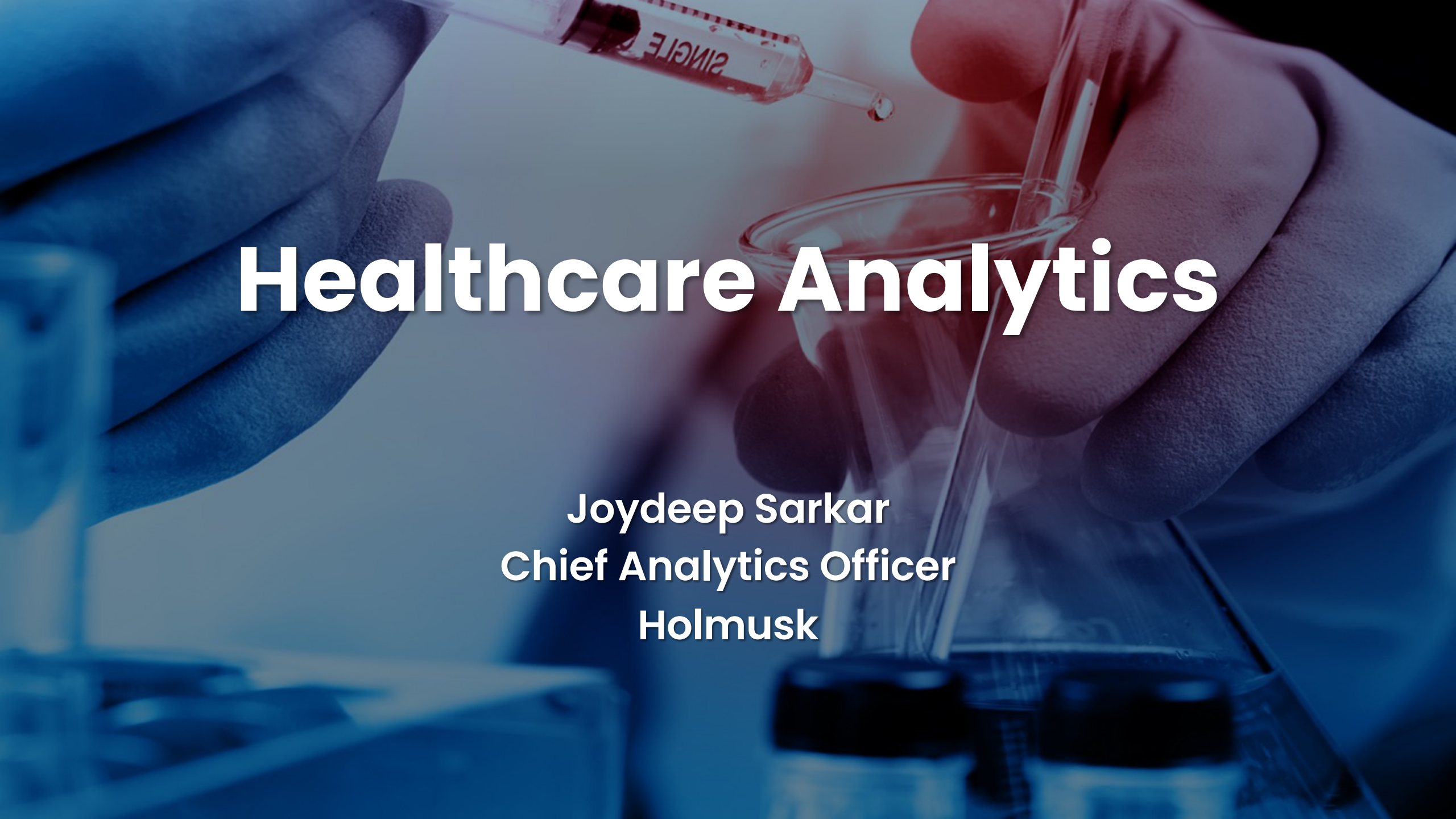




Healthcare Analytics

Joydeep Sarkar
Chief Analytics Officer
Holmusk

Introduction

Holmusk is a next-generation digital health and data analytics company, focused on solving complex problems in healthcare for chronic diseases & behavioral health

We develop predictive algorithms that offer actionable insights for personalized care and population health. Holmusk models leverage years of published scientific and clinical research and electronic health data sets to make clinically predictive models.

We are based in Singapore, Malaysia, USA, EU

Holmusk management team



Nawal Roy
Founder & CEO

Nawal is Founder and CEO of Holmusk. Prior to this, Nawal was Co-Founder and CEO of HelloPay (Rocket internet venture). Before leading HelloPay, Nawal was Junior Partner leading client advisory service line in McKinsey & Company. He has been deeply involved with serving clients across North American, Europe, South East Asia, India, China, Middle East & Africa.



Dr. Yau Teng Yan
Chief Medical Officer

Dr Yau Teng Yan (MBBS, M.Med, FRCR) is a medical doctor with 8 years of professional experience in Singapore. He trained in Diagnostic Radiology while practising at TTSH, SGH & NCC. Prior to that, he has worked in clinical departments in various hospitals, including Emergency Medicine, Surgical ICU & Anaesthesiology.



Dr. Waqas Awan
Chief Product Officer

Dr Waqas is a product development and health technology specialist with 10 years experience in consumer and corporate health management. Waqas earned his doctorate in bioinformatics at the University of Cambridge. He is passionate about utilising technology, design and data to humanise and increase access to healthcare.



Sai Subramanian
Chief Technology Officer

Subra is a Computer Engineer from NUS. He enjoys making things that work and solving hard problems, especially problems of scaling. He likes tinkering with all parts of the stack but spends most of his time with Haskell evangelism, much to the dismay of people who end up talking to him.



Joydeep Sarkar
Chief Analytics Officer

Joydeep has a background in Biomedical Engineering specialising in simulation modeling with over 10 years of experience in healthcare analytics. Prior to joining Holmusk, he worked with major providers, medical device manufacturers & most major pharmaceutical companies developing advanced analytics solutions. On the side he continues to work in healthcare research and has a proven track record of publications and presentations

McKinsey&Company



What is Healthcare Analytics?

Healthcare Analytics Market

Clinical Analytics

Claims Analytics

Supply Chain Analytics

Pricing Analytics

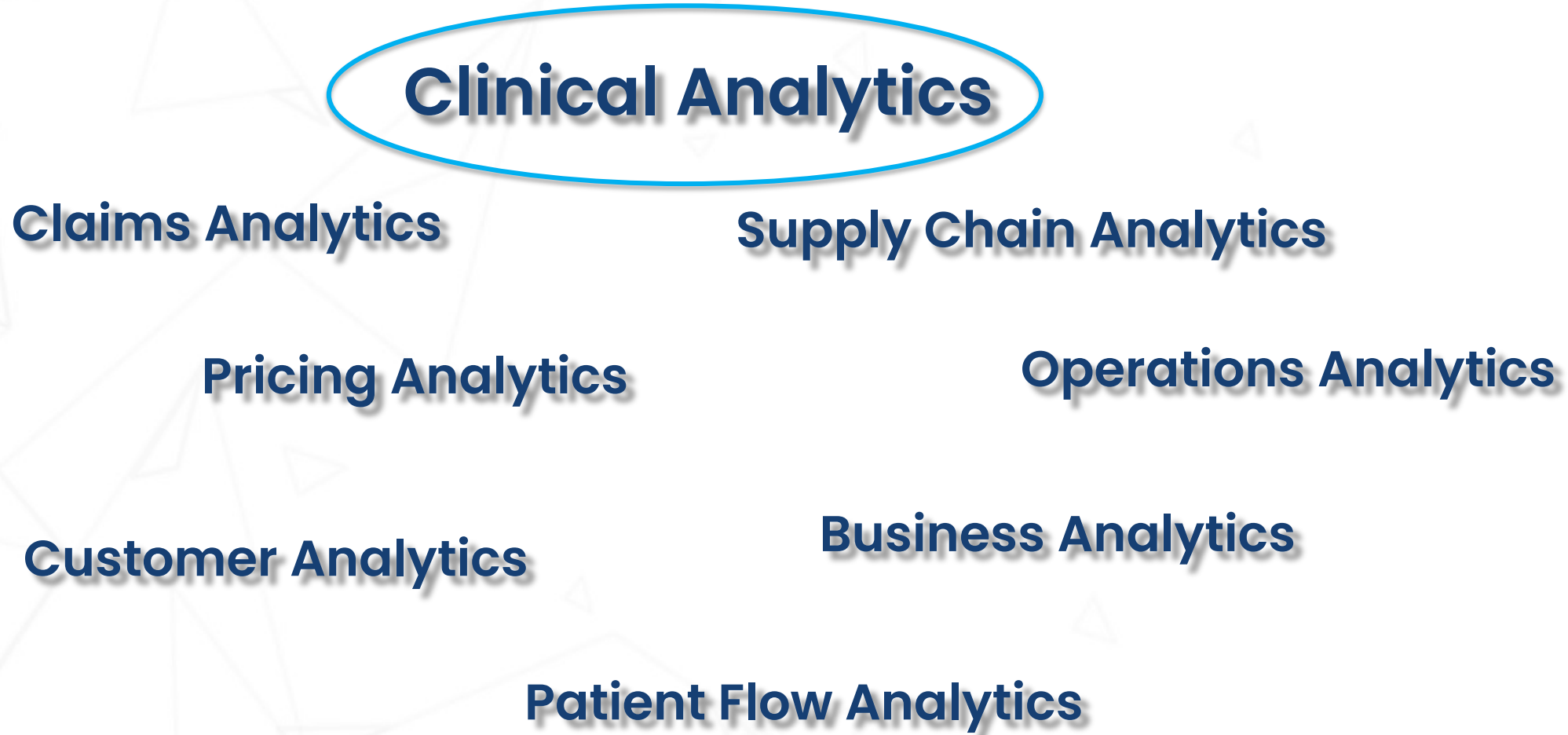
Operations Analytics

Customer Analytics

Business Analytics

Patient Flow Analytics

Healthcare Analytics Market



Clinical Analytics

Claims Analytics

Supply Chain Analytics

Pricing Analytics

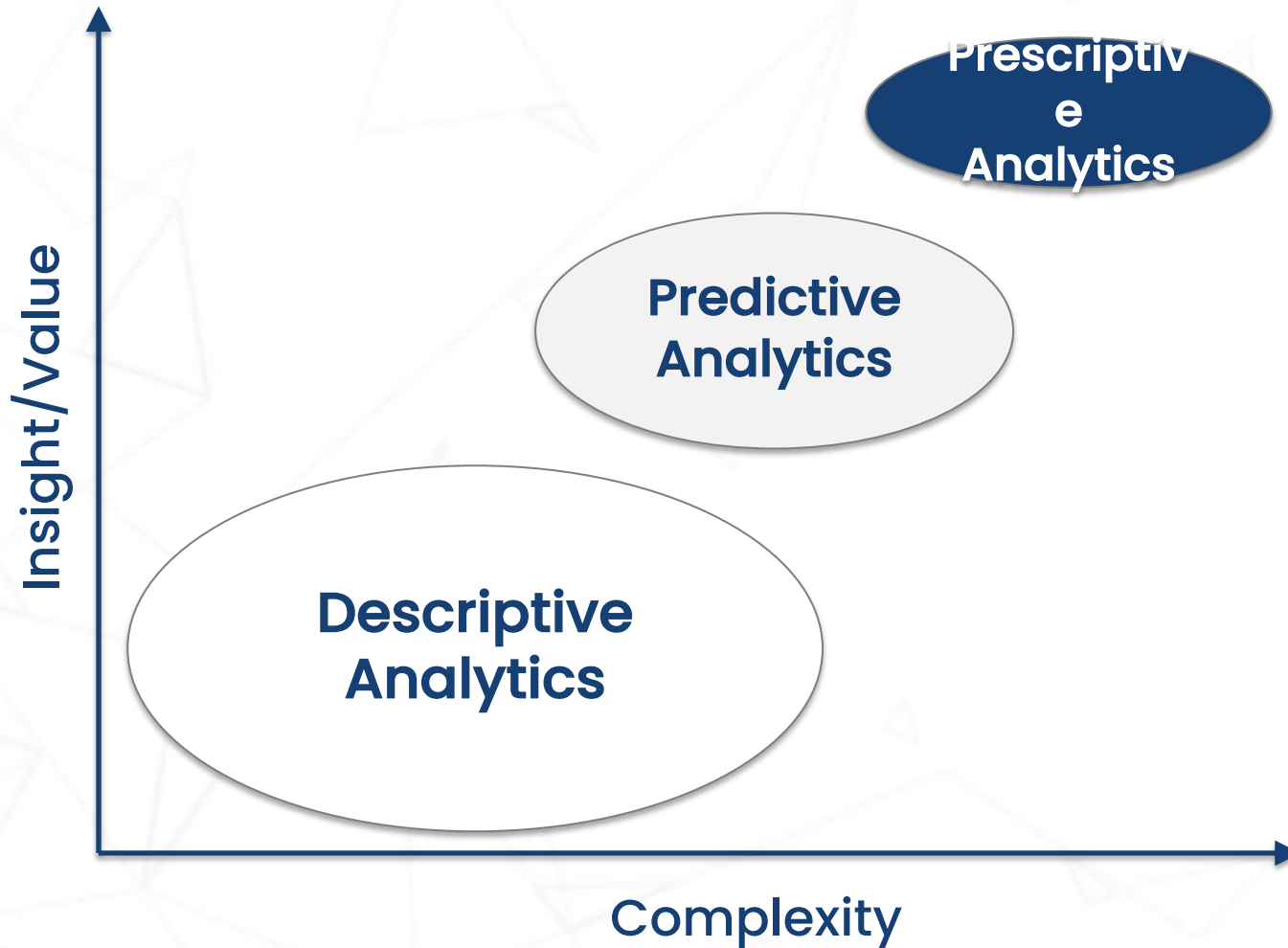
Operations Analytics

Customer Analytics

Business Analytics

Patient Flow Analytics

Types of Analytics



Simulation of "what if" scenarios for individual patients and can affect decision making

Disease diagnosis, risk stratification that has the potential for generating actionable insights

Summary statistics, trends, changes over time in the past over populations or cohorts of patients

Analytics Techniques

Descriptive Analytics

Hypothesis testing (statistical testing), Clustering (K-means, EM, Hierarchical, Latent class etc.), GMM

Predictive Analytics

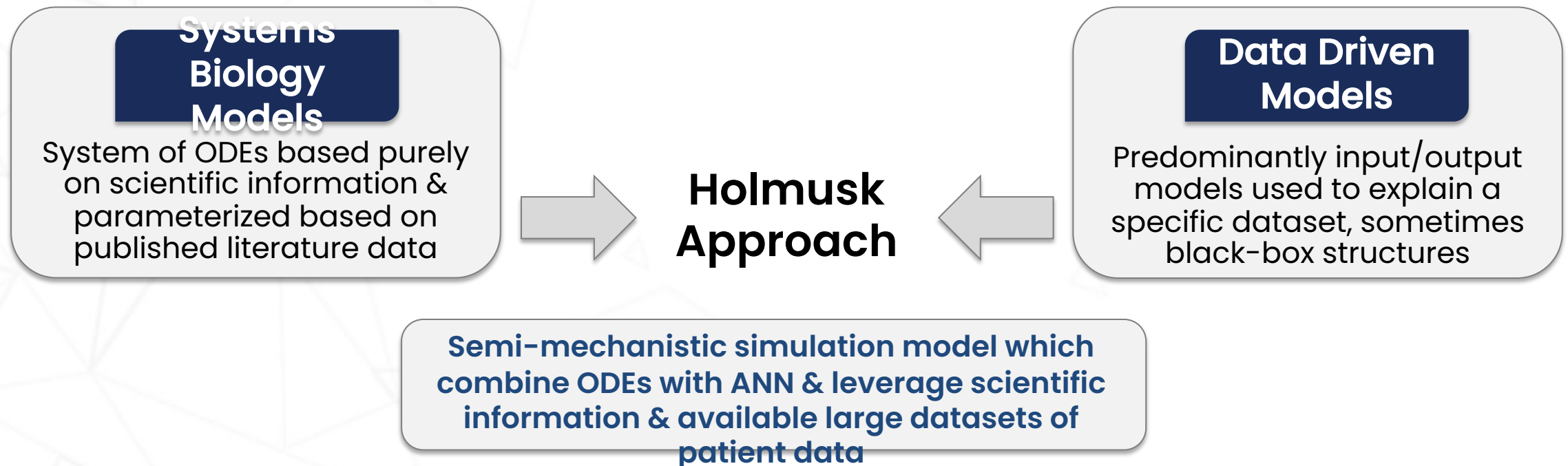
Classification models (Random Forest, Gradient Boosting, SVM, logistic regression)
Regression models (Neural networks, linear regression, ARIMA)
Deep Learning (CNN, RNN, LSTM), NLP

Prescriptive Analytics

Quantitative systems pharmacology
System dynamics models, discrete simulation models
Agent based models, Hybrid models

Holmusk Modeling Approach

- Challenges with analytics in healthcare & life sciences:
 - High dimensional systems
 - Time varying interactions that are not completely understood
 - Time varying interventions
- Clinical data in EHR is not consistent, longitudinal data is hard to get
- Data driven models are harder to explain biological/physiological causality



Major Depressive Disorder (MDD)

Can TRD patients be identified earlier in the treatment process to allow better treatment & use of new generation drugs

Greater than 50% of patients with MDD suffer from Treatment resistant depression (TRD)

It can take around 18–24 months before a patient is diagnosed with TRD, if at all

TRD patient cohort shows high rates of attrition & poor overall outcomes



MindLinc Global Database (MGD)



20

years

First EMR designed to support mental and health research by leaders in behavioral health at Duke University



30 Healthcare institutions

have deployed MindLinc, MGD is the largest behavioral health database in the world



Over 500,000 patients

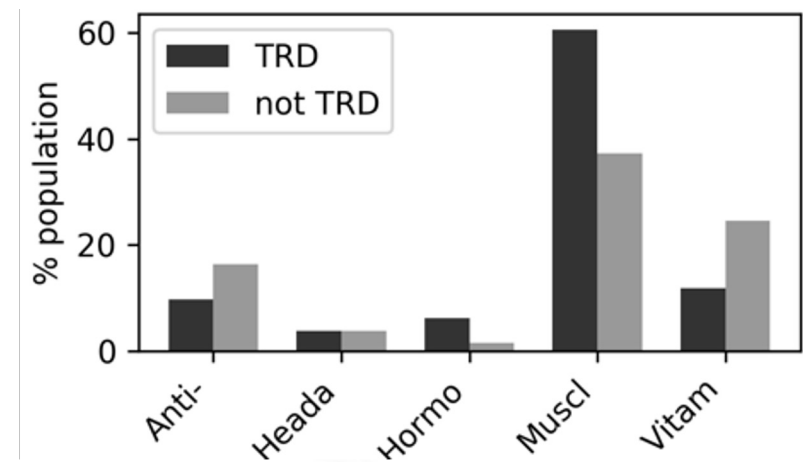
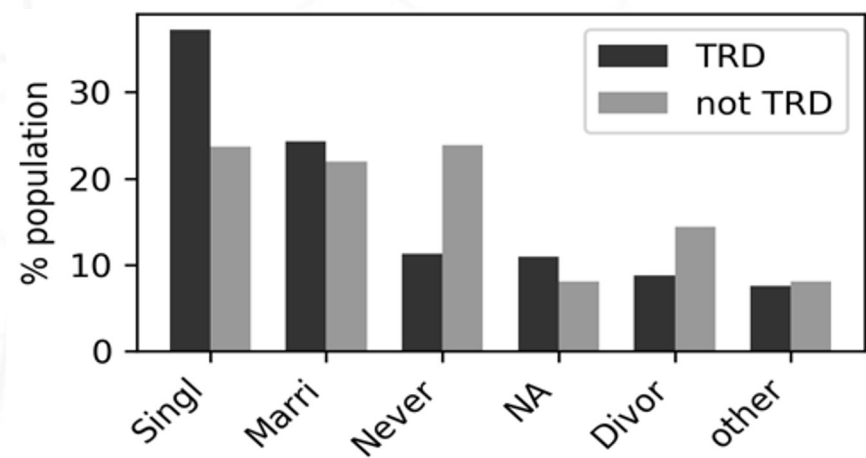
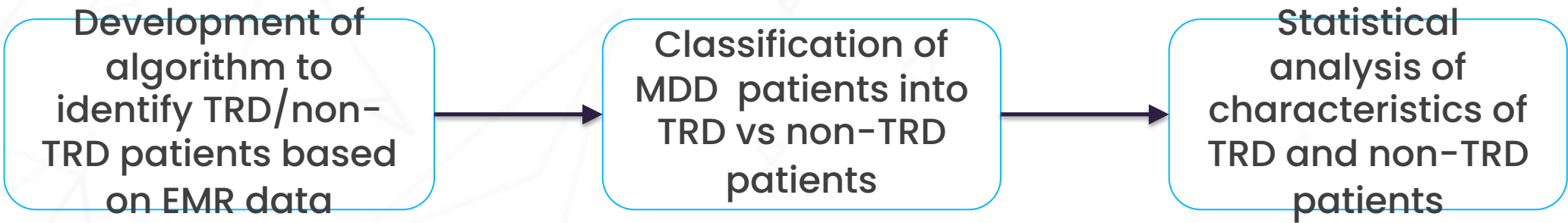
data collected during 7 million visits

MGD has over 140K patients with MDD with an median duration of data of 2 years over 15 visits

Data collected from patients:

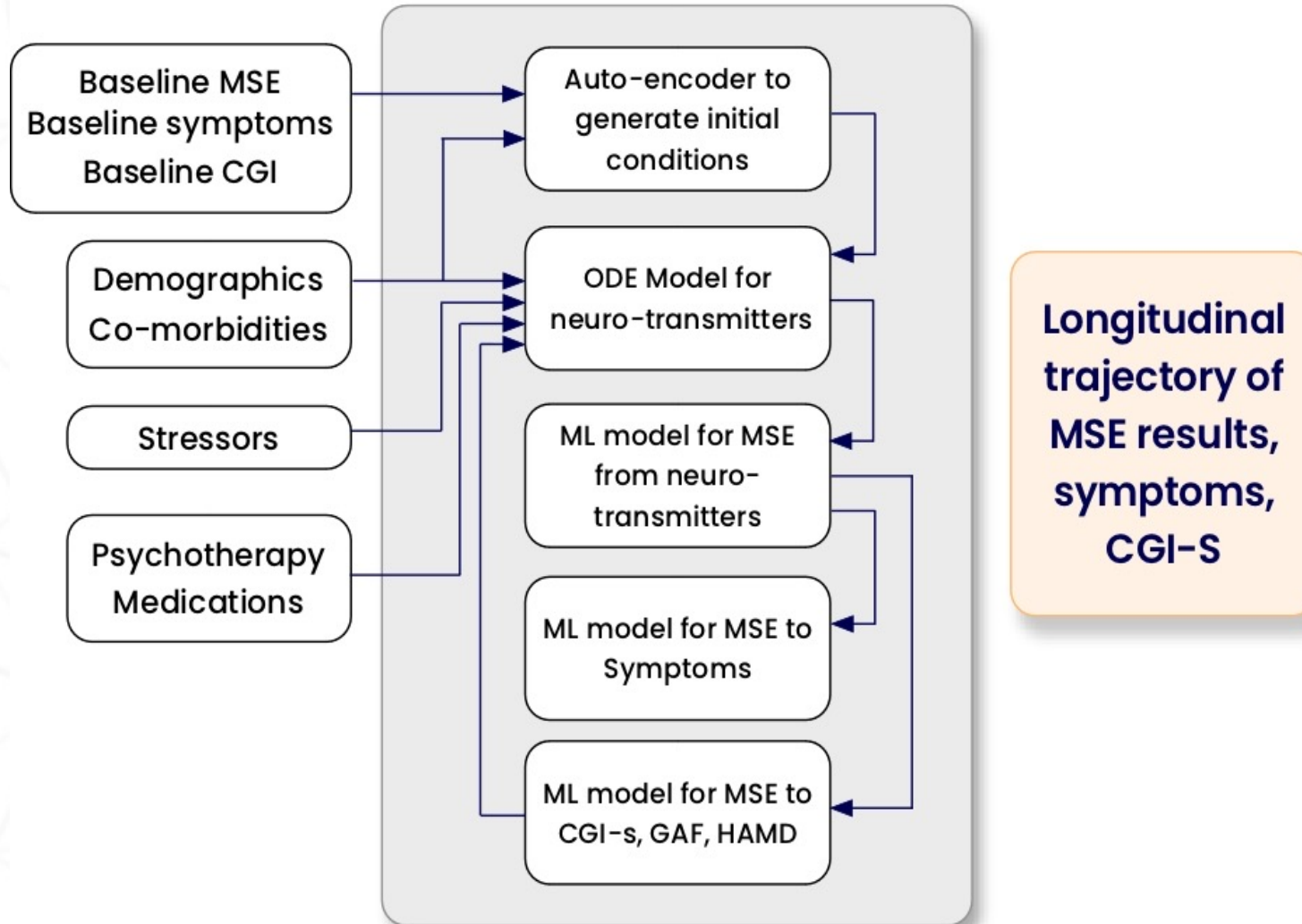
- Demographic information (age, gender, family size, ethnicity)
- Social information (marital status, living status, job status)
- Family history of mental health disorders
- Co-morbidities and associated medications (each visit)
- Current mental disorder related symptoms, GAF, HAMD scores (most visits)
- Mental state examinations (MSEs) (almost all visits)
- Clinical Global Impression Score (CGI-S) (mandatory)
- Medications, side effects (mandatory)

Statistical Analysis of MGD data for insights



Analysis of the EMR data from patients with Major Depressive Disorder (MDD) classified into TRD/non-TRD showed clear risk for patients who are single and patients who tend to be on muscle relaxants

Simulation Model of Major Depressive Disorder (MDD)



Simulation Model of Major Depressive Disorder is trained and tested on 80K patients before validation

Data from the first 3 visits is provided to generate initial prediction

Predictions are refined as data from each visit is added to the model

Early identification of TRD patients

The MDD simulation model was used to classify the patients into TRD/non-TRD

- The first prediction of classification was done at visit 1 (baseline)
- For each subsequent visit, the additional data was used to refine & update the prediction
- The predictions were compared to the classification of TRD/non-TRD from the 2 year data

Time	Visit 1	Visit 3	Visit 5	Visit 7
PPV (%)	55	65	69	73

The model will be further validated on an external dataset before publications and application in improved patient identification for inclusion into clinical trials for TRD patients

Cardiovascular Disease



Problem

National Heart Center Singapore (NHCS) wanted to achieve:

- Improved outcomes : Reduced risk of 1 year mortality, post operative bleeding and readmissions
- Reduced cost : Optimize their operations for increased efficiency to bring down overall operating cost

Approach

- NHCS provided operations, clinical and financial data for all patients admitted during 2007–2014
- Analysis was focused on the relationship between comorbidities, medications prescribed at discharge to outcomes and cost
- Predictive models based on machine learning methods were developed and simulation analysis was used to generate

Solution

- Comparison to metrics from Journal of Clinical Investigation, revealed shortcomings in the operations of NHCS
- Improved risk stratification of patients could help in focused follow-up of patients, reducing chances of adverse outcomes
- The analysis further revealed insights related to compliance with specific discharge medications that could improve outcomes

Improving on existing models of risk

In first phase of work, Holmusk data scientists working on a data from NHCS generated predictive models significantly more accurate than currently used models of risk

Risk score	Purpose	AUC (Risk score)	AUC (Holmusk model)
EuroSCORE II	In-hospital cardiac surgery mortality	80.0%	88.7%
STS*	Cardiac surgery mortality (from discharge up to 30-days)	78.0%	86.0%
ADHERE	In-hospital heart failure mortality	73.0%	88.0%
OPTIMIZE-HF	In-hospital heart failure mortality	75.4%	88.0%
MAGGIC	1-year heart failure mortality	64.7%	75.8%
SHFM*	1-year heart failure mortality	72.9%	75.8%

**Not tested with our SCDB data, as some of the features they used do not exist in our data*

How to improve outcomes for PCI patients?

MI patients undergoing emergency PCI who survive the initial hospital stay often suffer from MI, revascularization and other CVD related hospitalizations over the next year

The objective of this work was to:

- Risk stratify the patients post discharge
- Rank the drivers of risk in these patients
- Identify the modifiable risk factors, actionable interventions to improve outcomes

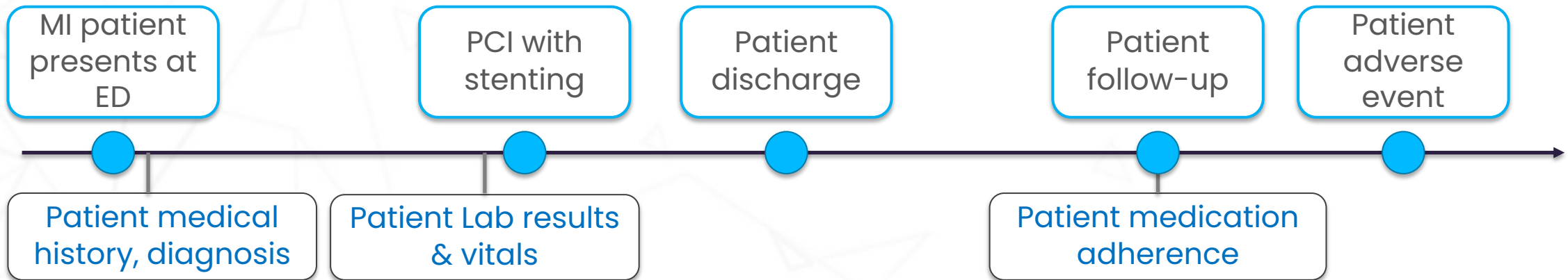
Holmusk data scientists used the **SingCLOUD** database to answer the above questions

SingCLOUD database & analysis

Singapore Cardiovascular Longitudinal Outcomes Database collects data from public hospitals

- Patients with MI and emergency PCI were collected
- Data consistency, availability filter were applied
- Approximately 3500 patients matched all criteria and were used for analysis

Patient Journey



Predictive Modeling of PCI patients



Due to data limitation the simulation was designed to be only have 12 state variables (7 labs/vitals and 5 risk variables)



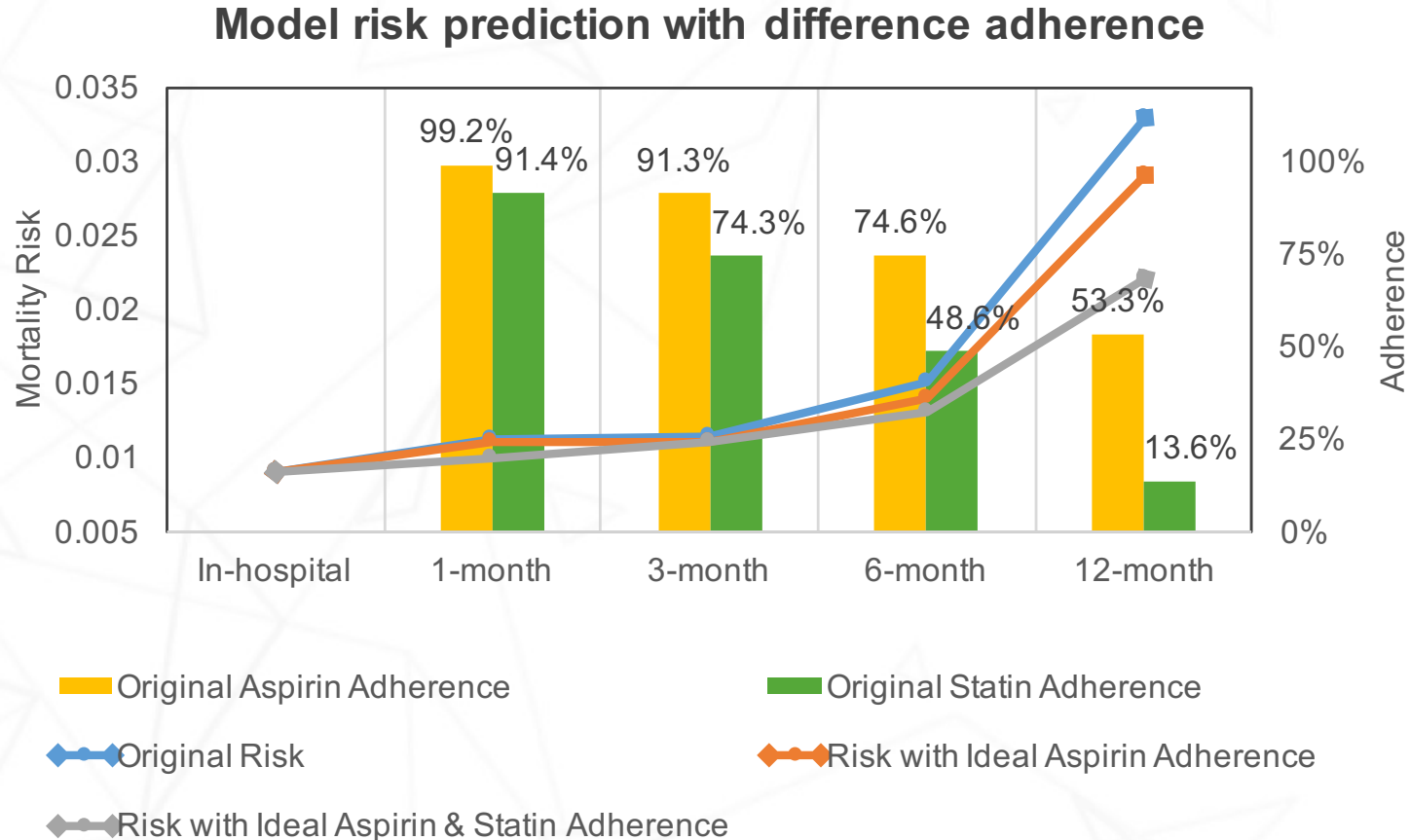
Effect of different prescription CV related drugs were obtained from literature and incorporated into the model

Predictability of mortality

time	discharge	30-day	90-day	6-months	12-months
AUC	0.9	0.89	0.87	0.85	0.79

- Using the model, patient drug adherence was identified one of the most important modifiable risk factor for outcomes post discharge
- The model was used to quantify the added risk of non-adherence of individual medications on individual patients

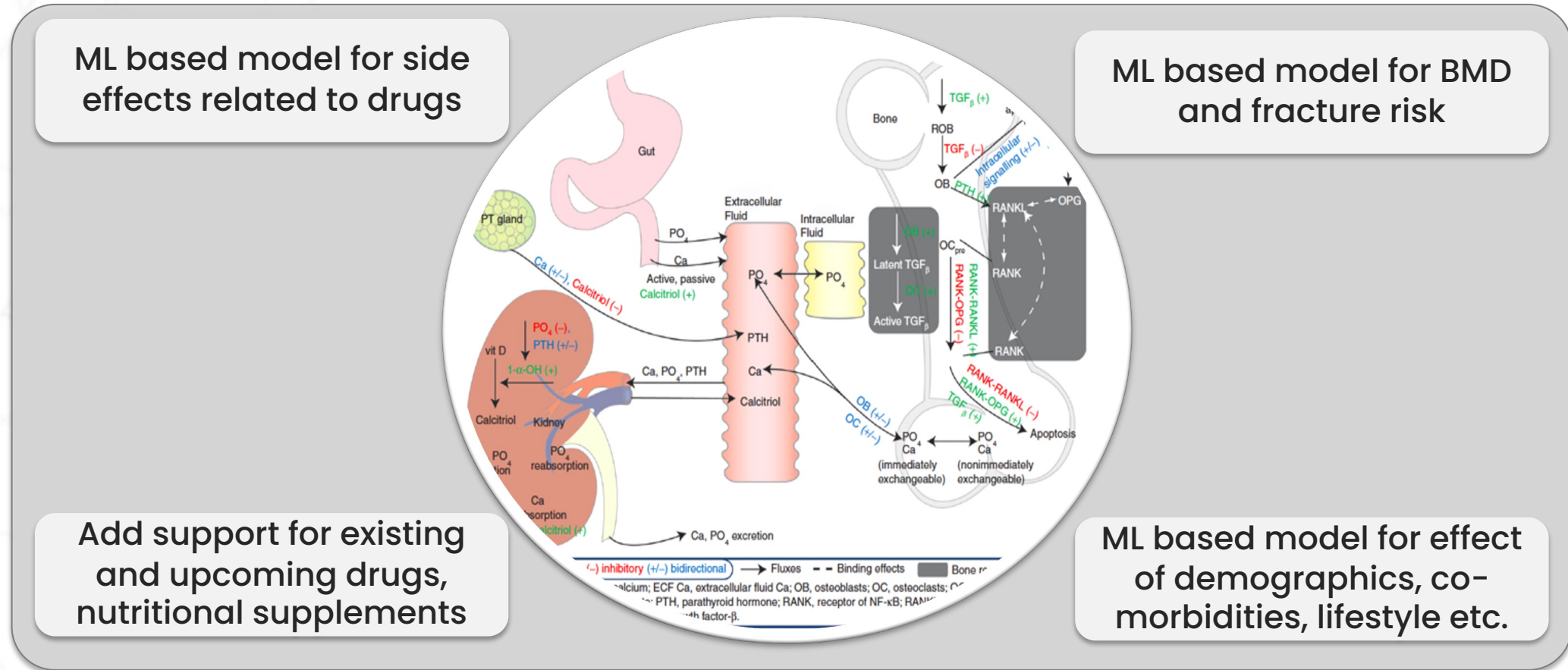
Simulating effect of medication adherence on patient risk using predictive model



- A **single patient's** data is selected as example
- Other inputs remain the same when the adherence is increased.
- The model is able to quantify the effect of non-adherence of each individual medication and combination on the patient's risk
- The model can help rank the importance of adherence to each individual medication and enable prioritization for clinicians

Where do we go from here?

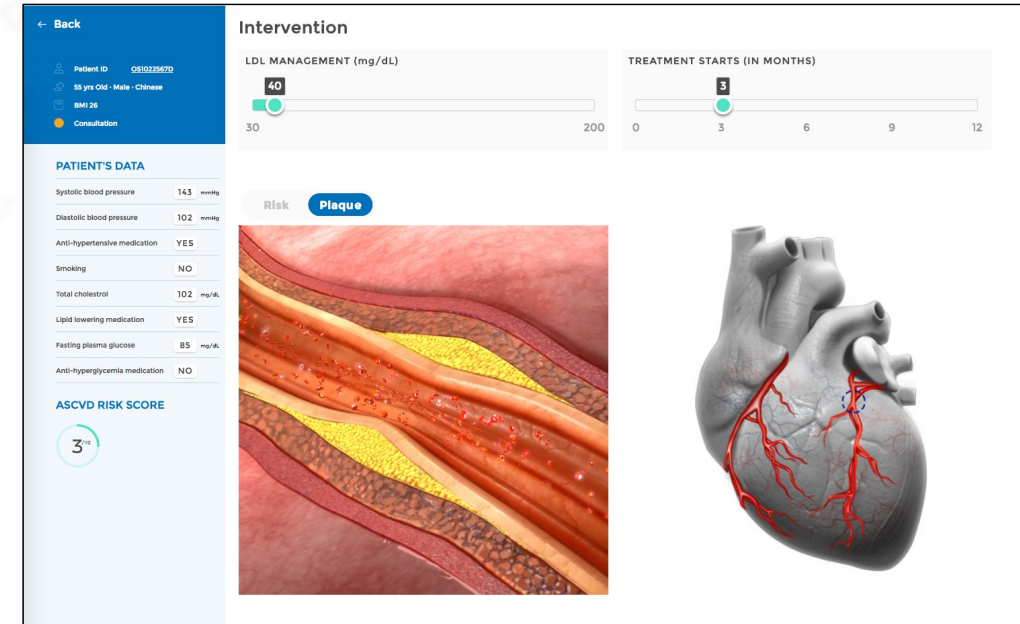
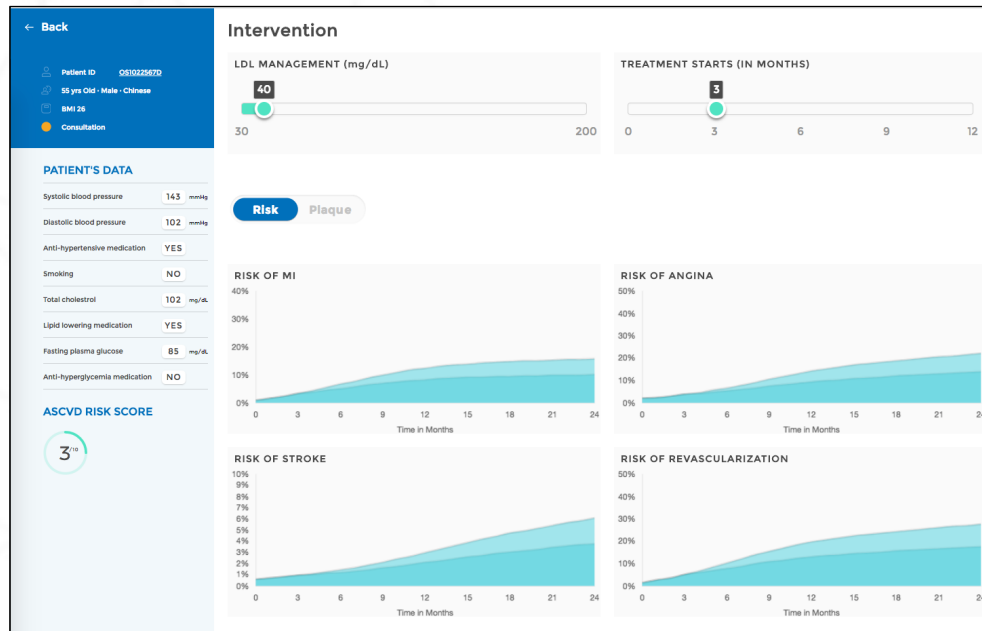
Predictive simulation model for osteoporosis progression



Hybrid simulation model with a biological core & interfaced with ML models to support outcomes and clinical measurements

Personalized Digital Health Solutions powered by Advanced Analytics

Example of a digital solution in CVD



Holmusk designers are involved in building patient centric dashboards powered by predictive models which are going to be used by clinicians to drive personalized care for MI patients

The dashboard incorporate engaging visuals and simulation of "what if" scenarios to better communicate risk & drive behavior change



big data
technology
healthcare

holmusk

www.holmusk.com