

# Making AI Actionable for Patients with Chronic Disease

---

Len Usvyat, PhD

Vice President

Applied Advanced Analytics

FMC Global Medical Office

**November 19, 2019**

# Agenda

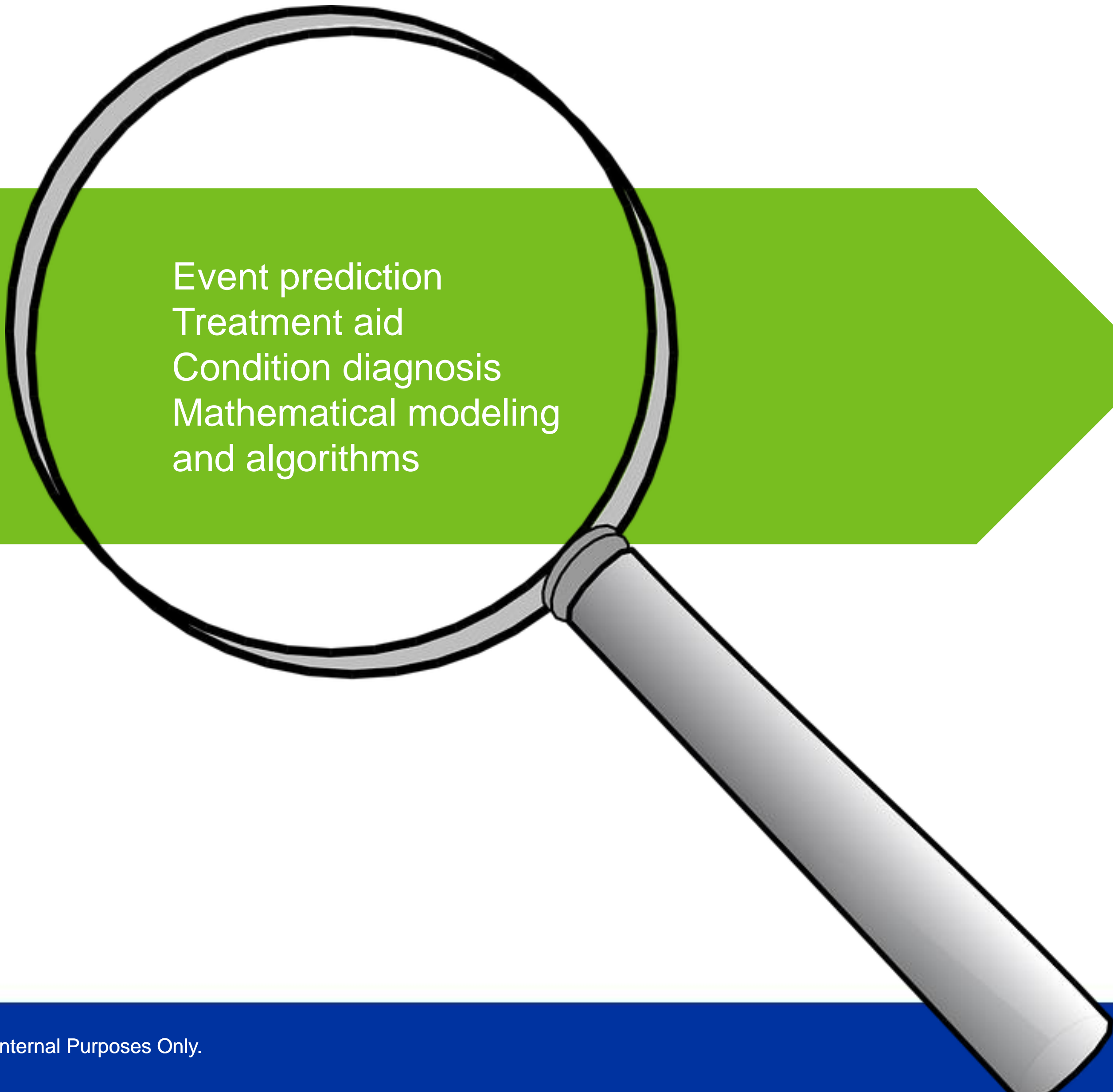
---

- **Analytics and Artificial Intelligence**
  - **About Fresenius Medical Care**
  - **Fresenius Medical Care and Data**
- **Advanced Analytics: Our Approach**
  - **Portfolio of Existing Efforts**
  - **Future of AI in Healthcare**

# **Analytics and Artificial Intelligence**

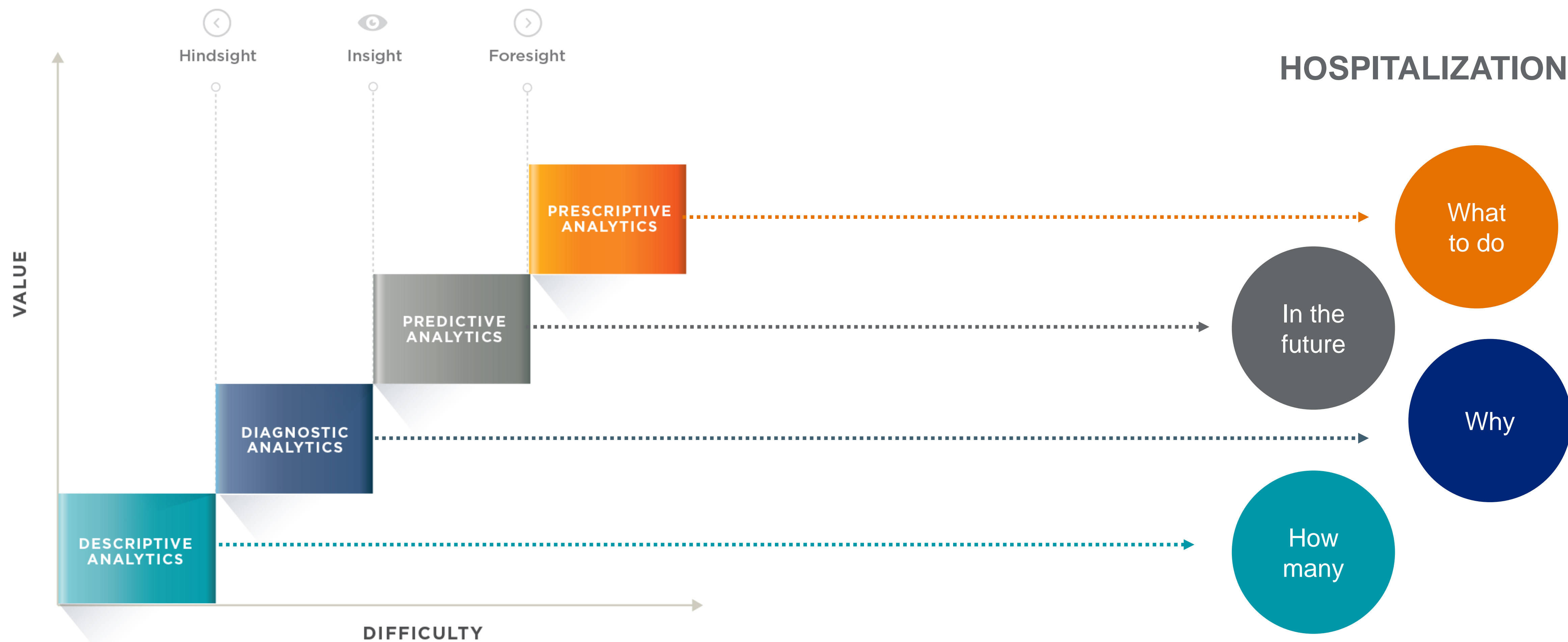
---

# TRADITIONAL ANALYTICS

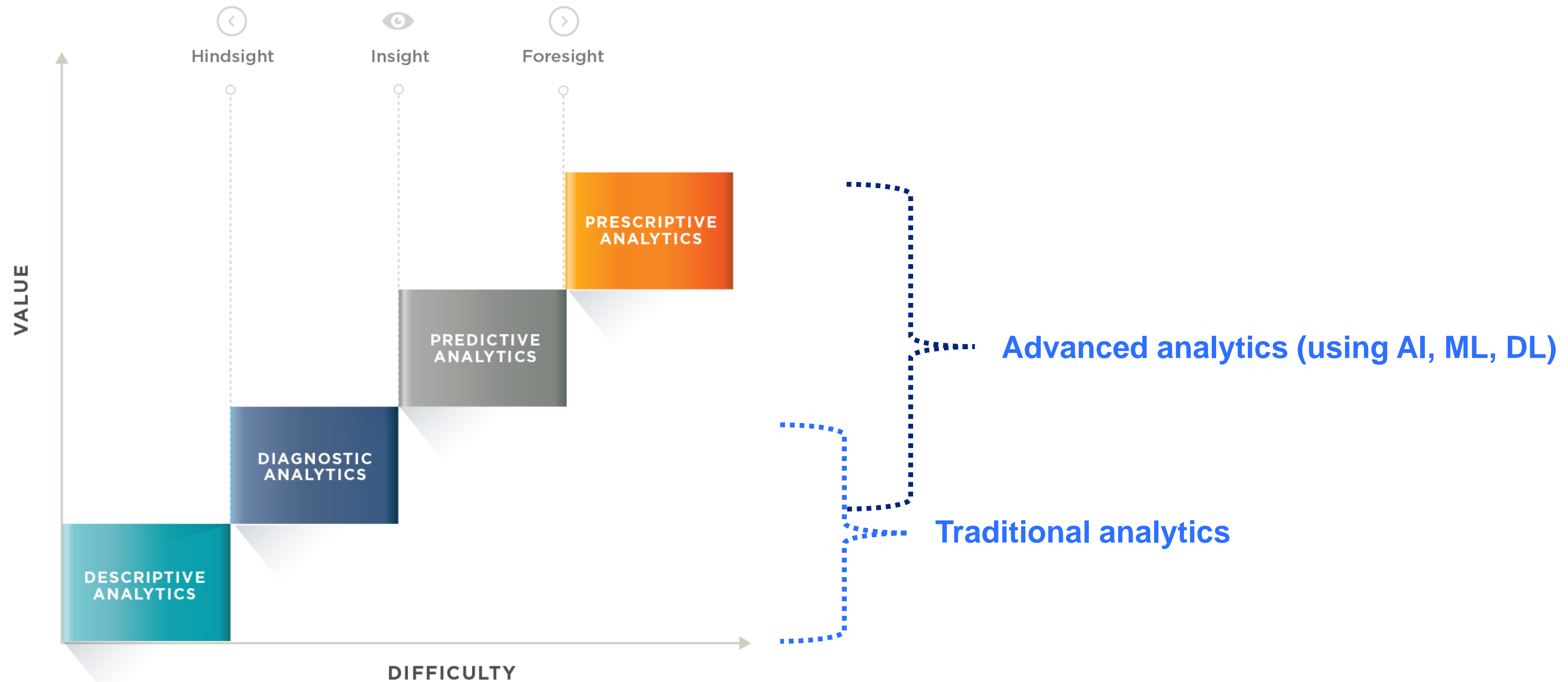


Event prediction  
Treatment aid  
Condition diagnosis  
Mathematical modeling  
and algorithms

# Analytics



# Analytics



# Fresenius Medical Care

---



# Fresenius Medical Care Portfolio

Health care  
services

13.27 BN €  
of total revenue

**16.55** BN €  
Revenue

Health care  
products

3.28 BN €  
of total revenue



# We Offer Dialysis Products

#1

supplier  
of dialysis  
products

Products for **hemodialysis, peritoneal dialysis, acute dialysis, liver support and therapeutic apheresis**, e.g.:

- Dialysis machines, dialyzer
- Bloodline systems
- Concentrates
- Water technology
- PD products

Dialyzers:

- Market share: ~50%
- ~165 M dialyzer produced in 2018

Dialysis machines:

- Market share: >50%
- 50,000 dialysis machines sold in 2018
- 1 of 2 dialysis machines worldwide is made by Fresenius Medical Care

42

producti  
on  
sites



# We Provide Dialysis Services



3,928 own dialysis centers

Around **50 M** dialysis treatments  
in 2018

In around **50** countries

Market share: **10%** worldwide

U.S. **38%** (patients treated)

Every **0.6  
seconds**  
we provide  
a **dialysis  
treatment**



# We Coordinate Care

Patients  
benefit from  
our  
**value-based  
care  
approach**



## CARE COORDINATION

Driven by our **holistic patient-centric approach** we add relevant services and therapies to our offerings.

**Focus:** Connected business with high relevance of shared services and patient data

## GOALS

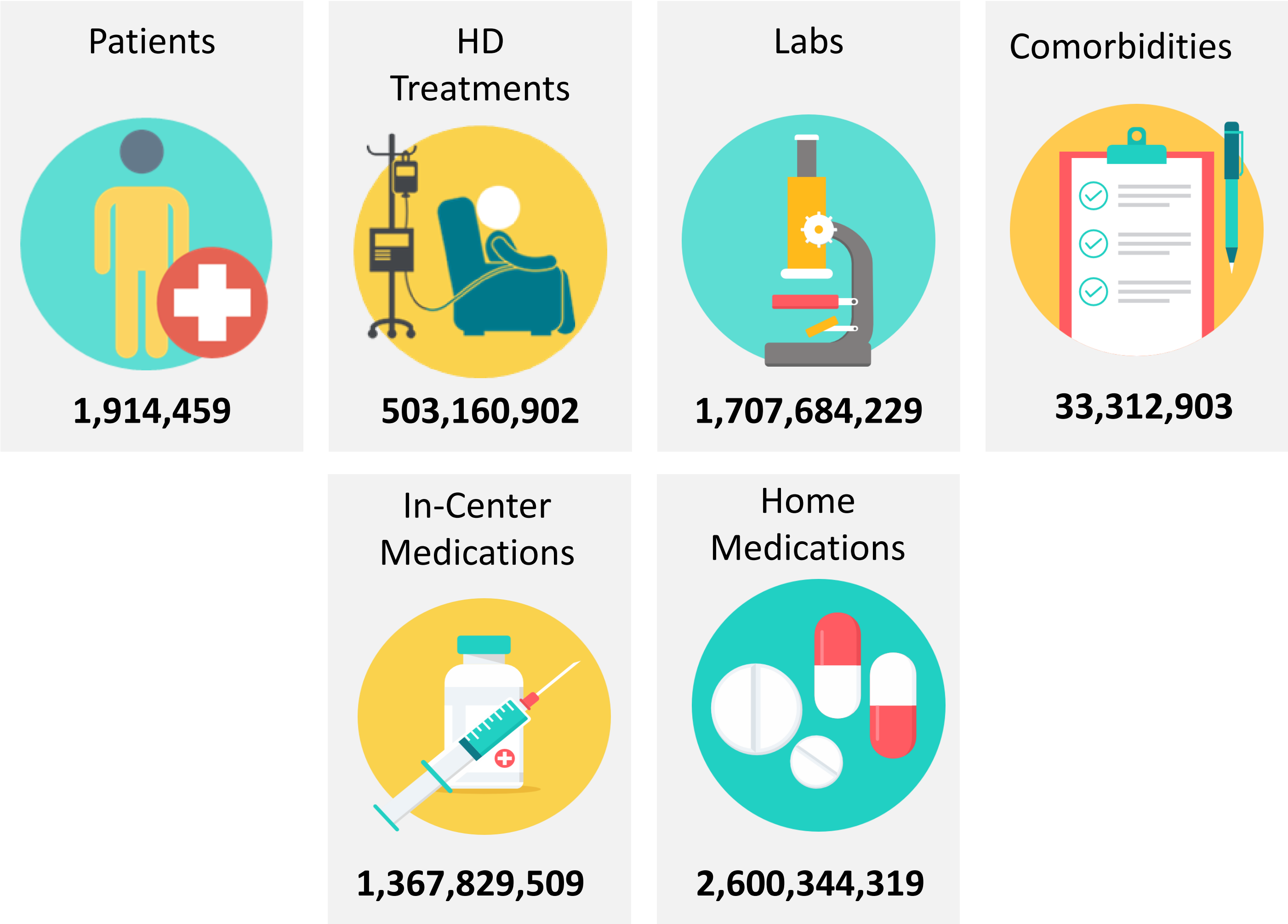
- Increase accessibility and high quality, integrated care for our patients
- Actively manage cost of chronically ill patients
- Gaining transparency to enable patient risk management
- Continuously optimize our portfolio of services

# FMC and Data

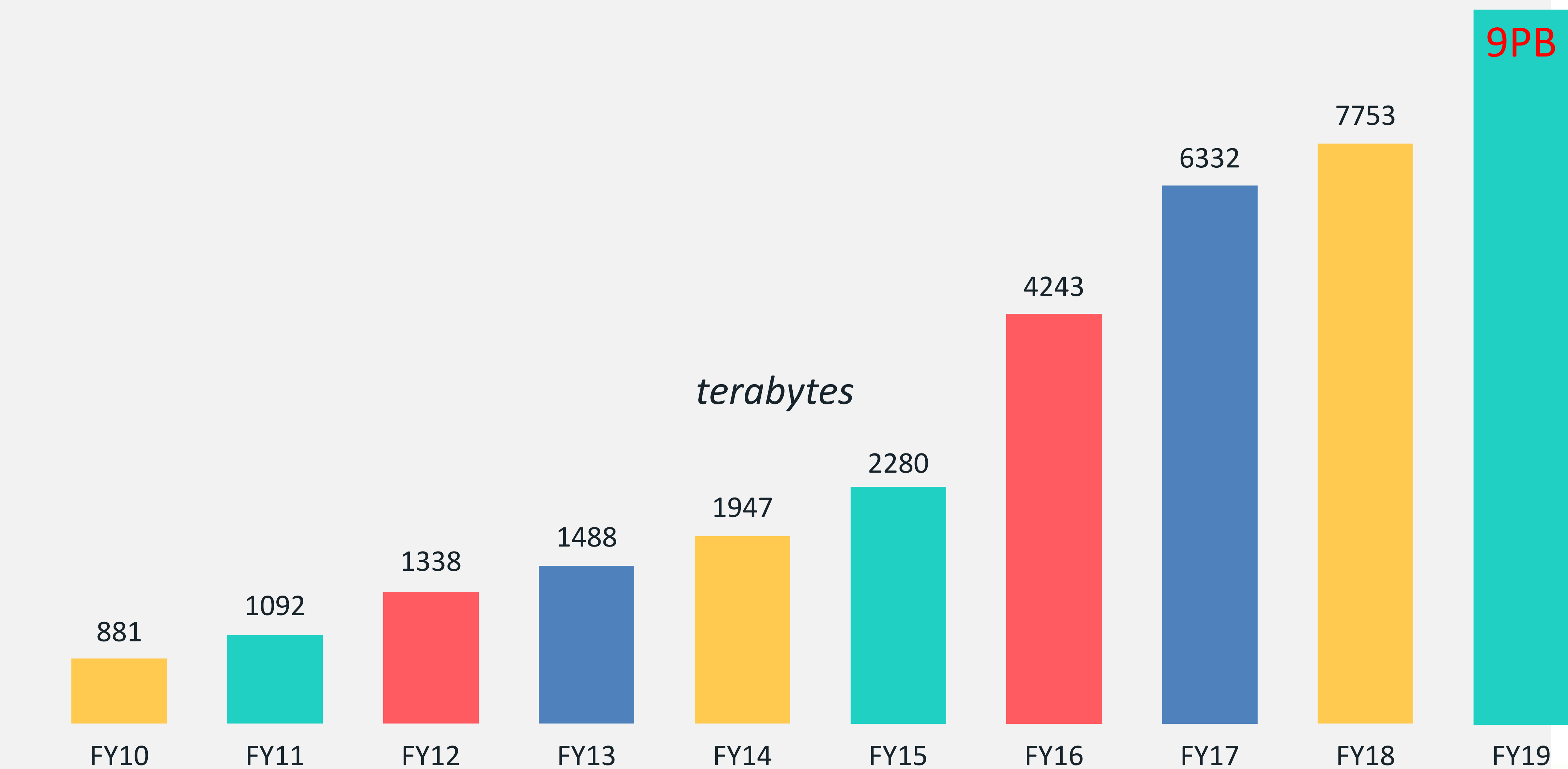
---



# FMC Global Data



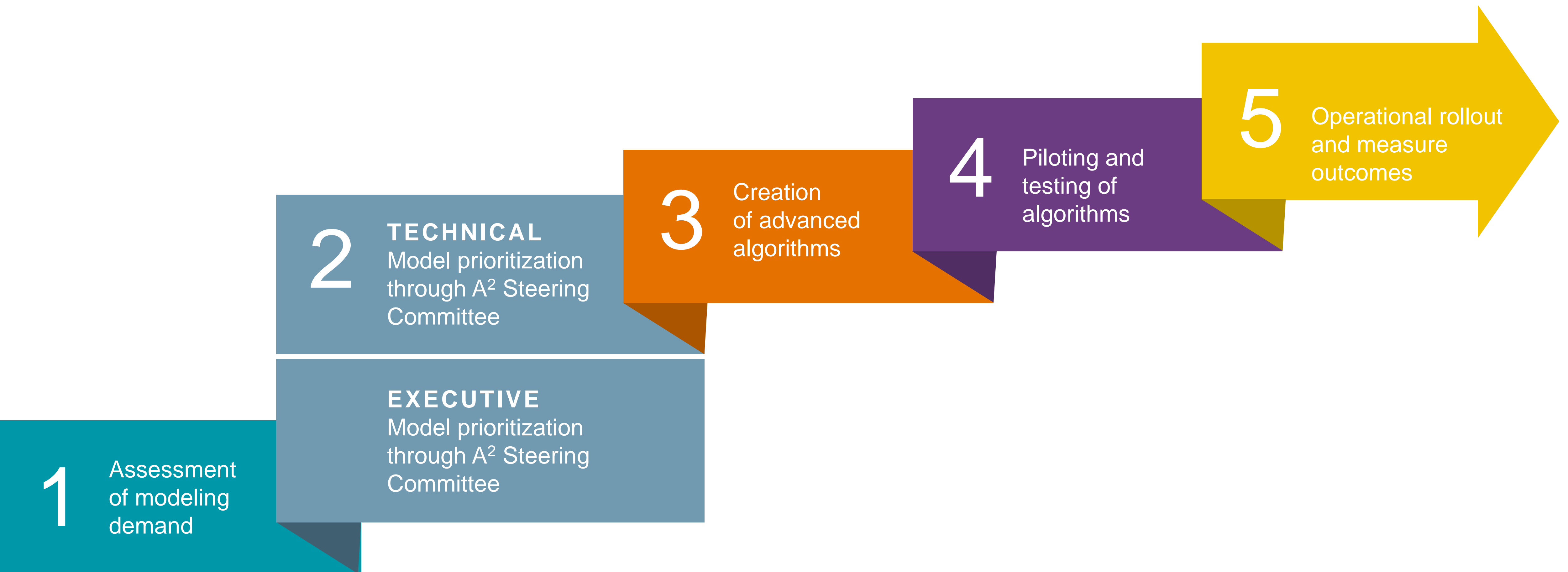
# FMC North America Data Storage



# Advanced Analytics: Our Approach

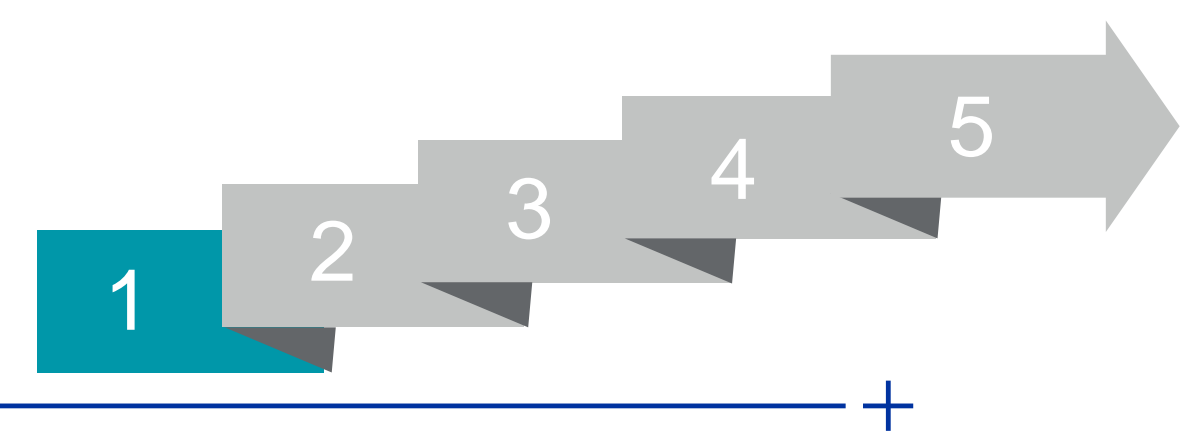
---

# Applied Advanced Analytical Process





# Assessment of Demand

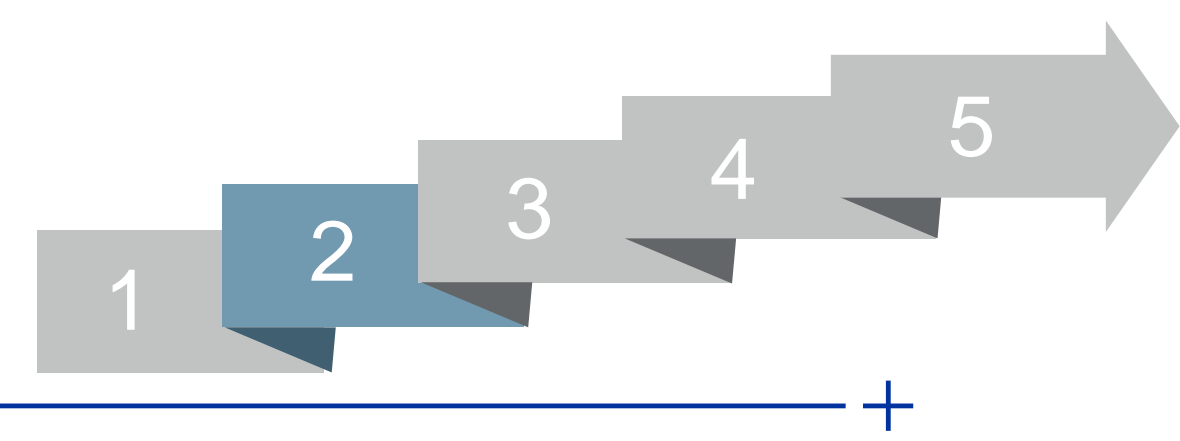


Listening to organizational needs

Pragmatic approach to advanced analytics



# Technical & Executive Steering Committee



## ► Executive Members

- Business leads from:
- FKC In-Center group
- FKC Home group
- FHP
- FreseniusRx
- AVC

## ► Global R&D

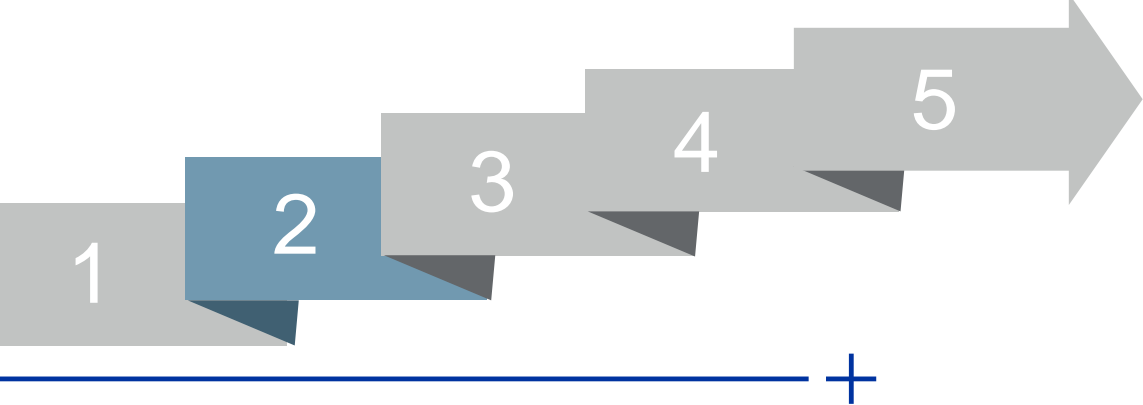


## ► Technical Members

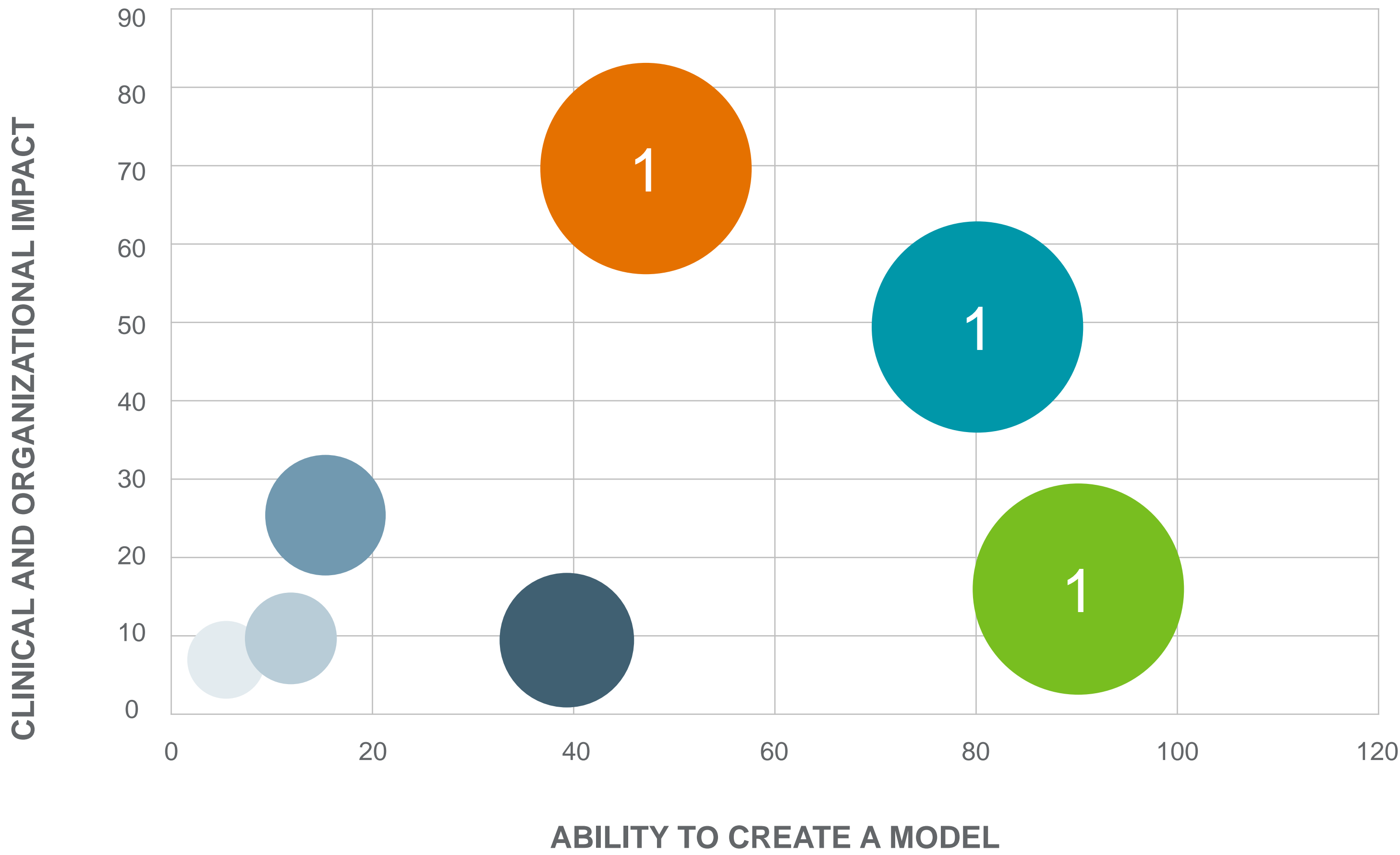
- Medical leads
- Business leads
- Operational leads
- IT
- Data Scientists



# Prioritization Process

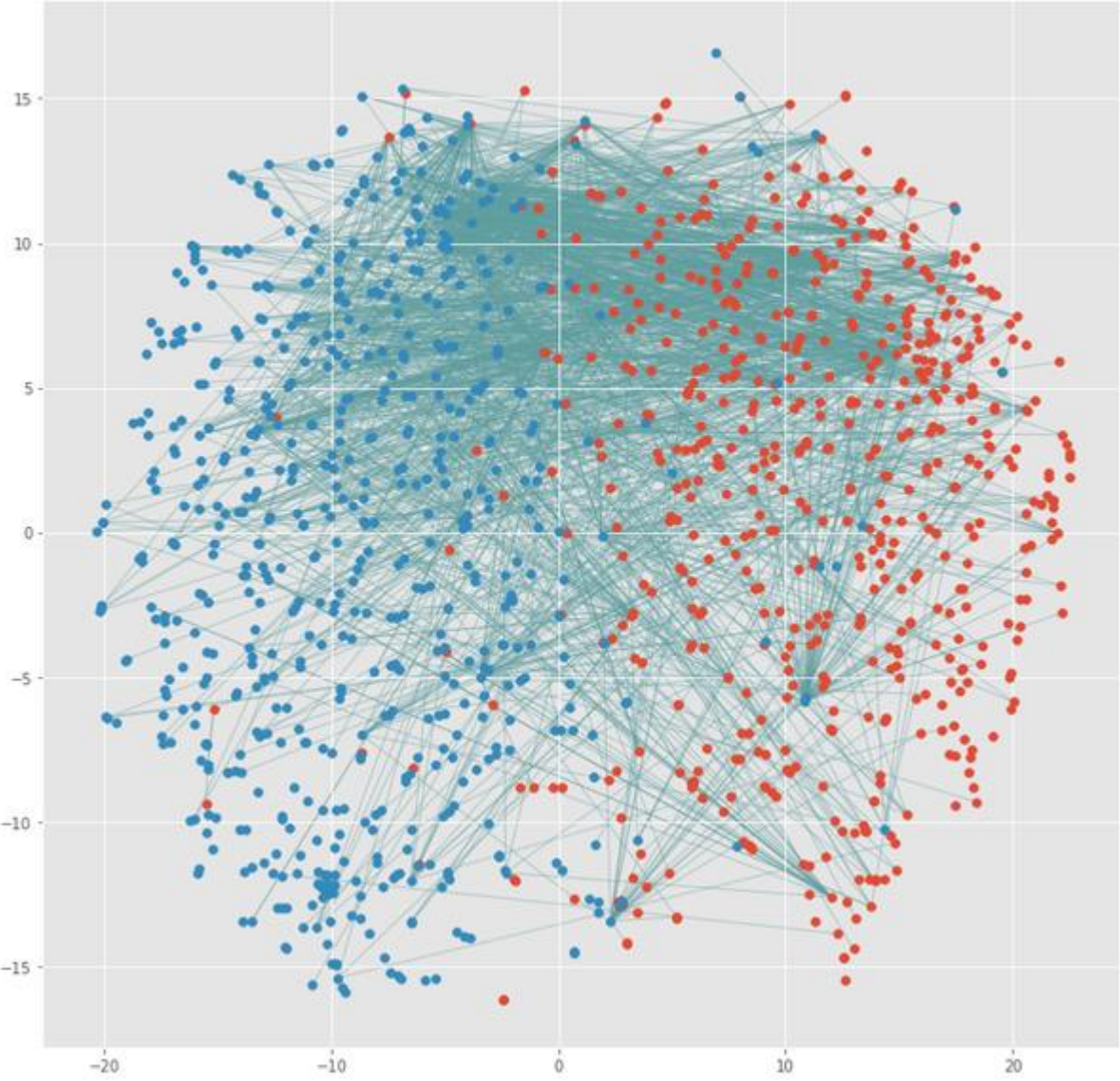


## How it Works

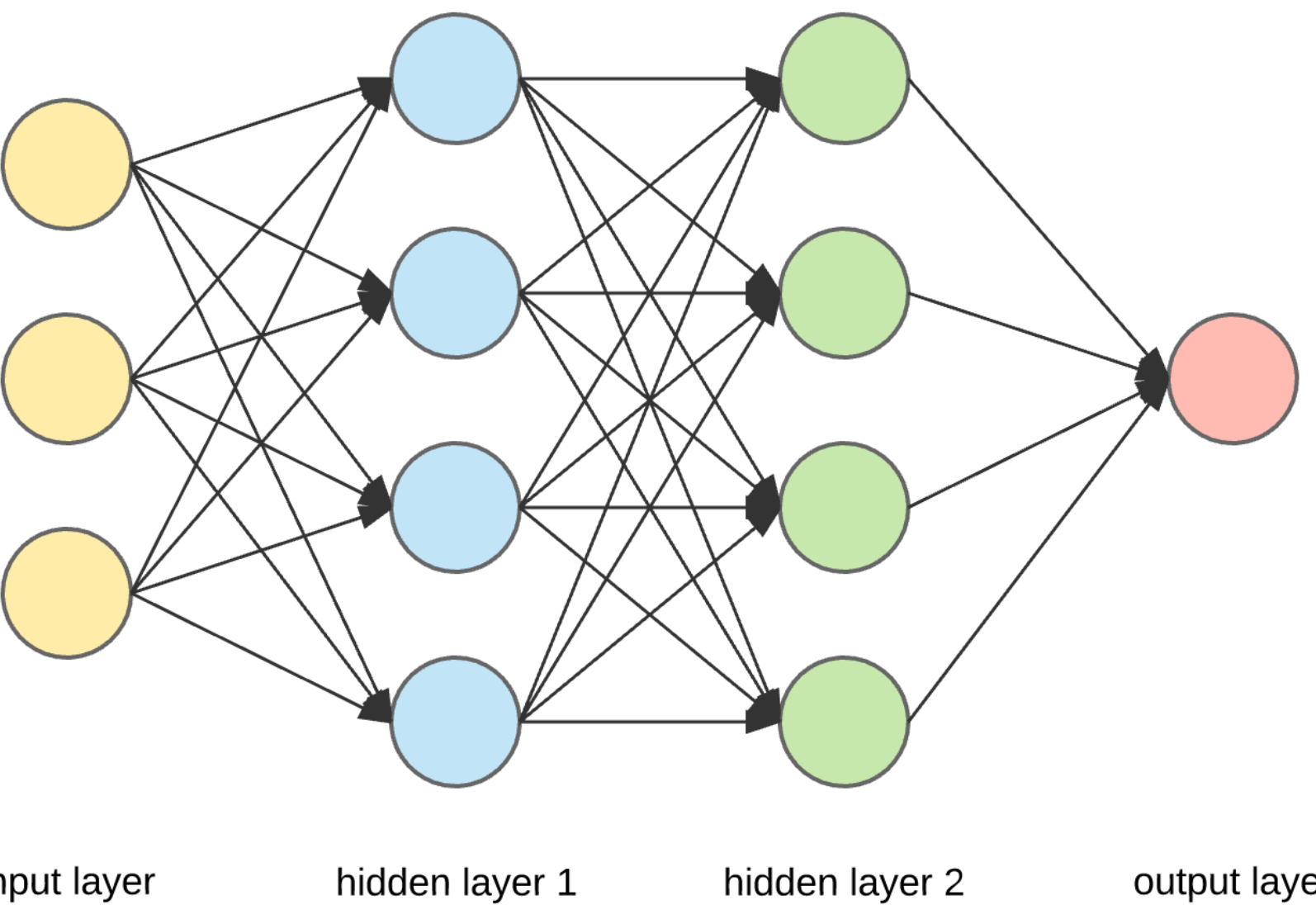
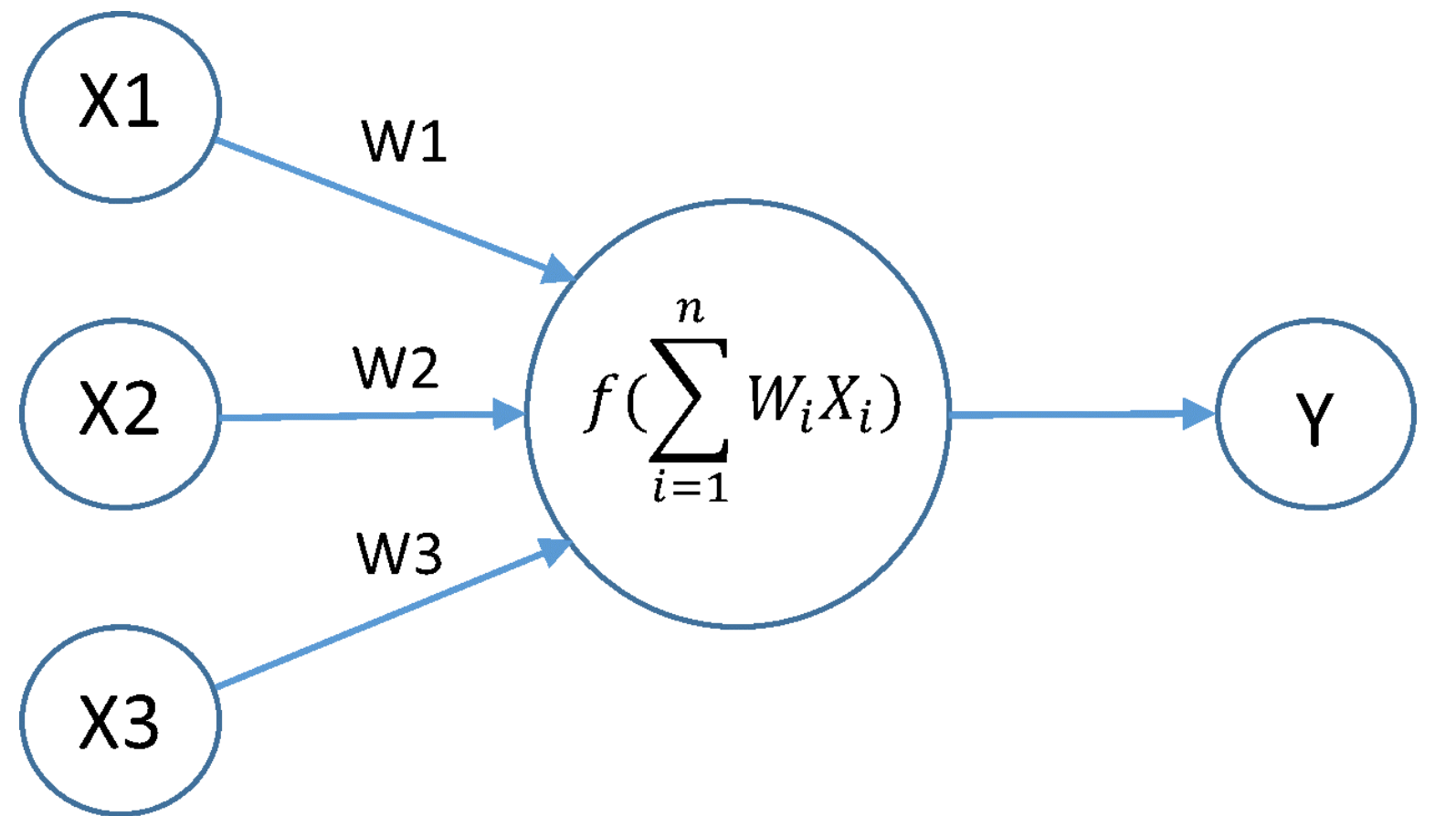
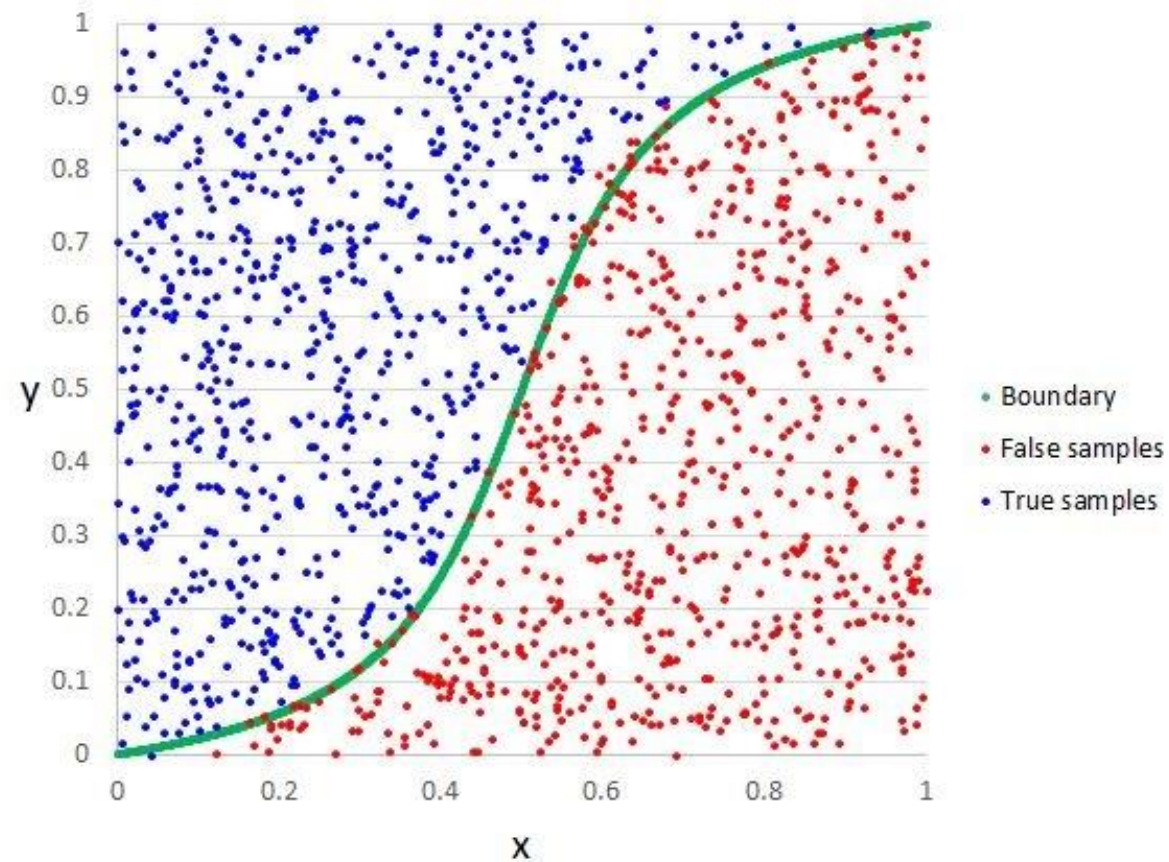
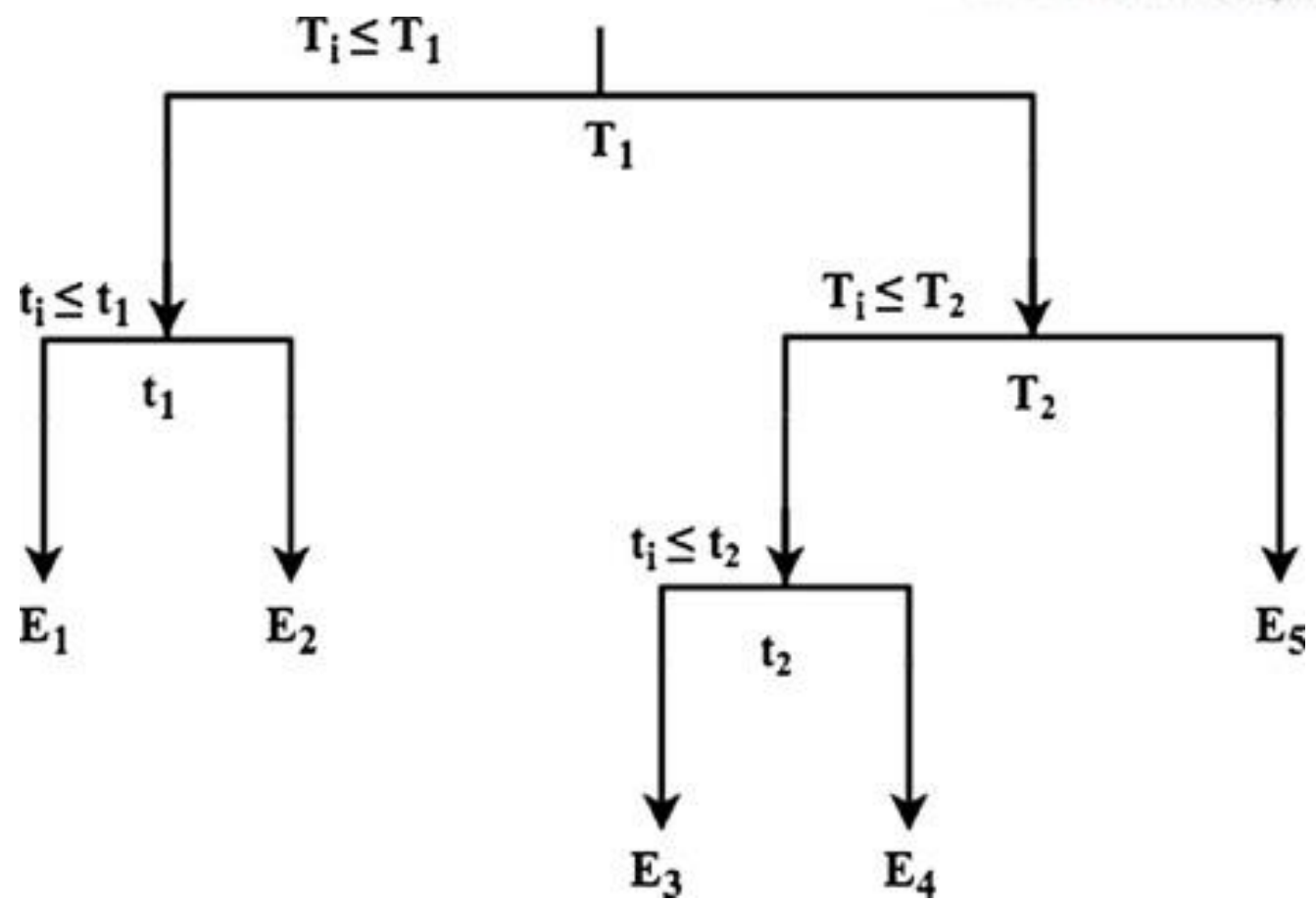




# Creation of Models

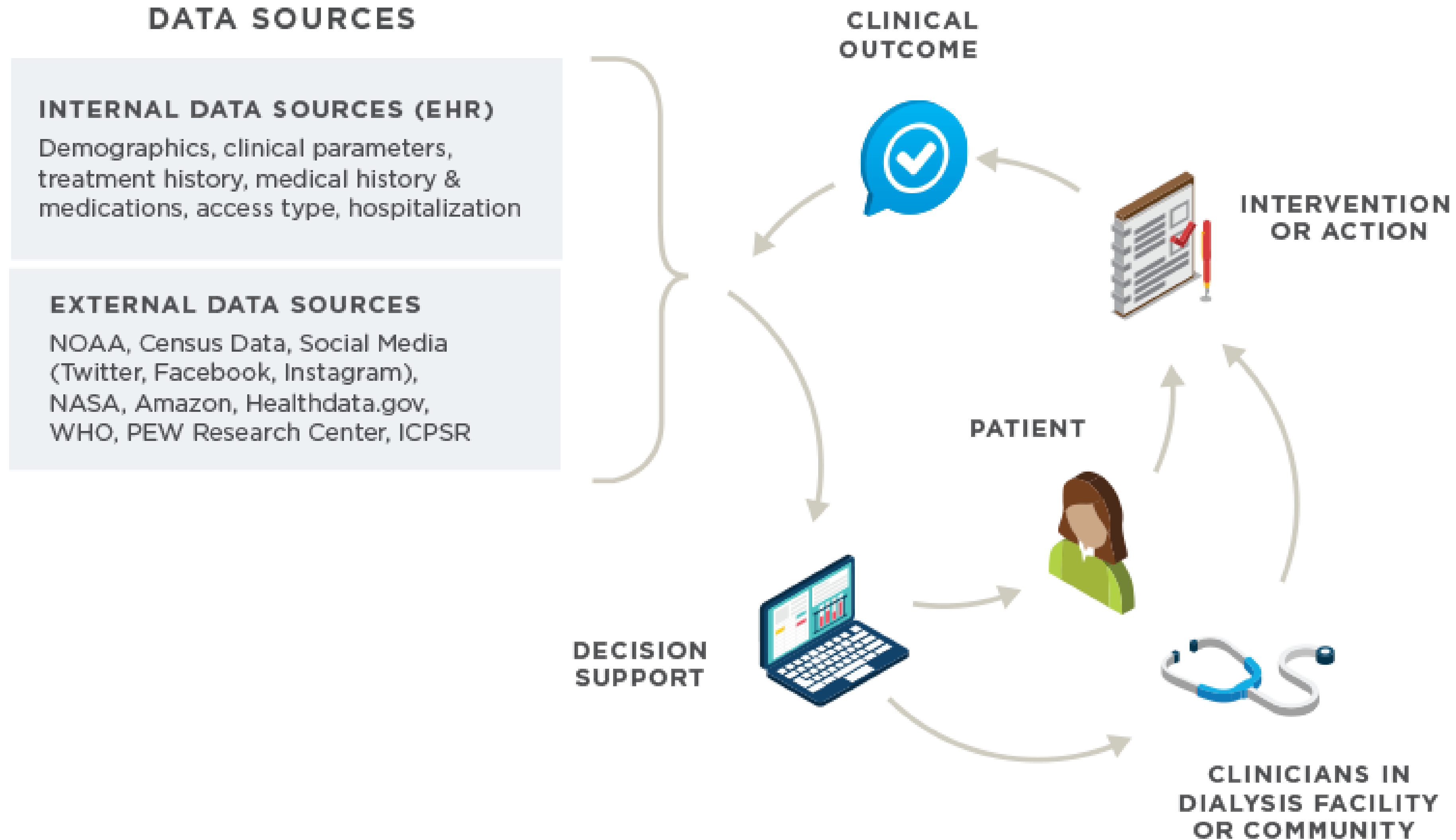
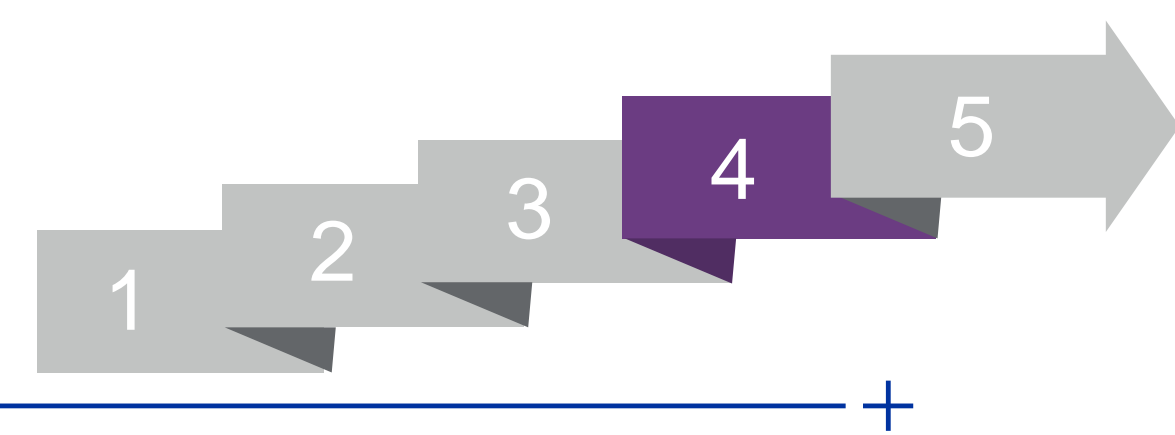


1. Initialize model with a constant value:  
$$F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma).$$
2. For  $m = 1$  to  $M$ 
  1. Compute so-called pseudo-residuals:  
$$r_{im} = - \left[ \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \dots, n.$$
  2. Fit a base learner  $h_m(x)$  to pseudo-residuals, i.e. train it using the training set  $\{(x_i, r_{im})\}_{i=1}^n$ .
  3. Compute multiplier  $\gamma_m$  by solving the following one-dimensional optimization problem:  
$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)).$$
  4. Update the model:  
$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$
3. Output  $F_M(x)$ .

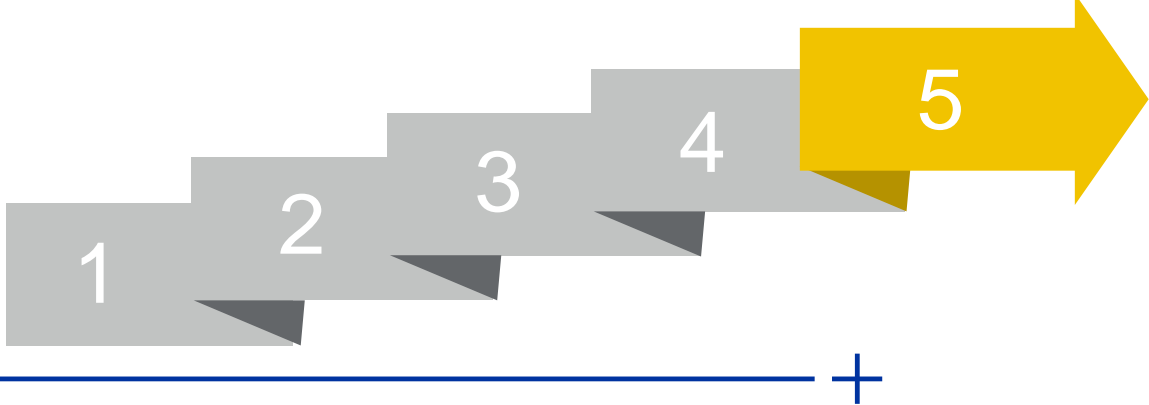




# Piloting and Testing of Advanced Algorithms



# Roll Out and Measure Outcomes



Broad Pervasive Data Sources



Automating Modeling Efforts



Delivering Personalized Treatment Plans Company-Wide



# Portfolio of Existing Efforts

---

# Key Areas of Applied Advanced Analytics Efforts



EVENT  
PREDICTION



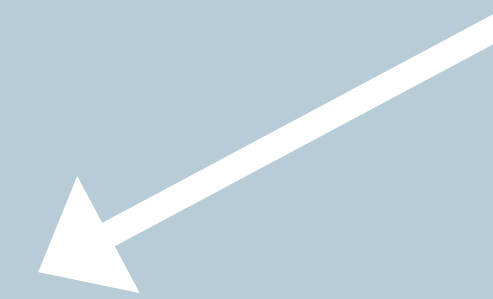
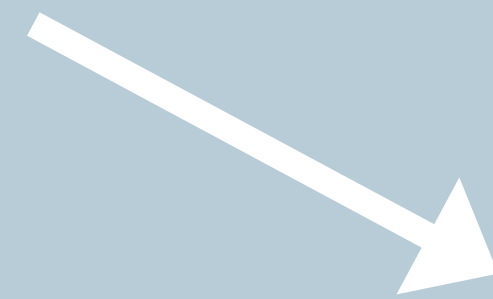
TREATMENT  
AID



CONDITION  
DIAGNOSIS



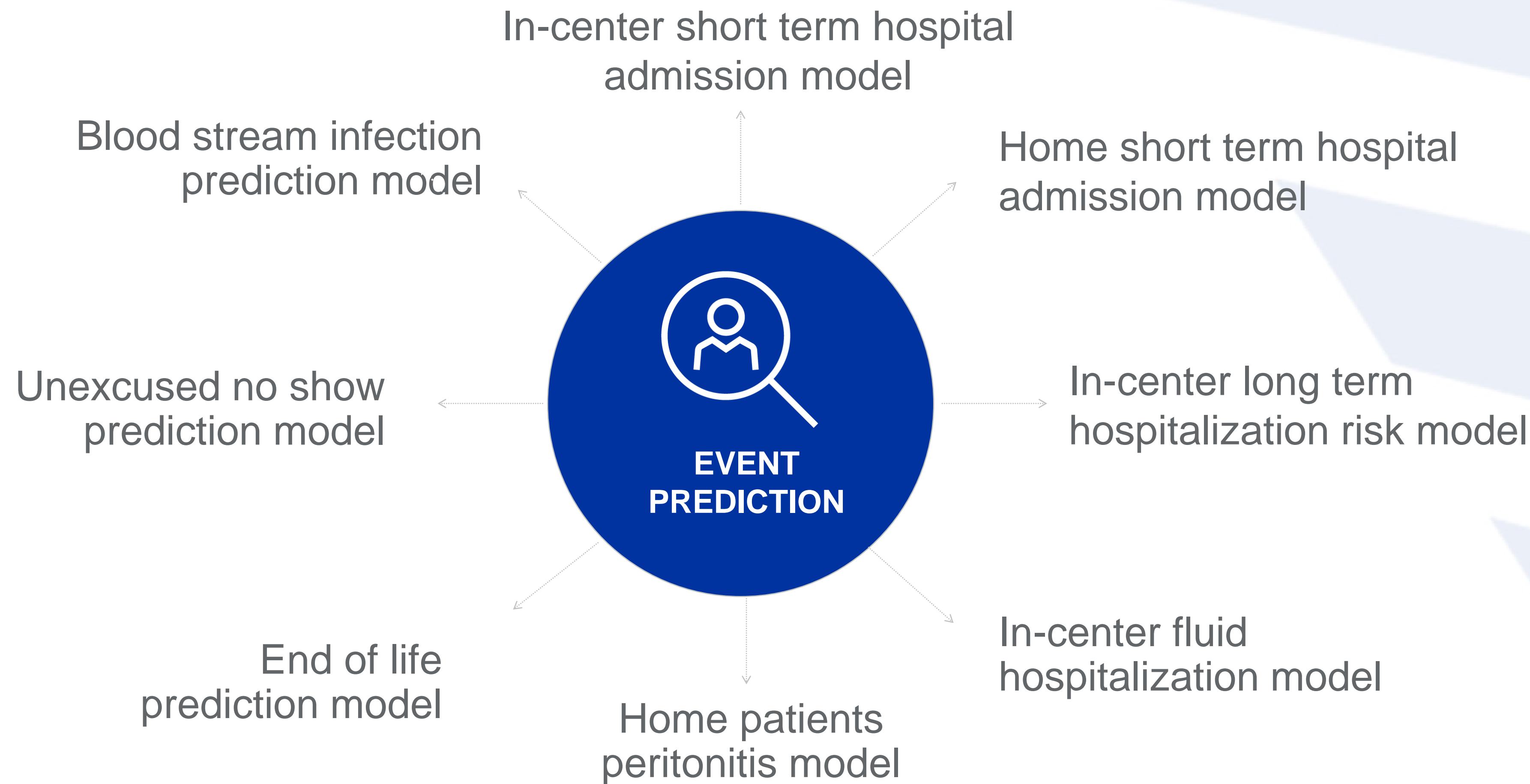
MATHEMATICAL  
MODELING AND  
ALGORITHMS



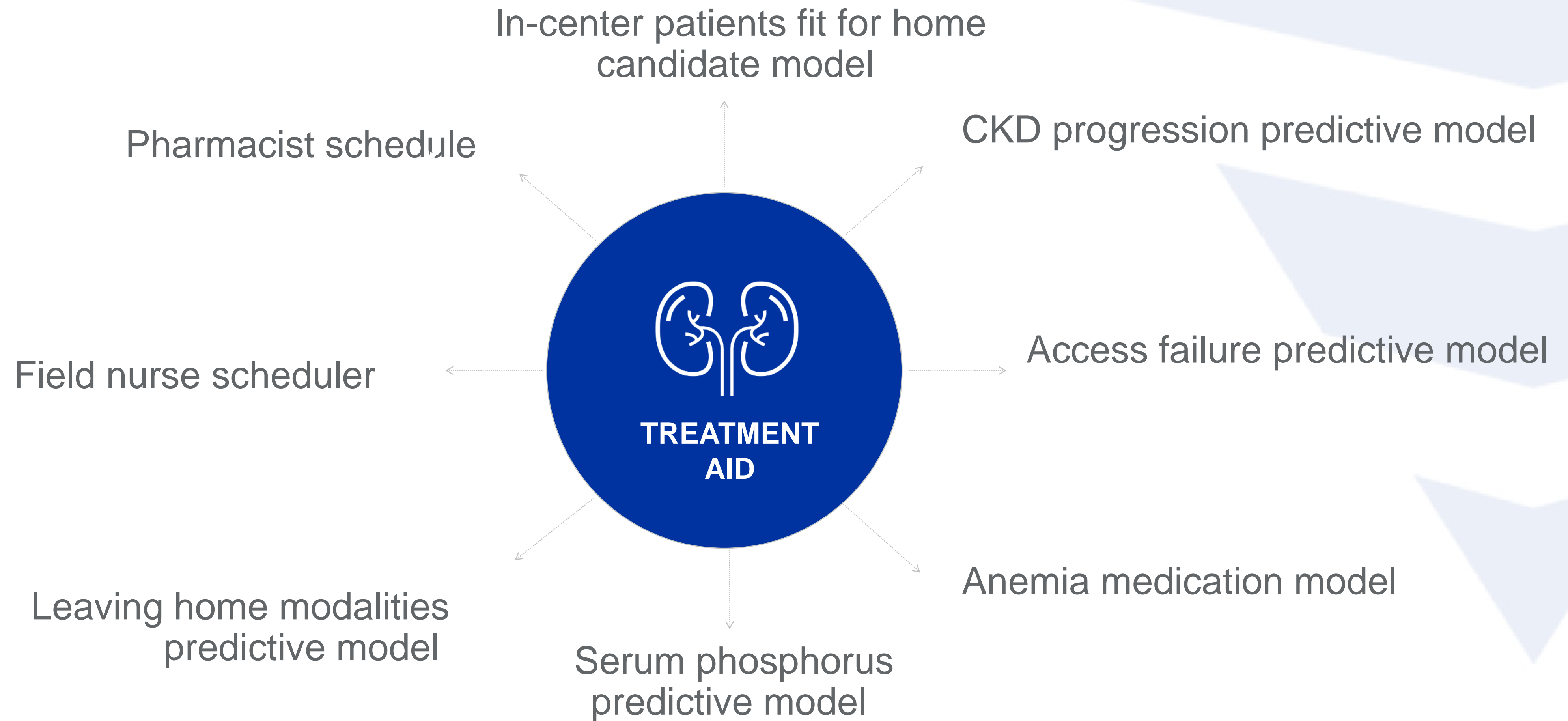
DELIVERY OF PERSONALIZED CARE AND OPTIMIZATION OF MULTIPLE PROCESSES  
WITHIN THE BUSINESS



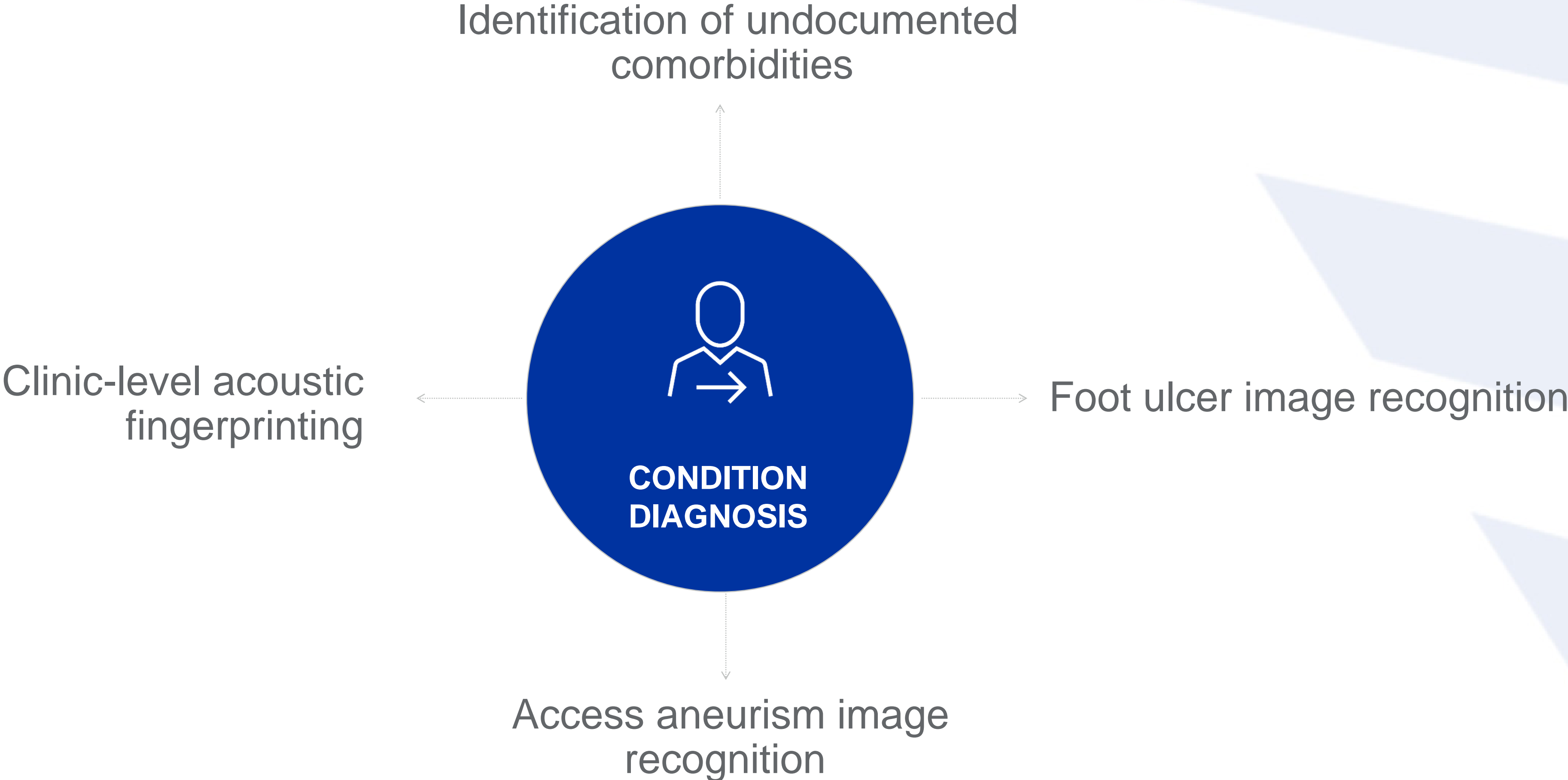
# Event Prediction



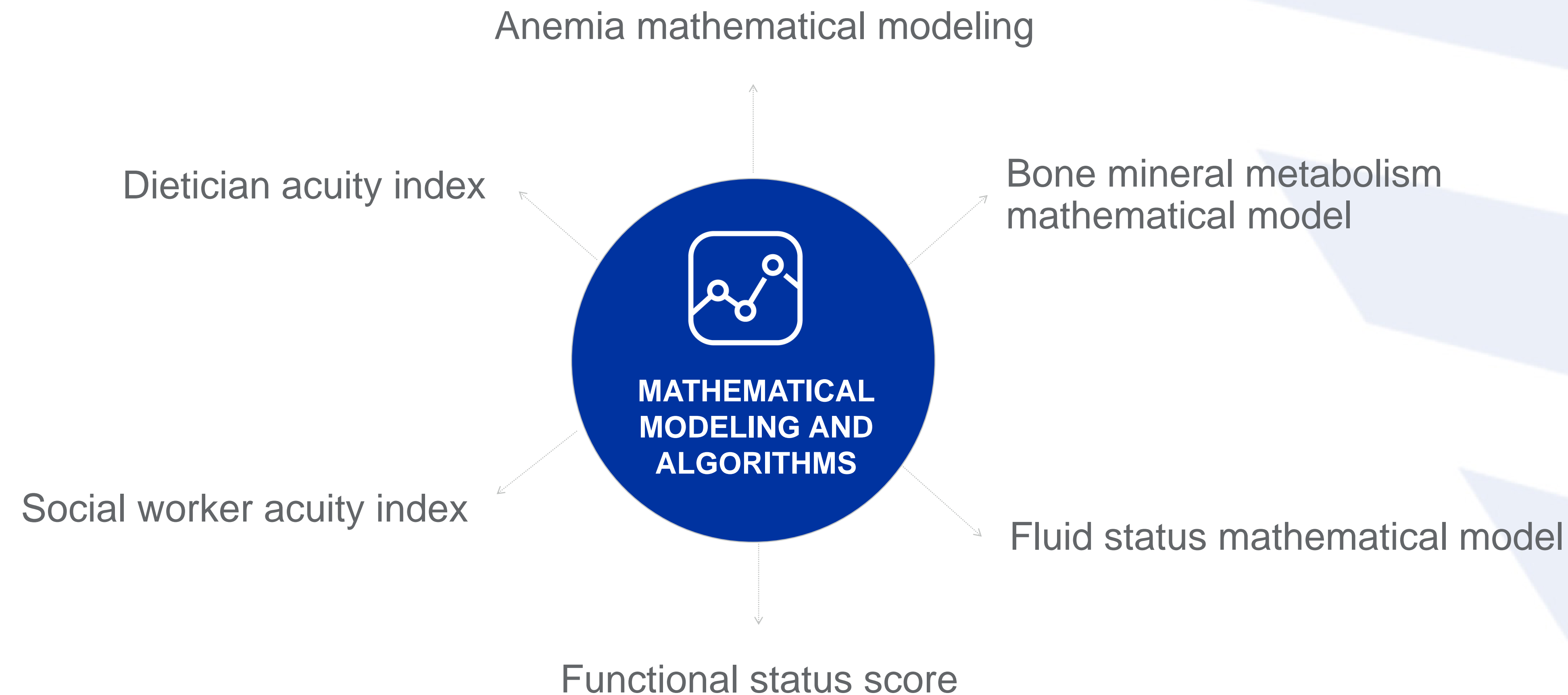
# Treatment Aid



# Condition Diagnosis



# Mathematical Modeling and Algorithms



# In-Center Short-Term Hospital Admission Model

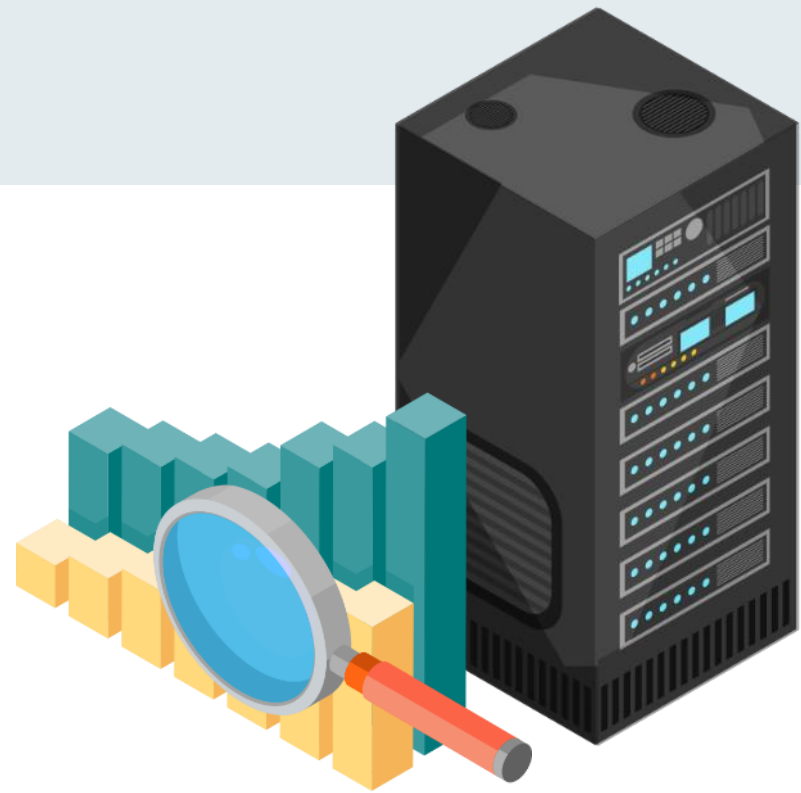
---

Work by FMC Global Medical Office and Fresenius Health Partners

Andy Long and Adriana Lindsey

# Model Definition

Predict which patients on the day of scheduled treatment are at high risk of hospital admission within 7 days



Data Extraction &  
Processing



Model Building &  
Optimizing



Deliverables

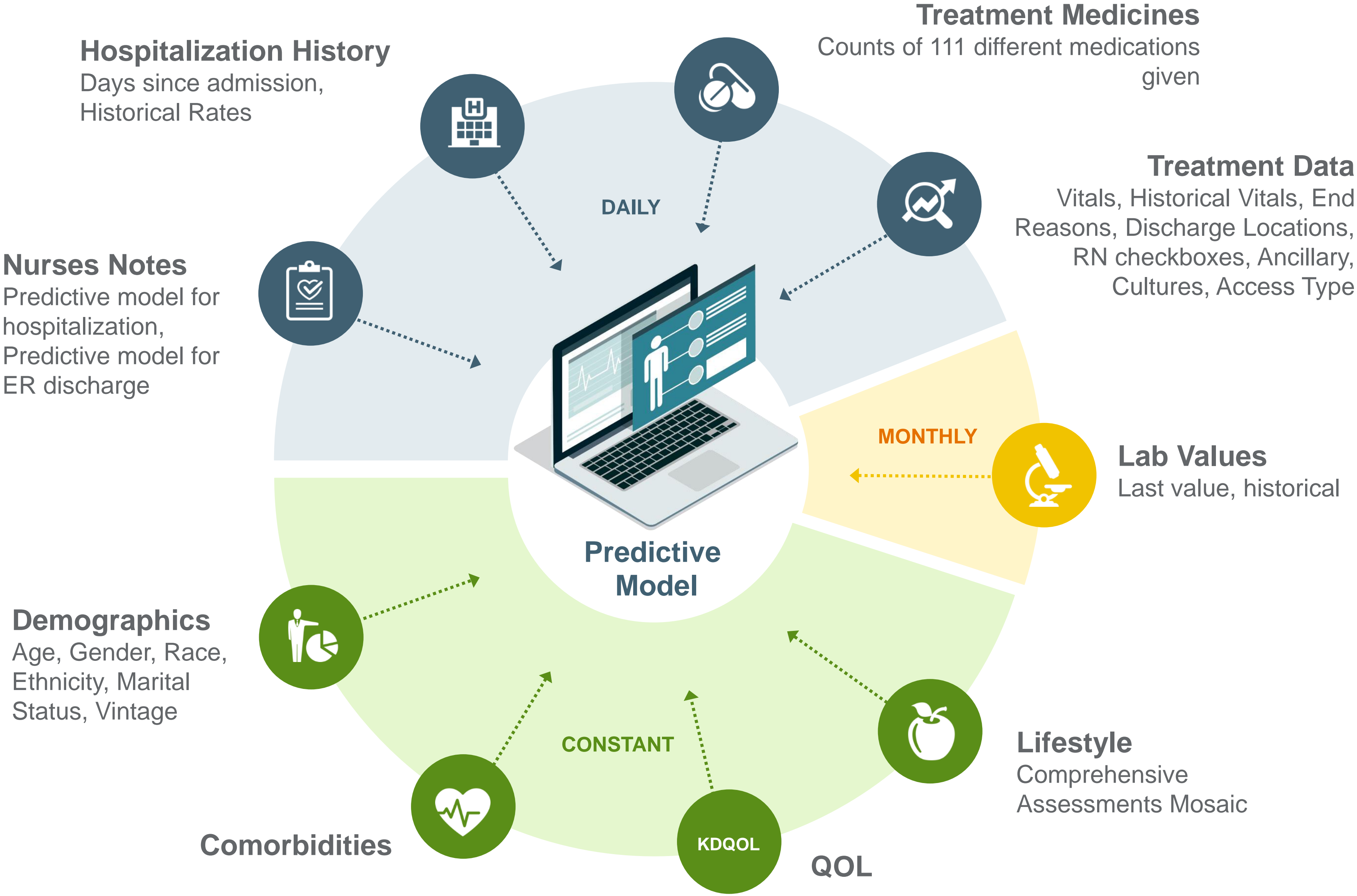


Interventions



# Data Extraction & Processing

- ▶ Data:  
Training: Jan – May 2017 (~130K hospitalizations)
- ▶ Testing: June 2017
- ▶ Number of predictors: 1,600



# Data Extraction & Processing: Nursing Notes

“Patient complains of chest pain”



## Nursing Notes

Abbreviations	PT C/O CP
Word Order	NO SOB, PT C/O CP” vs. “NO C/O SOB,CP”
Spelling Errors	'diarrhea','diahrrea','diarhea','dirrhea','diarrha', 'diarreha','diarrea','diarrrhea','diarrhe','d', 'diarhhea','diahrea','diarreah'

## Built models to predict hospitalization

- use these probabilities as features

# Model Building

---

- ▶ Model: XGBOOST
- ▶ Prevalence = 3%
- ▶ AUC = 0.8
- ▶ If we review 22% of patients, 21% of patients will be hospitalized



# Deliverables

- Implemented February 2019 on all ESCOs/Payor Programs in FHP
- Two types of interventions:
  - Phone assessment
  - Face to face visits

Nurse  
Bobbie Werth

LOB  
(All)

PT State  
(All)

Clinic ID  
(All)

L..	IHP..	MRN	LOB..
9	71.783		HUM
10	71.215		HUM
11	70.573		HUM
12	70.436		HUM
13	70.055		HUM
14	69.982		HUM

MRN

FACILITY:

State

PHONE:

Patients in same clinic

IHP..

MRN

LOB

71.783

HUM

Name

IHPM = 71.78 DOB:

MRN:

PT STATE:

GENDER:

SCHEDULE: M W F

Office RN: Bobbie Werth (HUM)

F2F RN:

TUE

Temporary Absences

Mar 1

Apr 1

May 1

Jun 1

Hospitalized

No Show

IHPM Reasons, MRN =

REASONS	Description	
Reason1	Number of hospital admissions i...	3.0
Reason2	days since end of last hospitaliz...	18.0
Reason3	history of pulse measurements r...	0.6
Reason4	history of weight measurement...	0.6
Reason5	days since start of last hospitali...	21.0
Reason6	COMORB: MI incl Cardiac Arrest	1.0
Reason7	length in days of last hospitaliza...	3.0
Reason8	Number of hospital admissions i...	2.0
Reason9	Potassium (mEq/L): standard de...	0.7
Reason10	pre-treatment standing systolic...	128.0

Patient Phone #

Home:

Cell: Null

Work: Null

First Dt Dialysis: 10/10/2017

Last Med Rev: 5/1/2019

Flu Vaccine (at FMC): 10/5/2018

Flu Assessment

PS Notes

Enter..

Note

2019-06-04..

Name

2019-05-14..

Clinic note 5/10 DrDosani ..

2019-05-14..

Pt noted to be back in the ..

2019-05-10..

Predictive model used: IH..

ECC Clinical Notes

Enter..

CLINICALNOTETEXT

2019-05-22..

J. Hall APRN here all labs, meds,

2019-05-10..

DrDosani here to see, all labs, me

2019-05-08..

J.Hall, APRN here to see pt, all la

2019-05-06..

0820 Husband called. pt SOB & h

Chairside Notes

Last T..

ALL\_NOTES

2019-06-03

2019-05-31

PRE-EVALUATION NOTE: .. POST-

2019-05-29

PRE-EVALUATION NOTE: .. POST-

2019-05-27

PRE-EVALUATION NOTE: .. POST-

Treatment Data

Dates

Time ON	09:49	09:38	09:39	09:46	09:59
IDWG (kg)	3.0	2.4	1.6	2.4	1.8
Pre Wt (kg)	60.8	60.2	58.1	59.8	60.0
Post Wt (kg)	57.1	57.8	57.8	56.5	57.4
EDW (kg)	57.5	57.5	57.5	57.5	58.0
Wt Loss (post - pre, kg)	3.7	2.4	0.3	3.3	2.6
% Post over EDW	-0.7	0.5	0.5	-1.7	-1.0
Actual Time (min)	265	277	250	267	257
Prescribed Time (min)	255	255	255	255	255
Lowest BP sit systolic	89	87	90	91	93
Associated BP sit dia	43	59	59	46	57
Pre BP sit systolic	141	142	103	123	120
Pre BP sit diastolic	62	73	55	66	56
Post BP sit systolic	117	127	152	121	122
Post BP sit diastolic	59	63	67	60	52
Pre Temp (F)	97.8	98.4	98.4	98.8	98.8
Post Temp (F)	97.4	97.8	98.4	98.0	98.8
Pre Pulse	87	82	94	87	93
Post Pulse	102	86	88	102	87

Last Lab Draws (hover or click for history)

ALBUMIN

3.8

HGB

10.5

K+

4.8

WBC

7.66

HD Orders

Start..	F	Order	EDW (k.	Prescri..
2019-05-27	In Ctr HD, MonWedFri, 4 h..	57.5	255.0	
2019-05-13	In Ctr HD, MonWedFri, 4 h..	58.0	255.0	
2019-05-03	In Ctr HD, MonWedFri, 4 h..	57.5	255.0	

Active Nutrition Orders

Start..	F	Status	Order
2019-01-28	Active	Diet Order, Accept Recommendatio..	

Active Anemia Orders

Start..	F	Status	Dose	Order
2019-06-12	Active	50	Mircera 50 mcg IVP During ..	

Access

Type	Status
AVFistula	Active (in use)

# Acoustic Fingerprinting



---

Work by FMC Global Medical Office

Caitlin Monaghan and Wendy Millette



# What is Acoustic Fingerprinting?

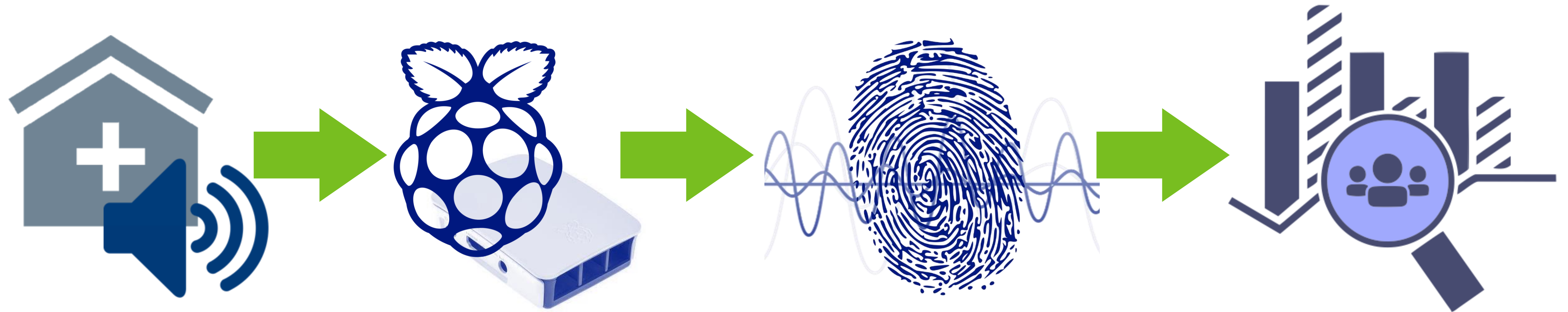
---



*Acoustic fingerprinting device (“acoustic sensor”) allows for creation of a unique audio signature of an environment without collecting any discernable sound*



# How Does It Work?



# Collected Data

- mean
- centroid
- spread
- skewness
- kurtosis
- decrease
- mel-frequency  
cepstral  
coefficients

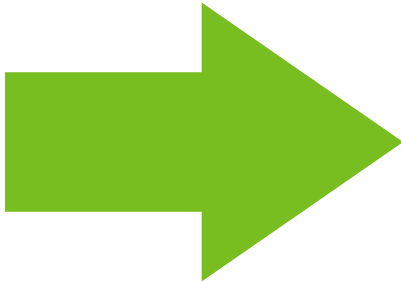
(13) . . .

	A	B	C	D	E	F	G	H	I	J	K	L
1	mean	centroid	spread	skewness	kurtosis	decrease	mfcc0	mfcc1	mfcc2	mfcc3	mfcc4	mfcc5
2	0.007759	1216.368	1717673	0.72928	2.111226	2.111226	-17.5196	1.506427	0.650881	0.455804	0.260037	0.198823
3	0.007799	1215.395	1722590	0.731666	2.112349	2.112349	-17.5072	1.518635	0.65832	0.460854	0.249059	0.195353
4	0.011475	923.999	1458066	1.246066	3.338375	3.338375	-16.0409	2.532	0.70216	0.509385	0.27007	0.106781
5	0.013044	856.7347	1349516	1.430557	3.974837	3.974837	-15.6322	2.609237	0.335869	0.623122	0.272578	0.063731
6	0.008034	1186.548	1712193	0.769397	2.164422	2.164422	-17.4041	1.518227	0.594461	0.509398	0.262881	0.210614
7	0.008062	1178.642	1711781	0.777699	2.175586	2.175586	-17.4172	1.567028	0.602185	0.476076	0.274659	0.196341
8	0.007933	1192.598	1716045	0.759679	2.148102	2.148102	-17.4375	1.548662	0.602626	0.468121	0.250198	0.176277
9	0.008043	1185.467	1713458	0.770667	2.165648	2.165648	-17.3984	1.541917	0.566621	0.454568	0.271528	0.1881
10	0.007885	1203.6	1722133	0.744534	2.127726	2.127726	-17.513	1.528027	0.646174	0.456419	0.240561	0.184783
11	0.007763	1210.253	1715395	0.738173	2.12482	2.12482	-17.5186	1.51952	0.67517	0.444031	0.238287	0.213678
12	0.007585	1254.37	1728907	0.685945	2.052459	2.052459	-17.5114	1.496119	0.638679	0.448225	0.237277	0.18106
13	0.007688	1228.25	1723621	0.716582	2.09193	2.09193	-17.5018	1.53411	0.674349	0.447073	0.222993	0.16829
14	0.007259	1290.473	1736635	0.64404	1.997306	1.997306	-17.5803	1.426311	0.509852	0.383508	0.223412	0.180037
15	0.00725	1290.004	1735445	0.644253	1.997851	1.997851	-17.5787	1.425405	0.50218	0.377021	0.206553	0.177284
16	0.007302	1289.089	1739703	0.645471	1.996885	1.996885	-17.5548	1.455731	0.509883	0.380191	0.212721	0.169758
17	0.007211	1300.903	1739812	0.63242	1.981234	1.981234	-17.5581	1.448972	0.503835	0.370136	0.208805	0.172889
18	0.007318	1284.787	1738840	0.651433	2.004595	2.004595	-17.5505	1.451786	0.51701	0.388863	0.216273	0.16872
19	0.007291	1289.026	1739298	0.646046	1.997957	1.997957	-17.5636	1.444484	0.509589	0.383973	0.214799	0.17262
20	0.007263	1288.831	1737717	0.645512	1.997355	1.997355	-17.5616	1.45879	0.516988	0.379011	0.209957	0.169144
21	0.007781	1218.012	1722135	0.728619	2.108603	2.108603	-17.5143	1.512625	0.675897	0.470822	0.257397	0.219608
22	0.007926	1200.685	1722879	0.747724	2.131195	2.131195	-17.5202	1.50892	0.638023	0.473911	0.266367	0.187448
23	0.007936	1199.161	1717570	0.750031	2.139053	2.139053	-17.5256	1.480899	0.628865	0.453105	0.25209	0.206329
24	0.00778	1220.379	1722827	0.724478	2.103035	2.103035	-17.5294	1.494082	0.6624	0.45946	0.256311	0.212779
25	0.007919	1204.29	1724058	0.743251	2.126017	2.126017	-17.5409	1.483456	0.639571	0.460003	0.248406	0.19063
26	0.007807	1217.191	1729275	0.727394	2.10023	2.10023	-17.5367	1.493128	0.630992	0.453087	0.242718	0.1897
27	0.00795	1183.767	1711248	0.768622	2.165613	2.165613	-17.5281	1.506564	0.644375	0.448177	0.241774	0.188836
28	0.007879	1207.823	1724527	0.738028	2.117956	2.117956	-17.5468	1.480478	0.625065	0.450859	0.253402	0.214074
29	0.008106	1174.565	1715280	0.779271	2.177213	2.177213	-17.5168	1.536657	0.696743	0.479608	0.268018	0.220527
30	0.007978	1190.684	1717036	0.759749	2.151189	2.151189	-17.5202	1.526726	0.664218	0.469632	0.254115	0.199673
31	0.007974	1191.514	1716384	0.758321	2.149117	2.149117	-17.5256	1.495643	0.648813	0.457052	0.256132	0.203402
32	0.007889	1204.673	1721563	0.74321	2.126609	2.126609	-17.5082	1.52388	0.661191	0.46711	0.247978	0.18745
33	0.00757	1254.887	1734588	0.683287	2.04513	2.04513	-17.5461	1.508946	0.653509	0.460737	0.238546	0.176968
34	0.007665	1238.908	1729529	0.702998	2.073038	2.073038	-17.5425	1.492553	0.664258	0.443376	0.241369	0.204717
35	0.007249	1297.153	1740591	0.636401	1.986882	1.986882	-17.5894	1.41538	0.514796	0.380107	0.209644	0.175441
36	0.007216	1302.675	1741736	0.632193	1.982274	1.982274	-17.574	1.42588	0.504687	0.380667	0.206231	0.176224



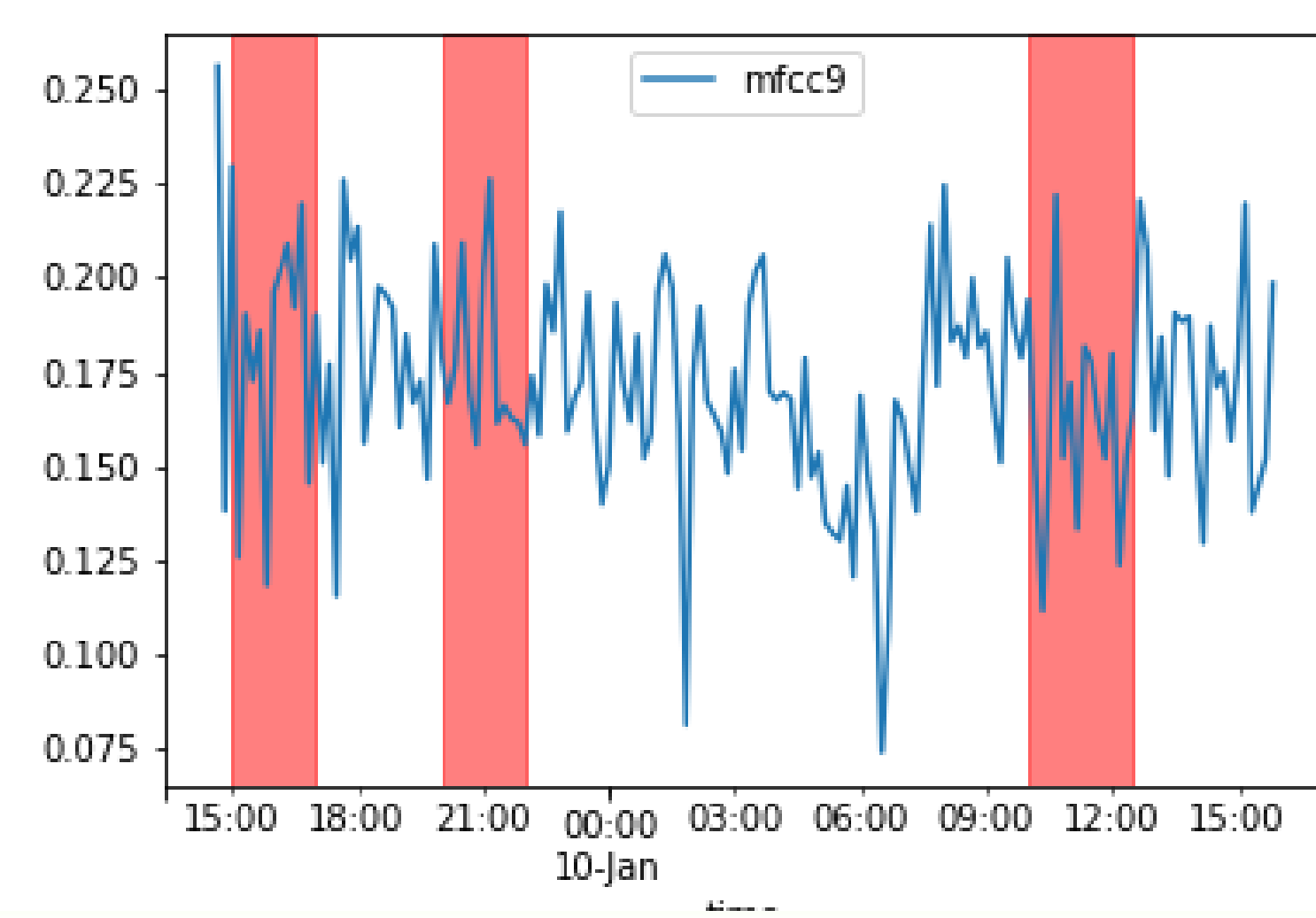
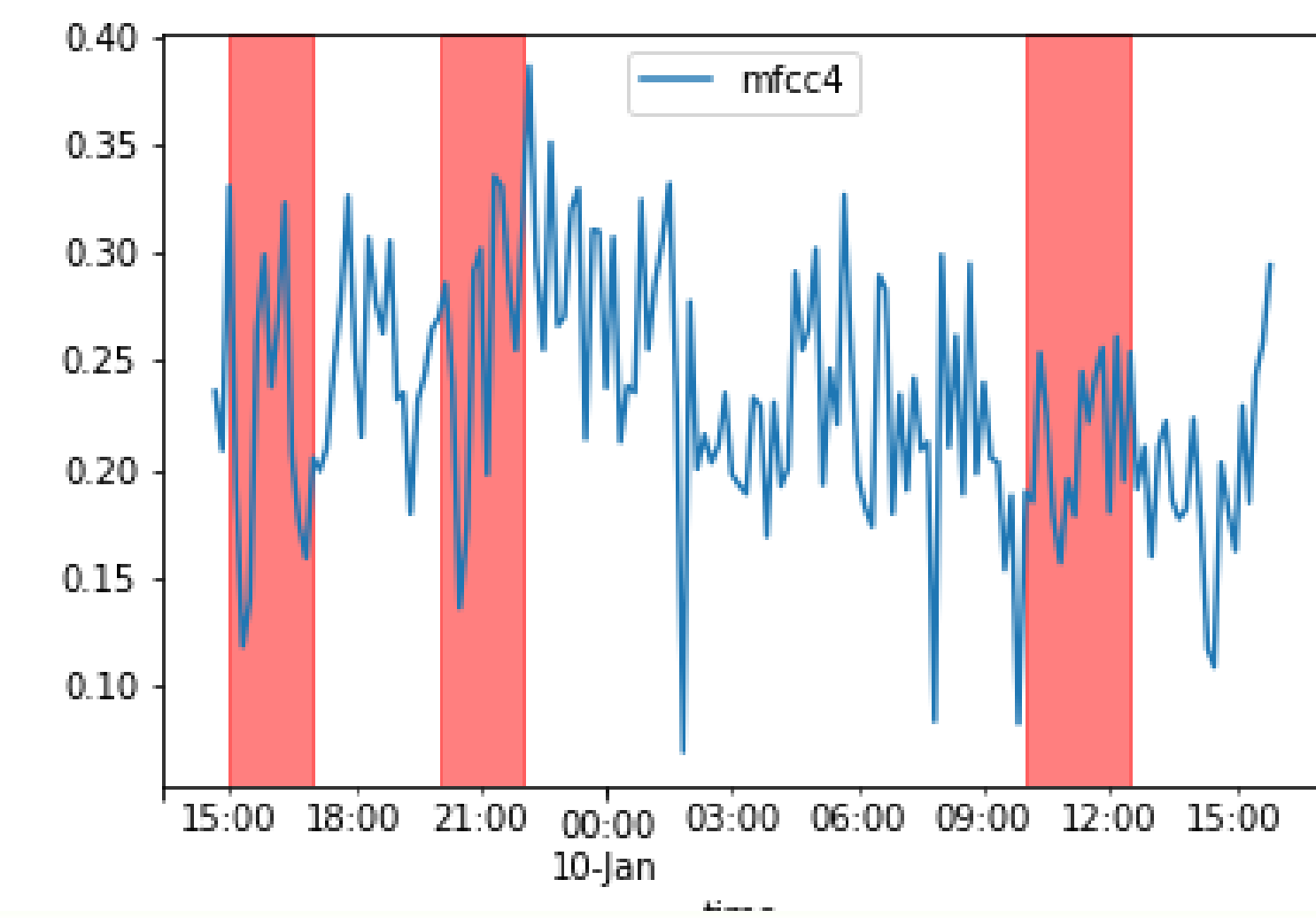
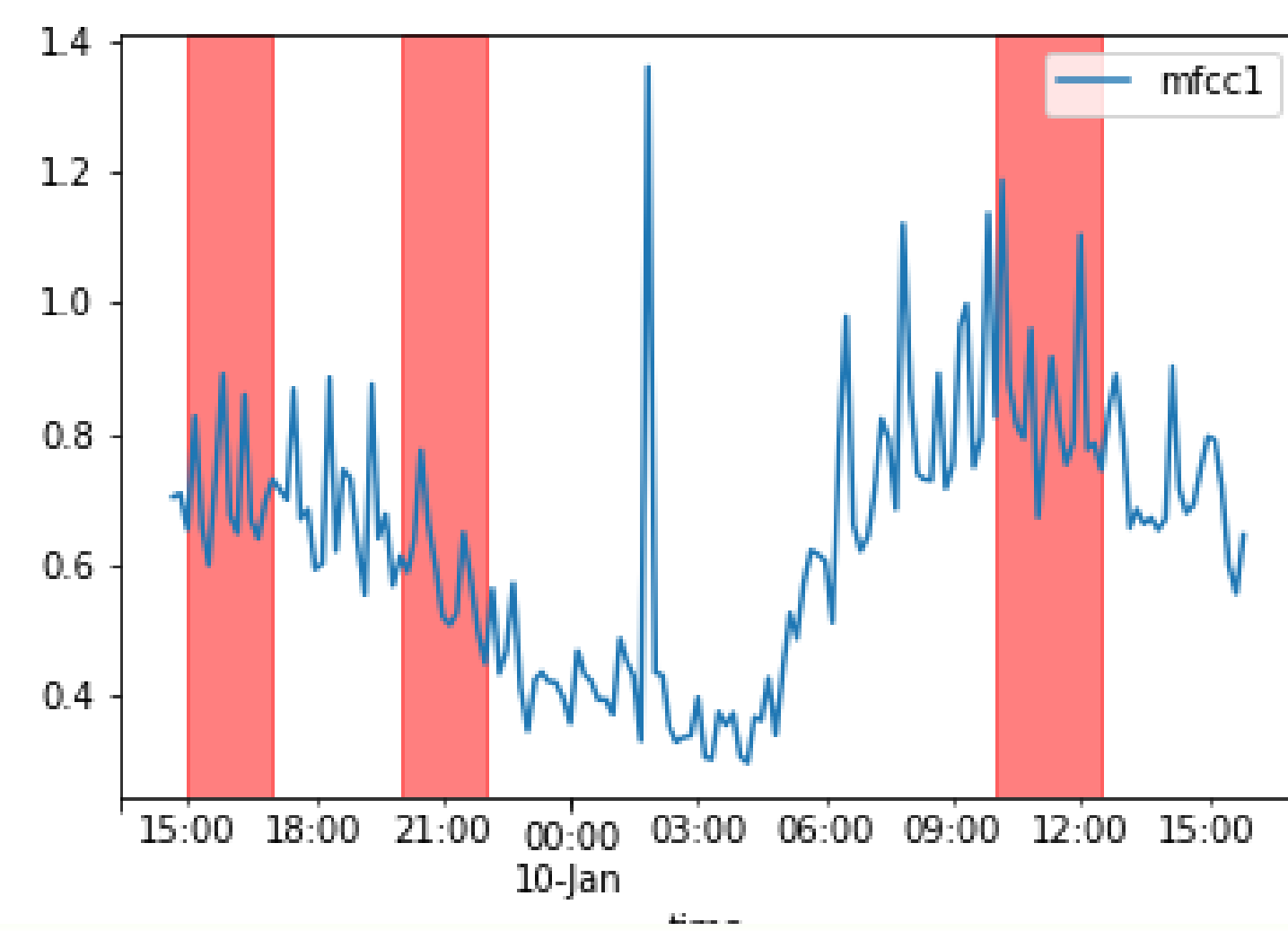
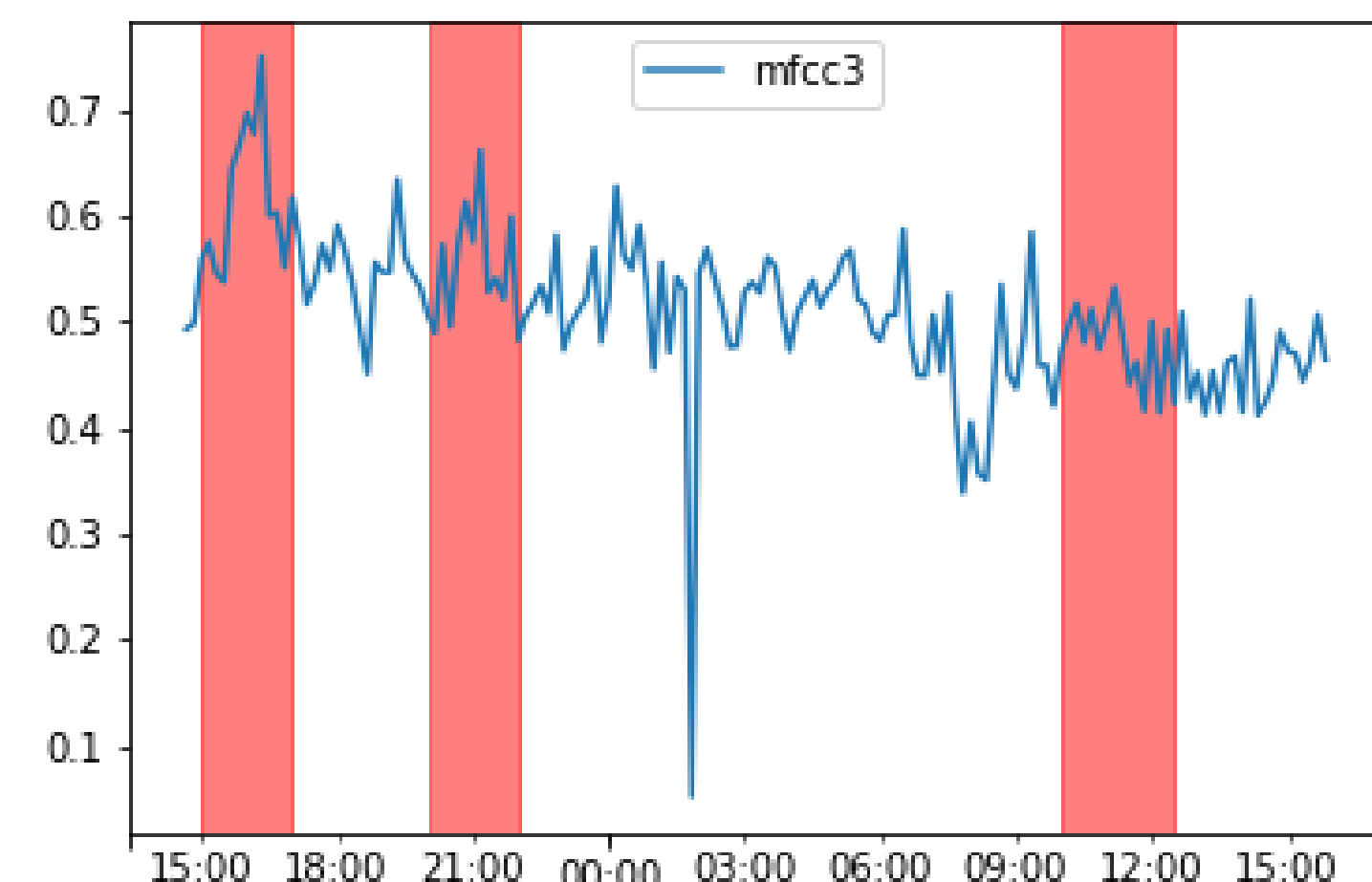
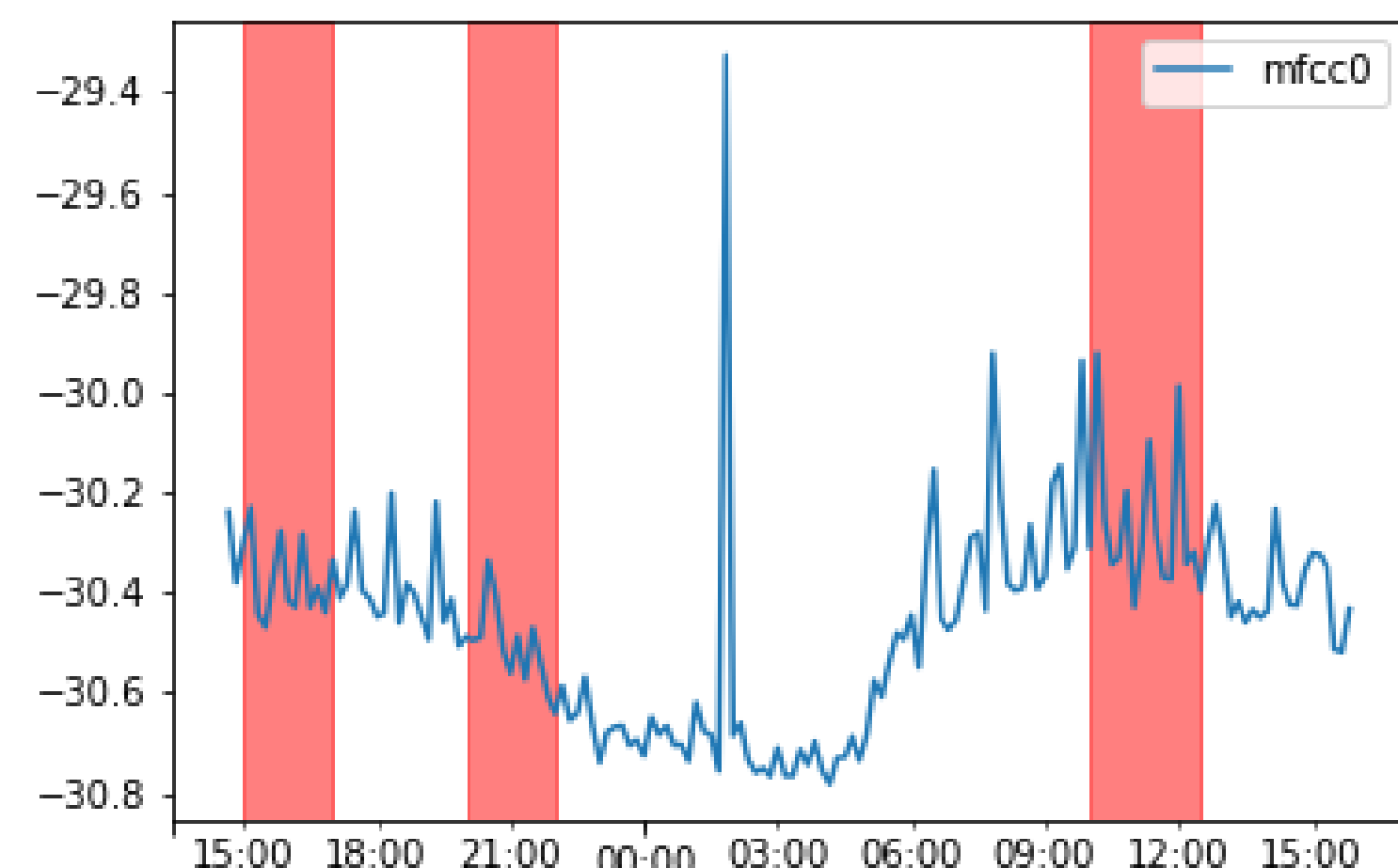
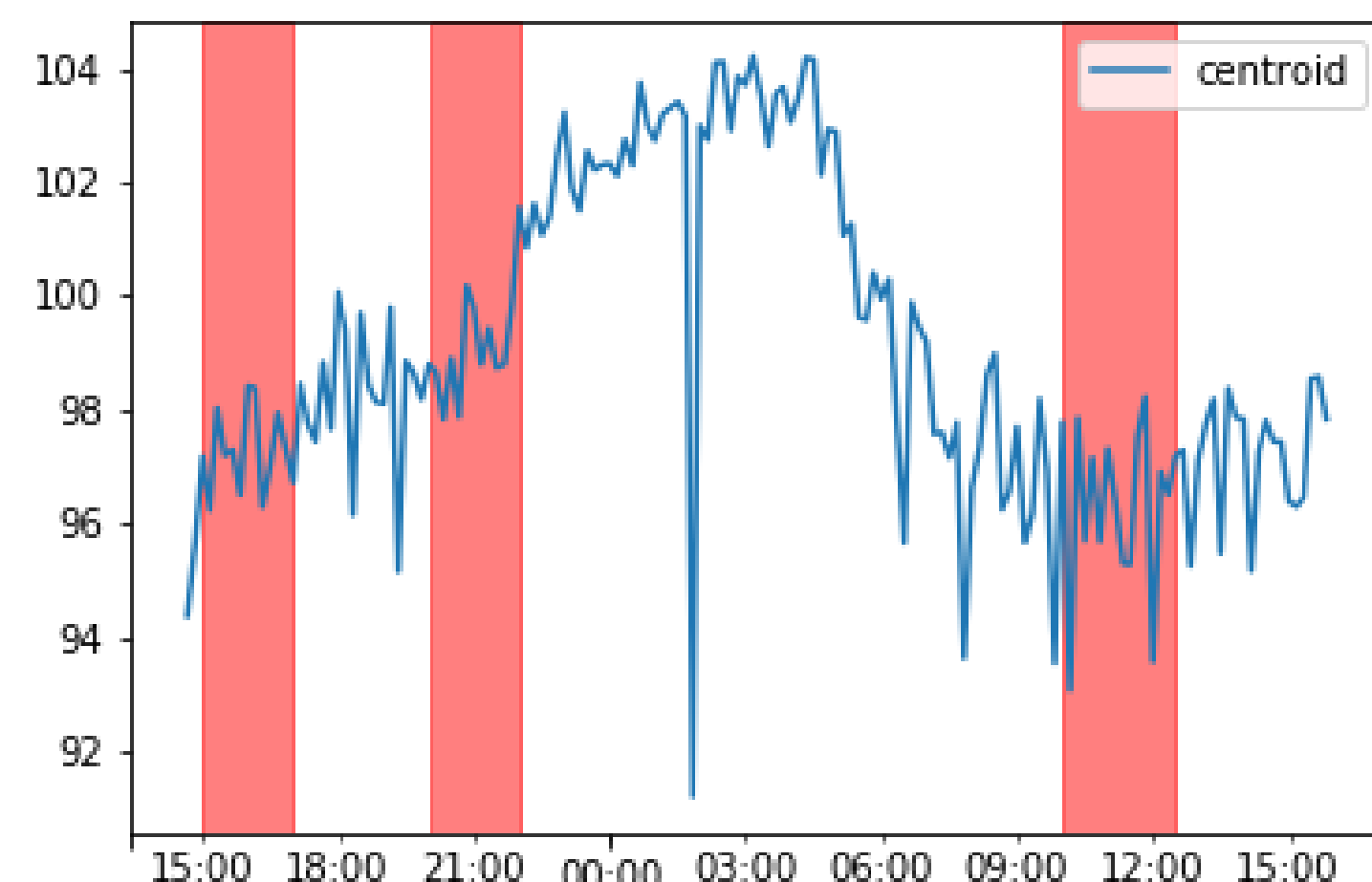
# What Happens with the Data

	A	B	C	D	E	F	G	H	I	J	K	L
1	mean	centroid	spread	skewness	kurtosis	decrease	mfcc0	mfcc1	mfcc2	mfcc3	mfcc4	mfcc5
2	0.007759	1216.368	1717673	0.72928	2.111226	2.111226	-17.5196	1.506427	0.650881	0.455804	0.260037	0.198823
3	0.007799	1215.395	1722590	0.731666	2.112349	2.112349	-17.5072	1.518635	0.65832	0.460854	0.249059	0.195353
4	0.011475	923.999	1458066	1.246066	3.338375	3.338375	-16.0409	2.532	0.70216	0.509385	0.27007	0.106781
5	0.013044	856.7347	1349516	1.430557	3.974837	3.974837	-15.6322	2.609237	0.335869	0.623122	0.272578	0.063731
6	0.008034	1186.548	1712193	0.769397	2.164422	2.164422	-17.4041	1.518227	0.594461	0.509398	0.262881	0.210614
7	0.008062	1178.642	1711781	0.777699	2.175586	2.175586	-17.4172	1.567028	0.602185	0.476076	0.274659	0.196341
8	0.007933	1192.598	1716045	0.759679	2.148102	2.148102	-17.4375	1.548662	0.602626	0.468121	0.250198	0.176277
9	0.008043	1185.467	1713458	0.770667	2.165648	2.165648	-17.3984	1.541917	0.566621	0.454568	0.271528	0.1881
10	0.007885	1203.6	1722133	0.744534	2.127726	2.127726	-17.513	1.528027	0.646174	0.456419	0.240561	0.184783
11	0.007763	1210.253	1715395	0.738173	2.12482	2.12482	-17.5186	1.51952	0.67517	0.444031	0.238287	0.213678
12	0.007585	1254.37	1728907	0.685945	2.052459	2.052459	-17.5114	1.496119	0.638679	0.448225	0.237277	0.18106
13	0.007688	1228.25	1723621	0.716582	2.09193	2.09193	-17.5018	1.53411	0.674349	0.447073	0.222993	0.16829
14	0.007259	1290.473	1736635	0.64404	1.997306	1.997306	-17.5803	1.426311	0.509852	0.383508	0.223412	0.180037
15	0.00725	1290.004	1735445	0.644253	1.997851	1.997851	-17.5787	1.425405	0.50218	0.377021	0.206553	0.177284
16	0.007302	1289.089	1739703	0.645471	1.996885	1.996885	-17.5548	1.455731	0.509883	0.380191	0.212721	0.169758
17	0.007211	1300.903	1739812	0.63242	1.981234	1.981234	-17.5581	1.448972	0.503835	0.370136	0.208805	0.172889
18	0.007318	1284.787	1738840	0.651433	2.004595	2.004595	-17.5505	1.451786	0.51701	0.388863	0.216273	0.16872
19	0.007291	1289.026	1739298	0.646046	1.997957	1.997957	-17.5636	1.444484	0.509589	0.383973	0.214799	0.17262
20	0.007263	1288.831	1737717	0.645512	1.997355	1.997355	-17.5616	1.45879	0.516988	0.379011	0.209957	0.169144
21	0.007781	1218.012	1722135	0.728619	2.108603	2.108603	-17.5143	1.512625	0.675897	0.470822	0.257397	0.219608
22	0.007926	1200.685	1722879	0.747724	2.131195	2.131195	-17.5202	1.50892	0.638023	0.473911	0.266367	0.187448
23	0.007936	1199.161	1717570	0.750031	2.139053	2.139053	-17.5256	1.480899	0.628865	0.453105	0.25209	0.206329
24	0.00778	1220.379	1722827	0.724478	2.103035	2.103035	-17.5294	1.494082	0.6624	0.45946	0.256311	0.212779
25	0.007919	1204.29	1724058	0.743251	2.126017	2.126017	-17.5409	1.483456	0.639571	0.460003	0.248406	0.19063
26	0.007807	1217.191	1729275	0.727394	2.10023	2.10023	-17.5367	1.493128	0.630992	0.453087	0.242718	0.1897
27	0.00795	1183.767	1711248	0.768622	2.165613	2.165613	-17.5281	1.506564	0.644375	0.448177	0.241774	0.188836
28	0.007879	1207.823	1724527	0.738028	2.117956	2.117956	-17.5468	1.480478	0.625065	0.450859	0.253402	0.214074
29	0.008106	1174.565	1715280	0.779271	2.177213	2.177213	-17.5168	1.536657	0.696743	0.479608	0.268018	0.220527
30	0.007978	1190.684	1717036	0.759749	2.151189	2.151189	-17.5202	1.526726	0.664218	0.469632	0.254115	0.199673
31	0.007974	1191.514	1716384	0.758321	2.149117	2.149117	-17.5256	1.495643	0.648813	0.457052	0.256132	0.203402
32	0.007889	1204.673	1721563	0.74321	2.126609	2.126609	-17.5082	1.52388	0.661191	0.46711	0.247978	0.18745
33	0.00757	1254.887	1734588	0.683287	2.04513	2.04513	-17.5461	1.508946	0.653509	0.460737	0.238546	0.176968
34	0.007665	1238.908	1729529	0.702998	2.073038	2.073038	-17.5425	1.492553	0.664258	0.443376	0.241369	0.204717
35	0.007249	1297.153	1740591	0.636401	1.986882	1.986882	-17.5894	1.41538	0.514796	0.380107	0.209644	0.175441
36	0.007216	1302.675	1741736	0.632193	1.982274	1.982274	-17.574	1.42588	0.504687	0.380667	0.206231	0.176224



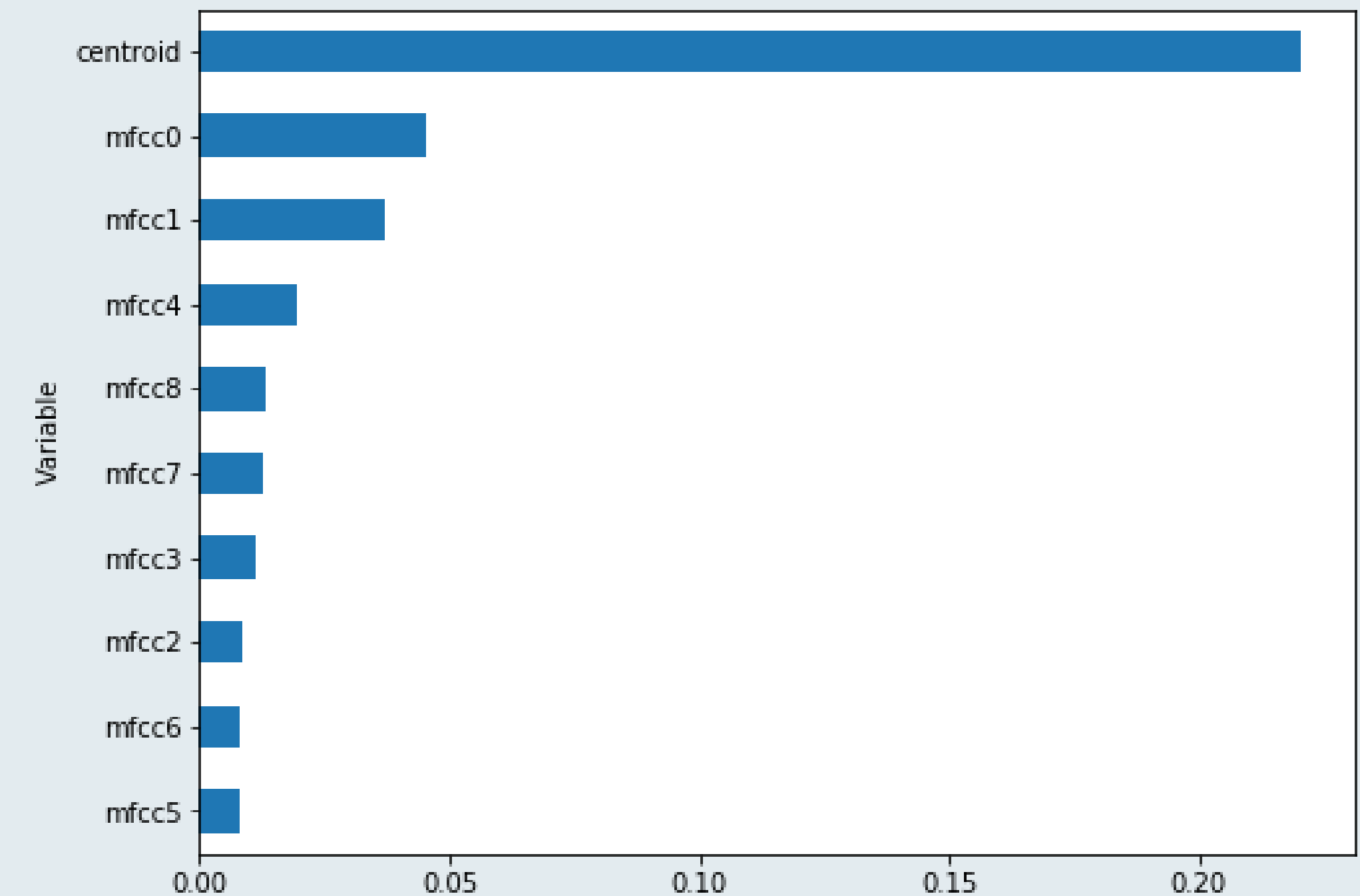
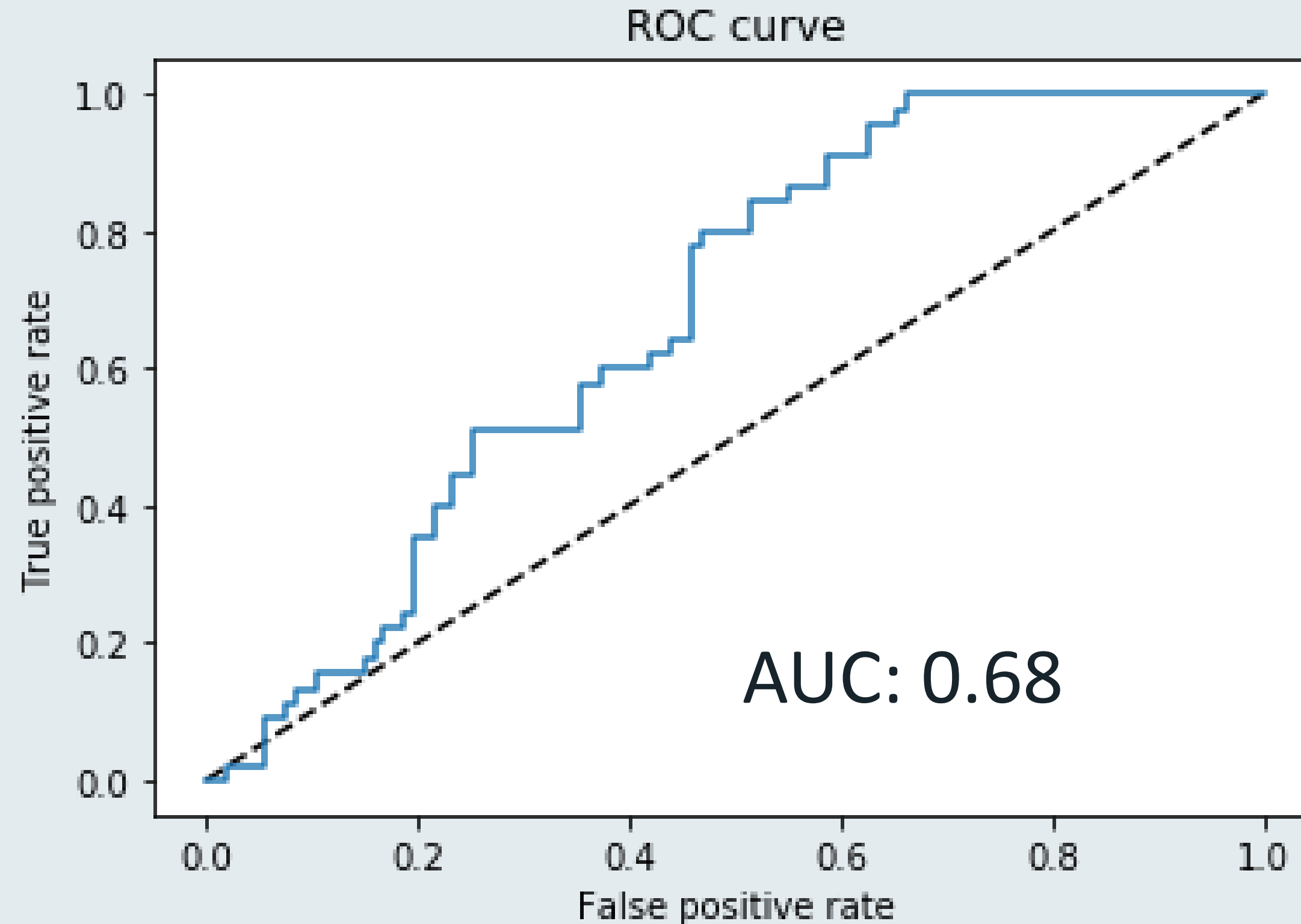


# Acoustic Fingerprinting in a Dialysis Clinic



# Acoustic Fingerprinting in a Dialysis Clinic

- Artificial intelligence was used to determine whether the device correctly “predicted” if patients were coming off dialysis



# Current Status

- ▶ Acoustic Fingerprinting Devices are running in 4 clinics in MA since July 2019





# Mathematical Modeling: Overview



---

Work by Renal Research Institute / FMC Global Research and Development

Peter Kotanko and Doris Fuerterer

# 21<sup>st</sup> Century Trend

- We want uniqueness in everything we do, we give and we own, right from clothes we wear to gifts we give, to coffee we drink.



BrainSINS

Solution Pricing About Support Blog Free Account

Home » Blog » eCommerce » eCommerce Trend Alert 2016 – Personalized Products

## eCommerce Trend Alert 2016 – Personalized Products

Search ... Search

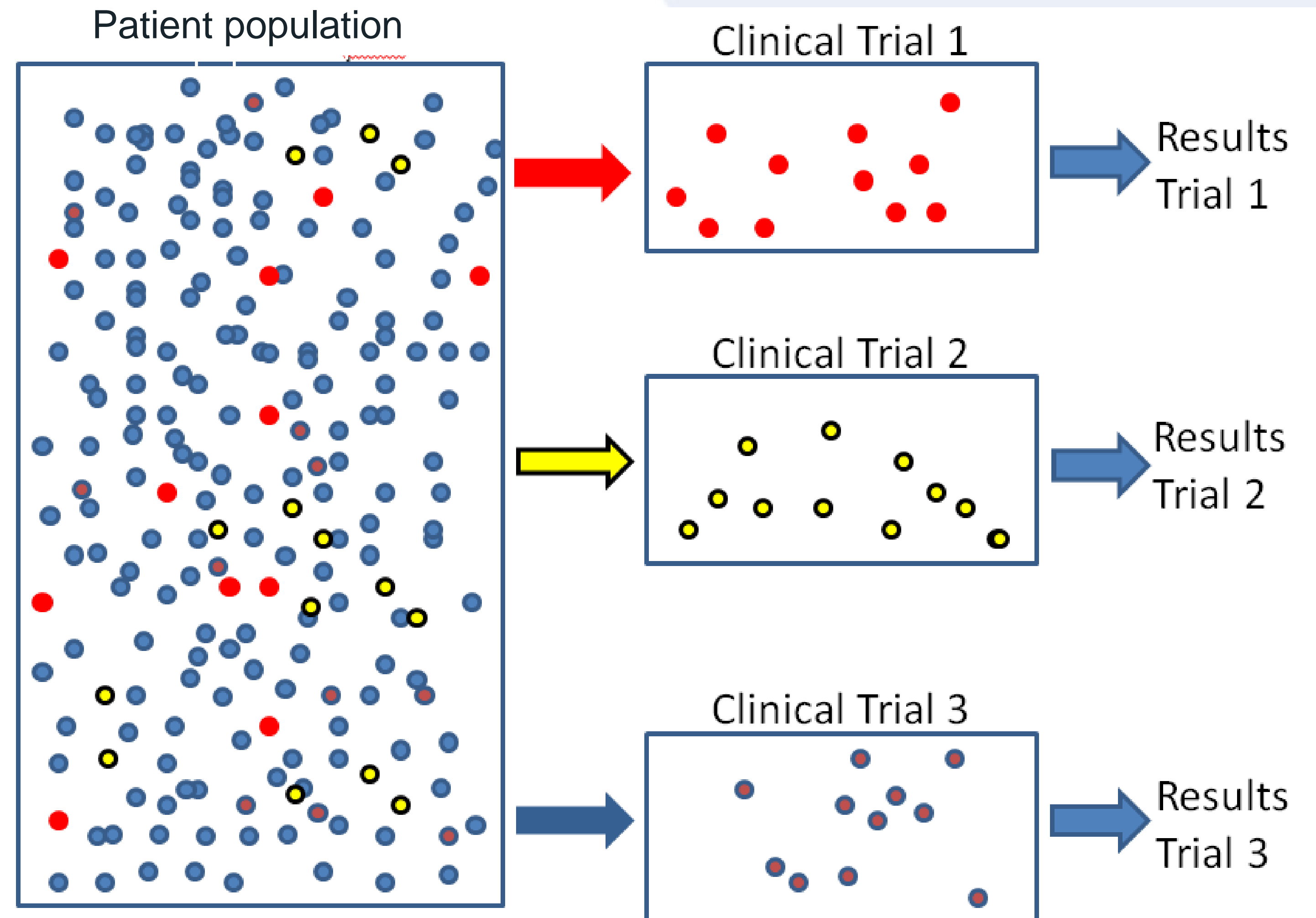
Newsletter

Email



# Traditional Clinical Trials

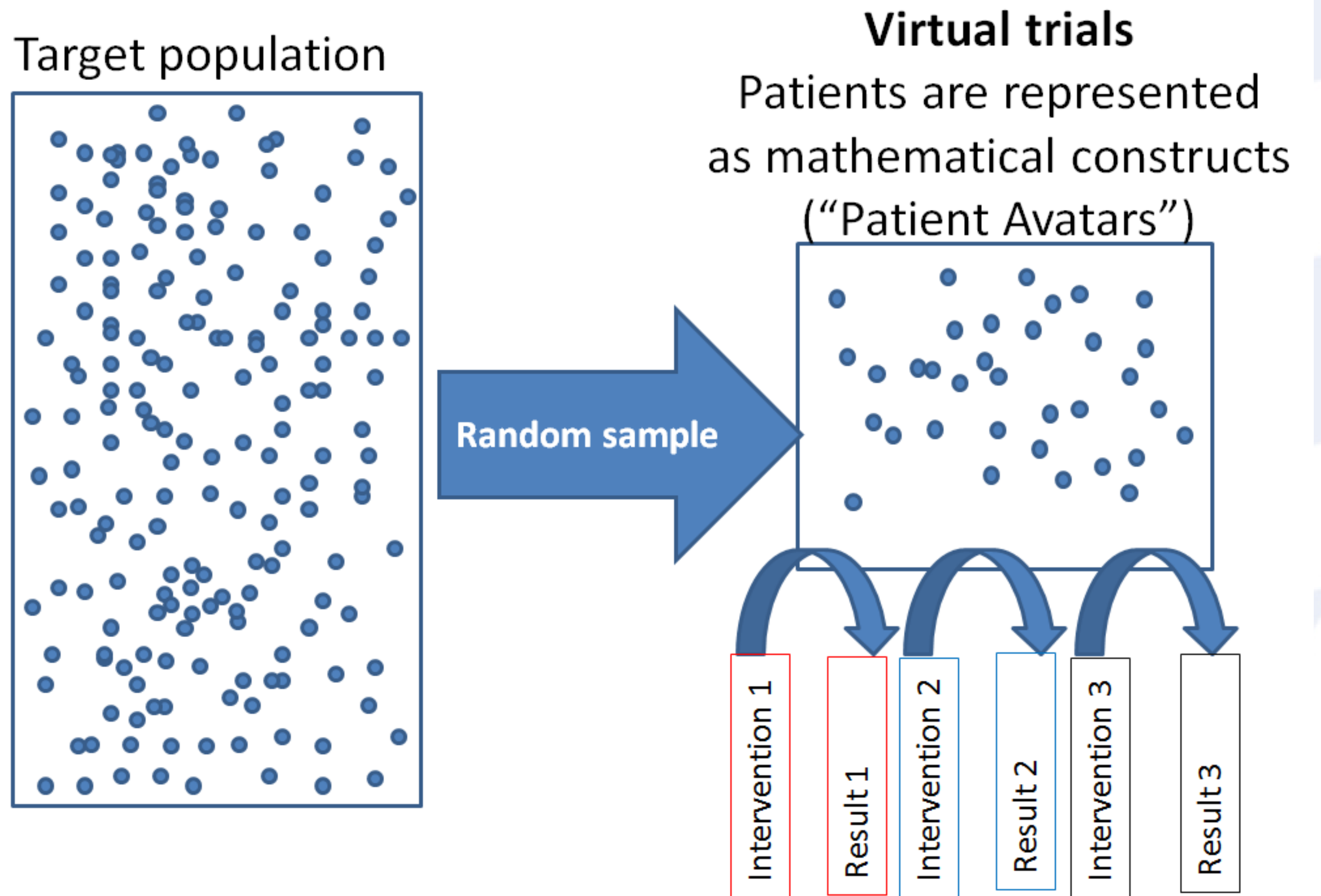
- ▶ A typical clinical trial provides only one set of results in a small & specific number of the overall patient population





# Can We Create a Virtual Clinical Trial?

- ▶ Can we use mathematical principles and create „virtual“ clinical trials?
- ▶ A Virtual Clinical Trial enables testing of multiple interventions in a random large sample of patients



# Modeling Process for Disease and Treatment

► FMC developed a “Virtual Dialysis Clinic” concept that differs from typical machine learning modeling approaches

► Process:

- Building generic mathematical models of (patho)physiological processes
- Creation of Avatars, representing individual patients of defined population
- Creation of a Virtual Clinical Environment to reflect the clinical ecosystem the patient finds himself in
- Simulation of clinical trials and drug response in individual patients



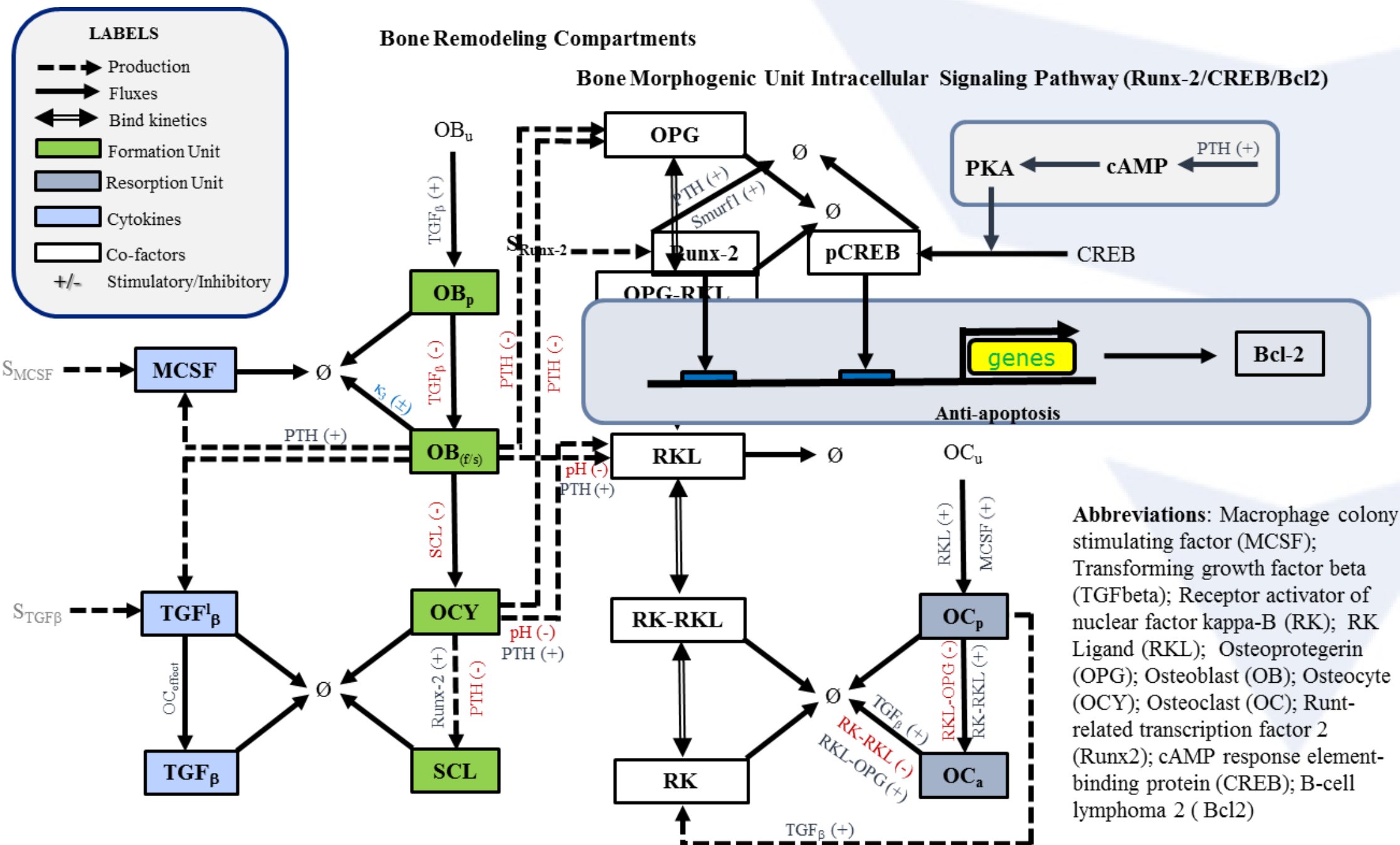


# Building Mathematical Models of Physiology

General physiological processes of human bodies...



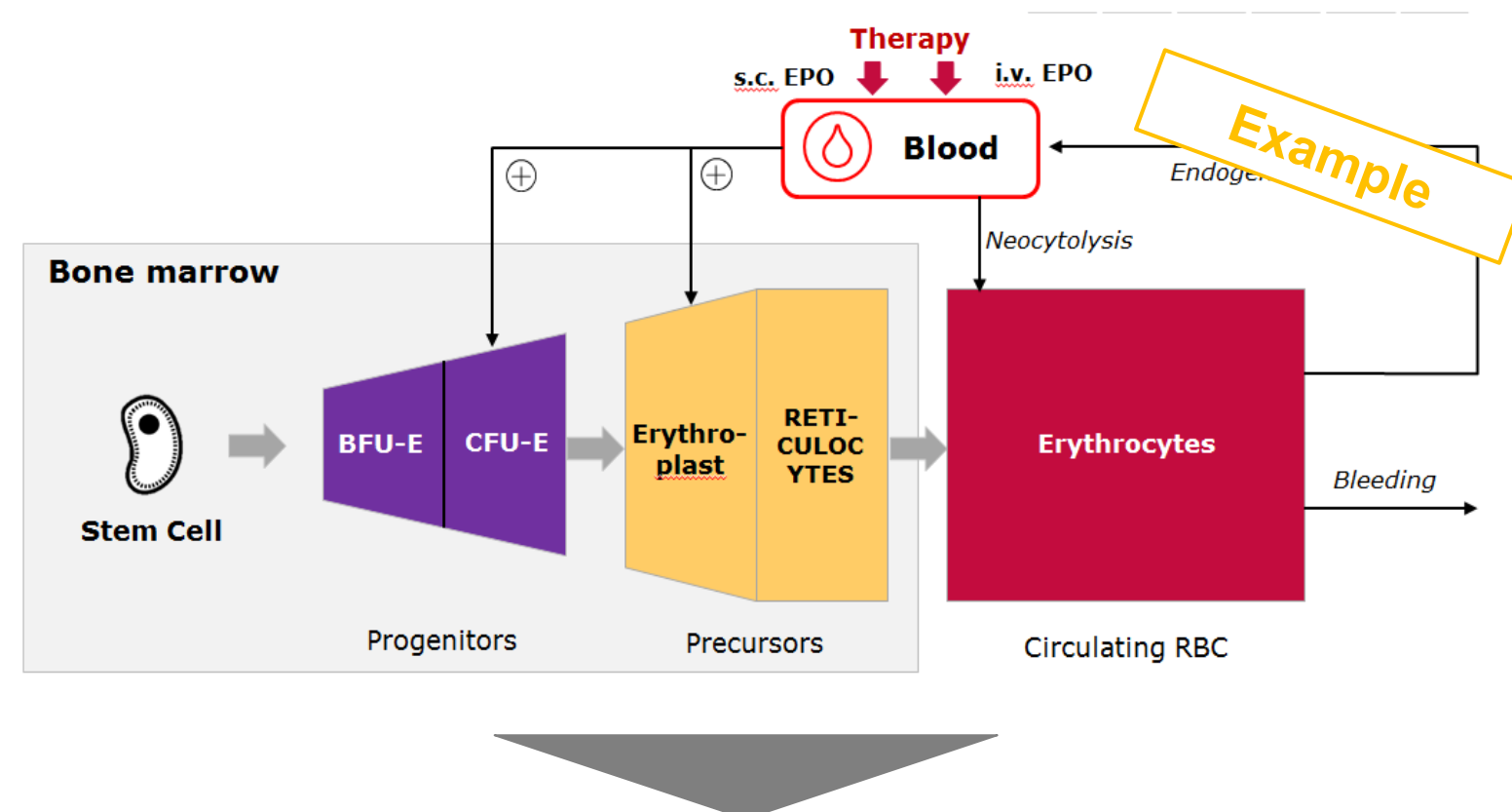
...can be represented as physiologically based mathematical models





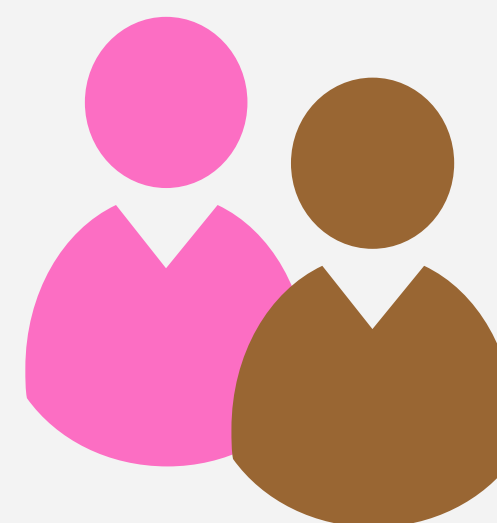
# Creation of Avatars Which Represent Individual Patients

## MATHEMATICAL MODEL OF PHYSIOLOGICAL PROCESSES



- Generally valid physiologically based mathematical model
- Model based on
  - Textbook knowledge
  - Expert opinion
  - Scientific literature
- Validation of model by specific test scenarios

## AVATAR



## PATIENT DATA

### General Patient Data



Gender



Height



Weight



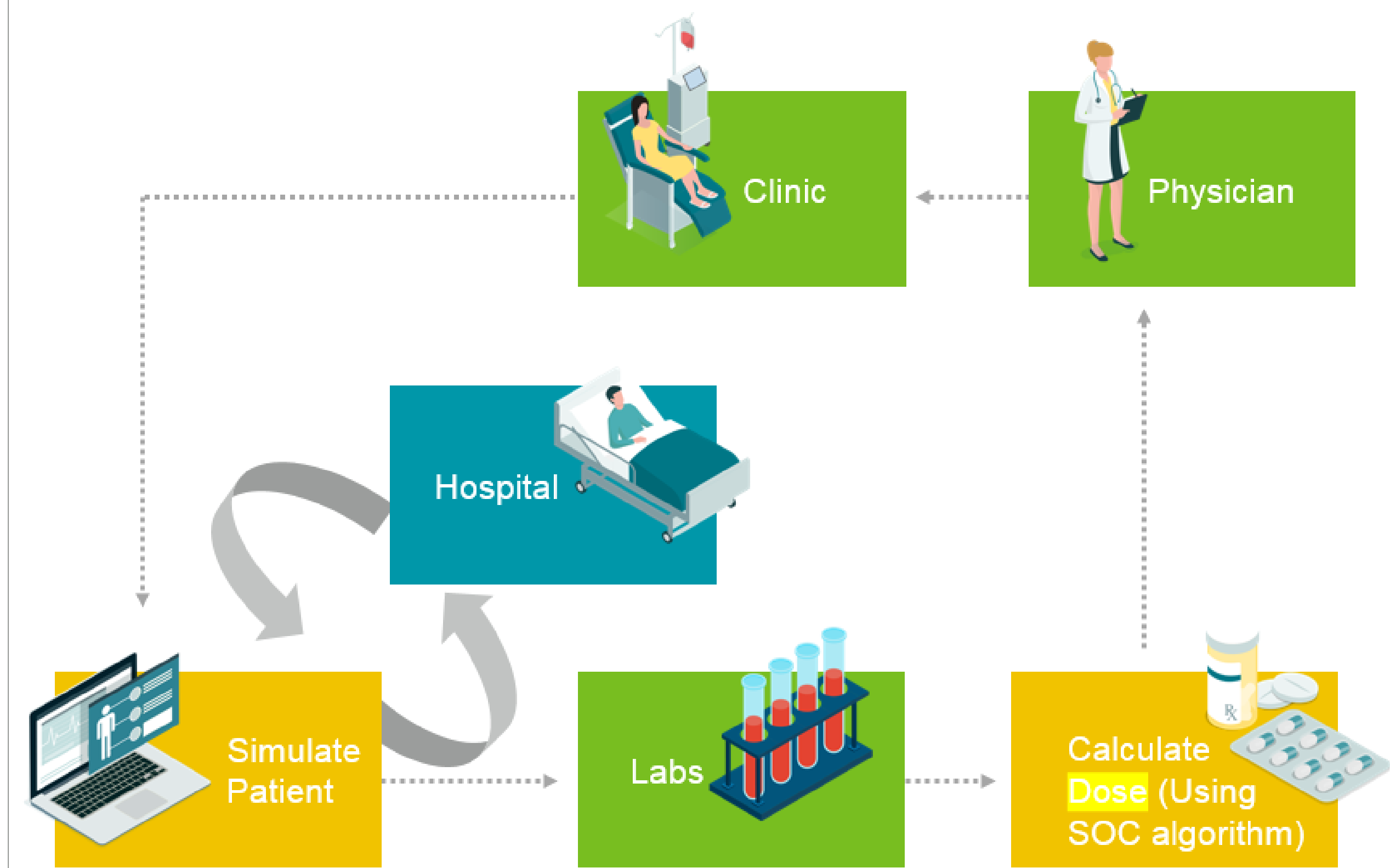
Drug admin & hemoglobin data

### Selection of patient population

- Patient selection determined by clinical unmet need & defined by available data:
  - Randomly
  - Subpopulations
  - Patients with unfavorable clinical outcomes

# Creation of Virtual Clinical Environment to Reflect the Clinical Ecosystem

► (Example: Anemia Treatment in Dialysis patients)



- Virtual Ecosystem integrates data from patient's daily life.
- The Virtual Ecosystem is an important part of the **Virtual Clinic**.
- In addition to **real patient representations by Avatars**, also the **clinical environment** is incorporated in a realistic **Virtual Trial**.

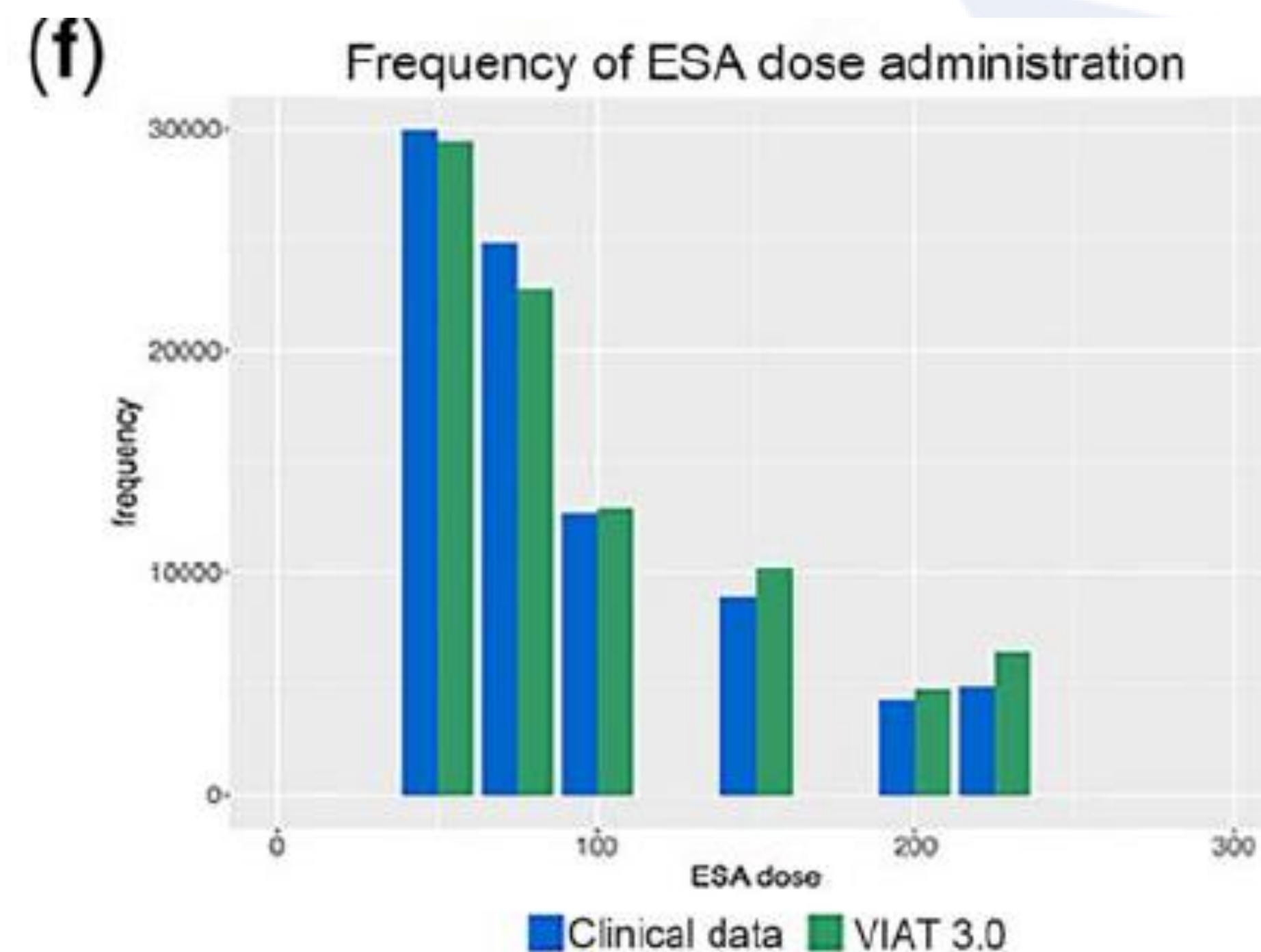
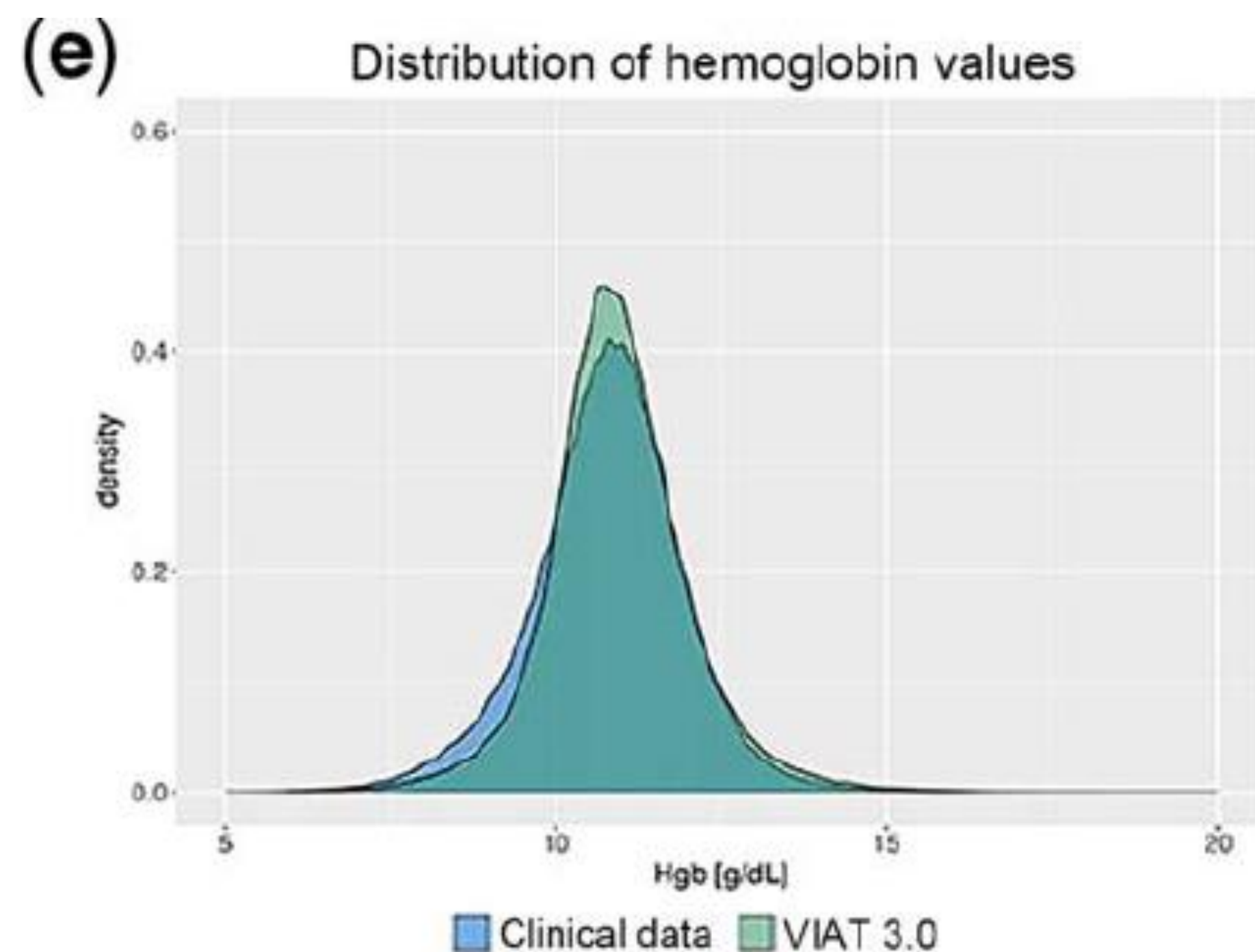
Citation: CPT Pharmacometrics Syst. Pharmacol. (2018) 00, 00; doi:10.1002/psp4.12276  
© 2018 ASCPT All rights reserved

ORIGINAL ARTICLE  
**The Virtual Anemia Trial: An Assessment of Model-Based *In Silico* Clinical Trials of Anemia Treatment Algorithms in Patients With Hemodialysis**

Doris H. Fuertinger<sup>1,2\*</sup>, Alice Topping<sup>1</sup>, Franz Kappel<sup>3</sup>, Stephan Thijssen<sup>1</sup> and Peter Kotanko<sup>1,4</sup>

# Simulation of Drug Response in Individual Patients

- ▶ A standard of care anemia treatment protocol was tested in ~6,700 Avatars for one virtual year and compared to one year of data from ~6,700 anemia patients treated with the same protocol



Fuertinger et al., CPT Pharmacometr. Syst. Pharmacol. (2018)



# Future of AI in Healthcare

---

# Future of AI in Healthcare

---

- Lots of excitement and energy
- Array of technologies are cropping up
- AI health field is wide: wellness, diagnostics, operational technologies
  - Yet, AI health applications typically perform just a single task
  - Regulatory framework has to catch up
  - Progress will be incremental

# 10 AI Applications to Change Healthcare

APPLICATION

Robot-assisted surgery

POTENTIAL ANNUAL VALUE BY 2026



KEY DRIVERS FOR ADOPTION

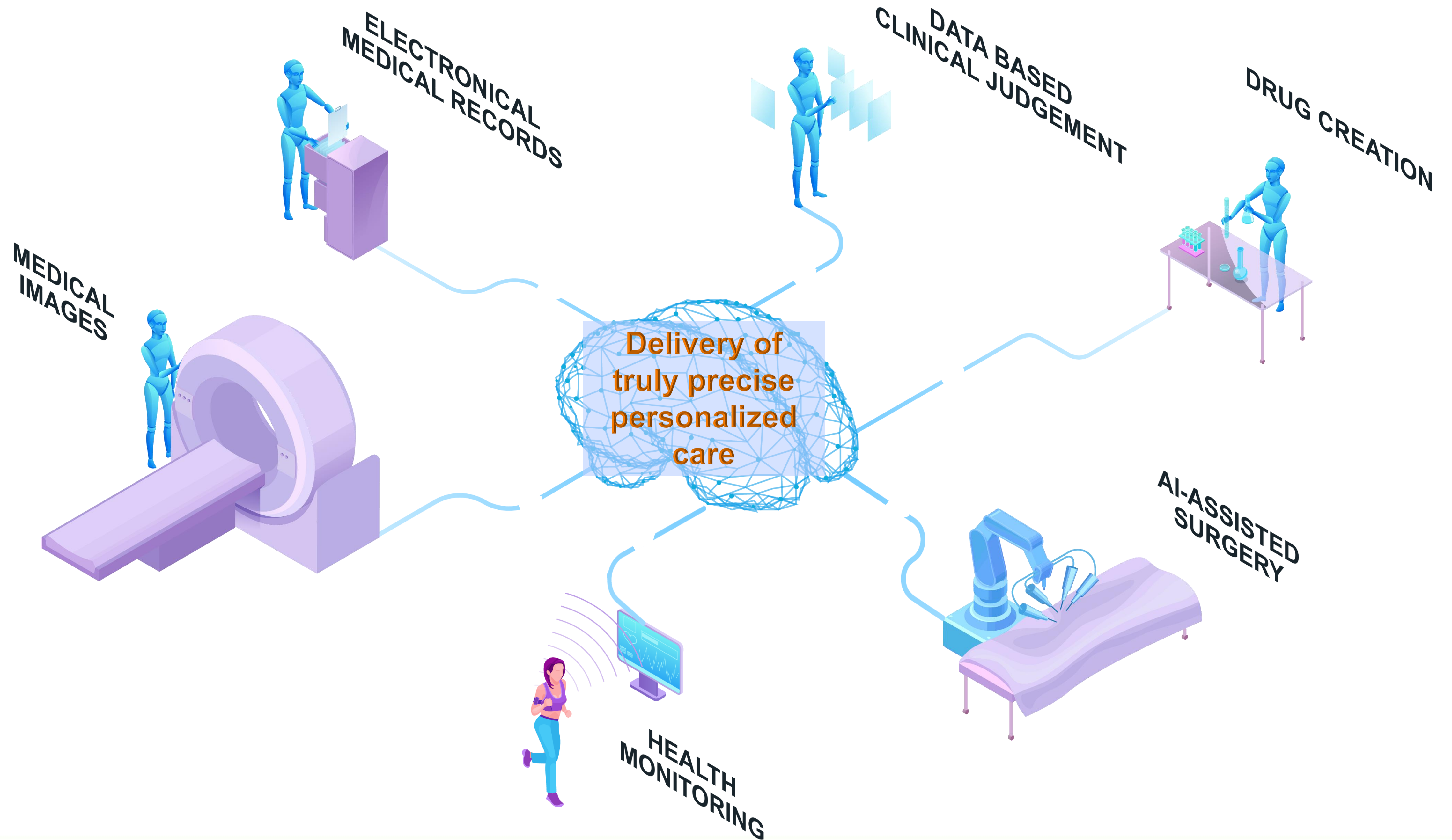
Technological advances in robotic solutions for more types of surgery

SOURCE ACCENTURE

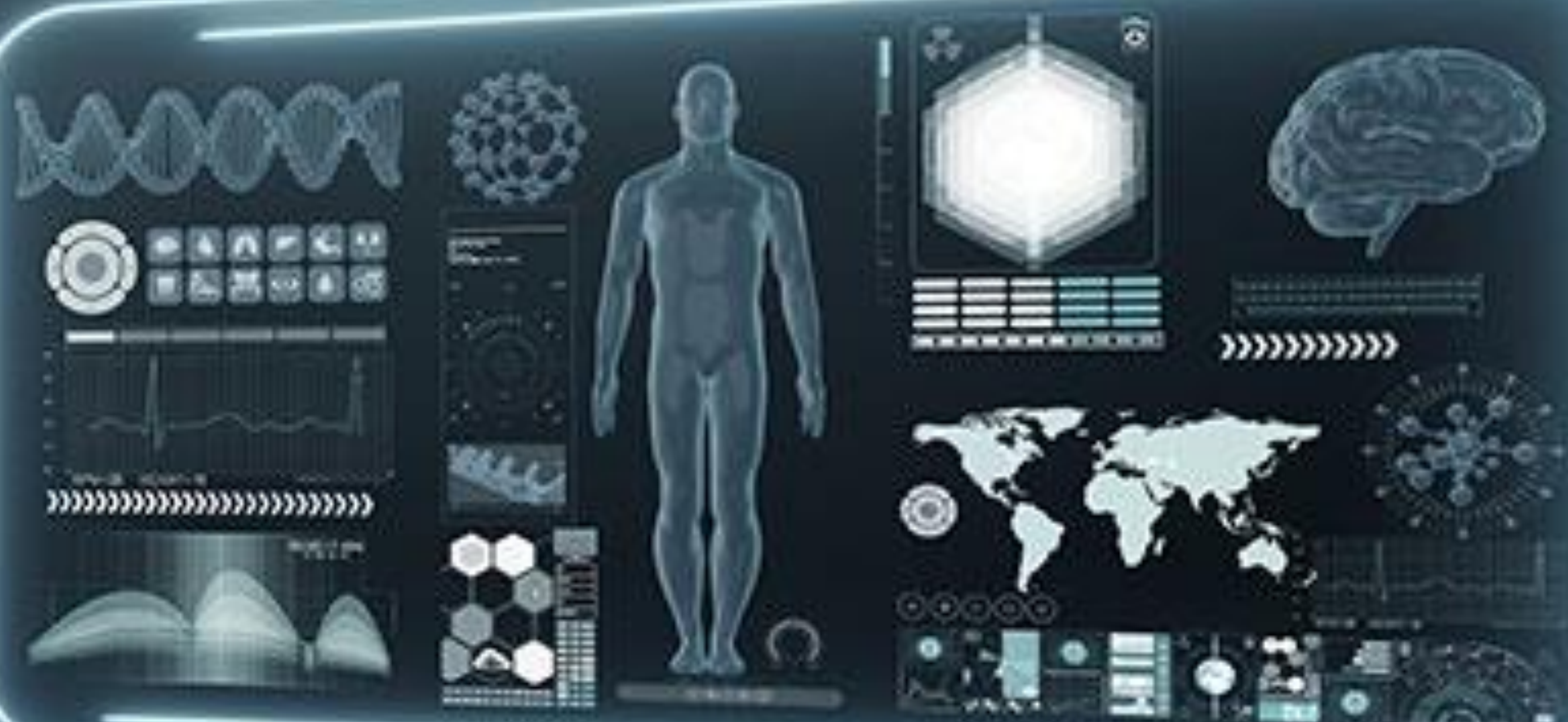
© HBR.ORG

<https://hbr.org/2018/05/10-promising-ai-applications-in-health-care>











**Thank You!**  
**감사합니다**

*Len.Usvyat@fmc-na.com*

