University of Kentucky

Center for Applied Artificial Intelligence
Pro Scientia et Humanitate

AI in Healthcare

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Accelerating discoveries to improve health℠

Spectrum of AI Abilities and Risk

Narrow AI (AI):

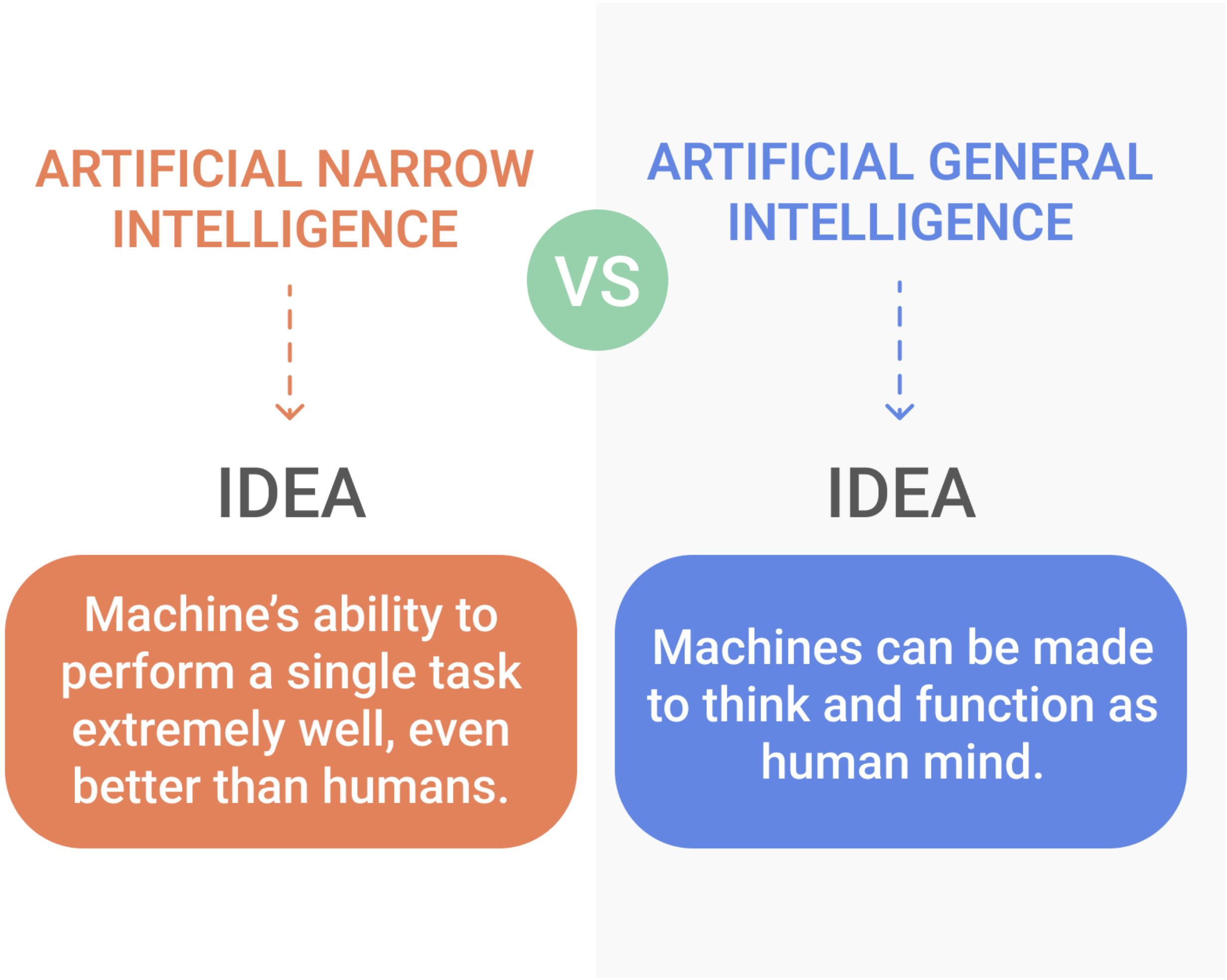
- Developed for a single job or set of tasks
- Disease detection: benign or malignant?
- **950 FDA-authorized AI Medical Devices**

Generative AI (GenAI):

- Seemingly cognitive capabilities and contextual understanding across a broader range of inputs (language, vision, etc.)
- Health Assistant: What programs or clinical trials do I personally qualify for?

~~**Artificial General Intelligence (AGI):**~~

- ~~Self-instructing~~
- ~~Design a new drug for X~~



https://www.plugger.ai/blog/general-ai-vs-narrow-ai-2022-guide

Predicting Extubation Readiness in Preterm Infants

The Journal of Pediatrics

Brasher, M.D., Virodov, M.S., Raffay, M.D., Bada, M.D., M.P.H., Cunningham, M.D., Bumgardner, Ph.D., Jawdeh M.D., Ph.D

Objective: To predict extubation readiness in preterm infants using machine learning analysis of bedside pulse oximeter and ventilator data.

Study Design: This is an observational study with prospective recordings of oxygen saturation (SpO_2) and ventilator data from infants < 30 weeks gestation age (GA). Research pulse oximeters collected SpO_2 (1 Hz sampling rate) to quantify intermittent hypoxemia (IH). Continuous ventilator metrics were collected (4-5 min sampling) from bedside ventilators.

Top performing models by data source and subset population.

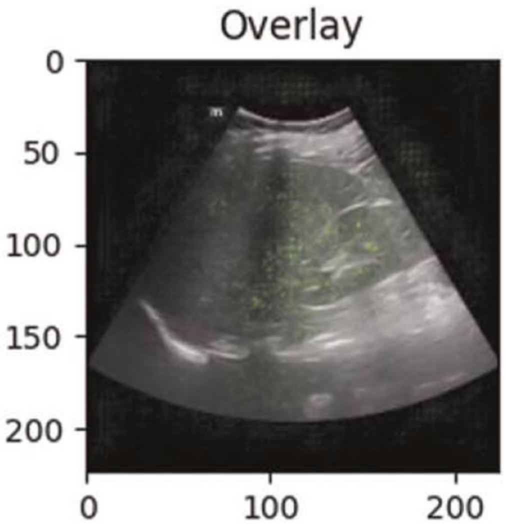
Data source	Population	n	Algorithm	AUC	Sens.	Spec.	PPV	NPV
IH + SIMV	All	65	Random Forest	0.77	0.59	0.91	0.74	0.84
	Age < 2 wks	24	Random Forest	0.94	0.78	0.85	0.78	0.86
	Age ≥ 2 wks	41	XGBoost	0.83	0.42	0.97	0.83	0.83
IH	All	73	SGDClassifier	0.74	0.47	0.81	0.50	0.80
	Age < 2 wks	27	XGBoost	0.77	0.56	0.72	0.42	0.79
	Age ≥ 2 wks	46	XGBoost	0.72	0.17	0.91	0.33	0.76
SIMV	All	100	Random Forest	0.71	0.13	0.88	0.31	0.75
	Age < 2 wks	51	Bagging	0.87	0.80	0.78	0.60	0.90
	Age ≥ 2 wks	49	XGBoost	0.71	0.36	0.92	0.75	0.83

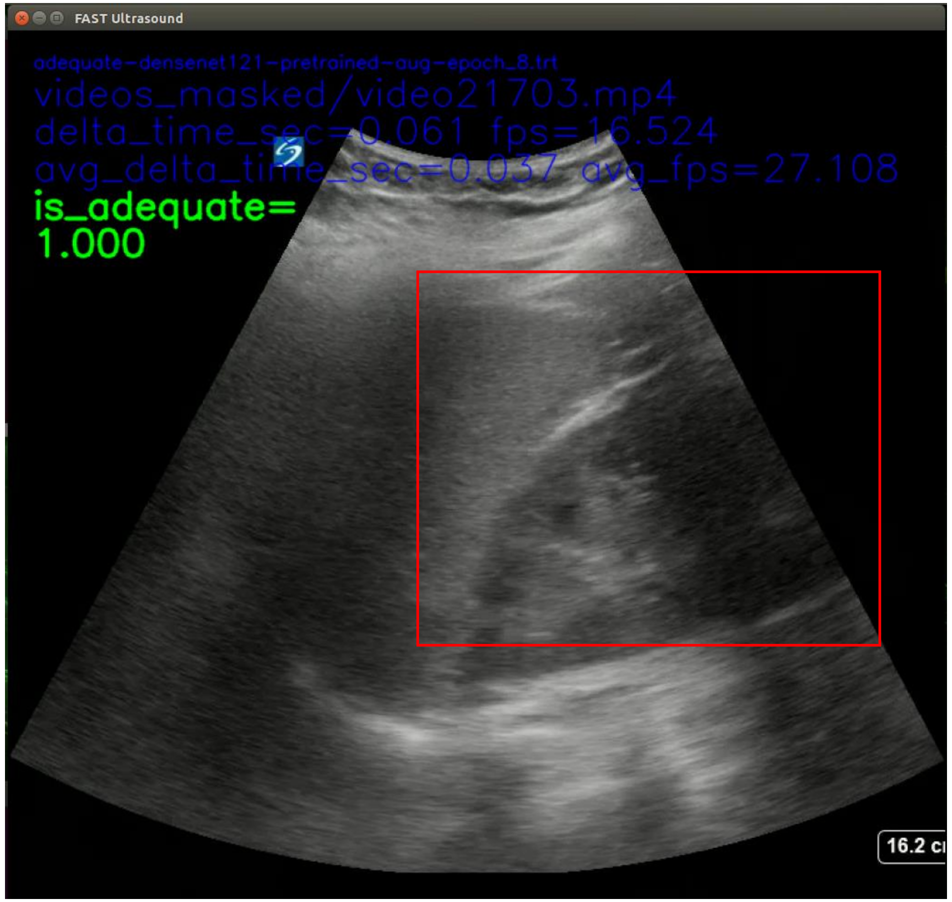
FAST Ultrasound (Focused Assessment with Sonography in Trauma)

Artificial intelligence evaluation of focused assessment with sonography in trauma

Brittany E Levy [1], Jennifer T Castle, Alexandr Virodov, Wesley S Wilt, Cody Bumgardner, Thomas Brim, Erin McAtee, Morgan Schellenberg, Kenji Inaba, Zachary D Warriner

Detect positivity and adequacy of FAST examinations with **94%** and **97%** accuracy, aiding in the standardization of care delivery with **minimal expert clinician input.**

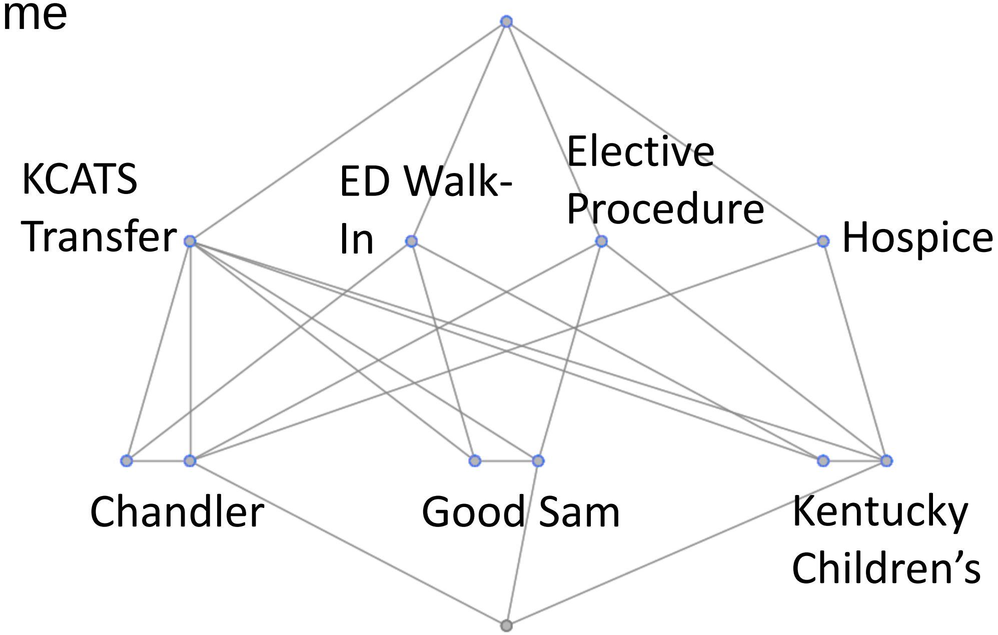




Hospital Operations

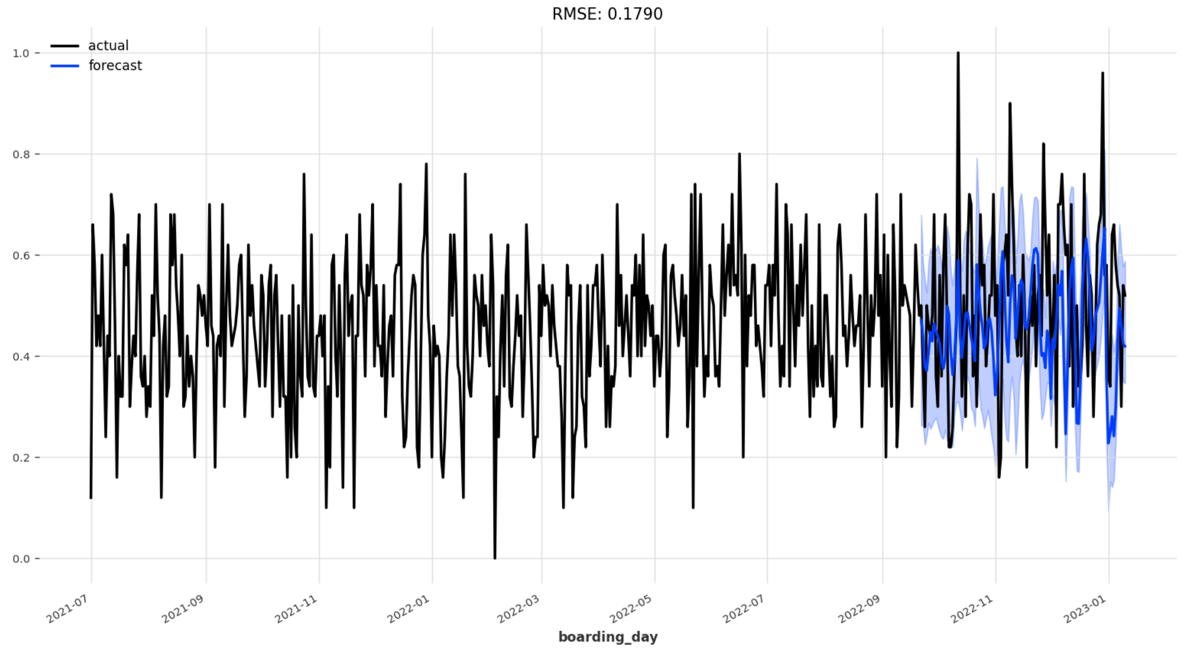
1. Queueing Model

- Modeling hospitals/EDs and sources of patients
- Edges are “queues” where patients wait to be serviced
- Arrival and service functions define flow of patients through system
- Queue data can be analyzed at different points in time



2. Prediction

- Can number of ED arrivals on a given day be predicted?
- Would help with staffing requirements and control of clinic transfers
- Uses many predicted values to make forecasts
  - Temperature, precipitation, snow, atmospheric pressure, air quality, and more



Strategic Planning in Healthcare

- Optimized estimates for CMS rankings
- Determine system-specific issues
- Provide tools to recalculate score on demand

Feature	SD's
ED_2B	-5.90
OP_13	-2.85
SEP_1	-2.51
PSI_4_SURG_COMP	-2.44
PC_01	-2.24
EDAC_30_PN	-1.81
MORT_30_AMI	-1.67
EDAC_30_HF	-1.61
PSI_90_SAFETY	-1.60
READM_30_HOSP_WIDE	-0.89

CMS Score Approximator

Provider ID: 180067

Mortality Measures

MORT_30_AMI: .144

MORT_30_CABG: .033

MORT_30_COPD: .082

MORT_30_HF: .132

MORT_30_PN: .163

MORT_30_STK: .141

PSI_4_SURG_COMP: 212.85

	Minimum	Maximum
STAR: 1	-2.208733	-0.883360
STAR: 2	-0.877353	-0.408683
STAR: 3	-0.406907	-0.043501
STAR: 4	-0.042455	0.343858
STAR: 5	0.347313	1.387677

	Variable Weight
PSI_4_SURG_COMP	-0.118523
ED_2B	-0.108400
MORT_30_AMI	-0.081034
EDAC_30_PN	-0.069375
PSI_90_SAFETY	-0.067217
EDAC_30_HF	-0.059938
OP_13	-0.052428
MORT_30_HF	-0.048141
SEP_1	-0.046385
PC_01	-0.041369
READM_30_HOSP_WIDE	-0.033152
HAI_5	-0.023096
OP_36	-0.019745
MORT_30_STK	-0.016313
MORT_30_PN	-0.014856
MORT_30_CABG	-0.013873
OP_35_ED	-0.012089
HAI_1	-0.010227
EDAC_30_AMI	-0.009778
H_COMP_3_STAR_RATING	-0.008769

Mortality Score	Safety Score	Readmission Score	Patient Experience Score	Process Scor	Summary Score	STAR Rating
-0.54323	-0.122939	-0.340259	0.056925	-1.738601	-0.417523	2

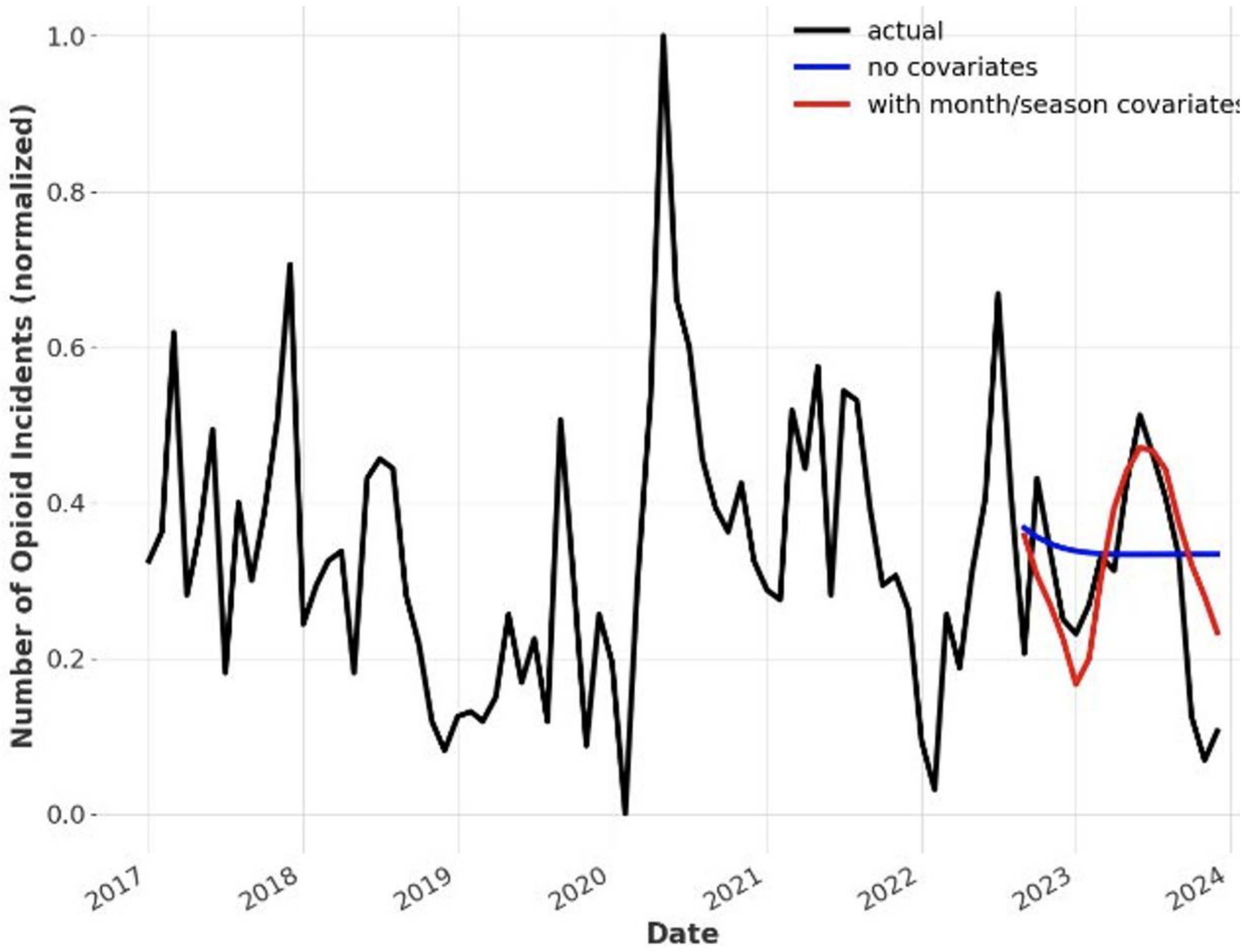
Public Health: Overdose Forecasting

- Covariates can be used to greatly improve forecast accuracy
- There are **differences across model performance based on race**, that can't be accounted for in dataset distribution

Overdose, by Race and Ethnicity

Stratification	MAPE Score
All opioid	18%
Hispanic	17%
Non-Hispanic White	30%
Non-Hispanic Black	50%

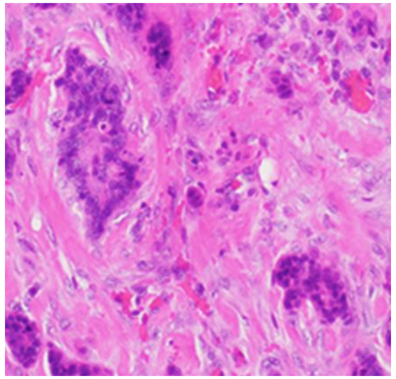
MAPE Interpretation	
< 10 %	Very good
10 % - 20 %	Good
20 % - 50 %	OK
> 50 %	Not good



Generative Models

Foundational Models

- Text, imaging, timeseries (EKG, eICU), genomics, etc.
- Observe large volumes of data and provide numeric characterizations of inputs (Cancer, Alzheimer's, etc. features)
- Allows us to holistically leverage medical data across disciplines like never before



age	sex	race	alb	tlc	f_0	f_1	...	f_767
35	0	1	3.2	0.58	0.019998	-0.0219	0.52670592	0.098922
66	0	1	2.9	0.72	0.110704	-0.31142	-0.0074099	-0.06965
43	1	1	1.2	1.7	-0.20204	0.098922	0.01999803	-0.00741
68	1	1	3.3	0.91	0.526706	-0.20204	0.11070408	0.019998
40	1	1	1.6	1.12	-0.06965	0.019998	-0.0219024	-0.31142
27	1	1	3.7	2.02	-0.31142	-0.20204	0.11070408	0.526706
31	0	1	2.8	0.87	0.098922	-0.06965	-0.0219024	-0.20204

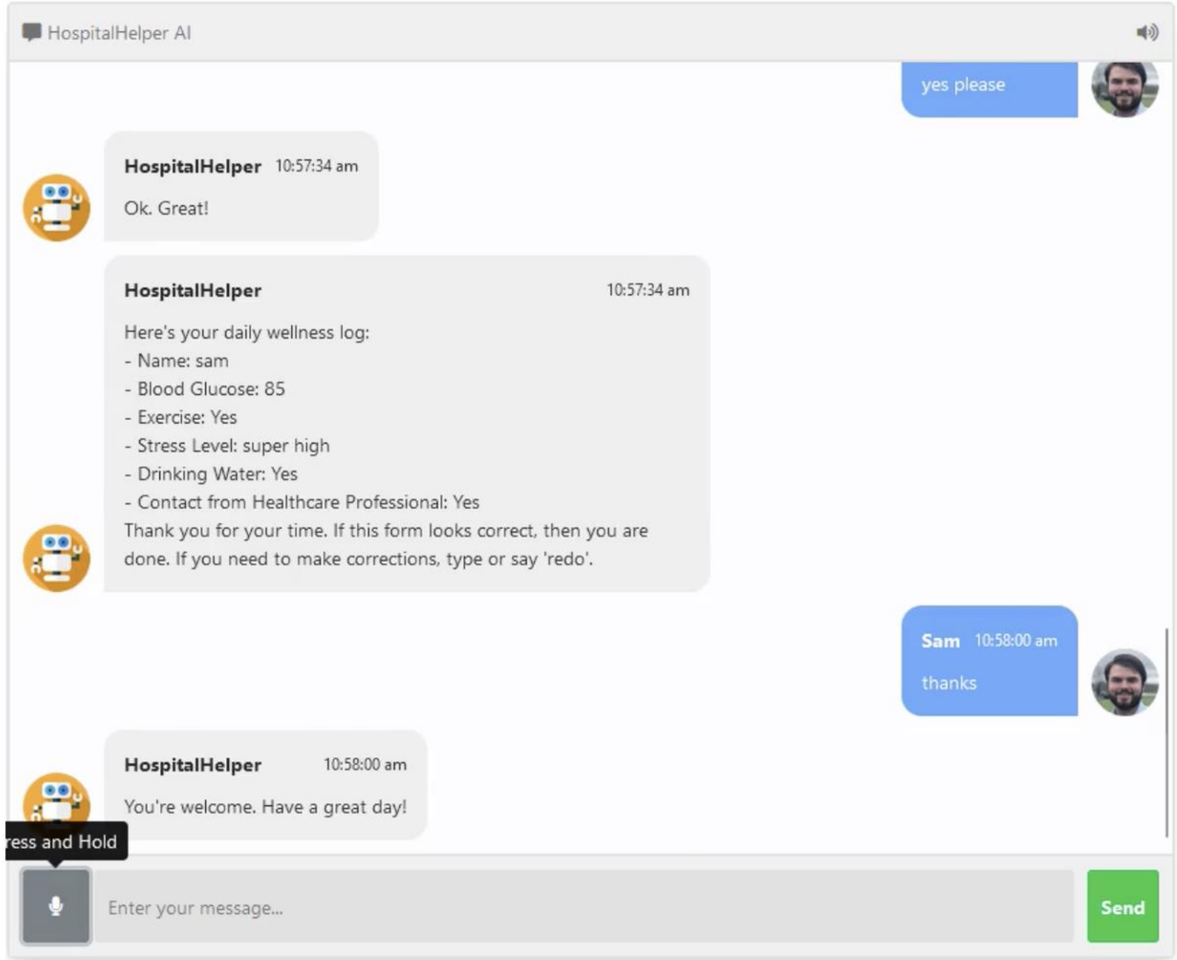
Case Data

Image + Genomic

AI Assistants and Agents (Today)

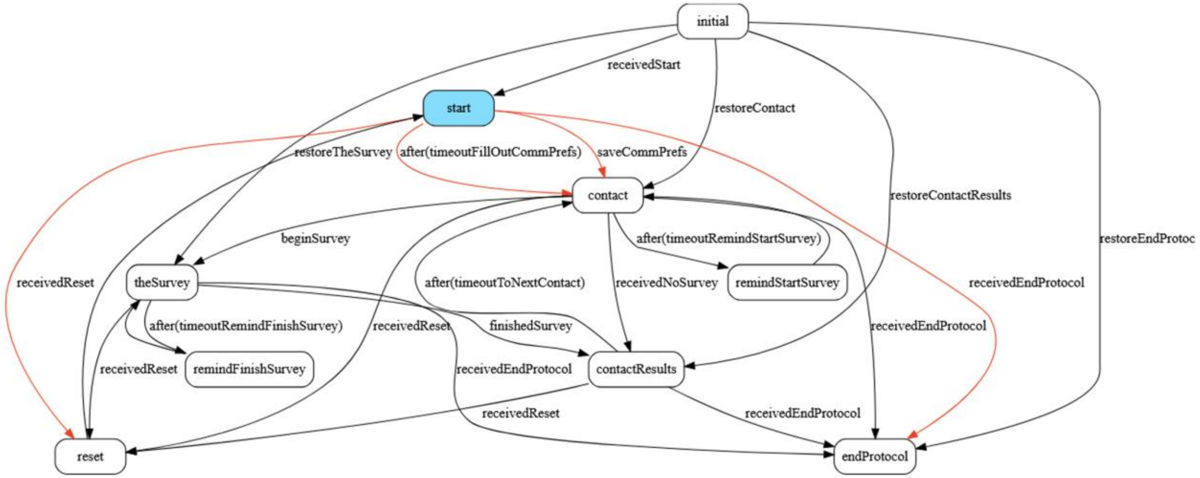
For Patient:
- Interpret questions
- Provide curated information
- Distill responses

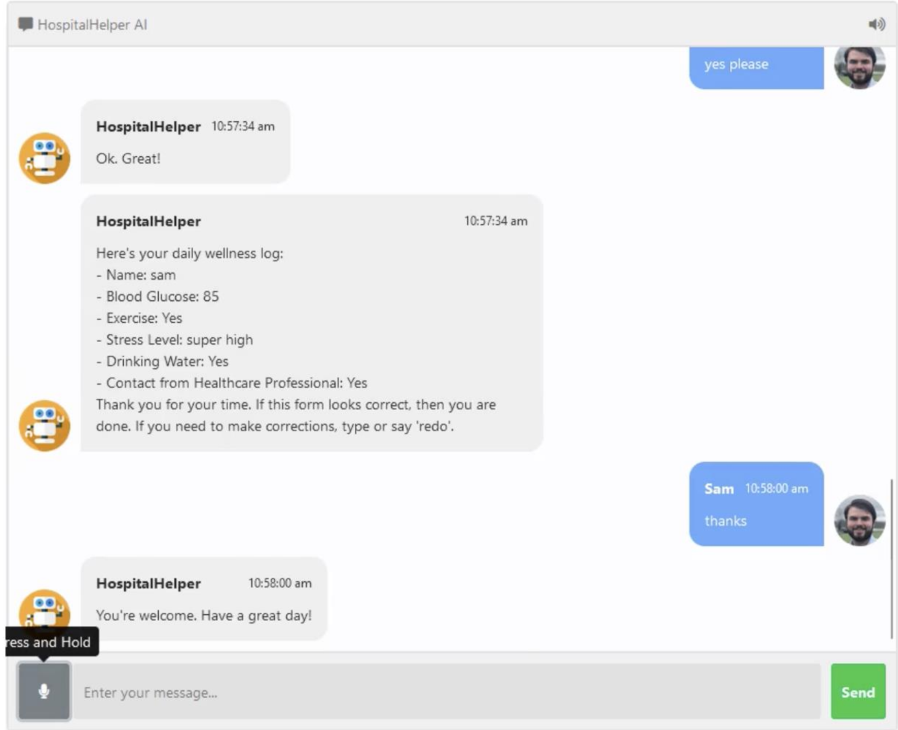
For Provider:
- Summarize/locate information
- Act as research agent:
  - PubMed discovery, phenotype identification, etc.
  - EMR -> clinicaltrails.gov



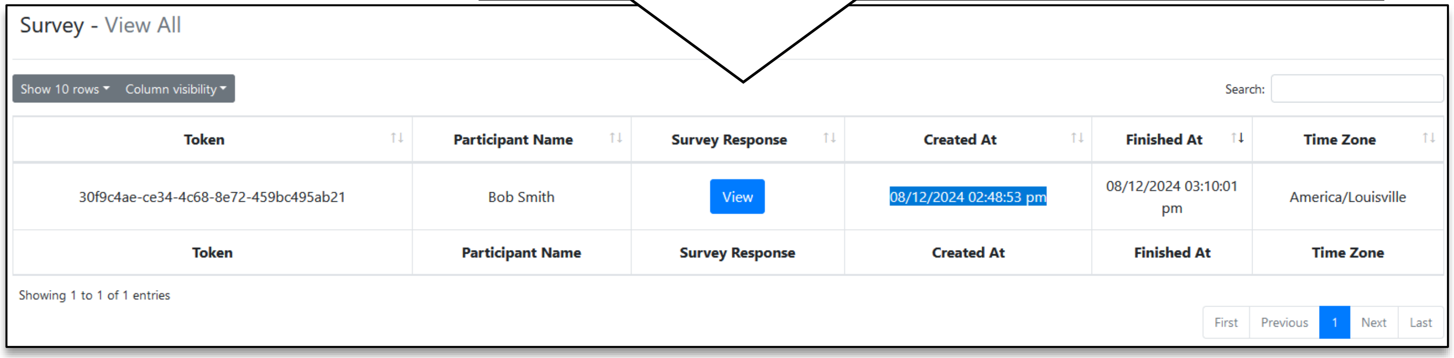
OptimalCT: AI-Assisted Structured Survey Response

- Guided chat with structured protocols
- Initial: Pre-op checklist and verification
- Expanded: Additional contacts/protocols and patient education prior to surgery





Q1: Overall Health? → **A1:** 3
Q2: Physical Activity? → **A2:** 1


Survey - View All

Show 10 rows · Column visibility · Search:

Token	Participant Name	Survey Response	Created At	Finished At	Time Zone
30f9c4ae-ce34-4c68-8e72-459bc495ab21	Bob Smith	View	08/12/2024 02:48:53 pm	08/12/2024 03:10:01 pm	America/Louisville
Token	Participant Name	Survey Response	Created At	Finished At	Time Zone

Showing 1 to 1 of 1 entries

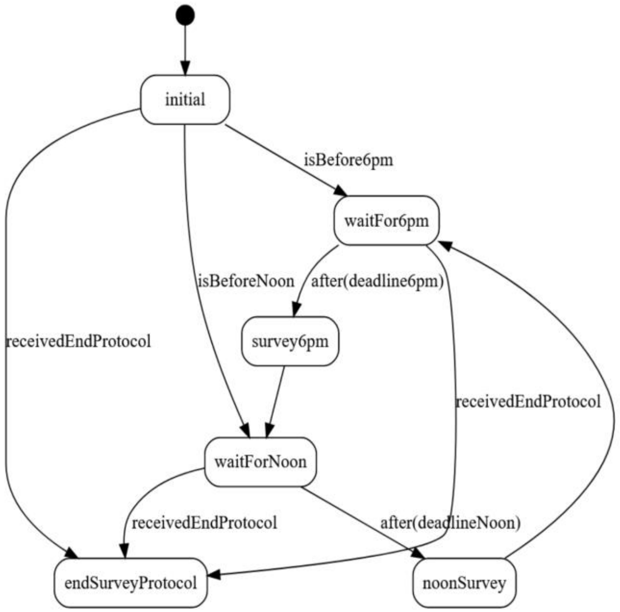
First Previous 1 Next Last

Formatted Data from Virtual Assistant Interactions

Physical interface to AI Assistants

Robotic assistants

- Interface for telemedicine, wayfinding, and AI assistants
- Currently deployed in hospitals and elder care
- AI & Smell Integration
- ~$6k each



What others are doing

- University at Buffalo: FY 2025 Budget Includes 10-Year, $275 Million Investment to Create a State-of-the-Art Artificial Intelligence Computing Center https://www.budget.ny.gov/pubs/press/2024/fy25-enacted-budget-launches-empire-ai-consortium.html

- University of Florida $140 Million in state funding for a new Data Center, plus $15 million per year from the State of Florida to hire 100 new faculty members. *https://www2.datainnovation.org/2022-ai-universities.pdf*

- Oregon State University: During the 2023 Oregon legislative session, OSU received over $70 million in state-paid bonding to match philanthropic and university contributions to the collaborative innovation complex. https://leadership.oregonstate.edu/huang-cic/faqs

Considerations

- Infrastructure
  - Historically, many states have launched and supported high-performance/scientific computing consortiums, is it time for Kentucky to do the same?
- Patients
  - Right to privacy is clear, but what about data sharing rights?
  - The U.S. Department of Health and Human Services (HHS) today released a final rule that establishes disincentives for health care providers that have committed information blocking. *https://www.hhs.gov/about/news/2024/06/24/hhs-finalizes-rule-establishing-disincentives-health-care-providers-that-have-committed-information-blocking.html*
- State
  - Should Kentucky patients be enrolled by default in a state-wide medical registry (could be deidentified data), like we do with cancer patients?
  - Foundational models for Kentucky patients could be developed with completely anonymized data and distributed back to the community.
  - Could our state laboratory be extended to include “send-out” AI-based analysis?
  - Should our state provide/support expertise in the use and validation of AI for clinical care?

    Not all AI health tools with regulatory authorization are clinically validated
    https://www.nature.com/articles/s41591-024-03203-3