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A machine learning early warning system can reduce inpatient morbidity and length of stay.

Cheryl McCullagh

Chief Product Officer

Beamtree®

Ainsoff Deterioration Index (ADI)

Beamtree®

Detection of the Deteriorating Patient

- Completely automated
- Machine learning model
- Integrated into the EMR
- Trends Demographics, vitals & labs

- Assists clinicians with narrative alerts
- More accurate than current EWS
- Improved clinical outcomes

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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.

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.

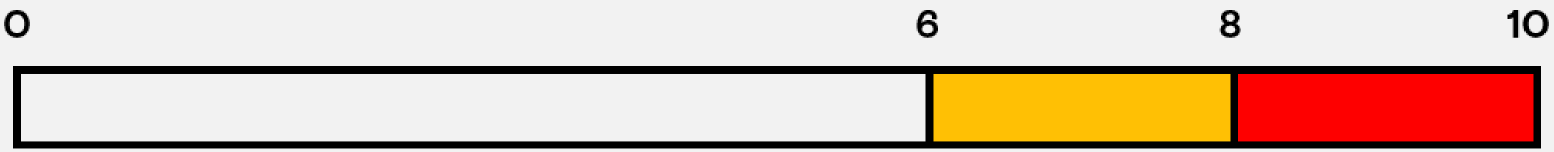
Early Warning Scores

- Aim to detect patients that are deteriorating and to escalate care
- Modified and National Early Warning Scores
- Between the Flags (East Australia)
- Ainsoff is different- providing a prediction
- Time to investigate and initiate treatment while the patient is relatively stable

Ainsoff Deterioration Index™ (ADI)

Built with historical data from over 300,000 Australian patients

ADI produces a score – the Ainsoff Index™ – and accompanying risk-adjusted alerts, to indicate the patient's risk of deterioration ahead of time

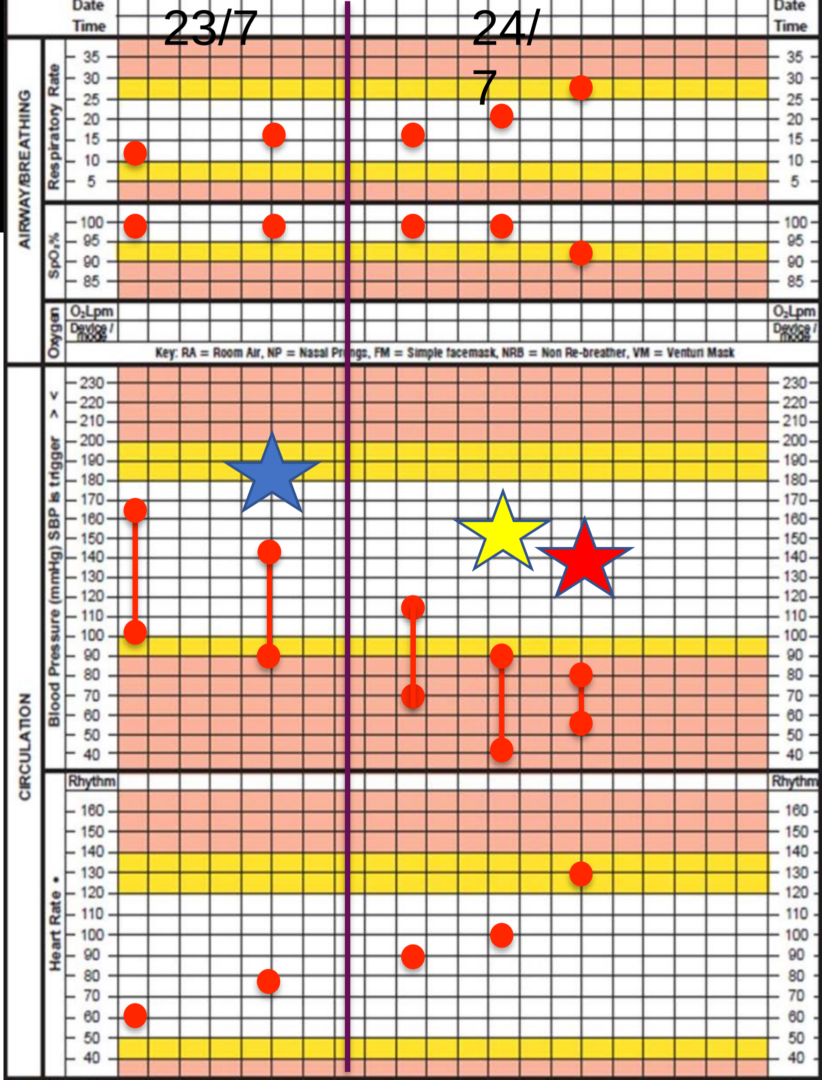


Yellow Alert
AI 6-7
60% chance of adverse event
Text to In-charge nurse
Discretion to escalate to Doctor

Red Alert
AI 8-10
72% chance of adverse event
Text to In-charge nurse
Doctor must review the patient

ADI difference

- Follows the trends
- Alerts to variance compared with the patient's baseline
- Direct to clinician information
- Greater sensitivity, specificity
- Longer prediction (lead) time



Further Clinical Trial publication

- July 2020 – April 2021
- Pre Ainsoff: Matched months in 2019 -2020
- Patient demographics and complexity were equivalent

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Resuscitation

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EUROPEAN RESUSCITATION COUNCIL

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

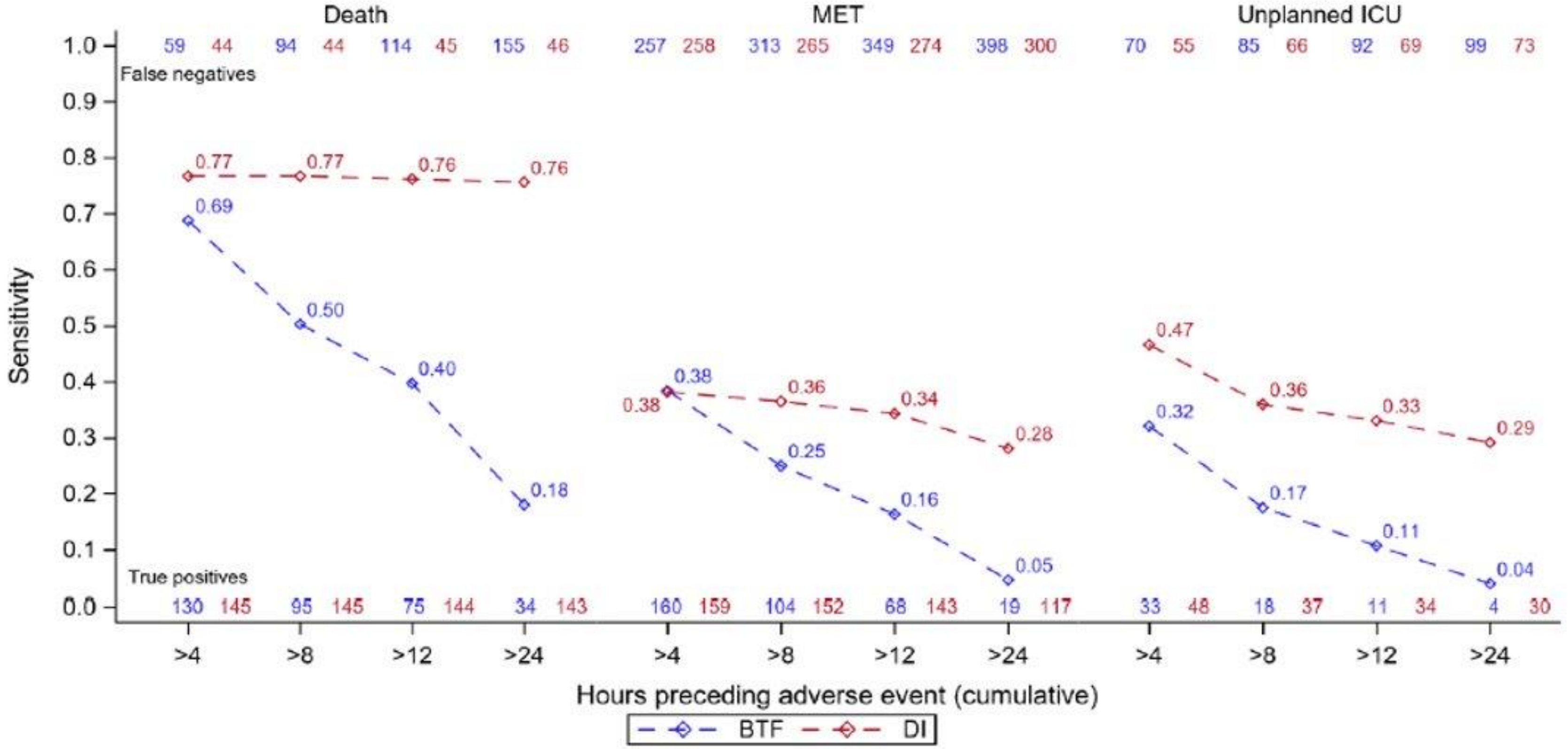
Background: Early Warning Scores (EWS) monitor inpatient deterioration predominantly using vital signs. We evaluated inpatient outcomes after implementing an Artificial Intelligence (AI) based intervention in our local EWS.

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

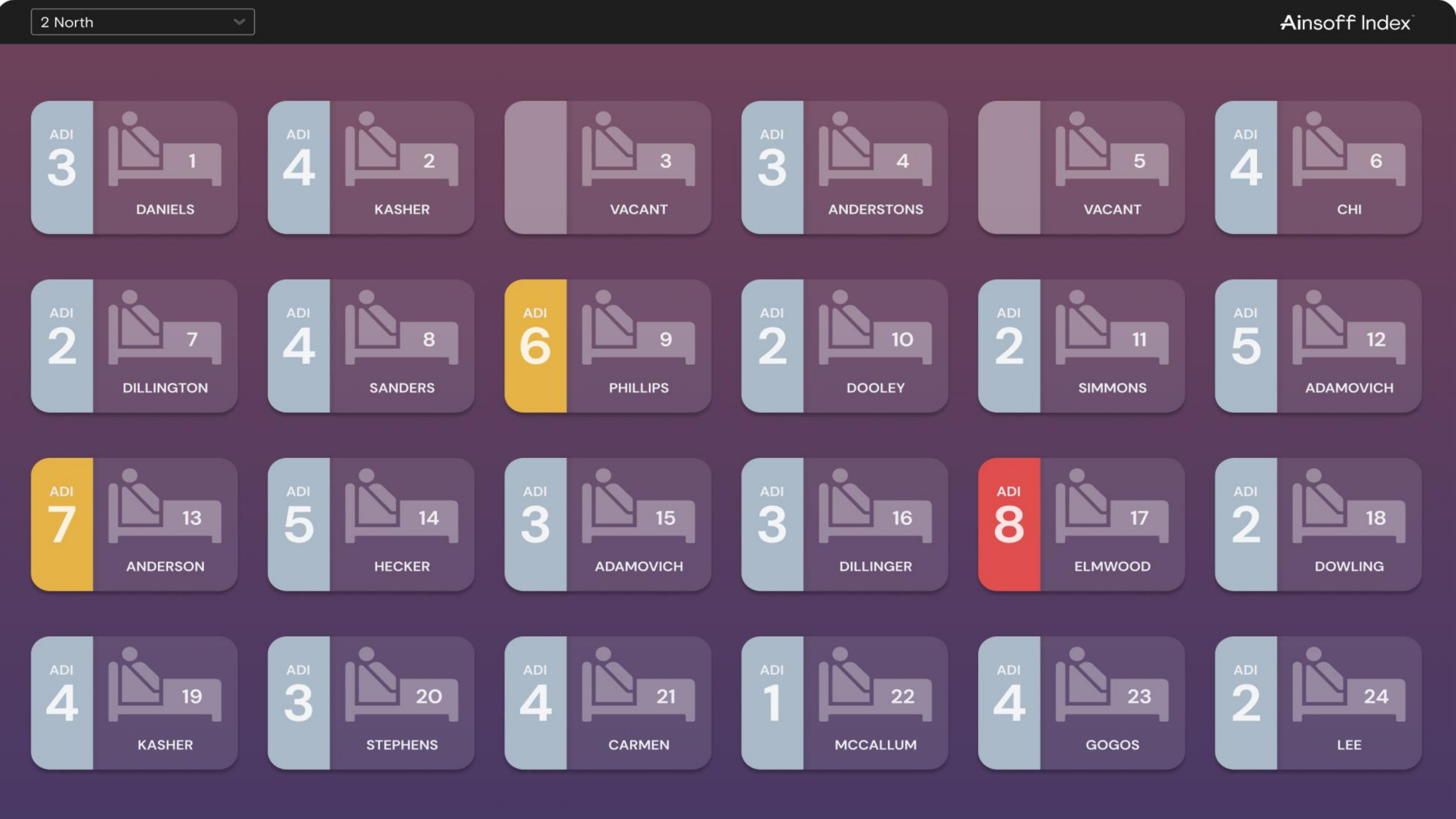

Death
MET
Unplanned ICU
59 44 94 44 114 45 155 46
257 258 313 265 349 274 398 300
70 55 85 66 92 69 99 73
False negatives
True positives
130 145 95 145 75 144 34 143
160 159 104 152 68 143 19 117
33 48 18 37 11 34 4 30
0.77 0.77 0.76 0.76
0.69 0.50 0.40 0.18
0.38 0.36 0.34 0.28
0.38 0.25 0.16 0.05
0.47 0.36 0.33 0.29
0.32 0.17 0.11 0.04
Sensitivity
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
>4 >8 >12 >24
Hours preceding adverse event (cumulative)
BTF
DI

@Th

Outcomes from a 10-month clinical trial at a 500-bed hospital

Trial assessed patient outcomes before and after institution of the ADI at the Sydney Adventist Hospital. The study included data from 28,639 patients

Clinical outcomes	Operational outcomes
19.3% reduction in low blood pressure events	**20.4% reduction** in unplanned ICU admissions
16.7% reduction in Major Adverse Events (death or unplanned ICU admission or Medical Emergency Team activation)	**5% reduction** in length of stay – 0.3 days reduced length of stay per patient admission
Predicted 76% of patients that passed away > 24 hours in advance compared to 18% for between the flags	Beamtree®


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

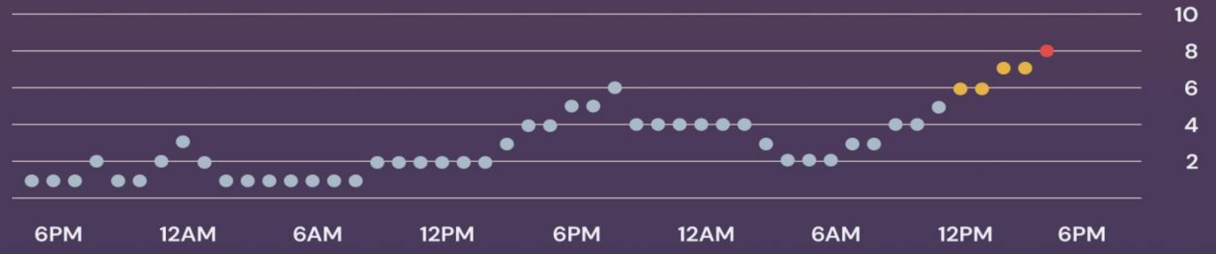
Bed: 201A
Ward: 2 North
Specialty: General Surgery

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

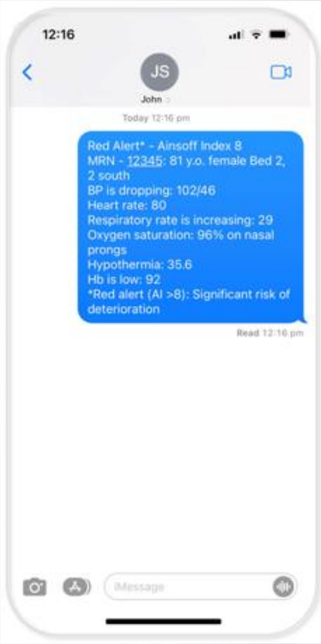
Pathology Results Analysed

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

ADI Trends



Useful clinical summary provided with the alert



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

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

Hospital View | All Wards - Average ADI Scores | Ainsoff Index

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

A machine learning early warning system can reduce inpatient morbidity and length of stay.

Extrapolated value for a 500-bed hospital, with 15,000 overnight admissions per year:

= 165 fewer ICU bed days

= 4,500 fewer ward bed days per annum

This represents a significant opportunity across hospitals to improve care, reduce morbidity, increase patient throughput and potentially reduce waiting periods or cost.

Resuscitation 2023

Critical Care Medicine 2021

Summary

- Patient deterioration is common
- Machine learning models can improve prediction of deterioration
- Many models have been built, but very few actually implemented
- Successful implementation has to be multi faceted:
  - Better prediction models
  - Clear communication to staff with alerts and visual cues
  - Minimise change in workflow
  - Minimise false alarms
- ADI has shown **clinical and operational benefits**