Collaborating for Success: combing AI with clinical expertise to enhance patient care

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Disclosures

I am the co-developer of the Ainsoff Deterioration Index (ADI)

I am a clinical advisor for Beamtree Ltd, Sydney Australia

I am a cardiothoracic surgeon

I am a computer scientist

I love flying

Background

- Patients often suffer an adverse event – unplanned ICU admission, large bleed etc
- Looking at each individual's notes, it was clear that they were deteriorating for hours or days and it wasn't picked up
- I figure that if we had enough patient data, we could build a model to predict deterioration
- This was much harder than I ever could have imagined!

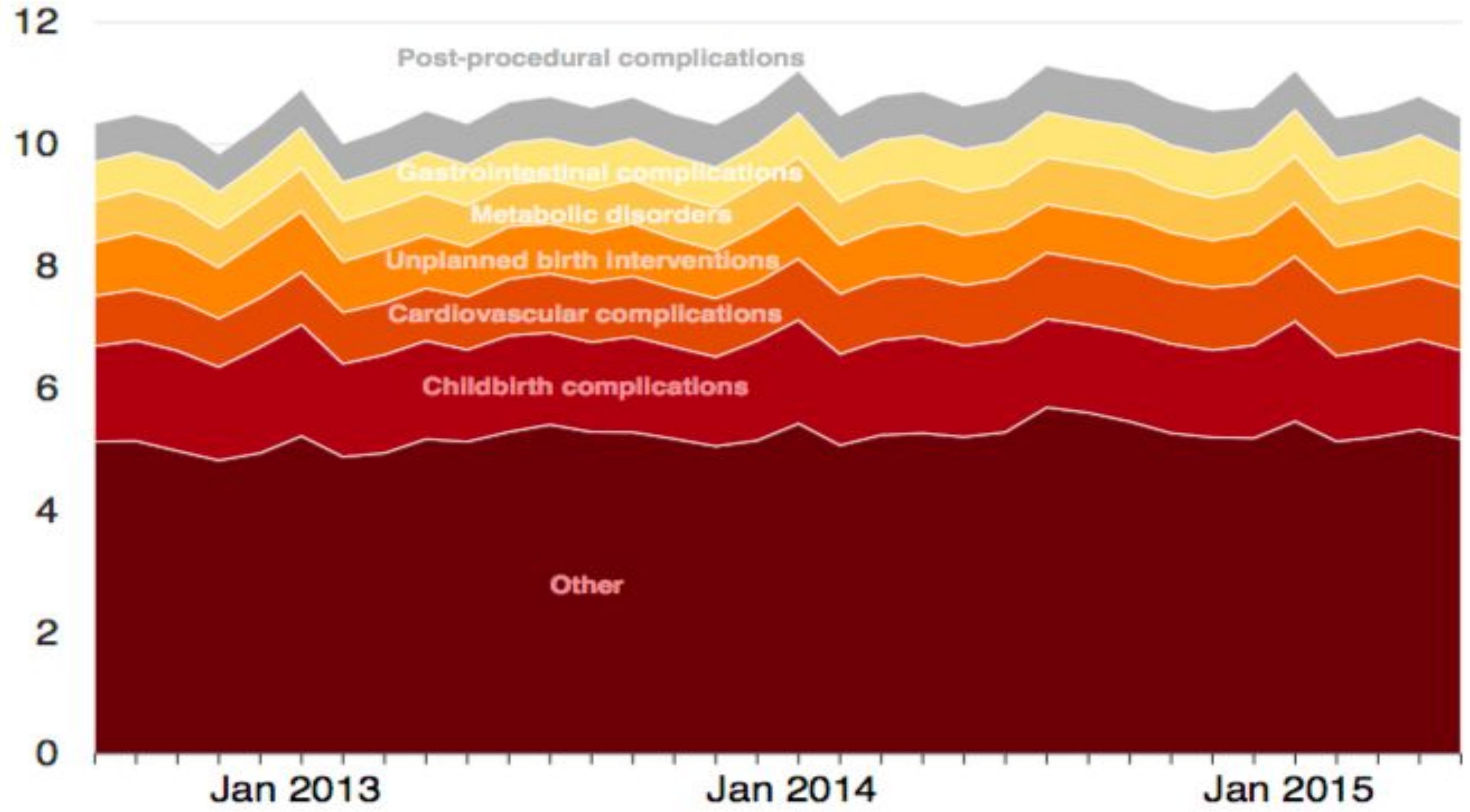
Inpatient complications are major source of morbidity and mortality

- 1/9 inpatients suffer a significant complication yearly
  - sepsis/pneumonia (20%)
  - pulmonary embolus (10%)
  - Myocardial infarction (10%)
  - Bleeding (5%)
  - other (cardiac tamponade, iatrogenic pneumothorax).

- A huge economic burden: complications cost Australian public hospitals nearly $5 billion a year, and private hospitals more than $1 billion a year.

Why we focus on inpatients?

Percentage of all inpatients experiencing a complication



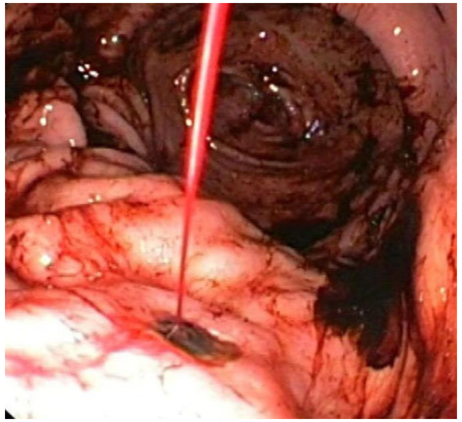
Despite the best efforts of humans, complication rates and associated morbidity and mortality are not improving

(Grattan institute, 2018)

Insult-Response Delay: IRD

The time it takes from the insult occurring to recognition by clinical staff

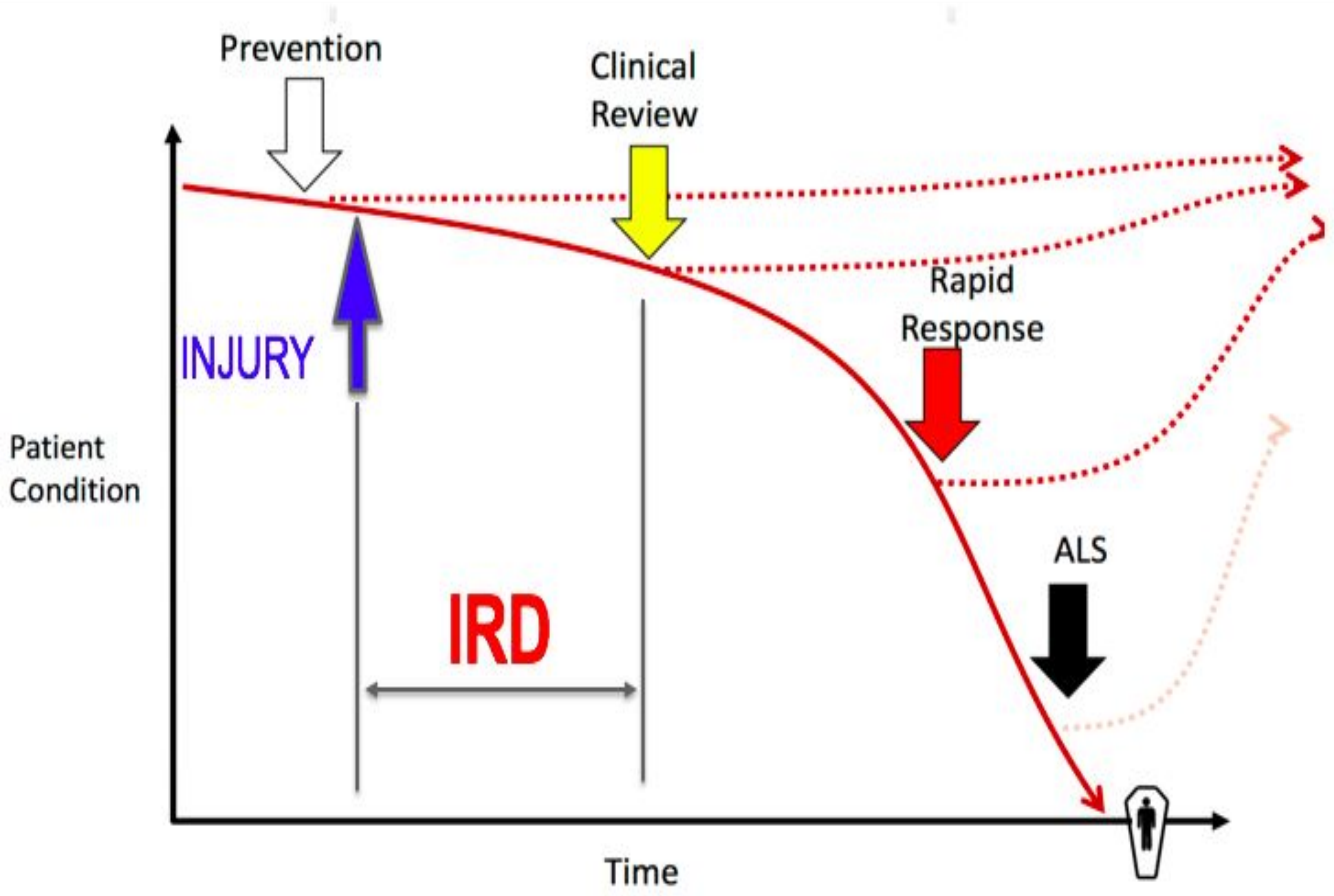
e.g. Onset of rupture gastric ulcer until clinical recognition



hours? days?

This leads to unnecessary morbidity, mortality, and costs

The Insult-Response delay



Complications themselves may be unavoidable, but their sequelae are often compounded by misdiagnosis or lengthy delays to detection.
What if nurses, doctors and patients knew they had a safety net that was always on call and analysing their data in

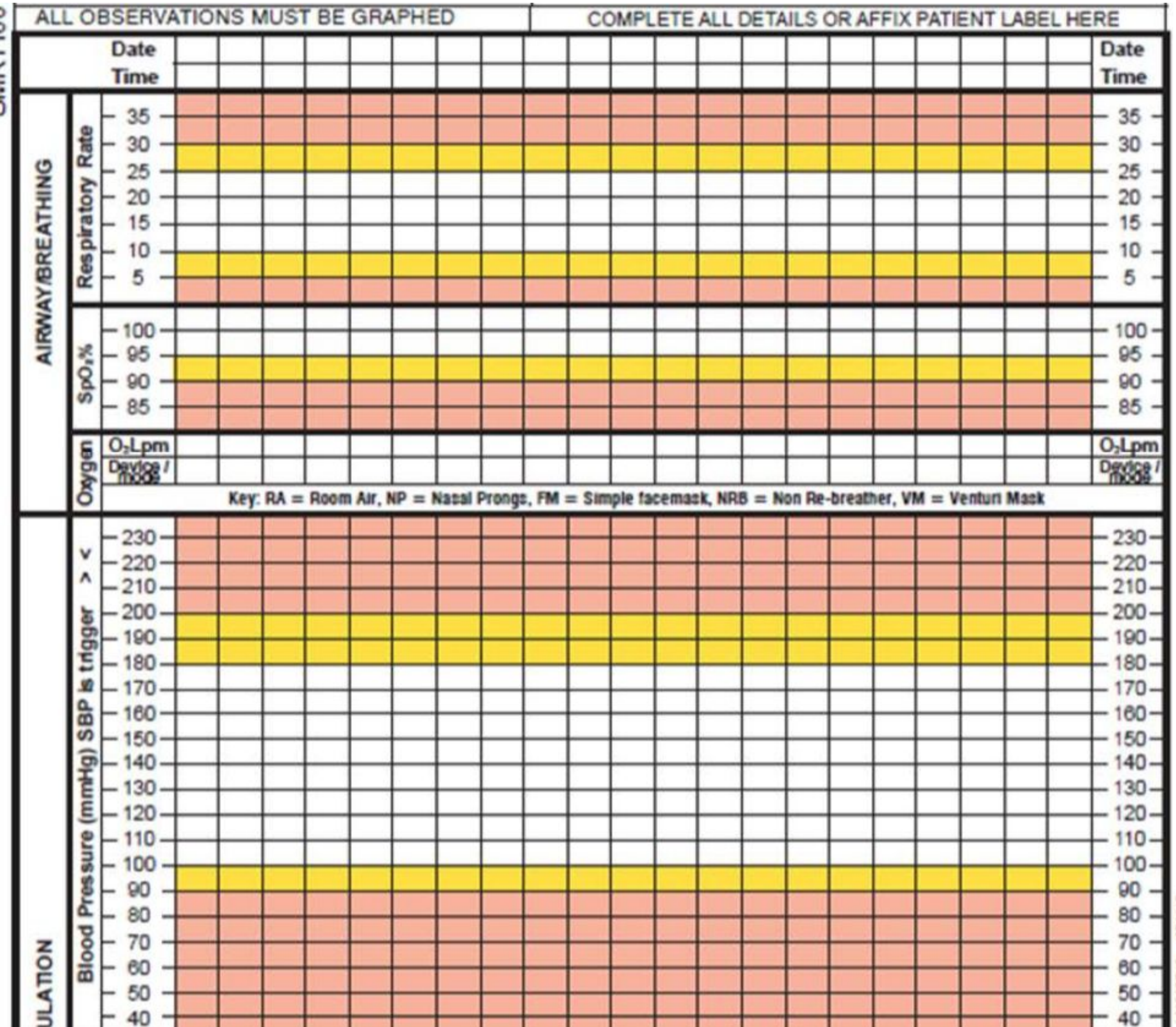
Causes of the Insult-Response Delay

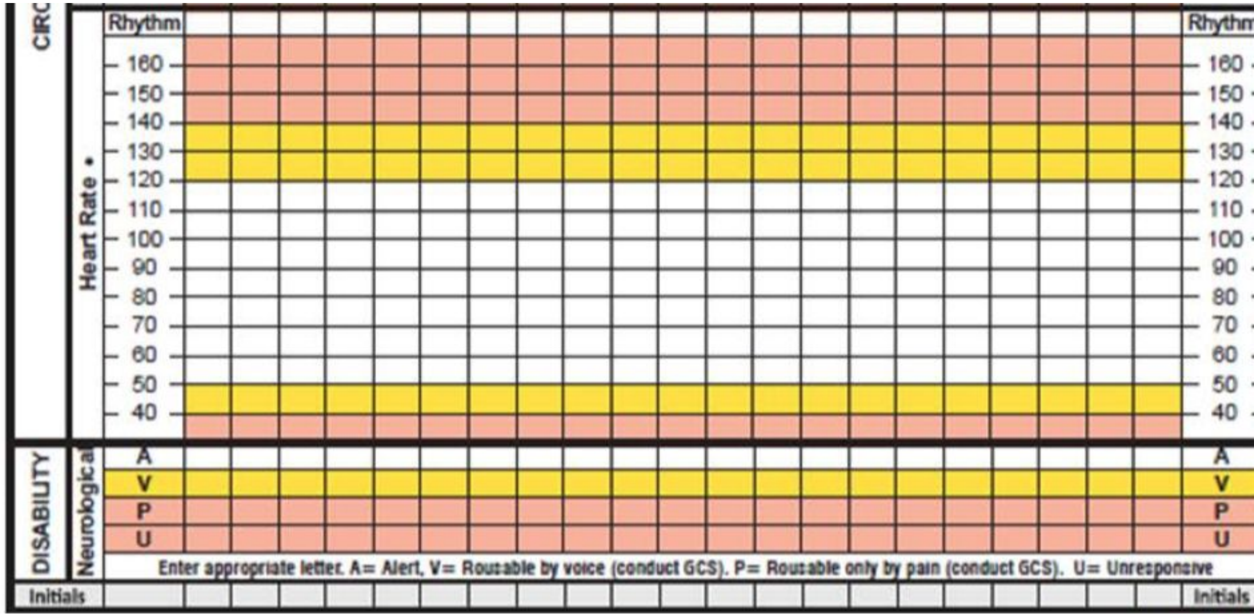
- Human error
- Limited resource of doctors and nurses
- Inexperienced ward doctors
- Current ‘escalation of care’ triggers are poor at flagging complications early.

Early Warning Scores

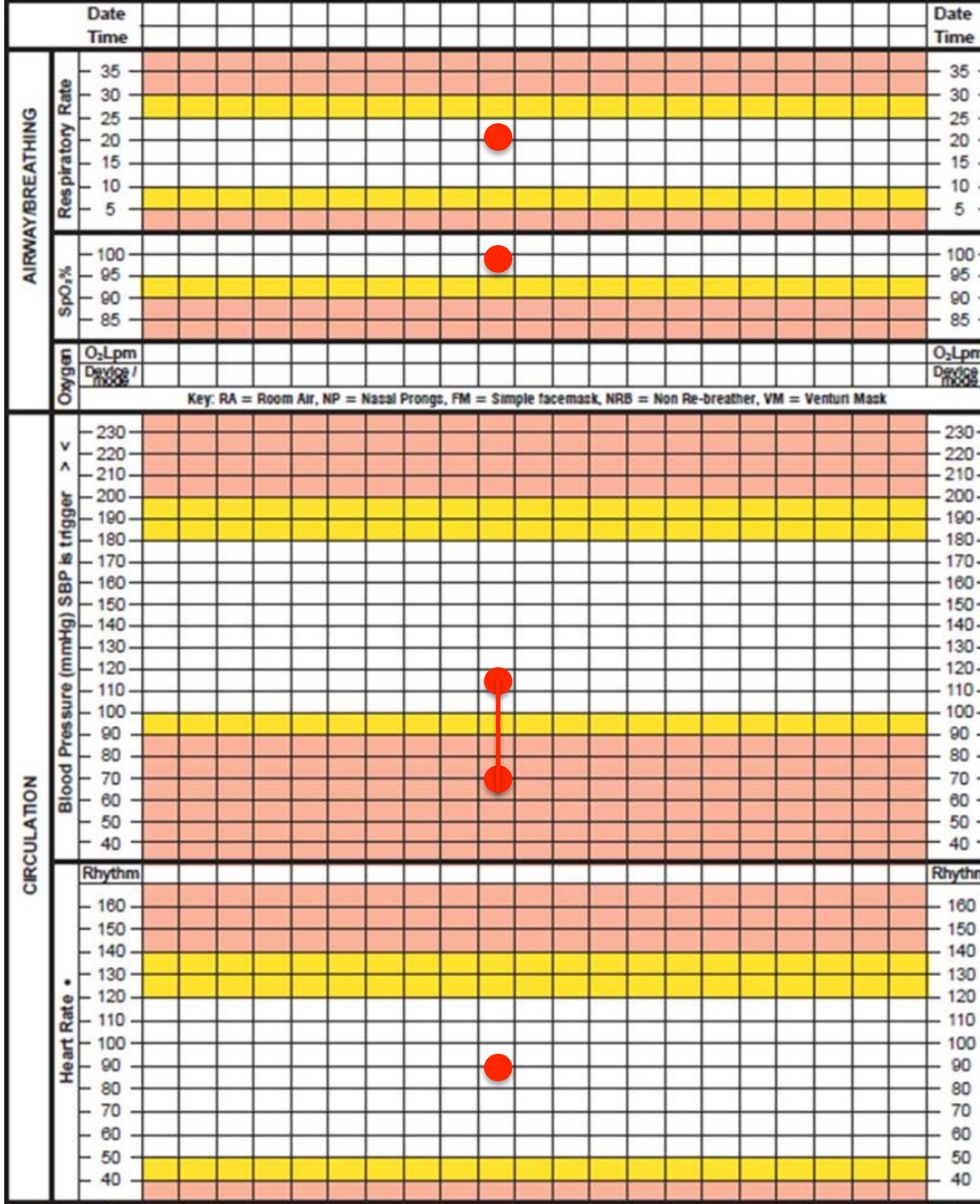
- Aim to detect patients that are deteriorating and to escalate care
- Modified and National Early Warning Scores
- Between the Flags (NSW)

Between the Flags (Sydney, Australia)



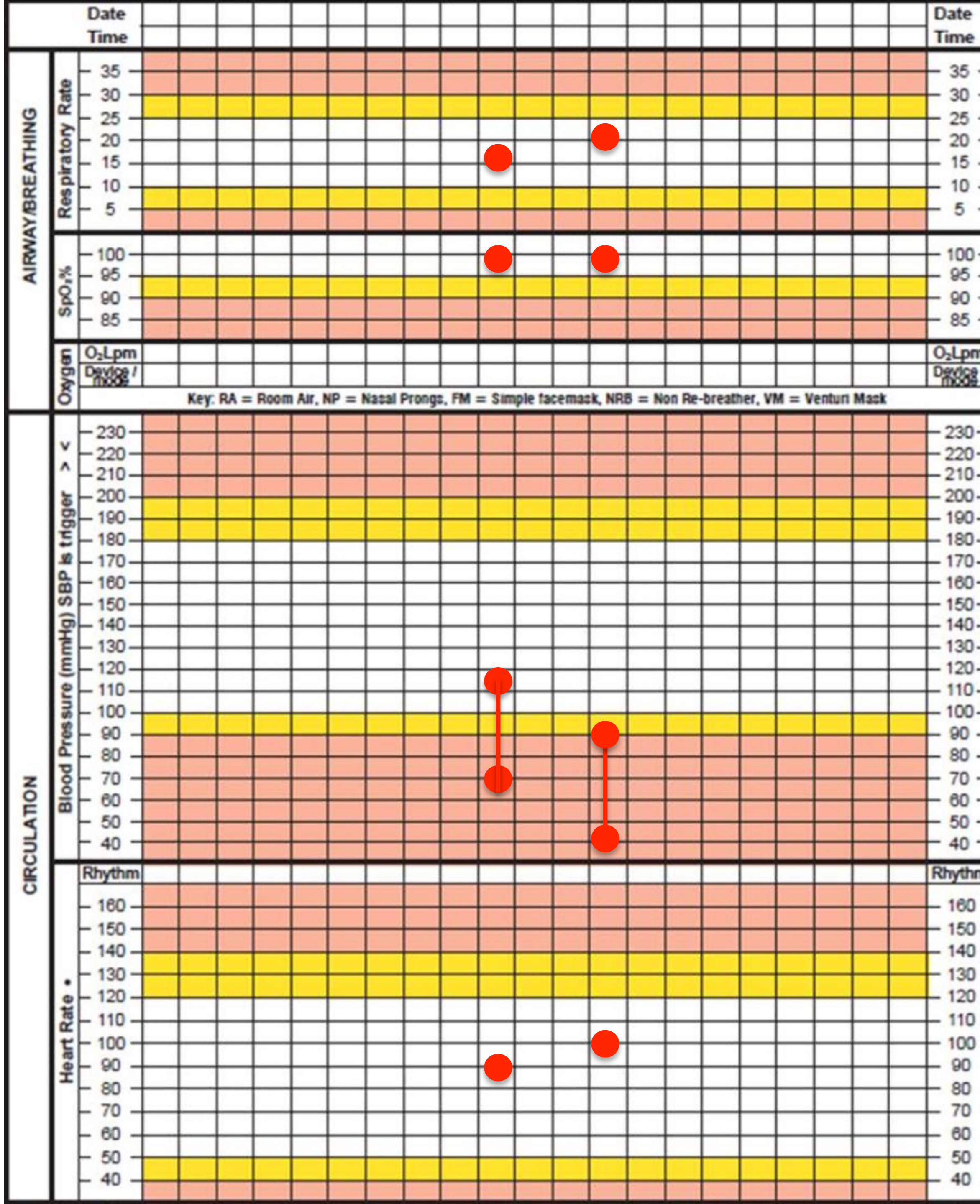


Is this patient sick?



Yellow Response

Doctor must review within 30 minutes (Can be a very junior)



Red Response

Rapid Response called

Patient is very unwell

Hb 50

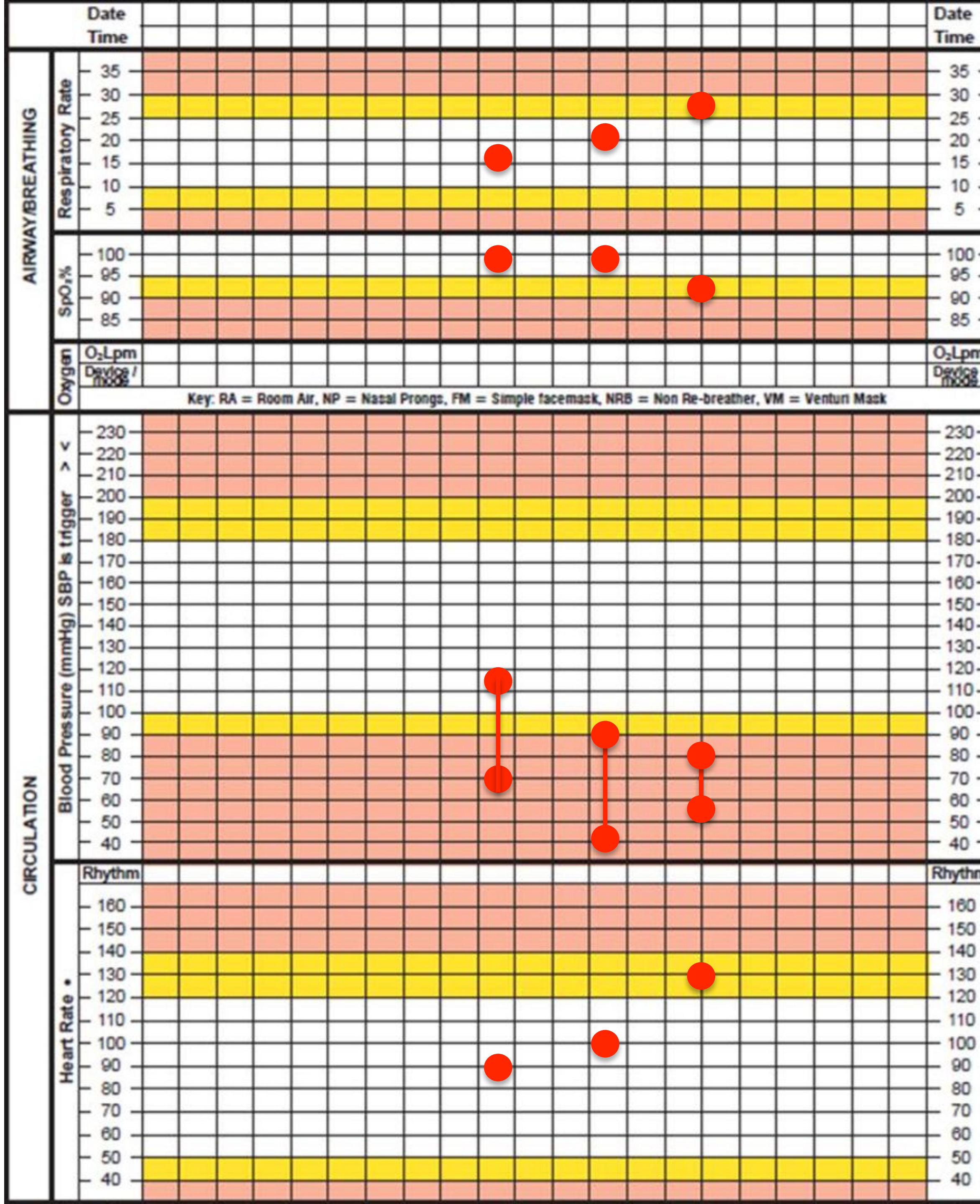
Hours since the insult

ICU admission

Blood transfusion

Acute renal injury

Acute neurological injury

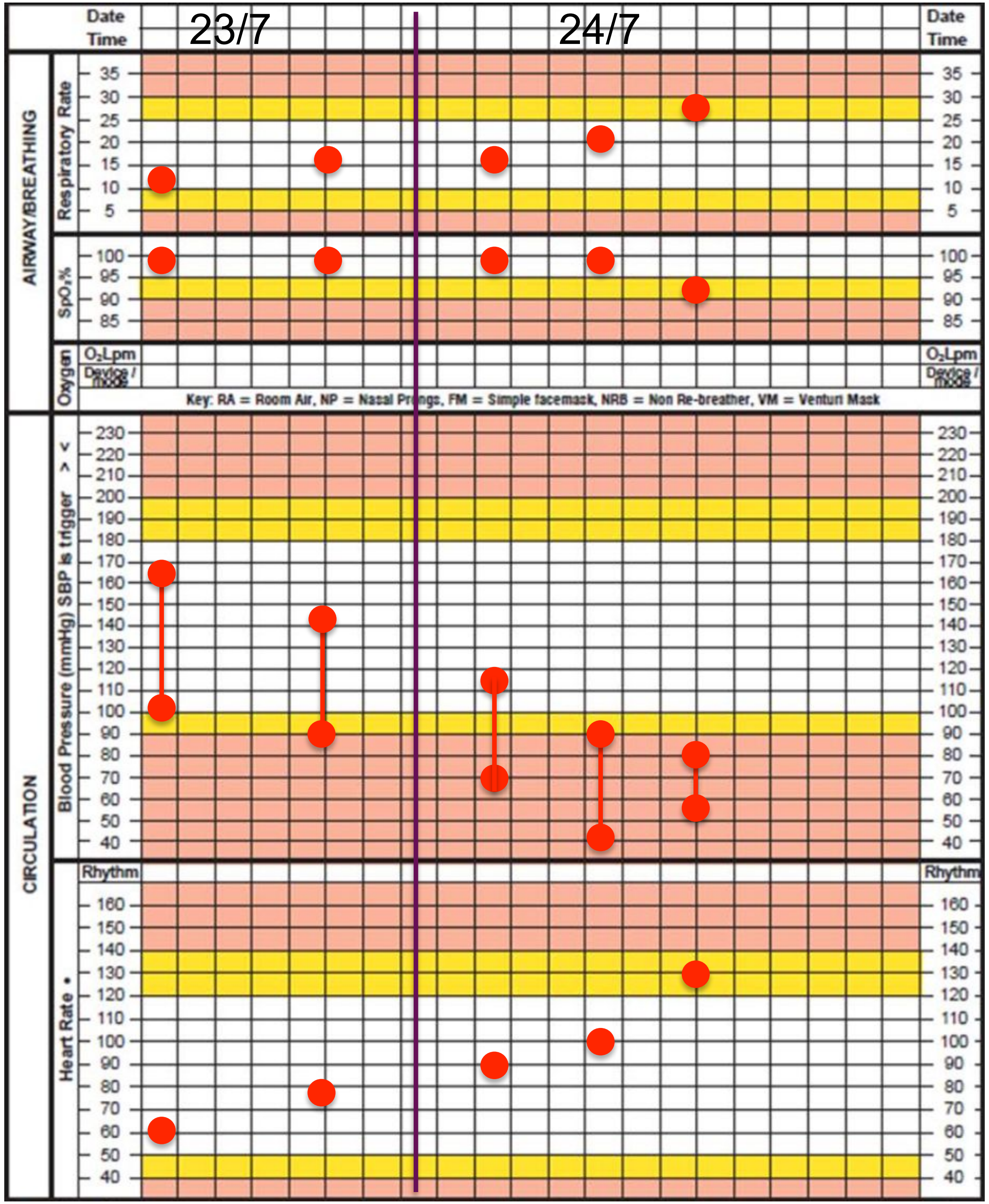


What did the data look like in the preceding 24hrs?

Very Clear progression

Medical staff are only notified when the systolic blood pressure is < 90 mmHg - but this patient has been deteriorating for 24 hours

What if we could provide an alert 12-24 hours in advance?



Modified Early Warning Score (MEWS)

	3	2	1	0	1	2	3
Respiratory Rate per minute		Less than 8		9-14	15-20	21-29	More than 30
Heart Rate per minute		Less than 40	40-50	51-100	101-110	111-129	More than 129
Systolic Blood Pressure	Less than 70	71-80	81-100	101-199		More than 200	
Conscious level (AVPU)	**U**nresponsive	Responds to **P**ain	Responds to **V**oice	**A**lert	New agitation Confusion		
Temperature (°c)		Less than 35.0	35.1-36	36.1-38	38.1-38.5	More than 38.6	
Hourly Urine For 2 hours	Less than 10mls / hr	Less than 30mls / hr	Less than 45mls / hr				

National Early Warning Score (NEWS)

National Early Warning Score (NEWS)*

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Level of Consciousness				A			V, P, or U

A Trend-Based Early Warning Score Can Be Implemented in a Hospital Electronic Medical Record to Effectively Predict Inpatient Deterioration

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OBJECTIVES: To determine whether a statistically derived, trend-based, deterioration index is superior to other early warning scores at predicting adverse events and whether it can be integrated into an electronic medical record to enable real-time alerts.

DESIGN: Forty-three variables and their trends from cases and controls were used to develop a logistic model and deterioration index to predict patient deterioration greater than or equal to 1 hour prior to an adverse event.

SETTING: Two large Australian teaching hospitals.

PATIENTS: Cases were considered as patients who suffered adverse events (unexpected death, unplanned ICU transfer, urgent surgery, and rapid-response alert) between August 1, 2016, and April 1, 2019.

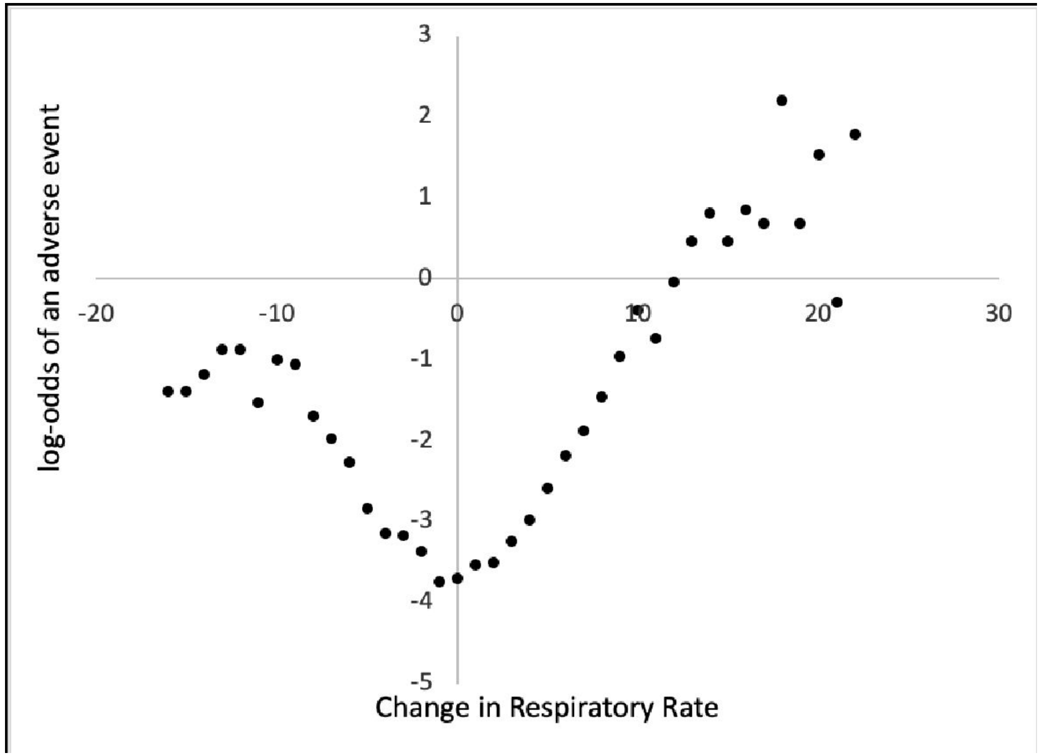
INTERVENTIONS: The logistic model and deterioration index were tested on historical data and then integrated into an electronic medical record for a 6-month prospective "silent" validation.

MEASUREMENTS AND MAIN RESULTS: Data were acquired from 258,732 admissions. There were 8,002 adverse events. The addition of vital sign and laboratory trend values to the logistic model increased the area under the curve from 0.84 to 0.89 and the sensitivity to predict an adverse event 1–48 hours prior from 0.35 to 0.41. A 48-hour simulation showed that the logistic model had a higher area under the curve than the Modified Early Warning Score and National Early Warning Score (0.87 vs 0.74 vs 0.71). During the silently run prospective trial, the sensitivity of the deterioration index to detect adverse event any time prior to the adverse event was 0.474, 0.369 1 hour prior, and 0.327 4 hours prior, with a specificity of 0.972.

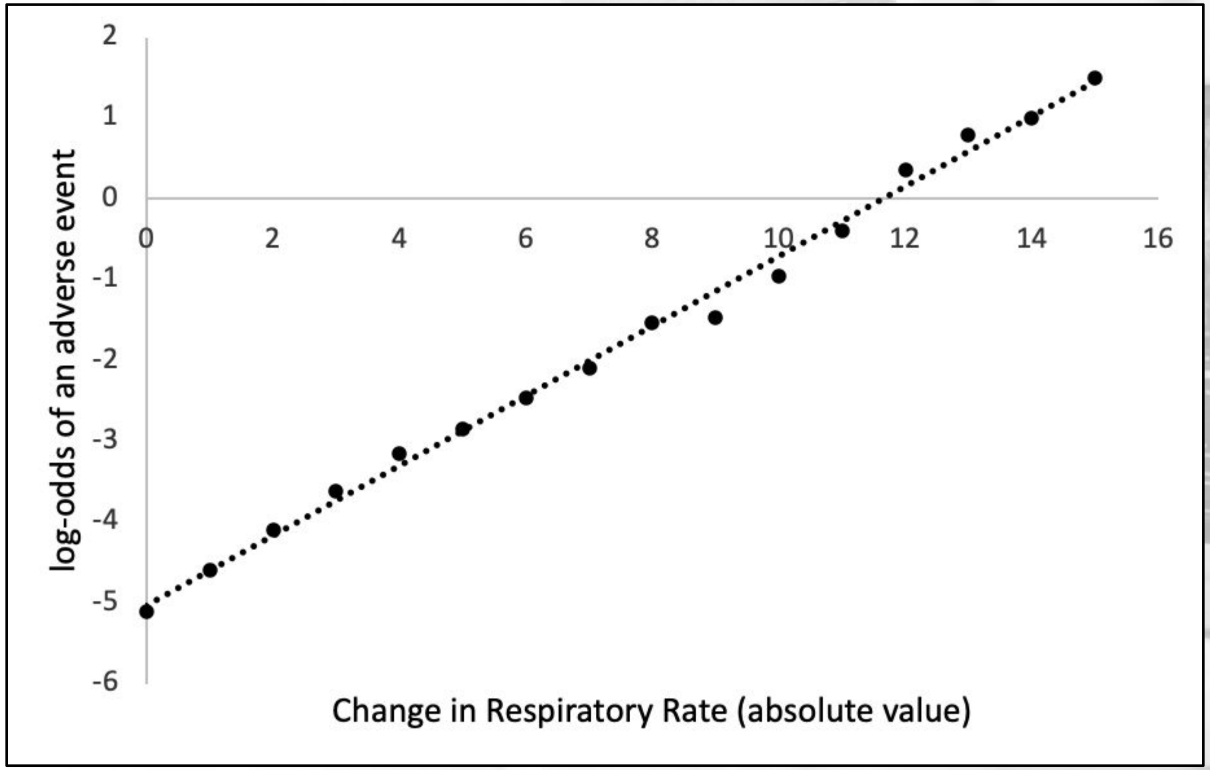
CONCLUSIONS: A deterioration prediction model was developed using patient demographics, ward-based observations, laboratory values, and their trends. The model's outputs were converted to a deterioration index that was successfully integrated into a live hospital electronic medical record. The sensitivity and specificity of the tool to detect inpatient deterioration were superior to traditional early warning scores.

Development of the Logistic Model

Change in RR vs odds of an Adverse Event



Arithmetic conversion of RR vs odds of an Adverse Event



Model variables and coefficients

Supplement e4, eTable6: The final logistic model variables and coefficients

Demographics	**coefficient**	**P value**	**Current laboratory values**	**coefficient**	**P value**
Age	2.84E-02	<0.001	Hb	-3.77E-02	<0.001
Sex	-1.87E-01	<0.001	WCC	1.24E-03	<0.001
General Anaesthetic	9.99E-01	<0.001	Urea	6.19E-02	<0.001
			eGFR	1.43E-02	<0.001
Current vital signs			**Trend in laboratory values**		
SBP	-1.07E-01	<0.001	Hb (TR_{BL})	7.61E-03	<0.001
DBP	-3.06E-04	<0.001	Hb (TR_1)	-2.45E-02	<0.001
RR	9.31E-02	0.038	WCC (TR_{BL})	-2.56E-02	<0.001
SpO_2	-7.49E-02	<0.001	WCC (TR_1)	6.33E-02	<0.001
HR	2.56E-04	<0.001	Urea (TR_{BL})	2.65E-01	<0.001
Conscious state	8.12E-01	<0.001	Urea (TR_1)	4.89E-02	<0.001
Temperature (^{0}C)	8.94E-01	<0.001	eGFR (TR_{BL})	-2.36E-02	<0.001
Total IV fluids (24hrs)	5.94E-04	<0.001	eGFR (TR_1)	2.21E-02	<0.001
Trends in vital signs			**Previous vital signs**		
SBP (TR_{BL})	1.00E-03	0.028	SBP	-3.44E-02	<0.001
SBP (TR_1)	-1.08E-02	0.002	SpO2	-9.40E-02	<0.001
SBP (TR_2)	-1.12E-02	<0.001	HR	2.45E-02	<0.001
DBP (TR_2)	-1.41E-03	<0.001	Conscious state	-7.62E-01	<0.001
RR (TR_{BL})	-5.04E-02	<0.001	RR	1.52E-01	<0.001
RR (TR_1)	5.29E-02	<0.001			
RR (TR_2)	9.12E-02	<0.001			
SpO_2 (TR_1)	-5.80E-01	<0.001			
SpO_2 (TR_2)	3.20E-02	<0.001			
SpO_2 (TR_{BL})	1.42E-01	<0.001			
HR (TR_{BL})	7.38E-03	0.002			
HR (TR_1)	3.23E-02	<0.001			
HR (TR_2)	-1.05E-04	<0.001			
Temperature (TR_{BL})	1.37E-01	<0.001			
Temperature (TR_1)	3.46E-01	<0.001			

Trend Analysis

TABLE 1. - The Impact of Additional Variables on the Logistic Model's Ability to Predict Adverse Events More Than 1 Hour Prior

Model Characteristics	Area Under the Curve	Sensitivity	Specificity
Current vital signs only	0.79 (0.78–0.8)	0.21	0.99
+ Demographics	0.83 (0.82–0.84)	0.31	0.99
+ Laboratory values	0.85 (0.84–0.86)	0.35	0.99
+ Vital sign trends	0.88 (0.87–0.89)	0.40	0.99
+ Laboratory values trends	0.89 (0.88–0.89)	0.41	0.99
Vital sign and laboratory trends only	0.83 (0.82–0.84)	0.31	0.99

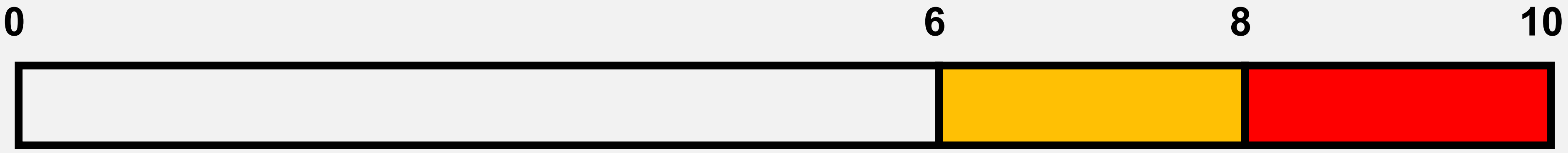
Clinical implementation

- A good predictive model is only one component of a complex system
- How do you implement such a major change in a hospital?
- Challenges:
  - Increased workload?
  - Paradigm shift to reviewing patients who may not look ‘sick’
  - Accepting advice from ‘AI’
  - Did the system improve healthcare?

Steps to implementation

- Meeting with key stakeholders: Nursing, medical, executive, IT
- Accepted feedback and modified the system
- Developed an education plan
- Stepwise roll out with time to address issues in real time
- Reviewed the results early, and often

Ainsoff Deterioration Index (ADI)

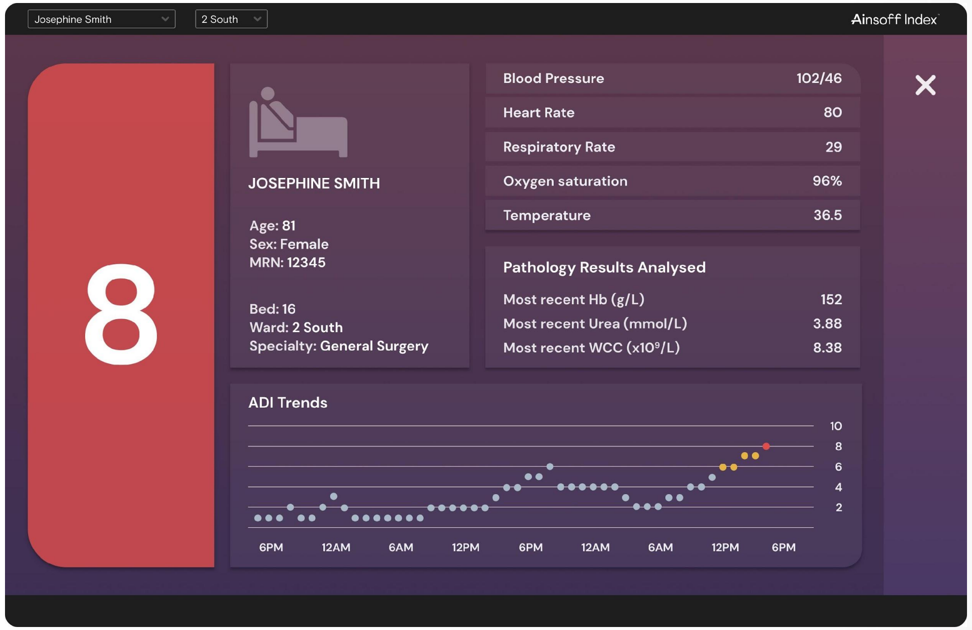


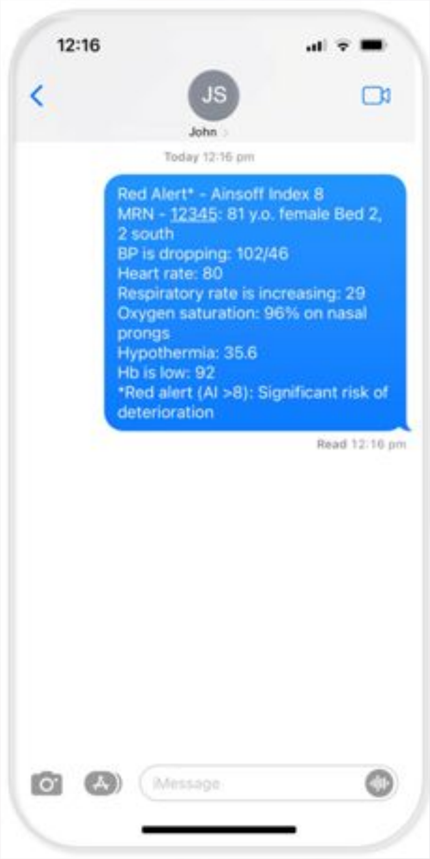
Yellow Alert
ADI 6-7
Text to In-charge nurse
Discretion to escalate to Doctor

Red Alert
ADI 8-10
Text to In-charge nurse
Doctor must review the patient

Useful clinical summary provided with the alert

Each alert contains relevant clinical information explaining the contributors to the score, empowering clinicians to escalate appropriately





Red Alert* - Ainsoff Index 8

MRN - 86365: 81 y.o female Bed 16, 2 south

BP dropping: 102/46

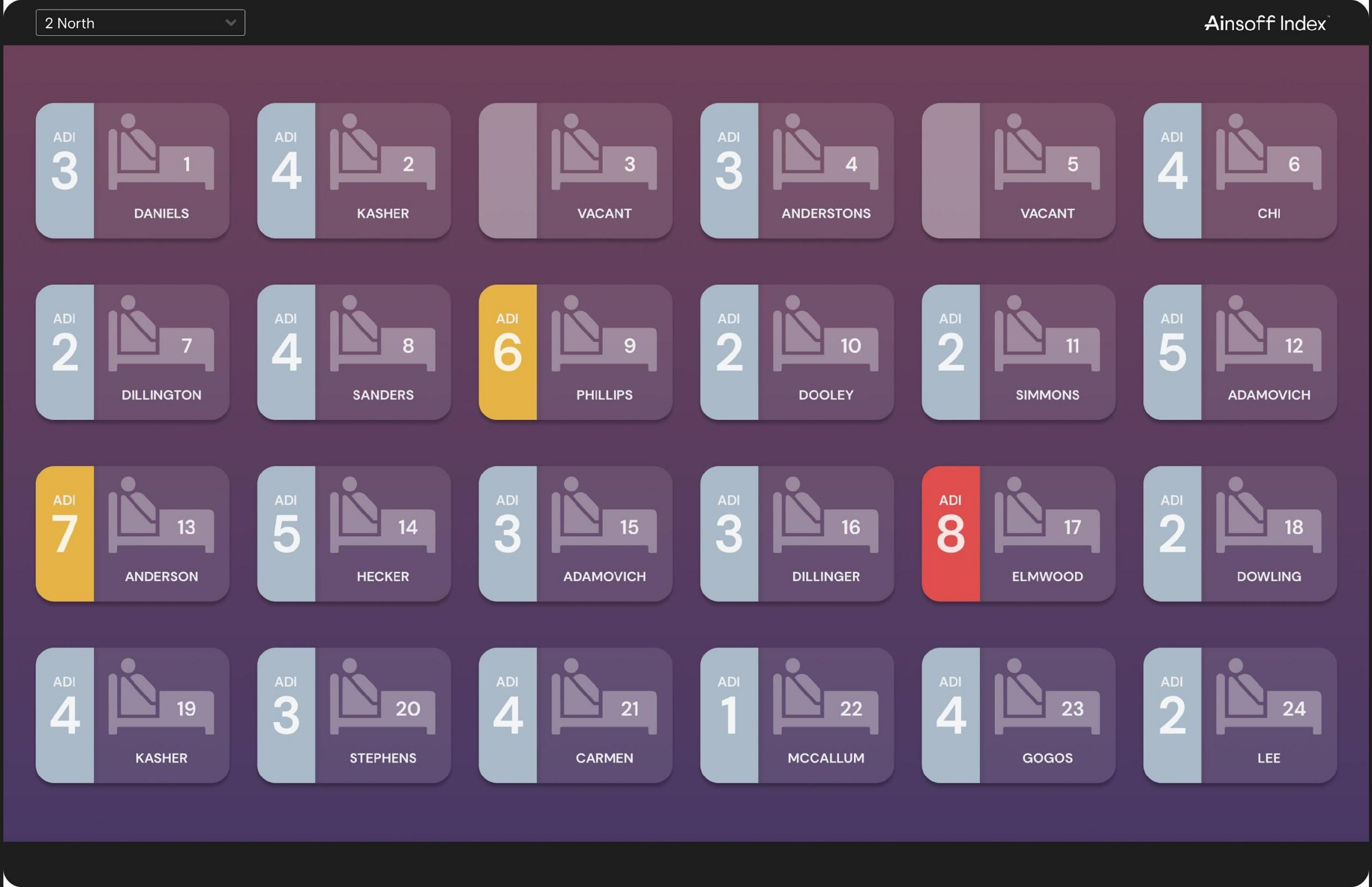
Heart rate is increasing: 29

Oxygen saturation: 96% on nasal prongs

Hypothemia: 35.6

Hb is low: 92

*Red alert (Ai>8): Significant risk of deterioration


2 North
Ainsoff Index
ADI 3 1 DANIELS
ADI 4 2 KASHER
3 VACANT
ADI 3 4 ANDERSTONS
5 VACANT
ADI 4 6 CHI
ADI 2 7 DILLINGTON
ADI 4 8 SANDERS
ADI 6 9 PHILLIPS
ADI 2 10 DOOLEY
ADI 2 11 SIMMONS
ADI 5 12 ADAMOVICH
ADI 7 13 ANDERSON
ADI 5 14 HECKER
ADI 3 15 ADAMOVICH
ADI 3 16 DILLINGER
ADI 8 17 ELMWOOD
ADI 2 18 DOWLING
ADI 4 19 KASHER
ADI 3 20 STEPHENS
ADI 4 21 CARMEN
ADI 1 22 MCCALLUM
ADI 4 23 GOGOS
ADI 2 24 LEE

Brett Elmwood | 2 North | Ainsoff Index

8

BRETT ELMWOOD

Age: 81
Sex: Male
MRN: 86365

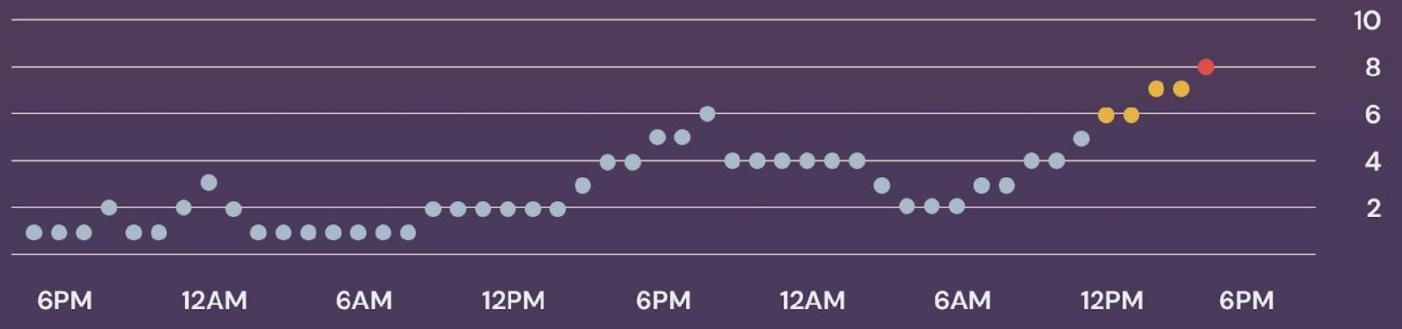
Bed: 201A
Ward: 2 North
Specialty: General Surgery

Blood Pressure	102/46
Heart Rate	80
Respiratory Rate	29
Oxygen saturation	96%
Temperature	36.5

Pathology Results Analysed

Most recent Hb (g/L)	152
Most recent Urea (mmol/L)	3.88
Most recent WCC ($x10^9$/L)	8.38

ADI Trends



Hospital View

All Wards - Average ADI Scores

Ainsoff Index

1 EAST	ADI 2.5 AVERAGE	1	0	23	IMMERSON
1 NORTH	ADI 2.1 AVERAGE	0	1	23	HUGHS
1 SOUTH	ADI 1.3 AVERAGE	0	0	24	
1 WEST	ADI 1.7 AVERAGE	0	1	21	MCLEOD
2 EAST	ADI 1.2 AVERAGE	0	0	24	
2 NORTH	ADI 3.7 AVERAGE	1	2	21	ELMWOOD, ANDERSON, PHILLIPS
2 WEST	ADI 1.2 AVERAGE	0	0	22	
3 EAST	ADI 3.1 AVERAGE	0	1	21	BACHI
3 NORTH	ADI 1.4 AVERAGE	0	0	24	
3 SOUTH	ADI 2.8 AVERAGE	0	2	18	JOHN, STEPHENS
4 EAST	ADI 1.3 AVERAGE	0	0	24	
4 SOUTH	ADI 1.4 AVERAGE	0	0	24	
4 NORTH	ADI 1.2 AVERAGE	0	0	0	
4 WEST	ADI 1.2 AVERAGE	0	0	24	
5 EAST	ADI 2.1 AVERAGE	1	0	19	JOHN
5 SOUTH	ADI 2.0 AVERAGE	0	1	23	PATERSON
5 NORTH	ADI 1.2 AVERAGE	0	0	24	
5 WEST	ADI 1.9 AVERAGE	0	1	19	SUMMERS
6 EAST	ADI 3.2 AVERAGE	0	2	8	WANG, PARKER
6 SOUTH	ADI 1.6 AVERAGE	0	0	24	

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Resuscitation

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Clinical paper

The implementation of a real time early warning system using machine learning in an Australian hospital to improve patient outcomes

Levi Bassin[a,b,*], *Jacques Raubenheimer*[c], *David Bell*[a]

Abstract

Background: Early Warning Scores (EWS) monitor inpatient deterioration predominantly using vital signs. We evaluated inpatient outcomes after implementing an Artificial Intelligence (AI) based intervention in our local EWS.

Methods: A prior study calculated a Deterioration Index (DI) with logistic regression utilising demographics, vital signs, and laboratory results at multiple time points to predict any major adverse event (MAE—all cause mortality, ICU admission, or medical emergency team activation). The current study is a single hospital, pre-post study in Australia comparing the DI plus the existing EWS (Between the Flags-BTF) to only BTF. Data were collected on all eligible inpatients (≥16 years, admitted ≥24 hours, in general non-palliative wards). Controls were inpatients in the same hospital between January and December 2019. The DI was integrated into the electronic medical record and alerts were sent to senior ward nurse phones (July 2020–April 2021).

Results: We enrolled 28,639 patients (median age 73 years, IQR: 60–83) with 52.3% female. The intervention and control groups did not show any statistically significant differences apart from reduced admissions via the emergency department in the intervention group (40.4% vs 41.6%, $P = 0.03$). Risk for an MAE was lower in intervention than control (RR: 0.81; 95%CI: 0.74–0.89). Length of hospital stay was significantly reduced in the intervention group (3.74 days, IQR 1.84–7.26) compared to the control group (3.86 days, IQR 1.86–7.86, $P = 0.002$)

Conclusions: Implementing the DI in one hospital in Australia was associated with some improved patient outcomes. Future RCTs are needed for further validation.

Keywords: Medical informatics, Early Warning Score, Patient Deterioration, Patient Monitoring, Implementation

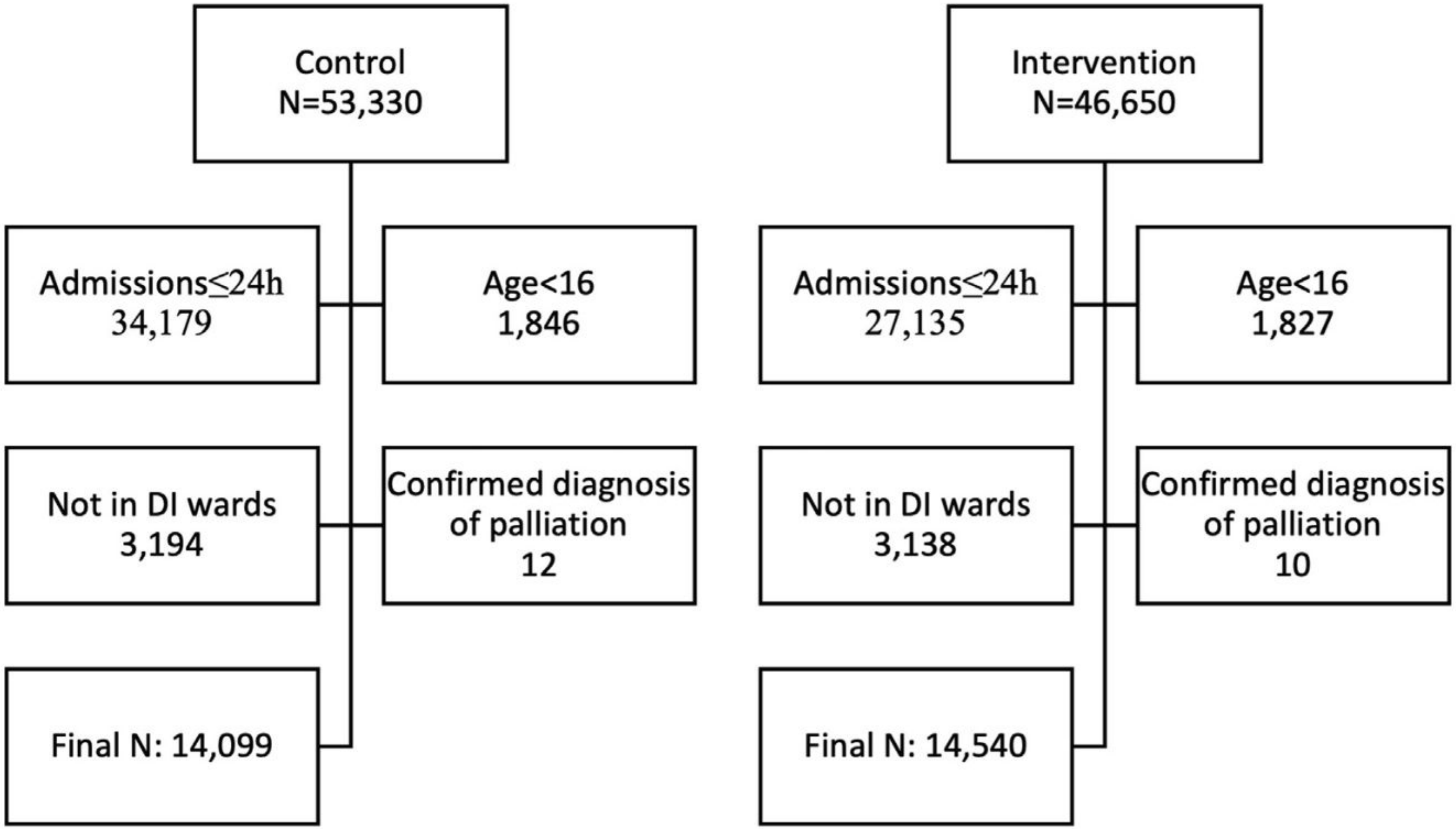

Fig. 1 – Eligible patients for the control and intervention groups.

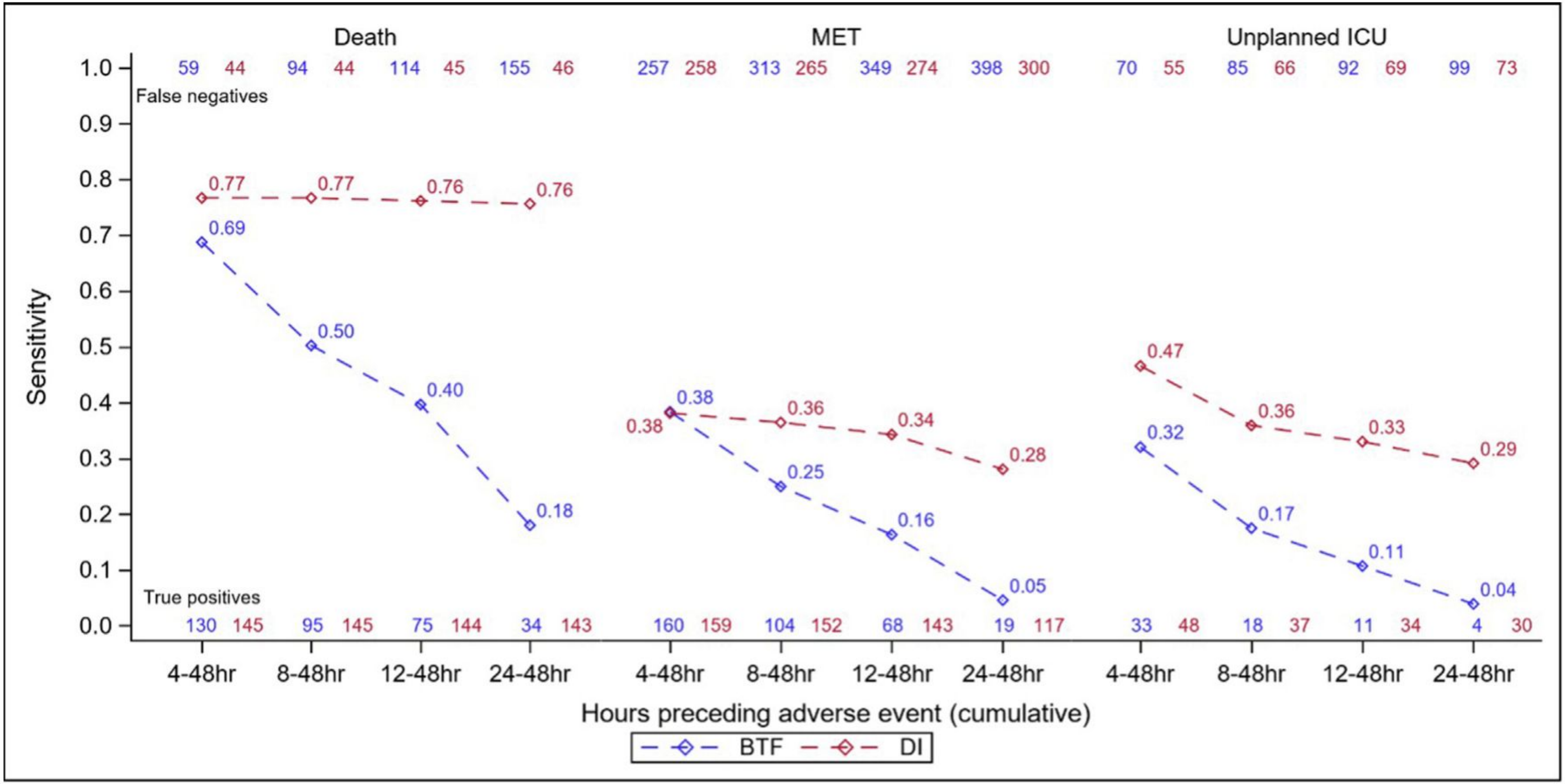

Fig. 2 – Sensitivity of the Between The Flags (BTF) system and the Deterioration Index (DI) by adverse event, at times prior to the adverse events.

Table 3 – Incidence and Relative Risk for the Main Outcomes by Intervention/Control.

Outcome	N (Rate/1000)		Relative Risk (95%CI)	P[a]
Event level (N = 29,090)	**Intervention N = 14,738**	**Control N = 14,352**		
Major Adverse event	852 (57.81)	1,024 (71.35)	0.81 (0.742–0.885)	<0.001
Unplanned ICU	105 (7.12)	132 (9.20)	0.775 (0.595–1.008)	0.057
MET call	544 (36.91)	653 (45.50)	0.811 (0.725–0.908)	<0.001
Patient level (N = 28,639)	**N = 14,540**	**N = 14,099**		
Death	133 (9.15)	151 (10.71)	0.854 (0.673–1.084)	0.202
Lactate >3 mmol/L	229 (15.75)	280 (19.86)	0.793 (0.664–0.946)	0.010
SBP <80 mmHg	426 (29.30)	528 (37.45)	0.782 (0.689–0.889)	<0.001
eGFR fall >15 ml/min/1.73 m^2	153 (10.52)	209 (14.82)	0.71 (0.574–0.878)	0.001

a: Continuity-adjusted chi-square.

Table 4 – Mann-Whitney Comparisons for Duration of Stay and ICU duration by Intervention/Control.

Variable	Group	N	Mean (SD)	Median (IQR)	P
Length of stay (days)	Control	14,099	6.36 (8.37)	3.86 (1.86–7.86)	0.002
	Intervention	14,540	6.06 (7.47)	3.74 (1.84–7.26)	
Days in ICU	Control	132	4.19 (5.48)	2.00 (2.00–4.50)	0.356
	Intervention	65	3.86 (3.11)	3.00 (2.00–5.00)	

Conclusions

- Patient deterioration is common and current escalation of care tools are poor predictors of adverse events
- Machine learning models can improve prediction of deterioration
- Many models have been built, but very few actually implemented
- Reducing the impact of deterioration has to be multi faceted:
  - Better prediction models
  - Clear communication to staff with alerts and visual cues
  - Multiple layers of safety
  - Minimise change in workflow
  - Minimise false alarms
- ADI has shown clinical benefits
- ADI has shown operational benefits