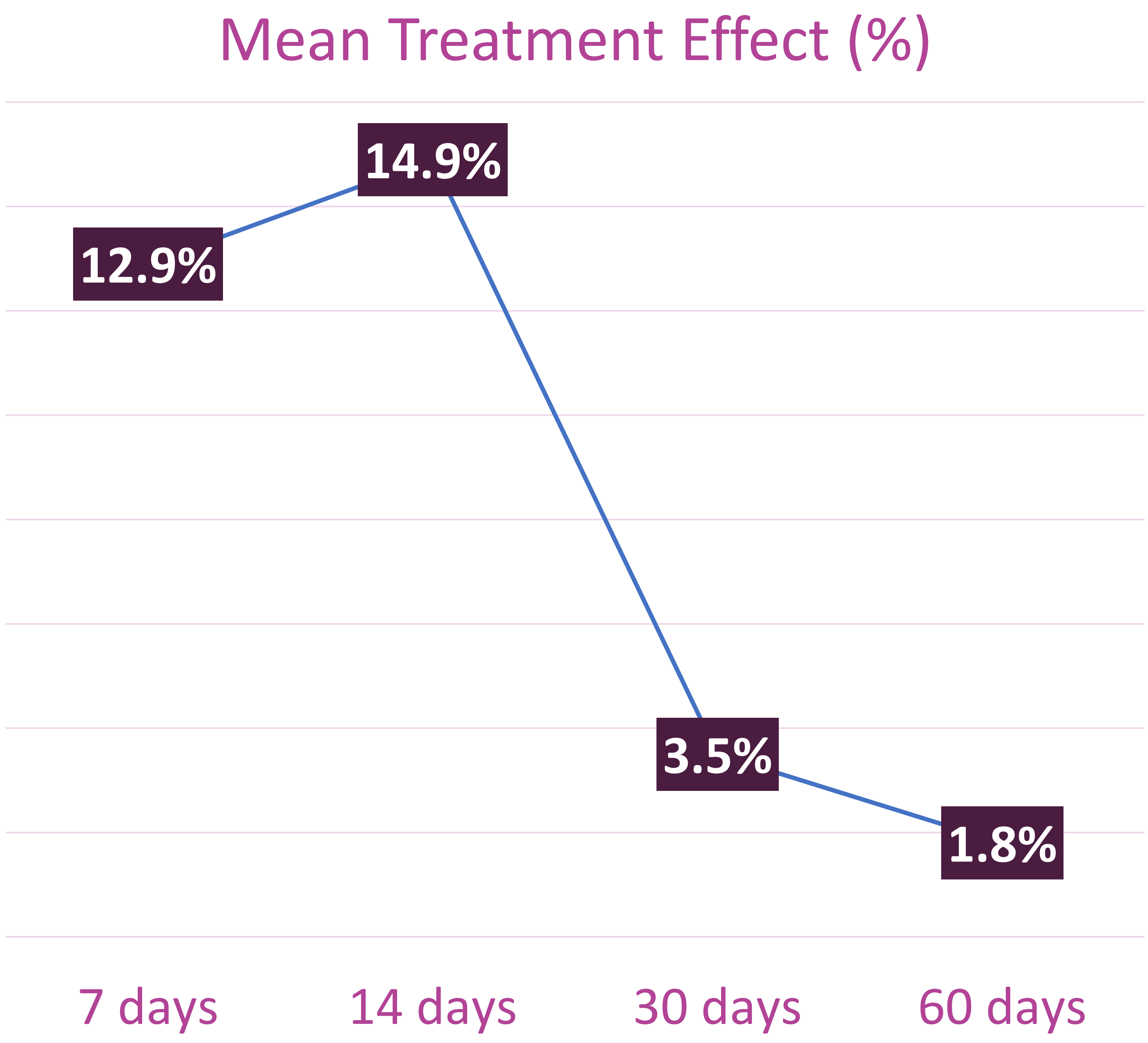
Pilot study showed 30% hospitalization and ED visit risk reduction [2].

Example 1: PREVENT

Large clinical just finished [R01NR018831].

N patients = 2,100 patients

Design: Quasi-Experimental pre and post design



COMPUTERS INFORMATICS NURSING

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2014

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FEATURES

Factors Affecting Patient Prioritization Decisions at Admission to Home Healthcare

A Predictive Study to Develop a Risk Screening Tool

Topaz, Maxim PhD, RN; Naylor, Mary D. PhD, RN; Holmes, John H. PhD; Bowles, Kathryn H. PhD, RN

IGNITE the

RESEARCH IN NURSING & HEALTH

2016

RESEARCH ARTICLE

Improving patient prioritization during hospital-homecare transition: A pilot study of a clinical decision support tool

Maxim Topaz, MaryGrace Trifilio, Donna Maloney, Ofrit Bar-Bachar, Kathryn H. Bowles

First published: 11 September 2018 | https://doi.org/10.1002/nur.21907 | Citations: 17

Published on 22.01.2021 in Vol 10, No 1 (2021): January

Preprints (earlier versions) of this paper are available at https://preprints.jmir.org/preprint/20184, first published May 12, 2020.

Improving Patient Prioritization During Hospital-Homecare Transition: Protocol for a Mixed Methods Study of a Clinical Decision Support Tool Implementation

Maryam Zolnoori[1]; Margaret V McDonald[2]; Yolanda Barrón[2]; Kenrick Cato[1]; Paulina Sockolow[3]; Sridevi Sridharan[2]; Nicole Onorato[2]; Kathryn Bowles[2,4]; Maxim Topaz[1,2]

2021

Factors Associated with Timing of the Start-of-Care Nursing Visits in Home Health Care

Jiyoun Song, PhD, AGACNP-BC, RN [a] · Maryam Zolnoori, PhD [a] · Margaret V. McDonald, MSW [b] · ... · Nicole Onorato, BSc [b] · Kathryn H. Bowles, PhD, RN, FAAN, FACMI [b,e] · Maxim Topaz, PhD, RN [a,b,f]

... Show more

Affiliations & Notes · Article Info

2023

Example 2: HOMECARE-CONCERN

Clinical notes contain key information for risk detection [3].

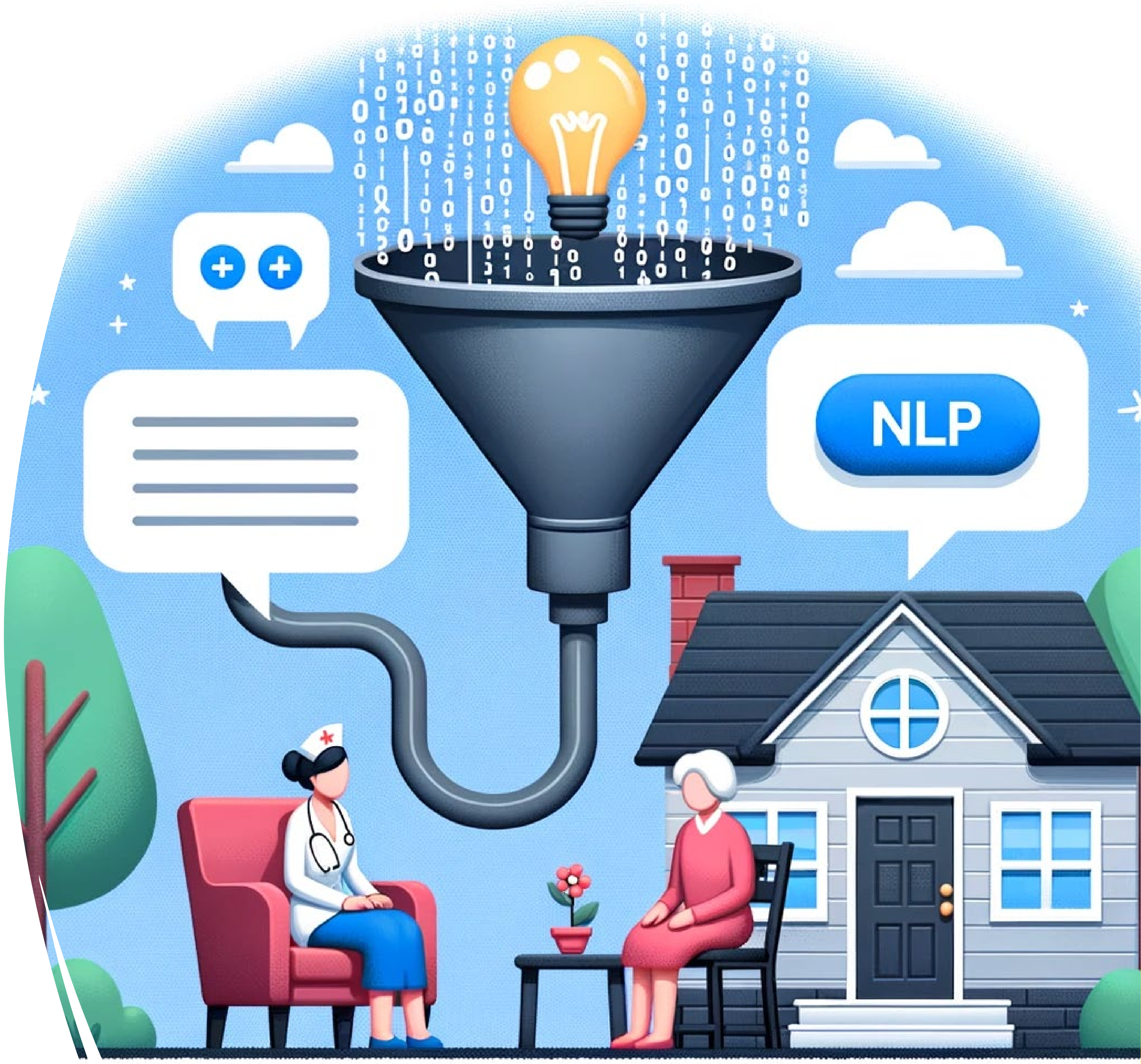
Busy clinicians struggle to review all information about their patients.

Example 2: HOMECARE-CONCERN

Using natural language processing to develop risk prediction during routine home healthcare services [4].

Making machine learning risk prediction unbiased and clinically explainable.

Large study [R01HS027742].



ORIGINAL ARTICLES

Detecting Language Associated With Home Healthcare Patient's Risk for Hospitalization and Emergency Department Visit

Song, Jiyoun; Ojo, Marietta; Bowles, Kathryn H.; McDonald, Margaret V.; Cato, Kenrick; Rossetti, Sarah Collins; Adams, Victoria; Chae, Sena; Hobensack, Mollie; Kennedy, Erin; Tark, Aluem; Kang, Min-Jeoung; Woo, Kyungmi; Barrón, Yolanda; Sridharan, Sridevi; Topaz, Maxim

Author Information

Nursing Research 71(4):p 285-294, 7/8 2022. | *DOI:* 10.1097/NNR.0000000000000586

TABLE 1 - Evaluation of Natural Language Processing Algorithm Performance Via Gold-Standard Manual Review (Total *N* = 1,000 Clinical Notes)

The Omaha System problems	Total frequency and proportion of documentation, % (*n*)	Precision	Recall	*F* score
Neuromusculoskeletal function	16 (78)	0.99	0.76	0.86
Pain	14 (68)	0.84	0.95	0.89
Circulation	9 (47)	0.94	0.80	0.86
Mental health	9 (47)	0.96	0.75	0.84
Skin	[illegible]	[illegible]	[illegible]	0.86
Healthcare supervision	[illegible]	[illegible]	[illegible]	0.76
Cognition	[illegible]	[illegible]	[illegible]	0.93
Respiration	[illegible]	[illegible]	[illegible]	0.86
Communicable infectious condition	[illegible]	[illegible]	[illegible]	0.87
Social contact	3 (17)	1.00	1.00	1.00
Digestion hydration	3 (14)	0.93	0.62	0.74
Medication regimen	2 (9)	0.88	0.68	0.77
Bowel function	2 (8)	1.00	0.89	0.94
Genitourinary function	2 (8)	1.00	0.73	0.84
Nutrition	2 (8)	1.00	0.44	0.62

Omaha System Problems

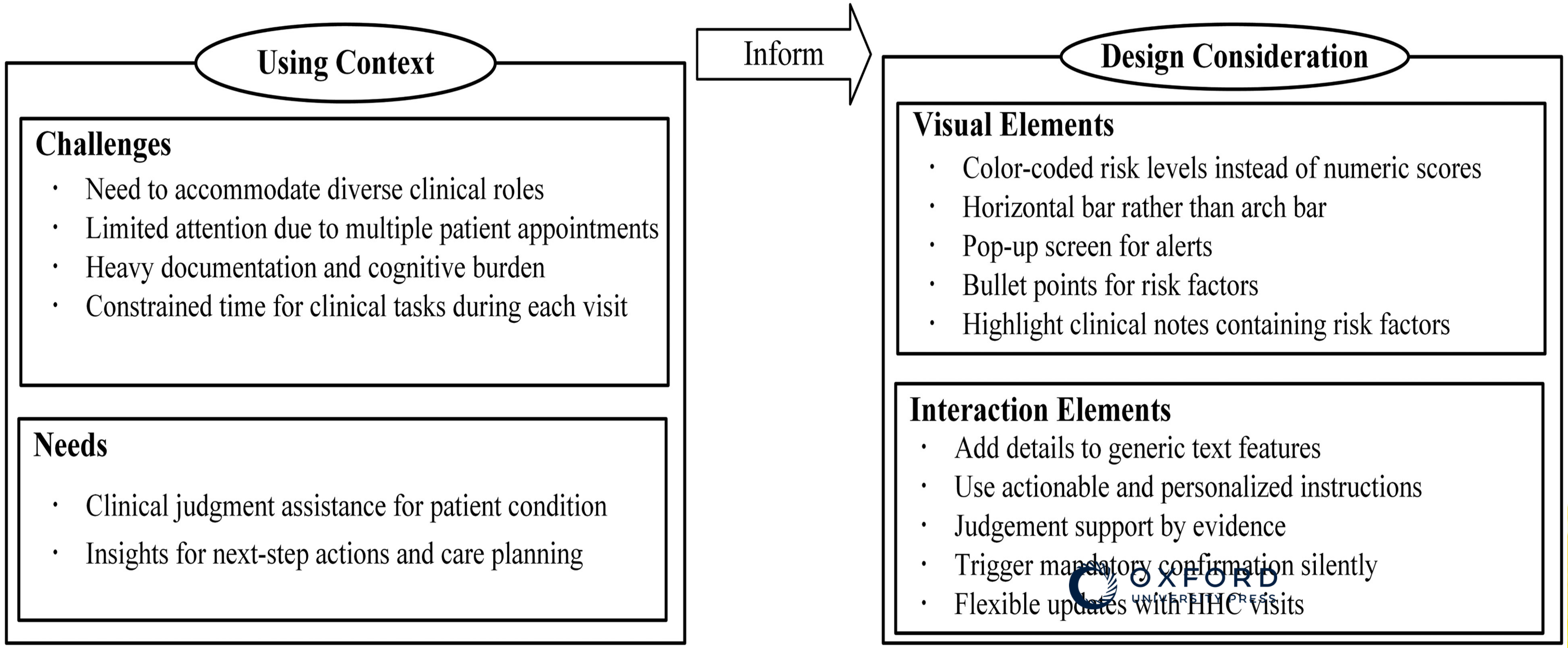
JOURNAL ARTICLE

Exploring home healthcare clinicians' needs for using clinical decision support systems for early risk warning

Zidu Xu, MMed, MPhil, Lauren Evans, DrPH, Jiyoun Song, PhD, RN, Sena Chae, PhD, RN, Anahita Davoudi, PhD, Kathryn H Bowles, PhD, RN, Margaret V McDonald, MSW, Maxim Topaz, PhD, MA, RN

Journal of the American Medical Informatics Association, ocae247, https://doi.org/10.1093/jamia/ocae247

Published: 20 September 2024 **Article history** ▾



JAMDA
The Journal of the Post-Acute and Long-Term Care Medical Association
PALTmed

ORIGINAL STUDY · Volume 26, Issue 2, 105417, February 2025

Building a Time-Series Model to Predict Hospitalization Risks in Home Health Care: Insights Into Development, Accuracy, and Fairness

Maxim Topaz, PhD, RN [a,b,c] · Anahita Davoudi, PhD [c] · Lauren Evans, PhD [c] · ... · Zhihong Zhang, PhD, RN [a,b] · Margaret V. Mcdonald, MA [c] · Kathryn H. Bowles, PhD, RN [c,d,h] ... Show more

The verbal signal is everywhere!

Human interaction is key in healthcare! We talk to patients and their families about issues, symptoms, social determinants, etc.

Some of those discussions will be documented in the electronic health records (but not everything:).

Can you guess the percentage of patient problems documented in electronic health records?

What percentage of problems in verbal nurse-patient discussions are documented in electronic health records?

A) Less than 25%
B) About 50%
C) More than 75%
D) Nearly all of them

Example 3: Speech recognition

50% of patient problems are <u>**not documented in electronic health record systems**</u> [5]

Identified the most accurate automatic speech recognition system

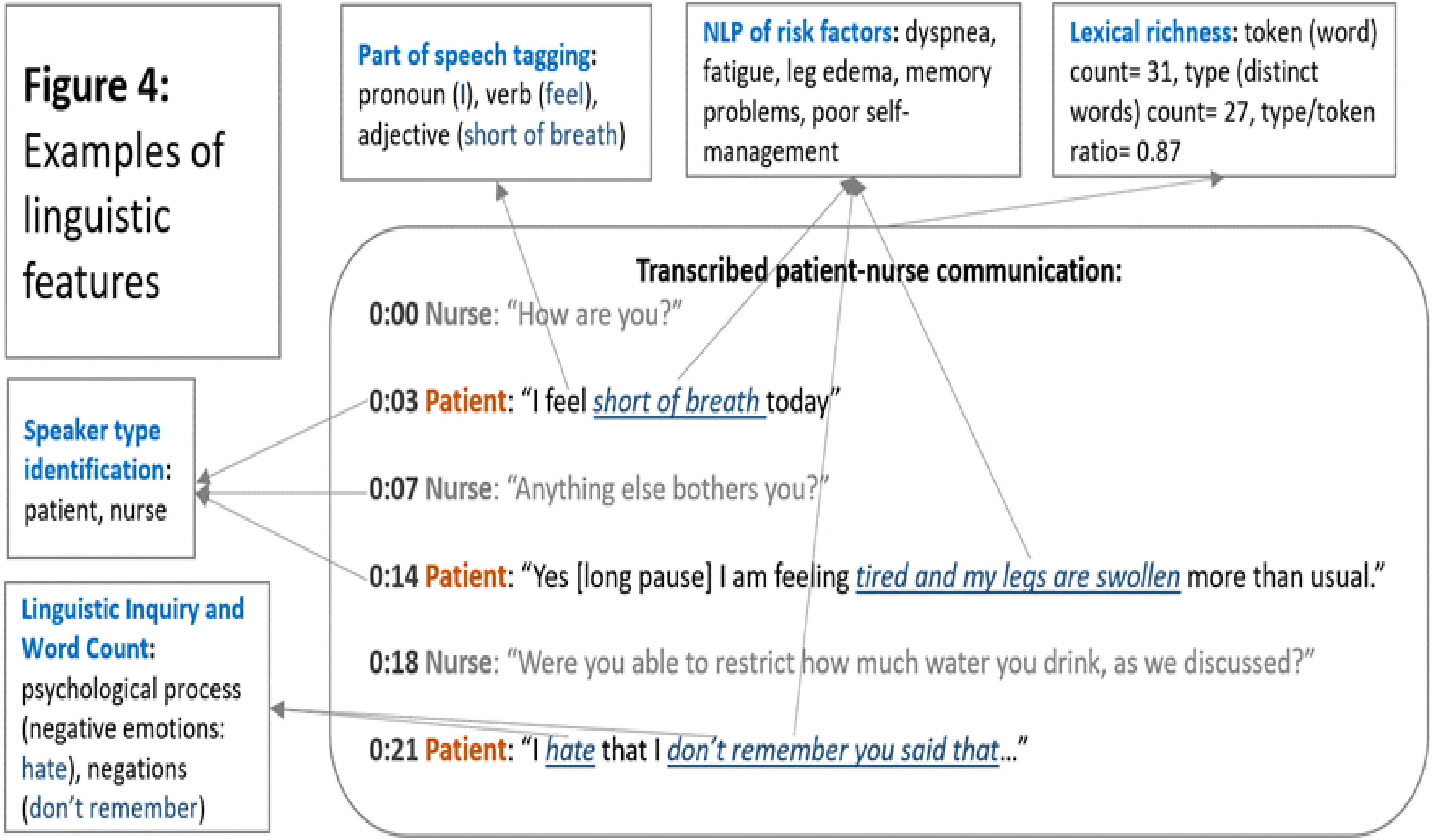
Under-documentation of problems among Black patients is **twice higher** (65%) than among White patients (34%)

Verbal signal is everywhere!

Study: Applying NLP to automatically identify risk factors in patient-nurse communication[6].

Methods: Modified our previously developed NLP algorithm and applied it on patient-nurse transcribed conversations.

Results: NLP algorithms achieved good risk factor identification performance levels (F-score= .91)



Can we improve risk prediction?

<u>26% improvement in models' risk predictive performance</u> when data extracted from audio recordings were added to models that used data from the standard assessment (OASIS) and NLP risk factors.

Combination of OASIS and clinical notes and audio-recorded encounters for all available encounters			
OASIS + features extracted from clinical notes	SVM-RBF	86.54	75.01
OASIS + features extracted from clinical notes + features extracted from the patient's speech during an encounter	XGB	96.79	87.5
OASIS + features extracted from clinical notes + features extracted from the patient's speech during an encounter + the nurse's speech during an encounter.	**SVM-RBF**	**99.68**	**94.12**

Can we improve risk prediction?

The analysis revealed that patients at high risk tended to:

1. Interact more with risk-associated cues

2. Exhibit more "sadness" and "anxiety”

2. Have extended periods of silence during conversation

Teaching AI to Speak Nursing

Mapping everyday conversations to standardized Omaha System terminology

Nurse–Patient Utterance	Omaha Problem	Standard Sign/Symptom
"I get short of breath on stairs."	Respiration	Abnormal breathing pattern
"How often do you check your blood sugar?" *"It was 174 this morning."*	Circulation	Hyperglycemia
"I'm eating less lately."	Nutrition	Loss of appetite
"Sometimes I worry about falling."	Environmental	Fear of falling
"I feel dizzy when I stand up."	Circulation	Orthostatic hypotension symptoms
"I ran out of my water pills this week."	Health Care Supervision	Medication management difficulty

Teaching AI to Speak Nursing

FEATURES

NimbleMiner

An Open-Source Nursing-Sensitive Natural Language Processing System Based on Word Embedding

Topaz, Maxim PhD, RN; Murga, Ludmila PhD; Bar-Bachar, Ofrit MSc, PT; McDonald, Margaret MSW; Bowles, Kathryn PhD, RN

Author Information

CIN: Computers, Informatics, Nursing 37(11):p 583-590, November 2019. | *DOI:* 10.1097/CIN.0000000000000557

BUY

Metrics

Teaching AI to Speak Nursing

AMIA Annual Symposium Proceedings Archive

AMIA INFORMATICS PROFESSIONALS. LEADING THE WAY.

▸ AMIA Annu Symp Proc. 2023 Apr 29;2022:992–1001.

Is Auto-generated Transcript of Patient-Nurse Communication Ready to Use for Identifying the Risk for Hospitalizations or Emergency Department Visits in Home Health Care? A Natural Language Processing Pilot Study

Jiyoun Song [1,*], Maryam Zolnoori [1,*], Danielle Scharp [1], Sasha Vergez [2], Margaret V McDonald [2], Sridevi Sridharan [2], Zoran Kostic [3], Maxim Topaz [1,2]

▸ Author information ▸ A

PMCID: PMC10148305 PMI

Risk factors (Omaha System Problem)	Human-generated transcripts			Auto-generated transcripts
	Precision	Recall	F-score	Precision
Circulation	0.94	0.81	0.87	0.89
Medication regimen	0.48	0.84	0.62	0.54
Neuromusculo-skeletal function	0.96	0.84	0.9	1
Pain	0.72	0.88	0.79	0.72
Respiration	1	0.56	0.72	0.66
Skin	0.75	0.88	0.81	0.92
Overall	**0.81**	**0.8**	**0.79**	**0.79**

* Note: Full annotation was not done on auto-generated transcripts, hence only precision was calculated

Teaching AI to Speak Nursing

Journal of Nursing Scholarship

JOURNAL OF NURSING SCHOLARSHIP

ORIGINAL ARTICLE

From Conversation to Standardized Terminology: An LLM-RAG Approach for Automated Health Problem Identification in Home Healthcare

Zhihong Zhang[1,2] | Pallavi Gupta[2] | Jiyoun Song[3] | Maryam Zolnoori[3,4] | Maxim Topaz[1,2]

[1]Data Science Institute, Columbia University, New York, New York, USA | [2]School of Nursing, Columbia University, New York, New York, USA | [3]University of Pennsylvania School of Nursing, Philadelphia, Pennsylvania, USA | [4]Columbia University Irving Medical Center, New York, New York, USA

Teaching AI to Speak Nursing

How We Taught the AI

A step-by-step approach to better understanding

1. **Listen**
   AI reads what the patient said

2. **Think**
   Is this a health problem or just conversation?

3. **Search**
   Find the right medical term from 377 options

4. **Match**
   Pick the best medical category

Teaching AI to Speak Nursing

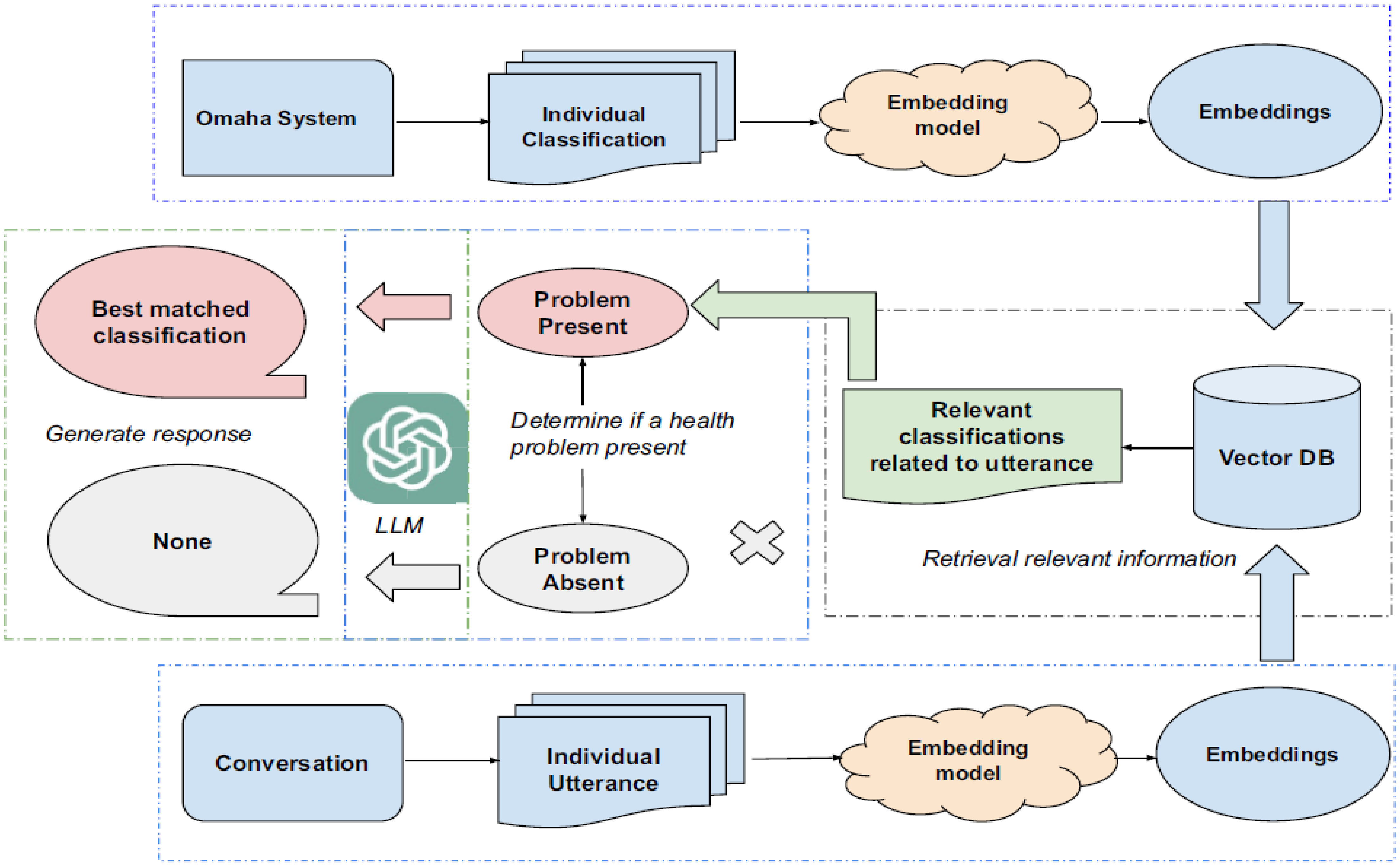


FIGURE 1 | Large language model with retrieval-augmented generation framework.

Teaching Method Comparison

Why examples and step-by-step thinking made the difference

Basic Instructions Only

73%

Accuracy

Just told the AI: "Find health problems and match them to medical terms"

Problems: Often guessed when unsure, made up problems that weren't there

With Examples + Reasoning

90%

Accuracy

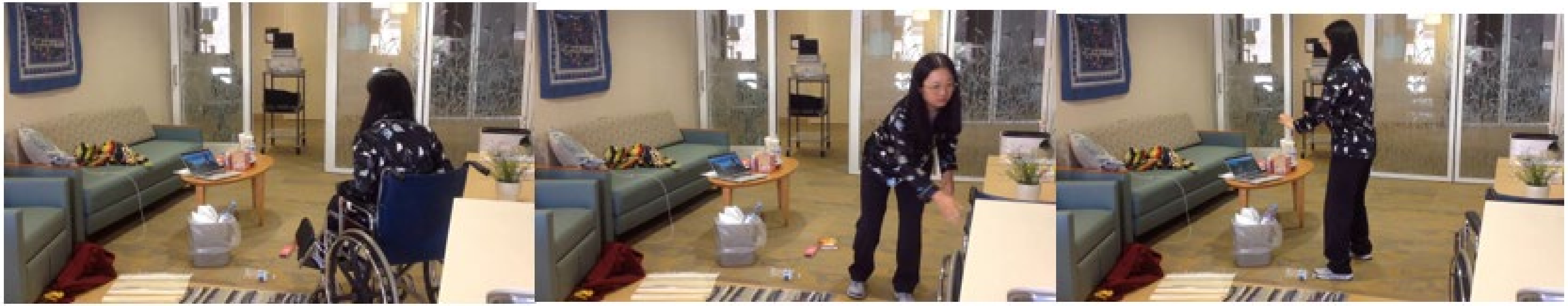
Showed the AI examples and taught it to think step-by-step

Success: Much better at knowing when NO problem exists, more consistent matching

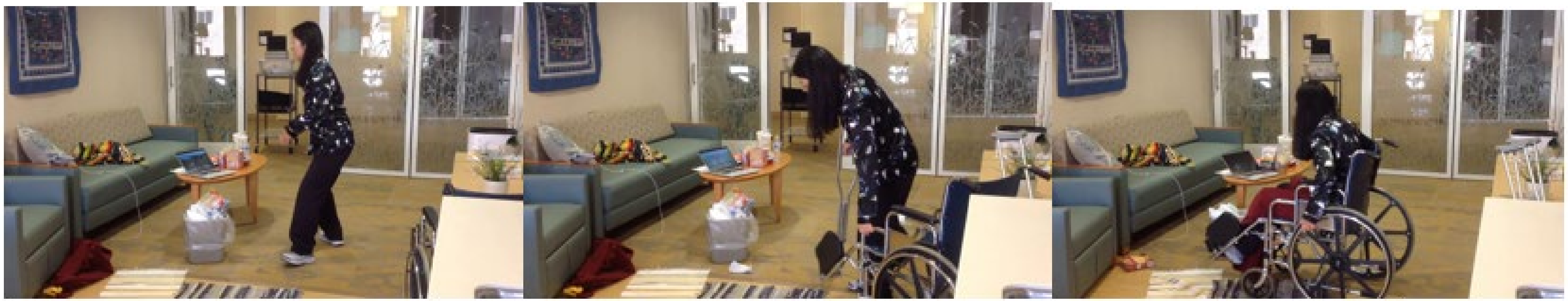
The Key Discovery

Giving the AI examples of correct answers and making it explain its thinking step-by-step improved accuracy from 73% to 90% — comparable to human nurses

Teaching AI to See Nursing



(a) (b) (c)



(d) (e) (f)

Figure 1: Sequential Frames Extracted from Video to Showcase Scenarios. (a) The patient is sitting in a wheelchair (b) The patient is a woman wearing glasses (c and d) The patient is doing exercise (e) The patient sat back in a wheelchair.

Teaching AI to See Nursing

A

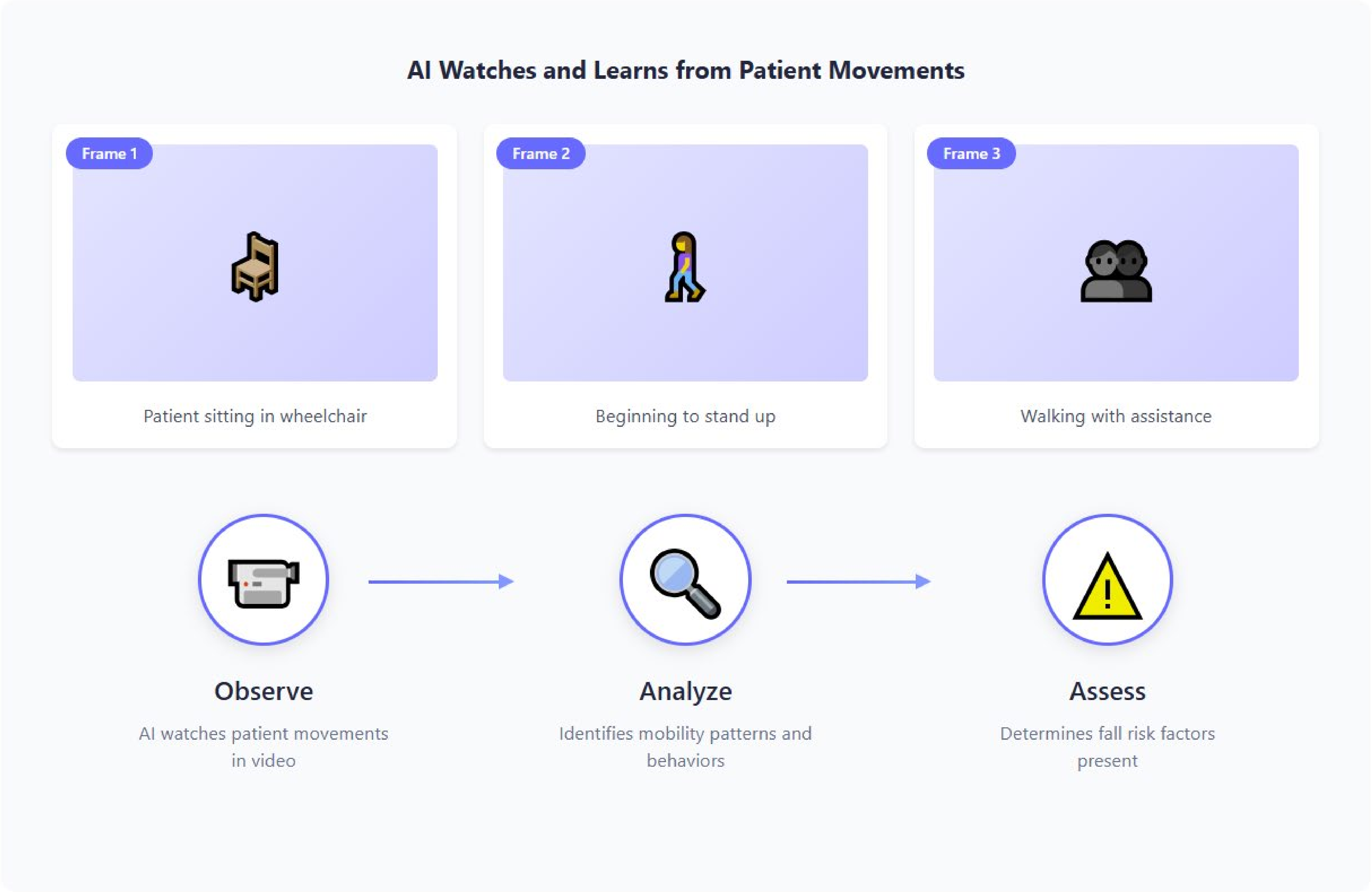
Insta360 GO 3 S

B

GoPro HERO11 Mini

C

OhO Smart Glasses


AI Watches and Learns from Patient Movements
Frame 1
Patient sitting in wheelchair
Frame 2
Beginning to stand up
Frame 3
Walking with assistance
Observe
AI watches patient movements in video
Analyze
Identifies mobility patterns and behaviors
Assess
Determines fall risk factors present

Teaching AI to See Nursing

Fall Risk Factors	Prompts	MLLM Results	Expert Evaluation
Category 1: Direct Prompts For Easy Inferences			
1. Age	Based on visible characteristics in the video, does the patient appear to be an older adult? Respond 'Yes, 'No,' or 'Insufficient information.'	Yes	No
2. Gender	Based on visible features in the video, does the patient appear to be a female or a male? Answer 'male' or 'female.'	Female	Female
3. Difficulty walking	Based on the video, does the patient display any visible signs of difficulty walking that could increase their risk of falling? Respond 'Yes, 'No,' or 'Insufficient information.'	Yes	Yes
4. Impaired Mobility	Based on the video, does the patient show any visible signs of impaired mobility that could increase their risk of falling? Respond 'Yes, 'No,' or 'Insufficient information.'	Yes	Yes

Teaching AI to See Nursing

Category 2: Elaborated prompts requiring deeper reasoning			
8. Wearing appropriate footwear	Analyze the video and determine what kind of shoes the patient is wearing. Assess whether the shoes provide adequate traction, support, or stability. Respond ’Yes, ’No,’ or ’Insufficient information.’	Yes	Yes
9. Exercise (Indoor home)	Analyze the video and determine if the person is exercising on the floor. For floor-based exercises, look for actions such as lying, sitting, kneeling, or placing hands/feet on the floor, and identify movements like push-ups, planks, yoga poses, or stretches. Observe upright movements such as squats, lunges, or balance drills for standing exercises. Note any use of mats, equipment, or visible effort to maintain stability during the exercise. Respond ’Yes, ’No,’ or ’Insufficient information.’	Yes	Yes

J Adv Nurs. 2025 Mar 24. doi: 10.1111/jan.16911. Online ahead of print.

An AI-Enabled Nursing Future With no Documentation Burden: A Vision for a New Reality

Martin Michalowski [1], Maxim Topaz [2], Laura Maria Peltonen [3]

Affiliations + expand

PMID: 40129115 DOI: 10.1111/jan.16911

The Documentation Crisis in Nursing

How AI can give nurses their time back

40%

Current Reality

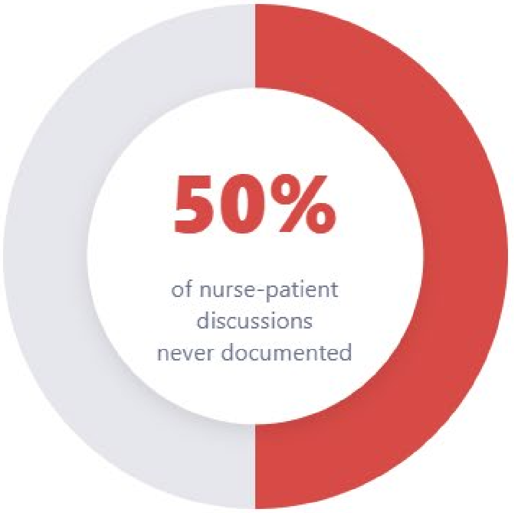
Time spent on documentation
Away from patient care
Leading to burnout

→

~0%

AI-Enabled Future

Automatic documentation
Focus on patient care
Improved satisfaction



Multimodal AI: The Game Changer

Capturing the complete picture of patient care automatically

Real-Time Data Integration

Audio

Captures conversations
Detects distress
Records verbal assessments

Video

Observes physical symptoms
Monitors environment
Captures non-verbal cues

Text

Integrates with EHR
Updates in real-time
Uses standard terminology

The Vision: Zero Documentation Burden

Imagine nurses who never touch a keyboard during patient visits. Who maintain eye contact, hold hands, and truly listen. Where every detail is captured automatically, accurately, and immediately available for the entire care team. This isn't science fiction — it's the near future of nursing.

AMERICAN NURSES FOUNDATION

Reimagining Nursing Initiative Grant Award

$466,000 to NurseAssist–AI

Led by M. Topaz, PhD, RN, MA, FAAN, FIAHSI, FACMI, in partnership with VNS Health, NurseAssist–AI harnesses video, audio, and electronic health record data to streamline documentation and empower home healthcare nurses with data-driven care decisions.

American Nurses Foundation

JOURNAL OF NURSING SCHOLARSHIP
Sigma

EDITORIAL

The Overlooked Dark Side of Generative AI in Nursing: An International Think Tank's Perspective

Maxim Topaz, Laura Maria Peltonen, Martin Michalowski, Lisiane Pruinelli, Charlene E. Ronquillo, Zhihong Zhang, Aleksandar Babic

First published: 05 May 2025 | https://doi.org/10.1111/jnu.70016

Five hidden risks:

- bias & hallucinations,
- opacity,
- deskilling,
- privacy threats,
- legal grey zones

International think-tank: 20 experts, 7 countries

Call to action: Embed health expertise in every AI lifecycle stage

Comment | Open access | Published: 24 September 2025

Beyond human ears: navigating the uncharted risks of AI scribes in clinical practice

Maxim Topaz, Laura Maria Peltonen & Zhihong Zhang

npj Digital Medicine 8, Article number: 569 (2025) | Cite this article

> J Contin Educ Nurs. 2025 Sep;56(9):358-359. doi: 10.3928/00220124-20250814-03. Epub 2025 Sep 1.

Invisible Scribes: Can Nurses Trust Ambient AI for Clinical Documentation?

Maxim Topaz [1]

Affiliations + expand

PMID: 40857680 DOI: 10.3928/00220124-20250814-03

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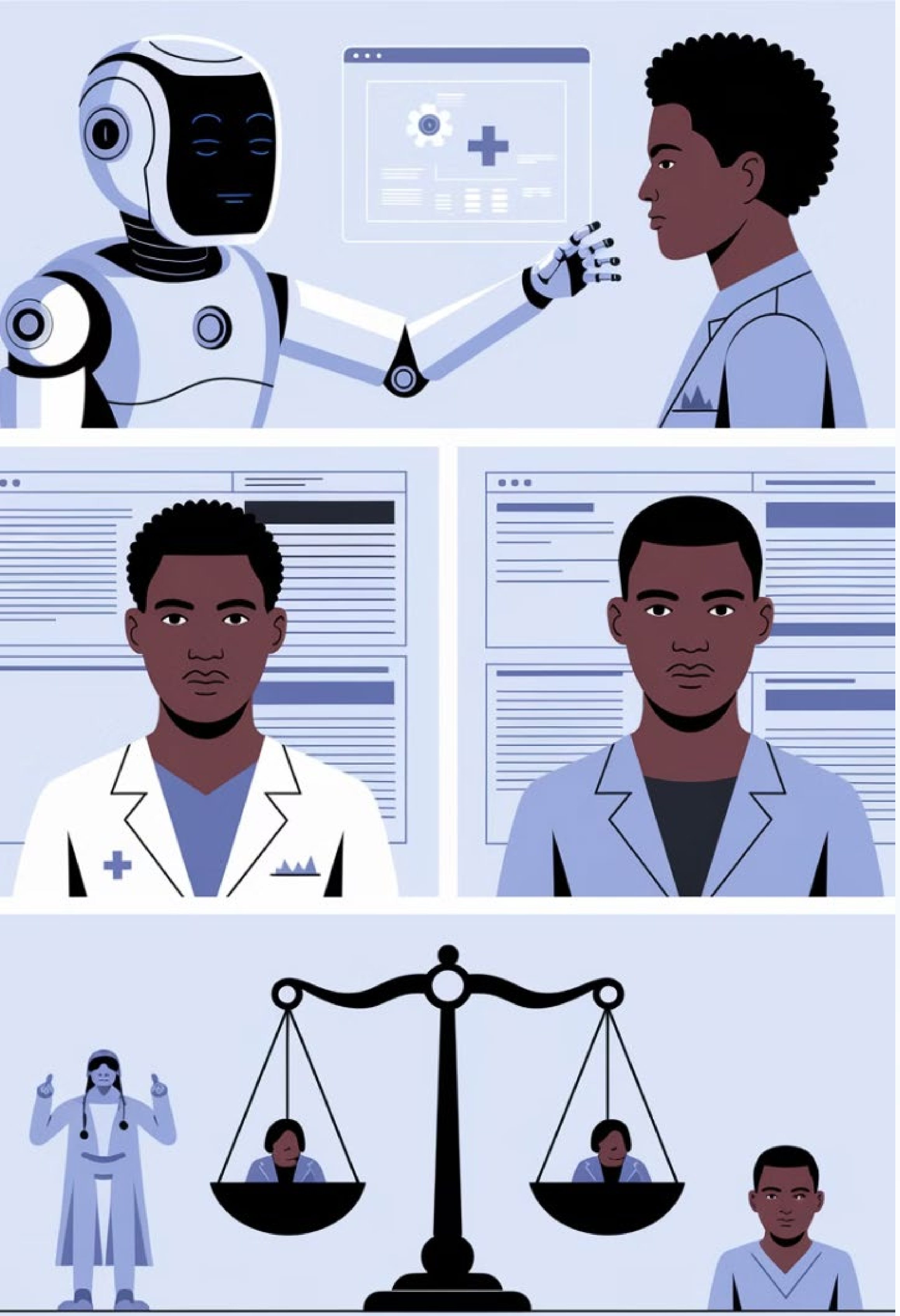
Leading Global Nursing Research

GUIDELINES AND CONSENSUS STATEMENTS | Open Access

Artificial intelligence in nursing: Priorities and opportunities from an international invitational think-tank of the Nursing and Artificial Intelligence Leadership Collaborative

Charlene Esteban Ronquillo PhD, RN, Laura-Maria Peltonen PhD, RN, Lisiane Pruinelli PhD, RN, Charlene H. Chu GNC(c), PhD, RN, Suzanne Bakken FAAN, PhD, RN ... See all authors

Highly cited: 400+ citations as of mid-2025



Bias and Fairness in AI

Area	Documentation Bias	Model Output
Child Abuse	Socioeconomic disparities	Over-flagging certain groups
Judgment Language	Varies by patient demographics	Perpetuates stereotypes
Perinatal Care	Racial documentation gaps	Missed warning signs

The Paradigm Shift

Past

15-year development cycles

Present

Rapid AI acceleration

Future

Nurses must lead now

Key Takeaways – Nursing Must Lead AI's Future

1. Create an AI-sharing network to track real-world impact
2. Develop AI simulation labs for pre-deployment testing
3. Establish ethical and safety standards for AI in nursing
4. Expand AI literacy for frontline nurses and students
5. Strengthen nursing's voice in AI policy & regulation

⚡ AI is reshaping nursing NOW. We must act NOW.

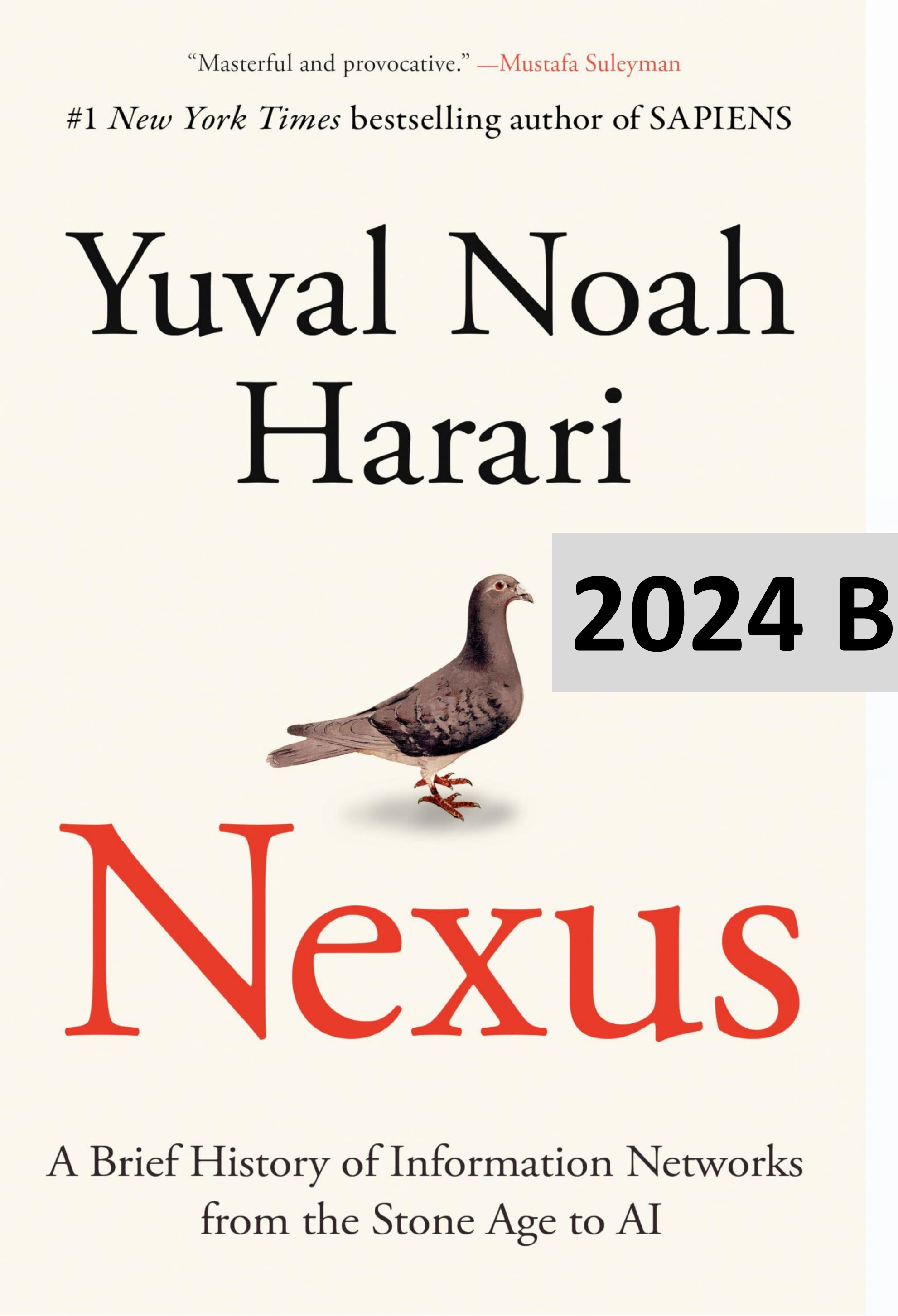
✅ Key Actions Nursing Must Take:

🚨 AI is here—nursing must lead, not follow.

How to stay updated with AI?

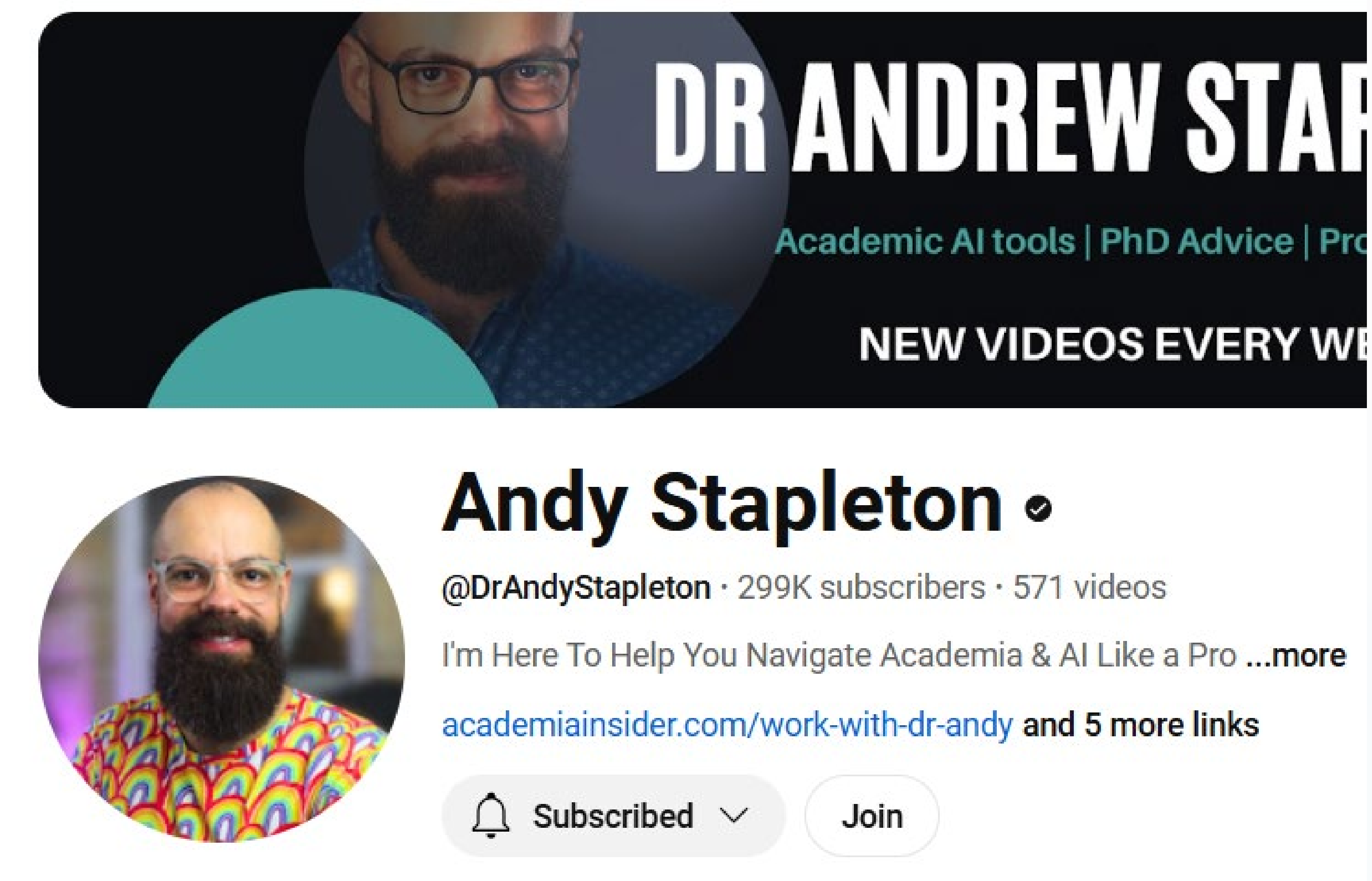
10 min daily

1 hr weekly



2024 Book

How to stay updated with AI?



YouTube

Search

Recommended AI Tools for Research & Productivity

LARGE LANGUAGE MODELS

Claude Opus 4.5 (Anthropic)- extended thinking!
Best for nuanced writing, analysis, coding

GPT-5.2 (OpenAI)- extended thinking!!!
Versatile, multimodal, widely integrated

Gemini 3 (Google)
Strong reasoning, Google ecosystem integration

RESEARCH & WRITING

Elicit / Consensus
AI-powered literature search and synthesis

Scite.ai
Citation analysis: supporting/contrasting evidence

Perplexity
Research with cited sources, fact-checking

PRESENTATIONS & VISUALS

Gamma.app
AI-generated presentations from prompts

CODING & DATA

Claude Code: Complex coding tasks, analysis

WRITING POLISH

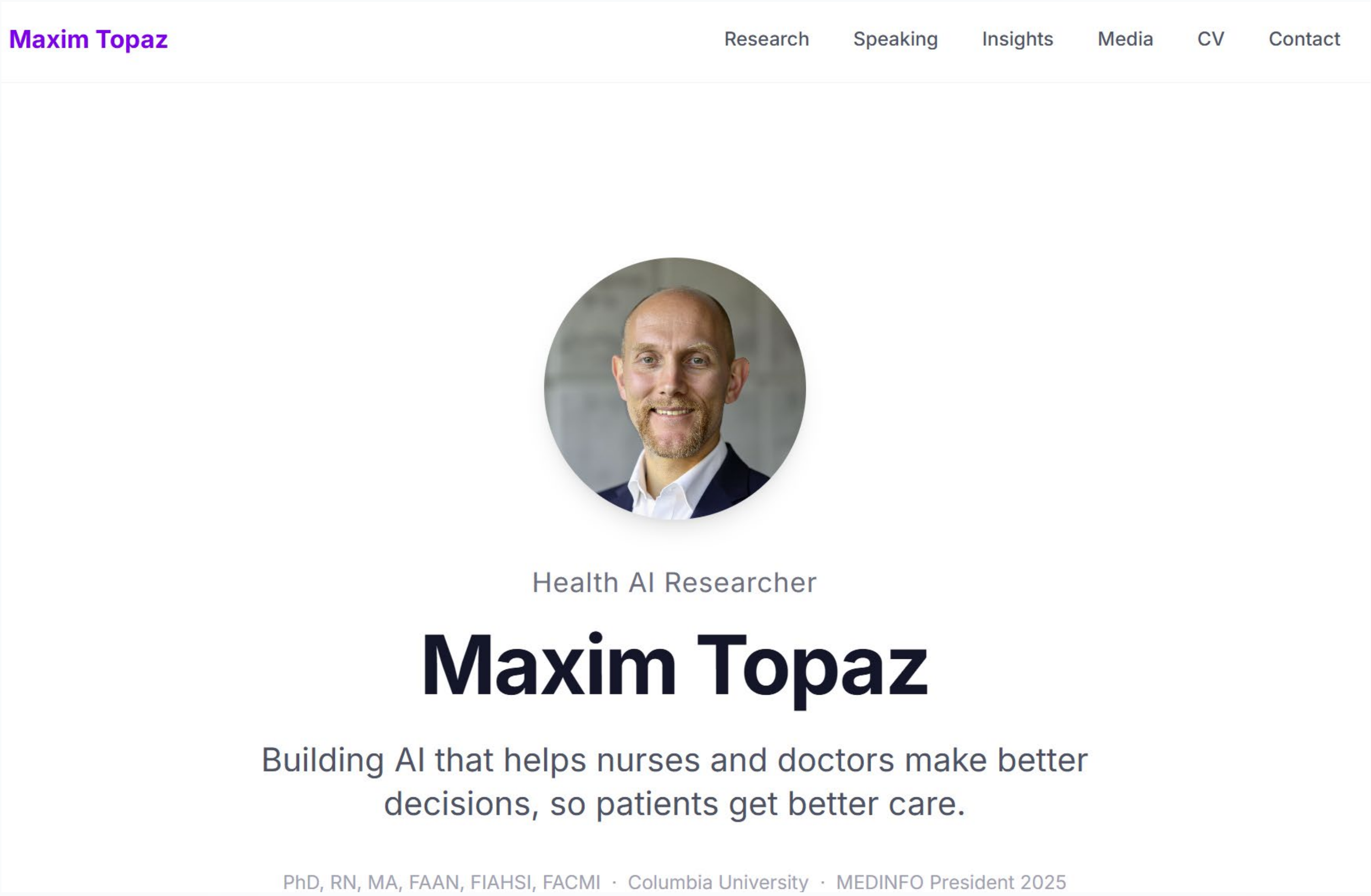
Grammarly: Grammar, clarity, tone

TRANSCRIPTION

Whisper: OpenAI's free transcription

Pro tip: Most powerful models now cost $20/month. Start with one (I recommend Claude) and explore others as needed. Free tiers exist but have significant limitations.

Claude code- from idea to product in minutes



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