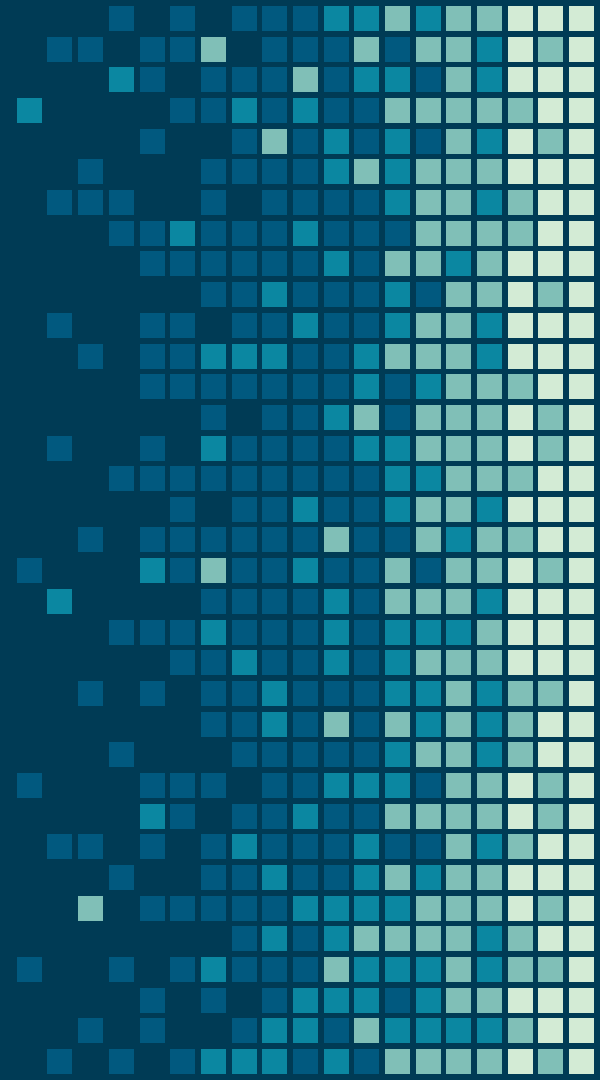


# Digital Health and the curse of Missing Data

David Wong, University of Leeds



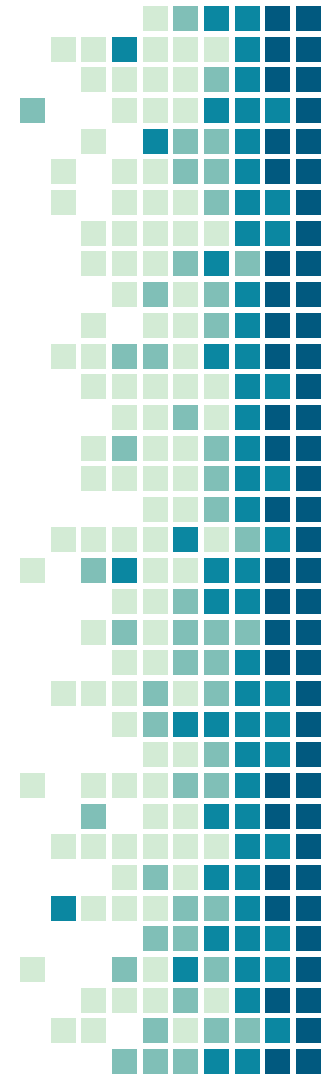
# Vital Signs – a brief intro

Vital signs are recorded by nurses in hospitals

- Heart rate, breathing rate, blood pressure etc.

Deviations in vital signs are associated with poor outcomes\*

In practice, deviations are quantified using Early Warning Scores



# Overview

## 1.) Missing and Unreliable Data

We will introduce the concept of missing and unreliable data, how it has caused problems for predictive modelling using three clinically examples.

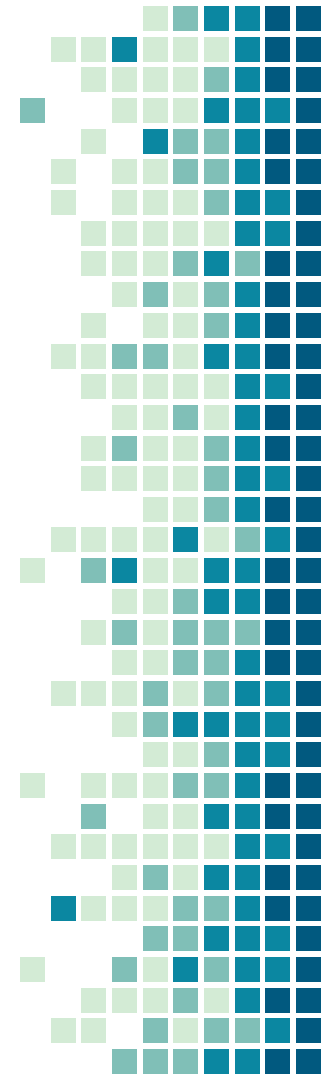
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Briefly, describe how methods from stats and signal processing can mitigate some problems with missing data. Discuss how problem can be solved by fixing processes.

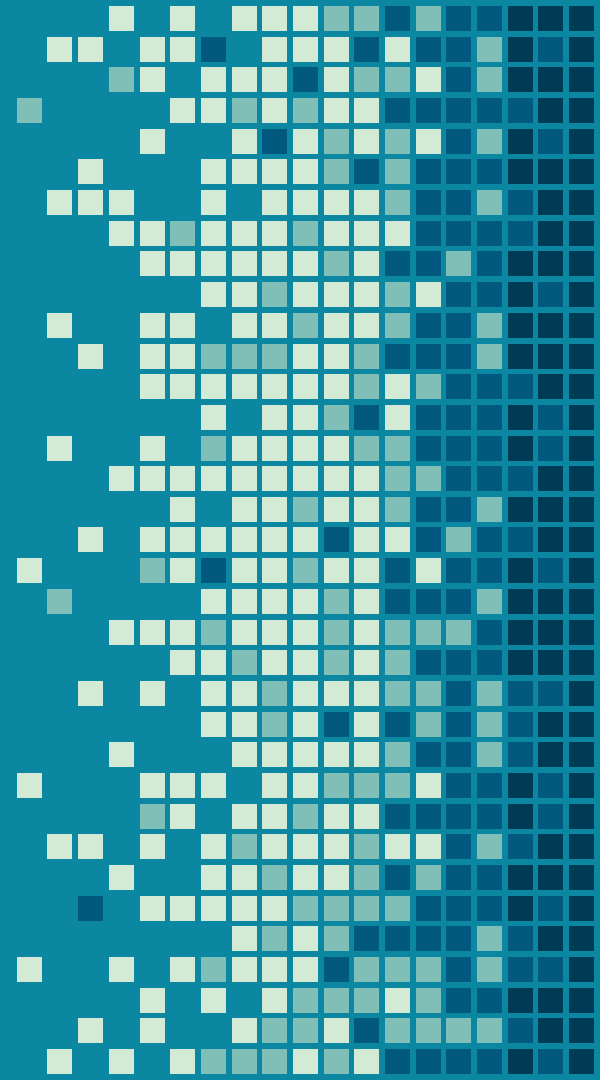
## Examples of research using cleansed data

Examples of large scale research that can be conducted after fixing data collection processes including:

- Evaluation of national standards
- Personalised deterioration models

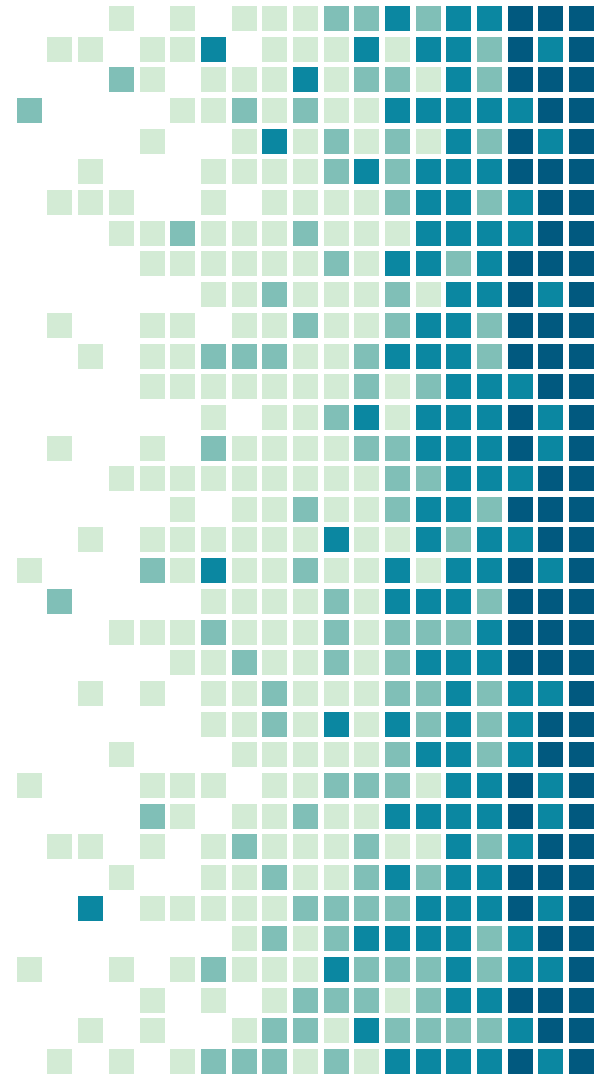


“ While it’s hard to predict the future, we know artificial intelligence, digital medicine and genomics will have an enormous impact on improving efficiency and precision in healthcare  
-Eric Topol



# 1. MISSING and UNRELIABLE DATA

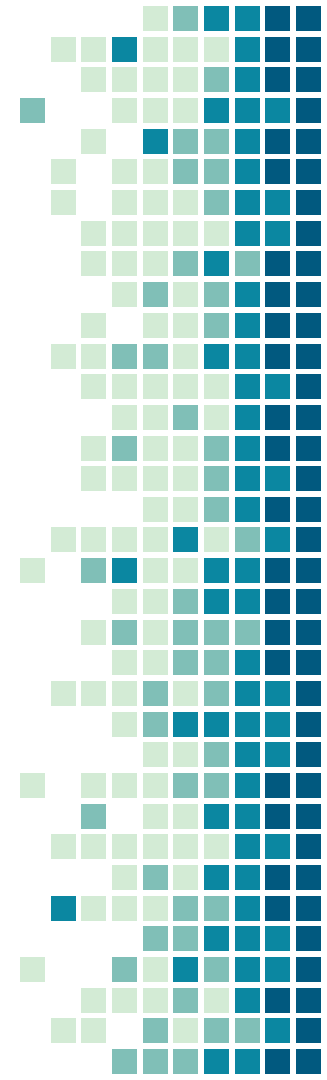
What is it and why does it matter?



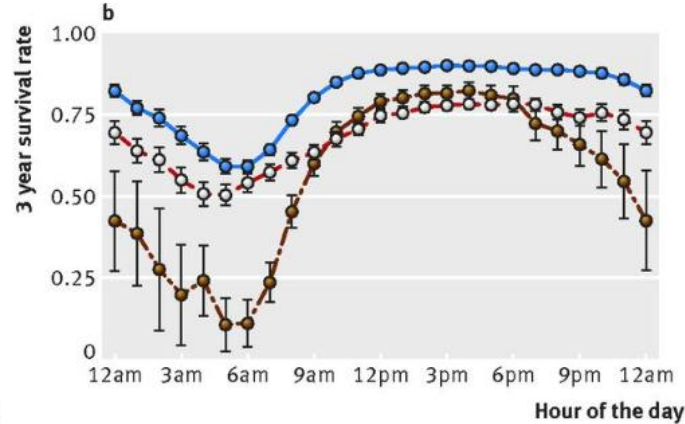
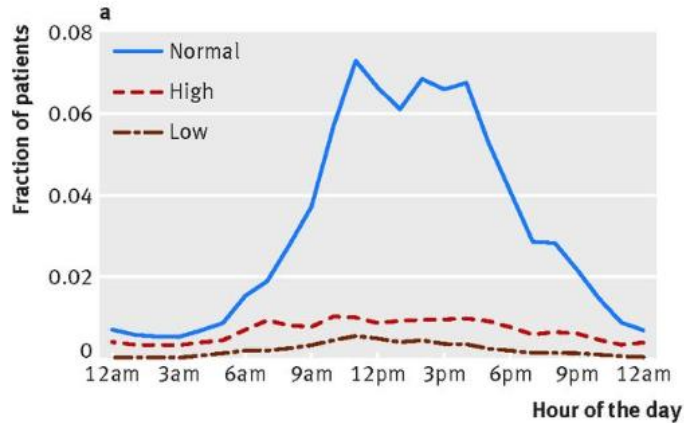
# 1.) Prediction of Mortality

- Attempted to predict survival based on lab test results
- Presence of test, was a significant predictor in 233/272 tests
- Time of test was **more** predictive than test results in 118/174 tests

Biases in electronic health record data due to processes within the healthcare system: retrospective observational study. Agniel et al. BMJ, 2018



# 1.) Prediction of Mortality

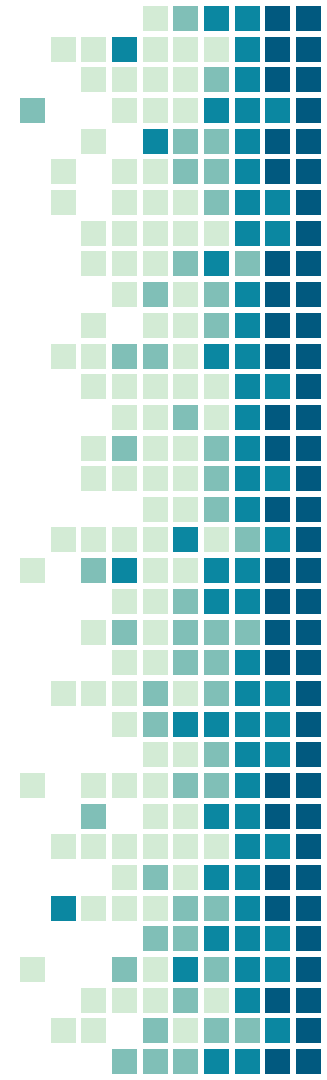


Biases in electronic health record data due to processes within the healthcare system: retrospective observational study. Agniel et al. BMJ, 2018

## 2.) Prediction of Mortality

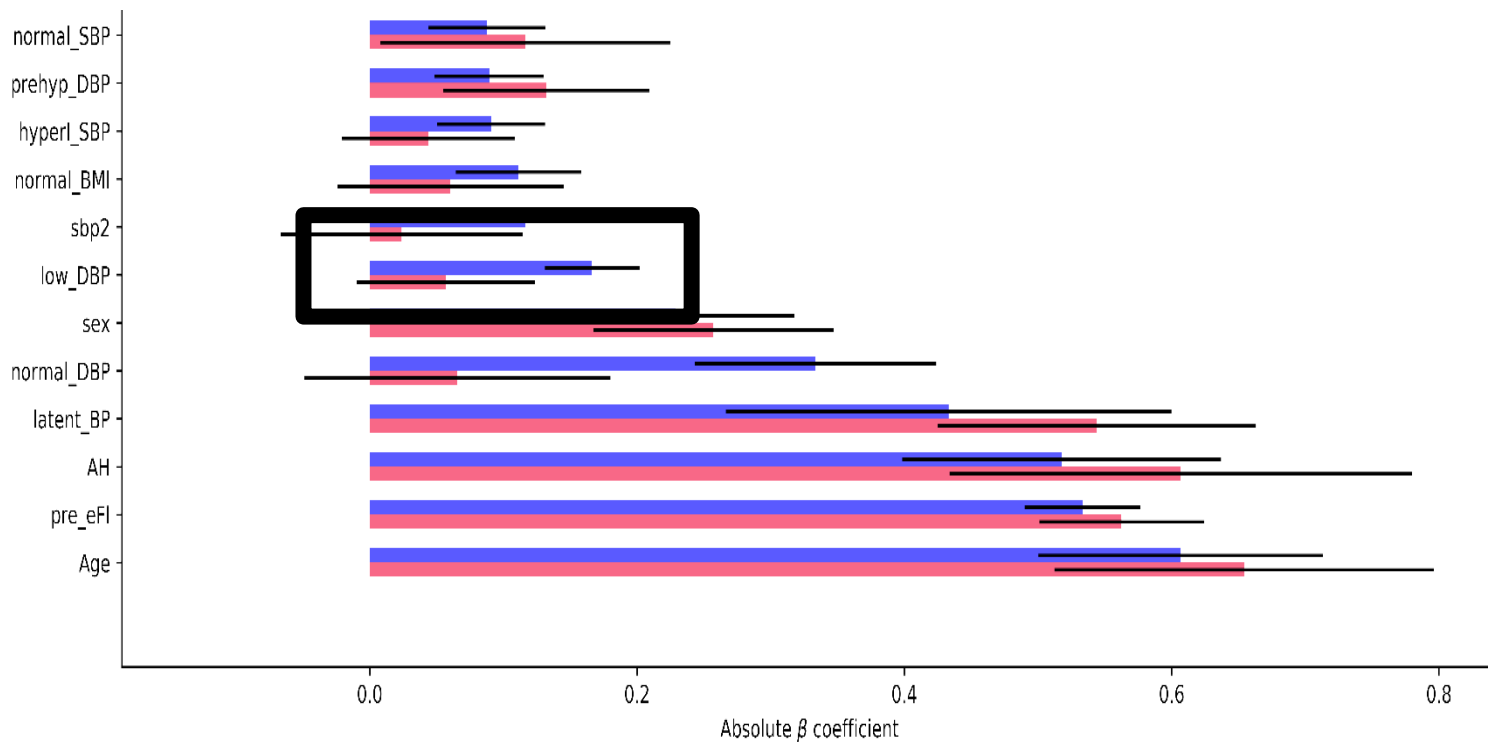
- Attempted to predict survival based on primary care variables
- Low Diastolic Blood Pressure was a significant factor
- Impact of low Diastolic Pressure insignificant after accounting for missing readings

Identification of clinical factors associated with poor surgical outcomes in a large primary care data set. Narganes et al. in Proc BioMedEng, 2018



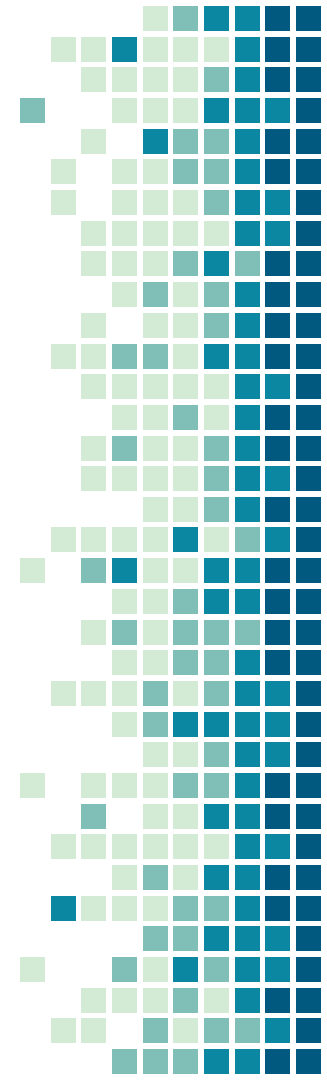


## 2.) Prediction of Mortality



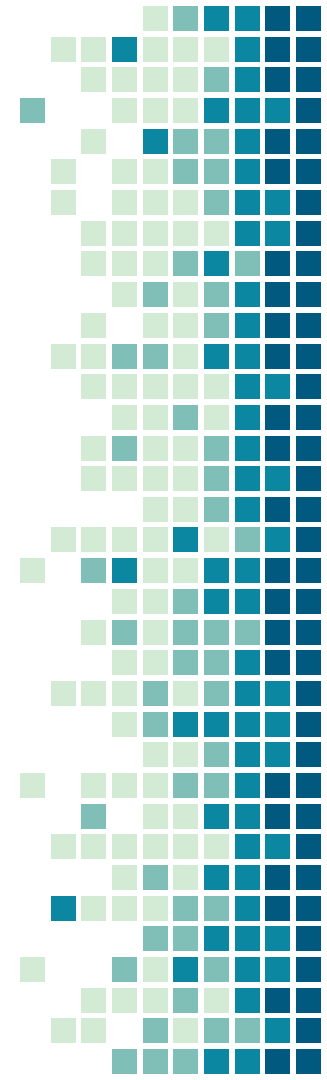
## 3.) Symptom Checker Predictions

The Babylon Triage and Diagnostic System – a new implementation after the previous generation [Middleton et al., 2016] – is based on a Probabilistic Graphical Model (PGM) [Koller and Friedman, 2009] of primary care medicine, which models the prior probabilities of diseases and the conditional dependencies between diseases, symptoms and risk factors via a directed acyclic graph.



## 3.) Symptom Checker Predictions

The structure of the graph (i.e., the connections between diseases, symptoms and risk factors) is created by medical experts and reviewed from a modelling perspective.



# 3.) Symptom Checker Predictions

Are disease priors and dependencies enough?

- Location
- Time



## Measles outbreak: Should your child be given the MMR vaccine as measles cases soar

MEASLES is making a resurgence throughout Europe, as cases of the once eradicated disease skyrocket amid anti-vaccination popularity. One of the best ways to combat the spread is to ensure your child is given the MMR vaccine.



# Recap

## 1.) Mortality

1.) missingness of test result affects the predictive model – those with test at higher risk

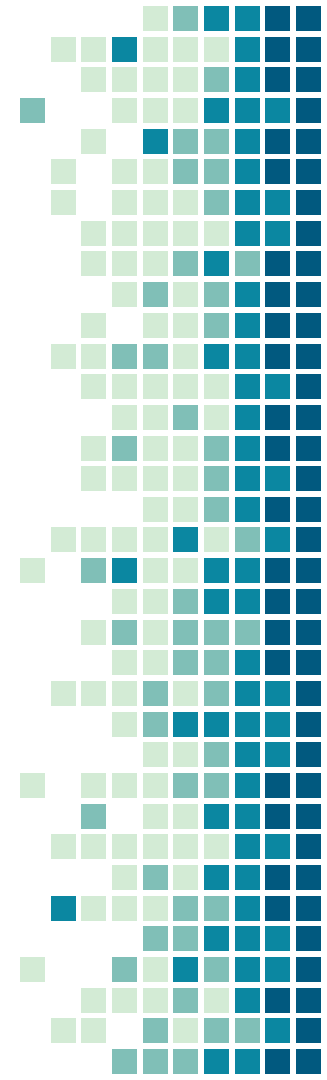
2.) presence of test results is conditioned on latent information (doctor's nous)

## 2.) Mortality (primary care)

1.) missingness of blood pressure measurement affects mortality prediction

## 3.) Symptom

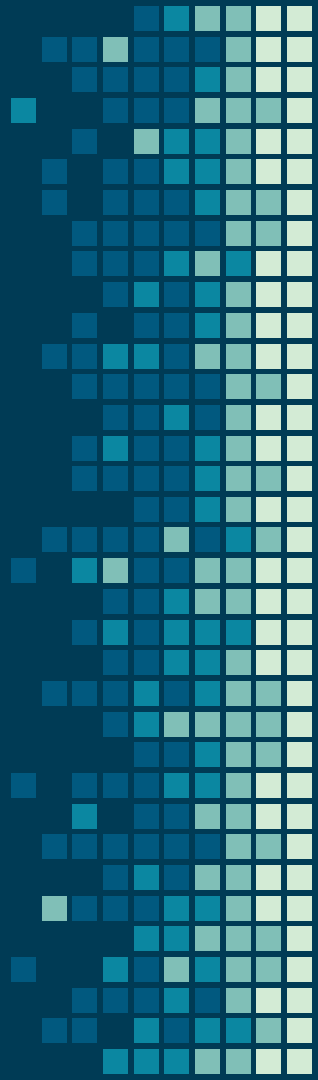
1.) missingness of 'superfluous' variables, location and time, could affect disease prediction.



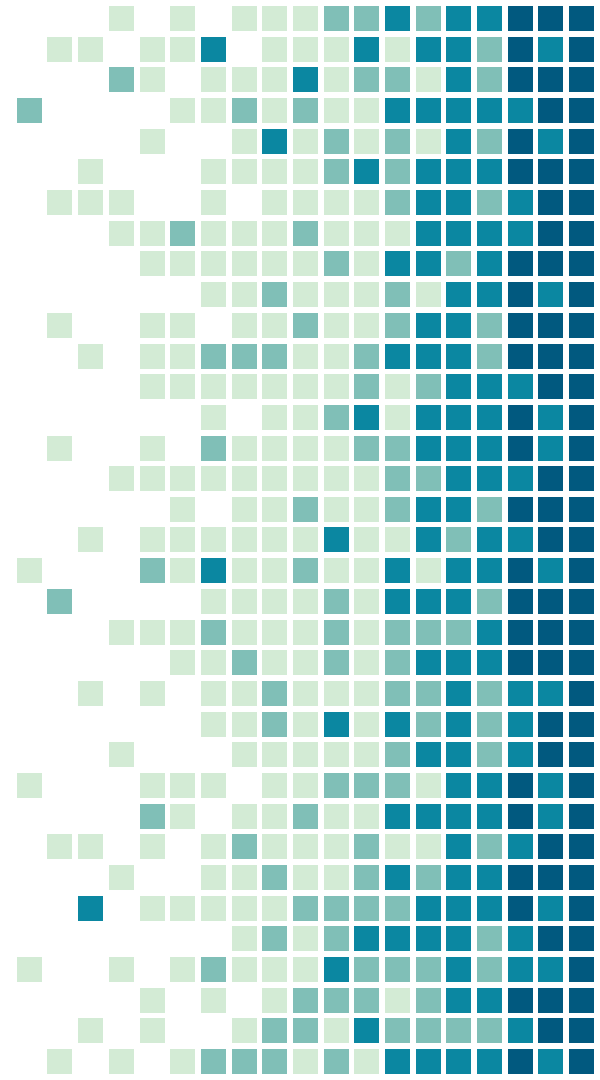


# DATA

are not agnostic to human bias

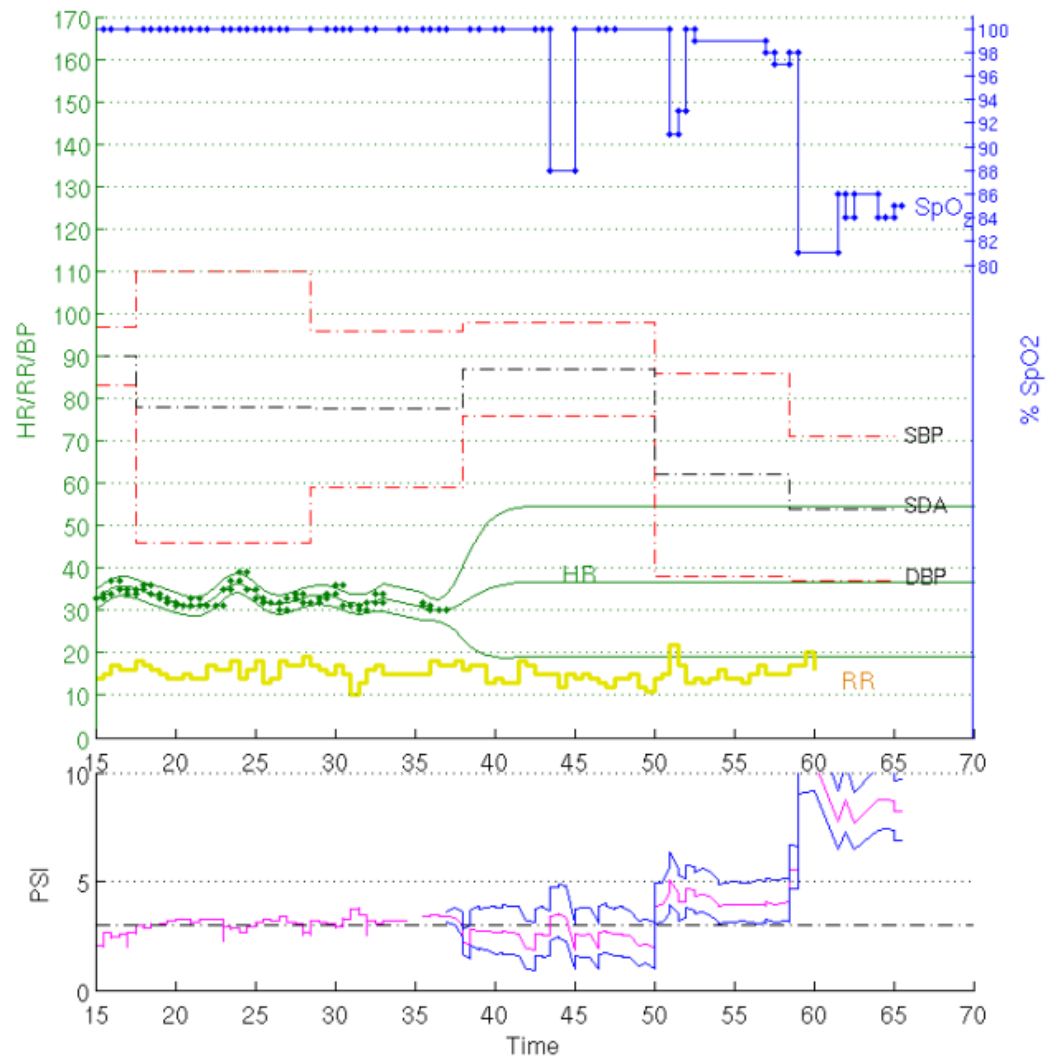


# 2. DEALING WITH MISSING DATA



# 3.) Temporal (GPs)

- Model time series as multivariate Gaussian
- Time covariance matrix is based on historic data
- Estimate missing values

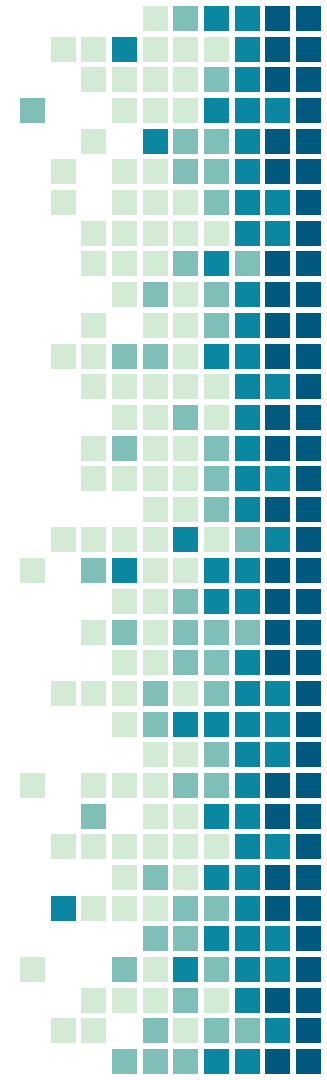






# The problem: it's hard.

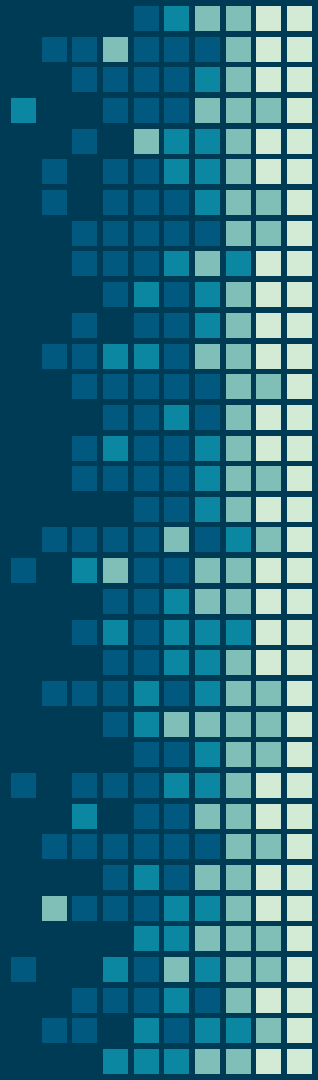
- 1.) Even for well-defined problems, like multiple imputation, work is computationally intensive
- 2.) We are making the best of a bad situation – trying to squeeze out a tiny bit more information.





# FIX THE INPUT


Make the process of collecting data easier, to get the right variables and reduce likelihood of bias



# Common Clinical Opinions

- Grassroots dissatisfaction with clinical systems (<https://github.com/dhinet/csus-2016-data>)
- General understanding that good record-keeping is important
- Summary – willingness to improve data collection, if it doesn't impact workload.

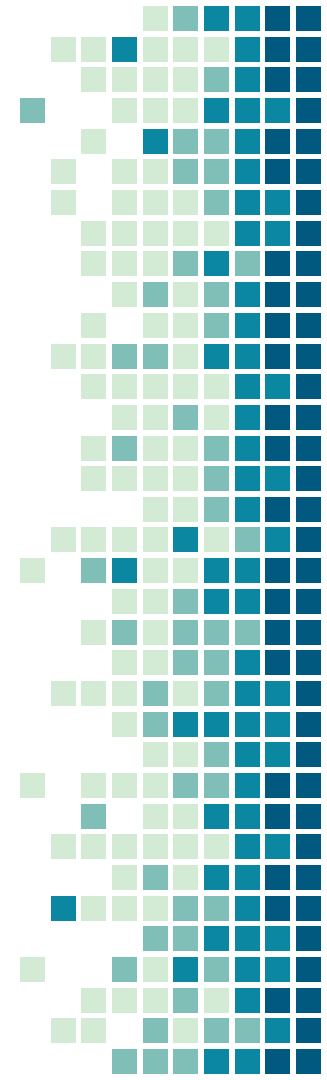




# SEND – System for Electronic Notification and Documentation

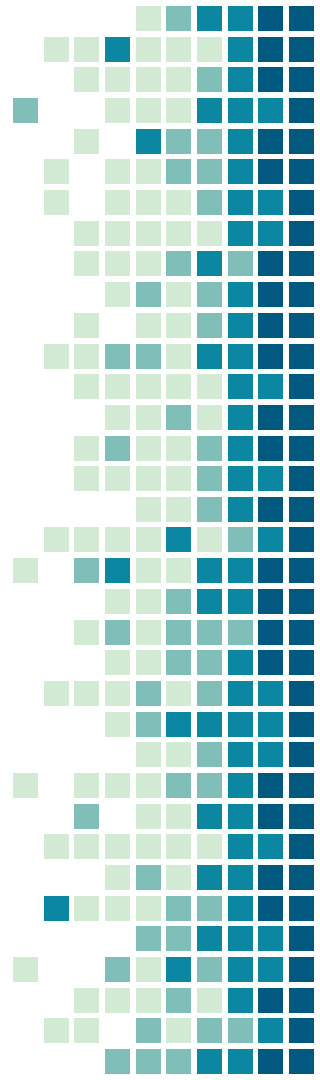
# Vital Signs – the problem

- C. 2011 – vital sign observations recorded on paper
  - Often illegible
  - Only accessible in one place
  - Goes missing (up to 30%!)
- Early Warning Scores calculated incorrectly in approx. 20% cases
- Opportunity to fix a clinical problem AND fix our data problem



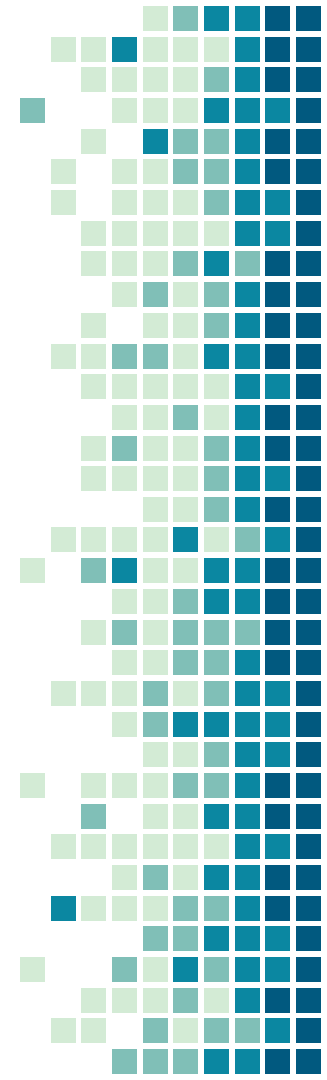
# SEND

- Redesign process to make data capture a natural part of the process
- Automate where possible



# SEND

- Redesign process to make data capture a natural part of the process
- Automate where possible



# SEND

ZZZTEST, CHARLOTTE (F) ★  
01 JAN 1990 (25 years old) NHS No: Not Recorded  
Hospital No: 10152429

Change Patient

DATE: 02/09 FRI 04/09/2015

TIME: 14:49

T & T: 1 0 2 0 2 4 0 1 0 9A 7G

TEMP (°C): 36.5 - 37.5

HEART RATE (bpm) & BLOOD PRESSURE (mmHg): 80 - 100 bpm, 100 - 140 mmHg

RESPIR RATE (min): 10 - 35

SATS	98	98	95	97	98	95	97	98	75	89
OXYGEN	RA	5L RM	RA	RA	RA	RA	RA	8.5L H2B	RA	8.5L TM
AVPU	A	A	A	A	A	A	A	A	V	P
GCS	15	15	15	15	15	15	15	15	11	13
Concern									A	G
T & T	1	0	2	0	2	4	0	1	0	9A 7G

TEMPERATURE: --

BLOOD PRESSURE: ---/--

HEART RATE: --

RESPIRATORY RATE: --

OXYGEN SATS: --

OXYGEN THERAPY: --

CONSCIOUSNESS: --

NURSE CONCERN: --

T&T SCORE

Temperature:  C

7 8 9 patient refused  
4 5 6  
1 2 3  
0 . / delete

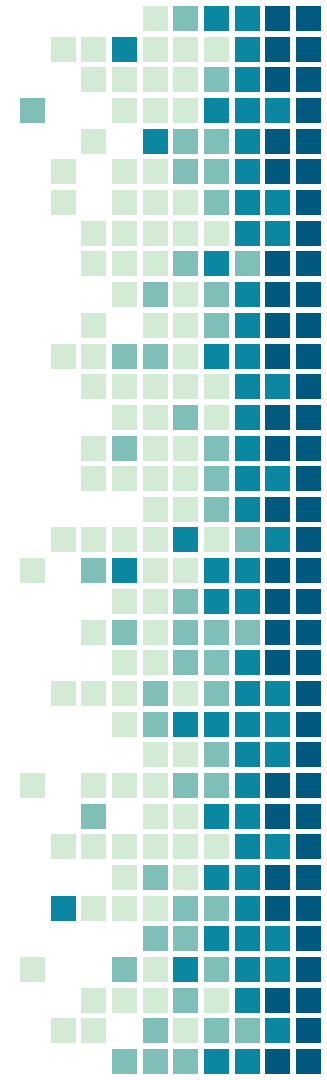
Δ Previous Next ▾

Chris FULTON is currently logged in Log Out



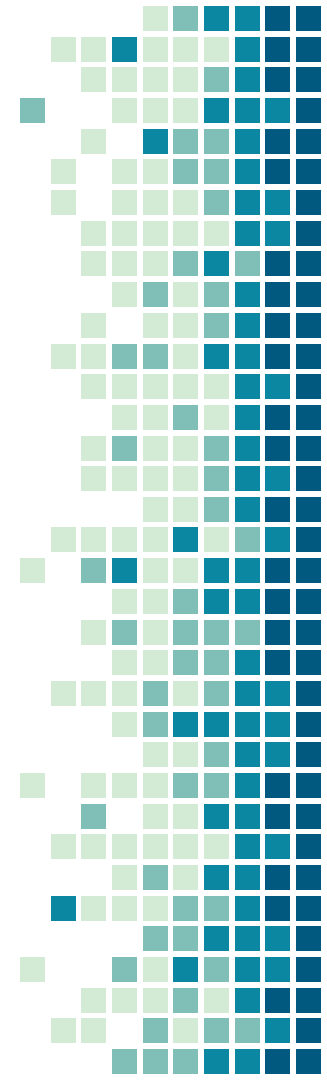
# SEND –clinical advantages

- Documentation – at least as fast as paper
- Information reviewable remotely – critical outreach teams can view data from anywhere
- Automation of regularly audits



# SEND – missing data advantages

- Multi-hospital data set.
- Data validated according to our own input rules
- Design process has helped in identifying further potential biases



65s\*

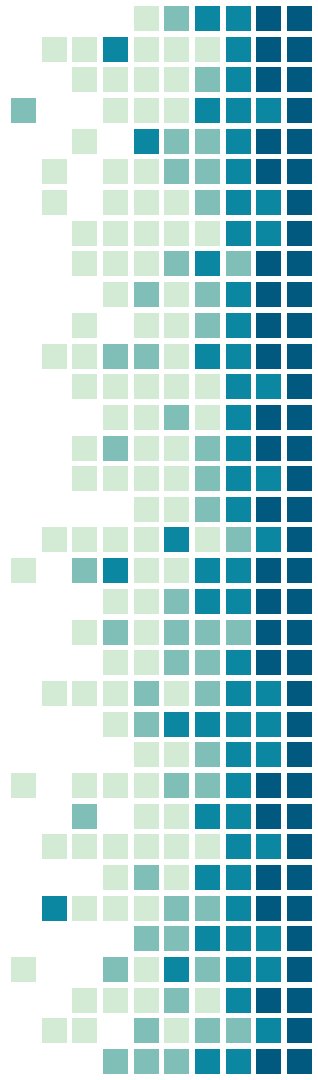
'Average' time saving per observation

2m vital sign sets

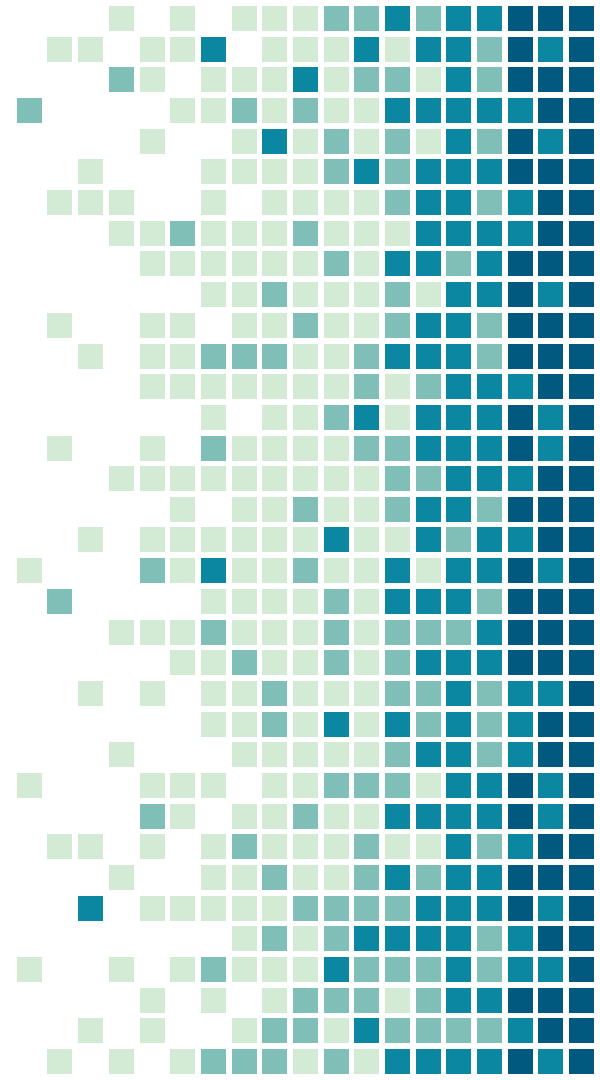
Across two hospital trusts

A ward-based time study of paper and electronic documentation for recording vital sign observations. Wong et al. JAMIA, 2017

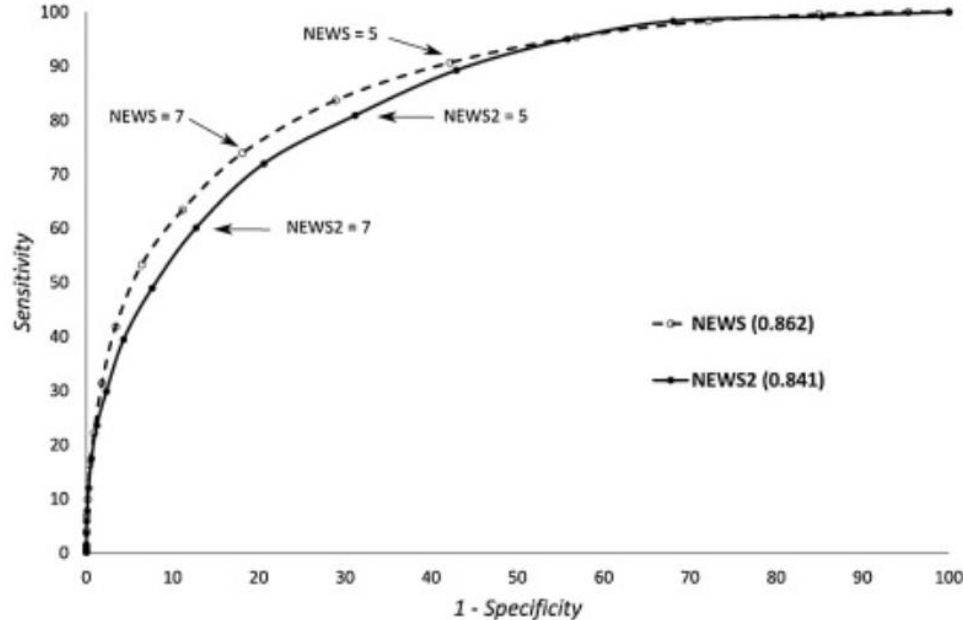
SEND: A system for electronic notification and documentation. Wong et al. BMC MIDM, 2015



# 3. APPLICATION OF SEND DATA



# EVIDENCE-BASED EVALUATION OF NATIONAL STANDARDS



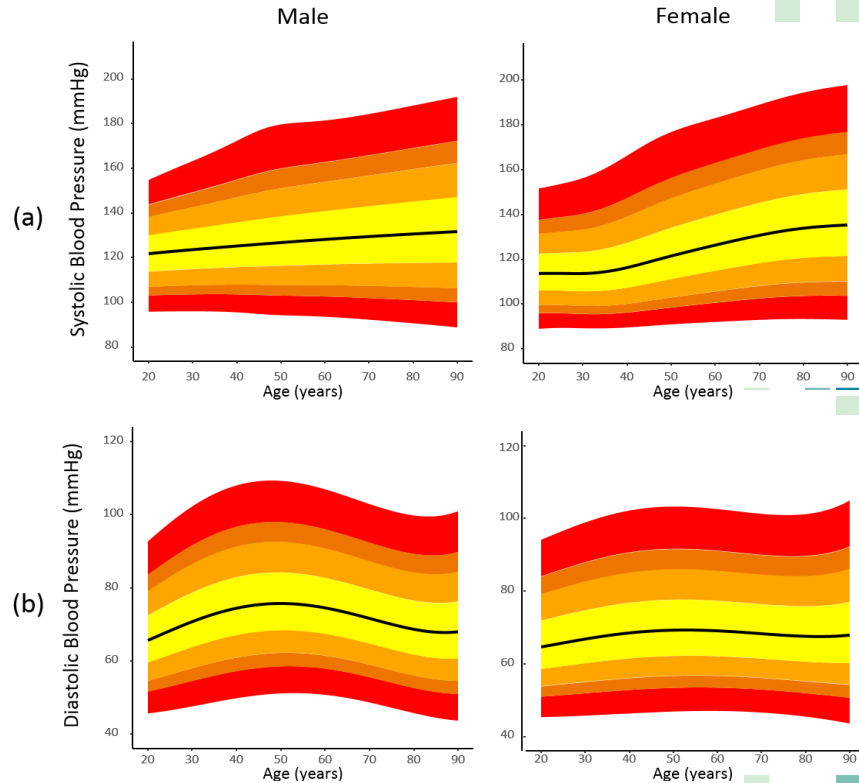
A comparison of the ability of the National Early Warning Score and the National Early Warning Score 2 to identify patients at risk of in-hospital mortality: a multi-centre database study

Pimentel et al,  
Resuscitation, 2018

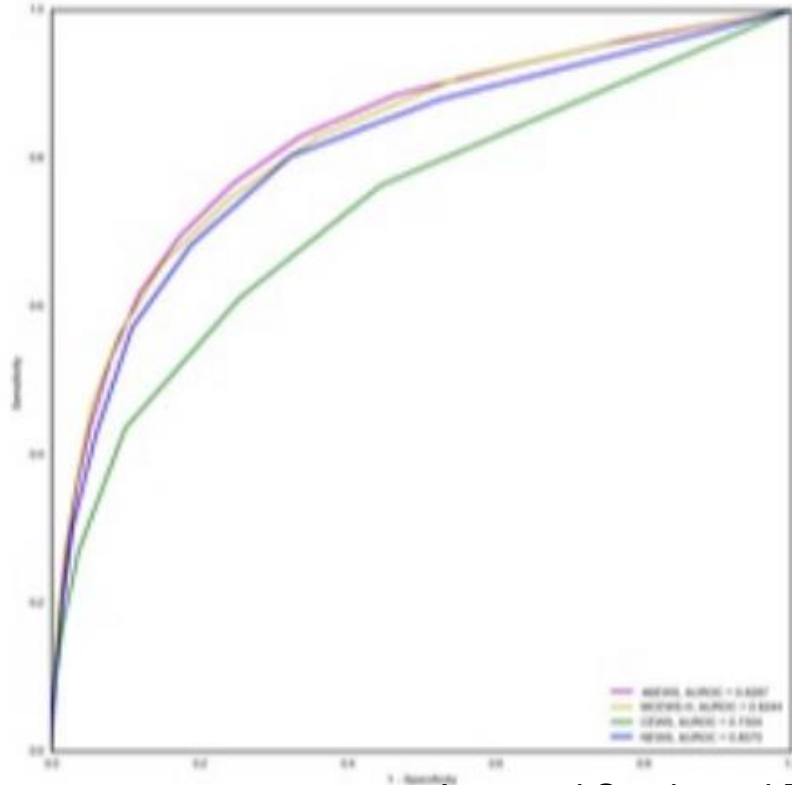
# Large cross-sectional studies with reliable data

## Blood Pressure Centiles

- Generation of blood pressure centiles by age and sex.
- Sub-group analysis by:
  - Emergency vs non-emergency
  - Hyper- vs normo-tensive



# Personalised Models of Deterioration



Inclusion of age-based centiles into Early Warning Score

Performance exceeds National Early Warning Score

Performance particularly better for younger adults (not shown here)

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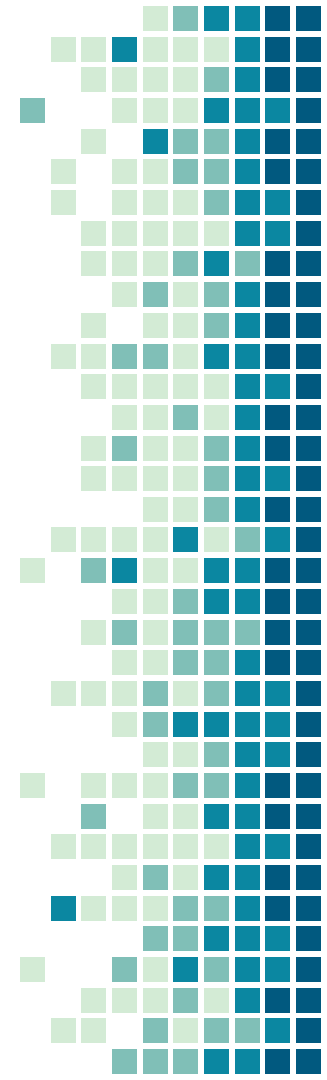
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# THANKS!

Any questions?

You can find me at:

@drdavecwong

d.c.wong@leeds.ac.uk

