



Applied Artificial Intelligence at Mayo Clinic

Atul Dhanorker, Adam Resnick
Mayo Clinic

5th Annual Research Roundtable: Data Analytics in Healthcare
March 22, 2022



Presentation Outline

- The Opportunity Space
- Artificial Intelligence (AI) Capability
- **Case Study 1:** Emergency Department Transfer
- **Case Study 2:** Breast Cancer Risk Prediction
- Discussion

Mayo Clinic – United States



TOTAL CLINIC EMPLOYEES – 63,078*

4,590 Physicians and scientists	58,488 Administrative and allied health staff
Rochester	34,660**
Health System	16,413
Arizona	6,448
Florida	5,557



2030 Bold. Forward. Strategic Plan



Cure



Connect



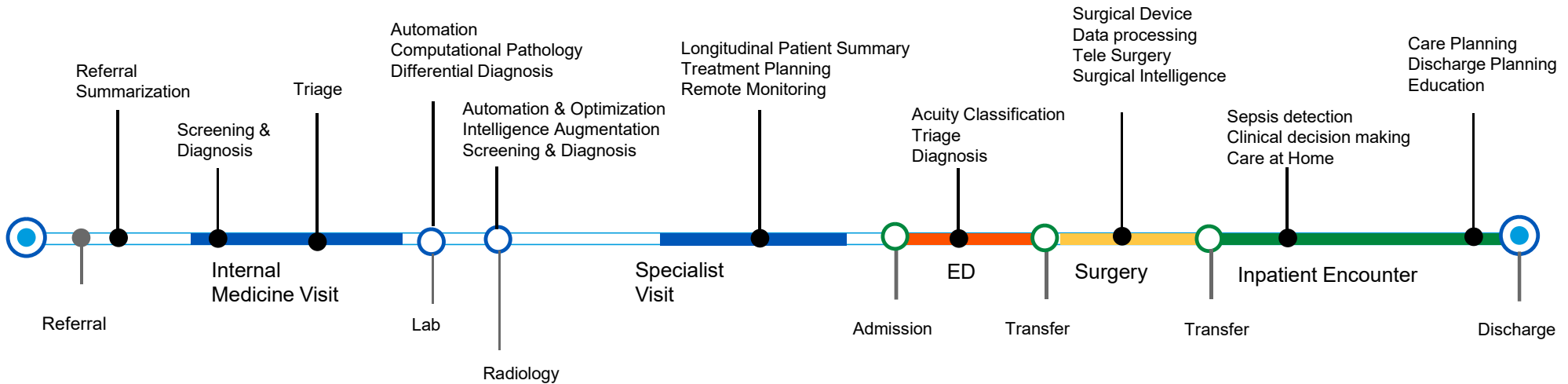
Transform



People, Innovation and Environment

Patient Journey Map and AI Impact

AI impact



Patient Journey

Capability Model: Ideas Based on Maturity



Idea

A hypothesis to solve a problem



Proof of Concept (POC)*

“Identifies operational feasibility of the concept and is for internal use”



Prototype*

“Offers the first look and feel of the project and can be presented to stakeholders”



Minimum Viable Product*

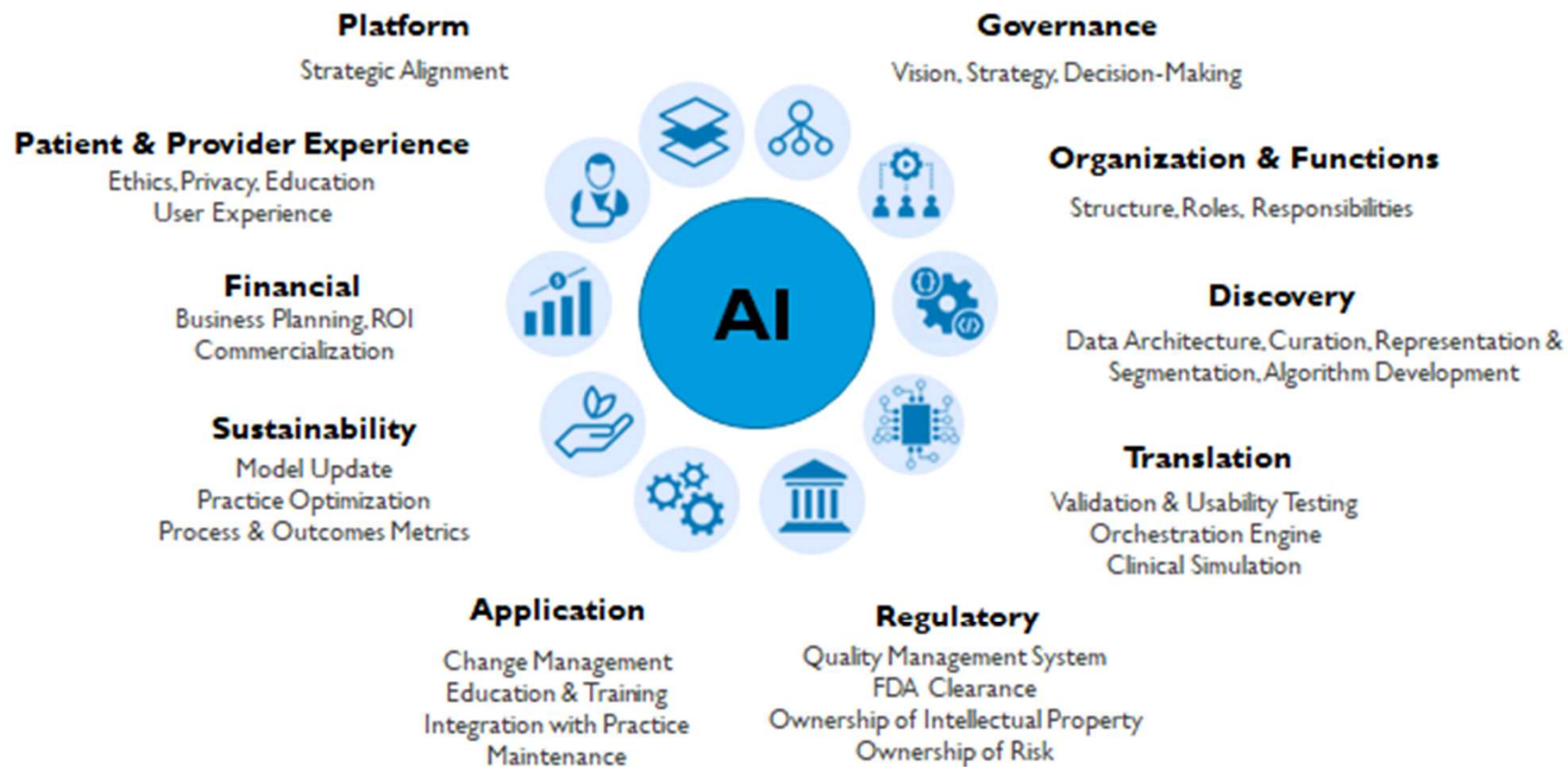
“Gives a basic working model that can be implemented and deployed into”



Vended Product / Applied IA

Available in the marketplace

Pillars of Clinical AI





Case Studies

Emergency Department Case Study

Product Pipelines



Clinical, Research
and Education

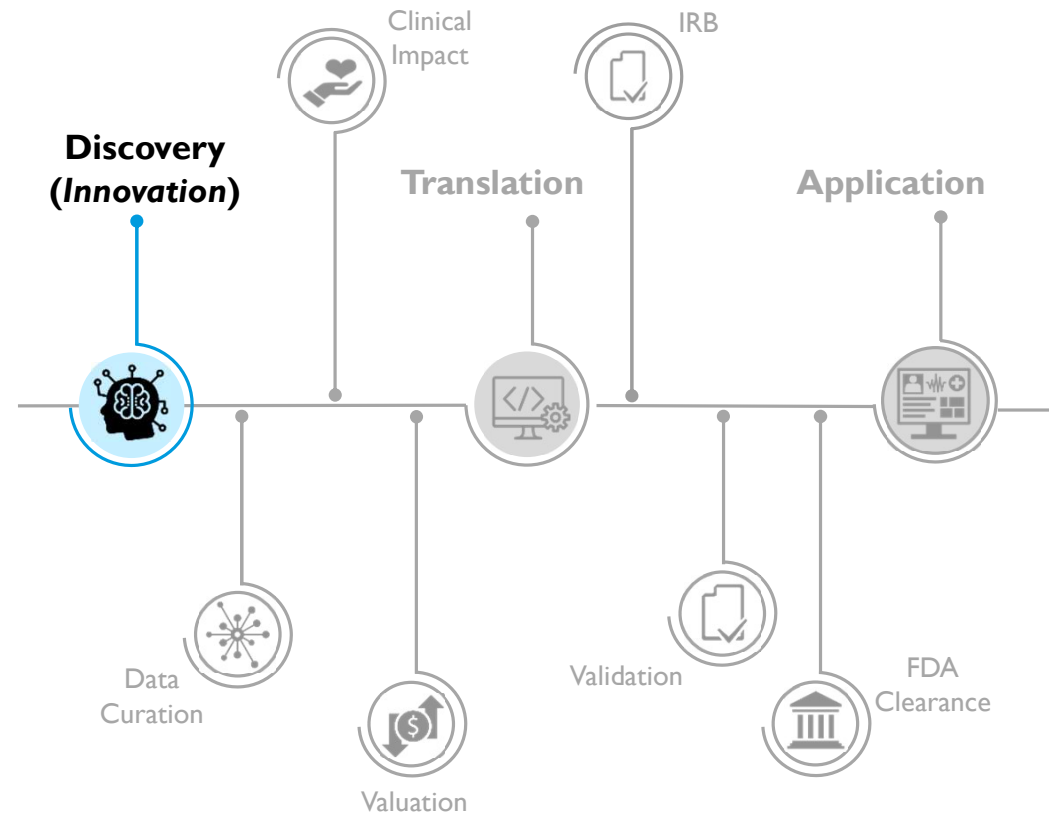


Business Intelligence &
Administrative



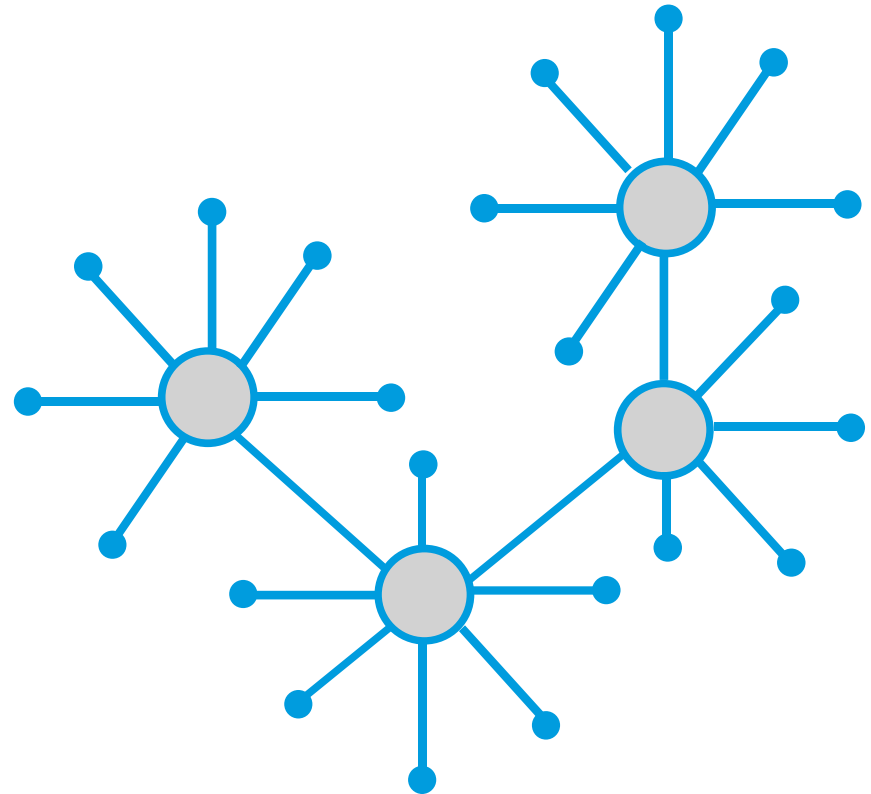
Direct-to-Consumer

Process



Mayo Clinic Midwest

- **Hub-and-spoke model**
 - "Hubs" can manage complex patients
 - "Spokes" have fewer resources
- **Goals:**
 - Manage patients locally as much as possible
 - Reduce unnecessary healthcare utilization



Purpose

Objective

To leverage machine learning to **predict which patients would require hospital transfer** to enable early preventative intervention

Benefits

- Earlier readiness of hospital transport
- Ability to intervene with telemedicine to prevent transfer
- Enable research to better understand trends in patient transfers

Purpose



**Proactively
Prepare Transport**



**Identify
Telemedicine Candidates**



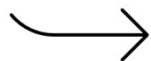
**Detect
Biases and Trend**

Approach



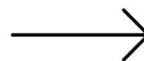
Input Data

- Demographics
- Triage status at arrival
- Problem list
- Vital signs
- Diagnosis
- Orders
- Medications
- Used data from 160,000 patients treated between July 2017-October 2020 from non-hub Mayo Midwestern sites



Neural Network



trained in Google
AutoML



Risk Score

Score 1-10 indicating risk of
transfer to hub site

Results

	Model Type	Accuracy	Percent of Flagged Patients Who Were Truly Transferred	Percent of Transferred Patients Who Were Flagged
Full Visit Data	 Neural Network	95.5%	77.4%	63.4%
Data at Triage	 Neural Network	92%	68.8%	8.1%

Null model: 92% accuracy

Conclusions



Feasibility

- It is **possible to accurately predict ED transfers** using machine learning
- Model accuracy is less clear with data only available at triage



Implementation

- The model **use case must be refined** for further development
- Minimum acceptable predictive performance must be established
- **Incorporation into clinical workflows** must be considered

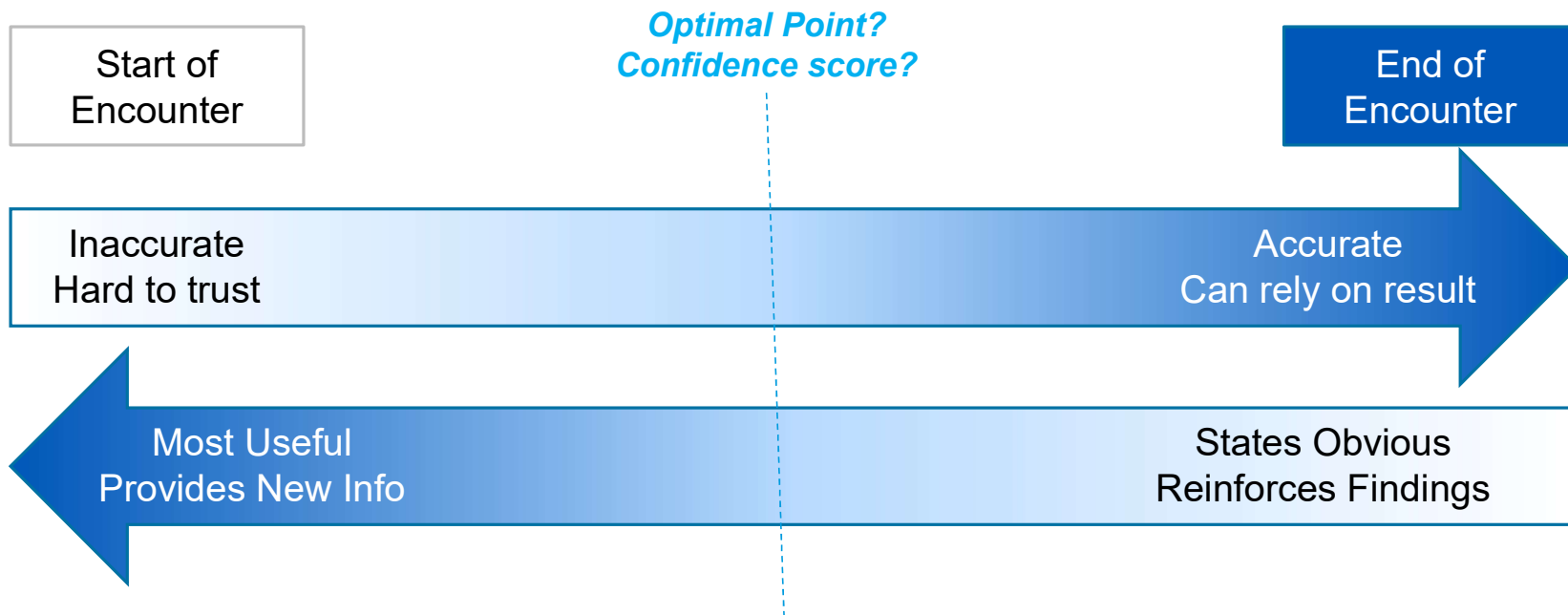


Items for Further Study

- The use **of additional predictive variables** may improve accuracy
- Other criteria for optimization may better meet the model use case

Possible Follow-Up Research Question

- **At which point of the patient journey is input from a model-based risk score most valuable?**

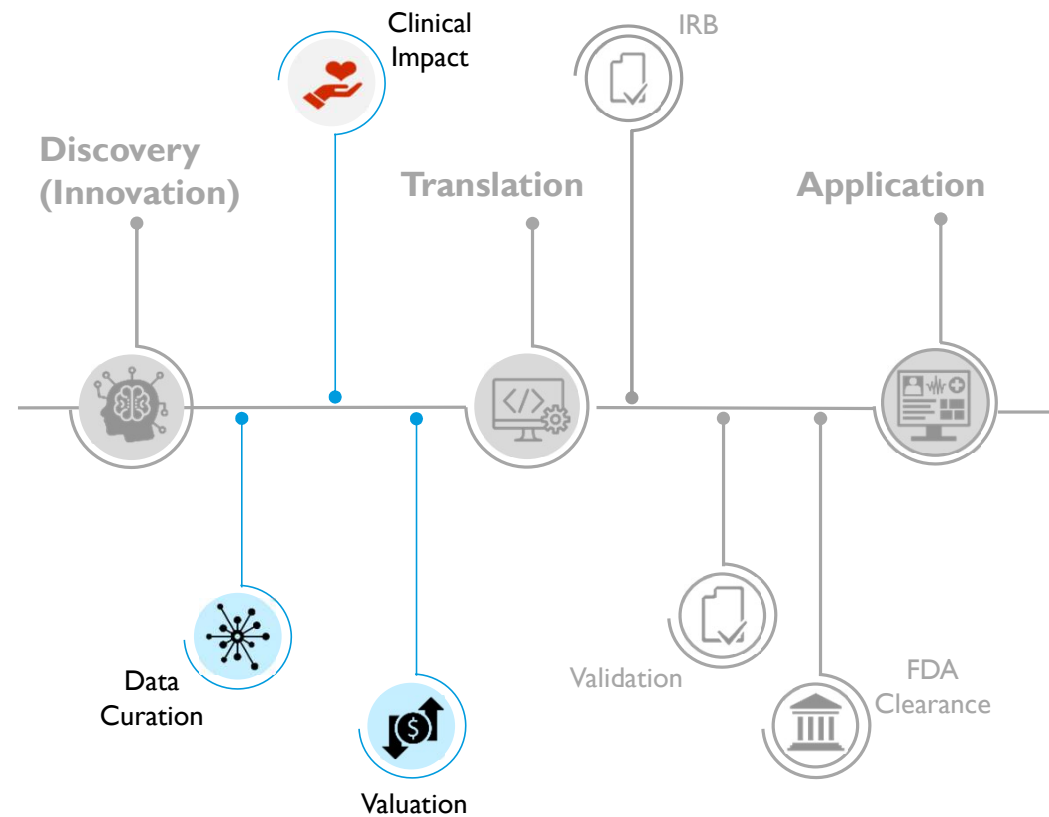


Automation of Breast Cancer Risk Assessment Case Study

Product Pipelines



Process



Background



Risk Assessment

- Tyrer-Cuzick model calculates patient's 10 year and lifetime risk of developing breast cancer
- It uses demographic, family history, radiology, breast biopsy, genetic etc data to calculate the risk



Point of Care use Challenges

- Physicians are spending 30-35% of their time documenting and retrieving information with EHR
- Data is scattered throughout electronic health record(EHR)
- Most of the data elements are stored in unstructured clinical notes.



Patient and Physician satisfaction

- Physician EHR usage present a challenge in developing meaningful relationship with patient
- Physician are under increasing time pressure resulting in stress and burnouts

Purpose

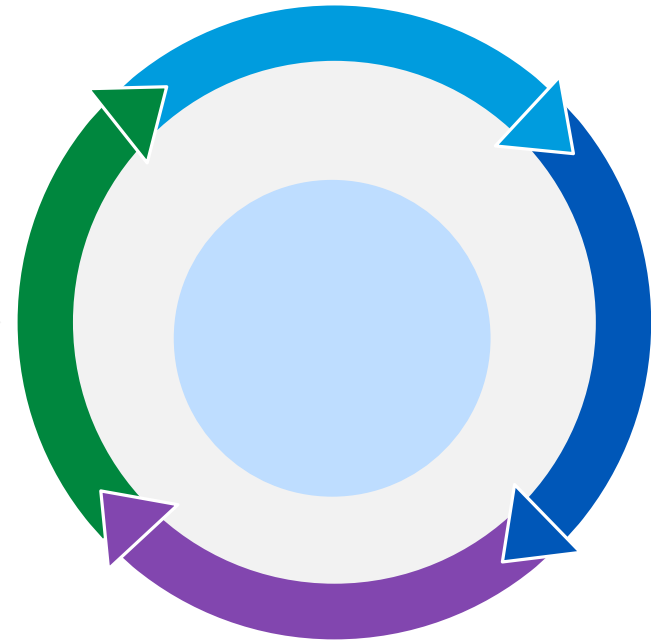
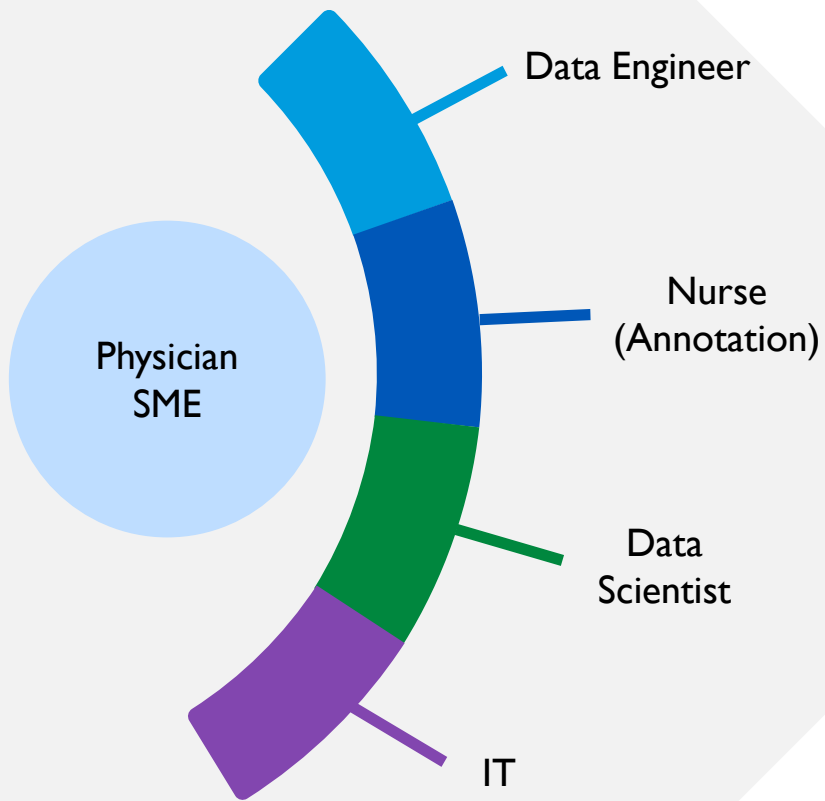
Objective

To leverage NLP and deep learning to **extract structured and unstructured data** element needed to prepopulate the TC risk prediction model

Benefits

- Improve patient provider interaction
- Reduce cognitive burden and stress
- Human in the loop design to enable physician to modify the data elements

Team



Challenges



Data

- 70% of data element present in clinical notes.
- Complex inclusion and exclusion criteria.
- Need specialized trained nurses for annotation.
- 80% of project effort in annotation.
- Coverage of data elements.



Process Engineering

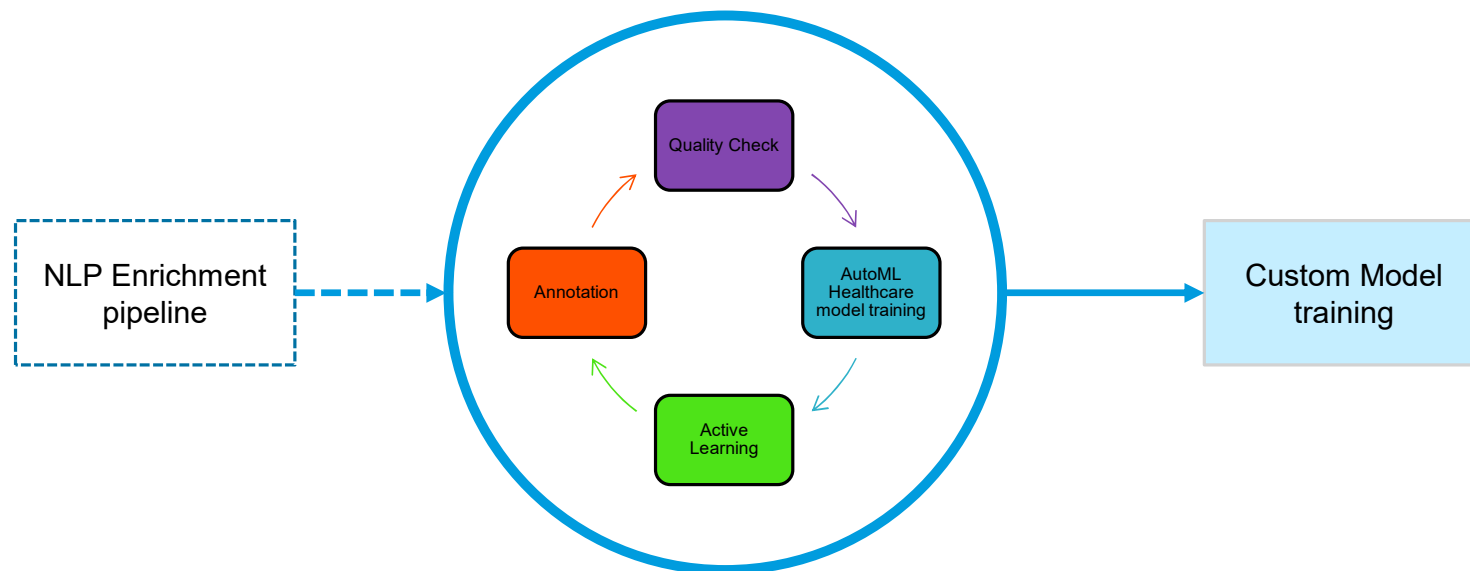
- Human in loop design: augment not automate the physician's workflow.
- Ethical, technical and quality standards



Agile Translation and Collaboration

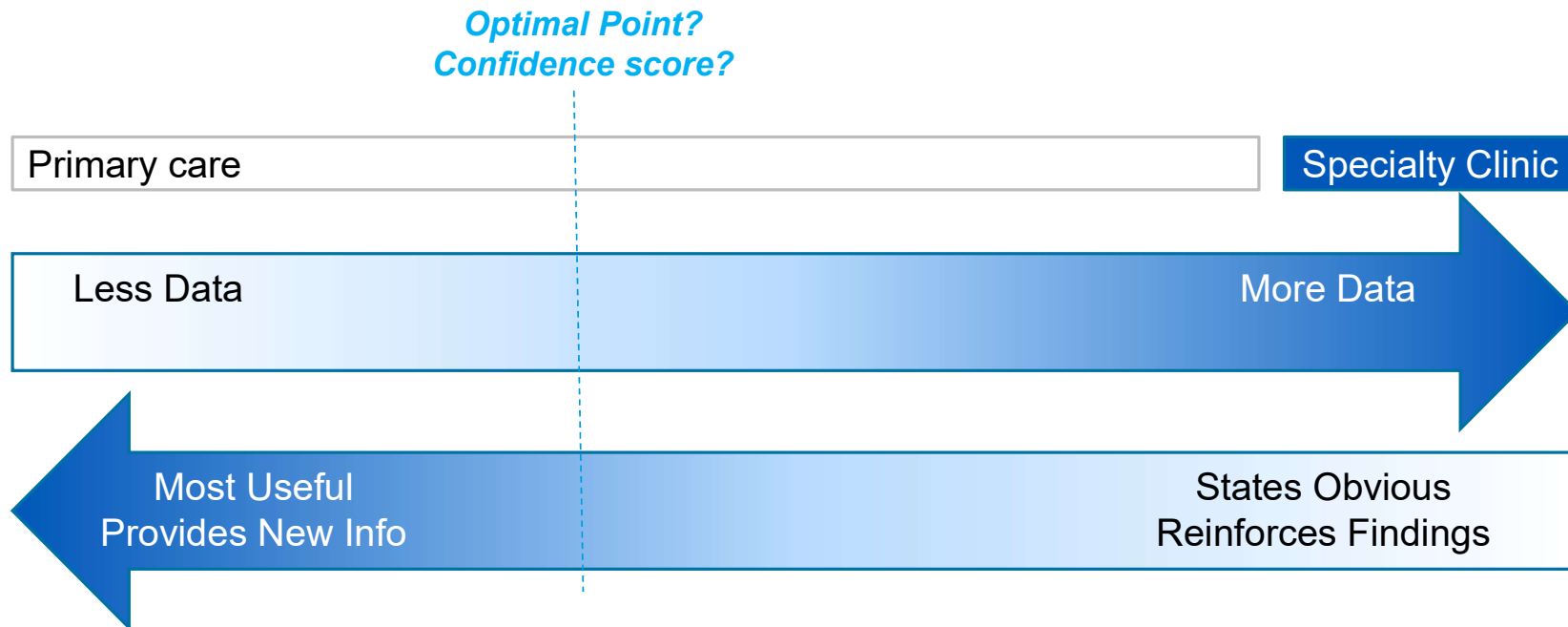
- **Technical collaboration** between team members with different domain expertise

Approach



Possible Follow-Up Research Question

- **At which point of the patient journey is input from Risk model most valuable?**





Discussion

