AI in nursing: cutting-edge trends

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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

Session Objectives

1. Define artificial intelligence & nursing policy implications
2. Discuss different methodologic approaches that incorporate artificial intelligence.
3. Explore fairness and bias in artificial intelligence in research.

Brief Bio

- **Education:**
  - 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
  - **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

Definitions: what is AI?

- AI technology mimics human cognition to enhance data processing, insight generation, and automation across domains.
- Utilizing state-of-the-art AI technology has the potential to refine clinical outcomes and enrich patients’ and their families lives:
  - Enhanced analysis and utilization of vast nursing data.
  - Improved healthcare delivery tailored to individual and community needs.
  - Empowered healthcare professionals in making informed, timely decisions.


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How frequently do you use generative AI tools such as ChatGPT, Gemini, or Perplexity?

1 / 1

Never

Once a month

Weekly

Daily

Cannot live without it!

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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, Ana Beduschi LLB, LLM, PhD, Kenrick Cato FAAN, PhD, RN, Nicholas Hardiker FAAN, PhD, RN, Alain Junger, Martin Michalowski PhD, Rune Nyrup PhD, Samira Rahimi Eng, PhD, Donald Nigel Reed, Tapio Salakoski PhD, Sanna Salanterä PhD, RN, Nancy Walton PhD, RN, Patrick Weber, Thomas Wiegand PhD, Maxim Topaz PhD, RN ... See fewer authors

ICN
International
Council of Nurses

Position Statement

Digital health transformation and nursing practice

The digital technology revolution is supporting the rapid and positive transformation of healthcare systems—it is facilitating the delivery of nursing care and how people engage with their health and wellness. The use of digital health technologies is part of contemporary nursing practice. Digital technologies have the potential to support equitable and universal access to health services, increase the efficiency and reliability of health systems, improve patient and health worker safety, respond to

AI in Nursing: Key Priorities

1. Understanding Data and AI Technology

Nurses must understand how their documentation impacts AI tools.

Integrate AI knowledge into nursing education.

2. Involvement in AI Development

Nurses should participate in AI development and implementation.

Foster interdisciplinary collaborations in education and practice.

3. Global Health and Humanitarian Efforts

Leverage nursing's potential to use AI for addressing healthcare disparities.

Enhance the role of nurses in shaping AI use globally.

Actionable Strategies and Opportunities

Education

- Develop 'Minimum AI in Nursing Competencies.'
- Incorporate AI knowledge at all levels of nursing curricula.

Practice

- Create AI taskforces for practicing nurses.
- Develop guidelines for safe AI implementation.

Research and Leadership

- Research AI's impact on nursing.
- Promote continuous discussion on AI implications.
- Ensure transparency of AI system outputs for nurses.

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Which area needs the most improvement for effective AI integration in nursing? 0 / 0

Education and competencies

Practical guidelines and implementation

Research and understanding impact

Leadership

All of those

Objectives:

1. Define artificial intelligence.
2. **Discuss different methodologic approaches that incorporate artificial intelligence.**
3. Explore fairness and bias in artificial intelligence in research.

Home healthcare

1. More than 9 million patients in U.S.
~10,000 home healthcare agencies

2. Service provided: nursing, occupational/physical therapy, social work

AI advances in the last year

* This picture was generated with Dalee3 (https://openai.com/dall-e-3). **Prompt**: Generate an infographic-style image to represent home healthcare in the U.S. Feature a large '9 million' at the center, surrounded by smaller icons of a home, a nurse, a therapist, and a social worker. Use a neutral color palette to ensure readability and professionalism.

Home healthcare

1. More than 9 million patients in U.S.
~10,000 home healthcare agencies

2. Service provided: nursing, occupational/physical therapy, social work


Perplexity.ai

VNS Health

Created in 1780 by L. Wald

Provides care to 40K patients daily in New York City

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

PREVENT

ule: **Sum scores as follows. Any score >26 would suggest high priority for the first home health visit.**

Question: (Response =Score)	Score
Count the NUMBER OF MEDICATIONS prescribed to the patient =	
Count the NUMBER OF COMORBID CONDITIONS patient has =	
Does the patient have a comorbid condition of DEPRESSION (e.g. Depressive disorder, NEC)? NO = 0 YES = 15	
Does the patient have WOUND of any type? NO = 0 YES = 15	
Does the patient have LIMITATION IN TOILETING 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].

Large clinical trial ongoing now [R01NR018831].

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 clinical trial ongoing now [R01HS027742].

> J Am Med Dir Assoc. 2023 Dec;24(12):1874-1880.e4. doi: 10.1016/j.jamda.2023.06.031. Epub 2023 Aug 5.

Social Risk Factors are Associated with Risk for Hospitalization in Home Health Care: A Natural Language Processing Study

Mollie Hobensack [1], Jiyoun Song [2], Sungho Oh [3], Lauren Evans [4], Anahita Davoudi [4], Kathryn H Bowles [5], Margaret V McDonald [4], Yolanda Barrón [4], Sridevi Sridharan [4], Andrea S Wallace [6], Maxim Topaz [7]

> Nurs Res. 2022 Jul-Aug;71(4):285-294. doi: 10.1097/NNR.0000000000000586. Epub 2022 Feb 16.

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

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

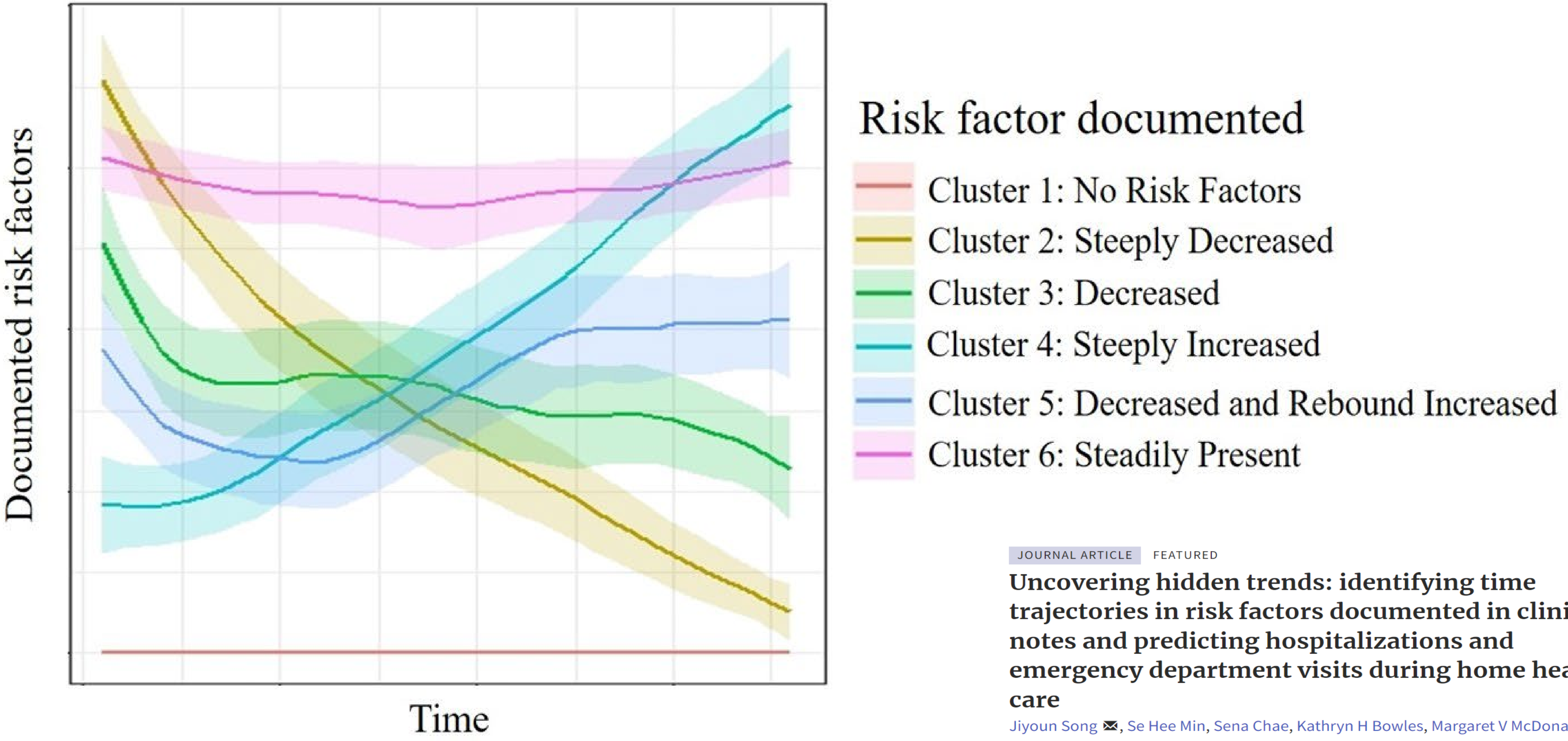
PMID: 35171126 PMCID: PMC9246992 DOI: 10.1097/NNR.0000000000000586

Table 1

Evaluation of NLP 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
Neuro-musculo-skeletal 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	9% (46)	0.93	0.80	0.86
Health care supervision	7% (35)	1.00	0.61	0.76
Cognition	7% (34)	0.97	0.89	0.93
Respiration	6% (32)	0.97	0.78	0.86
Communicable infectious condition	4% (18)	0.94	0.81	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

Figure 2. The temporal pattern of risk factors documented in clinical notes.



JOURNAL ARTICLE FEATURED

Uncovering hidden trends: identifying time trajectories in risk factors documented in clinical notes and predicting hospitalizations and emergency department visits during home health care

Jiyoun Song, Se Hee Min, Sena Chae, Kathryn H Bowles, Margaret V McDonald, Mollie Hobensack, Yolanda Barrón, Sridevi Sridharan, Anahita Davoudi, Sungho Oh ...
Show more

Journal of the American Medical Informatics Association, Volume 30, Issue 11, November 2023, Pages 1801–1810, https://doi-

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? Please share your estimates by raising a hand as I read through the scale below:

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Never
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Weekly
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Daily
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Example 3: Speech recognition

Verbal signal is everywhere!

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

Identified the most accurate automatic speech recognition system

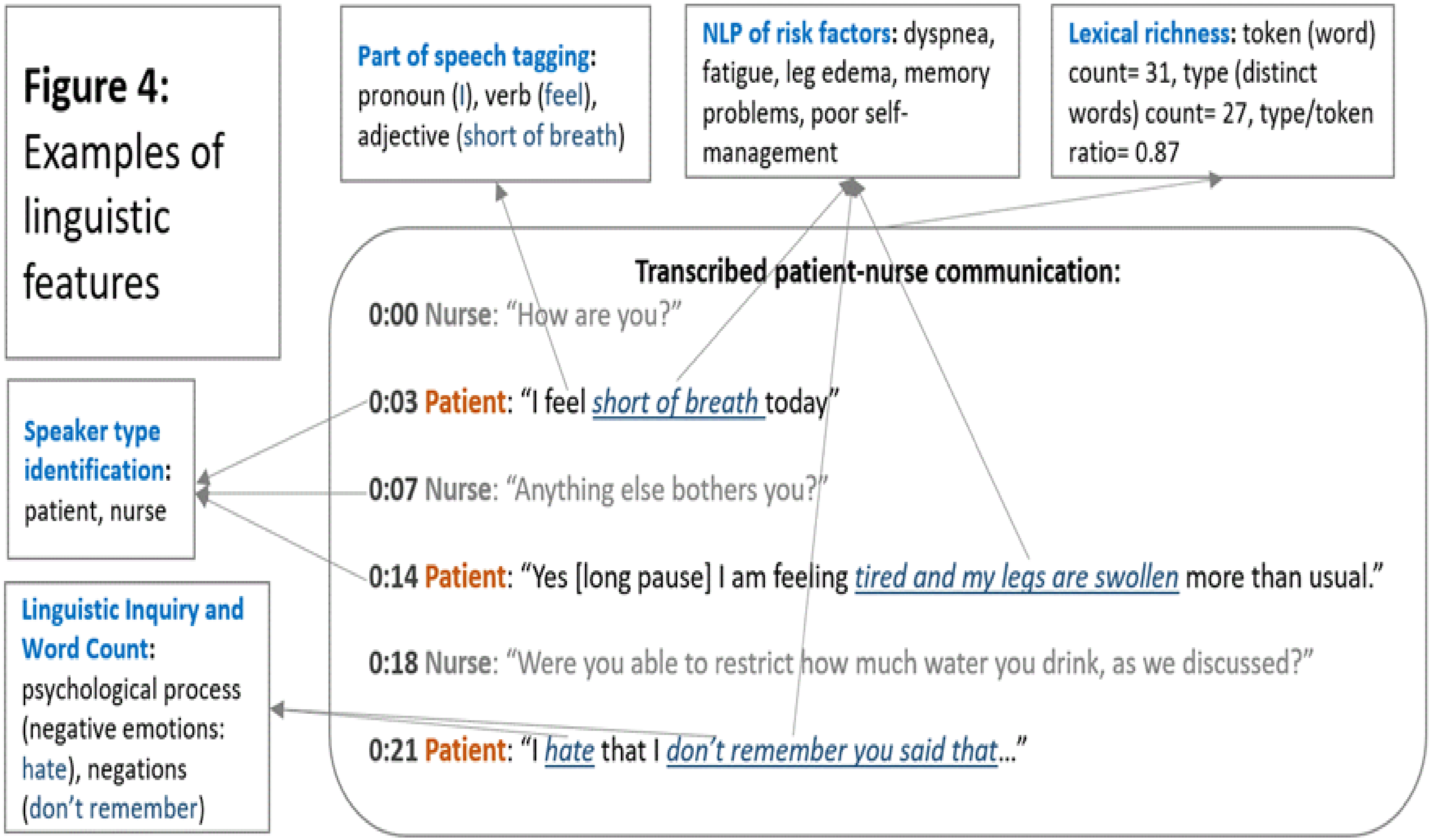
Under-documentation of problems among Black patients is **twice higher** (65%) than among White patients (34%)

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)



> J Am Med Inform Assoc. 2024 Jan 18;31(2):435-444. doi: 10.1093/jamia/ocad195.

Utilizing patient-nurse verbal communication in building risk identification models: the missing critical data stream in home healthcare

Maryam Zolnoori [1] [2], Sridevi Sridharan, Ali Zolnour [3], Sasha Vergez [2], Margaret V McDonald [2], Zoran Kostic [4], Kathryn H Bowles [2] [5], Maxim Topaz [1] [2]

Affiliations + expand

PMID: 37847651 PMCID: PMC10797261 (available on 2024-10-17) DOI: 10.1093/jamia/ocad195

Can we improve risk prediction?

Study: Using machine learning to improve the accuracy of hospitalization/ED visit risk prediction in HHC.

Methods: We used patient-nurse verbal communications with 46 unique patients. 15% were hospitalized or visited an ED during their HHC.

Results: **<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

Objectives:

1. Define artificial intelligence.
2. Discuss different methodologic approaches that incorporate artificial intelligence.
3. **Explore fairness and bias in artificial intelligence in research.**

What is bias in AI, and how do we use AI for bias detection?

Research Examples:

1. Bias in homecare risk prediction modeling
2. Bias in child abuse and neglect predictive modeling
3. Using AI to detect language bias in homecare and obstetrics

Summary & future directions

Example 1:
Fairness Analysis in the Prediction of Hospitalization or Emergency Department Visits for Home Healthcare Patients

Introduction

- AI models predict outcomes but may introduce bias.
- Developed an effective HF risk model.
- Assessing fairness across subgroups.

- **Objective**: to analyze biases, assess performance disparities, and discuss solutions to improve model fairness

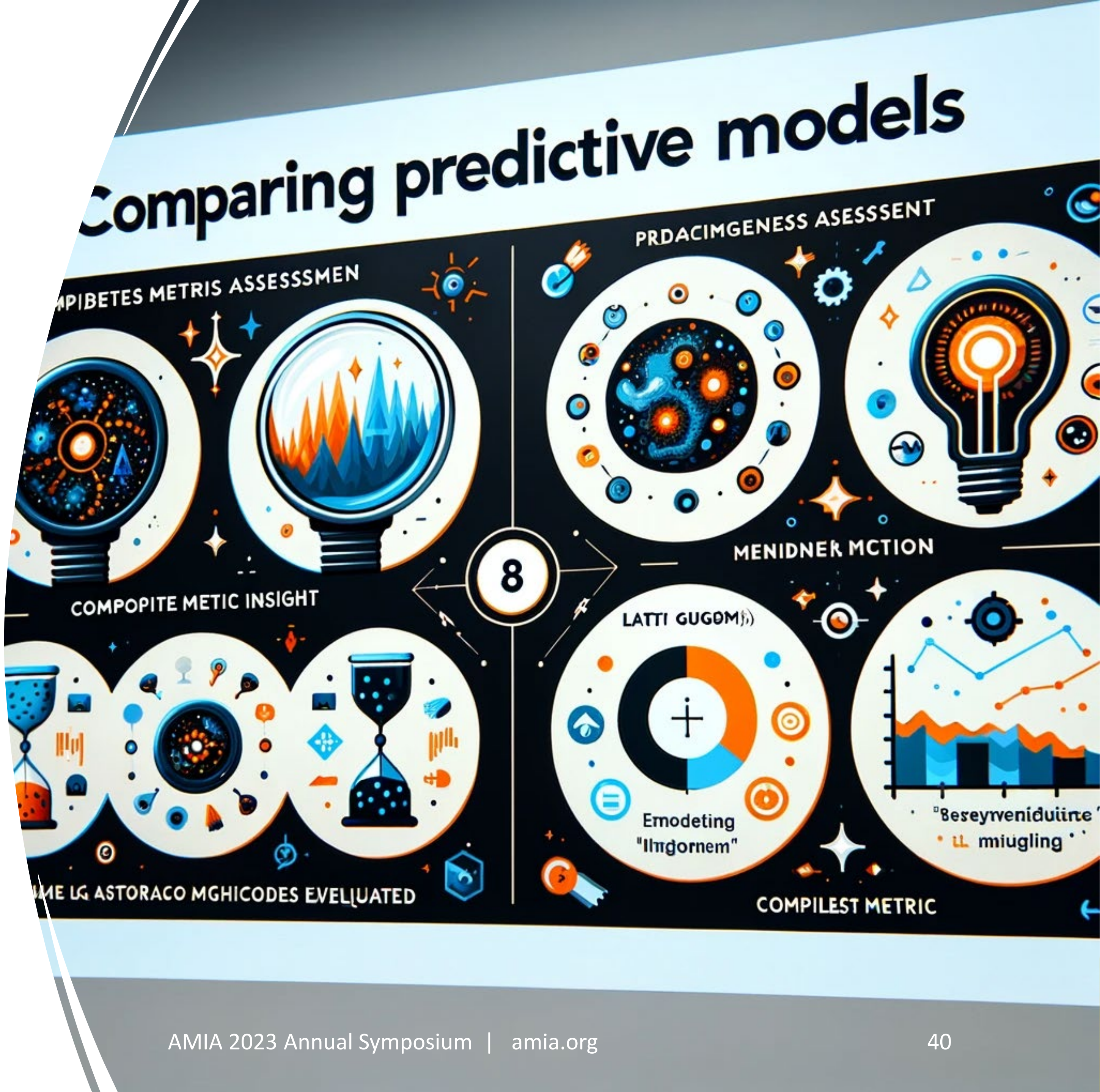
Davoudi, A., Chae, S., Evans, L., Sridharan, S., Barrón, Y., Song, J., Hobensack, M., Bowles, K.H., McDonald, M.V., Min, S.H., Oh, S., & Topaz, M.* Fairness Analysis in the prediction of Hospitalization or Emergency Department Visits in Home Healthcare for Patients with Heart Failure. AMIA 2023 Annual Symposium, New Orleans, LA. [Podium presentation]. 2023.

Methods - Study Population and Datasets

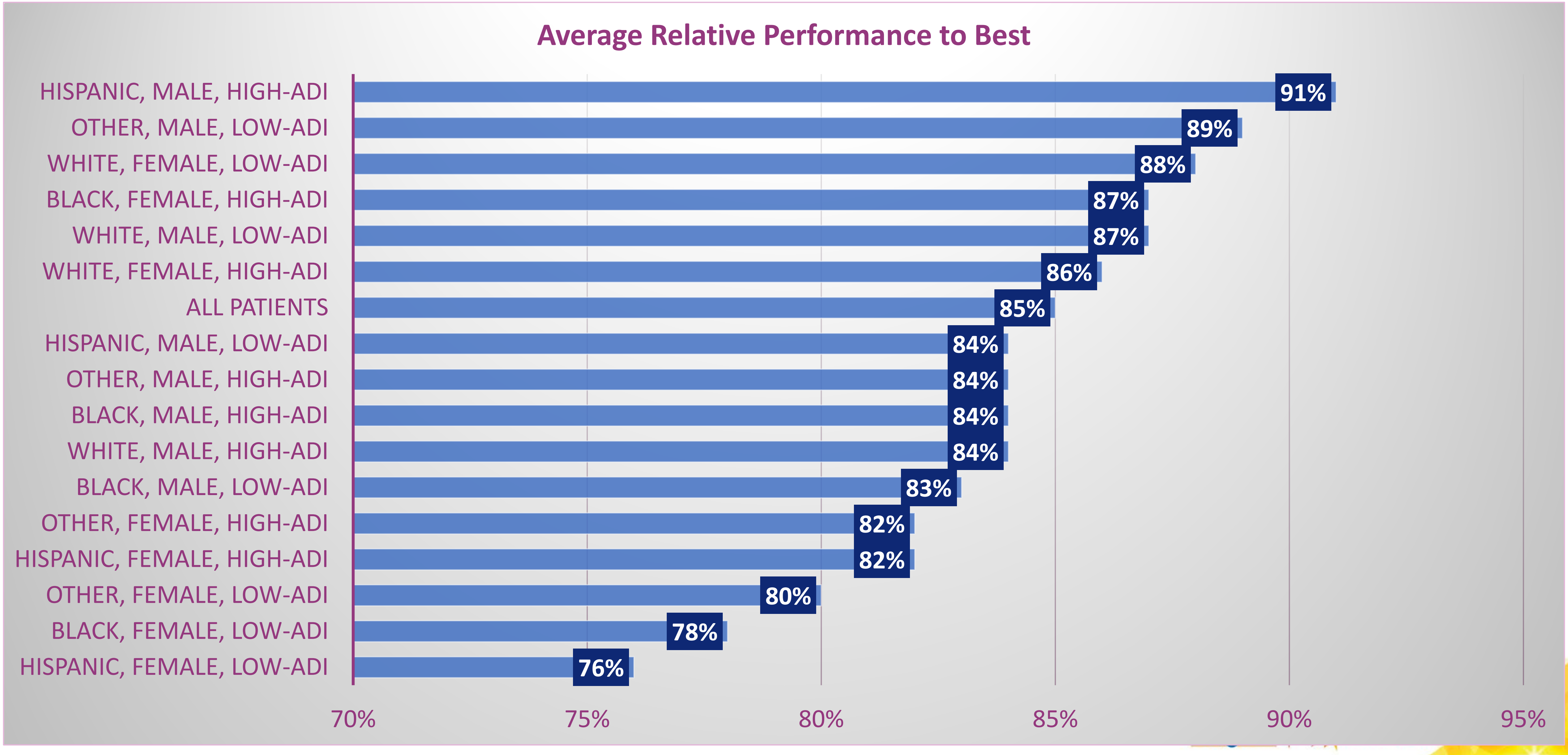
- Diverse Study Population
- Comprehensive Data Sources
  - Structured Data Insights
  - Unstructured Data Clarity
- Outcome (Hospitalization or ED visits)
- ADI Score
- NLP Techniques Leveraged

Methods - Risk Prediction Model

- Fairness Assessment Scope
- Six Metrics Evaluated
- Composite Metric Insight



Results



Average Relative Performance to Best
HISPANIC, MALE, HIGH-ADI
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WHITE, FEMALE, HIGH-ADI
ALL PATIENTS
HISPANIC, MALE, LOW-ADI
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BLACK, MALE, HIGH-ADI
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Discussion

- First study assessing fairness of AI-based risk prediction models for patient hospitalization/ED visits in HHC across diverse subpopulations.
- Introduced Average Relative Performance to Best, revealing substantial risk prediction disparities across patient demographics.
- Variations in key performance metrics, emphasizing the need for model refinement.

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How confident are you that current AI systems in healthcare are free from bias?

0 / 0

Very confident

Somewhat confident

Neutral

Not very confident

Not confident at all

RE-OPEN

HOW CONFIDENT ARE YOU THAT CURRENT AI... 4/5

Example 2: Bias in AI

Detecting Child Abuse and Neglect

The Challenge in Detecting Child Abuse and Neglect

- **Problem Statement**: Child abuse and neglect are prevalent but often go undetected.
- **Need for Timely Detection**: Risk models can improve detection, but development is complex.
- **Data Bias Concern**: Existing U.S. data shows disproportionate evaluation of Black and Hispanic children compared to White children, potentially reflecting societal biases.

The Dilemma in Developing Risk Models

- **Impact of Bias**: Using biased data risks perpetuating these disparities in new models.
- **Key Question**: How do we develop effective risk models without embedding existing societal biases?

Study 1: Considerations for Child Abuse and Neglect Phenotype

- **Objective**: Develop a phenotype for child abuse and neglect using Emergency Department (ED) data from EHRs, with implications for reducing racial bias.
- **Methodology**: Qualitative study with 20 pediatric clinicians in a pediatric ED.
- **Results**:
  - Challenges in diagnosing abuse and neglect.
  - Variations in documentation styles across health disciplines.
  - Potential racial bias in documentation.
- **Conclusions**: The study highlights the challenges in building an EHR-based risk phenotype for child abuse and neglect and underscores the need for further research in this area

Landau AY, Blanchard A, Cato K, Atkins N, Salazar S, Patton DU, Topaz M. Considerations for development of child abuse phenotype with implications for reduction of racial bias: a qualitative study. J Am Med Inform Assoc. 2022 Jan 29;29(3) 10.1093/jamia/ocab275. PMID: 35024857; PMCID: PMC8800508

Study 2: Ethical Challenges in AI Models

Objective: To discuss the ethical challenges in developing machine learning models for identifying child abuse and neglect using EHR data.

Seven Key Ethical Challenges:

1. **Data Biases**: Risk of perpetuating existing racial and socioeconomic biases.
2. **Documentation System Issues**: Inconsistencies and inaccuracies in clinical notes.
3. **Lack of Standardized Assessment Methods**: No uniform criteria for identifying abuse and neglect.
4. **Privacy Concerns**: Ensuring patient confidentiality while using sensitive data.
5. **Model Transparency**: Difficulty in interpreting complex machine learning models.

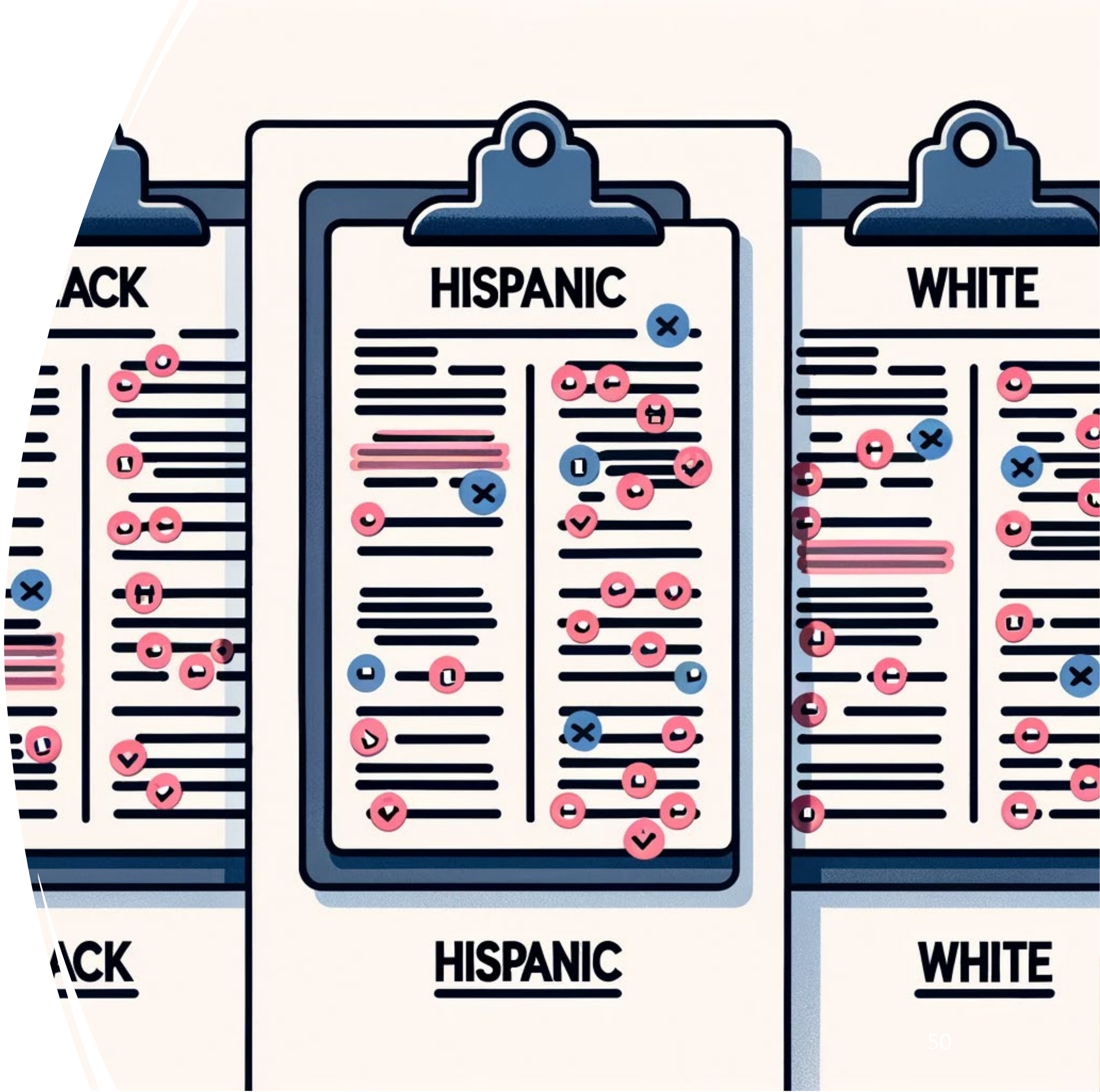
Landau AY, Ferrarello S, Blanchard A, Cato K, Atkins N, Salazar S, Patton DU, Topaz M. Developing machine learning-based models to help identify child abuse and neglect: key ethical challenges and recommended solutions. J Am Med Inform Assoc. 2022 Jan 29;29(3):576-580. doi: 10.1093/jamia/ocab286. PMID: 35024859; PMCID: PMC8800514

Example 3: Linguistic Bias in Home Healthcare/ Birth & Delivery

Example: Identifying biases via language

- **Study question**: Investigate racial differences in judgment language use in clinical notes.

- **Methods**: Data from 45,384 patients who received home health care services in 2019, using a natural language processing algorithm to detect judgment language in clinical notes.



Example: Identifying biases via language

Results:

Judgment language observed in 38% of patients, with higher usage in Hispanic and Black patients' notes.

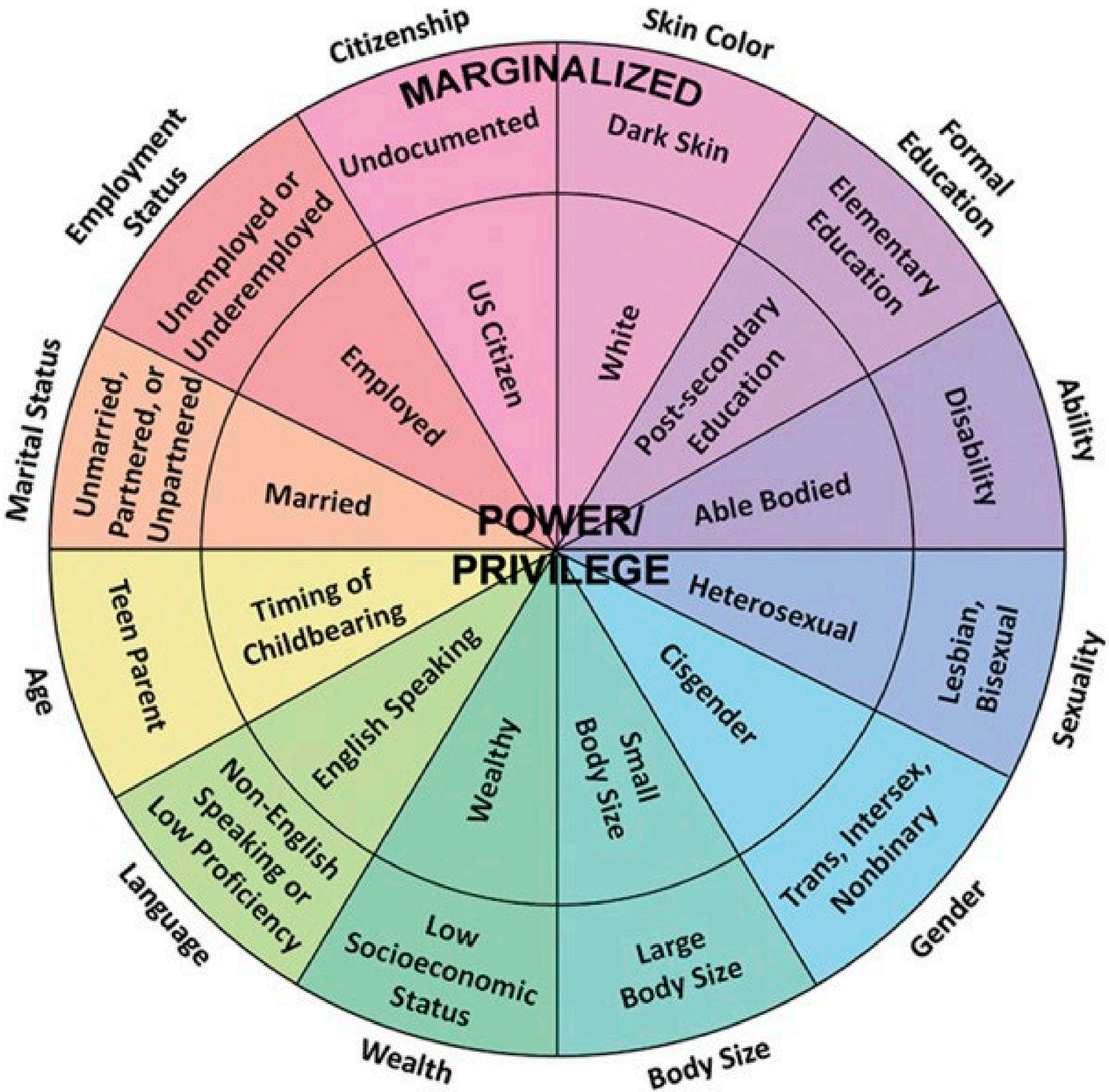
Black and Hispanic patients were 14% more likely to have notes with judgment language than White patients.

Large clinical trial ongoing to observe a nationwide sample

Examples from clinical notes
"…*claims* smoking cessation but ash tray still noted on night stand."
"pt [patient] *claims* he had fever in past, but no thermometer in use."
"He has a rw [rolling walker] but pt [patient] only uses it to get up fr [from] the bed. pt demoed another safe method of getting out of the bed, but pt *insisted* of doing it on his own manner."

The Power of Language in Hospital Care

- **Objective**: Analyze the role of language in pregnancy and birth care, focusing on marginalized identities.
- **Results**:
  - Highlighted how stigmatizing language perpetuates power dynamics and biases.
  - Recommendations for alternative language use at individual and systemic levels.
- **Conclusions**: Proposed a cultural shift in hospital-based care for birthing people to center their needs and experiences



Barcelona V, Horton RL, Rivlin K, Harkins S, Green C, Robinson K, Aubey J, Holman A, Goffman D, Haley S, **Topaz M.*** (2023). The power of language in hospital care for pregnant and birthing people: A vision for change. Obst & Gyn. [*ACCEPTED June 2023*].

Stigmatizing Language in Birth Admission Clinical Notes

- **Objective**: Identify stigmatizing language in clinical notes of pregnant people during birth admission.
- **Results**:
  - Found stigmatizing language in categories such as Disapproval, Questioning patient credibility, and Power/privilege.
  - Stigmatizing language was most frequent in triage notes.
- **Conclusions**: The study underscores the need for tailored interventions to improve perinatal outcomes and address biases in clinical documentation

Examples of stigmatizing language

1. **Questioning Patient Credibility**
   1. "Reports ‘no time to get depressed with 4 kids’"
   2. "SW is uncertain as to whether the patient was answering SW's questions truthfully"
2. **Disapproval**
   1. "Postpartum birth control method - patient states that she prefers to use condoms and will continue to readdress"
   2. "The writer asked if the patient wanted to see the lactation consultant again and the patient refused"
3. **Stereotyping**
   1. "When the SW intern asked where the baby will be sleeping upon arrival home. The father of the baby states that the baby will sleep in their bed. SW intern discussed that although this may be cultural, it is important for the baby to have his own bed"

#Barcelona, V., Scharp, D., Idnay, B. R., Moen, H., Goffman, D., Cato, K., & Topaz, M.* (2023). A qualitative analysis of stigmatizing language in birth admission clinical notes. Nurs Inq, 30(3), e12557. https://doi.org/10.1111/nin.12557 PMID: 37073504

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Do you believe healthcare professionals receive adequate training on understanding and addressing AI biases?

0 / 0

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Personal AI use

- Drafts of recommendation letters (e.g., GPT-pro, Gemini, Claude 3 Opus)
- Refine (shorten/expand/edit) my and others writing (e.g., GPT-pro, Gemini, Claude 3 Opus)
- Write programming code (e.g., GPT-pro, Gemini, Claude 3 Opus)
- Brainstorm ideas (e.g., GPT-pro, Gemini, Claude 3 Opus)
- Search the internet for specific things (e.g., Perplexity.ai)

Key Takeaways

Implement AI-Based Analysis: Regularly utilize AI tools to enhance nursing data analysis to improve patient care. This could involve adopting specific AI software or methodologies.

Tailor Healthcare Delivery: Integrate AI insights into healthcare practices to provide more personalized care to individuals and communities, reflecting the diverse needs and health profiles.

Emphasize Ethical AI Use: Educate and empower healthcare professionals to recognize and address fairness and bias in AI applications, ensuring the ethical use of AI in research and clinical practice.

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