Talk: *Cognitive Science Institute Group*

Reinventing Healthcare with Big Data & Machine Learning

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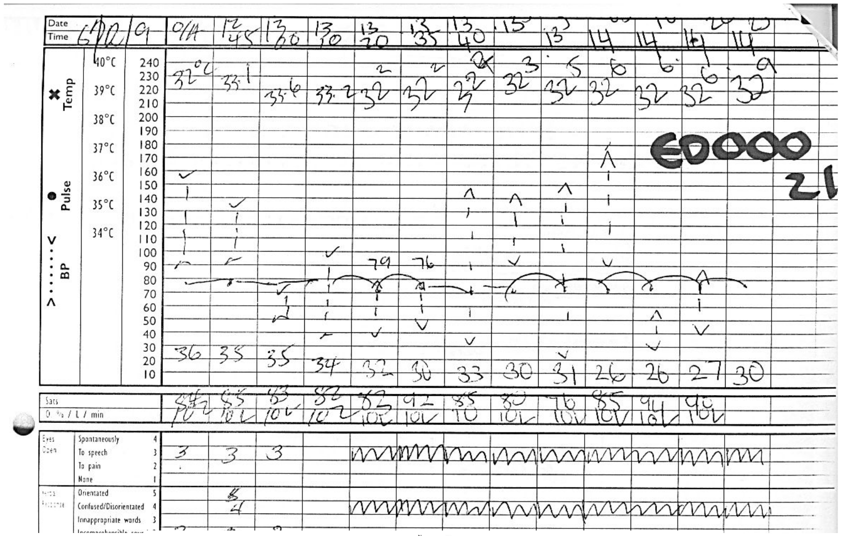
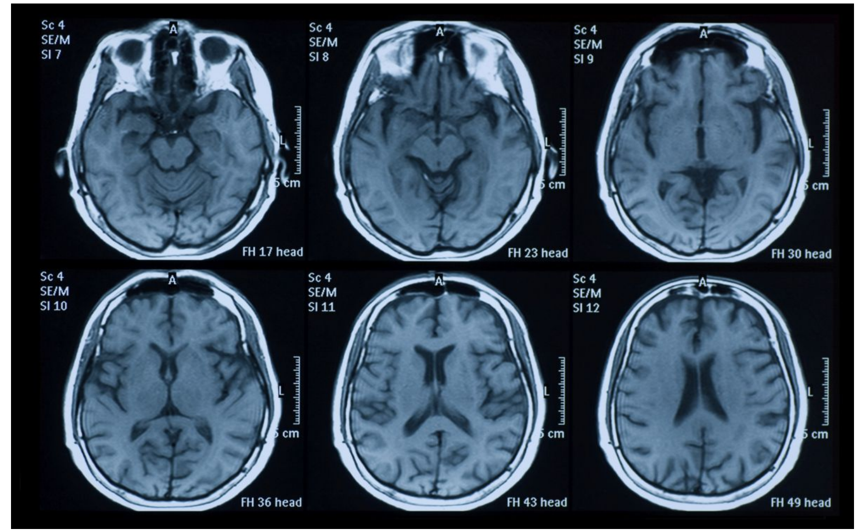
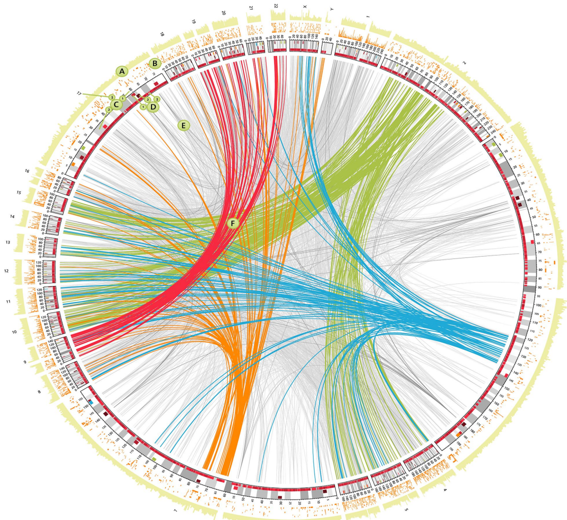
Data in Healthcare







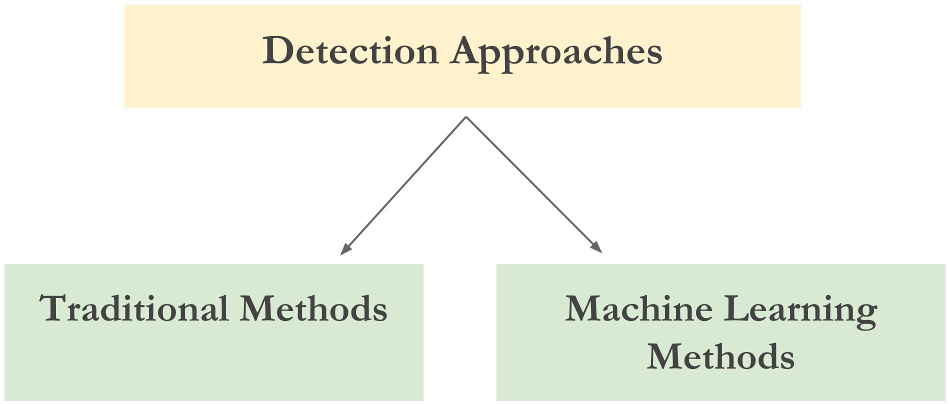
Research Focus

1 Personalized patient time-series modeling due to the added advantage of **massive scale** and the possibility of **patient-specific analysis.**

2 **Novelty detection of clinical deterioration** through **fully-predictive means**, rather than merely identifying deterioration as it begins.

Motivation: Detecting Clinical Deterioration

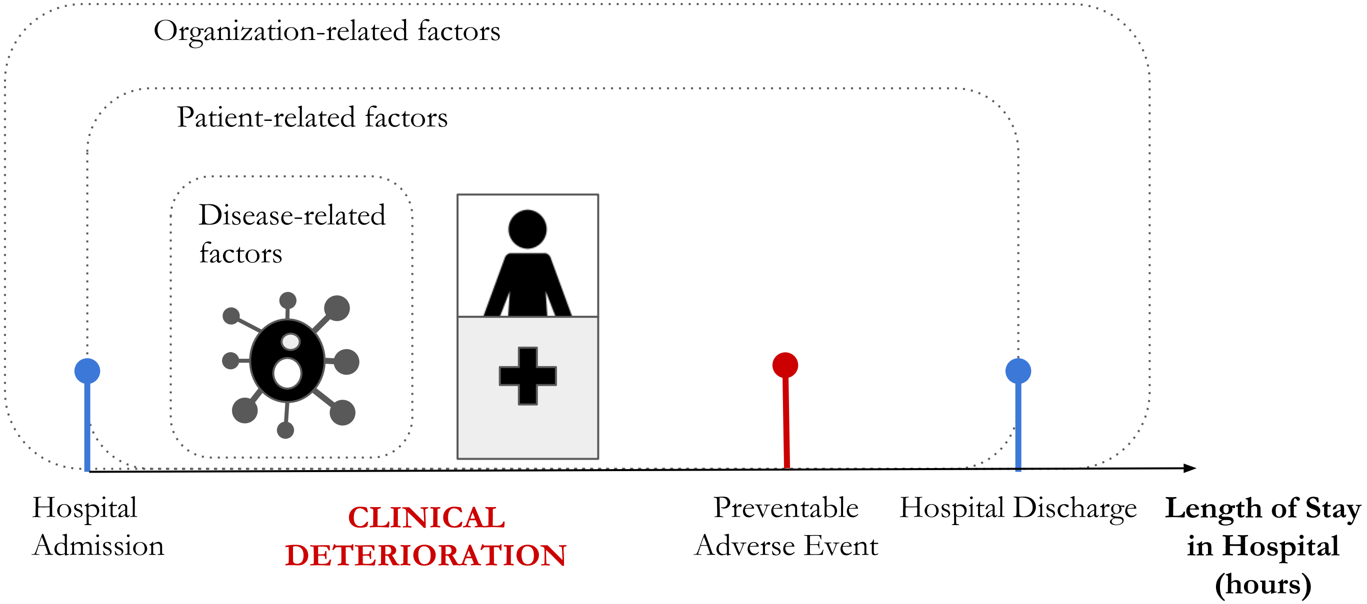
1. One of the main contributory factors is **inefficient ward management.**
2. **High costs** of preventable adverse events (Prolonged hospital stays, litigation, staff time, burden on patients, and broader economic consequences)
3. **Massive scale of available data**, acquired from the HAVEN Database.
4. Most existing models **merely identify deterioration as it begins**.



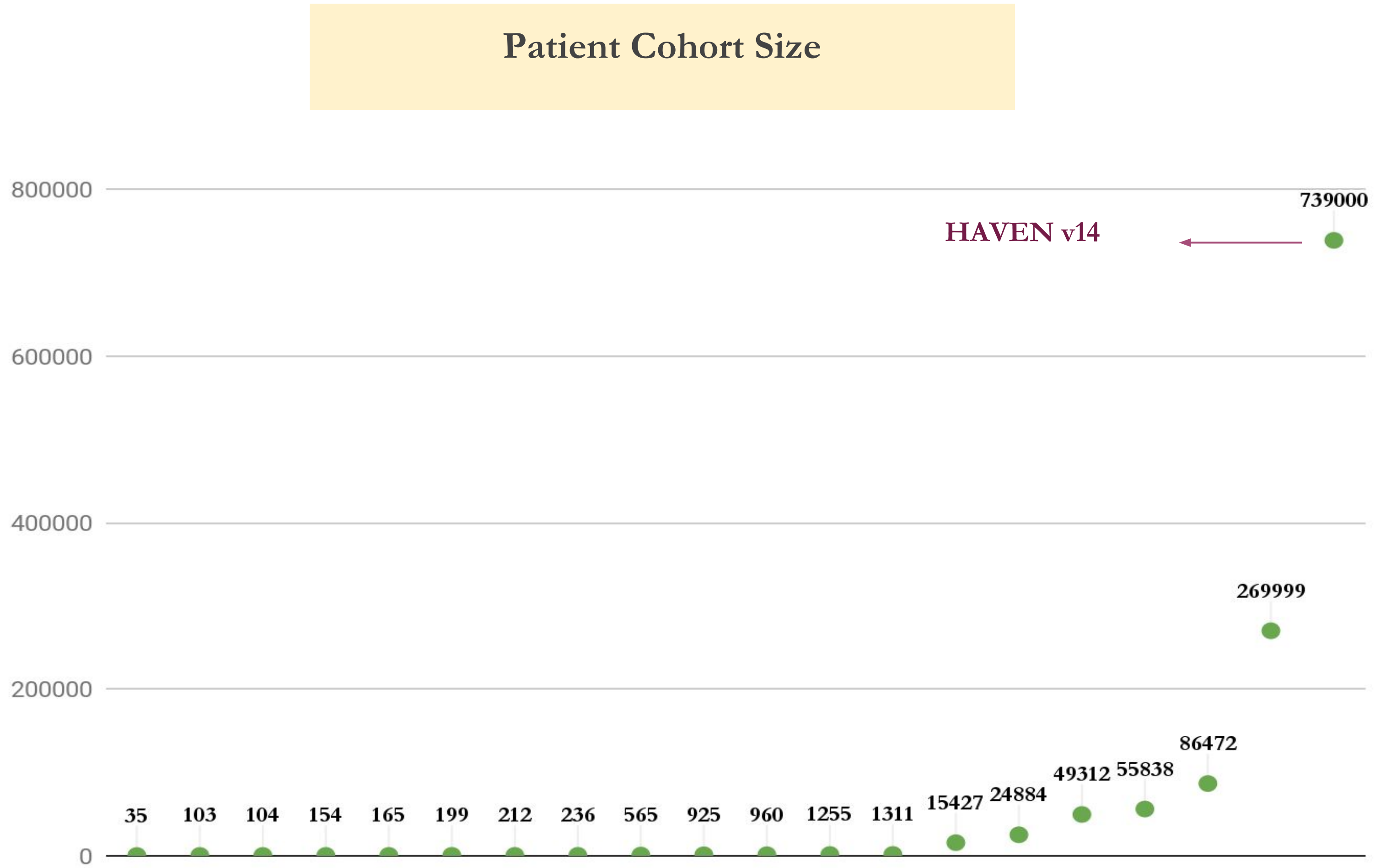
Clinical Deterioration on Hospital Wards

Clinical Deterioration refers to the **worsening of a patient's condition** on hospital wards, and is **assessed by medical staff** through routine observations and protocols.

Preventable adverse events are **avoidable injuries or complications** where there was **enough knowledge and accepted practices** to to have avoided the event [15].

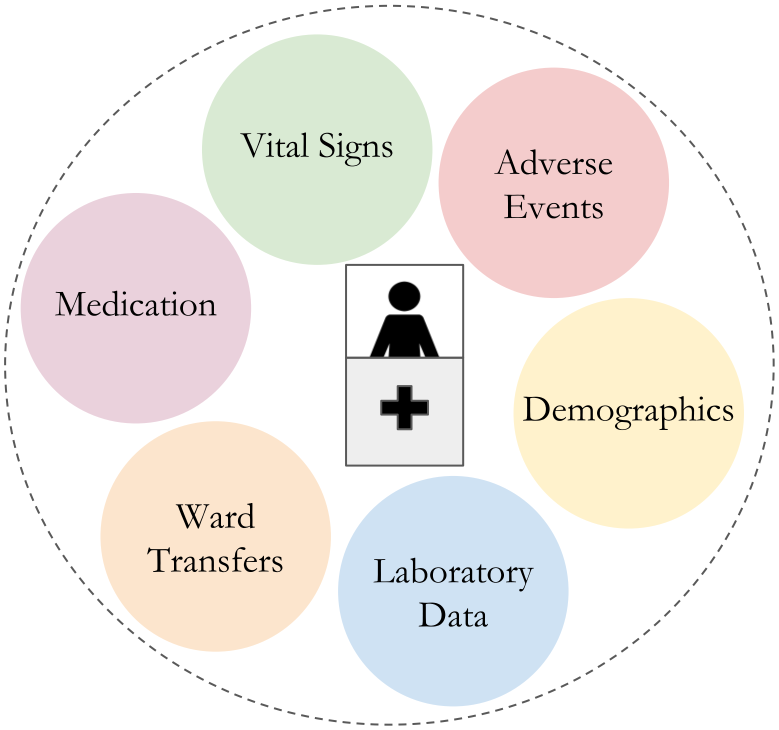


Electronic Health Records (EHRs) - HAVEN Database

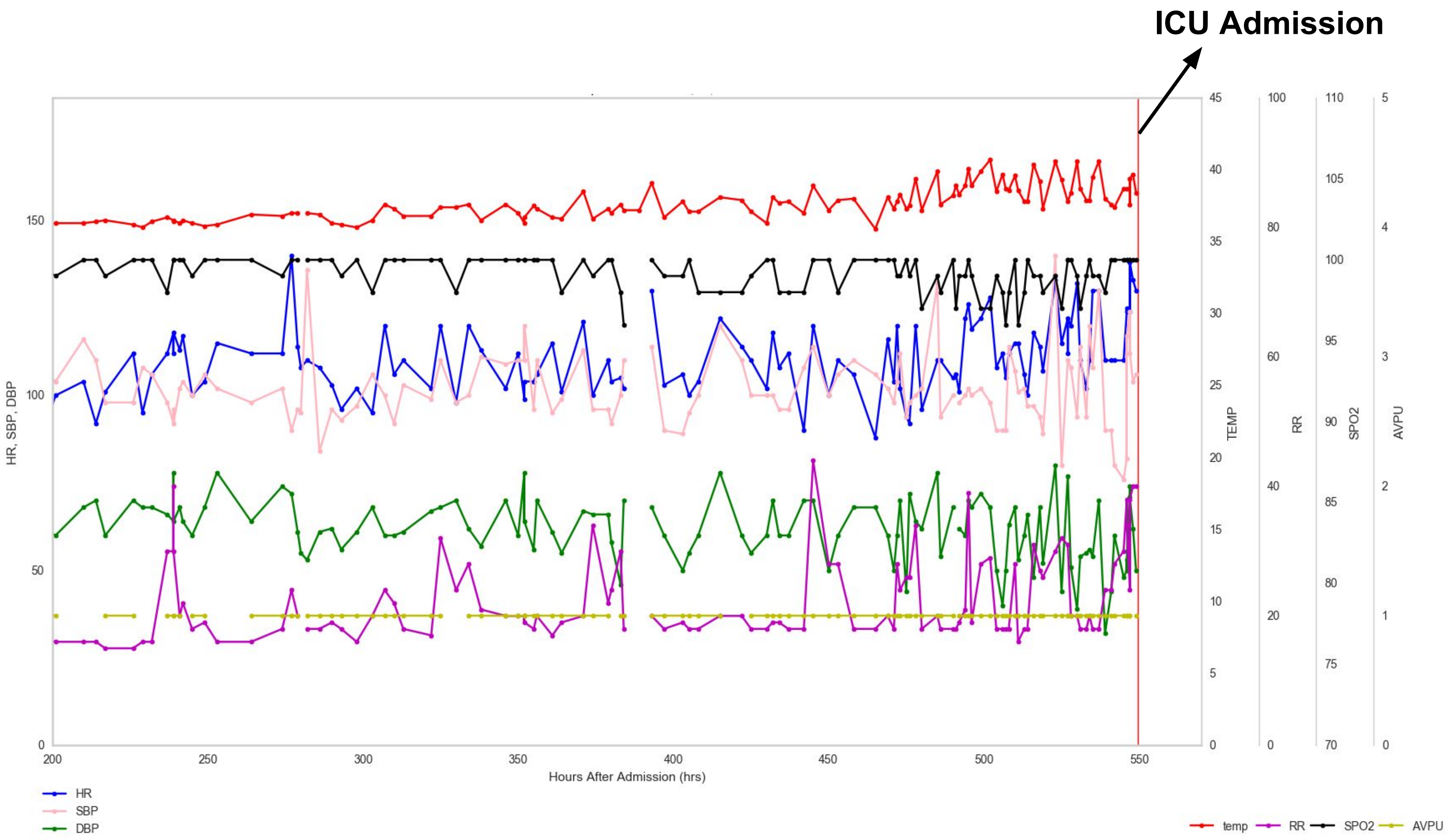


Electronic Health Records (EHRs) cont.

1. <u>Definition:</u> "Longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting" - HIMSS
2. <u>Uses:</u> Extraction of patient cohorts (phenotypes), early warning scores, machine learning
3. <u>Challenges:</u>
   a. Complexity
   b. Completeness
   c. Correctness
   d. Currency
4. <u>Data Preparation for Analysis:</u>
   a. Raw data
   b. Derived Parameters
   c. Statistical Measures
   d. Time Series Features



Snapshot of a Patient Admission



EHRs Workflow

Step 1: Extract Patient Cohort

1. Elective vs. Emergency Admissions
2. Surgical vs. Non-surgical patients
3. Clinical Phenotype

Step 2: Data Pre-processing

1. Physiologically implausible values
2. Sparsity & missingness
3. Varying lengths of stay
4. Fusing different types of data
5. Effect of interventions
6. Multiple consecutive outcomes

Step 3: Data Processing

Traditional Methods vs. Machine Learning methods

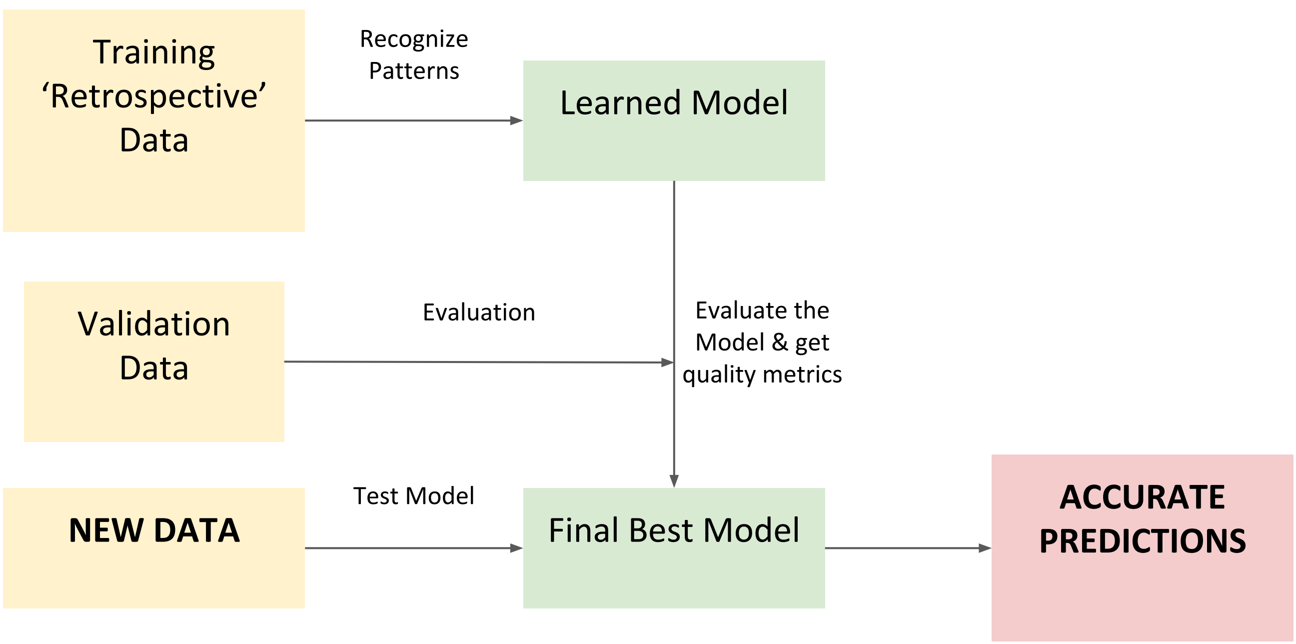
Traditional Methods: Early Warning Scores

- Common Objective: secure timely and effective responses for patients with deteriorating medical conditions, rather than to predict a particular outcome (RCP, 2012).
- Methodology: Mainly **heuristically-developed**, while some are **statistical**
- Examples: ViEWS, NEWS, CEWS, MEWS, MCEWS, etc…

Advantages	**Disadvantages**
Aids medical staff	Lack of generalizability across hospitals
Easy to understand and implement	Limited input variables
Good performance	Assumes homogeneity across patients

Machine Learning Applications in Healthcare

Machine Learning (ML) is an application of Artificial Intelligence (AI) that allows computers to **learn automatically from experience** (i.e. retrospective data).
Examples: classification of handwritten digits, self-driving cars, gaming such as chess, ultrasound images segmentation, predict housing prices, etc…



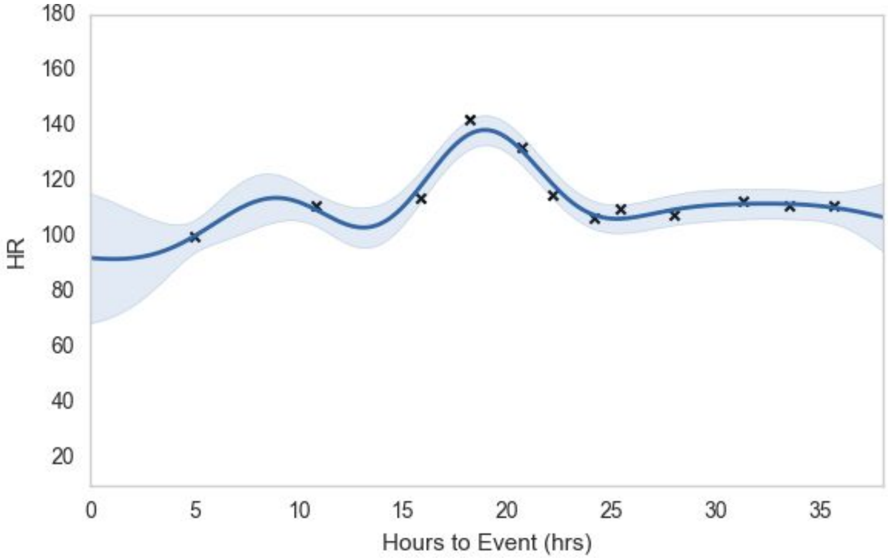
1. Personalized Early Warning Score

Vital Sign	Reported Changes with Age/Sex
Heart Rate (HR)	Increases
Systolic Blood Pressure (SBP)	Gradually increases, with a higher incidence amongst females
Diastolic Blood Pressure (DBP)	Increases until the fifth decade and then slowly decreases
Respiratory Rate (RR)	Increases
Temperature (TEMP)	Core body temperature decreases

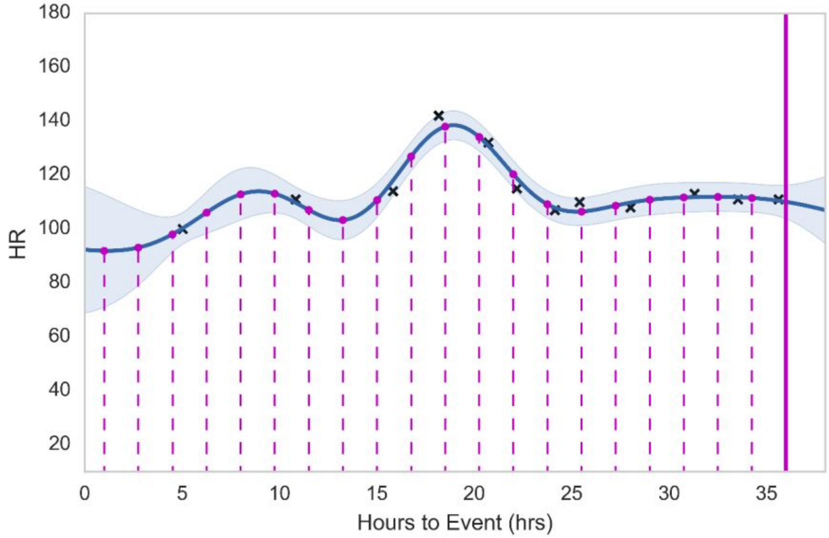
Motivates the development of an Age- and Sex- Based Early Warning Score to alert for adverse events within 24 hours to event. Adverse event defined as cardiac arrest, ICU admission or mortality.

2. Predictive Inference

1. Time Series Modelling



2. Extraction of Features



Modelled Vital Signs

Gaussian Processes

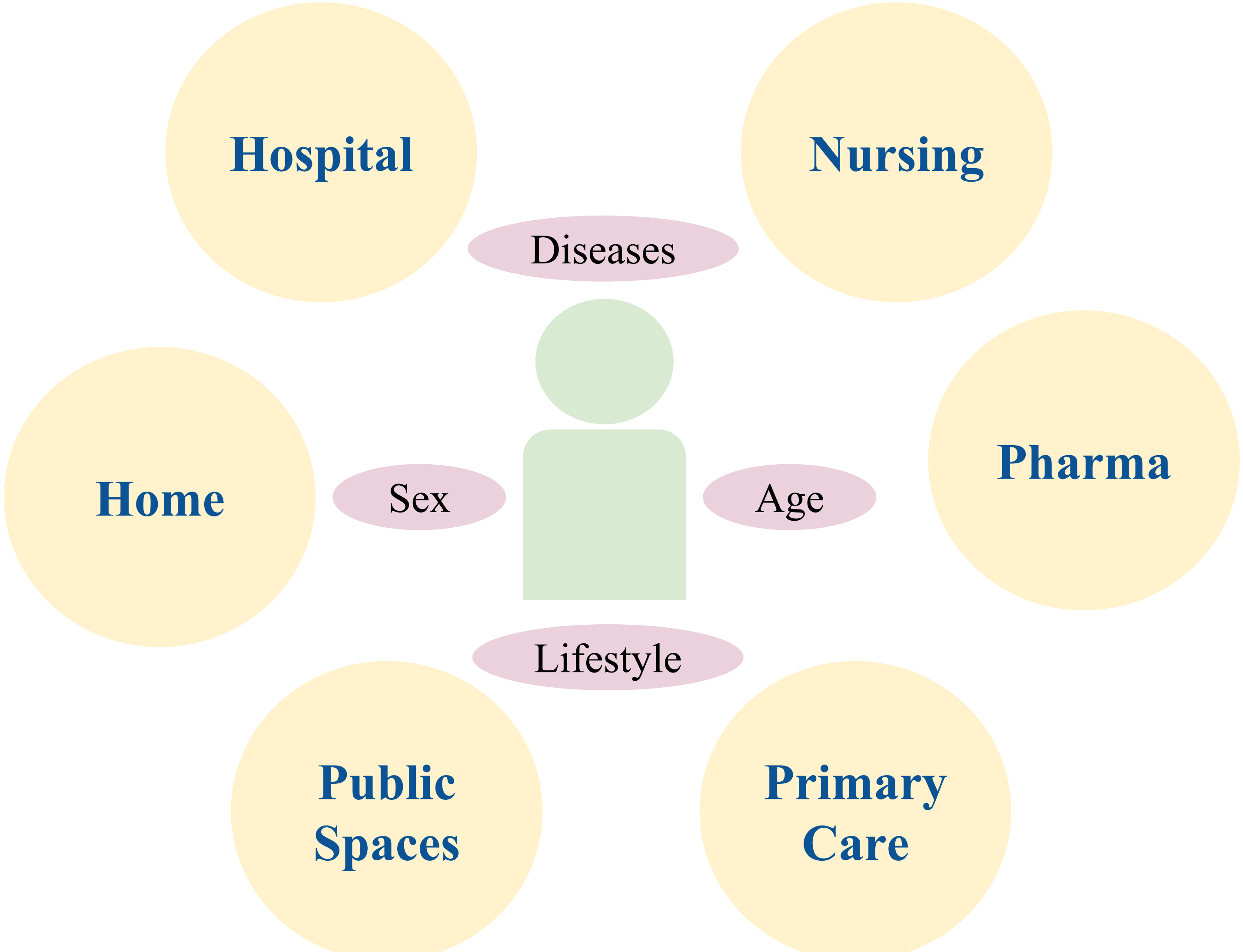
Deep Learning Model

Vital Signs

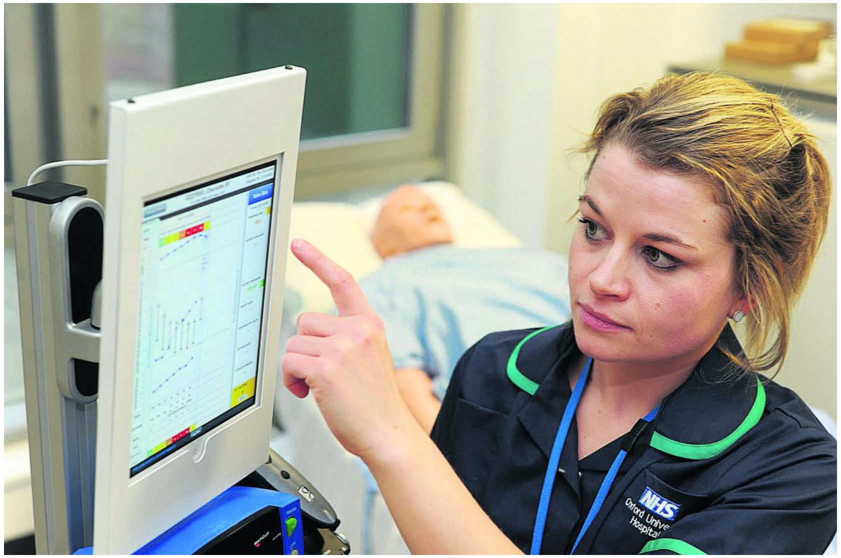
3. Stroke prediction

1. **Strokes,** or cerebrovascular accidents, are the **second leading cause of death worldwide** according to the World Health Organization.
2. The **burden of stroke** due to illness, disability and early death is expected to **double worldwide during the next 15 years.**
3. Current objectives:
    a. Predict the risk of having a stroke for patients admitted into hospital
    b. Distinguish between ischaemic and haemorrhagic strokes

Who, what and where?



1. Data Collection-driven Solutions



System for Electronic Notification & Documentation

(http://www.send-system.co.uk/)

Depression management using self-reported data

(http://www.thelancet.com/pdfs/journals/lanpsy/PIIS2215-0366(15)00471-X.pdf)

2. Diagnostic Tools

Diagnosis of sleep apnea amongst children

(https://www.atsjournals.org/doi/abs/10.1164/rccm.201708-1688ED?journalCode=ajrccm)

Early Warning Score for Pregnant Women

(http://www.nnuh.nhs.uk/publication/modified-early-obstetric-warning-score-meows-mid33-ao13-v4-2/

3. Prevention

Intelligent Hand Hygiene using Computer Vision

(https://aicare.stanford.edu/projects/hand_hygiene/)

Real-time fall detection for elderly patients

(https://arxiv.org/abs/1711.11200)

Translation of research into clinical settings

1. Generalizability of models across different clinical settings

2. Availability of an infrastructure to support new technologies

3. Designing and delivering solutions alongside ‘Human Factors’ approaches

4. Creating solutions to <u>real and relevant</u> problems!

Thank you for listening!

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