Using linked ieMR data to support operational and clinical decisions

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Outline

1. Operational Decision Support: Patient flow @ Logan Hospital
   - Ambulance-ED interface - Linked QAS, EDC and QHAPDC data from Statistical Services Branch
   - Patient journey through the ED
   - The effect of inpatient occupancy
   - Inpatient bed configuration
   - Discharge timing

   ieMR data from Metro South Clinical Informatics

25 Biggest hospitals
6 years

- QH
- QAS
- UQ
- CSIRO

EMF Emergency Medicine Foundation Queensland

Request for Submissions – Study on Patient Flow in Queensland's public hospitals

2. Clinical decision support: Predicting Patient Deterioration
   - Predicting the "Between The Flags" clinical deterioration criteria
     - ieMR data from Metro South Clinical Informatics

Between the Flags

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Bed Configurations

- Simulation modelling for bed allocation strategies and ward capacities


Emergency Medicine Australasia

Emergency Medicine Australasia (2023) 35, 434–441

ORIGINAL RESEARCH

New bed configurations and discharge timing policies: A hospital-wide simulation

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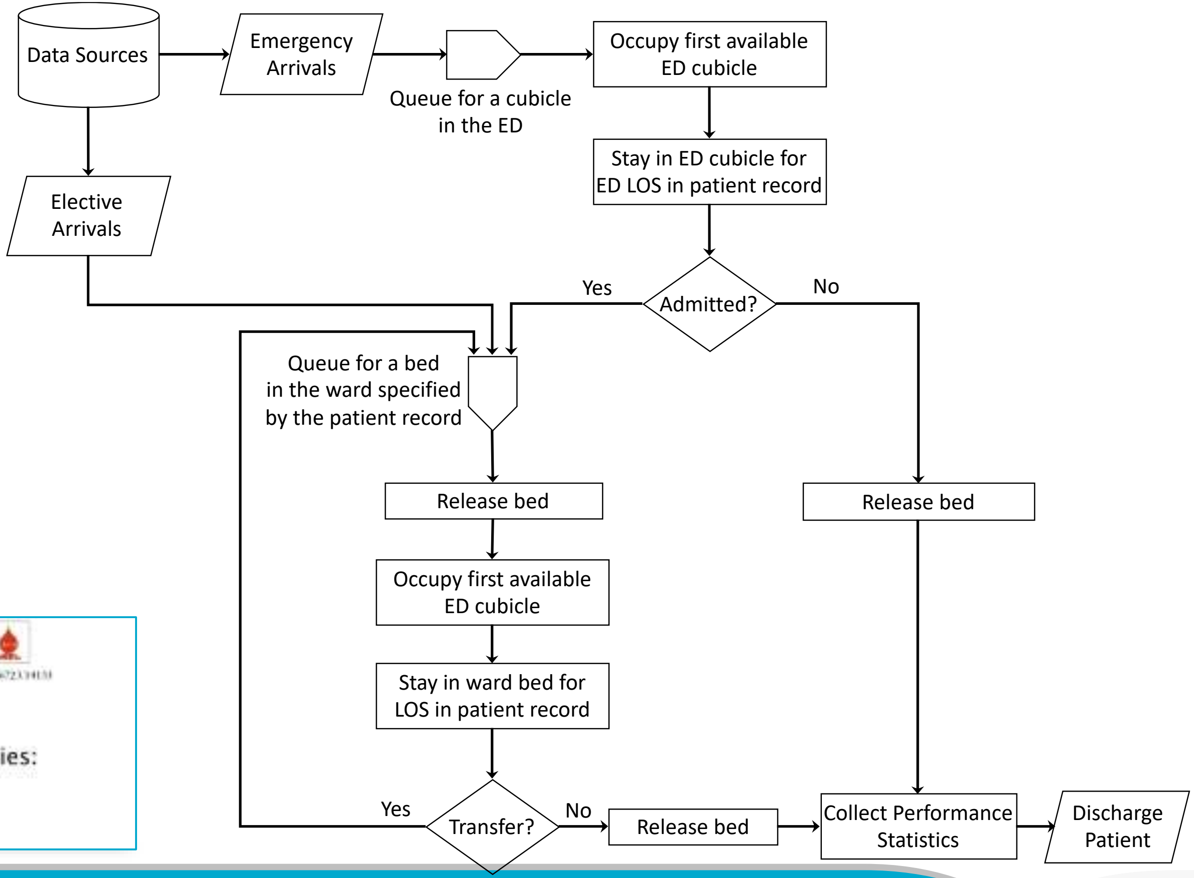
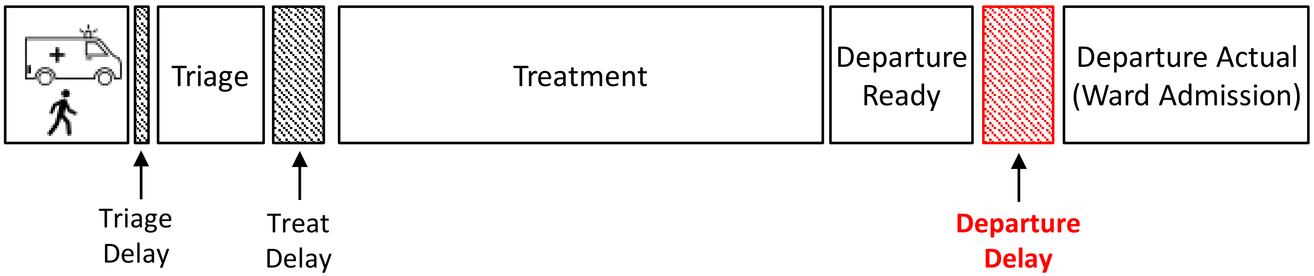


Bed Configurations

- Performance Measures:
  - NEAT (4hr ED LOS compliance)
  - Average and Total ED LOS
  - Average waiting time in ED
  - Bed utilisation= $\frac{Actual\ Bed\ Days}{Available\ Bed\ Days}$

Focus

- ED Timeline for admitted patients



Baseline vs Zero Departure Delays

- ED-related performance measures
- How removing the recorded departure delays in the data affects the simulation:

	Baseline Departure Delay	Zero Departure Delay
NEAT	68.98%	69.49%
Total ED LOS	9323 days and 11h:19m	7340 days and 13h:18m
Average ED LOS	04h:45m	03h:44m
Average Waiting Time	1 Hour	0

Baseline vs Clustering Wards

Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

SCENARIO	Beds	Bed Utilisation	NEAT	Avg EDLOS	Total EDLOS (minutes)	Avg Waiting Time (minutes)
BASELINE	427	80%	69%	285 mins	9323 days	60 mins
Achieving baseline Performance with cluster-level capacity Management	411	82%	69%	264 mins	8640 days	40 mins

Medical Cluster

Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

Ward	Beds	Actual Bed Days	Available Bed Days	Bed Utilisation	# ED2IP Encounters	# Discharged <= 4hr	NEAT
3A	30	913.6	930	98.24%	98	2	2.04%
3B	30	772.38	930	83.05%	101	9	8.91%
3C	16	483.54	496	97.49%	46	3	6.52%
3CCARD	5	91.11	155	58.78%	7	3	42.86%
AMU	8	254.93	248	102.79%	26	1	3.85%
MAPU	16	380.84	496	76.78%	101	20	19.80%
TOTAL	105	2896.4	3255	88.98%	379	38	10.03%
Cluster 1	100	2893.99	3100	93.35%	379	39	10.29%

Surgical Cluster

Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

Ward	Beds	Actual Bed Days	Available Bed Days	Bed Utilisation	# ED2IP Encounters	# Discharged <= 4hr	NEAT
2H	30	820.69	930	88.25%	33	10	30.30%
2I	12	337.52	372	90.73%	23	8	34.78%
SURGSS	14	341.69	434	78.73%	19	2	10.53%
TOTAL	56	1499.9	1736	86.40%	75	20	26.67%
Cluster 2	54	1499.33	1674	89.57%	75	20	26.67%

Mental Health Cluster

Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

Ward	Beds	Actual Bed Days	Available Bed Days	Bed Utilisation	# ED2IP Encounters	# Discharged <= 4hr	NEAT
2A	10	134.89	310	43.51%	6	4	66.67%
2B	20	666.55	620	107.51%	19	0	0.00%
2C	19	512.15	589	86.95%	22	0	0.00%
2J	11	219.29	341	64.31%	6	1	16.67%
2K	10	266.09	310	85.83%	13	2	15.38%
2L	5	101.58	155	65.54%	4	0	0.00%
TOTAL	75	1900.55	2325	81.74%	70	7	10.00%
Cluster 3	66	1761.95	2046	86.12%	70	7	10.00%

ED Short Stay Wards

Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

Ward	Beds	Actual Bed Days	Available Bed Days	Bed Utilisation	# ED2IP Encounters	# Discharged <= 4hr	NEAT
EDSSW	20	442.22	620	71.33%	1352	928	68.64%
EDCDU	20	391.36	620	63.12%	1250	1229	98.32%
TOTAL	40	833.58	1240	67.22%	2602	2157	82.89%
Cluster 4	39	808.64	1209	66.88%	2602	2157	82.89%

Childrens Cluster

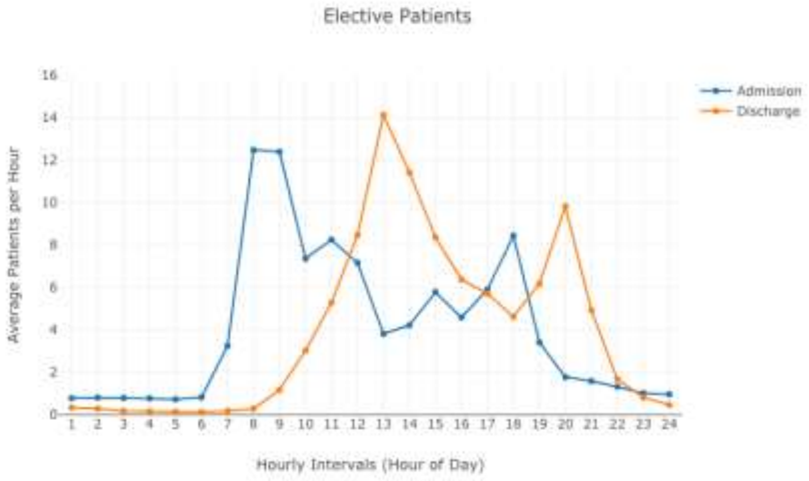
Cluster ID	Cluster Name	Wards
1	Medical	3A, 3B, 3C, AMU, MAPU, 3CCARD
2	Surgical	2H, 2I, SURGSS
3	Mental Health	2B, 2C, 2J, 2K, 2L, 2A
4	(Adult) ED Short Stay	EDSSW, EDCDU
5	Children	CIU, EDSSC

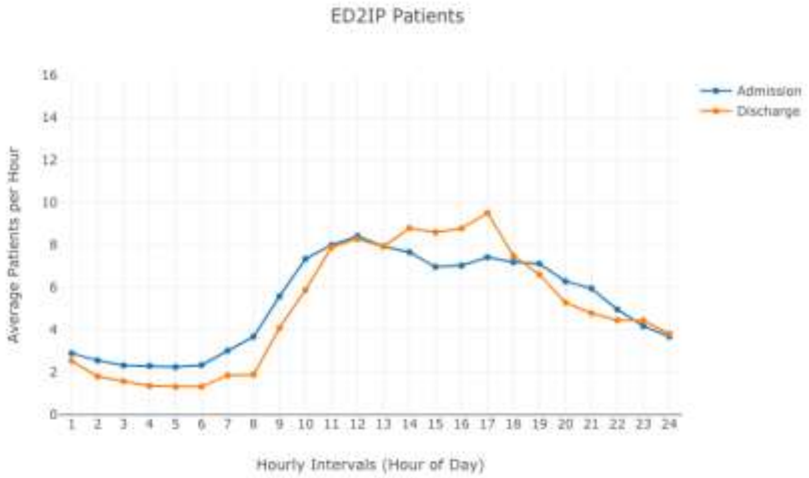
Ward	Beds	Actual Bed Days	Available Bed Days	Bed Utilisation	# ED2IP Encounters	# Discharged <= 4hr	NEAT
CIU	20	368.85	620	59.49%	95	52	54.74%
EDSSC	8	111.6	248	45.00%	521	473	90.79%
TOTAL	28	480.45	868	55.35%	616	525	85.23%
Cluster 5	25	482.33	775	62.24%	616	525	85.23%

Early Discharging

- Quantifying the impact of inpatient discharge timing

- Flow parameters:
  - Ø NEAT
  - Ø Average and Total ED LOS
  - Ø Average waiting time
  - Ø Bed utilisation $= \dfrac{Actual\ Bed\ Days}{Available\ Bed\ Days}$

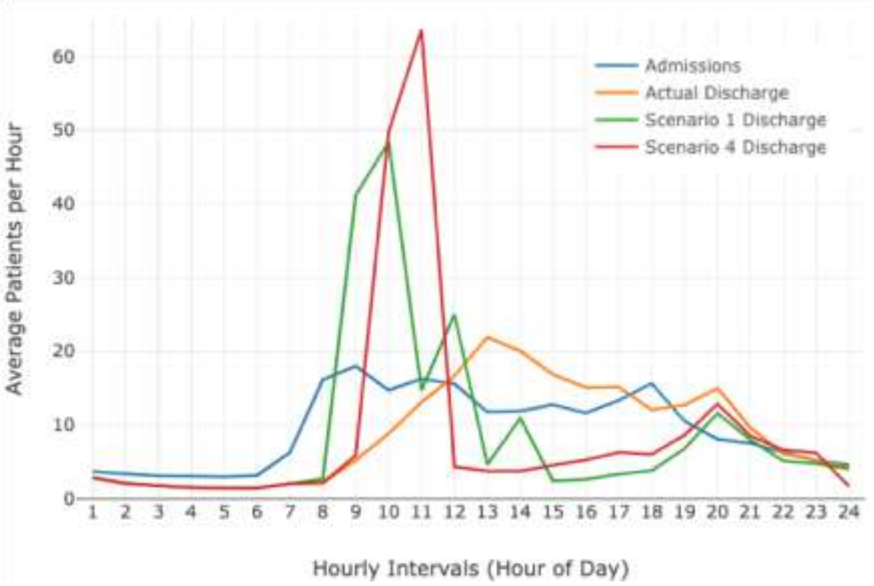




Early Discharging Scenarios

- Seven discharge scenarios investigated

Scenario	Discharge Target
Scenario 1	50% by 10am, 80% by 12pm, 100% by 2pm
Scenario 2	35% by 11am, 70% by 2pm, 100% by 5pm
Scenario 3	50% by 11am, 70% by 2pm, 100% by 5pm
Scenario 4	80% by 11am
Scenario 5	40% by 10am, 70% by 2pm, 90% by 5pm, 100% by 10pm
Scenario 6	Discharge all patients 1 hour earlier
Scenario 7	Discharge all patients 2 hours earlier



Results

	NEAT	Average EDLOS (minutes)	Average Waiting Time (minutes)	Bed Utilisation
BASELINE	69.0%	285	60	80%
SCENARIO 1 (50% BY 10AM, 80% BY 12PM, 100% BY 2PM)	69.3% (0.4%)	**239 (-16%)**	**15 (-75%)**	**75% (-6%)**
SCENARIO 2 (35% BY 11AM, 70% BY 2PM, 100% BY 5PM)	69.2% (0.4%)	251 (-12%)	27 (-55%)	77% (-4%)
SCENARIO 3 (50% BY 11AM, 70% BY 2PM, 100% BY 5PM)	69.3% (0.4%)	244 (-14%)	20 (-67%)	76% (-5%)
SCENARIO 4 (80% AT 11AM)	69.2% (0.4%)	**241 (-15%)**	**17 (-72%)**	**75% (-6%)**
SCENARIO 5 (40% BY 10AM, 70% BY 2PM, 90% BY 5PM, 100% BY 10PM)	69.3% (0.4%)	243 (-14%)	19 (-68%)	76% (-5%)
SCENARIO 6 (1 HOUR EARLIER)	69.2% (0.3%)	257 (-10%)	32 (-47%)	78% (-2%)
SCENARIO 7 (2 HOURS EARLIER	69.3% (0.4%)	250 (-12%)	25 (-58%)	76% (-5%)

Clinical decision support: Predicting Patient Deterioration

- Predicting risk of Between The Flag (BTF) alert 2-8 hours before alert

Between the Flags

Data Source

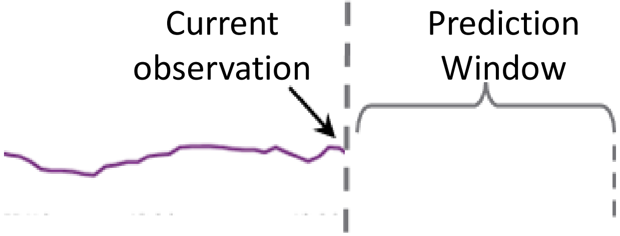
- ieMR data from the PA Hospital
  - Encounters, Vital Signs, Deteriorating Alerts, etc.
- Inpatients, adults, acute care, in hospital for more than 24 hours
- Challenges
  - Big data (more than 10M rows in the vital signs table and more than 70M rows in the deterioration alerts table)
  - Considering as many risk factors as possible
  - Keeping the real-time aspect
  - Preparing ground truths (response variables)

ieMR data from Metro South Clinical Informatics

```
 18G CM_CCL_Deteriorating_Alerts.csv
3.9M CM_CCL_Deteriorating_RRT_Orders.csv
2.8G CM_CCL_EncounterExtract.csv
3.7G CM_CCL_Encounter_Location_Extract.csv
150M CM_CCL_FN_EDRealTime_Extract.csv
539M CM_CCL_FN_Extract.csv
826M CM_MRR_ADL_Assessment.csv
609M CM_MRR_Alerts_Problems.csv
235M CM_MRR_Allergy.csv
 37M CM_MRR_Allergy_Reaction.csv
 41M CM_MRR_Anaesthesia.csv
1.3G CM_MRR_Anaesthesia_Action_Detail.csv
526M CM_MRR_Anaesthesia_Actions.csv
 43G CM_MRR_Anaesthesia_Parameter_Values.csv
 19M CM_MRR_Blood_Transfusion_Information.csv
928M CM_MRR_Consult_Orders.csv
281M CM_MRR_Diagnosis.csv
129M CM_MRR_Falls_Assessment.csv
 19M CM_MRR_IV_Immunoglobulins.csv
308M CM_MRR_Measurements.csv
 37G CM_MRR_Med_Orders.csv
3.4G CM_MRR_Pain_Assessment.csv
3.7G CM_MRR_Path_Orders.csv
2.3G CM_MRR_PrePostop_Assessment.csv
571M CM_MRR_Rad_Orders.csv
774M CM_MRR_Radnet_Orders.csv
115M CM_MRR_SN_Cases.csv
108M CM_MRR_SN_Procedures.csv
1.0G CM_MRR_Surgical_Safety_Checklist.csv
3.9G CM_MRR_Vital_Signs.csv
418M CM_MRR_Waterlow_Assessment.csv
142K Cardiac_Arrest_data.csv
6.8M RRTDataNew.csv
```

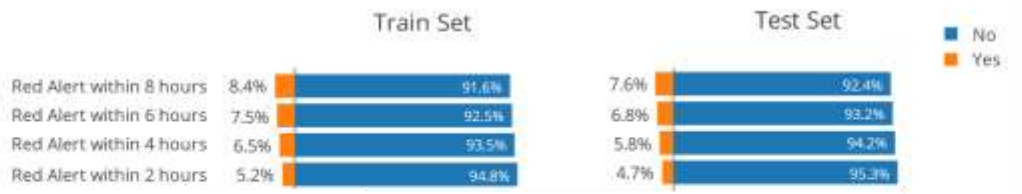
Risk Factors Identification

- Real-time availability of data for modelling
- Selected Vital Signs:
  - Systolic & Diastolic BP, Mean arterial pressure, Heart Rate, Temperature, Respiratory Rate, Oxygen Saturation (SpO2), O2 flow rate, and AVPU
- Looking back past 24 hours
  - Min, Max, Mean, Median, Standard Deviation, and Frequency
  - Last (most recent) valid value
  - Slope: between the two most recent observations
  - Interval in between the last two observations
  - Number of currently measured vital signs
  - Number of overall observations (past 24hr)
  - LOS since admission (in minutes)
  - Demographic/admin information: gender, age, admission mode



Training/Validation Periods

- Training period:
  - Jan 2016 to Dec 2018
- Validation period:
  - Jan 2019 to September 2019
- Number of observations:
  - Training period: 2,418,646
  - Testing Period: 598,757



Results

- Performance Measures:
  - Area Under the Curve of the Receiver Operating Characteristic (AUC-ROC), Precision, Recall, F1-Measure, Area Under the Curve of the Precision and Recall (AUC-PR)

Model	AUC-ROC	Precision	Recall	F1	AUC-PR
RF 2hr	0.90	0.72	0.59	0.64	0.63
4hr	0.87	0.70	0.50	0.58	0.58
6hr	0.85	0.70	0.44	0.54	0.55
8hr	0.84	0.71	0.41	0.52	0.54


scientific reports

OPEN Explainable machine learning for real-time deterioration alert prediction to guide pre-emptive treatment

https://www.nature.com/articles/s41598-022-15877-1

Future Plan

- Model improvements
  - Include other risk factors: pathology results, medications, procedures, wards movements
  - Overarching patient representation (embedding)
  - Including QADDS as response variable

- Proof of concept trial
  - Feasibility study with ICU clinicians
  - Implementation plan covering trial design, training, support and evaluation currently being drafted for ethics

Key messages

- Share beds across wards in clusters
- Time-based early discharge reduced ED LOS and patient wait time
- Early detection of clinical deterioration as a clinical decision support tool helps improving care delivery

Thank You

The Australian e-Health Research Centre

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