

# Artificial Intelligence and Data Science in Emergency Care

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# Artificial Intelligence (AI)

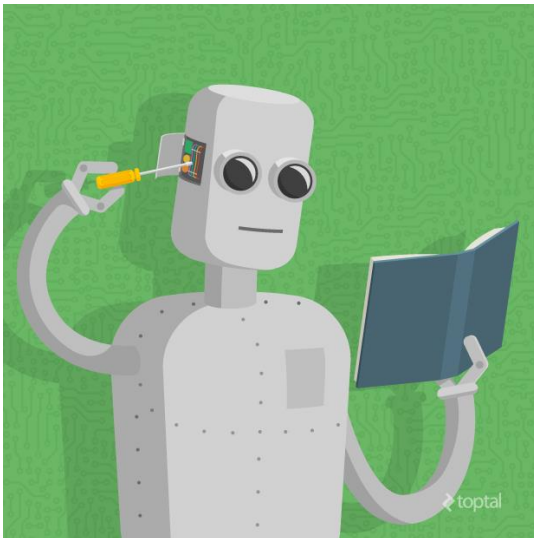
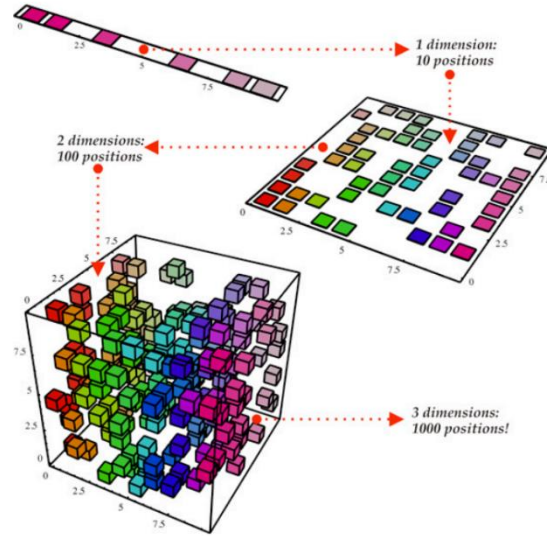
- ❑ AI and machine learning (ML) explore the study of algorithms that can **learn from data**
- ❑ As subfields of computer science, AI & ML have **strong ties** to **statistics and mathematical optimization**
- ❑ When employed in industrial contexts, machine learning methods may be referred to as **predictive analytics** or **predictive modelling**



***AI is Everywhere!***

***Medical Diagnosis, Search Engine, Stock Trading,  
Robot Control, Law, Remote Sensing, Scientific  
Discovery and Toys, among others***

# What Can AI Do



- ❑ **General Data Analytics:** Variable selection, feature extraction / dimensionality reduction, classification and regression, unsupervised clustering
- ❑ **Natural Language Processing (NLP):** Speech and audio processing and recognition, text mining
- ❑ **Computer Vision and Understanding:** Analyzing videos and images, e.g. imaging enhancement, segmentation, 2D/3D image analysis, etc
- ❑ **Information / Sensor Fusion:** Data fusion and integration, sensor information fusion

*AI and ML will play key roles in internet of things (IoT), large-scale data retrieval and management*

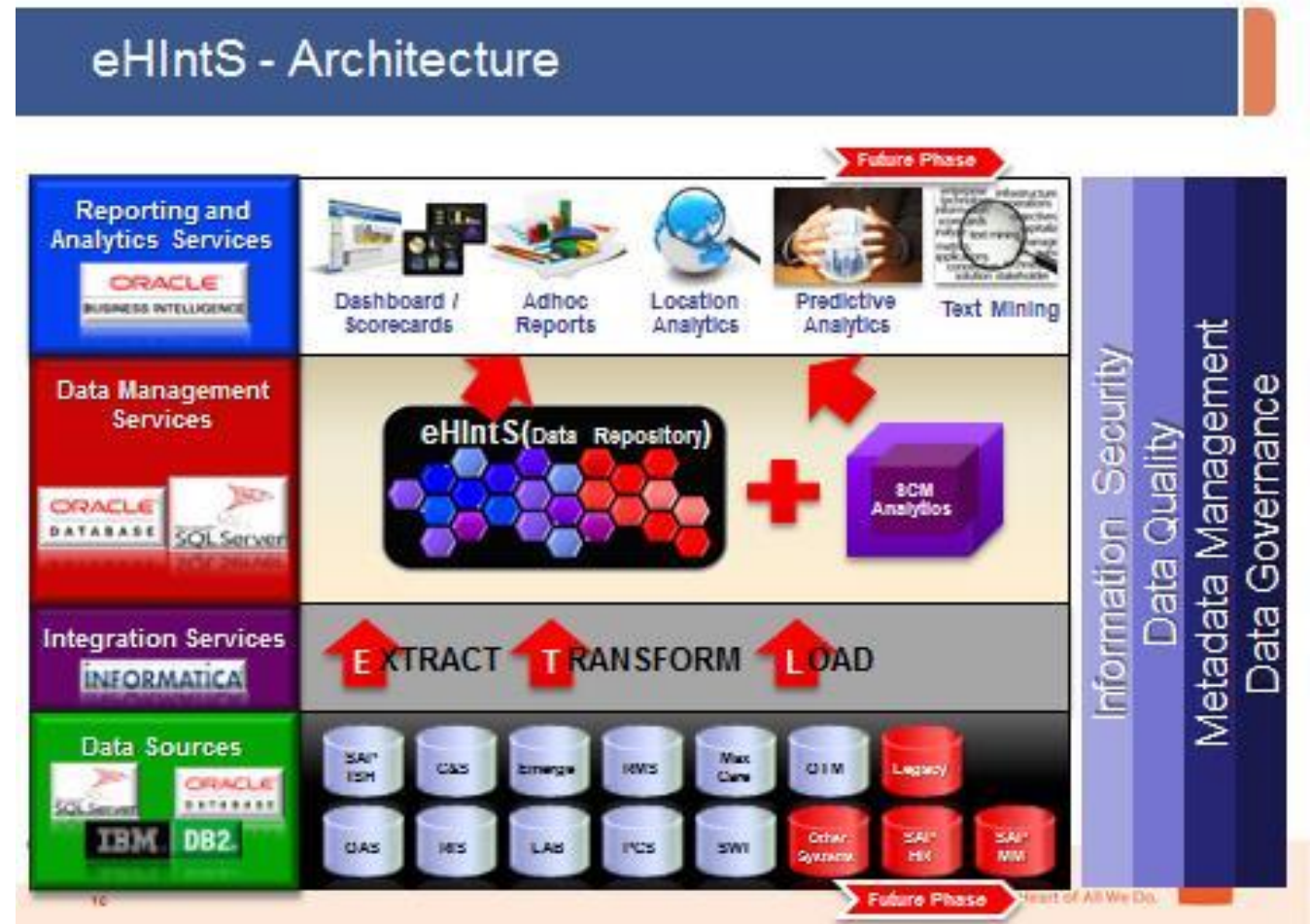


# Why Do We Need AI in Medicine



# Why Do We Need AI in Medicine

- ❑ Hospitals have moved **from paper-based information management to Electronic Health Record (EHR)**. This has enabled the retrieval of massive data (e.g. text, image, video, audio)
- ❑ Conventional statistical and mathematical methods continue to play important roles while new **emerging technologies like AI, Machine Learning and Data Mining** have established reputations in solving complex problems



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# Artificial Intelligence-Based

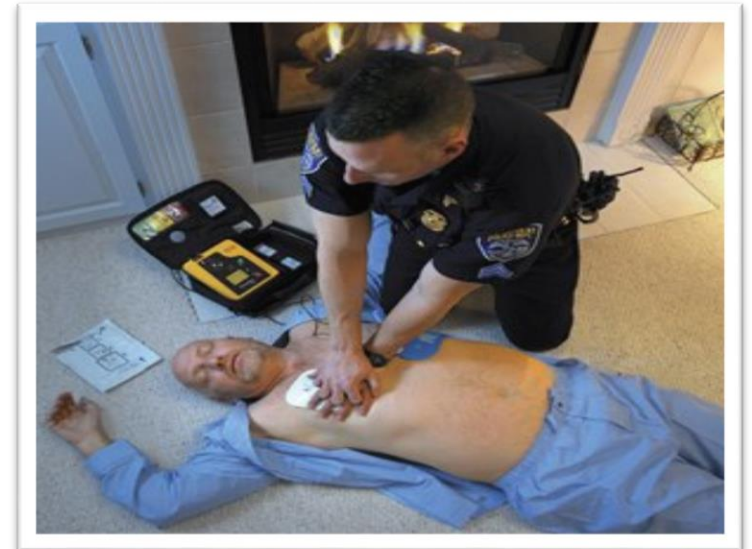
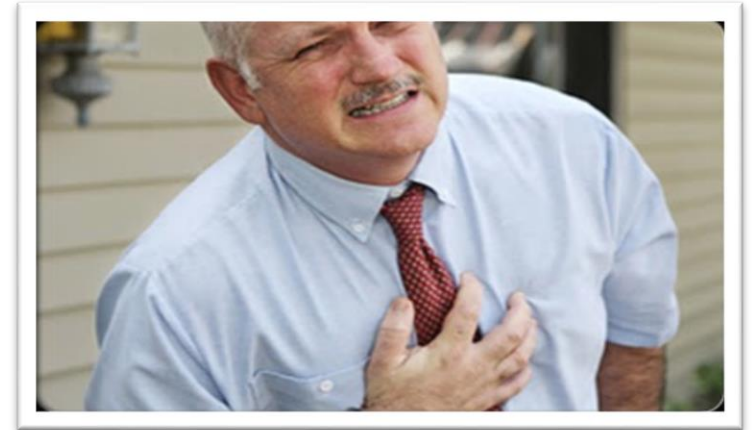
## Prediction of Major Adverse Cardiac Events (MACE)

### in the Emergency Department



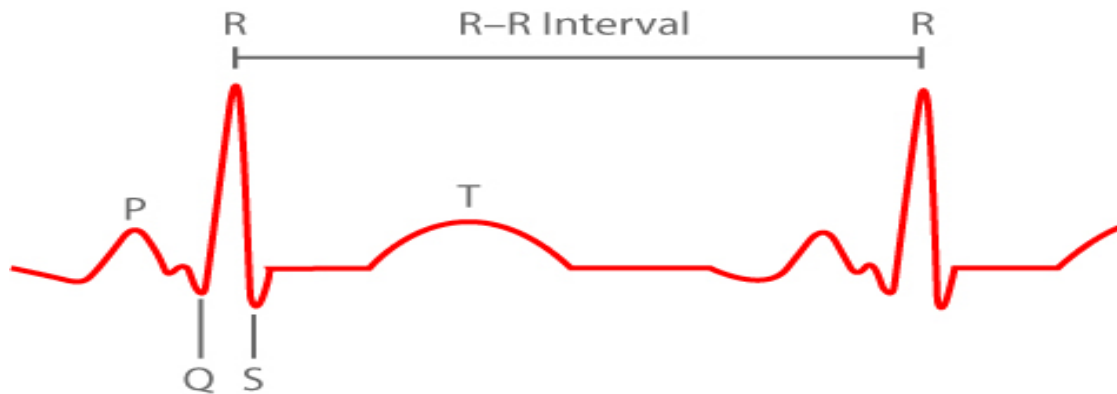
# Clinical Motivation

- ❑ Triage is the clinical process of rapidly screening large numbers of patients to assess severity and assign priority of treatment
- ❑ Currently, triage is generally done by nurses and depends on traditional vital signs
- ❑ Medical resources are limited. Numbers of doctors, nurses, medical facilities may not be sufficient for fluctuating demand
- ❑ We need an **objective, fast and accurate triage tool** to quickly identify high risk patients ("**chest pain**" in **this example**) in the Emergency Department (ED)



# Background: Heart Rate Variability

Heart rate variability (HRV) is a type of physiological measures of autonomic system's effect on cardiovascular system, defined as change in time interval between heartbeats



More variation in heart rate intervals is indicative of better parasympathetic activity

## Time Domain HRV Parameters

- ❑ Average width of RR interval
- ❑ Standard deviation of RR intervals

## Frequency Domain HRV Parameters

- ❑ Ratio of low-frequency to high-frequency power
- ❑ Power in different frequency ranges

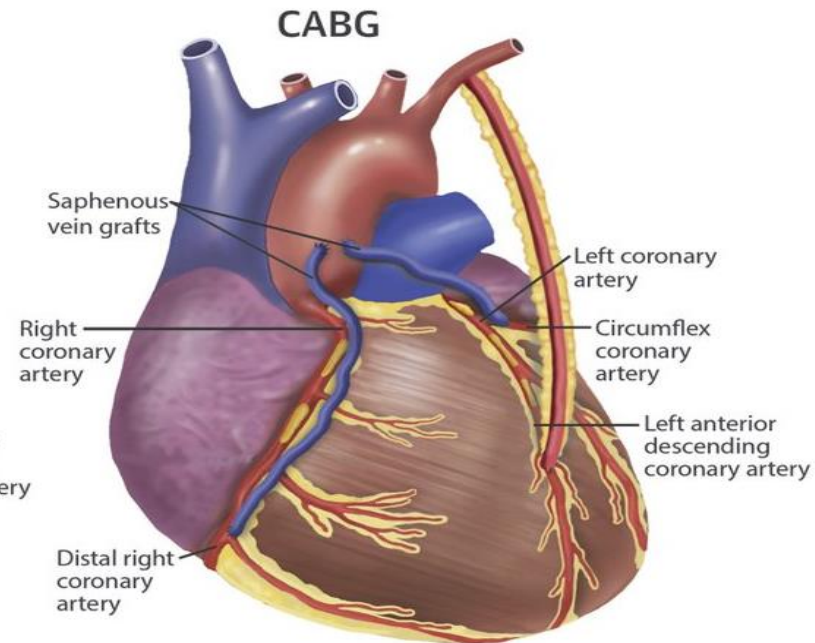
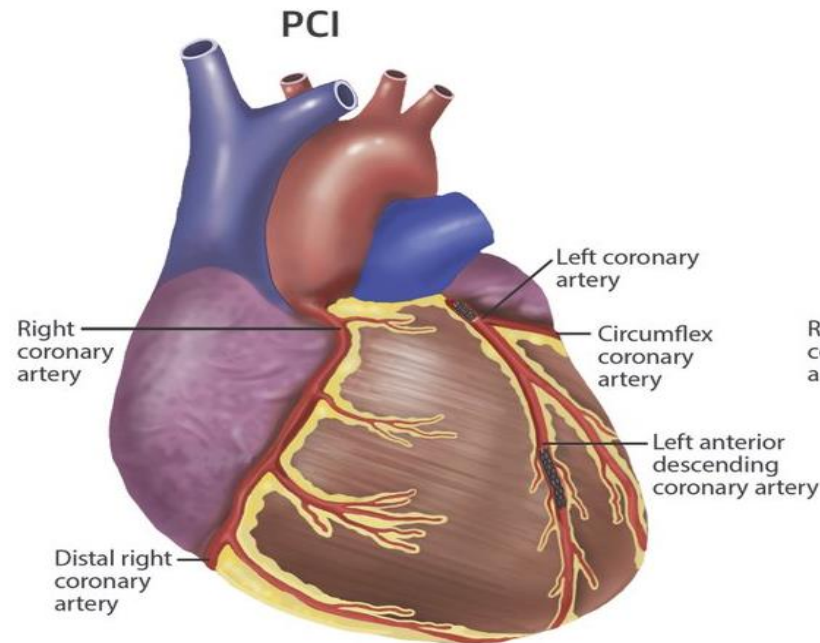
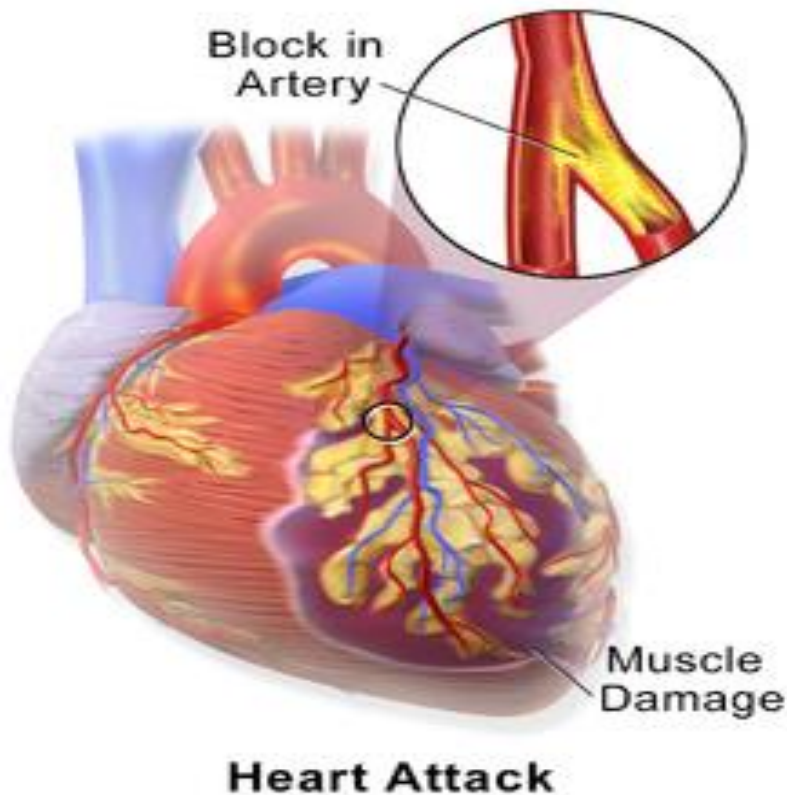
## Nonlinear HRV parameters

- ❑ Poincaré plot, approximate entropy, correlation dimension
- ❑ Detrended fluctuation analysis

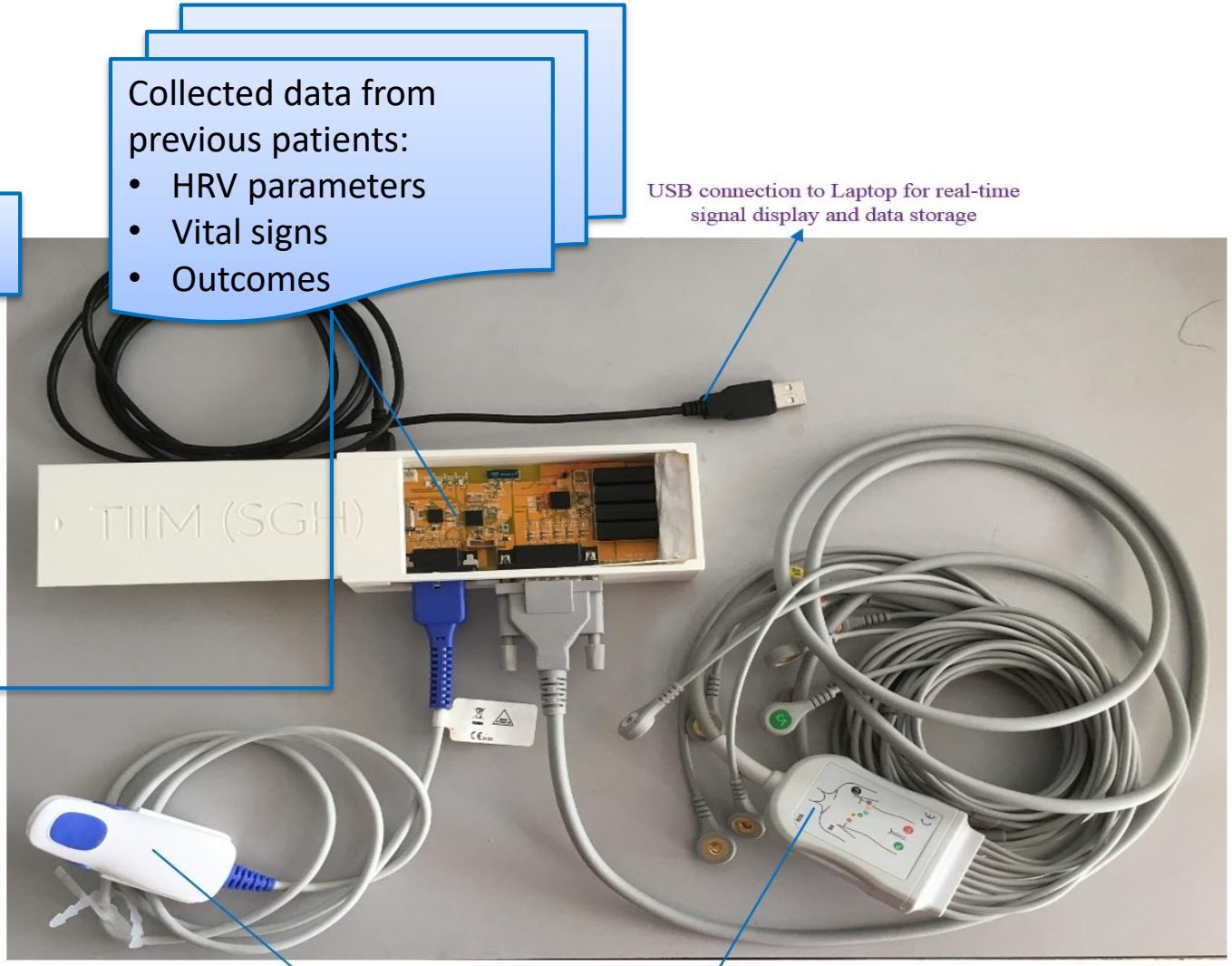
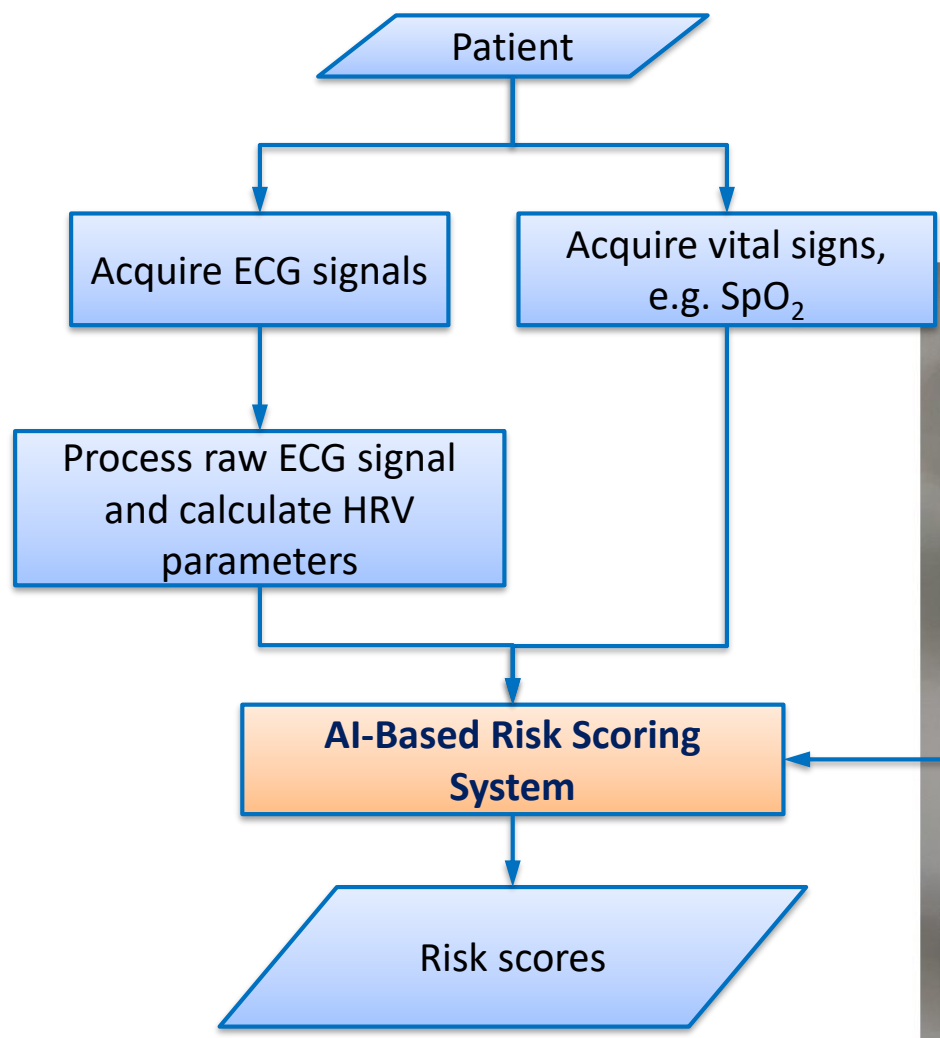


# Clinical Outcomes

Occurrence of a **Major Adverse Cardiac Events (MACE)**, including mortality, acute myocardial infarction (AMI), percutaneous coronary intervention (PCI), and coronary artery bypass graft (CABG), within 30 day of presentation to the ED



# Design and Setting



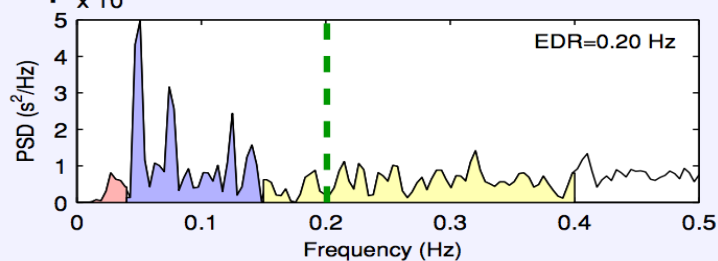
Commercial Pulse Oximeter Finger Probe

Commercial 12-Lead ECG wires

# System Variables

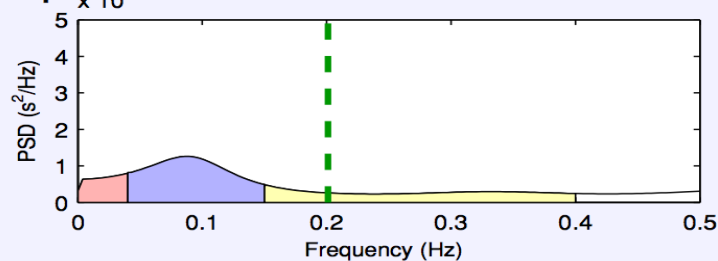
## Frequency–Domain Results

**FFT spectrum** (Welch's periodogram: 256 s window with 50% overlap)



Frequency Band	Peak (Hz)	Power (ms <sup>2</sup> )	Power (%)	Power (n.u.)
VLF (0–0.04 Hz)	0.0273	11	3.8	
LF (0.04–0.15 Hz)	0.0508	133	46.6	48.4
HF (0.15–0.4 Hz)	0.3203	140	49.0	50.9
Total		286		
LF/HF		0.951		

**AR Spectrum** (AR model order = 16, not factorized)

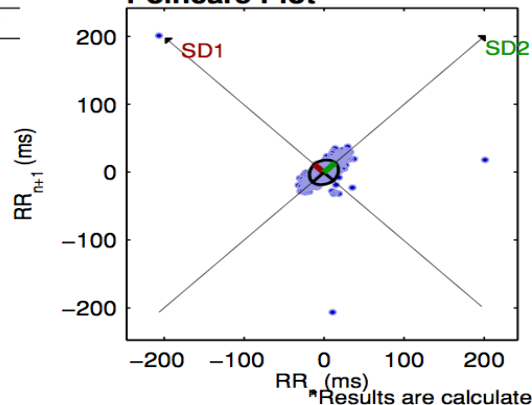


Frequency Band	Peak (Hz)	Power (ms <sup>2</sup> )	Power (%)	Power (n.u.)
VLF (0–0.04 Hz)	0.0391	27	13.3	
LF (0.04–0.15 Hz)	0.0859	106	52.4	60.4
HF (0.15–0.4 Hz)	0.1523	69	34.1	39.3
Total		202		
LF/HF		1.536		

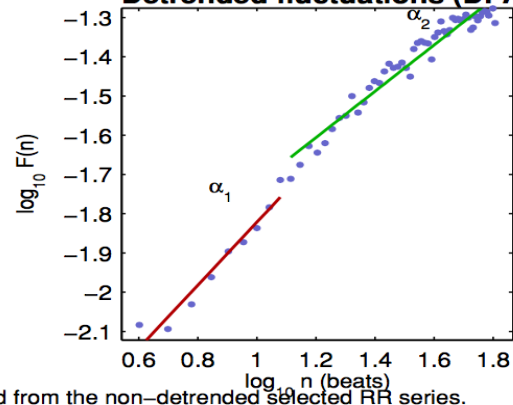
## Nonlinear Results

Variable	Units	Value
<b>Poincare plot</b>		
SD1	(ms)	16.9
SD2	(ms)	20.2
<b>Recurrence plot</b>		
Mean line length (Lmean)	(beats)	16.01
Max line length (Lmax)	(beats)	240
Recurrence rate (REC)	(%)	55.83
Determinism (DET)	(%)	99.44
Shannon Entropy (ShanEn)		3.623
<b>Other</b>		
Approximate entropy (ApEn)		1.133
Sample entropy (SampEn)		1.079
Detrended fluctuations (DFA): $\alpha_1$		0.802
Detrended fluctuations (DFA): $\alpha_2$		0.589
Correlation dimension (D2)		0.031
Multiscale entropy (MSE)		0.465 – 2.013

**Poincare Plot**



**Detrended fluctuations (DFA)**



\*Results are calculated from the non-detrended selected RR series.

## Heart Rate Variability

Average and standard deviation of the RR intervals, mean of heart rate, root mean square of differences between adjacent RR intervals, etc

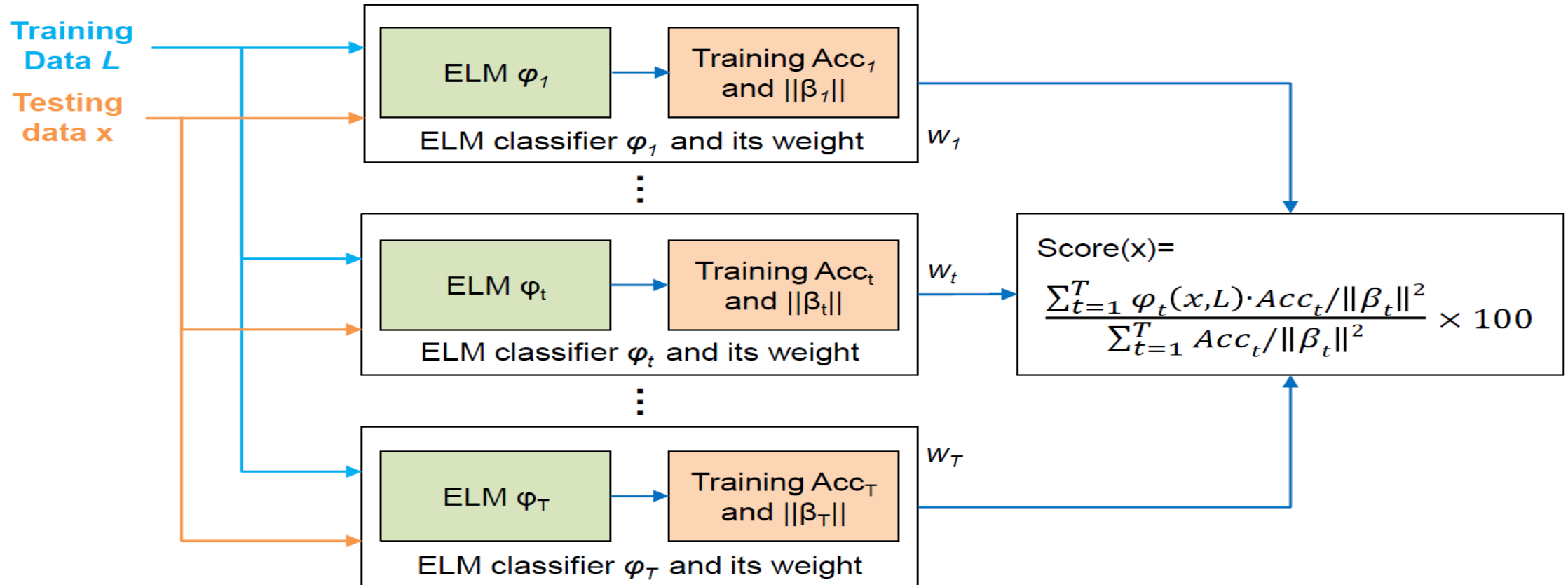
## Vital Signs

Heart rate, systolic and diastolic blood pressure, temperature, pain score and oxygen saturation, etc

## ECG Changes

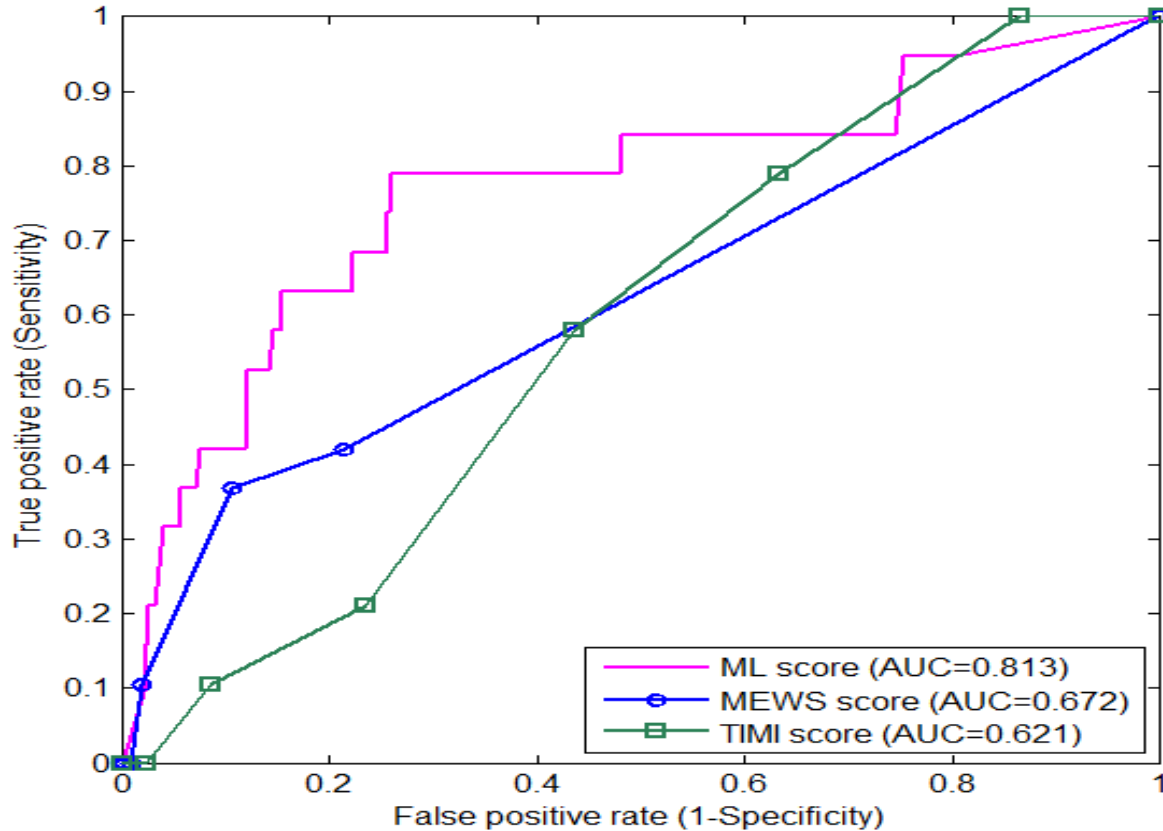
ST elevation, ST depression, T wave inversion, Q wave, QT interval correction (QTc), QRS axis, left-bundle branch block, right-bundle branch block, etc

# AI-based Decision Making



- ❑  $\|\beta\|$ , the norm of output matrix weights, is closely associated with ELM generalization performance. Small  $\|\beta\|$  leads to better generalization ability.
- ❑ To achieve a trade-off between training accuracy and the generalization performance, we also introduce training accuracy to determine the weight

# System Performance



	ML	MEWS	TIMI
<b>AUC</b>	<b>0.813</b>	0.672	0.621
<b>Sensitivity</b>	<b>78.9%</b>	42.1%	78.9%
<b>Specificity</b>	<b>74.1%</b>	78.5%	36.7%
<b>PPV</b>	<b>9.6%</b>	6.4%	4.2%
<b>NPV</b>	<b>99.0%</b>	97.5%	98.0%

**ML:** Machine learning; **MEWS:** The modified early warning score;  
**TIMI:** Thrombolysis in myocardial infarction

# Smart Device – Latest Version

**aiTriage** uses AI to identify high-risk chest pain patients in real-time, using a patient monitor and tablet application.

- Fast diagnosis
- No blood tests needed
- Reduces variability in patient management
- Reduce workload on hospital staff
- Reduce overtriage
- Hospitals save time and cost



Patient vital signs recording for 5 minutes

Algorithm gives clinician MACE stratification score

Triage decision is made

Immediate treatment or quicker discharge

aiTriage dramatically improves hospitals' efficiency and quality of care

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# Data Science-Based

## Prediction of Inpatient Mortality for Patient Triage in the Emergency Department



# Backgrounds and Objectives

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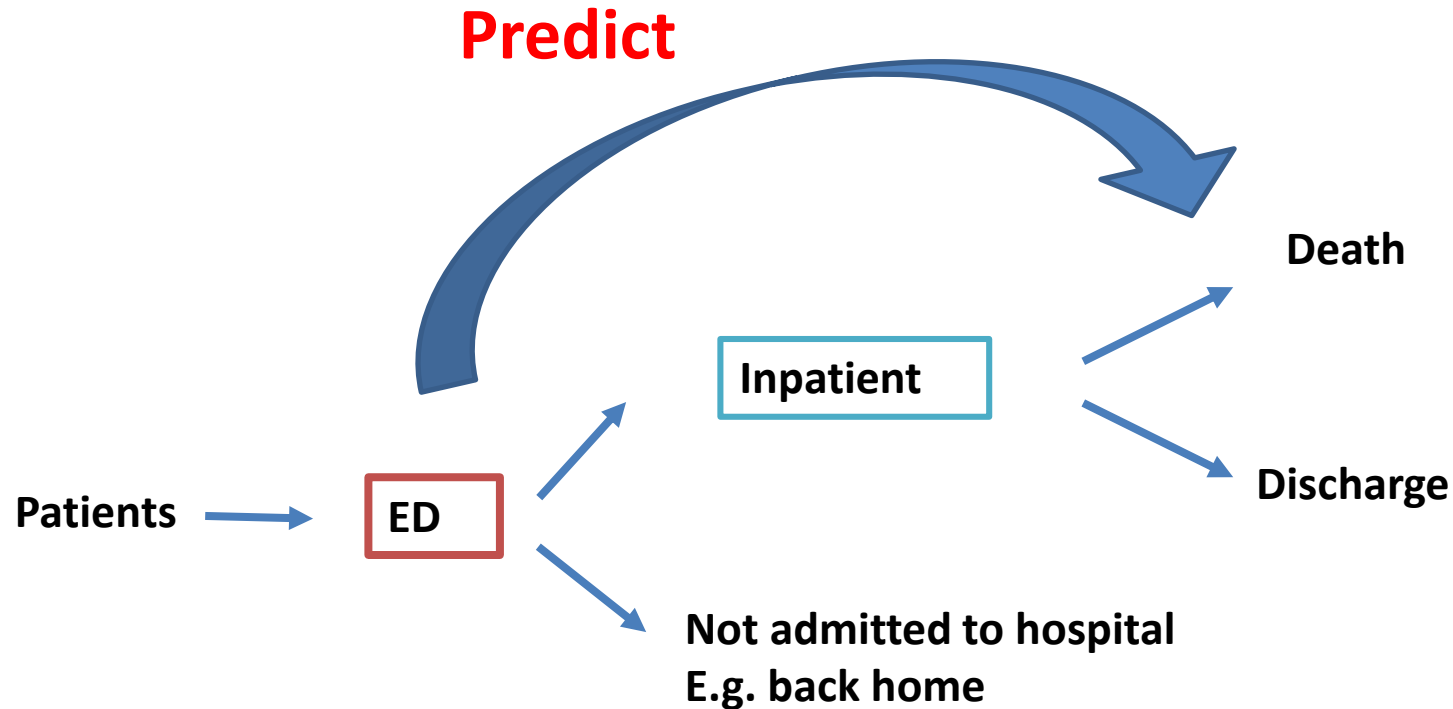
- ❑ Risk stratification in the EDs in Singapore is a **symptom based approach** to sort patients into 4 groups based on national Patient Acuity Category Scale (PACS)
- ❑ Current ED triage is done by a nurse, thus the triage process is subjective and depends on **1) knowledge of the staff** as well as, **2) patients' symptoms**
- ❑ **Limitations of current Early Warning Systems:** for example, over-sensitivity, low specificity, low discriminative ability

## Our objectives:

- ❑ Utilize features collected at the ED
- ❑ Anticipate imminent adverse events during the inpatient stay
- ❑ Allow physicians to respond appropriately and timely



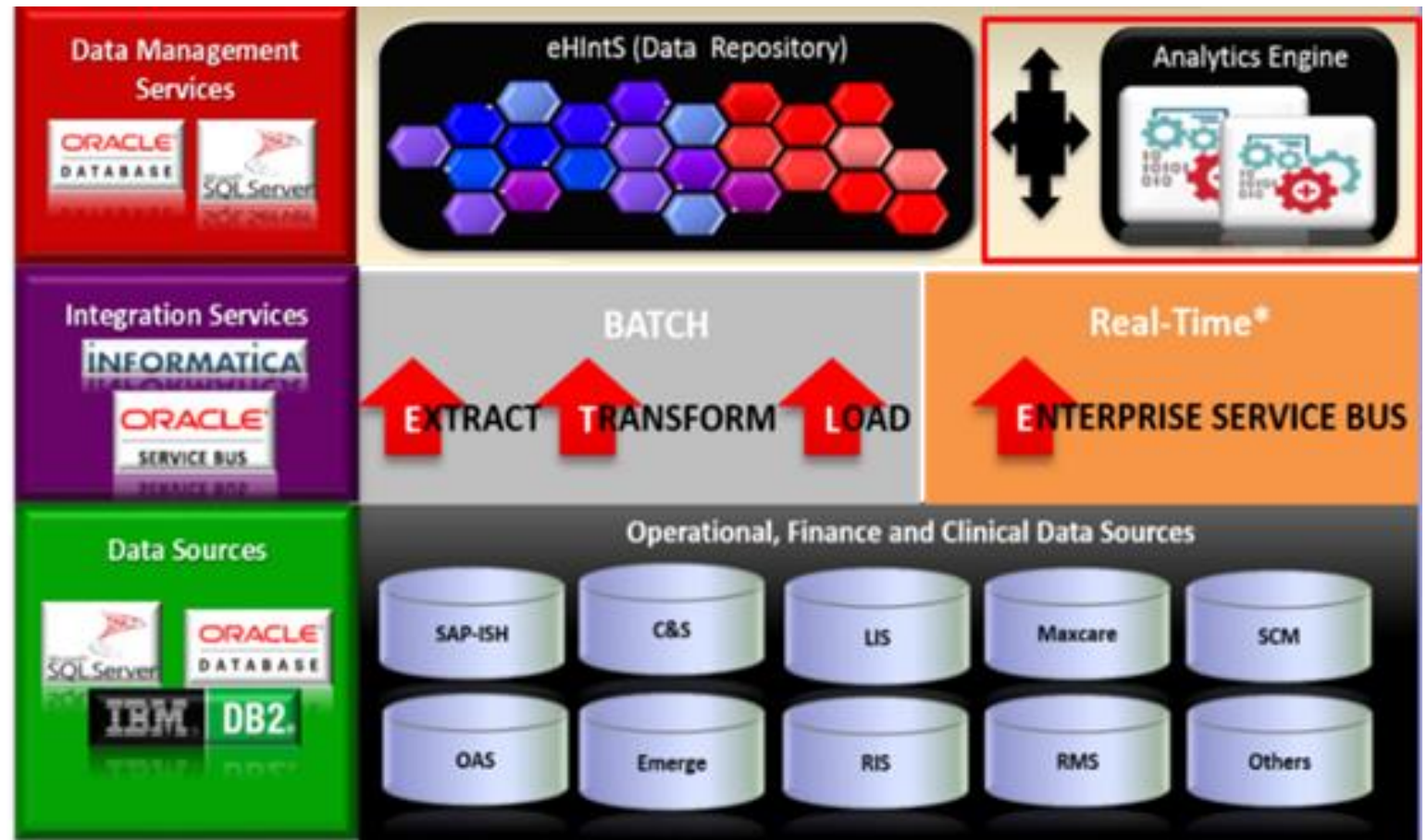
# General Flow of Emergency Admission



**4 demographical**  
**5 ED administrative**  
**11 clinical features from ED**

# Study Design & Data Extraction

- ❑ **Data Source:** 10 year (1 Jan 2008 to 31 Oct 2017) SGH ED to inpatients raw EHR data (under retrieval)
- ❑ **Inclusion Criteria:** Patients above 21 years old admitted through SGH ED
- ❑ **Data Use:** Data will be split into training and validation datasets
- ❑ Plot ROC curve and compare our model with **Cardiac Arrest Risk Triage (CART)** score



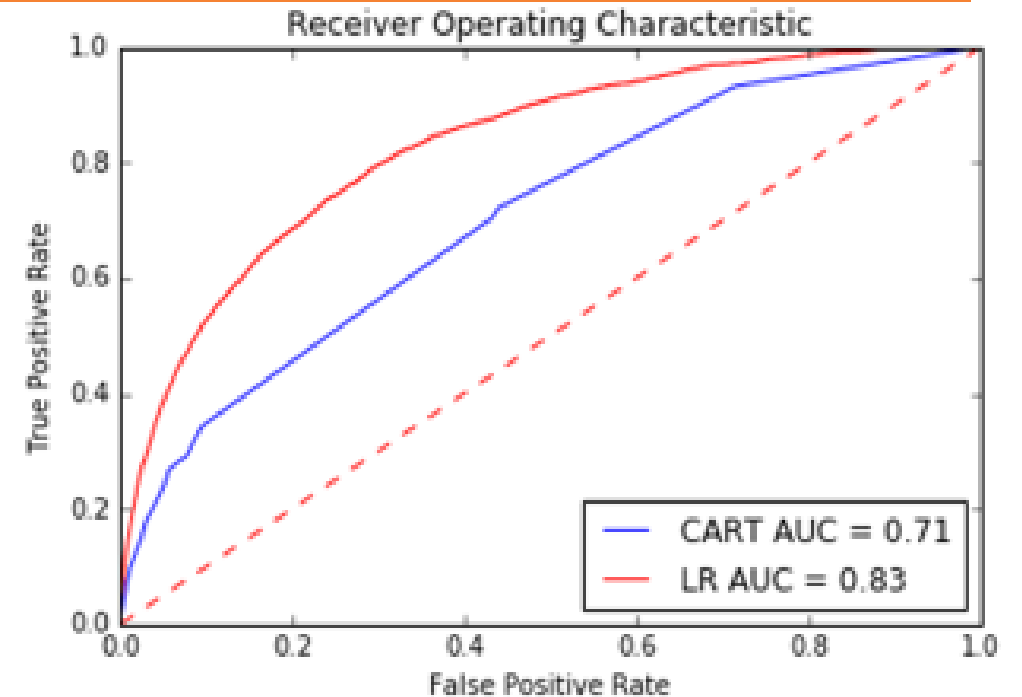
# Results

- A total of **433,187** unique emergency admission episodes
- **15,758** episodes (**3.64%**) : inpatient mortality
- Some finally included variables:

**Age, Gender, Race**

**Triage class, ED boarding/ waiting time**

**Blood gas, Pulse, Respiration rate, FiO<sub>2</sub>, SPO<sub>2</sub>,  
Systolic BP, Bicarbonate, Potassium, Sodium**



## CART:

Sensitivity: 0.730 Specificity: 0.561

Score threshold: 9

## Logistic Regression(LR):

Sensitivity: 0.770 Specificity: 0.733

Score threshold: 0.035

# Discussions

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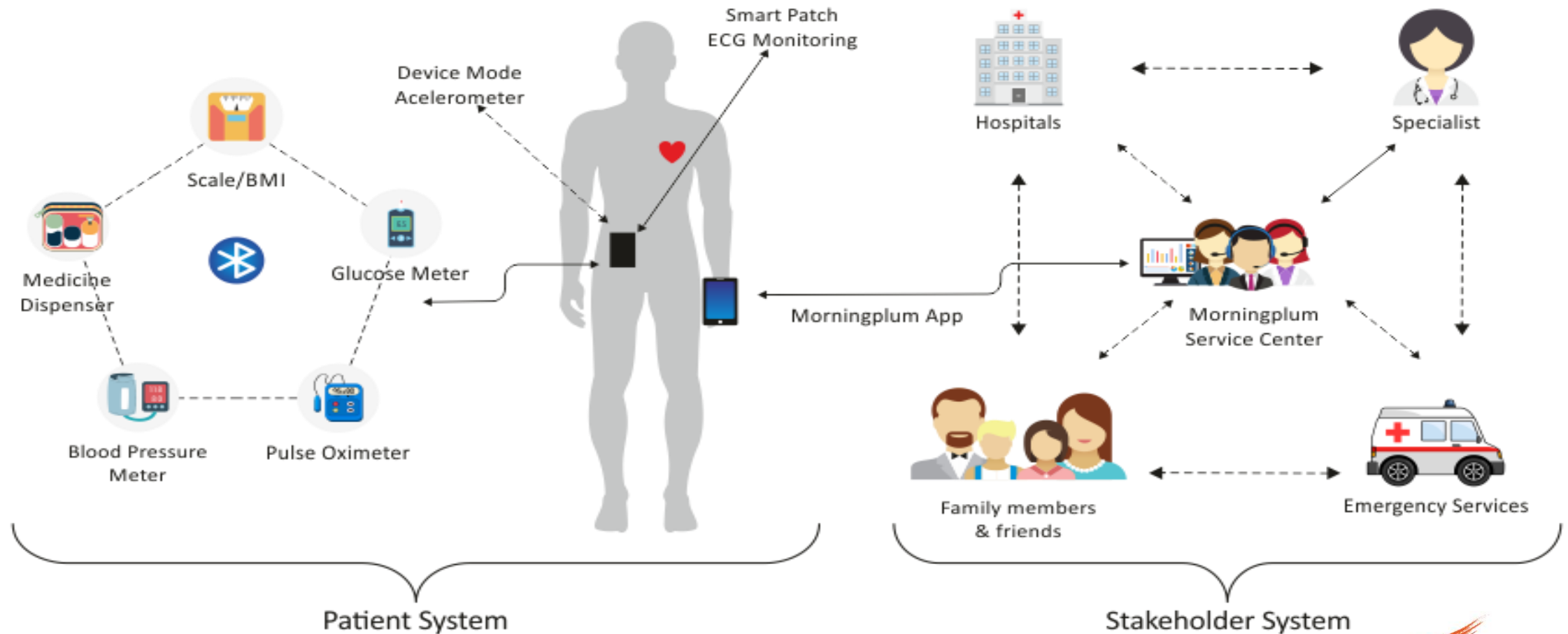
- ❑ ED parameters could be of potential to predict inpatient mortality
- ❑ Better discriminative power than the CART score (AUC, 0.828 vs. 0.705) on the same validation set
- ❑ The model is a useful tool for risk stratification
- ❑ **Strengths:** extremely large data size, various features and clinical usefulness
- ❑ **Limitation:** Only routinely collected information, single-site study, included some regional features
- ❑ **The above represent key features of most data science projects**

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# opportunities



# Remote Monitoring & Big Data



# Summary

- ❑ **AI/Data Science + Health** aims to improve patient care and optimize healthcare resources
- ❑ **Hardware + AI** will play a **key role** in medical care and innovations



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# *Thank You*

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