

Overcoming Barriers to the Adoption and Implementation of Predictive Modeling and Machine Learning in Clinical Care: Lessons from US Academic Medical Centers & Duke Health's Way Forward

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Data Science Challenges in the Real World



Overcoming Barriers to the Adoption and Implementation of Predictive Modeling and Machine Learning in Clinical Care: Lessons from US Academic Medical Centers

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Study Goals



Given intense interest in Machine Learning and Predictive Modeling in healthcare:

- Define and disseminate the common challenges in developing and/or implementing machine learning models in healthcare organizations
- Understand and share current best-practices for overcoming these challenges

Study Methods (1)

- Semi-structured Interviews (~45 minutes) with Experts at Academic Medical Centers (AMCs)
- Targeted Experts: individuals who participate in the creation and/or implementation of Machine Learning/Predictive Modelling (ML/PM) algorithms
 - Recruitment through list of accredited Clinical Informatics Fellowship Directors
 - Assumption: AMCs are more likely to be ahead of non-academic institutions in encountering challenges and developing solutions



Study Methods (2):

- Discussion Guide Development
 - Definition of ML/PM in the Clinical Context
 - Literature review and Research Team Discussion
 - Life-Cycle Framework. Challenges & Best Practices during:
 - Model Development
 - Model Implementation
 - Model Maintenance
- Content Analysis of Interview Transcripts using Nvivo:
 - Grounded Theory approach
 - Preliminary → Final Code List
 - 3 pairs of Transcript Coders, each pair Coding 1/3 of Interview Transcripts



Characteristics of Informants:

33 Informants from 19 AMCs

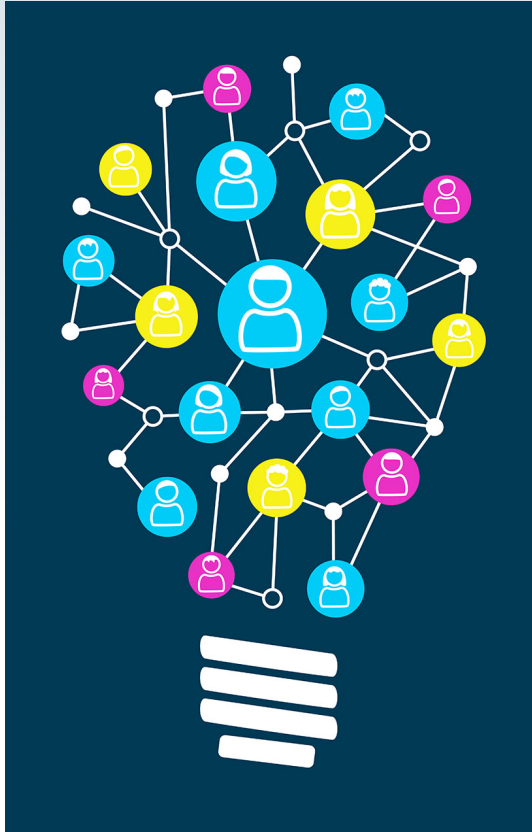


Table 1. Characteristics of informants and their home institutions

Location of institution by region ($n = 19$)	
Northeast	8
South	3
Midwest	3
West	5
Number of models in production ($n = 19$)	
<3 models in production	13
>3 models in production	6
Educational background of informants ($n = 33$)	
MDs	58%
PhDs	9%
Data Science	27%
MD/PhDs	6%
Seniority of informants ($n = 33$)	
Executive/senior role	64%
Non-executive	36%

Challenges & Facilitators:

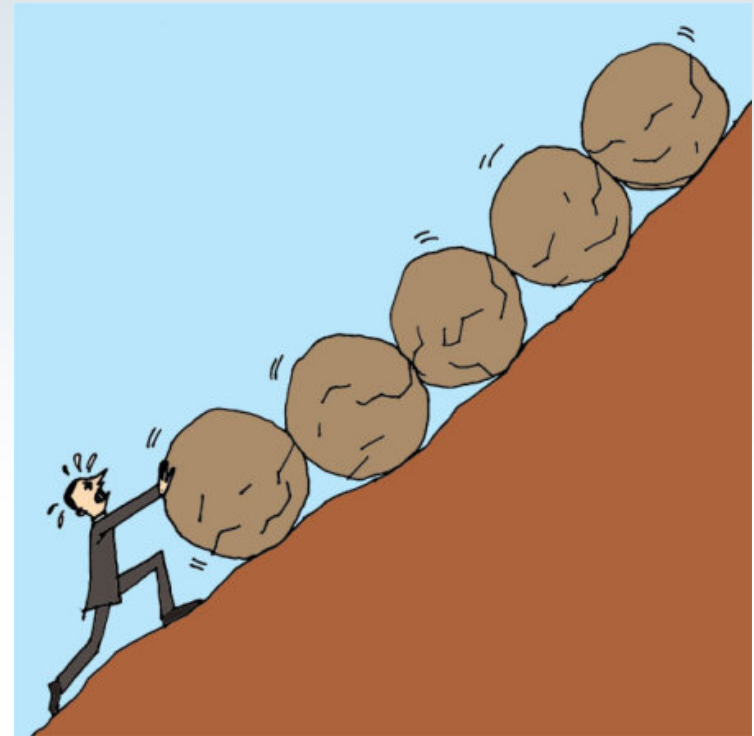
5 Key Themes

- Culture and Personnel
- Clinical Utility
- Financing
- Technology
- Data



Challenges & Facilitators: 5 Key Themes

- Culture and Personnel
- Clinical Utility
- Financing
- Technology
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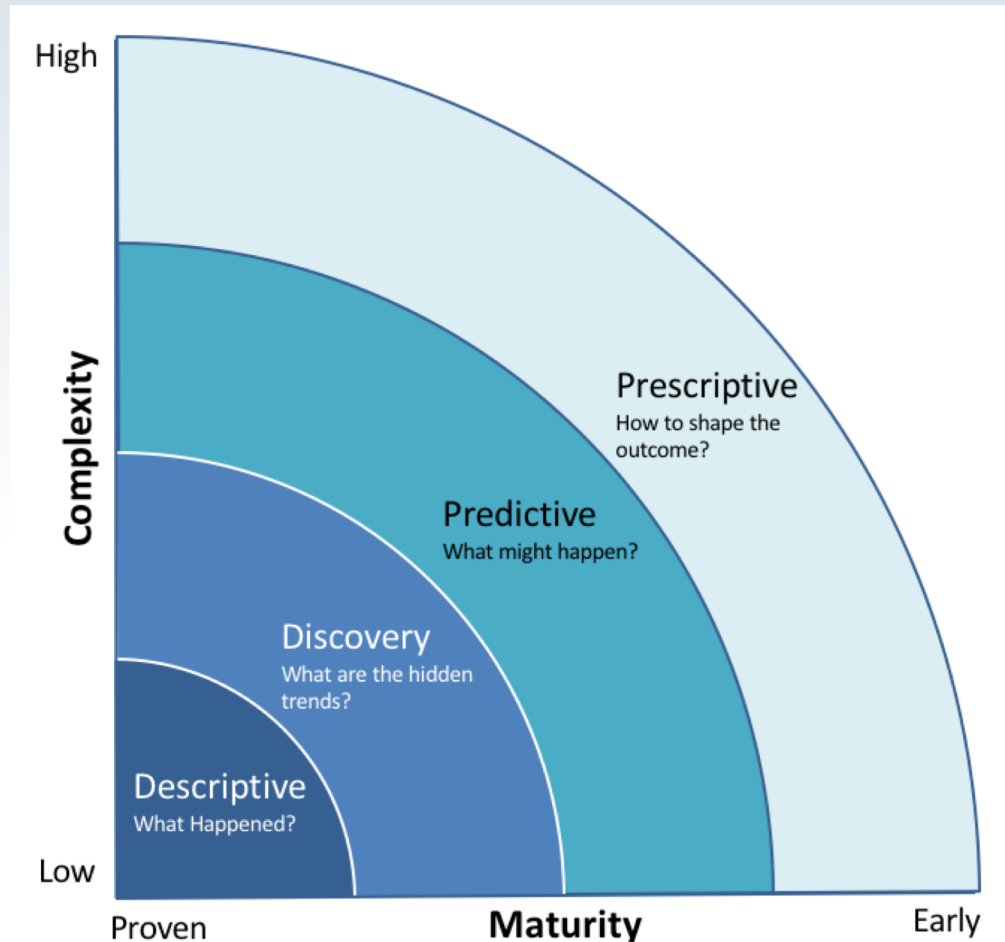


Culture and Personnel (1)

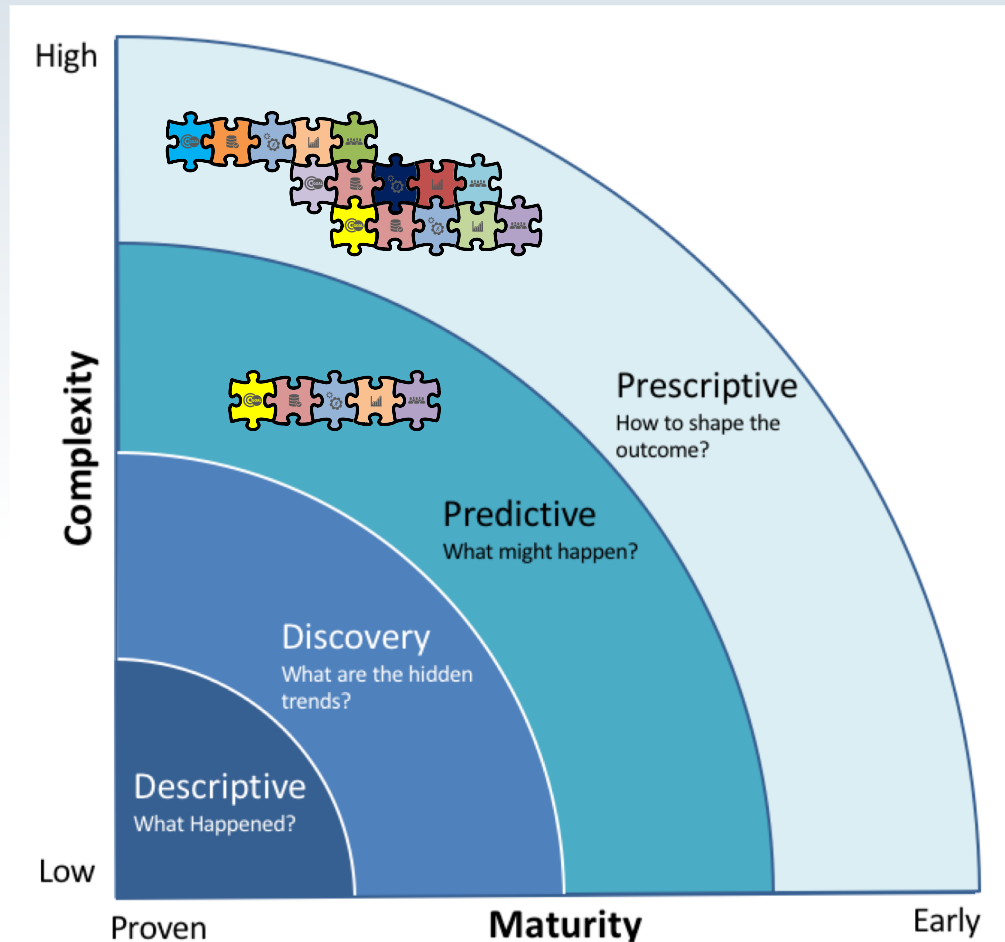
- Consensus Building & Direction Setting
 - Myriad of Stakeholders Needed in Collaboration:
 - Clinical and Data Experts need to Work Together From Early Stages of Model Development
 - “..more of the work is actually going to be focused on the intervention and the program to support that intervention in a sustainable way. The tech[nical] ..and analytics parts are getting easier and easier..”
 - Expectation Management: hype vs reality
 - Time Consuming



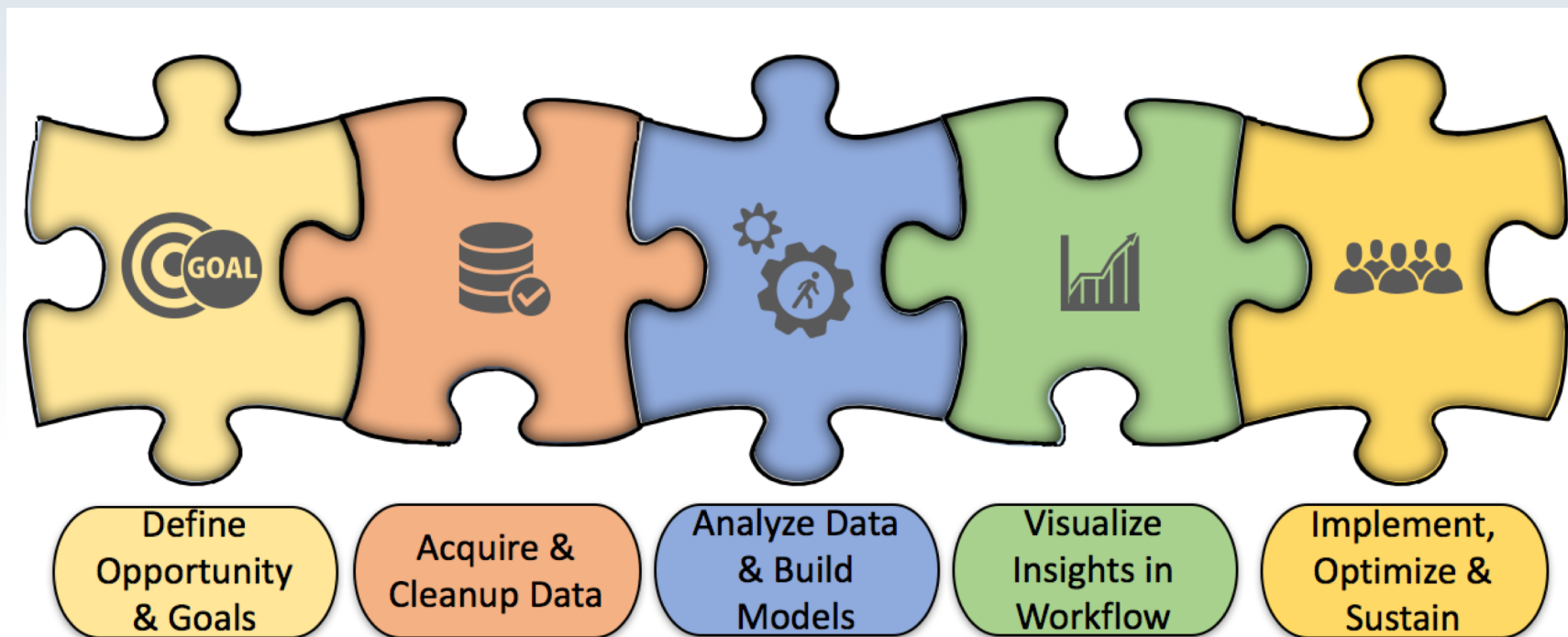
Spectrum of Analytics: Hindsight to Foresight



Spectrum of Analytics: Hindsight to Foresight

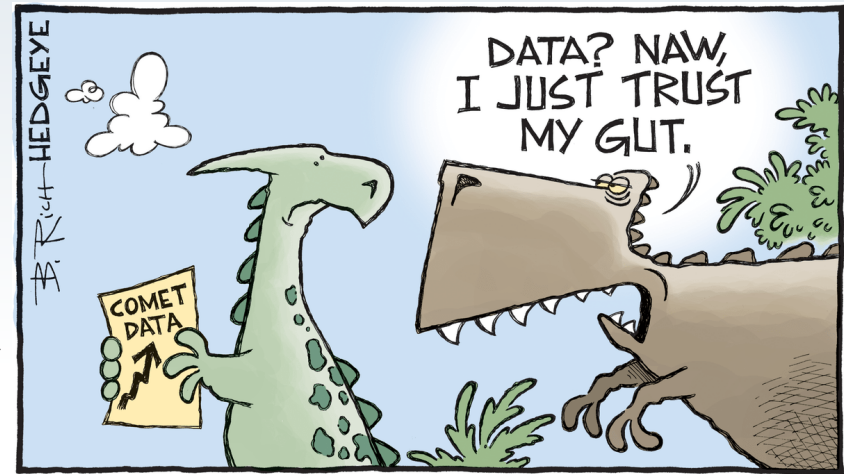


Anatomy of Impactful Advanced Analytics Projects



Culture and Personnel (2)

- Lack of Clinicians' Trust in ML/PM Model
 - Lack of Clinician Comfort Level with ML/PM Performance Metrics
 - 'Novel' algorithms often lack evaluation rigor/gravitas
 - Many high-performing models are 'black box' algorithms



Building Clinicians' Trust in ML/PM



- Transparency by Vendors & Model Developers
 - Reveal ‘Inner Workings’
 - Interpretable AI
 - Retraining/Retuning of Model using local data
 - Evaluation Framework

Culture and Personnel (3)

- Demand for staff skilled in development and maintenance of models far outstrip supply
- Vulnerability with Staff Turnover:
 - “When people with institutional knowledge [and] knowledge of models in production...move on to other institutions,.. It creates a knowledge gap”



Challenges & Facilitators: 5 Key Themes

✓ Culture and Personnel

- Clinical Utility
- Financing
- Technology
- Data

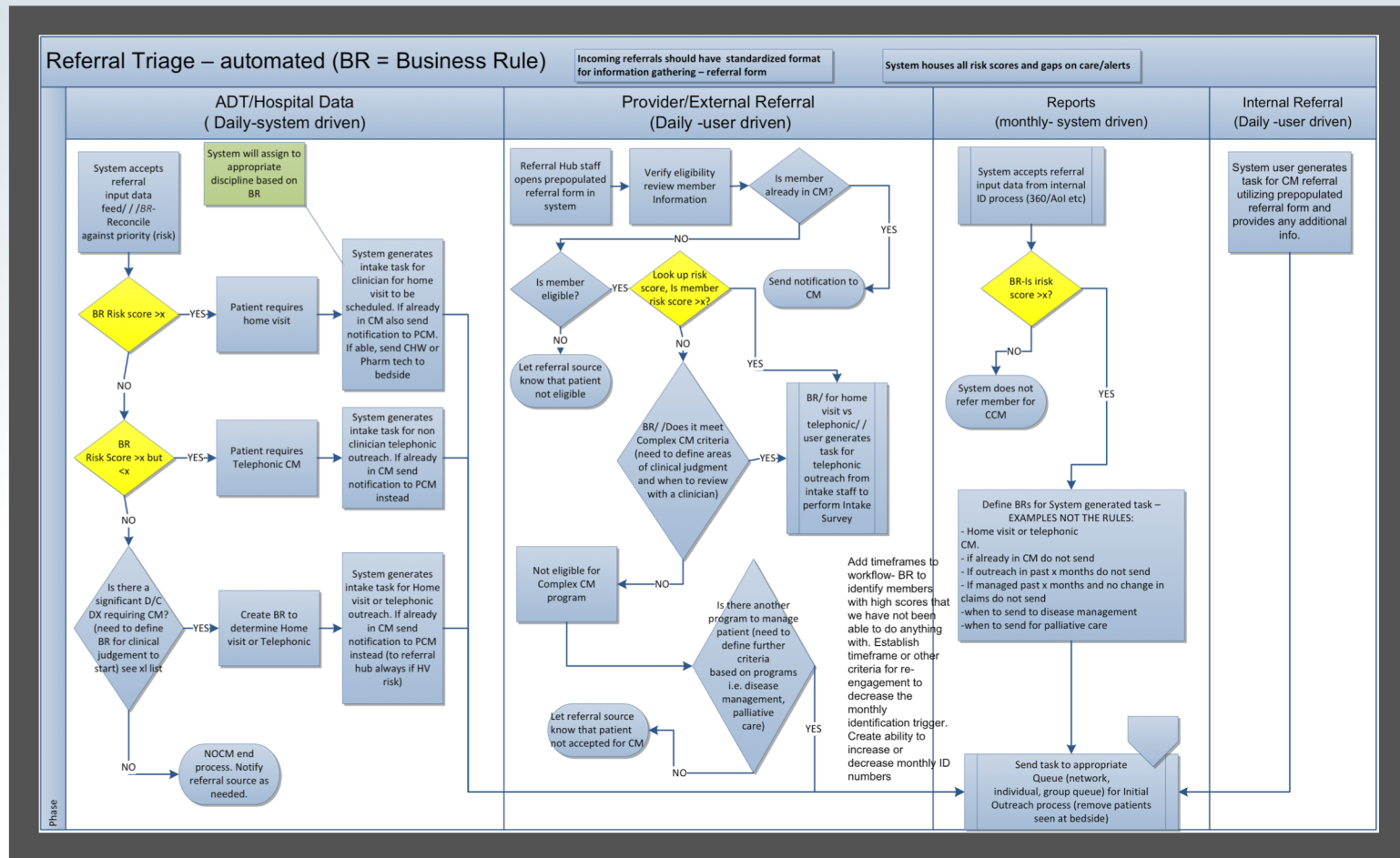


Clinical Utility

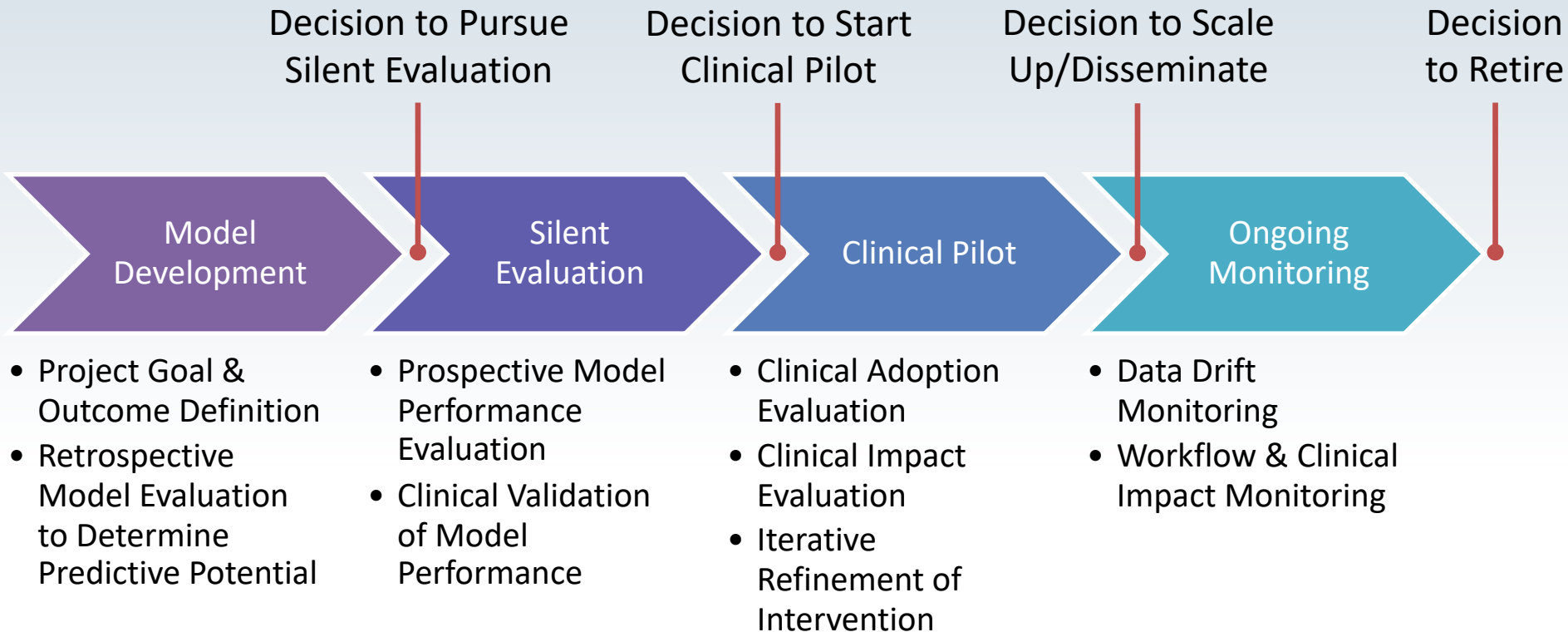
- Models need to be created with the end-goal in mind
 - Risk Stratification → Actionable advice → clinical intervention
 - “They validated that higher scores [indicate] a high risk of readmission, but what we don’t know for sure whether you can do something about it”
- Will clinicians pay attention?
 - Alarm/Alert fatigue
 - “What signals should you send, who(m) to send them to, when, and how.”



Workflow, Workflow, Workflow...



Predictive Model Evaluation Framework: v1.0 @ Duke



Challenges & Facilitators:

5 Key Themes

- ✓ Culture and Personnel
- ✓ Clinical Utility
- **Financing**
- Technology
- Data



Financing

- Not hard to get started, but challenging to complete a project
 - Data Wranglers
 - Data Scientists
 - Integration
 - Change Management
 - Model Maintenance
- Mishmash of funding without sustainability plan
- Vendors may have a role particularly for smaller institutions, but no standard integration/interoperability approaches



Local Governance and Oversight



- Building Predictive Modelling on top of Standard of Care and Established Best Practices
- 5 Rights of Predictive Modeling
- Manage Prediction Fatigue Proactively
- Ensure initial and ongoing accuracy of predictive models through evaluation framework
- Oversee communication and user education

Challenges & Facilitators:

5 Key Themes

- ✓ Culture and Personnel
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Technology Challenges



- Integration with EHR workflow
 - “How do you [implement ML/PM] in a standardized way [so] that a third party can build one tool and deploy it across different EHRs?.. Right now, none of the vendors have really sophisticated ways. The process is extremely naïve right now”
- Immature technology platform for PM and ML
 - “A key challenge is integration with legacy technology... Machine learning leverages the most modern tools, .. And integrating these modern tools with existing frameworks can pose interesting challenges”

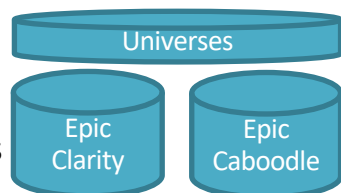
Data Science Technology Stack – Reference Architecture

Health
Applications



Model Run-Time Layer	Pipeline & Container Orchestration	Burst Computing for NLP & AI	Model Performance Monitoring			
Model Dev Layer	Pipeline & Container Orchestration	Burst Computing for NLP & AI	PACE	Analytic IDE	Model Validation	Code Repository
Data Access Layer	Access Controls	RESTful APIs	Direct SQL	Cohort Generation	Self Service Data Exploration	Data Obfuscation
Data & Meta-data Curation Layer	PORT & DART Teams	Dept & Project Data Teams	Data Profiling & Ongoing QA	Info Asset Repository	Terminology Dictionaries	
	Data Curation			MetaData Curation		

Primary
Analytic
Data Sources

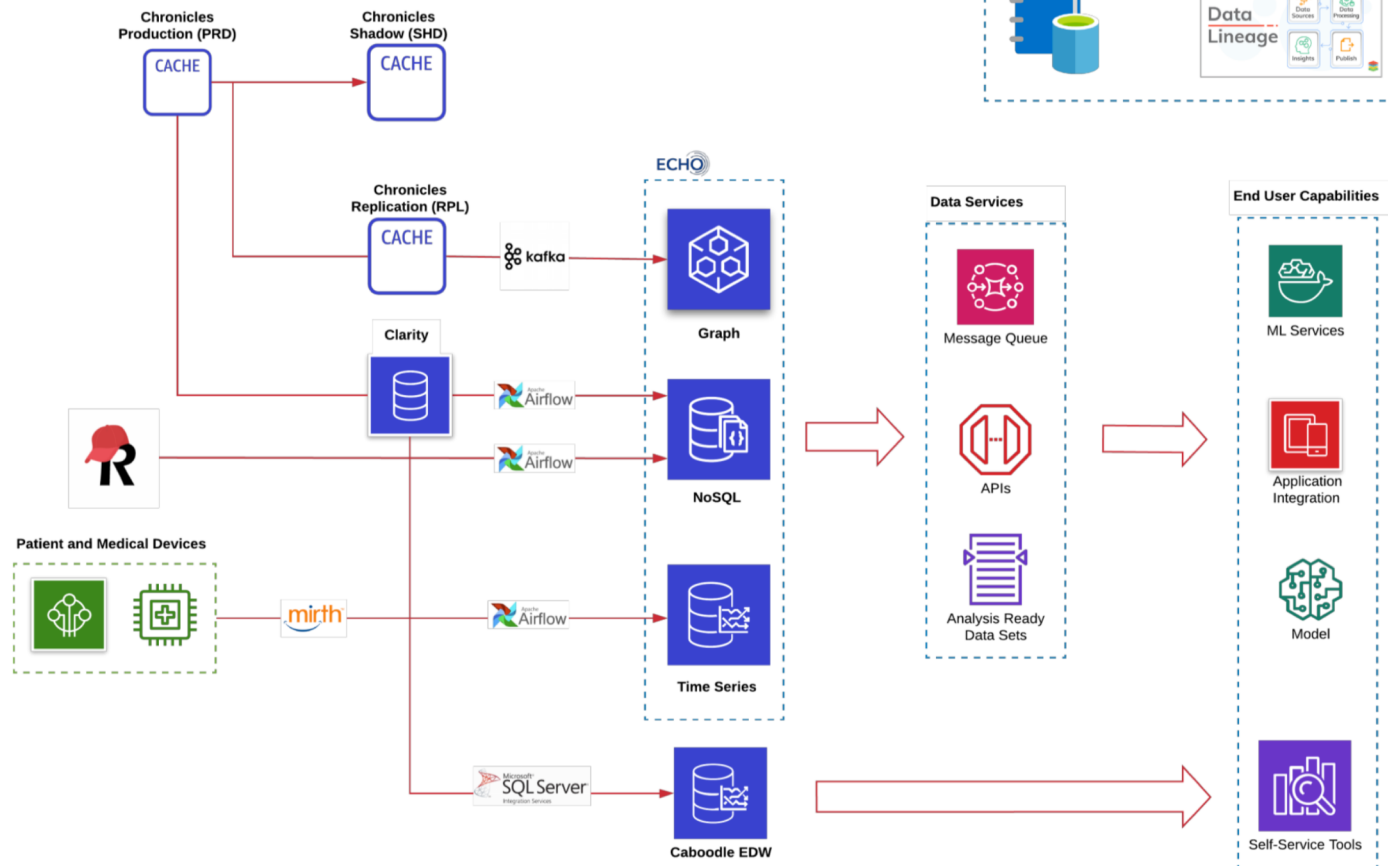


Transactional
Data Stores

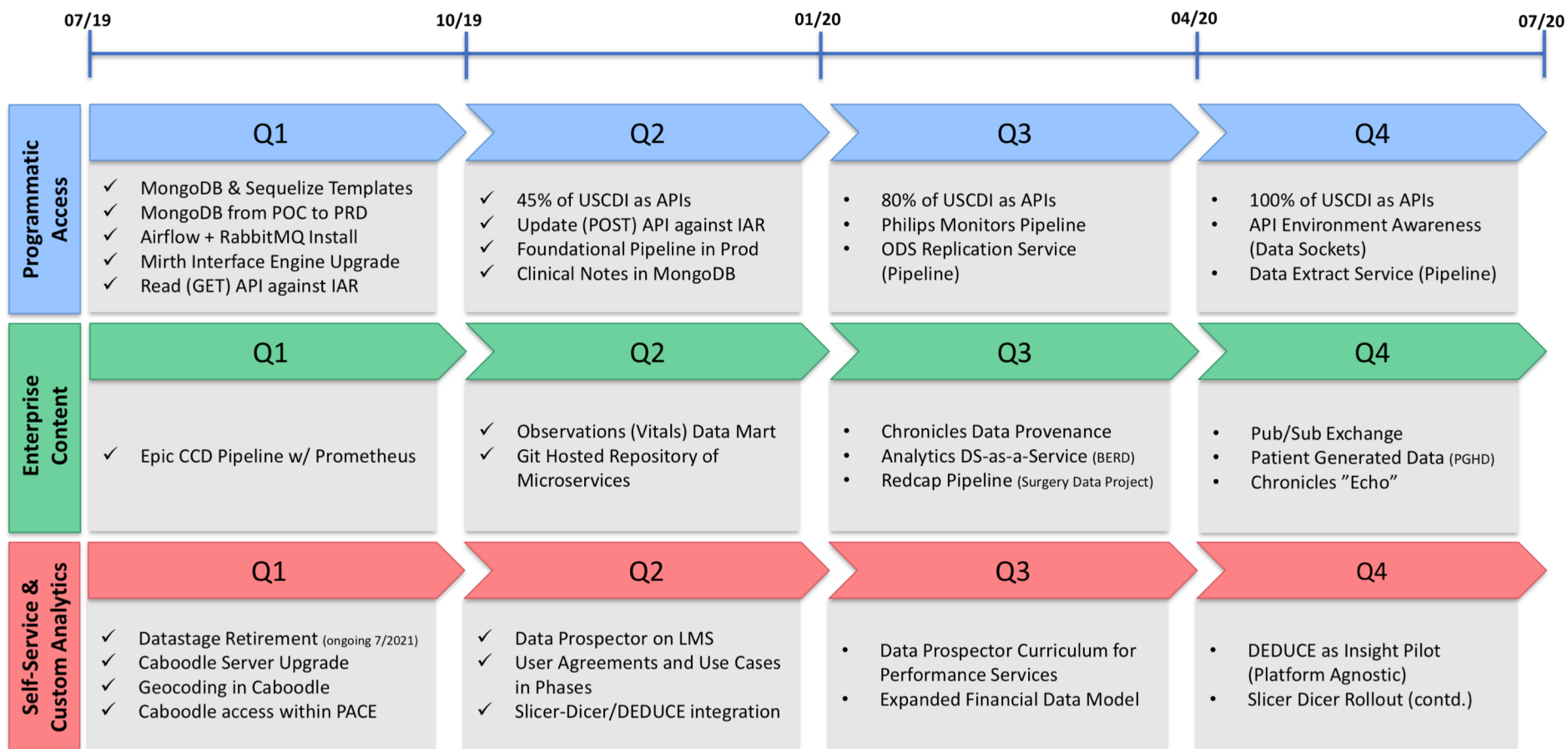


Data Architecture for Now & Future

Duke Health Enterprise Data Environment



Progress Towards Reference Architecture



Challenges & Facilitators:

5 Key Themes

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- ✓ Technology
- Data

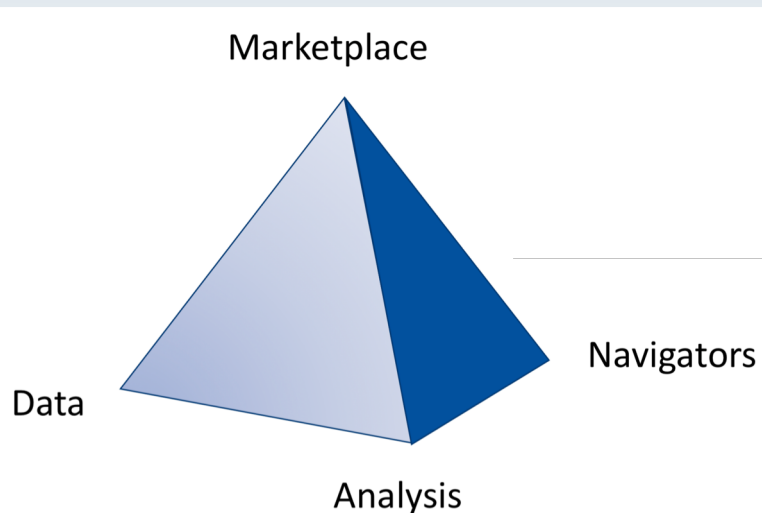


Data Challenges

- Variable Data Quality from EHRs that May not reflect clinical reality
 - “There are many times when we pull data that look meaningful and carries a lot of signal, and when we talk to the clinicians, that data filed is laughed at. They don’t use it, or it’s just something that they have to enter for billing reasons, and they are horrified that we would actually use that in a model.”
- Unstructured Data & Associated Methodological Challenges
- Variable Workflows across Health Systems

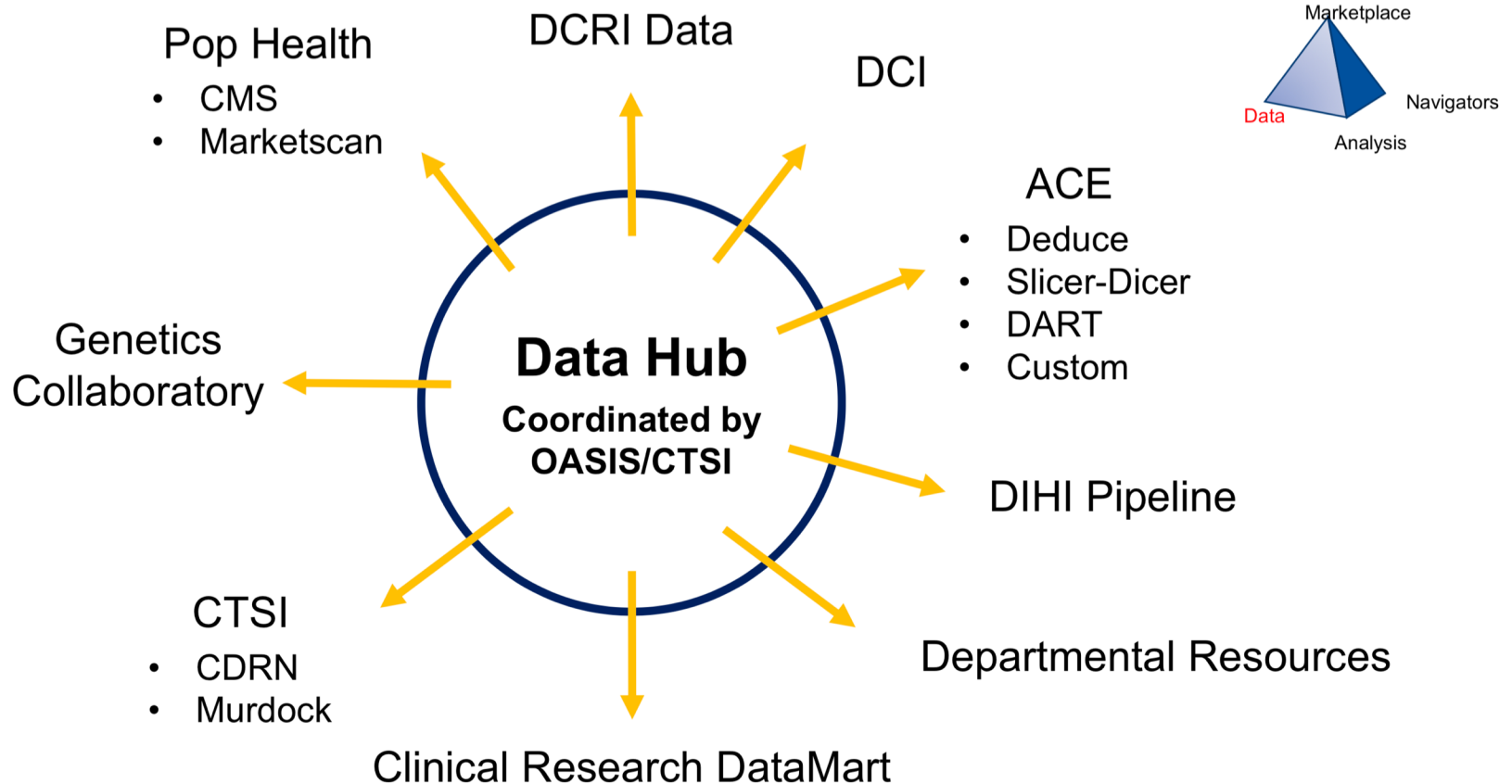


Data and Analytics Navigation: Duke Data & Analysis Resource Center


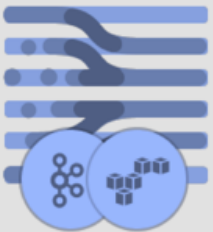





- A Front Door (one-stop shopping) to data resource for research at Duke (and beyond)
- Self-serve or facilitated (warm hand-off) access to data assets
- Connection to Appropriate Methodological Experts

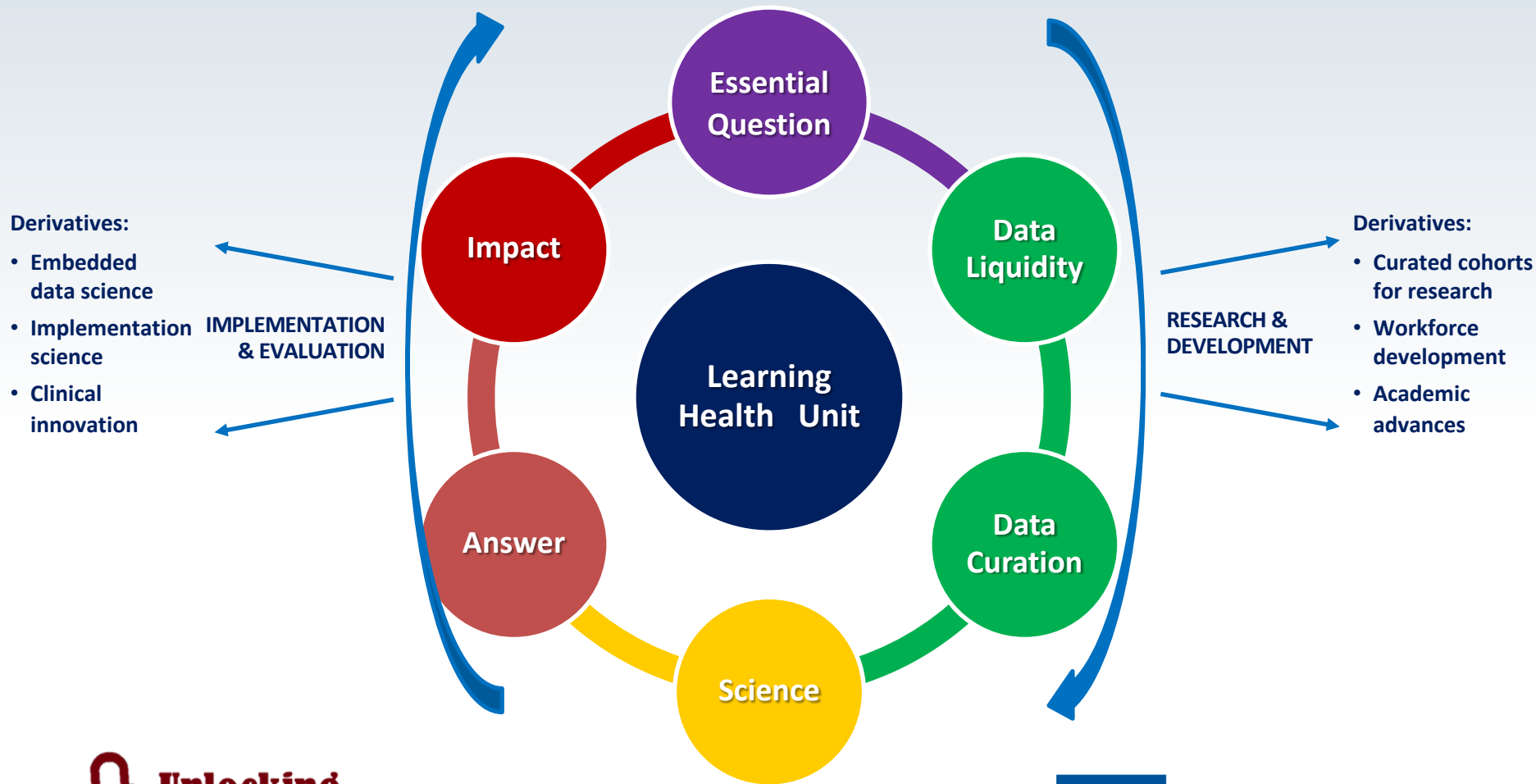
Data Hub



Approaches for Servicing the Data Hub

	Self-Service: Data Discovery Tools	Self Service: Data Science Pipeline	Custom Data Set Preparation	Shared Services: Dedicated FTEs	Shared Services: Dedicated Team
Offering					
Examples	DEDUCE Slicer Dicer	FHIR; Pythia; Data Sockets	Ad Hoc Fee-for- Service Data Extracts	Ortho; OB/Gyn; Transplant	PORT; PHMO Analytics
Cost	Free	\$ to build Free to Reuse	\$	\$\$\$	\$\$\$\$\$

Learning Health Units: Bridging Research, Quality Improve and Data Science



Key Insights from Duke and Other AMCs

- Big Data Needs to be Played as a Team Sport
 - Multi-disciplinary approach
 - ‘End-to-End’ Thinking
- Key Facilitators
 - Data Navigators
 - Clinical Workflow and Mindflow Expertise
 - Novel yet Scalable Technology Deployed on Reliable Platform
 - Comprehensive Evaluation and Sustainability Plan
 - Governance and Coordination

Thank You!

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