Cognitive Computing and Patient Data Management Systems

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Outline

- It’s all about data
- Cognitive systems & Watson
- Analytics
- Clinical decision support

It’s all about data

Data – the air we breath

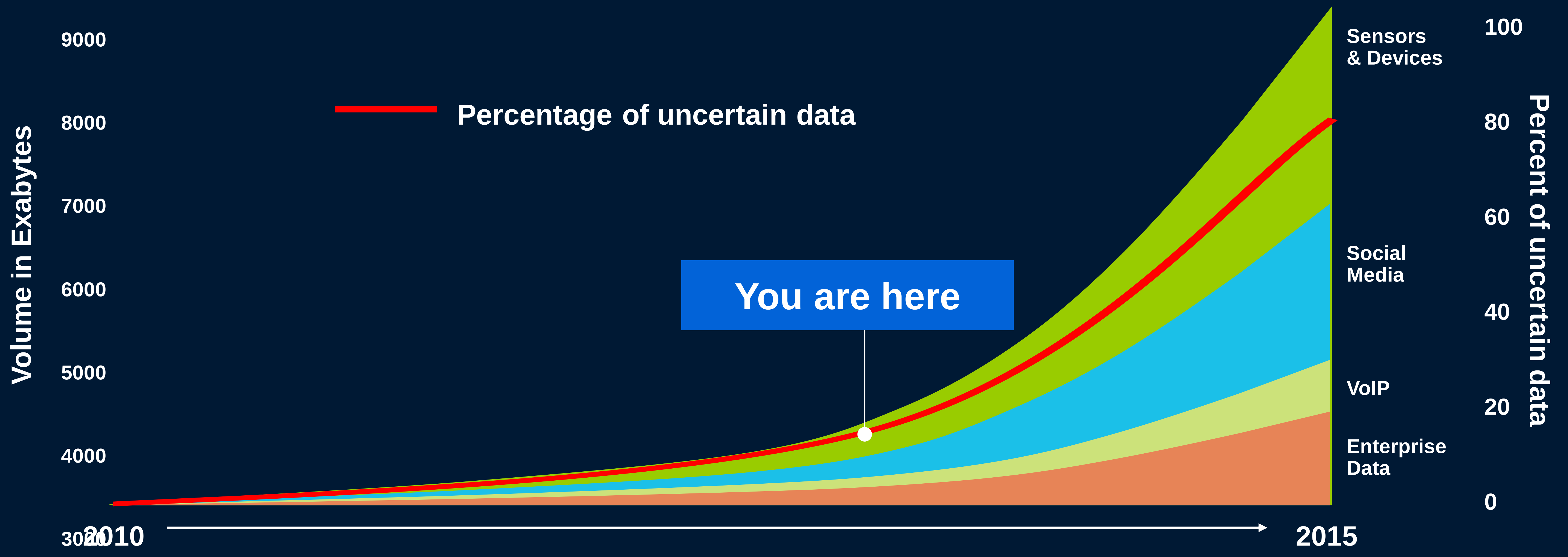
Cloud

Mobile

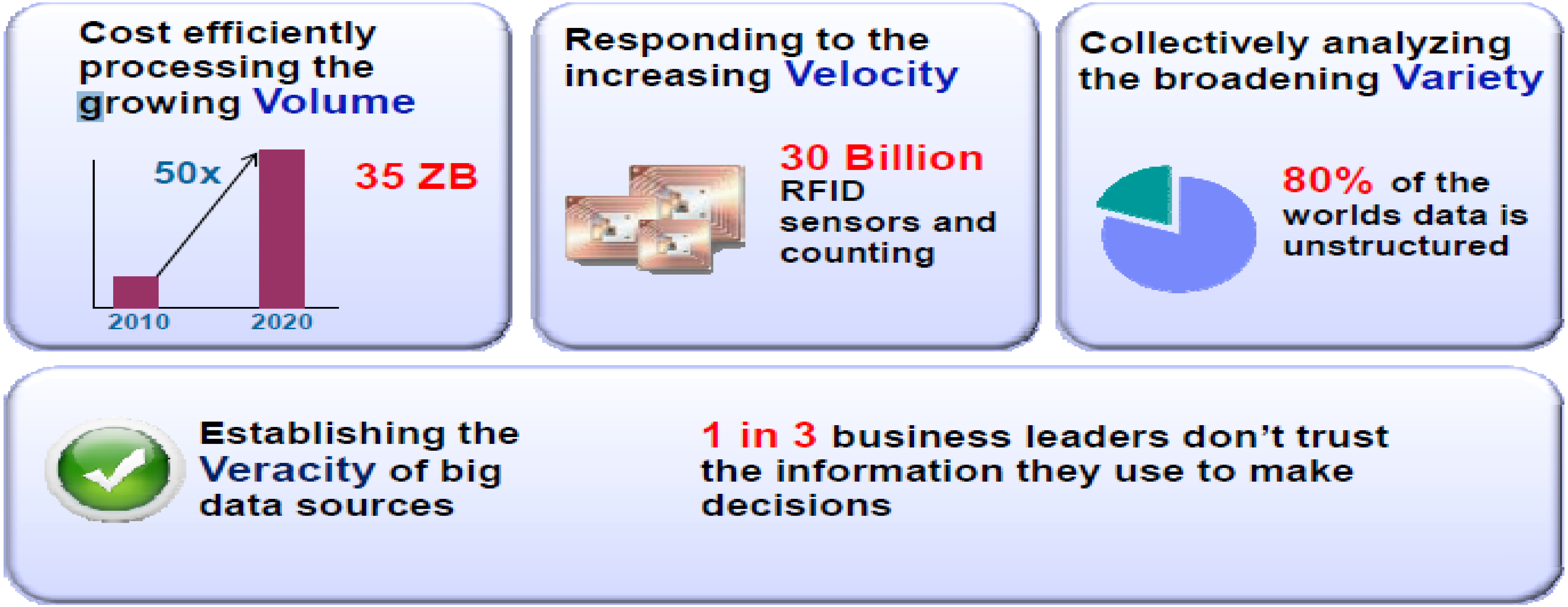
Social

Internet of Things

Big Data: This is just the beginning

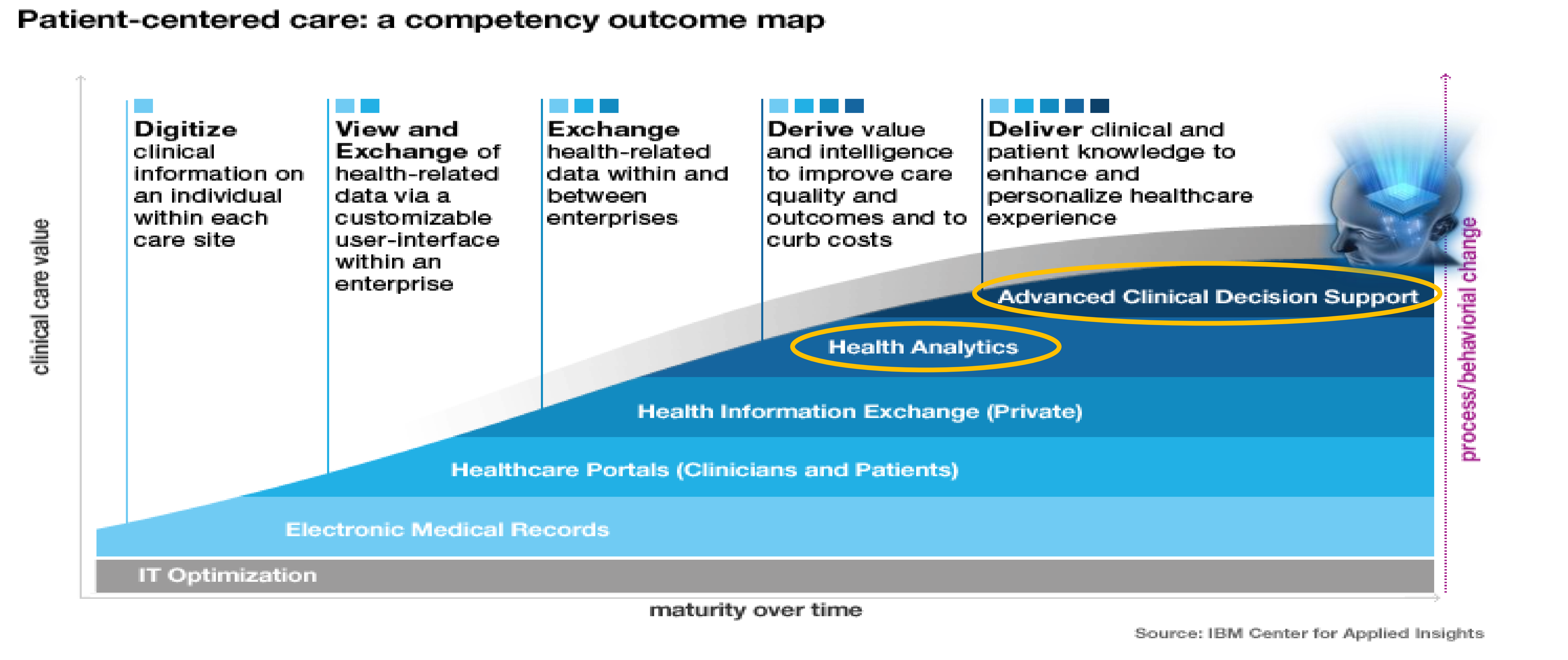


The characteristics of Big Data

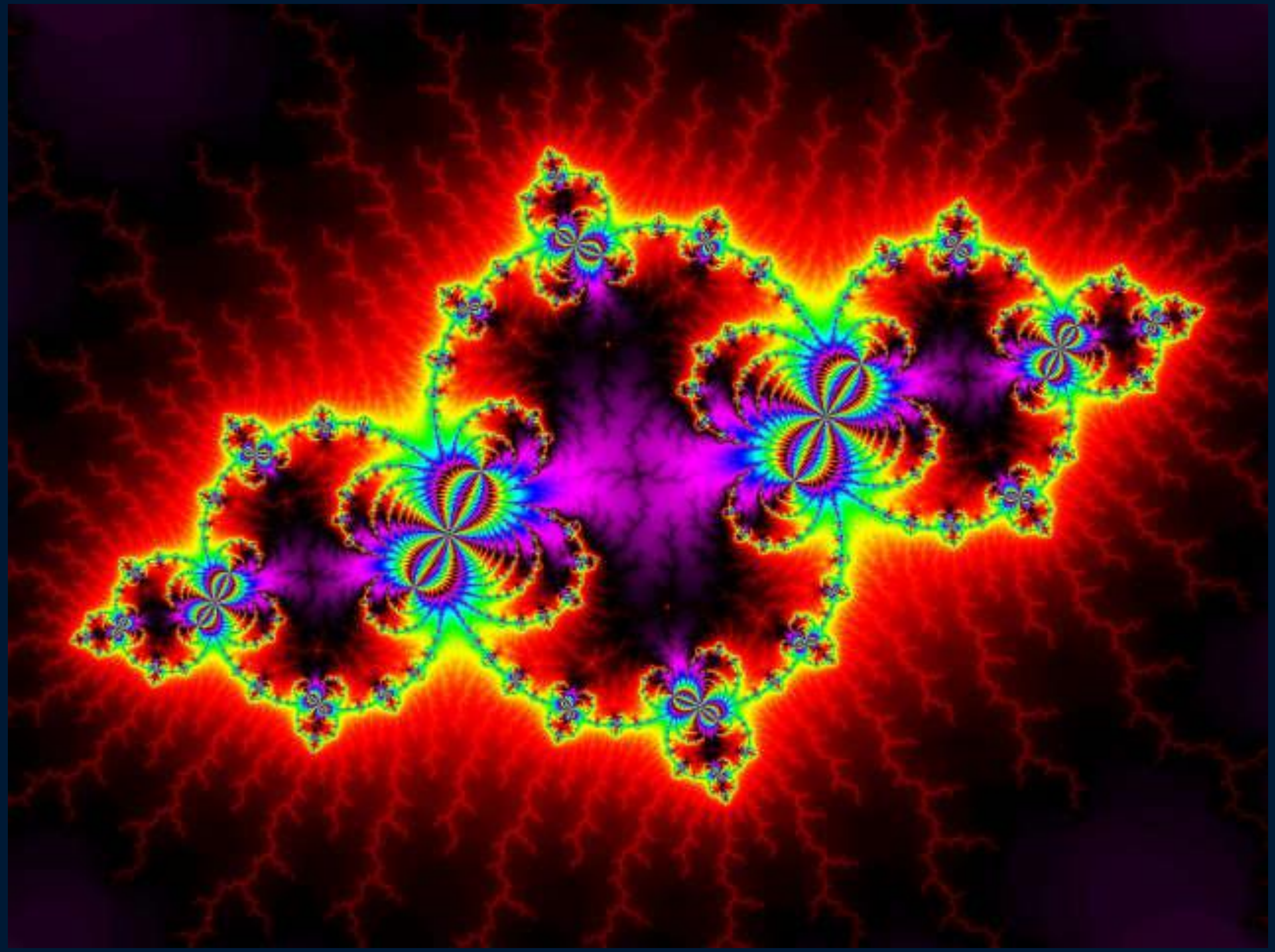


Healthcare challenge: Poly-structured data

A vision for patient care:
How data becomes the first line of treatment



Cognitive computing & Watson



Eras of Computing

Tabulating Systems Era

Programmable Systems Era

Search
Deterministic
Enterprise data
Machine language
Simple outputs

Cognitive Systems Era

Discovery
Probabilistic
Big Data
Natural language
Intelligent options

Watson


PIENSE
THINK
ΣΚΕΨΟΥ
DENKE
PENSER
$300,000
$1,000,000
$200,000
KEN
WATSON
BRAD

Taking Watson beyond Jeopardy!

Understanding

Specific Questions

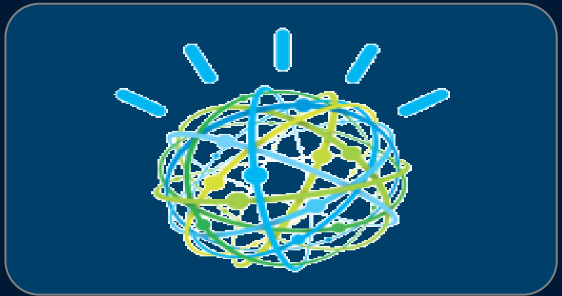
The type of murmur associated with this condition is harsh, systolic, and increases in intensity with Valsalva

From specific questions to rich, incomplete problem scenarios (e.g. EHR)

Rich Problem Scenarios

Interacting

Question-In/Answer-Out



Evidence analysis and look-ahead, drive interactive dialog to refine answers and evidence

Input, Responses

Refined Answers, Follow-up Questions

Interactive Dialog Teach Watson

Explaining

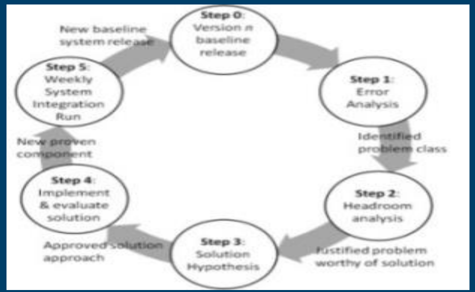
Precise Answers & Accurate Confidences

Move from quality answers to quality answers and evidence

Comparative Evidence Profiles

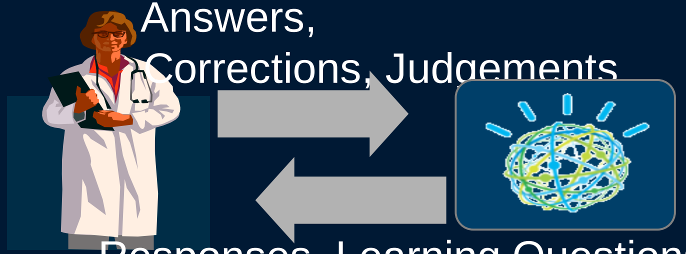
Learning

Batch Training Process



Scale domain learning and adaptation rate and efficiency

Answers, Corrections, Judgements



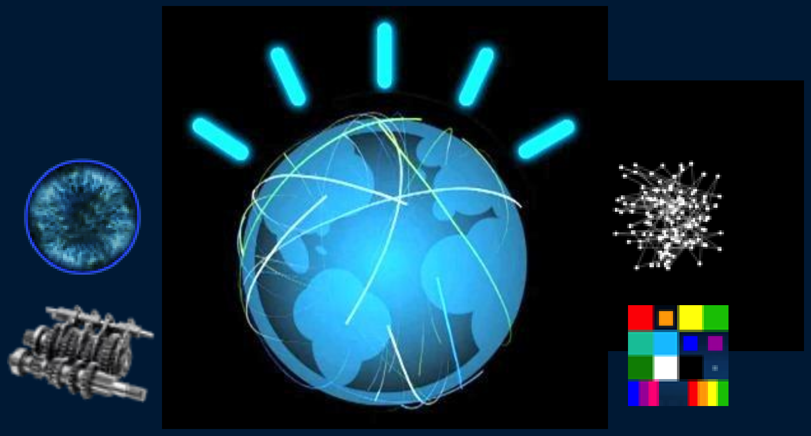
Responses, Learning Questions

Continuous Training & Learning Process

Capabilities of Cognitive Systems

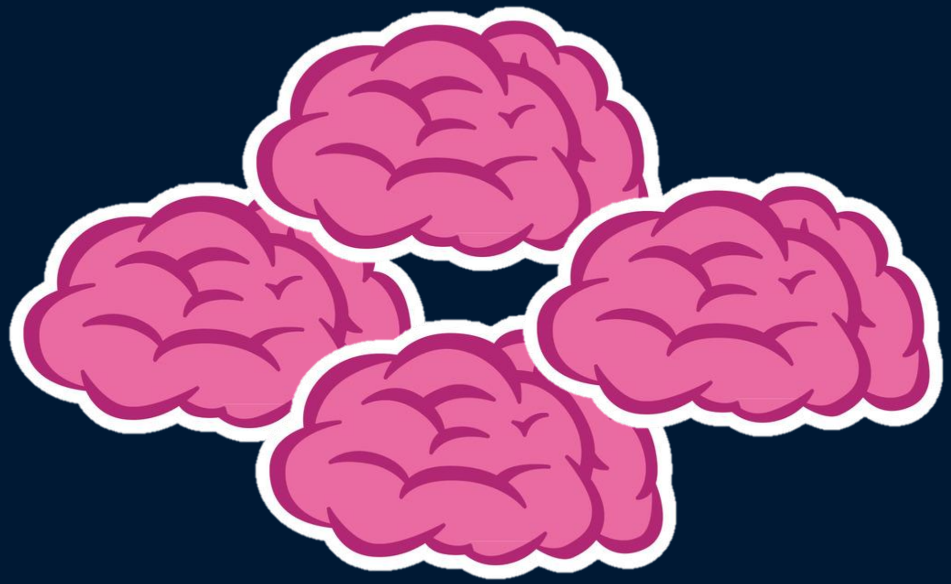
	Watson 1.0	Watson 2.0	Watson 3.0
Memory	✓	✓	✓
Learning	✓	✓	✓
Judgment	✓	✓	✓
Perception		✓	✓
Multi-modal			✓
Reasoning			✓

A New Partnership for a New Era of Computing



Learning & Reasoning Systems

The Cognitive Experience



Humans

Cognitive Computing

Complex reasoning and interaction extends human cognition

Finance
Enhance decision support

Healthcare
Surface best protocols to practitioners

Legal
Suggest defense/ prosecution arguments

Telemarketing
Next generation – persuasive – call center

Analytics

Prediction models are based on the data features

- A patient is represented as a vector of features

Genomic
Single Nucleotide polymorphism
Copy number variation
whole genome sequence

Unstructured
EHR/EMR
Physician's summary
Textual information

Text analytics

Drugs
Prescriptions, Dosages,
Day supply etc.
Toxicity
Rescue Treatments

Features

Demographics
Age
Gender
Others

Procedures
Prescriptions, Dosages,
Day supply etc.
Treatment changes
Rescue Treatments

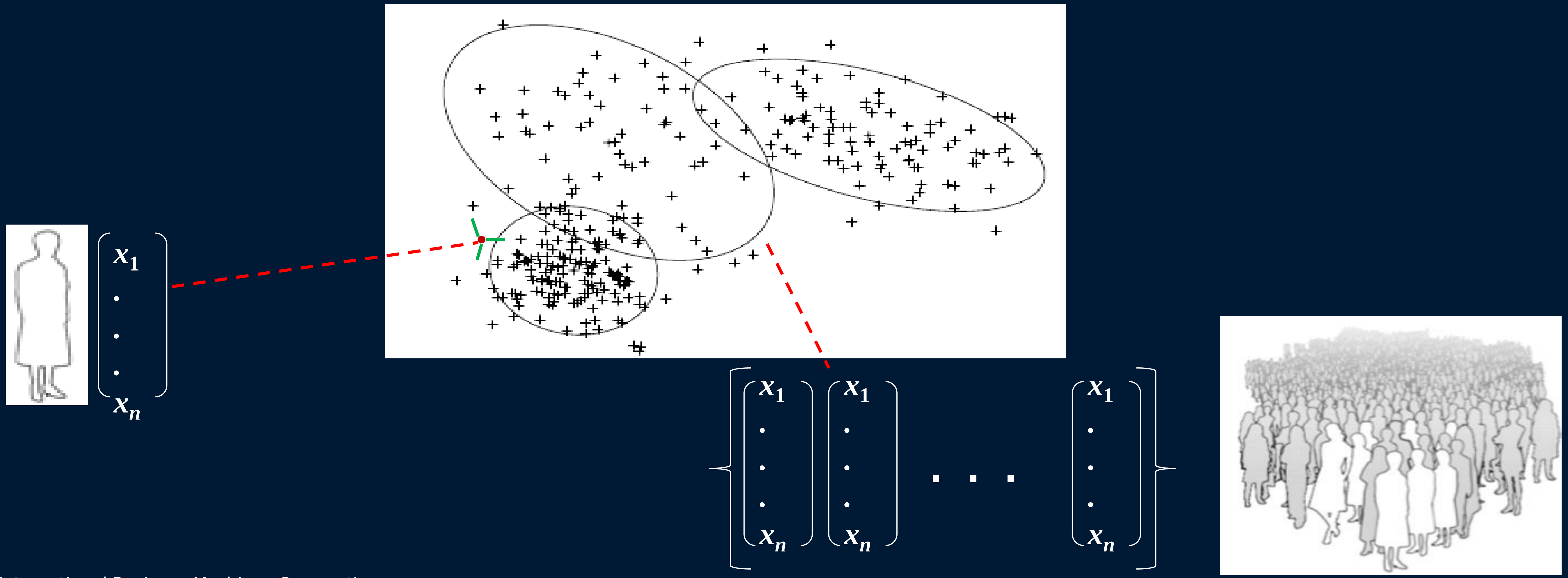
Diagnoses
ICD9 codes
Past diagnoses
Co morbidities

Hospitalizations
Hospitalization events
Days in hospital
Hospitalization type:
Inpatient, outpatient, ER

$$\begin{pmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_n \end{pmatrix}$$

Patient feature vector

Patient Similarity Analytics



The Machine Learning Paradigm: Predictive analytics

Collect
real data

Medical health records /
provided services / lab tests

Training

Periodic Training:
Learn from the latest
data

1. Learning

Statistical Prediction Models

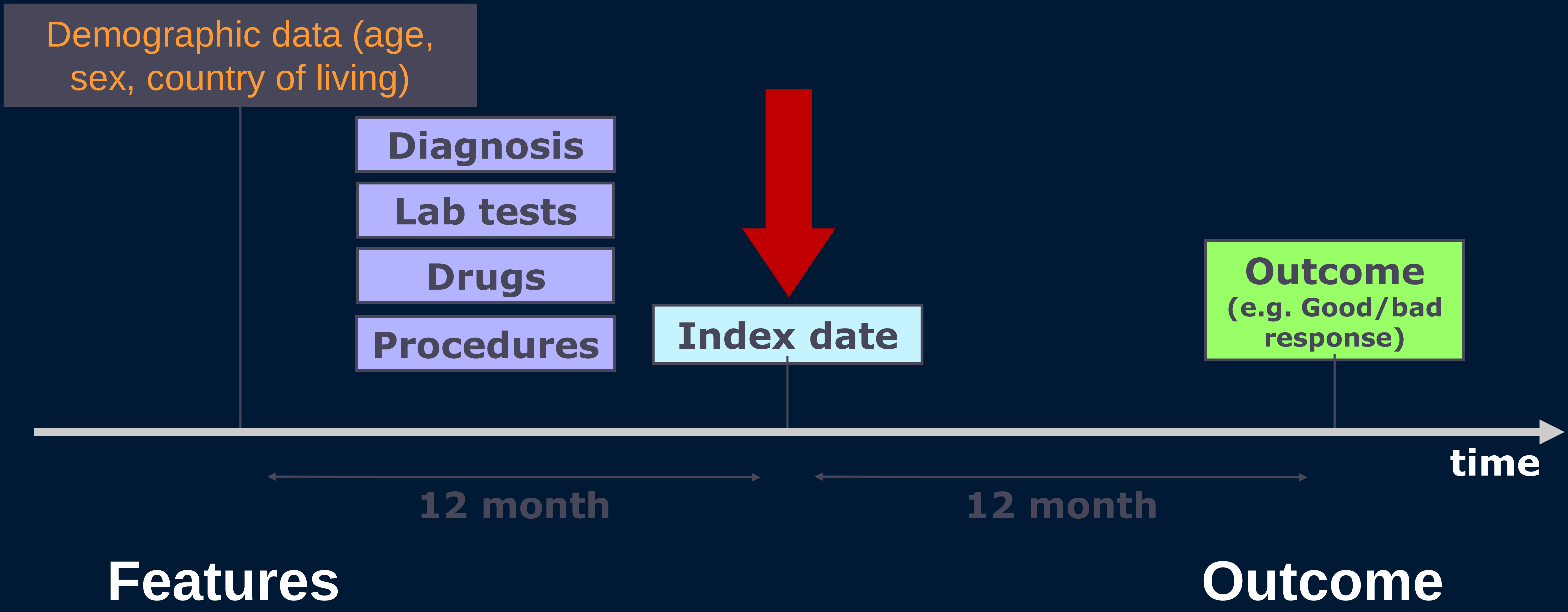
2. Analysis – runtime process

A new Patient /
change in disease
state / new
condition

Analysis

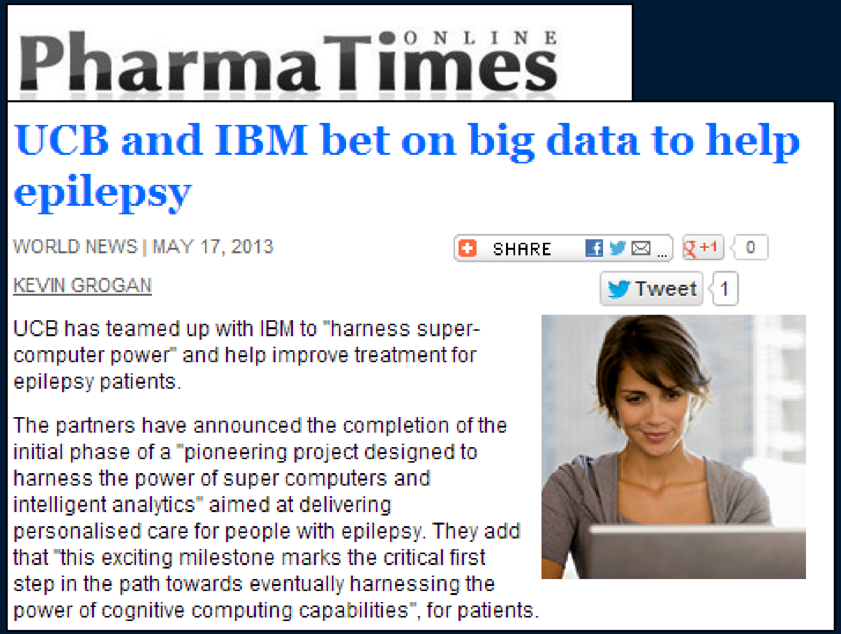
Output:
alerts
predictions
recommendations
categorization
visualization …

From Features to Outcome



Analytics and decision support in care provisioning

Epilepsy – optimizing treatment



PharmaTimes ONLINE

UCB and IBM bet on big data to help epilepsy

WORLD NEWS | MAY 17, 2013 SHARE +1 0

KEVIN GROGAN Tweet 1

UCB has teamed up with IBM to "harness super-computer power" and help improve treatment for epilepsy patients.

The partners have announced the completion of the initial phase of a "pioneering project designed to harness the power of super computers and intelligent analytics" aimed at delivering personalised care for people with epilepsy. They add that "this exciting milestone marks the critical first step in the path towards eventually harnessing the power of cognitive computing capabilities", for patients.

- Epilepsy is highly heterogeneous making it an ideal disease to leverage real world evidence for a personalized treatment approach

- Analytics used to process large volumes of claims data

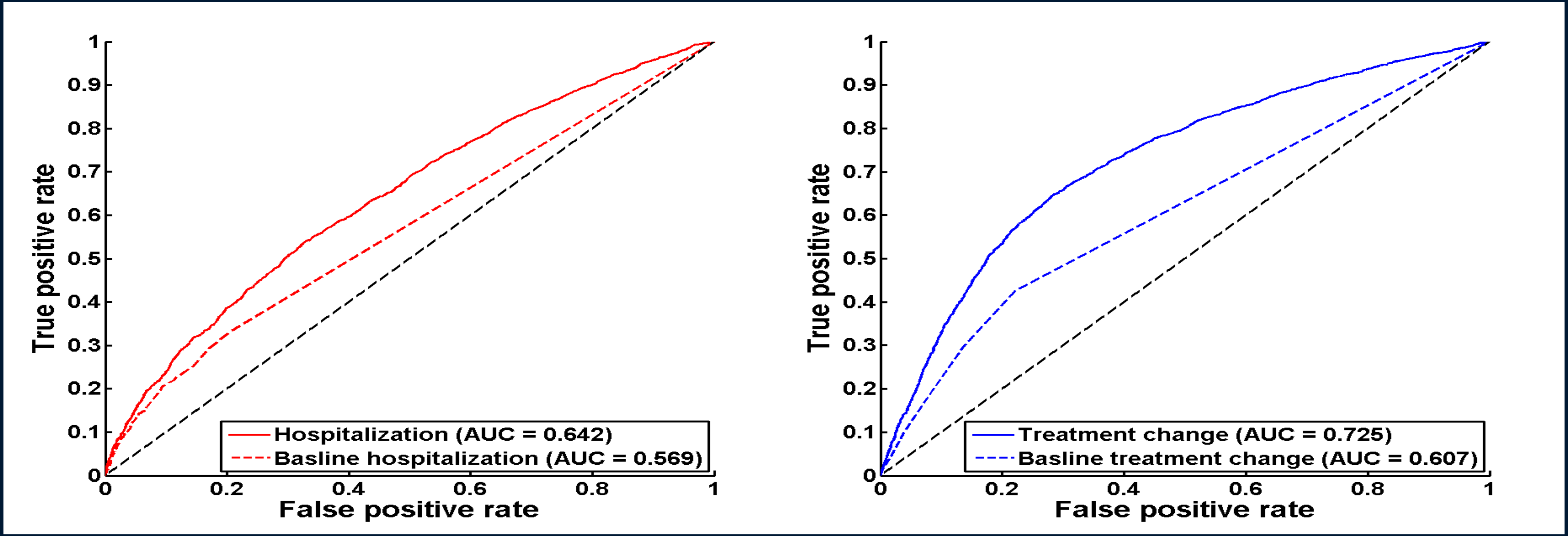
- Goal: estimate outcomes of candidate therapies and assist in designing optimal treatment regimen

- Patients with epilepsy often desire different outcomes → a treatment's success is not determined solely by its efficacy at treating symptoms

Step 1: Predicting the Patient's Outcome

Hospitalization outcome

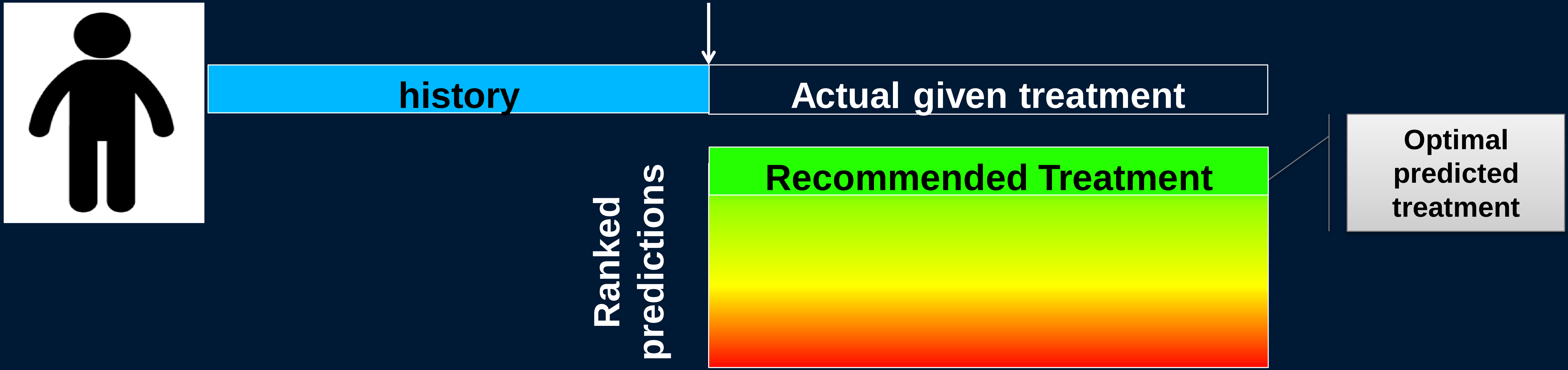
Treatment change outcome



Approaches Explored

- Patients and features clustering
  - K means (Euclidean)
  - Newman (spectral clustering)
  - Iclust (Based on information theory)
- Learning algorithms
  - Logistic regression
  - Random Forest
  - KNN
  - SVM
    - With linear, polynomial and RBF(Gaussian) kernel
  - Hierarchical model
    - Based on failure event type
    - Based on time to event

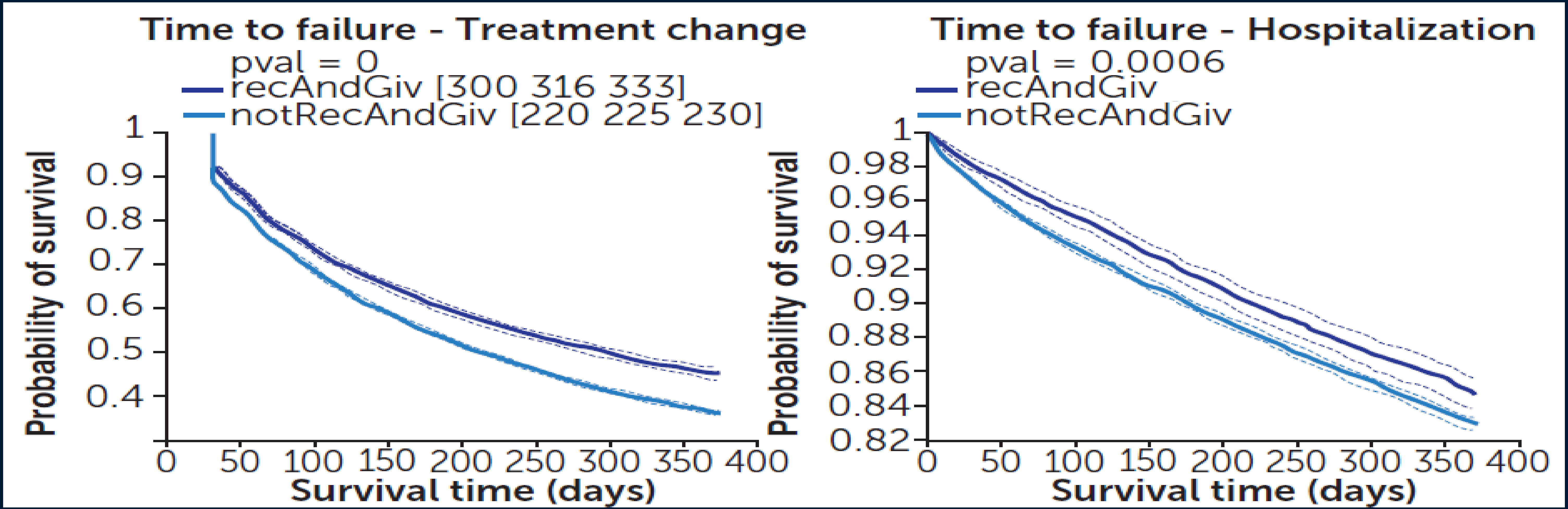
Step 2: Assigning the Optimal Treatment



Optimal Treatment Prediction Evaluation

- Will the recommended treatment improve the patient’s outcome?
  - Only a clinical trial can tell
- But
  - Comparing the outcome in case of agreement/disagreement of the given treatment with the predicted optimal treatment should provide support

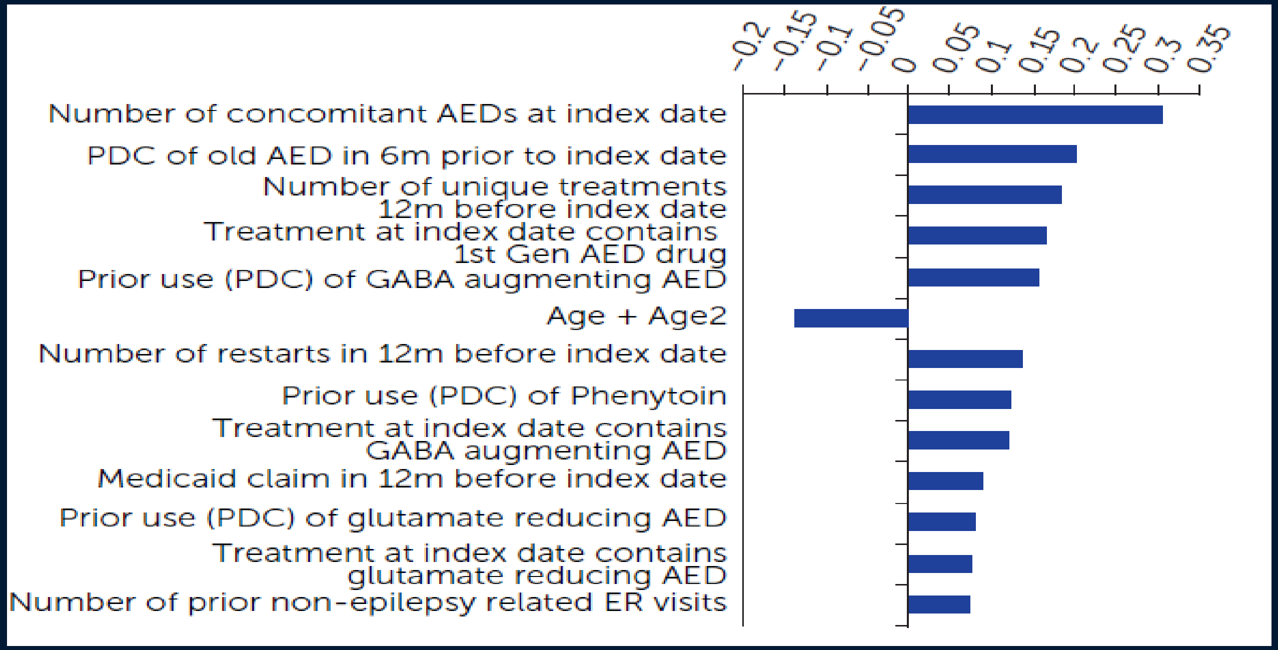
Use of the system has the potential to significantly impact patient health

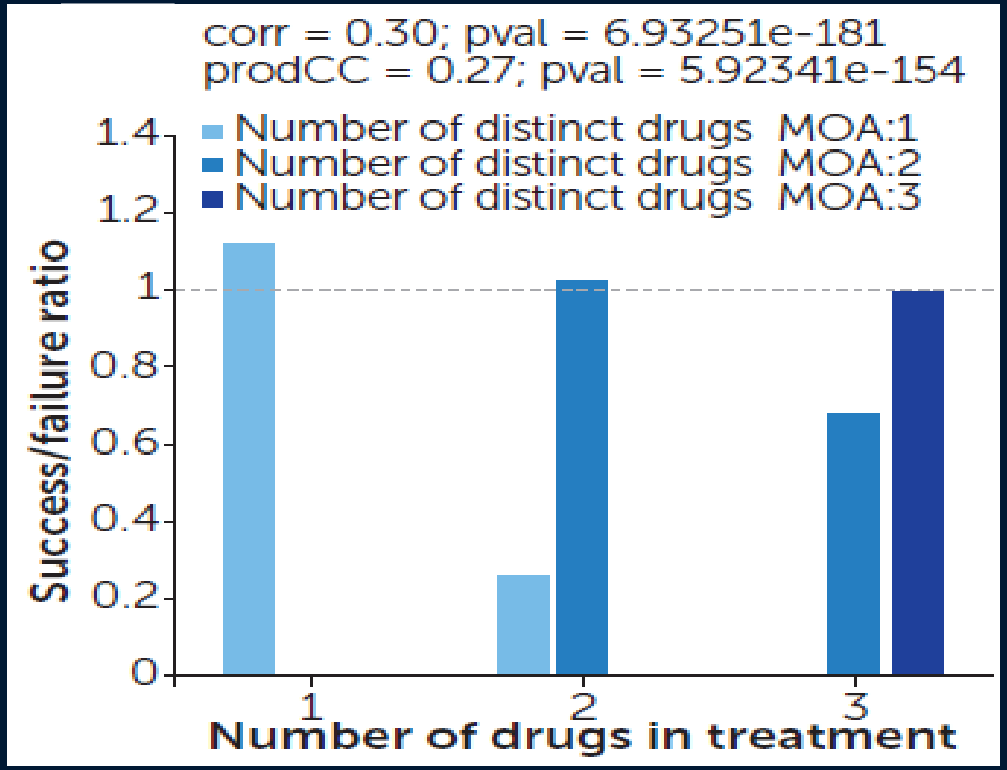


Patients who were given the treatment recommended by the system had longer survival rates for treatment change and the hospitalization outcomes

What can the model tell us?

top features that correlated to a negative treatment change outcome

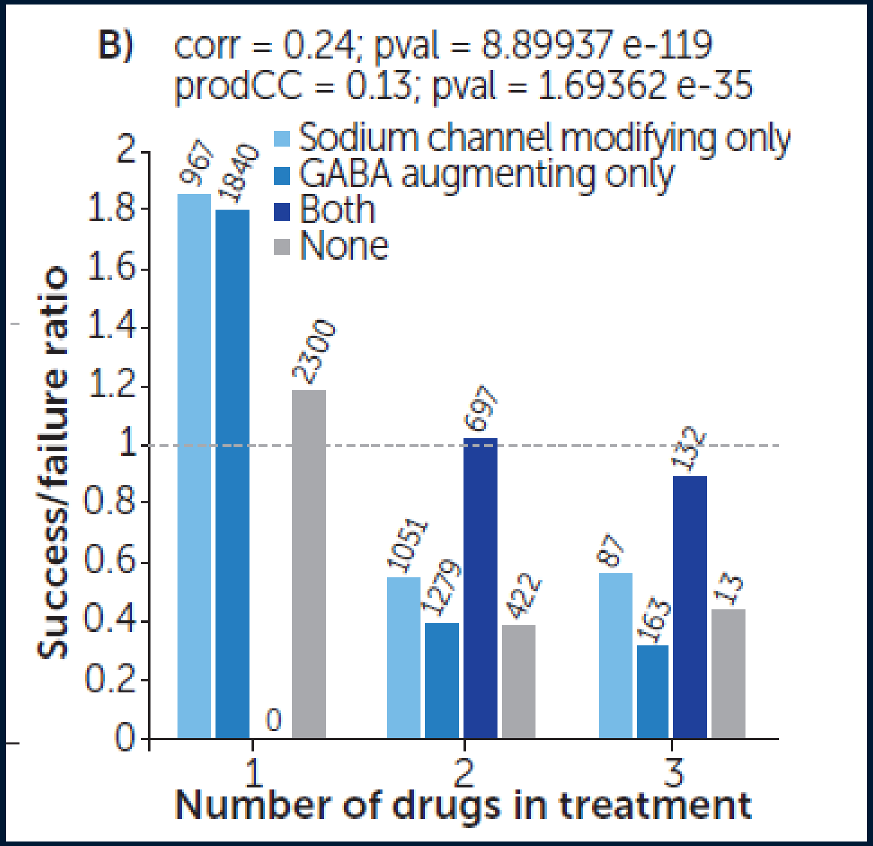




the probability of success with polytherapy is increased when the drugs selected have different mechanisms of action

Using analytics on RWE data we can start to make generalizations about which combinations provide the best outcomes

In patients taking sodium channel modifying and GABA augmenting agents, the probability of success is higher if rational polytherapy is employed

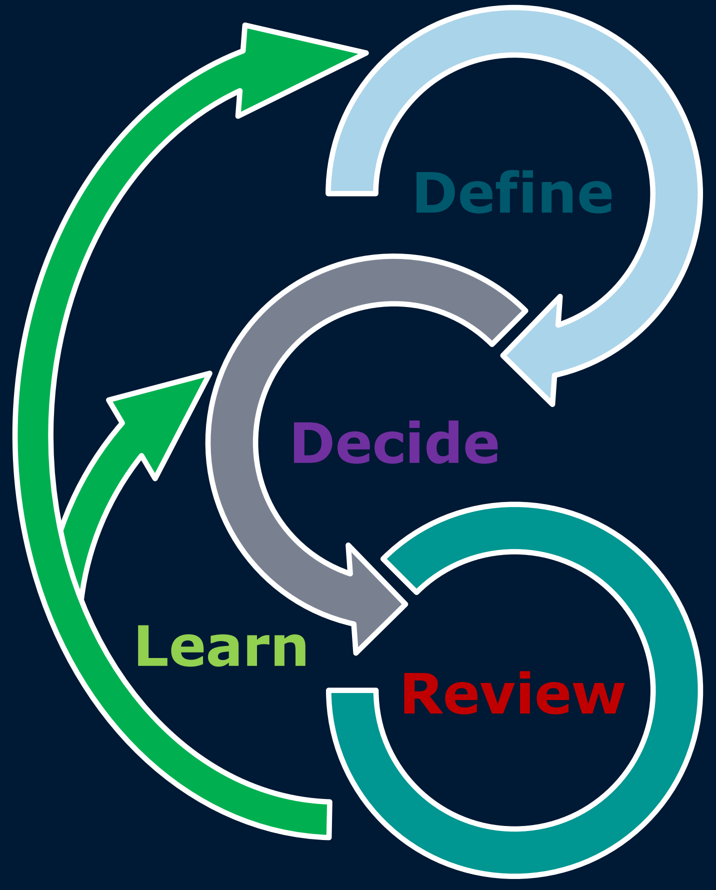


Supporting cancer care

- Oncology **CareTrio** – Interactive decision support system
- Precision oncology based on genomics
- Decision support for policy makers

Oncology Care Trio

- CareEdit – Clinical Guideline Editor:
  - Defines, edits and maintains clinical guidelines at the organization level
    - Reflects standard of care
    - Evidence based as well as data driven
- CareGuide - Physician Advisor:
  - Point of care decision support tool
    - Guideline based and Data driven (on top of the guidelines)
- CareView – Decisions Review:
  - Retrospective analysis of past care decisions
    - Comperes guidelines to provided treatment at the population level
    - Enables guideline refinements and personalized medicine
    - Generates clinical insights for better care at lower cost



Oncology Care Trio – User Roles

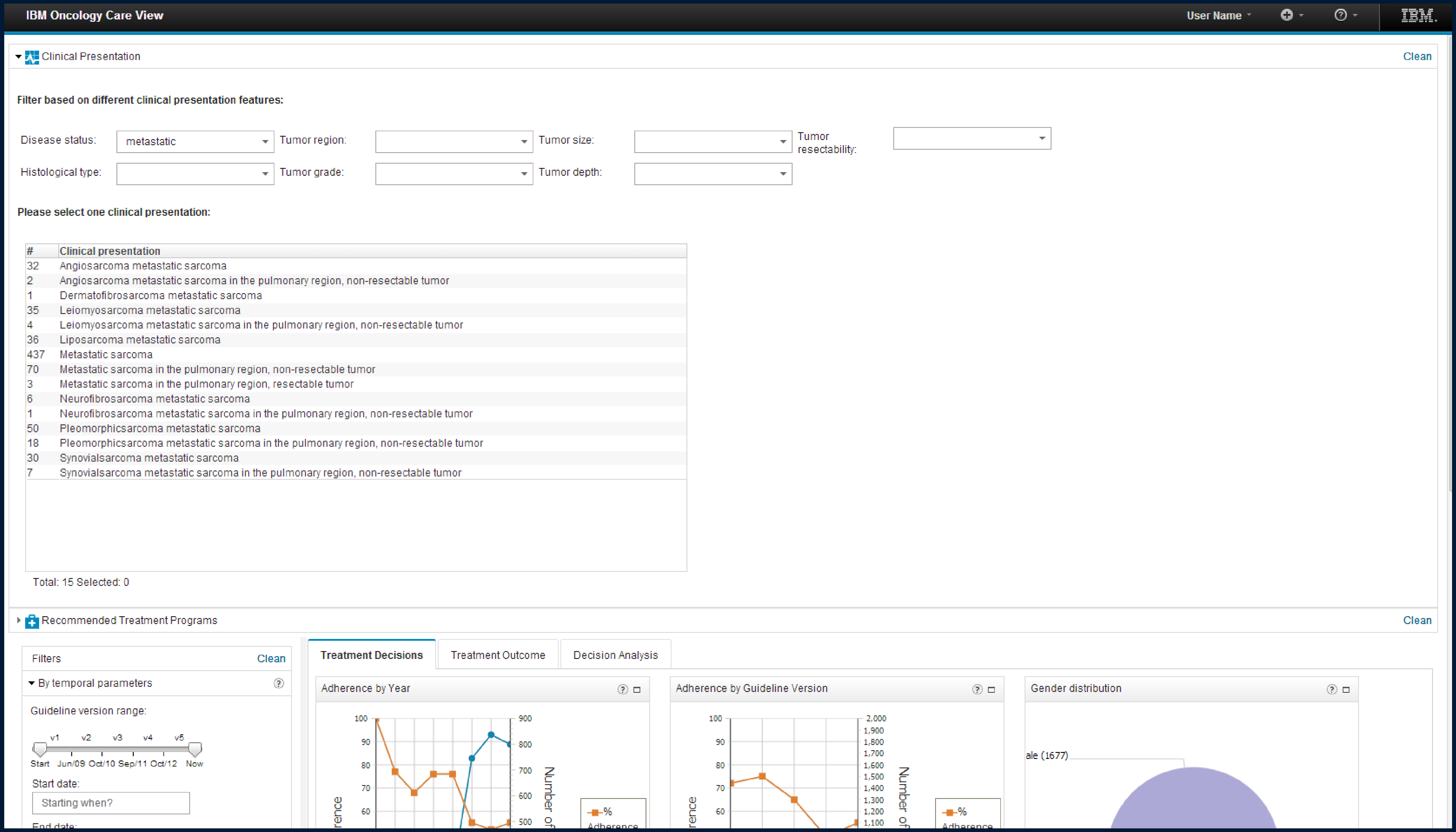
- The experts panel uses **CareEdit** to define the organization's guidelines to support best standard of care

- The physician uses **CareGuide** to decide on the best treatment based on the guidelines, her experience and proficiency and additional inputs from patients and peers

- The ward manager uses **CareView** to review past decisions against organization guidelines and achieved outcome. She can then educate physicians and/or recommend to modify organization's guidelines

System deployed in INT

Fondazione IRCCS
Istituto Nazionale dei Tumori
via Venezian, 1 20133 Milano



#	Clinical presentation
32	Angiosarcoma metastatic sarcoma
2	Angiosarcoma metastatic sarcoma in the pulmonary region, non-resectable tumor
1	Dermatofibrosarcoma metastatic sarcoma
35	Leiomyosarcoma metastatic sarcoma
4	Leiomyosarcoma metastatic sarcoma in the pulmonary region, non-resectable tumor
36	Liposarcoma metastatic sarcoma
437	Metastatic sarcoma
70	Metastatic sarcoma in the pulmonary region, non-resectable tumor
3	Metastatic sarcoma in the pulmonary region, resectable tumor
6	Neurofibrosarcoma metastatic sarcoma
1	Neurofibrosarcoma metastatic sarcoma in the pulmonary region, non-resectable tumor
50	Pleomorphicsarcoma metastatic sarcoma
18	Pleomorphicsarcoma metastatic sarcoma in the pulmonary region, non-resectable tumor
30	Synovialsarcoma metastatic sarcoma
7	Synovialsarcoma metastatic sarcoma in the pulmonary region, non-resectable tumor

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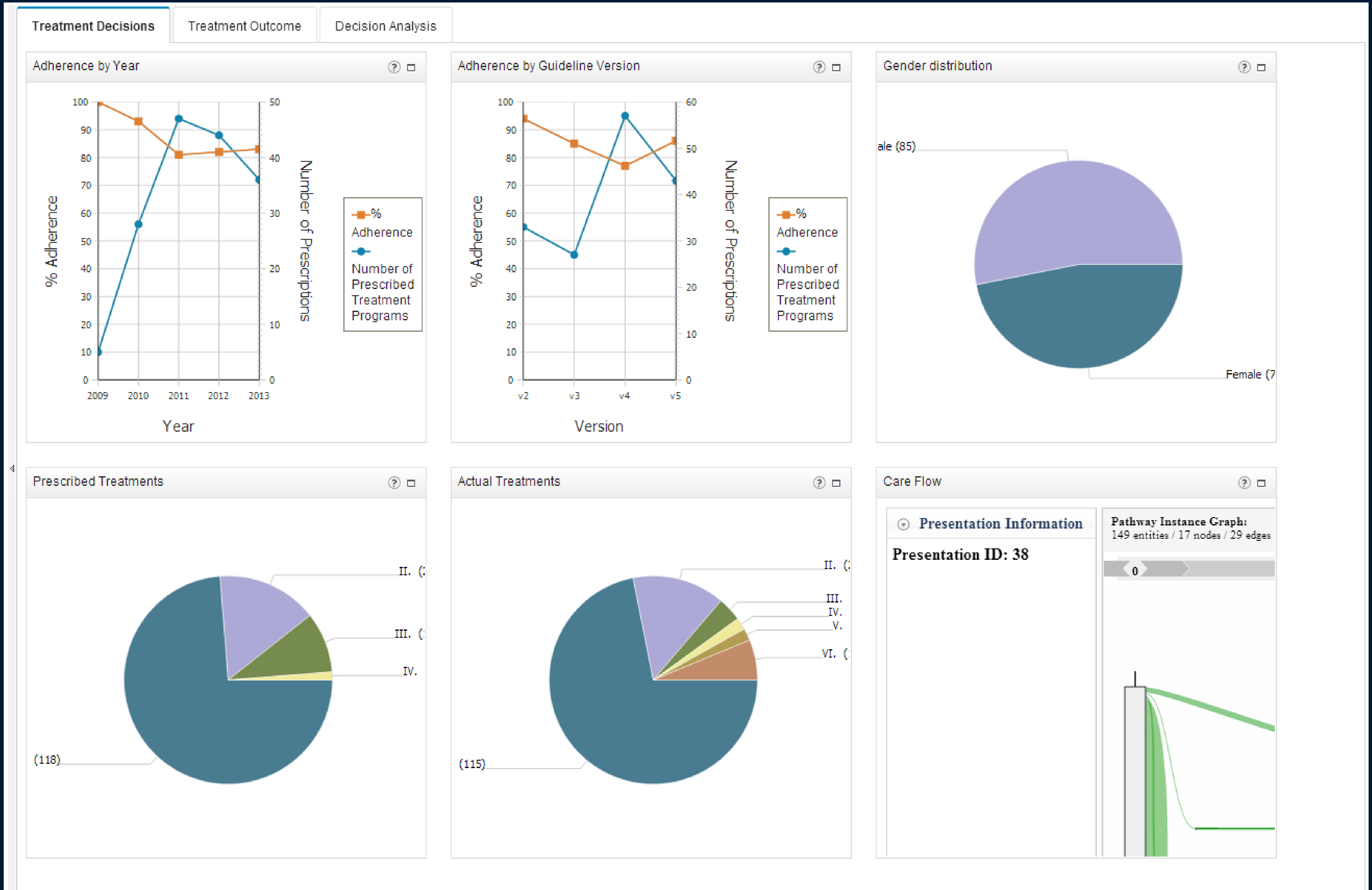

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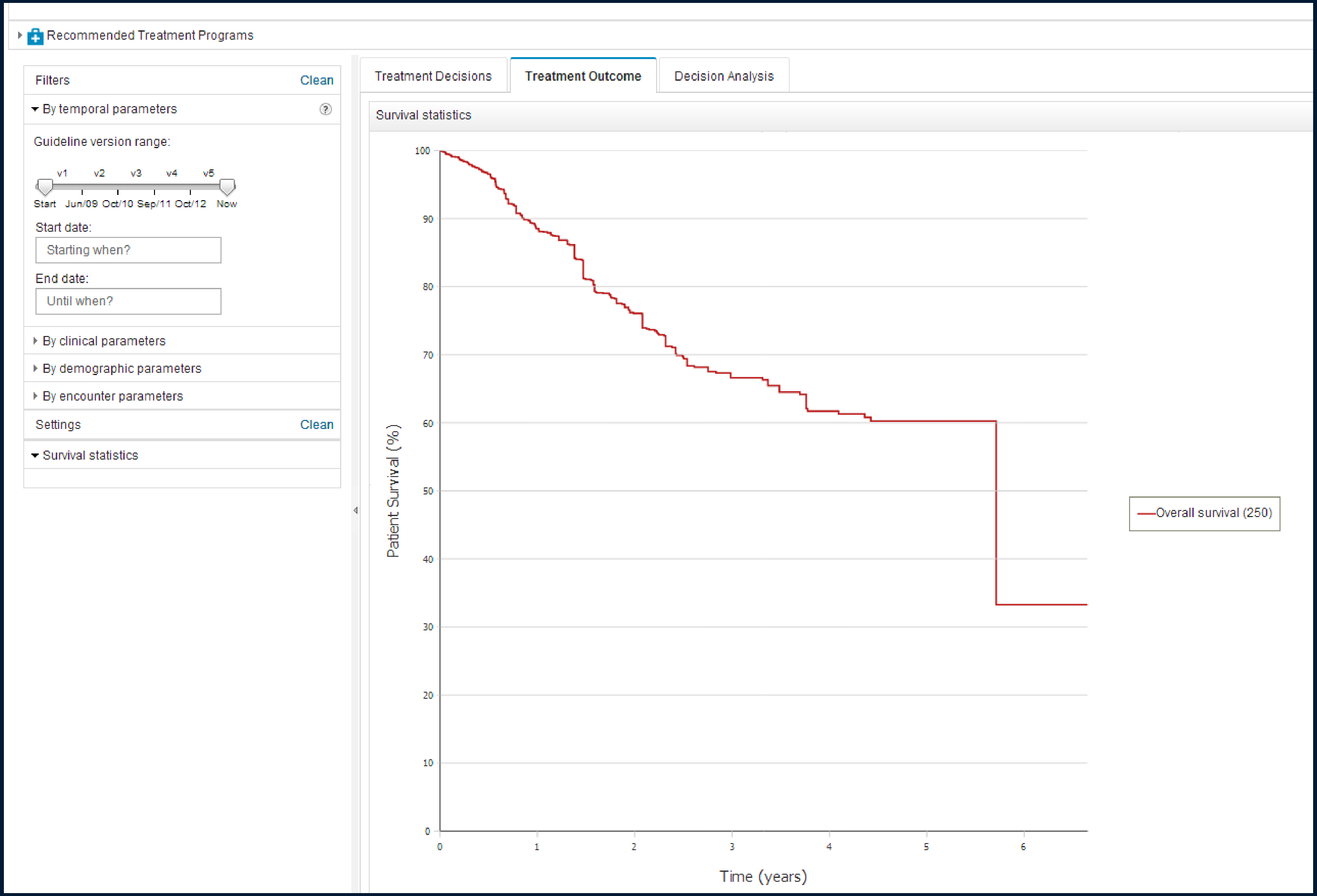
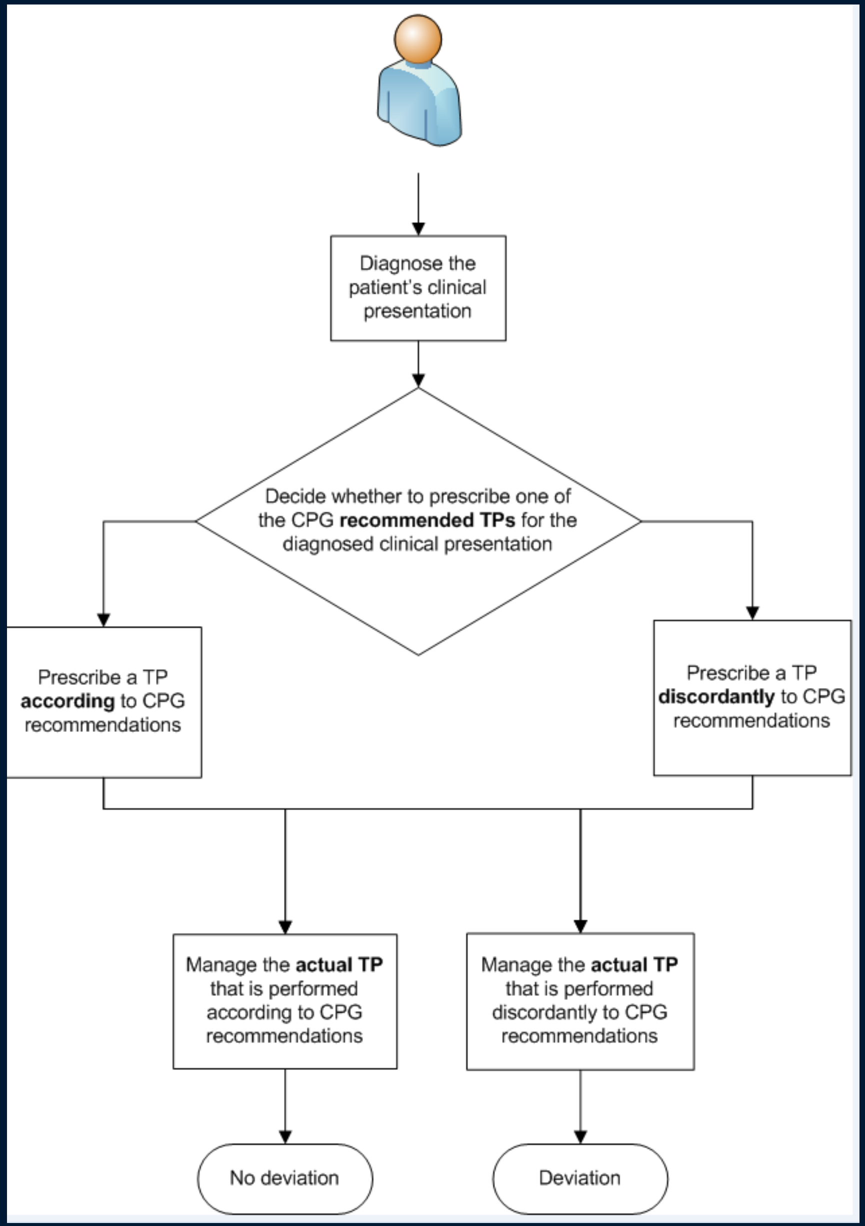
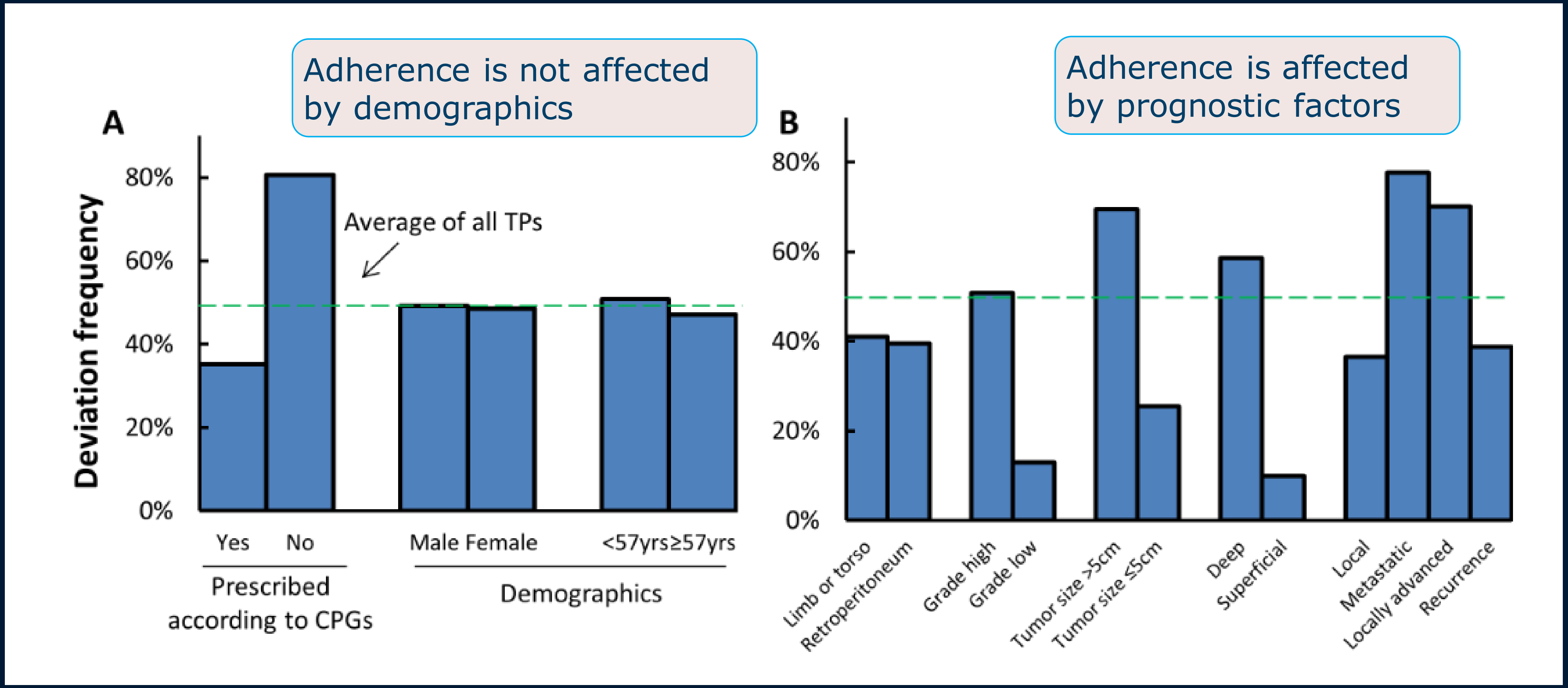
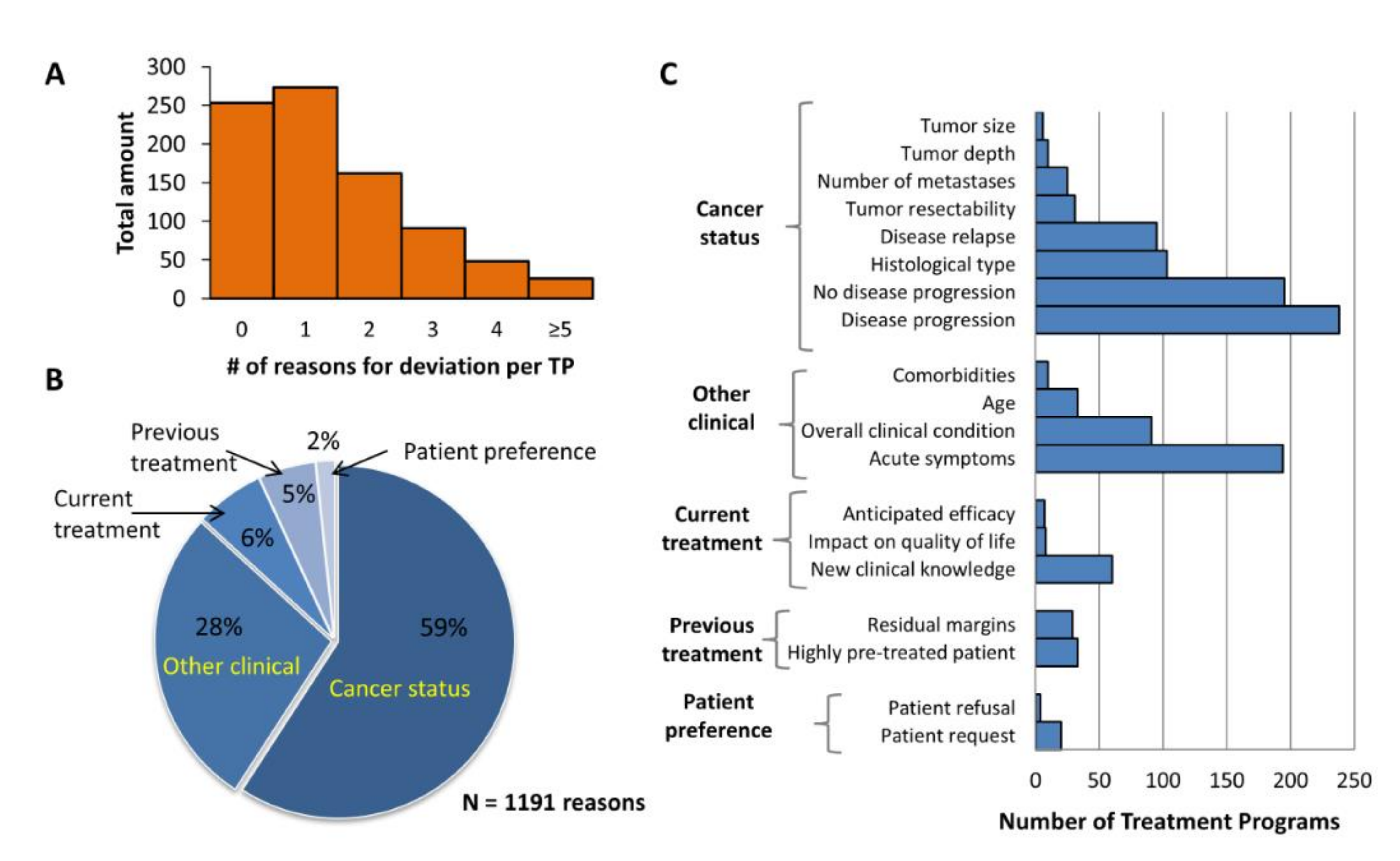


Adherence assessment and deviations from clinical practice guidelines

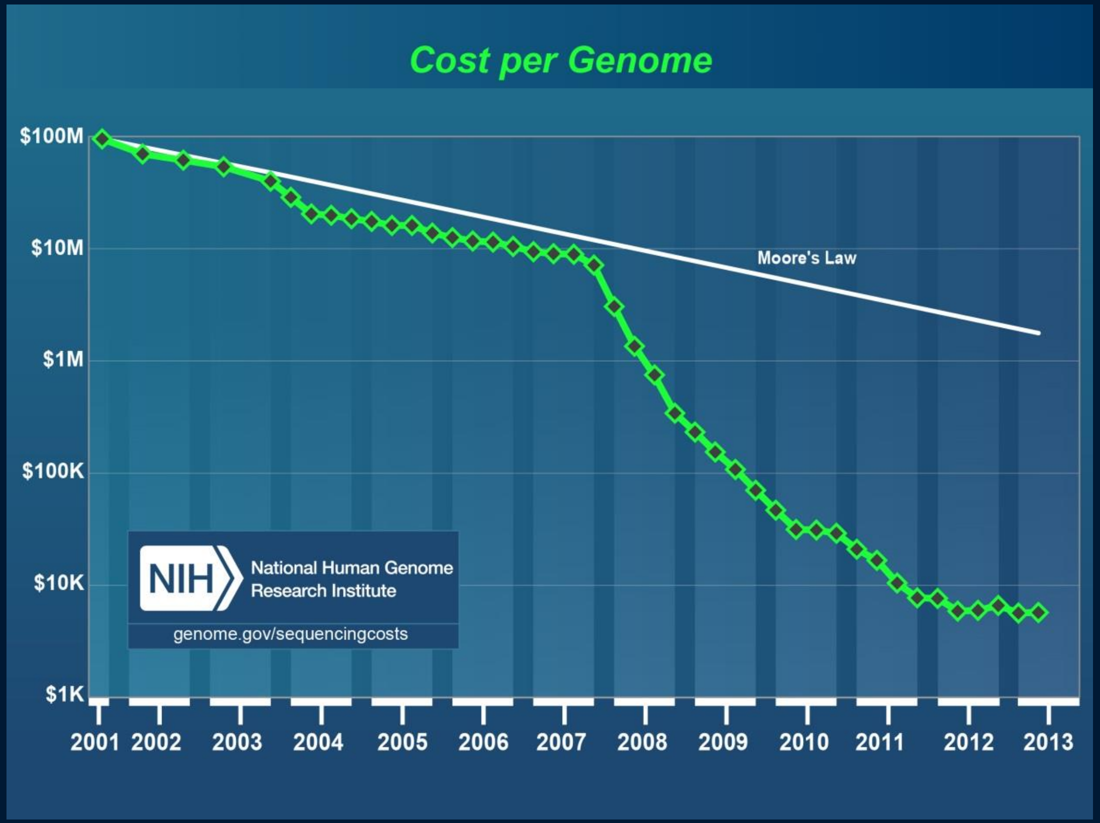


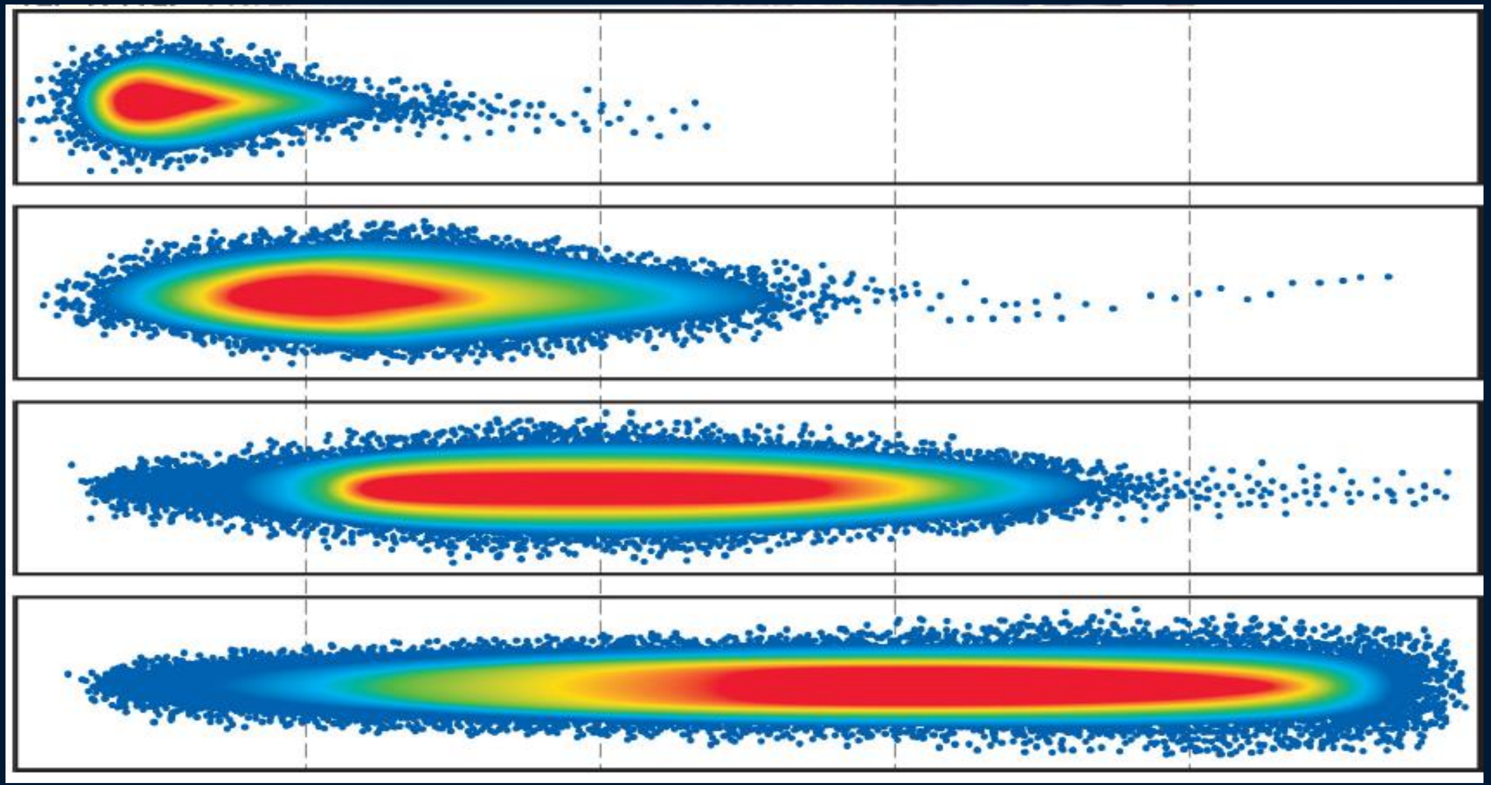


Understanding rationale for deviations from guidelines



The genomics revolution





1990-2003 Human Genome Project

2004-2010

2011-2020

Beyond 2020

Structure of Genomes | **Biology of Genomes** | **Biology of Disease** | **Science of Medicine** | **Translation to Healthcare**

Charting a course for genomic medicine from base pairs to bedside (Nature 2011).
Green ED, Guyer MS, National Human Genome Research Institute.

Personalization of cancer treatment based on genomics

We now know that each cancer patient, and even each patient’s tumor, has a unique molecular profile

- Thousands of mutations
- 20,000 genes
- Hundreds of pathways

This tumor heterogeneity is being addressed by the development of hundreds of new targeted drugs

- **Cancer trials account for about 40% of all clinical trials**

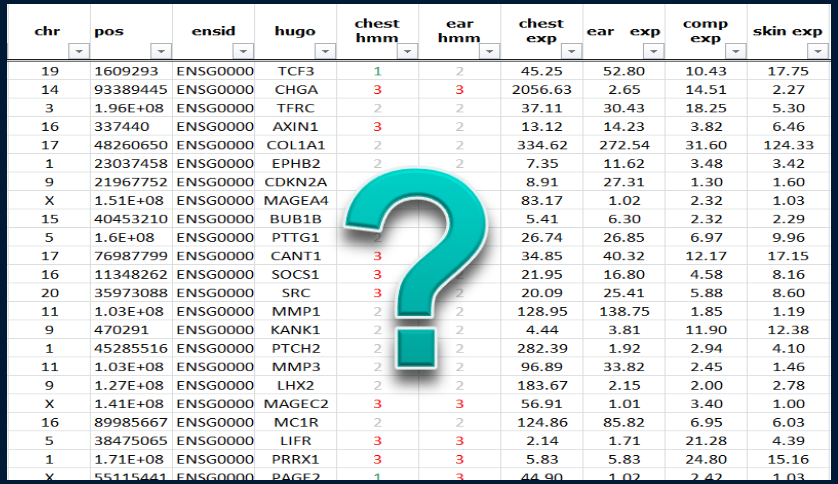
Prescribing drugs to cancer patients becomes a complex task which is beyond the capability of even an expert oncologist

As a results, precision oncology decision support will become the standard of care

The vision: precision oncology cloud service

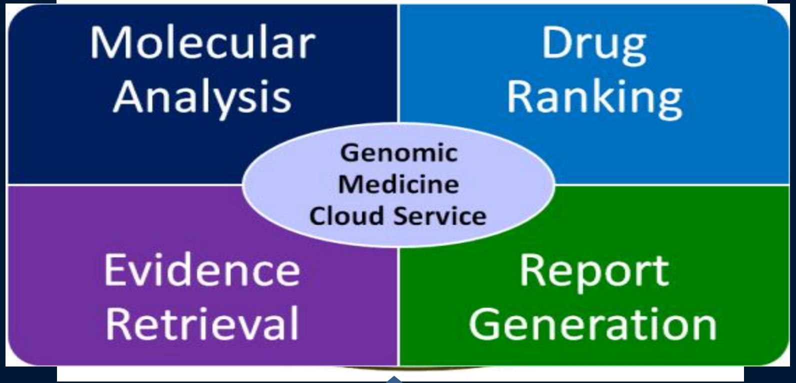
A clinical report that provides ranked list of treatment options based on tumor molecular profile

The 'query':
Tumor molecular profile

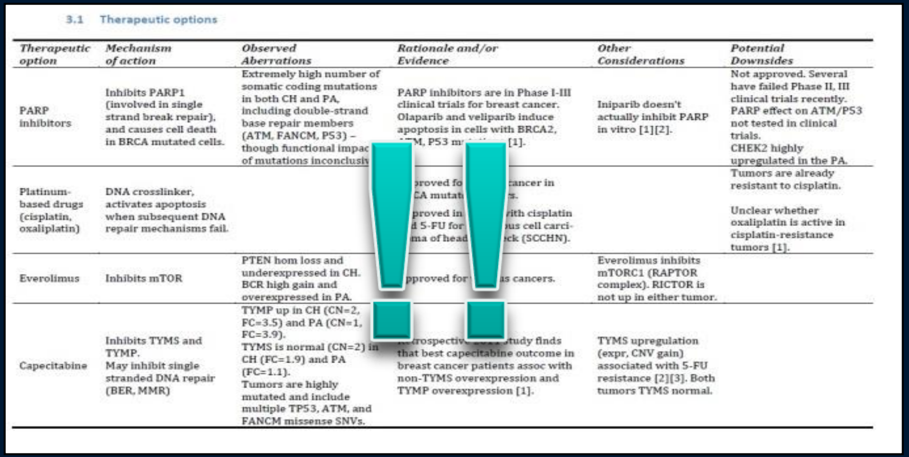


chr	pos	ensid	hugo	chest hmm	ear hmm	chest exp	ear exp	comp exp	skin exp
19	1609293	ENSG0000	TCF3	1	2	45.25	52.80	10.43	17.75
14	93389445	ENSG0000	CHGA	3	3	2056.63	2.65	14.51	2.27
3	1.96E+08	ENSG0000	TFRC	2	2	37.11	30.43	18.25	5.30
16	337440	ENSG0000	AXIN1	3	2	13.12	14.23	3.82	6.46
17	48260650	ENSG0000	COL1A1	2	2	334.62	272.54	31.60	124.33
1	23037458	ENSG0000	EPHB2	2	2	7.35	11.62	3.48	3.42
9	21967752	ENSG0000	CDKN2A	[illegible]	[illegible]	8.91	27.31	1.30	1.60
X	1.51E+08	ENSG0000	MAGEA4	[illegible]	[illegible]	83.17	1.02	2.32	1.03
15	40453210	ENSG0000	BUB1B	[illegible]	[illegible]	5.41	6.30	2.32	2.29
5	1.6E+08	ENSG0000	PTTG1	2	[illegible]	26.74	26.85	6.97	9.96
17	76987799	ENSG0000	CANT1	3	[illegible]	34.85	40.32	12.17	17.15
16	11348262	ENSG0000	SOCS1	3	2	21.95	16.80	4.58	8.16
20	35973088	ENSG0000	SRC	3	2	20.09	25.41	5.88	8.60
11	1.03E+08	ENSG0000	MMP1	2	2	128.95	138.75	1.85	1.19
9	470291	ENSG0000	KANK1	2	2	4.44	3.81	11.90	12.38
1	45285516	ENSG0000	PTCH2	2	2	282.39	1.92	2.94	4.10
11	1.03E+08	ENSG0000	MMP3	2	2	96.89	33.82	2.45	1.46
9	1.27E+08	ENSG0000	LHX2	2	2	183.67	2.15	2.00	2.78
X	1.41E+08	ENSG0000	MAGEC2	3	3	56.91	1.01	3.40	1.00
16	89985667	ENSG0000	MC1R	2	2	124.86	85.82	6.95	6.03
5	38475065	ENSG0000	LIFR	3	3	2.14	1.71	21.28	4.39
1	1.71E+08	ENSG0000	PRRX1	3	3	5.83	5.83	24.80	15.16
X	55115441	ENSG0000	PAGE2	1	3	44.90	1.02	2.42	1.03

Future: IBM Precision Oncology Service



The results:
Report containing ranked list of evidence-supported drug options



3.1 Therapeutic options

Therapeutic option	*Mechanism of action*	*Observed Aberrations*	*Rationale and/or Evidence*	*Other Considerations*	*Potential Downsides*
PARP inhibitors	Inhibits PARP1 (involved in single strand break repair), and causes cell death in BRCA mutated cells.	Extremely high number of somatic coding mutations in both CH and PA, including double-strand base repair members (ATM, FANCM, P53) – though functional impac[illegible] of mutations inconclusiv[illegible]	PARP inhibitors are in Phase I-III clinical trials for breast cancer. Olaparib and veliparib induce apoptosis in cells with BRCA2, [illegible]M, P53 m[illegible] [1].	Iniparib doesn't actually inhibit PARP in vitro [1][2].	Not approved. Several have failed Phase II, III clinical trials recently. PARP effect on ATM/P53 not tested in clinical trials. CHEK2 highly upregulated in the PA.
Platinum-based drugs (cisplatin, oxaliplatin)	DNA crosslinker, activates apoptosis when subsequent DNA repair mechanisms fail.		[illegible]proved fo[illegible] cancer in [illegible]CA mutat[illegible]s. [illegible]proved in [illegible]ith cisplatin [illegible]d 5-FU for [illegible]ous cell carci-[illegible]ma of head [illegible]ck (SCCHN).		Tumors are already resistant to cisplatin. Unclear whether oxaliplatin is active in cisplatin-resistance tumors [1].
Everolimus	Inhibits mTOR	PTEN hom loss and underexpressed in CH. BCR high gain and overexpressed in PA.	[illegible]pproved for [illegible]s cancers.	Everolimus inhibits mTORC1 (RAPTOR complex). RICTOR is not up in either tumor.	
Capecitabine	Inhibits TYMS and TYMP. May inhibit single stranded DNA repair (BER, MMR)	TYMP up in CH (CN=2, FC=3.5) and PA (CN=1, FC=3.9). TYMS is normal (CN=2) in CH (FC=1.9) and PA (FC=1.1). Tumors are highly mutated and include multiple TP53, ATM, and FANCM missense SNVs.	[illegible]rospectiv[illegible] study finds that best capecitabine outcome in breast cancer patients assoc with non-TYMS overexpression and TYMP overexpression [1].	TYMS upregulation (expr, CNV gain) associated with 5-FU resistance [2][3]. Both tumors TYMS normal.	

Batch processing: Comprehensive corpora of biomedical insights and supportive evidence

Public health for Africa: Cervical cancer

Africa’s **second highest cause of mortality**, stems in **poor awareness**, **scarce access to timely screening** and treatment and **lack of strategic public health infrastructure.**

Our goal:

- boost awareness about Cervical Cancer
- improve monitoring and decision making
- promote a proactive approach to public health in Africa

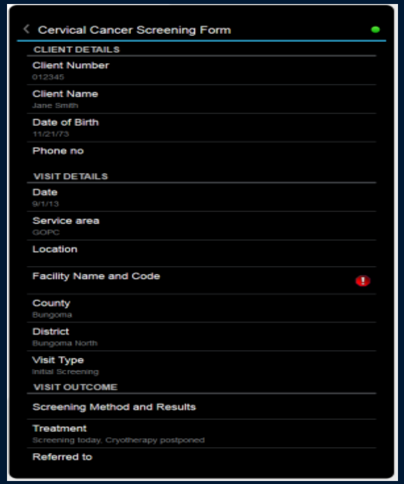
Method

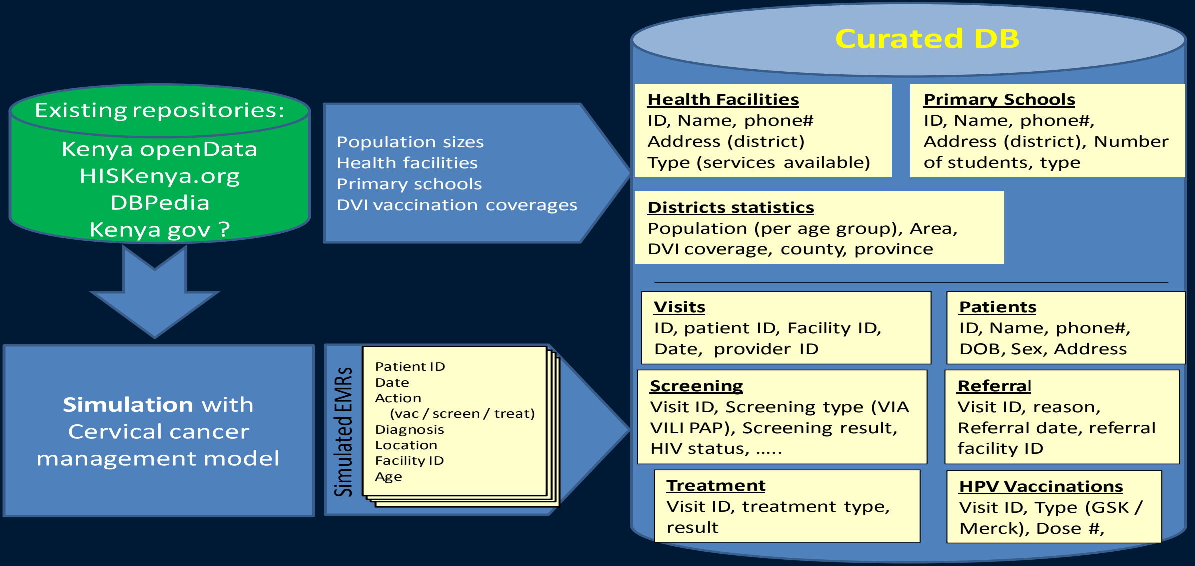
- A new system that leverages cloud and mobile technologies to gather, manage, analyze and visualize data on cervical cancer in Kenya

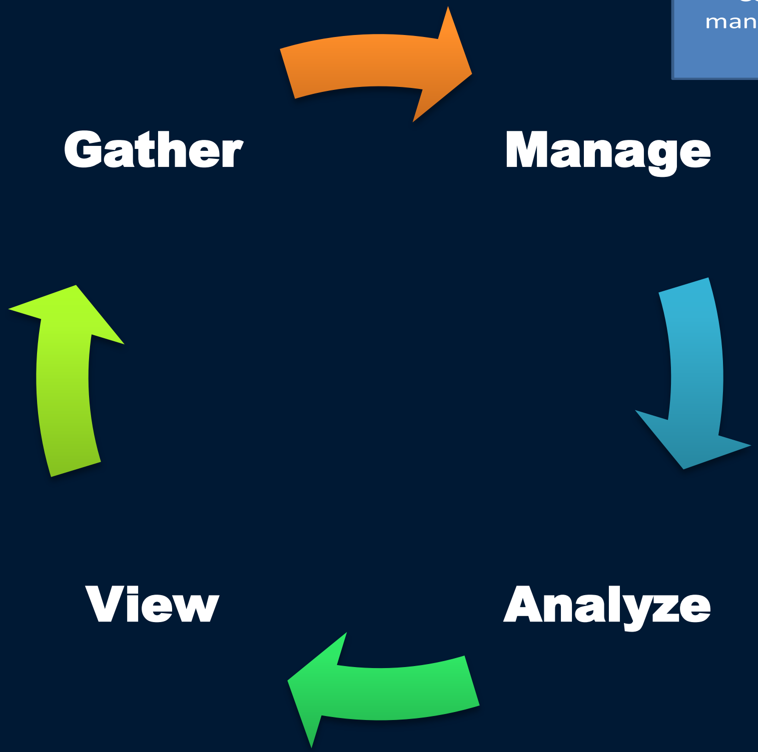
“Instead of waiting for the patient to come to the clinic, the clinic comes to the patient”

Solution Architecture

Mobile apps:
Mobile clinic,
Collect data from
the field

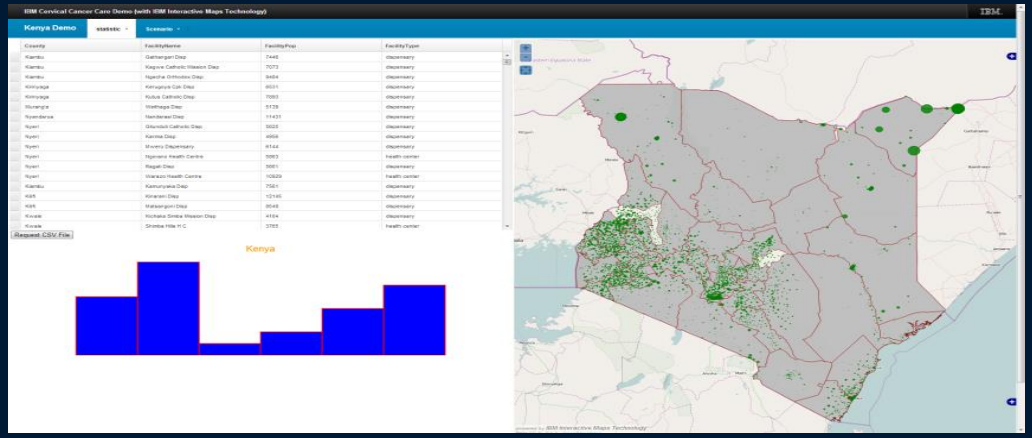

Cervical Cancer Screening Form
CLIENT DETAILS
Client Number
Client Name
Date of Birth
Phone no
VISIT DETAILS
Date
Service area
Location
Facility Name and Code
County
District
Visit Type
VISIT OUTCOME
Screening Method and Results
Treatment
Referred to

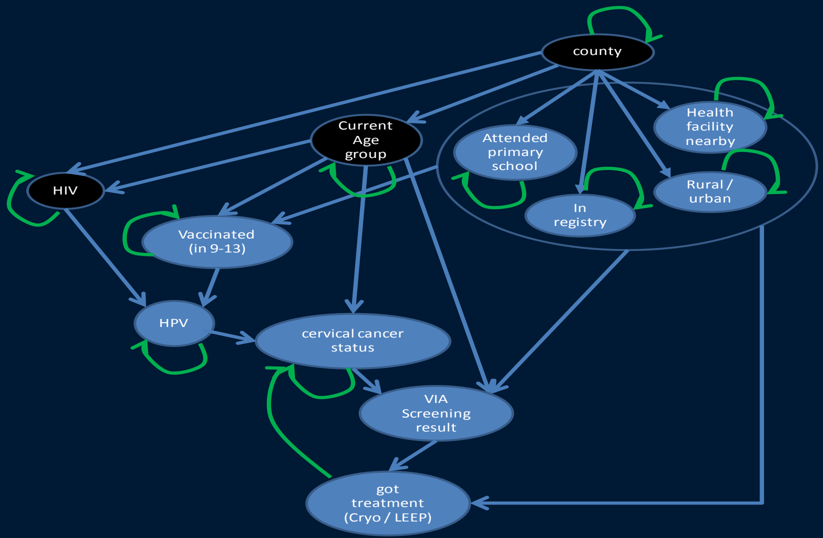




Centralized registry

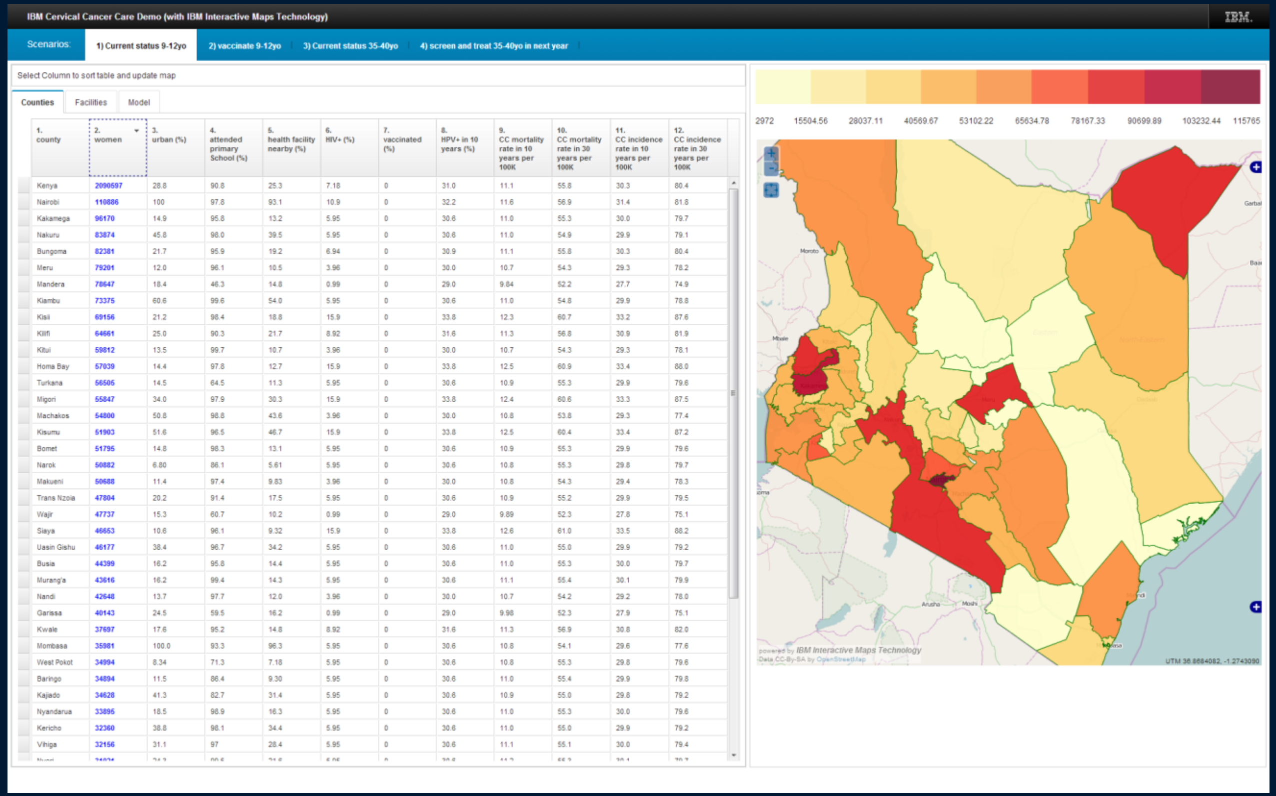
Data access and visualization application for decision support





Probabilistic graphical model of cervical cancer care

Specific Scenarios of interest and their future impact can be checked



	9-12 year olds, current situation	vaccinate 9-12 year olds	35-40 year olds, current situation	screen and treat 35-40 year olds	units
cost	0	17090159	0	12464287	dollars
lives saved in 10 year period	0	262.77	0	1439.6	women
lives saved in 30 year period	0	6526.99	0	4817.01	women
years of life saved in 10 year period	0	214.63	0	1436.12	years
years of life saved in 30 year period	0	18260.82	0	17092.3	years
women in age group	2090597	2090597	1194738	1194738	women
healthcare savings in later 10 years	0	13786	0	25130	dollars
cancer incidence rate in 10 years	30.29	18.57	103.32	78.43	women per 100,000
cancer incidence rate in 30 years	80.37	50.25	158.13	154.38	women per 100,000

Comparing the two plans, screening and treating all the 35-40 year olds has a large short term effect and is cheaper while the vaccination costs more but saves more lives in the 30 year period

New technology for a better quality of life

Thank you

The 5th

Clinical Genomics Analysis Workshop
June 15, 2014 @ IBM Haifa

Co-Chaired with
The Safra Bioinformatics Center, Tel Aviv University

Medical Informatics Innovation day
June 16, 2014 @ IBM Haifa

Keynote: Prof Isaac Kohane, Harvard Medical School

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