AI SUMMIT

Cultivating a **Community of Practice to Ensure** the Safe, Effective, and Equitable Use of Al

Mark Sendak, MD, MPP

**Population Health & Data Science Lead** 

**Duke Institute for Health Innovation** 

RAPS HEALTHCARE PRODUCTS COLLABORATIVE



Co-Lead, Health AI Partnership

Inspiring Collaboration. Leading Innovation. Making a difference.





Duke Institute for Health Innovation	2 mins
Health AI Partnership	2 mins
Trustworthy AI Throughout the Lifecycle	10 mins



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### Duke Institute for Health Innovation2 mins

Health Al Partnership

2 mins

### Trustworthy AI Throughout the Lifecycle **10 mins**





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### **Duke Institute for Health Innovation**

### Our Mission: Catalyze innovations at Duke

Catalyze transformative innovation in health and healthcare through highimpact research, leadership development and workforce training and the cultivation of a community of entrepreneurship

### Our Approach: Innovation by design

Understand user workflow, desired outcomes and problems (needs) and then collaboratively develop concepts and prototypes, and iterate through to finalize solution







### **DIHI domains of innovation**



#### **Duke Institute for Health Innovation**

DIHI

#### Implementation and Health Delivery Science

- Catalyze
   multidisciplinary
   teamwork
- New care models
- Structured interface to Duke Health
- Living laboratory to incubate, refine, validate, and scale new ideas

#### Health Technology Innovation

- Leverage a growing health data infrastructure
- Create a connected digital health ecosystem
- Collaboration and codevelopment of technology
- Responsible development of datascience solutions

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- Train current and future leaders across health care : Leadership Management Innovation Quantitative health sciences
- Contribute to developing the workforce of the future

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#### Best Practices Development and Dissemination

- Disseminate best practices derived through internal R&D to elevate health innovation across ecosystem
- Convene stakeholders across settings to address common challenges in health innovation

# Industry Best-practice Approach to Catalyzing innovation

### RFA

Structure

III Duke Institute

for Health Innovation

### **DIHI RFA approach**

### "Top-down + Bottom-Up" approach to sourcing innovations

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- Duke Health leadership develops mission-aligned strategic themes for innovation
- Front-line faculty and staff propose "problems" aligned with strategic themes and novel solutions
- Systematic review and due diligence: Assessments on team, feasibility, resource needs, impact and value to patients
- Operational Lead engaged right from the proposal stage
- 8-12 innovations funded each year; Duration: 12-15 months
- DIHI members embedded within project innovation teams to rapidly catalyze the innovations
- · Pivots as needed to support rapid evolution to create value
- Metrics: clinical utility, economic utility, cultural impact, IP and academic outputs





740+ Proposals

### **DIHI Innovation Jam**

#### A Health focused Shark Tank at Duke

- Solicits and identifies high-potential healthcare and health innovations ready for commercialization
- Duke Leadership as Sharks:
  - DUHS leaders, Department Chairs, Deans of School of Medicine, Nursing, Engineering, OLV, I&E, MedBlue, Center and Institute Directors
- Innovation proposals from students, faculty, trainees and staff across campus
- Funding to support entrepreneurship / formation of company and also develop the product/service etc.
- Inventors offer portion of their share of Duke internal returns for investment from the sharks
- Internal syndicated investment agreements documented through MOUs.





### **DIHI Spectrum of Value Creation**



	Hospital at Hor	ne	HIV Pre-Exposure Prophylaxis Identification	Community COVID-19 Support	Medical Students Scholarship
Mortality M (inpatient / 3	lodels 30-day) Hig	ıh-utilizer dashboard	CKD Patient Education Dissemination	Patient Reported Outcomes for Cancer Patients	Data Science in Health masters
Operatio Enhancen	nal C nent	complex Care Plans	Community-Based Palliative Care	Outpatient Procedure Concierge Program	course in BME
Procedure	Safety	dex Admissions with MSSP	High Value Analyte Ordering	Cancer Distress Coach	• Summer Fellowship in Data Science
Medication	Safety (S	Readmissions ocial Drivers for HF)	NAFLD population health rounding	Autism and Beyond	Case Studies and Data Camp
Early Detec Deteriora	tion of ation	SNF transition	CKD population health rounding	Voices of Duke	Journal Club
Inpatie Innovati	ent Tra ions Tra	ansition Setting	Outpatient/ Gaps in Care	Patient & Community	Immersion in innovation and data science
Tect	hnology Infrasti	ructure	Research and D	Dissemination	Education and Training

Duke Institute for Health Innovation [DIHI] – Spectrum of value creation across the ecosystem

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### Duke Institute for Health Innovation2 mins

### Health AI Partnership

2 mins

### Trustworthy AI Throughout the Lifecycle **10 mins**





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**Our Mission:** Empowering healthcare professionals to use Al effectively, safely, and equitably through **communityinformed up-to-date standards** 

### **Our Values:**

### advance health equity

prioritize solutions that advance health equity and eliminate the AI digital divide

### improve patient care

ensure that Al adoption is driven by patient care needs, not technical novelty

# improve the workplace

surface sociotechnical challenges in AI use and foster a positive work environment

### build community

create safe spaces to share learnings and consult peers

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# Phase One (Apr 22 – Aug 23) Milestones



### Standard AI Solution Procurement Milestones

- Community-informed best practices sourced from across the network of organizations
- Multiple co-design workshops with IDEO.org

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- Focused on AI solutions used for:
  - Diagnosis or treatment decisions for individual patients
  - Prioritization of patients for healthcare services (e.g., surgery scheduling, care management prioritization, ED triaging)

### Health Equity Across the AI Lifecycle (HEAAL) Framework

- Developed to answer the question: "our health system is considering adopting a new solution that uses AI; how do we assess the potential future impact on health inequities?"
- Convened multi-stakeholder workshop featuring case studies, expert discussants, and framework developers
- Developed detailed procedures for healthcare organizations to follow for AI procurement





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for Health Innovation





# Duke Institute for Health Innovation2 mins

Health AI Partnership

2 mins

### Trustworthy AI Throughout the Lifecycle **10 mins**





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### health ai partnership **Align Front-Line Staff and Organizational Leaders Create Alignment Throughout Project Selection**

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# Align Front-Line Staff and Organizational Leaders *Create Alignment Throughout Project Selection*

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### **Development and Validation of ML-DQA**

	Pediatric Sepsis Prediction	Lung Transplant Complication Prediction	<u>Sepsis</u> <u>Prediction at</u> <u>Jefferson</u> <u>Health</u>	Immune- Related Adverse Event Prediction	<u>Maternal</u> <u>Morbidity and</u> <u>Mortality</u> <u>Prediction</u>
Phase I: Data Element Pre-Proc	cessing				
Pre-existing groupers	108	109	30	39	310
Project-specific groupers	73	35	59	41	12
Phase II: ML-DQA Checks					
Completeness checks	144	144	70	508	404
Conformance checks	122	144	132	225	69
Plausability checks	123	144	61	301	404
Total quality checks	389	432	267	1,034	877
		HEALTHCARE			

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RAPShttps://proceedings.mlr.press/v182/sendak22a.html





### **Disappearing Sepsis Events**



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### **Disappearing Sepsis Events**

**Component Name** 



















### **Example Categories of Measures**



<b>Category</b>	<u>Definition</u>	Example Metrics	
Model performance	Effectiveness, accuracy, and reliability of the Al model or algorithm in fulfilling its intended tasks within the clinical or healthcare context.	Sensitivity (recall, true positive rate), Specificity (true negative rate), Area Under the ROC Curve (AUC-ROC), F1 Score, Precision (positive predictive value).	
Software performance	Efficiency and responsiveness of processing tasks, delivering results, and overall performance of the software components and its interactions.	Inference time, throughput, model latency, response time, resource utilization, scalability.	
Clinical effectiveness	Assessment of impact of product use on healthcare outcomes.	Mortality rate, intensive care unit requirement, complication rate	
Usability	Quality of users' interactions with the Al-based medical software.	Clinician satisfaction, user error rates, ease of use.	
Safety and security	Safely and securely operating software, evaluating harm to patients and protection against unauthorized access, data breaches, and cyber threats.	Number of identified safety risks and mitigations, adherence to cybersecurity standards, detection of adversarial attacks, incident response time.	
Business	Business objectives and outcomes  AFDO HEALTHCARE PRODUCTS RAPS COLLAROPATIVE	Reduction in diagnostic time, cost savings.	











# **Custom Workflow to Reduce Alarm Fatigue**





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10-0-5

₫

requirements



### **Sepsis Watch User Interface**



#### *"*<sup>©</sup> SEPSIS WATCH **+**

Last updated a few seconds ago.

M3G4N4C · Reeves, L · 72 F		SCREEN
SEP	Bed 197 · Admit 9/24 05:33 AM	MONITOR
	T 37.9 · P 69 · BP 111/70 · MAP 2 · R 22	TREAT
🔅 Met	sepsis criteria 9/24 05:04 AM	
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	SCREEN	
SEP	Unk Loc · Admit 9/24 05:53 AM	MONITOR
	T 37.5 · P Unk · BP 113/69 · MAP 70 · R Unk	
🔆 Met	sepsis criteria 9/24 06:01 AM	
	i izomaw alma tisiize wisij mungigret jilepo	
	VOCF0DM · Cobb. I · 64 F	SCREEN
HIGH	Bed 190 · Admit 9/24 06:14 AM	MONITOR
	T 38.0 · P 67 · BP 106/63 · MAP 184 · R 23	TREAT

By Sepsis Bundle Disposition at 9/23 12:47 AM

Triage

- Sepsis identified every 5 minutes and sepsis risk computed every hour
- System normalizes data, groups clinically related concepts into meaningful features, and ensures valid inputs to deep learning model
- Deployed on-premise cloud with Docker containers
- Black = meets sepsis criteria
- Red = high risk of sepsis

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### **Sepsis Watch User Interface**

TREAT

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		VOCF0DM · Cobb. I · 64 F	SCREEN		
	HIGH	Bed 190 · Admit 9/24 06:14 AM	MONITOR		

Sepsis Bundle Disposition at 9/23 12:47 AM

T 38.0 · P 67 · BP 106/63 · MAP 184 · R 23

#### 🖓 SEPSIS WATCH 🕇

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### **Sepsis Watch User Interface**

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Sepsis Bundle Disposition at 9/23 12:47 AM

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6ZLNC5 · Pearce, B · 77 M SEP Bed 880 · Admit 9/24 06:01 AM T 38.1 · P Unk · BP 117/61 · MAP 22 · R 24	SCREEN TREAT
Chart Review Exam Called MD Called Nurse Called Surse Met sepsis criteria 9/24 06:49 AM	
OEYQK3B · Puccini, C · 76 F HIGH Bed 459 · Admit 9/24 05:58 AM T 37.8 · P 72 · BP 113/61 · MAP 190 · R 21	SCREEN



#### 🖓 SEPSIS WATCH 🖶

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Зеd 382 Г 37.7 · Р 63 · ВР 119/66 · МАР 194 · F	t Unk	
WBC 6.5 · Lactate 2		ADMINISTE
3 Hour Bundle	6 Hour Bundle	
2:22 remaining	5:22 remaining	
	🗆 Repeat Lactate 🚱	
Blood Cultures	Vasopressors <b>2</b>	
Antibiotics	Volume Assessme	ent 🛛
🗆 IV Fluids 🕑		
<b>Å</b> Moved to Sensis Bundle Today :	at 7:56 AM	
William Constant Developer Statistics of the		
Bepsis Bundle disposition after	Today at 1:56 PM	
Sepsis Bundle disposition after	Today at 1:56 PM	
BJPRZ1K · Cunningham, L · 72 F	Today at 1:50 PM	STOP BUNE
BJPRZ1K · Cunningham, L · 72 F 3d9 S04 · Admit 9/24 06:39 AM	100ay at 1:50 PM	STOP BUNE
жа Sepsis Bundle disposition arter BJPRZ1K · Cunningham, L · 72 F 3ed 504 · Admit 9/24 06:39 AM Г 37.8 · P Unk · ВР 109/75 · MAP 95 · F WBC 7.3 · Lactate 2	100ay at 1:56 PM	STOP BUND
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Treat



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Pediatric sepsis prediction

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- Outcome definition: Blood Culture ∩ Antibiotics for 4 days ∩ Acute organ dysfunction
- LSTM with 6-hour prediction window and 3-hour snooze
- Retrospective training set: 17,491 unique encounters for children between 30 days old and 18 years old between November 1, 2016 – December 31, 2020
- Temporal validation set: 6,545 unique encounters for children between 30 days old and 18 years old between January 1, 2021 – June 30, 2022



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	<u>AUROC</u>	<u>AUPRC</u>	PPV at 20% sensitivity (with 3hr snooze)	PPV at 50% sensitivity (with 3hr snooze)
Retrospective test set	0.816	0.483	0.769	0.612
Temporal validation	0.862	0.386	0.851	0.611



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- Silent trial results
  - Model ran on 1,475 unique encounters over 2 months
  - Model generated 30 alarms per day >> 2 alarms per day expected
  - Model fired alarm on almost all patients in ED within first hour of arrival



- Label leakage due to layer normalization in LSTM
  - In retrospective training data:
    - set maximum encounter length to 168 hours
    - truncated sepsis encounters at time of sepsis
  - Shorter encounter  $\rightarrow$  more padding of encounter hours with 0s  $\rightarrow$  smaller mean after layer normalization
  - Longer encounter  $\rightarrow$  less padding of encounter hours with 0s  $\rightarrow$  larger mean after layer normalization
  - In retrospective data, model learned to associate early hours of encounter with sepsis





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 Retrained LSTM without layer normalization using the same hyperparameters

	AUROC	AUPRC
Retrospective test set (with layer normalization)	0.816	0.483
Temporal validation (with layer normalization)	0.862	0.386
Retrospective test set (without layer normalization)	0.782	0.01













### health ai partnership **Build Modular Infrastructure to Support Many Projects** Flexible Data Pipeline Technology Infrastructure

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### **Model Labels**

Model Facts	Mode	el name:	Deep Sepsis	Loca	le: Duke University Hospital
Approval Date: 09/22/2	019	L	ast Update: 09/	24/2019.	Version: 1.0
Summary This model uses EHR input data collected from a patient's current inpatient encounter to estimate the probability that the patient will meet sepsis criteria within the next 4 hours. It was developed in 2016-2019 by the Duke Institute for Health Innovation. The model was licensed to Cohere Med in July 2019.					
Mechanism  Outcome Output Patient population Time of prediction Input data source Input data locati Training data locati Model type	on and time-		sepsis within th - 100% probabilit dult patients >18 lemographics, and	e next 4 hou y of sepsis c y.o. presenti el alytes, vitals,	ars, see (1) for sepsis criteria ing to DUH ED and admitted our of a patient's encounter ectronic health record (EHR) medication administrations DUH, 10/2014 – 12/2015 Recurrent Neural Network
Validation and perform	nance			1 600/	
	revalence		PPV (a) Sensitivi	TV OT 60%	Sensitivity (a) PPV of 20%

	Prevalence	AUC	PPV @ Sensitivity of 60%	Sensitivity		
Local Retrospective	18.9%	0.88	0.14	0.50		
Local Temporal	6.4%	0.94	0.20	0.66		
Local Prospective	TBD	TBD	TBD	TBD		

TBD

#### Uses and directions

TBD

External

Operational use case(s): Every hour, data is pulled from the EHR to calculate risk of sepsis for every
patient at the DUH ED. A rapid response team nurse reviews every high-risk patient with a physician
in the ED to confirm whether or not to initiate treatment for sepsis.

TBD

TBD

- General use: This model is intended to be used to by clinicians to identify patients for further
  assessment for sepsis. The model is not a diagnostic for sepsis and is not meant to guide or drive
  clinical care. This model is intended to complement other pieces of patient information related to
  sepsis as well as a physical evaluation to determine the need for sepsis treatment.
- Examples of appropriate decisions to support: Patient X has a high risk of sepsis according to the model. A rapid response team nurse discusses the patient with the ED physician caring for the patient and they agree the patient does not require treatment for sepsis.
- Before using this model: Test the model retrospectively and prospectively on local data to confirm
  generalizability of the model to the local setting.
- Safety and efficacy evaluation: Analysis of data from clinical trial (NCT03655626) underway. Preliminary data shows rapid response team, nurse-driven workflow was effective at improving sepsis treatment bundle compliance.

### Presenting machine learning model information to clinical end users with model facts labels



Mark P. Sendak <sup>™</sup>, Michael Gao, Nathan Brajer & Suresh Balu

npj Digital Medicine **3**, Article number: 41 (2020) Cite this article

14k Accesses | 63 Citations | 74 Altmetric | Metrics

#### Warnings

- General warnings: This model was not trained or evaluated on patients receiving care in the ICU. Do
  not use this model in the ICU setting without further evaluation. This model was trained to identify
  the first episode of sepsis during an inpatient encounter. During long inpatient stays with multiple
  sepsis episodes, model accuracy needs to be further evaluated. The model is not interpretable and
  does not provide rationale for high risk scores. Clinical end users are expected to place model output
  in context with other clinical information to make final determination of diagnosis.
- Examples of inappropriate decisions to support: This model may not be accurate outside of the target population, primarily adults in the non-ICU setting. This model is not a diagnostic and is not designed to guide clinical diagnosis and treatment for sepsis.
- Discontinue use if: Clinical staff raise concerns about utility of the model for the indicated use case or large, systematic changes occur at the data level that necessitates re-training of the model.

#### Other information:

- Outcome Definition: https://doi.org/10.1101/648907
- Related model: http://doi.org/10.1001/jama.2016.0288
- Model development & validation: arxiv.org/abs/1708.05894
- Model implementation: jmir.org/preprint/15182
- Clinical trial: clinicaltrials.gov/ct2/show/NCT03655626
- Clinical impact evaluation: TBD
- For inquiries and additional information: please email mark.sendak@duke.edu

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# AI System Monitoring at DIHI



Effective monitoring of AI/ML solutions also requires multidisciplinary combination of technical and human capabilities, including expertise in engineering, data analysis, AI/ML, and clinical domain knowledge employed during the solution development phase.

#### **Model Monitoring**

- Data quality monitoring
  - Input data accurate, complete, and up-to-date
  - Entity/grouper monitoring
  - Continuous monitoring
- Performance comparison
  - auroc, auprc wrt. training
- Analysis cadence: M/Q/Y
- Output drift monitoring
- Data distribution
- Category distribution

#### **Solution Monitoring**

- Outcome monitoring
  - Project specific measures
  - Bi-annual for most solutions
- Workflow changes
  - Observation / documentation
- Usage monitoring
  - UI tools/dashboard usage
  - Secondary data analysis
- User feedback
  - Survey for model & solution

#### **Operations Monitoring**

- Alerting & notification
  - Flexible rules-based engine for alerting
  - Used in clinical workflow
  - Email/page/spok/sms etc.
- Technical monitoring
  - Model run times, failures etc.
  - Service level monitoring
- Regulatory & Policy
  - Compliance monitoring for regulation & Duke policies
  - Ethical and legal standards

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# Sepsis Watch Post-Integration Lifecycle Management

		Monitoring & Evaluation		<u>Update</u>		Operational Management
Event based	•	Debug issues that arise (e.g., data endpoint unexpectedly goes down)	•	Customize the UI for different user groups Train new versions of the model for new clinical settings	•	Update user access Update reporting functionalities to support clinician management
Recurring	•	Monitor technical elements of the model and source data in pipeline Monitor changes that affects work environment and use of model	ents of the a in pipeline affects work of model • Regularly schedul maintenance (e.g. groupers every 6		•	Conduct bi-annual end user training to ensure baseline knowledge of Al system
Semi- Recurring	•	Audit the solution for impact on clinical and operational outcomes and impact on work environment	•	<ul> <li>Improve the UI (e.g., add comment feature, automatically check boxes)</li> <li>Scale to different use cases</li> </ul>		Convene governance committee monthly Secure ongoing funding for AI system use
One-off	•	Create channels for end users to report issues and provide user support services	•	Create process and criteria to scope responses to user requests	•	Determine ownership of model (e.g., clinical lead, technical lead)



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# **Engage with our community of practice!**

Mayo Clinic

MAYO CLINIC

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☐ NewYork-□ Presbyteria

NYP

Hackensack

Meridian Health

Jefferson

Health

Duke Health

WellCare, NC

University of

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# Breakout Activity





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### Remainder of (Table Number) / 4 = X

X = 0	X = 1	X = 2	X = 3
(Table 4,	(Table 1,	(Table 2,	(Table 3,
8, 12,)	5, 9,)	6, 10,)	7, 11,)
Procurement	Development & Adaptation	Clinical Integration	Lifecycle Management





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R X = 0	emainder of (Tab X = 1	le Number) / X = 2	4 = X X = 3
Procurement	Development & Adaptation	Clinical Integration	Lifecycle Management
1 Identify and prioritize a problem	3 Develop measures of outcomes and success of the AI product	6 Execute change management,	7 Monitor and maintain the Al product
2 Evaluate Al as a viable	4 Design a new optimal workflow to facilitate integration	workflow integration, and scaling strategy	8 Update or decommission the Al product
component of the solution	5 Evaluate pre-integration safety and effectiveness of the AI product HealthCare Collabora		





### **Discussion Questions**

- How does your own organization carry out this part of the AI product lifecycle?
- What are common pitfalls you have seen organizations make as they carry out this part of the AI product lifecycle?
- What are the most effective ways you have seen organizations carry out this part of the AI product lifecycle?

Between now and 12 PM, discuss these questions with colleagues at your table and prepare a 45 second reportout to share a best practice with the group









**4**9

# **Report Out**





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# Thank you mark.sendak@duke.edu