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RESEARCH AND DELIVERY SCIENCE

UNIVERSITY OF COLORADO
CHILDREN'S HOSPITAL COLORADO



Leveraging AI with implementation science methods to enhance patient engagement and health equity

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How can IS and AI intersect to improve health equity and patient engagement?

Talk Agenda:

Dr. Maw: How can implementation science methods enhance AI effectiveness and equity?

Dr. Trinkley: How can AI enhance implementation science methods?

Dr. Goss: Example of AI used to enhance SDoH data capture and increase patient engagement

The Role of Pragmatic Implementation Science Methods in Achieving Equitable and Effective Use of Artificial Intelligence in Healthcare

Anna M. Maw, MD, MS^{1,2} , Katy E. Trinkley, PharmD, PhD^{1,3}, and Russell E. Glasgow, PhD²

Talk Agenda:

- Predictive AI applications
- Challenges to implementation of predictive AI in healthcare : lack of replicability and bias
- Applying the complex intervention paradigm to AI applications
- Learning health system Infrastructure paired with IS methods can make robust evaluations for equity and effectiveness feasible and pragmatic

Disclosures

- Consultant for Ultrasight

AI Interventions in Healthcare

Great potential to improve care and efficiency but only if implemented thoughtfully.

Predictive AI models

- Offers a probability of event

Examples:

- Sepsis
- Readmissions
- Pressure wounds
- Appointment absenteeism

- Currently AI applications are being taken up, but not rigorously evaluated

Challenges in AI: Replicability and maintenance of algorithm performance

- Considered one of the biggest barriers to AI improving clinical outcomes in healthcare
- Data is different setting to setting
- predictive performance is not generalizable across clinical environments
- Algorithms are considered “brittle”
- Model “drift” is also a challenge in dynamic environments



*Beam et al, *JAMA*. 2020

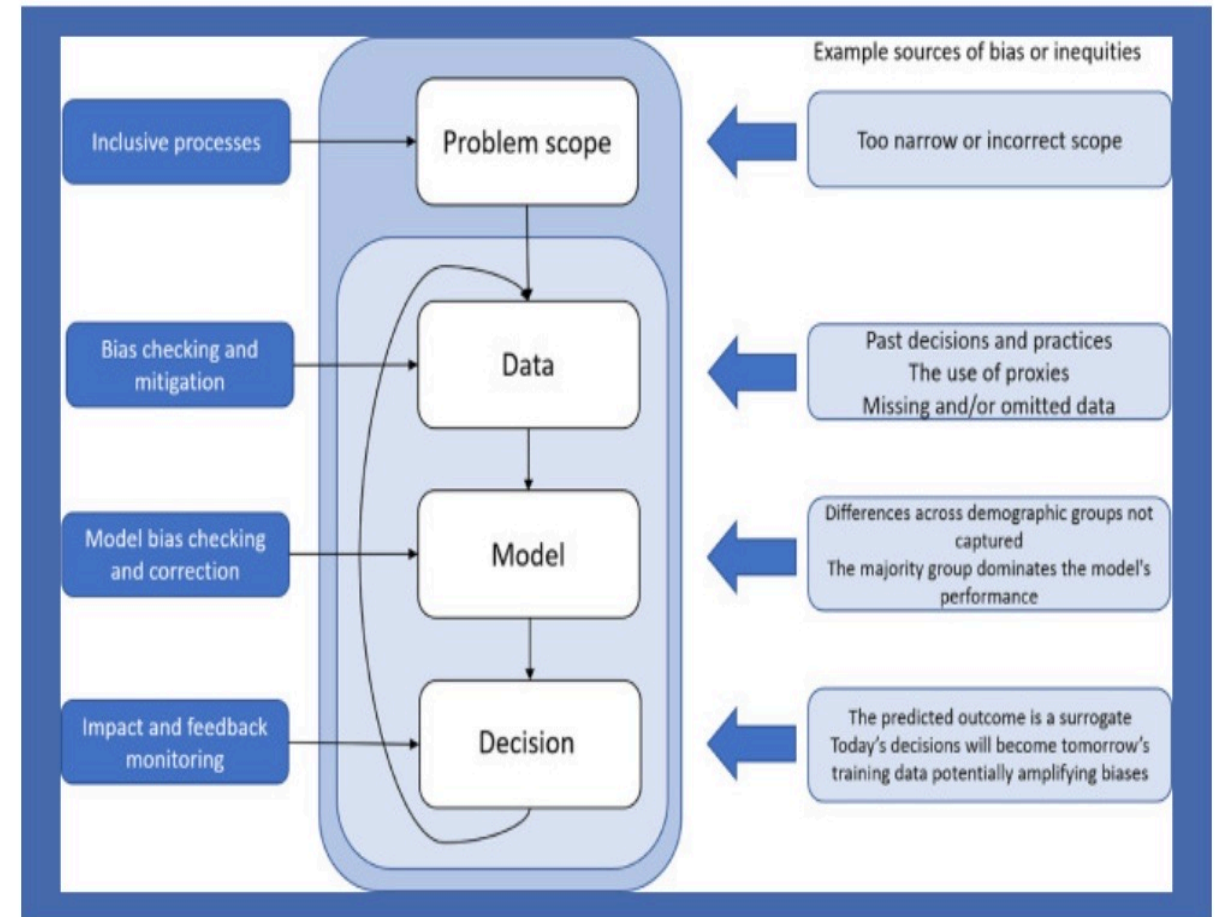
*Futoma et al, *Lancet Digit Health*. 2020

Challenges in AI : high risk of bias

Original Article/Research

Addressing algorithmic bias and the perpetuation of health inequities: An AI bias aware framework

R. Agarwal^b, M. Bjarnadottir^a  , L. Rhue^a, M. Dugas^c, K. Crowley^d, J. Clark^a, G. Gao^b



Challenges in AI: high risk of bias

Dissecting racial bias in an algorithm used to manage the health of populations

ZIAD OBERMEYER , BRIAN POWERS, CHRISTINE VOGELI, AND SENDHIL MULLAINATHAN 

SCIENCE • 25 Oct 2019

- Investigators evaluated high risk care management prediction model for bias
- found that black patients did worse clinically than white patients with the same risk score***
- source of bias: *cost* was used as a surrogate measure for severity of illness



How can implementation science help address the problem of replicability and bias?

AI as a complex context-dependent intervention

AI interventions meet the definition of a complex intervention

Skivington et al BMJ 2021

Has multiple components:

- AI model offers a probability
- Decision component is the system or human response to the probability offered

Has multi-level determinants

- Decisions made by leadership
- Responses by clinicians and patients

Example:

Sepsis Prediction Models

(Complex) AI intervention

AI Model

component:

ensure prediction performance is robust across all groups and over time given dynamic context

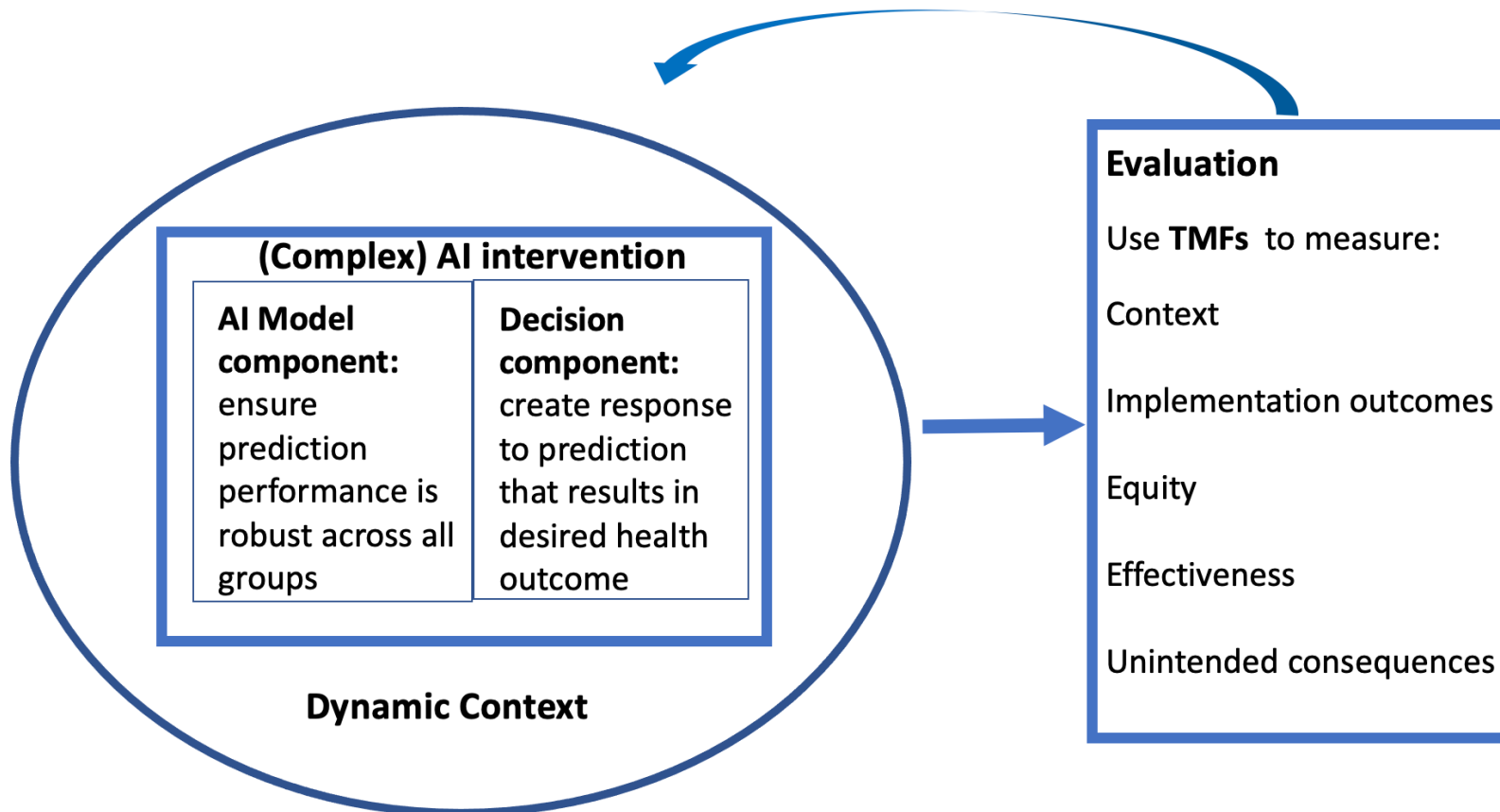
Decision

component:

Use of diverse multi level partner perspectives to create response to prediction that results in desired health outcome

Use D&I methods to optimize contextual fit

Iterative Adaptation



**Learning Health System
 Infrastructure
 Can make iterative
 adaptations pragmatic*



Example : Using Iterative RE-AIM to enhance hospitalist adoption of lung ultrasound in the management of patients with COVID-19: an implementation pilot study

Maw et al PMID: 35962441

Study Objective: Rapidly implement lung ultrasound within a large hospitalist group during COVID

Initial Implementation strategies:

Iterative PRISM process

RE-AIM Dashboard

Methods

- **Study Design:** Mixed Methods Implementation Pilot Study
- **PRISM** was our guiding Framework
 - **Study outcomes:** *Reach, Adoption, Implementation*
 - **Contextual domains of PRISM** used to guide qualitative interviews of hospitalists aimed at characterizing dynamic implementation barriers

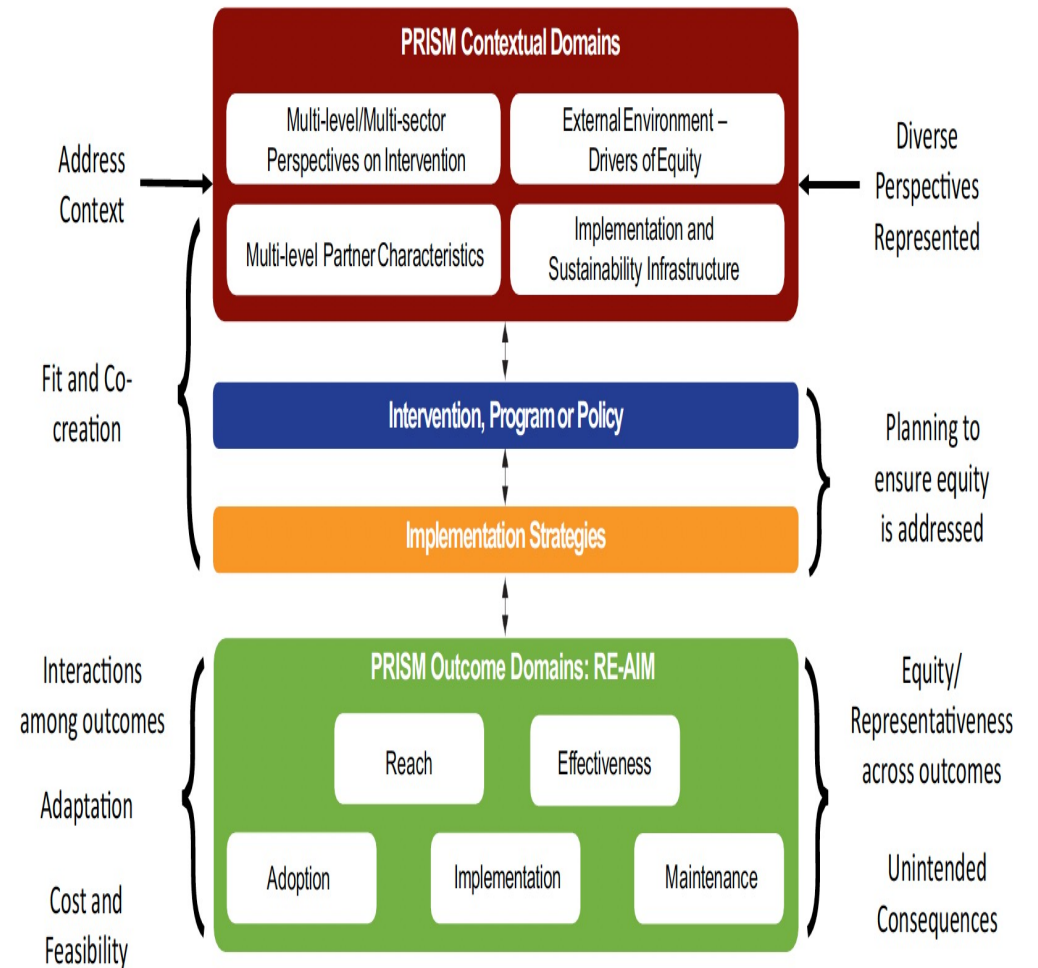
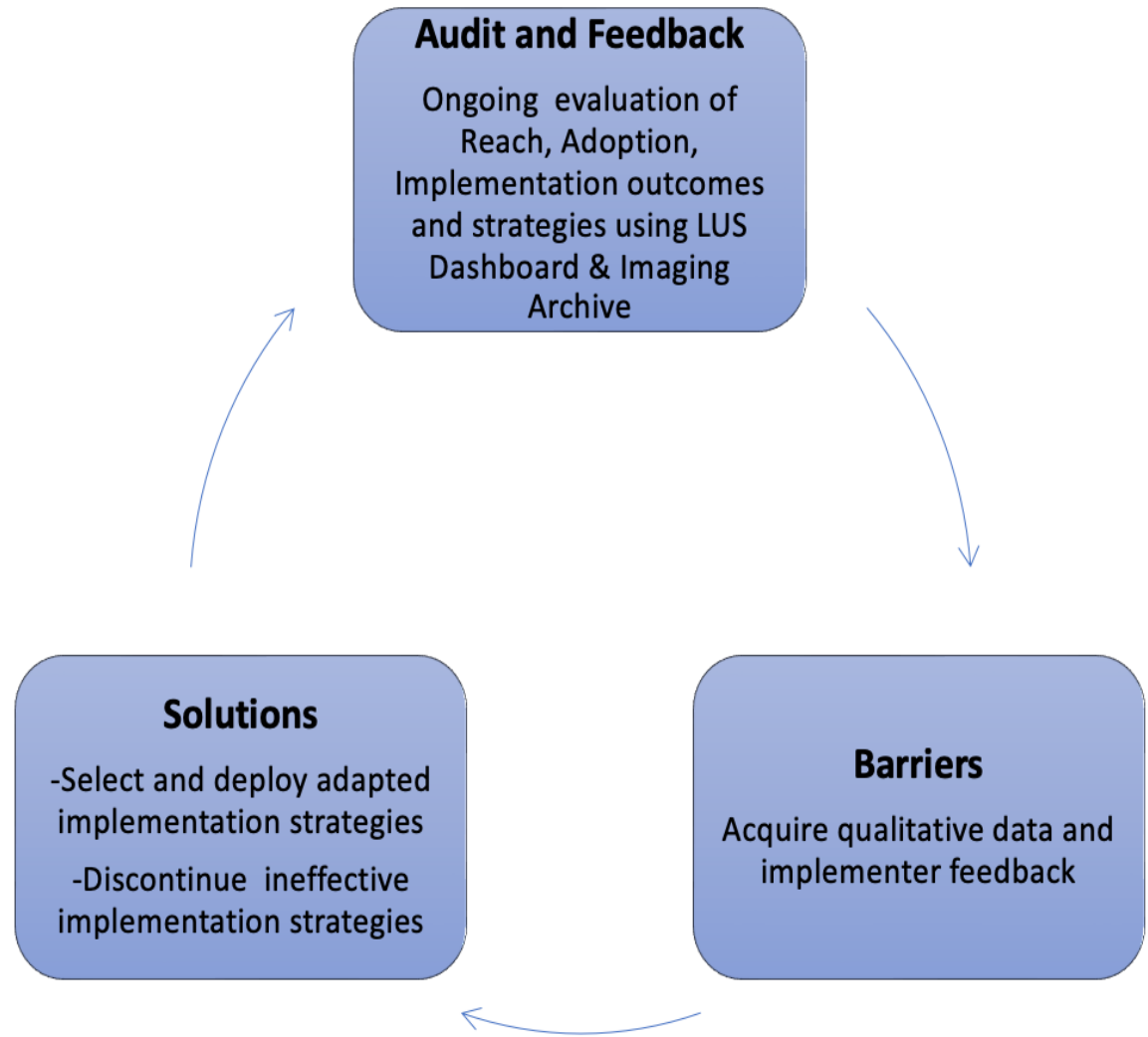


Figure 1 How the Practical Robust Implementation Sustainability Model (PRISM) facilitates equitable implementation of health interventions.



I-PRISM Process

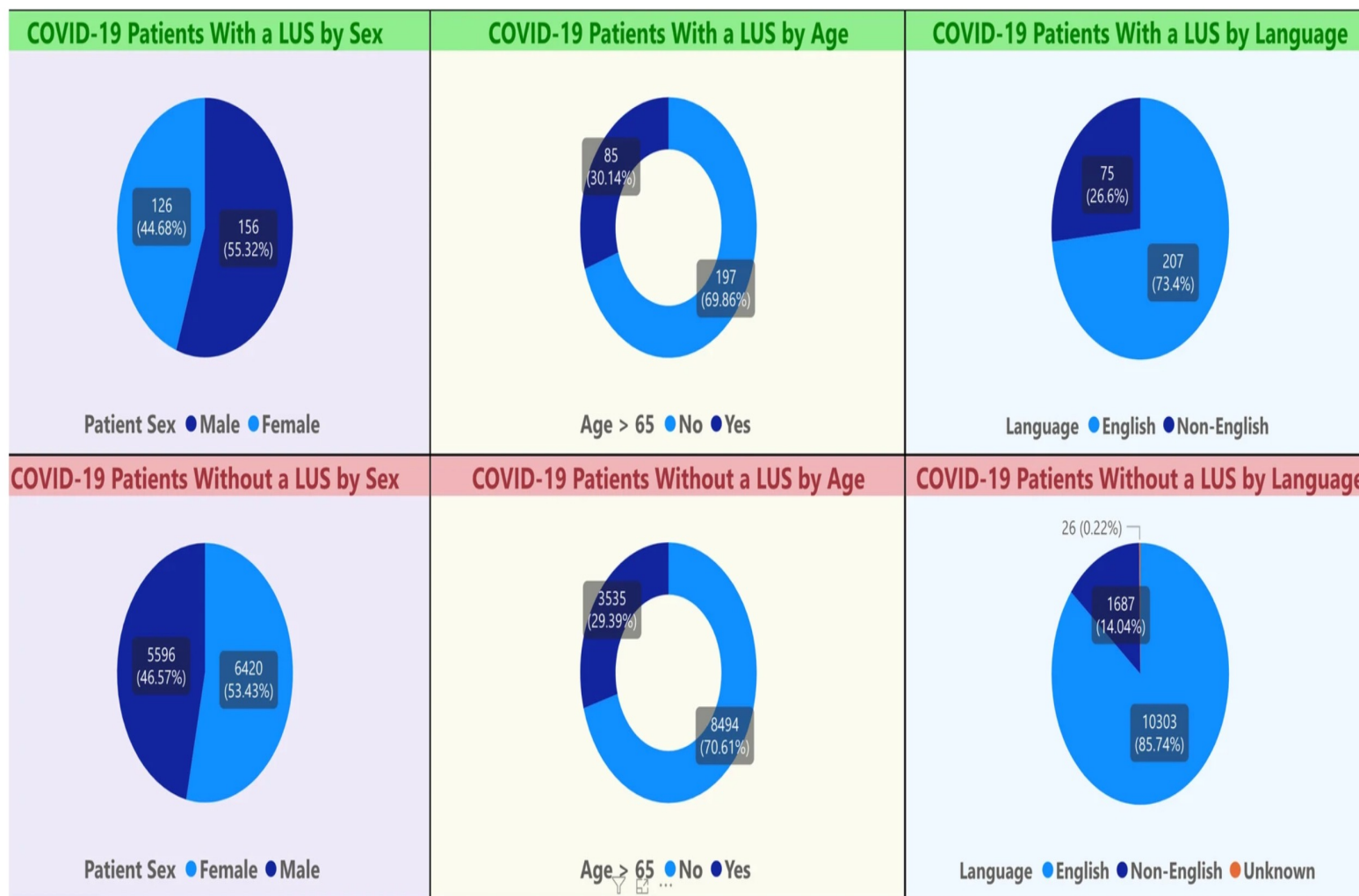
- Implementation Team: four LUS hospitalist faculty
- Met every 2 weeks
- Reviewed RE-AIM Dashboard data to screen for barriers to Adoption and Reach (prioritized implementation outcomes)
- Reviewed interview data acquired to identify and characterize barriers
- Select adaptations in implementation strategies in response to this qualitative and quantitative data





RE-AIM Dashboard

- Quantitative data on **Reach** and **Adoption** extracted from the EHR via an external Power BI dashboard
- Displayed the number and demographics of Clinicians finalizing and ordering the LUS
- Representativeness of patients in which LUS were ordered
- Data automatically updated every 48 hours
- Low burden way to monitor progress of implementation and representativeness





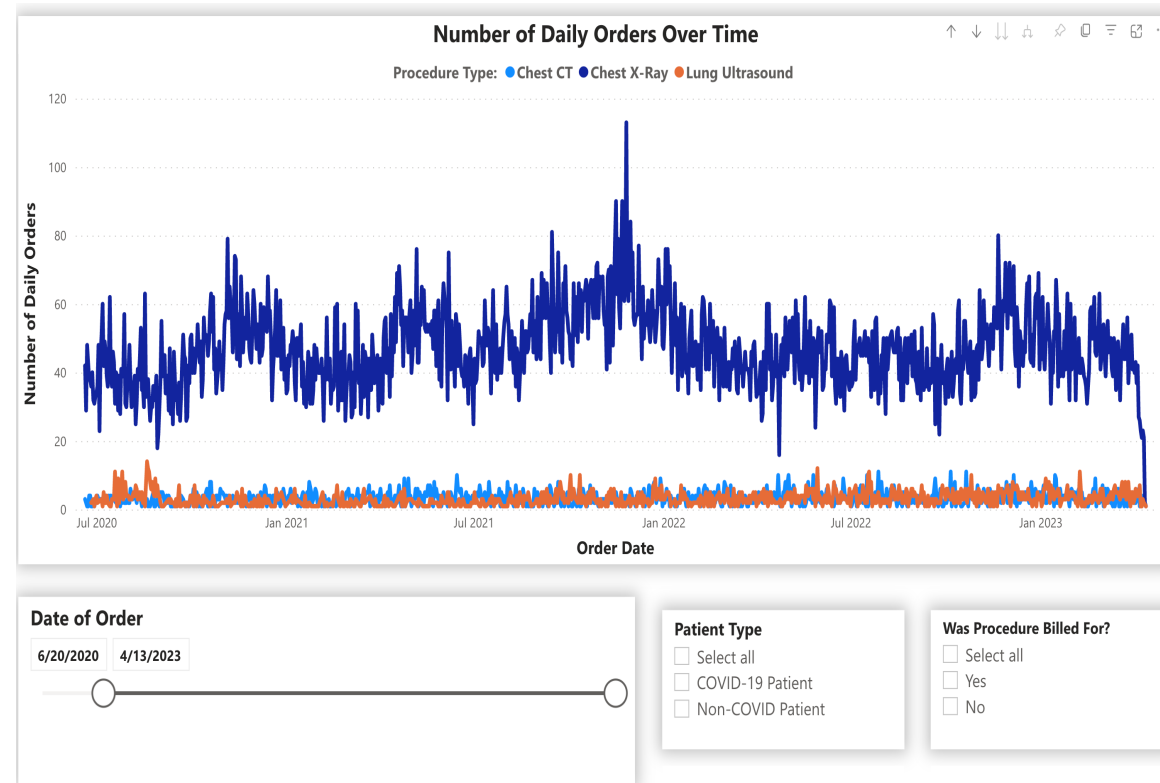
Future Directions

Automate measures of context and screen for unintended consequences

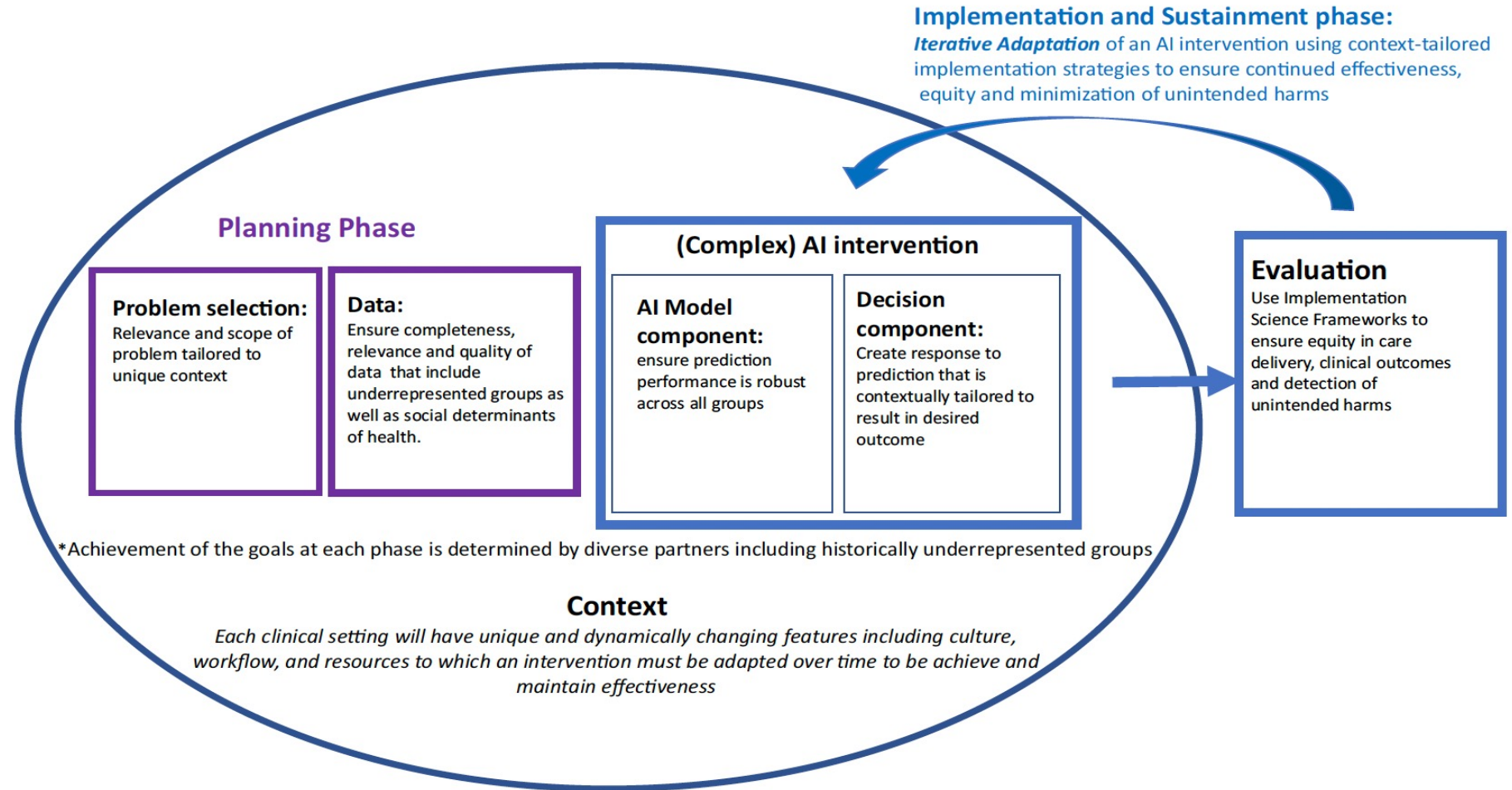
- **PRISM** Dashboards
- Explore whether NLP can assist with rapid qualitative assessments to make them more pragmatic?

Better detect and address disparities

- *Use AI to improve capture of high quality and complete data collection across patient demographics and SDoH measures*



IS/Equity lens must also be applied to planning phase



Thoughts:

- *Application of IS methods can help improve contextual fit thereby improving effectiveness, replicability and equity of AI interventions.*
- *AI and LHS infrastructure can be leveraged to improve the pragmatism and feasibility of these methods of implementation and evaluation with the ultimate goal of integration of these processes into health system operations.*



Using Artificial Intelligence (AI) to Augment Implementation Science (IS)



The Colorado Implementation
Science Center for Cancer Control

NHLBI K23 HL161352

NCI P50 CA244431

NCI P50 CA244688

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Acknowledgments: Anna Maw, Russ Glasgow, Ruopeng An, Ross Brownson

Disclosures

- Grants from NHLBI and AHA
- No other disclosures


Goals

DEBATE

Open Access

Leveraging artificial intelligence to advance implementation science: potential opportunities and cautions



Katy E. Trinkley^{1,2,3,4*} , Ruopeng An⁵, Anna M. Maw^{2,6}, Russell E. Glasgow^{1,2} and Ross C. Brownson^{7,8}

- Describe some ways AI can augment IS and examples
 - Equity
 - Assessing context
 - Speed



(select) Key IS challenges

1. Equity
2. Depth/breadth of assessing context and causality
3. Speed

→ Opportunities for AI to help



1. Equity is an IS challenge

- **Language barriers to participation**
- **Historically underrepresented groups**
 - May mistrust
 - Require tailoring
 - Underrepresented in traditional data sources

→ *can exacerbate inequities*



1. Equity is an IS challenge

AI can help!

- Language barriers to participation
 - AI-enhanced translation
- Historically underrepresented groups
 - May mistrust
 - Require tailoring
 - Underrepresented in traditional data sources

AI can expand data sources and recruitment strategies

AI-enabled culturally adapted chatbots - can address trust and SDoH

Zhang K, et al. *JAMIA*. 2017;24(4):781–787.

Miller MI, et al. *Neurotherapeutics*. 2023;30:1-15.

Mane H, et al. *JPHMP*. 2023;29:663-670.

→ ***can exacerbate inequities***



Example: Using chatbots to deliver culturally adapted education



Example: Rosie chatbot

Problem:

- Communities of color have higher maternal and infant mortality

Goal

- Close racial gaps by providing new mothers with culturally relevant health information

What they did

- Created/piloted an AI-enabled chatbot app (Rosie)
- With community input

What they found

- >90% likely to use



2. Assessing context/causality is an IS challenge

- Relies on ‘stated’ via qual data or ‘realized’ with *a priori* signal
- Often limited to:
 - Cross sectional
 - Descriptive and non-causal assessments
 - Simplifying complex relationships into linear relationships



2. Assessing context/causality is an IS challenge

AI can help!

- Relies on ‘stated’ via qual data or ‘realized’ with *a priori* signal

AI algorithms to identify de novo signals

- Often limited to:

- Cross sectional
- Descriptive and non-causal assessments
- Simplifying complex relationships into linear relationships

AI algorithms to account for complex interactions and look at trends

Sanchez et al. R Soc Open ci 2022;9:220638

Xiong. Artificial Intelligence and Causal Inference. <https://doi.org/10.1201/9781003028543>

Trinkley, An, Maw, Glasgow, Brownson. Implement Sci. 2024;19:17



Example: Using AI to identify de novo signals for IS



Example: Heart Failure Prescribing

Problem:

- Global gaps in prescribing critical meds for these high-risk patients

Goal

- Design interventions to address barriers to clinician prescribing

What was known

- Many known barriers → using traditional IS mixed methods
- The gap has persisted for > 10 years despite STRONG evidence and many interventions
- **Are we missing something?**



AI to identify barriers to prescribing

What we did

- Applied machine learning to EHR data to identify tangible barriers
- Collaborated: clinician scientists, implementation scientists and data scientists

What we found

- Validated some known barriers (e.g., older age)
- Identified some potentially new barriers (e.g., relationship status, substance use)

Next steps

- Conducted qualitative interviews to understand quant findings and solutions
- Designed alerts in the EHR to address these barriers



3. Speed is an IS challenge

- Its methods *take time*
 - Partner engagement conduct
 - Mixed methods data collection and analyses



3. Speed is an IS challenge

AI can help!

- Its methods *take time*
 - Partner engagement conduct
AI-enabled chatbots
 - Mixed methods data collection and analyses
AI can automate

Chang T, et al. J Mix Methods Res 2021;15:398–412

Lennon RP, et al. Fam Med Community Health. 2021 Nov;9(Suppl 1):e001287

Trinkley, An, Maw, Glasgow, Brownson. Implement Sci. 2024;19:17



3. Speed is an IS challenge

AI can help!

- Its methods *take time*
 - Partner engagement conduct
AI-enabled chat bots
 - Mixed methods data collection and analyses
AI can automate

AI may also reduce costs

Chang T, et al. J Mix Methods Res 2021;15:398–412

Lennon RP, et al. Fam Med Community Health. 2021 Nov;9(Suppl 1):e001287

Trinkley, An, Maw, Glasgow, Brownson. Implement Sci. 2024;19:17



Example

NLP versus traditional qual analysis

Findings/Conclusions:

- Traditional approach best for nuanced details
- NLP can identify major themes
- NLP can be used to validate traditional themes

[J Med Internet Res.](#) 2018 Jun; 20(6): e231.

PMCID: PMC6045788

Published online 2018 Jun 29. doi: [10.2196/jmir.9702](https://doi.org/10.2196/jmir.9702)

PMID: [29959110](https://pubmed.ncbi.nlm.nih.gov/29959110/)

Augmenting Qualitative Text Analysis with Natural Language Processing: Methodological Study



Some pontification

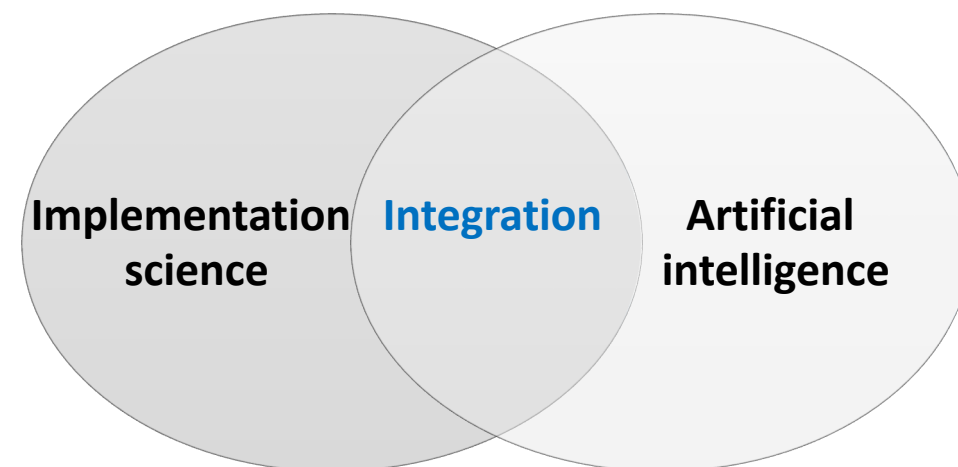
- IS and AI working together can...

-Accelerate the speed of knowledge generation and translation

-Maximize

- ✓ **Sustainability**
- ✓ **Equity** of impact
- ✓ **Scalability** and reproducibility

- Collaboration with AI experts is needed



Trinkley, An, Maw, Glasgow, Brownson. Implement Sci. 2024;19:17.

Maw, Trinkley, Glasgow. J Gen Intern Med. 2024;39:1242

Health Related Social Needs and AI

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DISCLOSURES

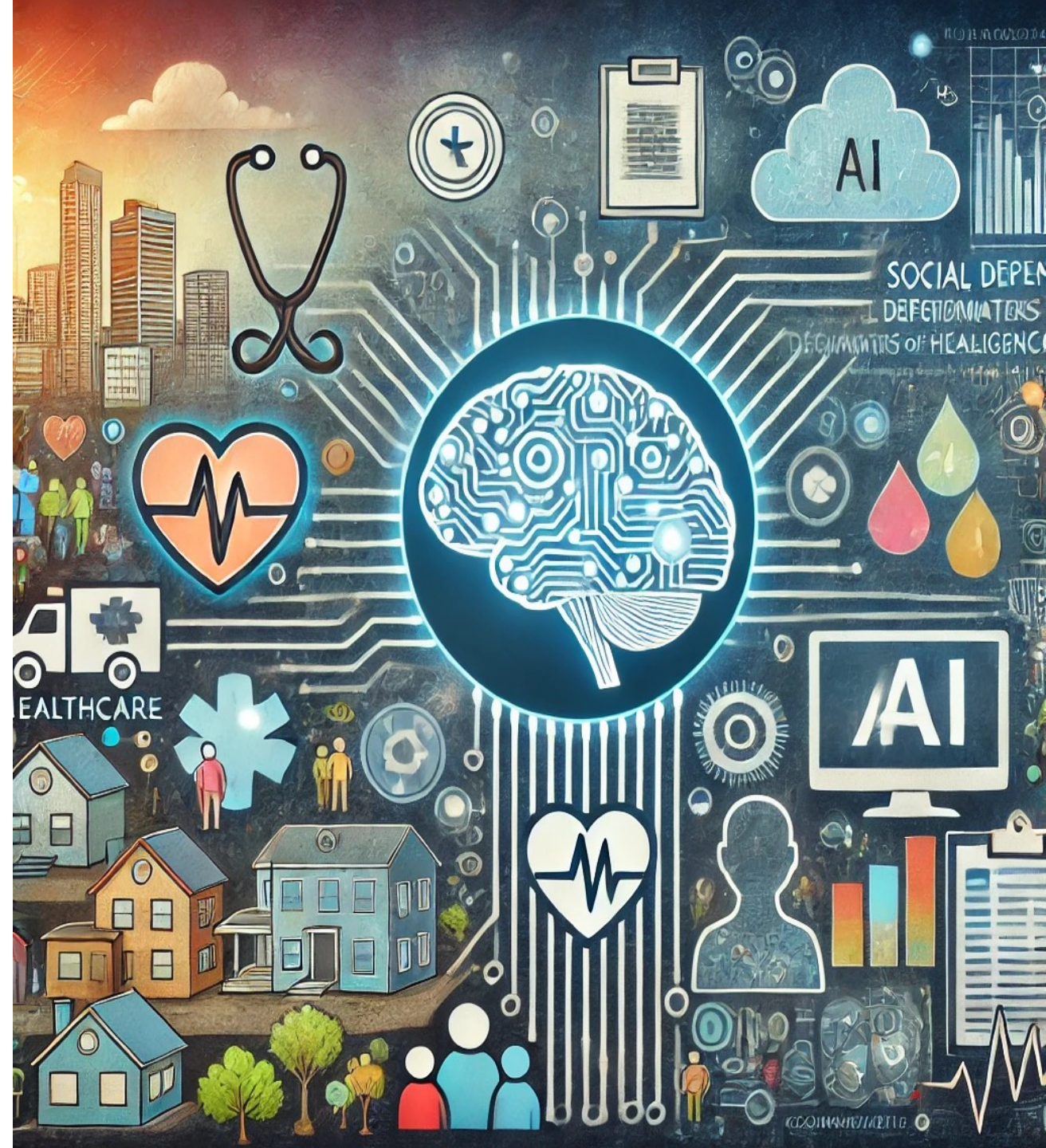
- Grants from National Institute on Minority Health and Health Disparities and The National Institute of Nursing Research.
- No other disclosures were reported.

AGENDA

Discuss new and innovative methods to capturing health related social needs (HRSN)

TOPICS

- HRSN in the ED
- Narrative Medicine
- AI and EHR workflows
- Future Directions



UCHealth Univ of Colorado Hospital (UCH)



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1.8M outpatient visits

50,779 inpatient/observation visits

166,088 ER visits

703 available beds

2022

HRSN IN THE ED

HRSN are prevalent in the Emergency Department and often where sex, race, identity, illness and policy converge.

BACKGROUND

- Recent studies show **17%-31% ED patients** reported at least **one social need**
- **ED visits 8 times higher** for patients experiencing **homelessness** comparable patients with stable housing
- The recent COVID-19 pandemic and entry of migrant populations into the U.S. have amplified both inequalities and disparities. (e.g., UCHealth has cared for almost **5,800 new migrant patients/4mo**).

5,259

Homeless Patients

4,030

Patient Nav Consults

2,448

Social Work Consults

Abuse/Neglect	131
Family Support	145
Financial Barriers	357
Family Support	123
Homelessness	669
MentalHealth (resources)	369
Substance abuse	1282
Other(specify comments)	in 426

UCHealth – last 6 months (2023)

TARGET AREAS

Housing insecurity

“In the last 12 months, was there a time when you did not have a steady place to sleep or slept in a shelter (including now)?”

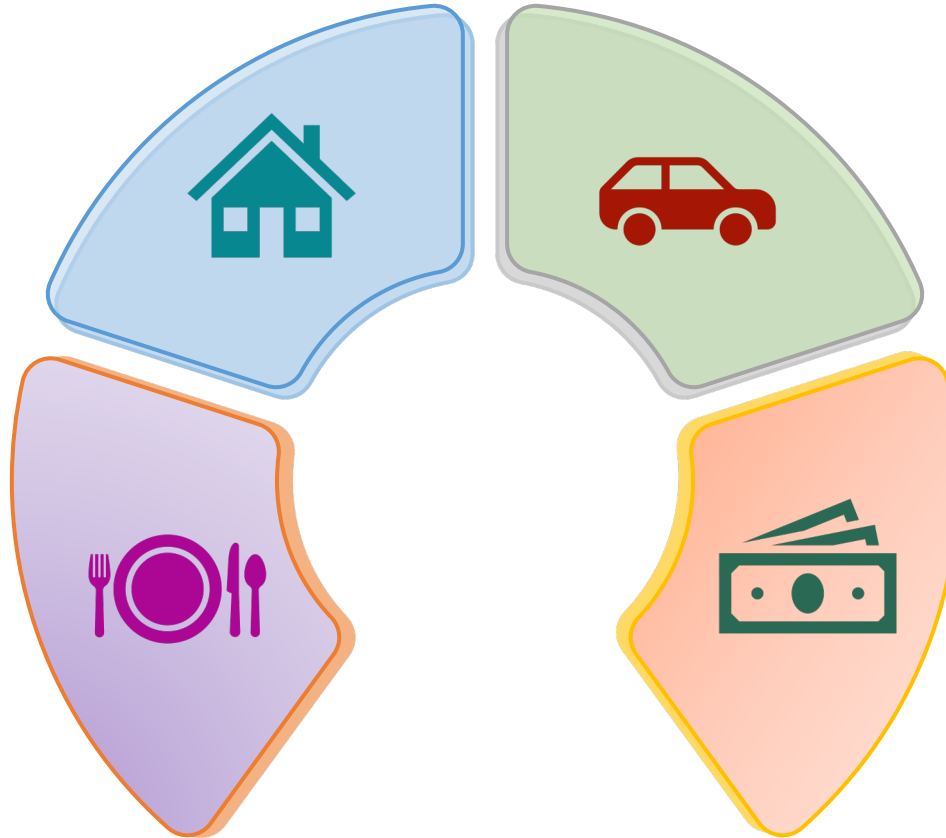
Registration

Food insecurity

“Within the past 12 months, the food you bought just didn't last and you didn't have money to get more?”

“Within the past 12 months, you worried that your food would run out before you got the money to buy more?”

Pt Nav



Transportation

“In the past 12 months, has lack of transportation kept you from medical appointments or from getting medications?”

Pt Nav

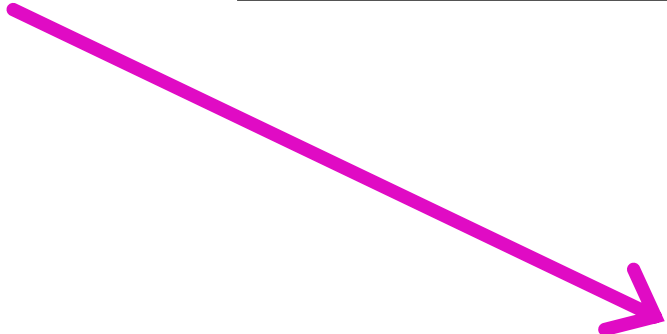
Financial strain

Registration collects information on health insurance. No insurance registration through “Self Pay” status is used as a proxy for the HRSN of financial needs.

Registration

RISK STRATIFICATION

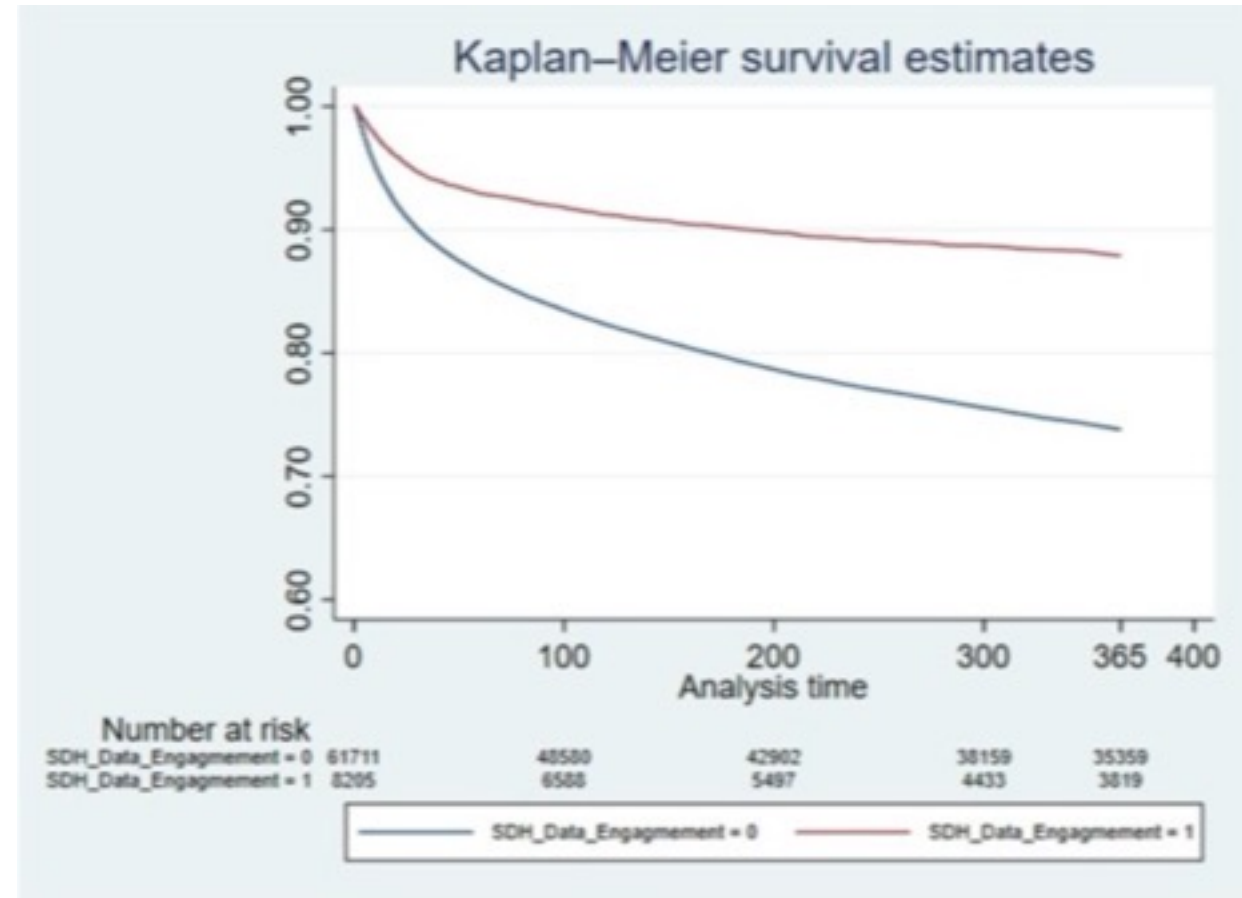
No	Low	Medium-High
No HRSN identified	HRSN identified	>1 HRSN identified
	English proficient	>2 ED visits in last month
	Access to reliable internet	>1 chronic illness
		Limited English proficiency
		Need for ASL services
		Vision impairment



ENGAGEMENT WITH DATA

SDOH information matters in patient outcomes.

- Prior studies have shown that discrete **social history** question fields were only used in 0.03% of hospitalizations and discrete SDOH documentation in the **problem list for 0.09%** of hospitalizations
- Study by **Lott BE** et al found reduced readmissions when clinicians engaged with SDOH information.
- Disparities noted older patients; Black, African American, Hispanic, and Latino patients; and publicly insured patients



Kaplan-Meier survival estimates for 1 year readmission given SDH data engagement: UCSF Health (February 1, 2018–April 30, 2021, n.69 916). SDH: social determinants of health; UCSF: University of California, San Francisco.

CAPTURING HRSN DATA

Despite clear value for capturing HRSN information, controversies exist on how to best capture this information in routine care

- **Questionnaires/ predefined questions** and answer choices may **not cover all relevant SDOH factors**, (e.g., provider talks about smoking history, but patient wants to talk about the unreliable source of heat in their appt)
- Patients may **misinterpret** the questions (e.g., due to cultural differences, language barrier).
- Quantitative data collected **might not provide insight** into the reasons behind certain conditions or behaviors, limiting the development of targeted interventions.

Show As ...

ing

everyone should have the opportunity for health. Some things like not having enough food or reliable transportation can make it hard to be healthy. Please answer the following questions to help us better understand you and your care. You may not be able to find resources for all of your needs, but we will try and help as much as we can.

past 12 months, did you worry that your food would run out because you didn't have enough money to buy more? Yes No

past 12 months, did the food you bought just not last because you didn't have money to get more? Yes No

Housing

past 12 months, have you ever stayed: outside, in a tent, in an overnight shelter, or temporarily in someone's home (i.e. couch-surfing)? Yes No

Are you worried about losing your housing? Yes No

past 12 months, have you been unable to get electricity when it was really needed? Yes No

Transportation

past 12 months, has a lack of transportation kept you from getting to medical appointments or from doing things needed for your health? Yes No

Safety

Are you physically or emotionally unsafe where you live? Yes No

past 12 months, have you been hit, slapped, kicked or physically hurt by anyone? Yes No

past 12 months, have you been humiliated or bullied by anyone? Yes No

Immediate Need

Are your needs urgent? For example, you don't have enough food, you don't have a place to sleep tonight, you are worried you will get hurt if you go home today. Yes No

Do you like help with any of the needs that you have? Yes No

NARRATIVE MEDICINE

*Our **social reality** is created through **stories** of shared language and context.*

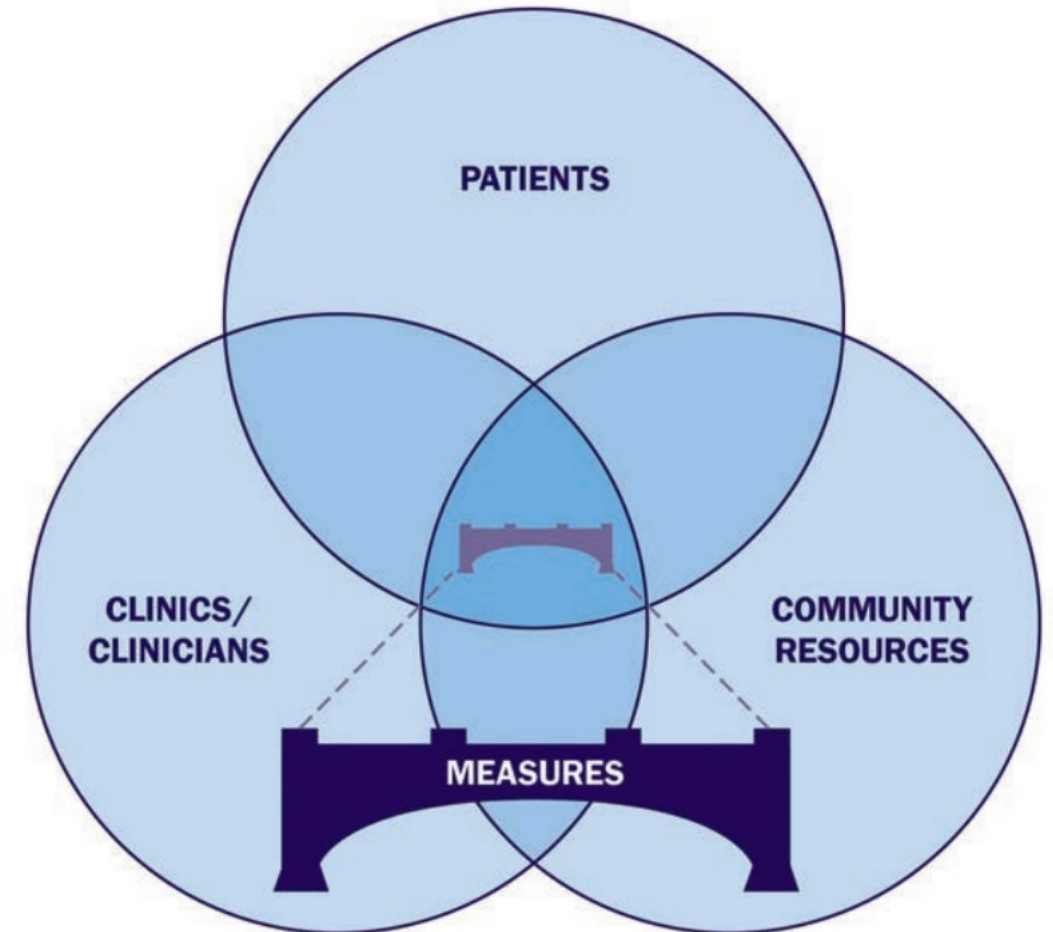
- This social, historical, and cultural context provides **key concepts that may be overlooked** by the restrictive nature of structured questionnaires.
- Narrative medicine improves a clinician's ability to hear, interpret, and respond to a patient story
- Narrative medicine shifts the focus from a provider-centric perspective to a **patient-centered** approach that values the complexity of individual experiences.



CHALLENGES AHEAD

SDOH information is often captured in free text and not regularly screened for a variety of reasons

- **WHY?** Time constraints, clinician experience/comfort in asking, patient fears of sharing potentially stigmatizing information.
- As **free-text or unstructured data**, difficulty to leverage clinical decision support to target interventions.
- **Tools that leverage AI** can advance our ability to capture this information using a framework in which the **clinician, individual, and community are interconnected spheres** that work together to achieve health equity and reduce disparities



HOW DO WE CAPTURE PATIENT NARRATIVES AND TRANSLATE THEM INTO ACTION



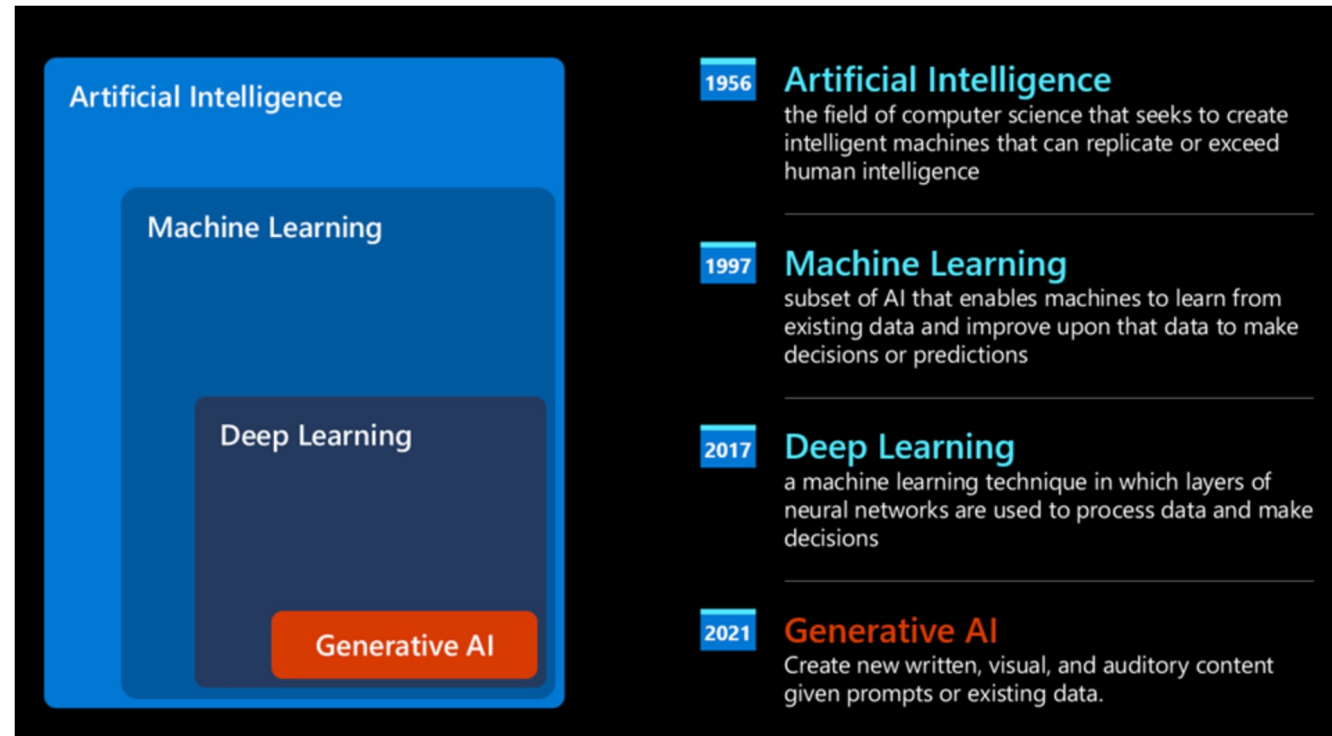
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GENERATIVE AI

Large Language Models have simplified the ability to capture unstructured data (e.g., narratives of the patients' social needs)

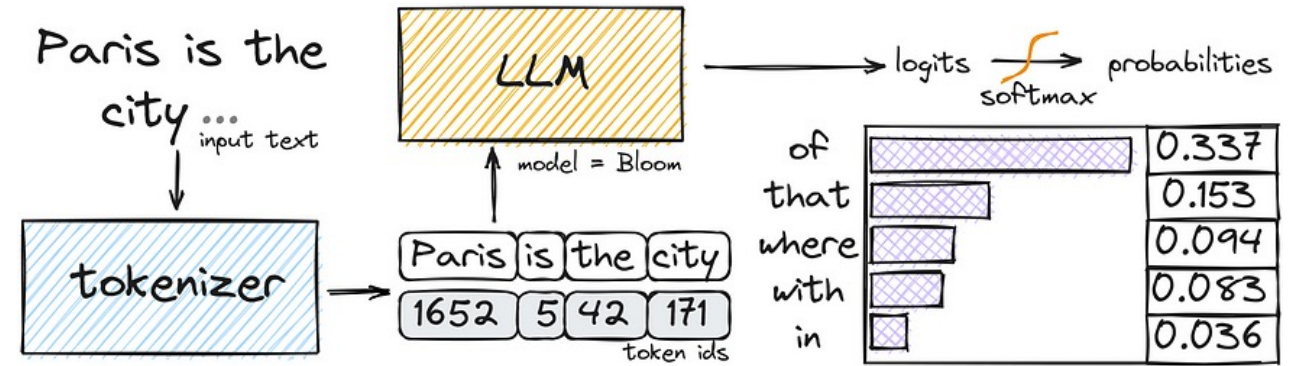
EVOLUTION

- Generative AI is a subfield of artificial intelligence.
- Trained on a large number of unlabeled data from multiple sources (e.g., websites, books, articles) and can be applied to a number of tasks
- Can work with textual inputs and generate a response in human language.



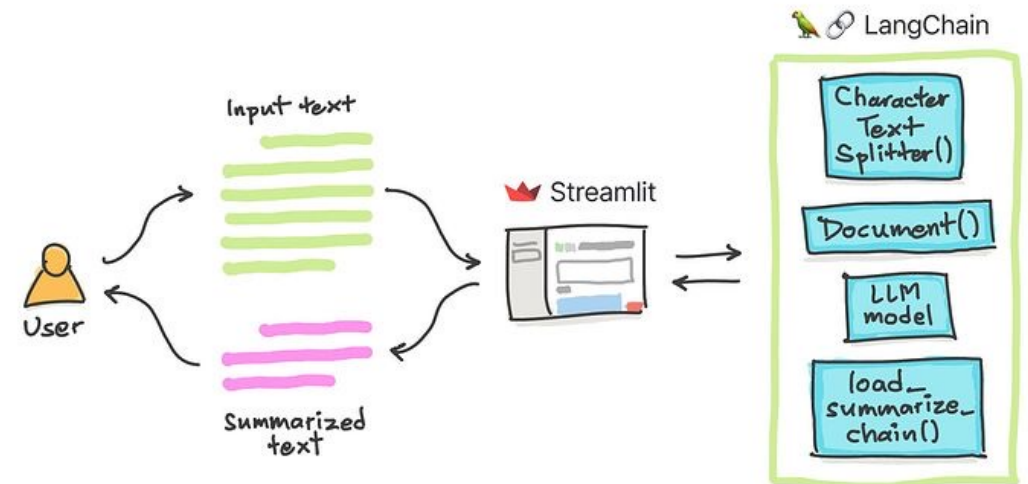
TYPES OF MODELS

Many different types of large language models, and choice depends on the use case, your data.



EXAMPLES

- **Audio and speech recognition** (e.g., Whisper, DAX/Abridge products)
- **Image generation** (e.g., DALL-E and Midjourney)
- **Text generation** (e.g., Gpt 3.5, 4.0, 4.5)
- **Multi-modality** (Gpt-4 turbo, Gpt 4o)



NARRATIVES - TEXT

Model Input

Q: Tell us about your housing situation. Where are you living right now?, Do you worry about your finances?

A (Patient): "There was a time in the last year when I couldn't pay my rent on time. Money was really tight because I had lost some hours at work, and it seemed like bills were piling up faster than I could handle them. I had to use the little money I had for other important stuff, like food for me and my kids, and making sure we kept the lights on and the water running. It was a tough spot to be in. I remember feeling really stressed and worried because I didn't want to lose our home. I talked

under:
not
ma

Q: "Cuéntanos sobre tu situación de vivienda. ¿Dónde estás viviendo actualmente? ¿Te preocupan tus finanzas?"

A (Patient): "Sí, hubo un momento en el último año cuando no pude pagar mi alquiler a tiempo. El dinero estaba realmente ajustado porque había perdido algunas horas de trabajo, y parecía que las facturas ...

Model
Prompt

Model Output

Economic Stability: Struggles with paying rent on time due to financial constraints and loss of work hours.

Employment: Reduced work hours affecting income and financial security.

Food Security: Prioritizing limited funds for food, indicating potential challenges in accessing adequate nutrition.

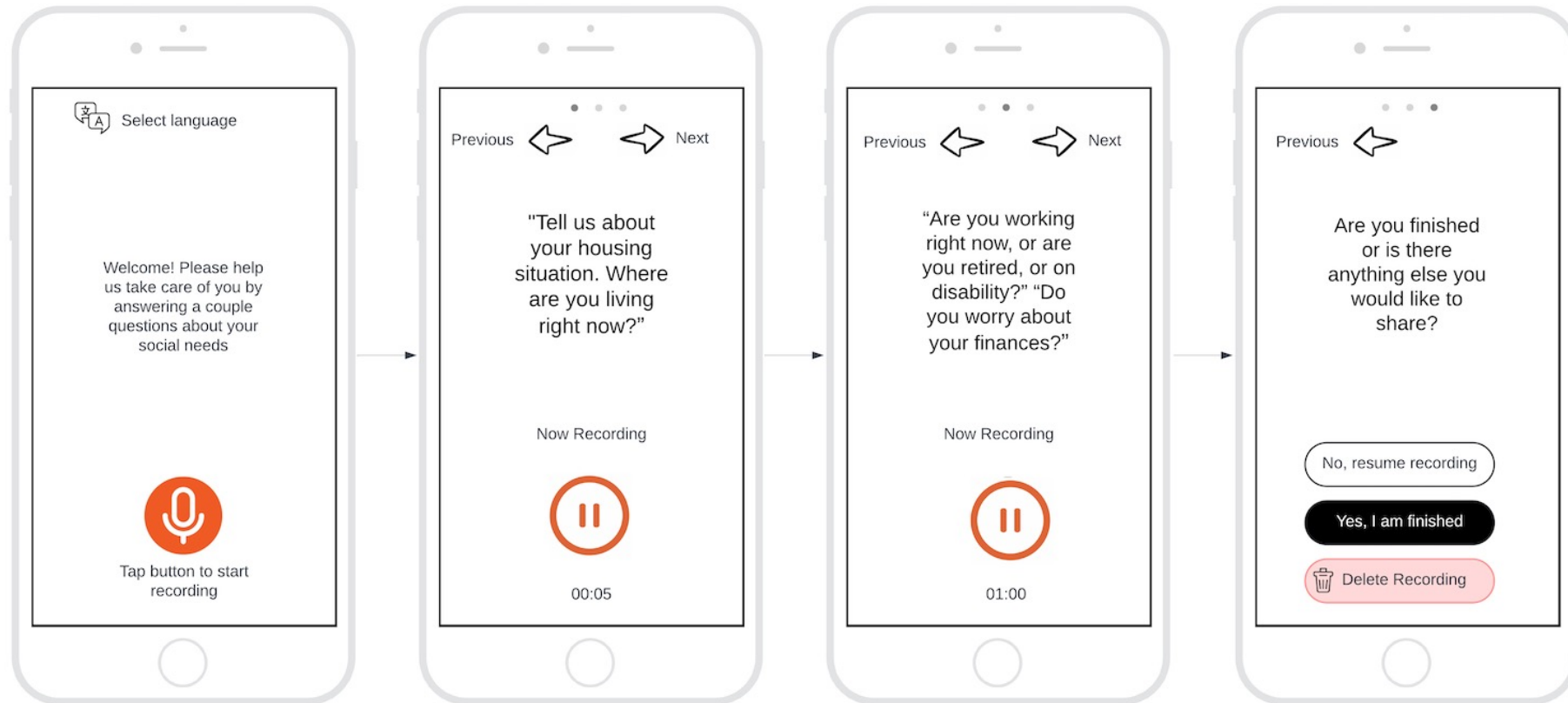
Housing Stability: Concerns about losing their home due to inability to pay rent.

Utilities: Prioritization of funds for essential utilities (lights, water), suggesting a risk of living without basic services.

Stress: The emotional impact of financial hardship and housing insecurity, affecting mental health.

Access to Healthcare: Not explicitly mentioned, but financial constraints often lead to limited access to healthcare services.

NARRATIVES - VOICE



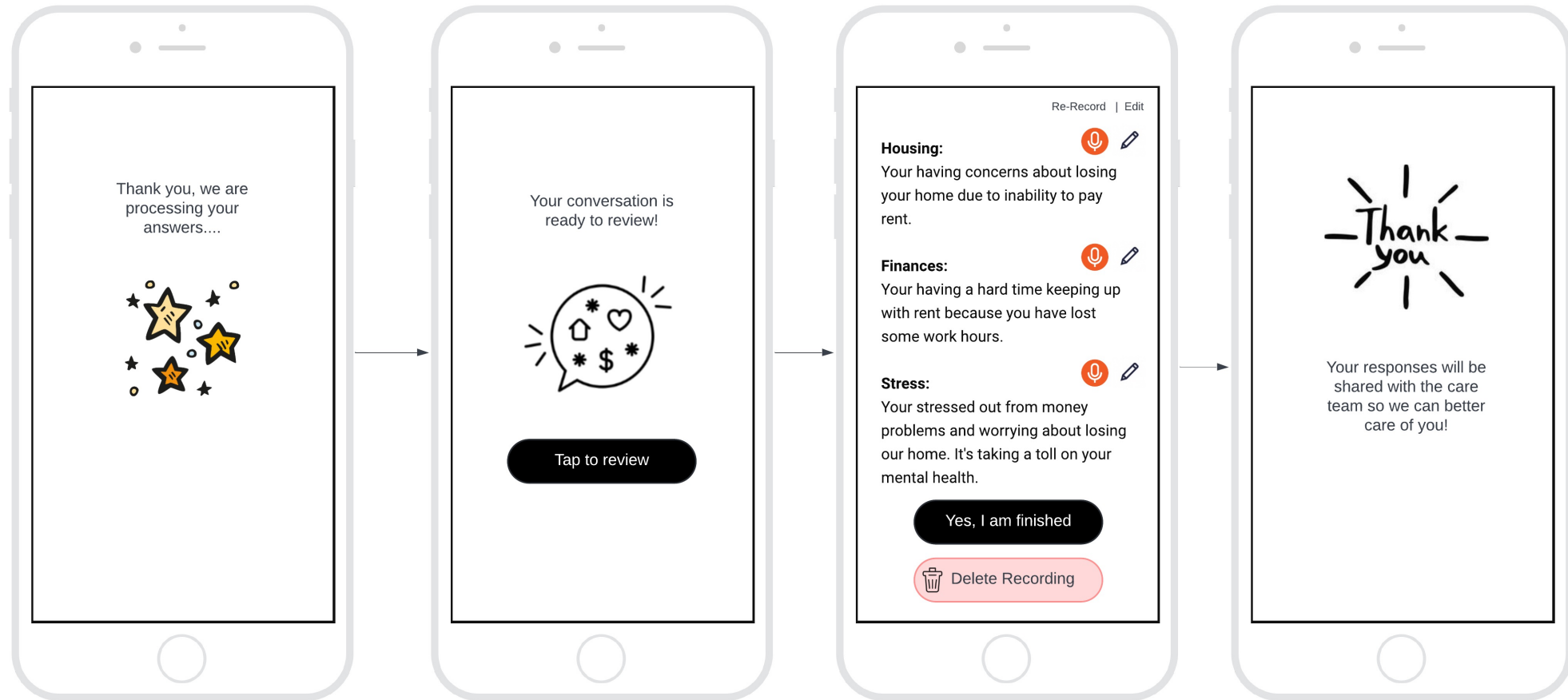
Starting point - patient can select language (optional) and then tap button to see next question.

Recording in process, patient can respond to open ended question.

Recording in process, patient can respond to open ended question.

Patient can continue recording or select that they are finished.

NARRATIVES - VOICE



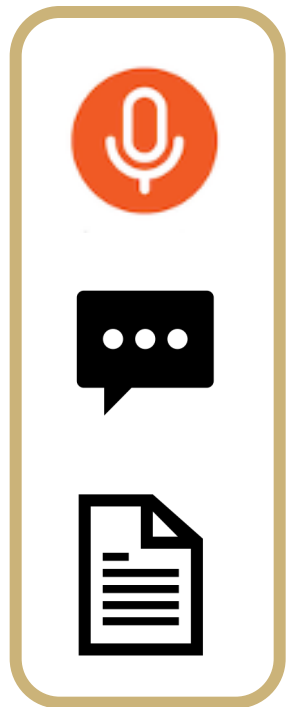
LLM is processing the patient's responses to open ended questions.

Results of are ready for the patient to review

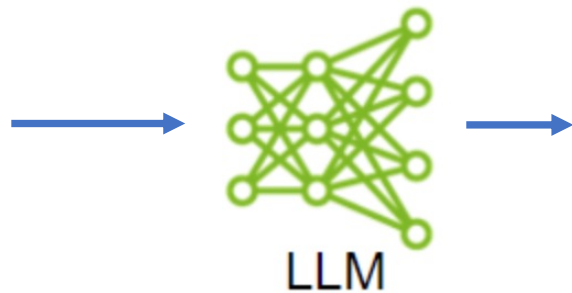
Patient can review information collected and make any edits or re-record a particular response. If they are satisfied with response, they can say they are finished.

Thank you screen at end of workflow.

SDOH DATA IN THE EHR



Multi-modality



Social Determinants of Health

Physical Activity

On average, how many days per week do you engage in moderate to strenuous exercise (like a brisk walk)?

5 days taken today

0 days 1 day 2 days 3 days 4 days **5 days** 6 days 7 days Patient refused

On average, how many minutes do you engage in exercise at this level?

30 min taken today

0 min 10 min 20 min **30 min** 40 min 50 min 60 min 70 min 80 min 90 min 100 min 110 min 120 min 130 min 140 min 150+ min Patient refused

Financial Resource Strain

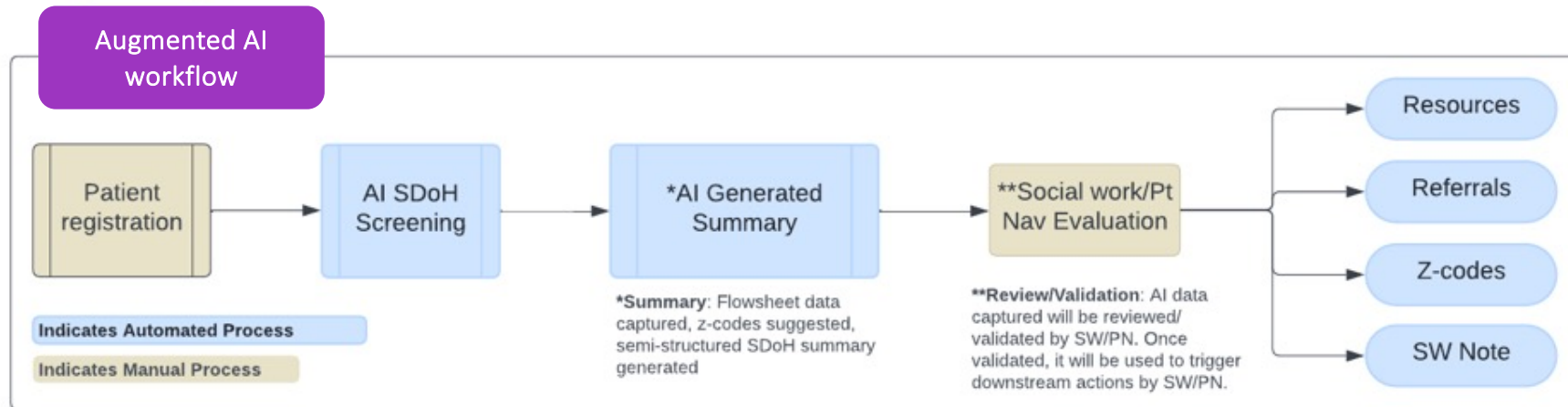
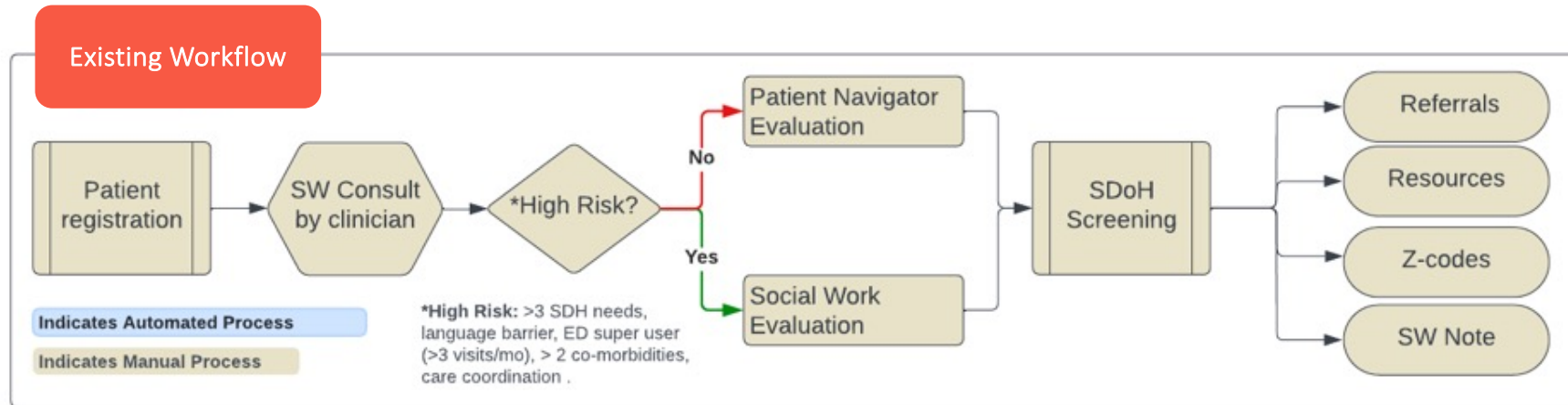
How hard is it for you to pay for the very basics like food, housing, medical care, and heating?

Not hard at all taken today

Very hard Hard Somewhat hard Not very hard **Not hard at all** Patient refused



AI AUGMENTED WORKFLOWS



FUTURE DIRECTIONS

We will be evaluating this modality of using large language models using the RE-AIM framework

GRANT (AHRQ – pending)

- Building a large language model to accomplish Social Need Screening
- Advance Clinical Decision Support in this area
- Pragmatically Study the impact of this AI to help capture SDOH information and improve patient care.

Domain	Measures
Reach	% Eligible patients who received the intervention; Qualitative interviews to access for barriers to Reach
Effectiveness	1° outcome: # of return ED visits 2° outcomes: # of referrals, # of Z-codes documented; # evaluations by HTT team; qualitative interviews to screen for unintended consequences
Adoption	% of social workers who acted on SDOH consult orders 100% of the time
Implementation	Fidelity: % of times all 4 core intervention components were successfully implemented Feasibility/Acceptability: clinician & patient survey results
Maintenance	Qualitative surveys from operations leaders, social workers, and clinicians.



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THANK YOU