VAHI: SEMINAR SERIES – Deriving value from health system analytics

MC: Dr Lance Emerson, CEO

THURSDAY, 22 AUGUST 2019 | 10:30–12:00 PM
Deriving Value from Health System Analytics

Rob Grenfell, Rajiv Jayasena, Sankalp Khanna
CSIRO Australian e-Health Research Centre

August 2019
CSIRO: Australia’s National Science Agency

- Over 5000 Research Scientists
- 58 Sites globally, Research activities in 80 Countries
- $1 Billion Annual budget
- Top 1% Of Global research agencies
- Hosts Boeing’s largest R&D facility outside of the US
- Run NASA’s spacecraft tracking facilities in Australia
- Invented WiFi, used in five billion devices globally.
CSIRO’s Future of Health report

OBJECTIVE
Shape future investments in the health system by providing a vision for how Australia’s health system can transition from a focus around illness treatment to health and wellbeing management.

CONTRIBUTORS
Over 30 organisations from across the health sector
Health sector challenges

- Changing national health profile
- Unsustainable financing
- Inequity in access and experience
- Consumer behaviour and trust
- Adjusting to an increasingly digital world
- Fragmented and inflexible health systems
Our vision for Australia’s future health

Managing health and wellbeing

Precision health solutions

Holistic and predictive approach

Improving quality of life over a lifetime
Enablers

1. Empowering consumers
2. Addressing health inequity
3. Unlocking the value of digitised data
4. Supporting integrated and precision health solutions
5. Integrating with the global sector

→ All intrinsically digital
The Australian e-Health Research Centre
CSIRO’s National Digital Health Program

- Australia’s first and largest e-health research hub, opening in 2003
  - Joint venture with Queensland Health + additional investment from CSIRO to grow
  - 100 scientists and engineers and 30 students in Brisbane, Perth, Sydney and Melbourne

- We provide an evidence base for the digital transformation of healthcare

- Success built on our partnerships with government, clinicians, industry, SMEs and more
CSIRO’s Digital Health Research Program

**HEALTH INFORMATICS**
Improving health system performance & productivity from electronic health data

**How**: Meaningful data interoperability and analysis for decision support, analytics, modelling and reporting

**BIOMEDICAL INFORMATICS**
Biostatistics, imaging and genomics based - clinical workflows

**How**: Leveraging operational & clinical data through analytics, modelling, decision support & automation

**HEALTH SERVICES**
Improving access to services & management of chronic diseases

**How**: Service delivery models utilising telehealth, mobile health & remote monitoring
Health System Analytics

Value-based performance and productivity for the Health System

HEALTH INTELLIGENCE

The science behind helping the health system increase productivity and safety through optimising patient, clinician and resource flows, and providing intelligent decision support.

HEALTH IMPLEMENTATION SCIENCE

Health system evaluation, translating research into practice.
Motivation: The Australian Health System

Over the Past Decade

Health Spending 50%
Population Growth 17%

<table>
<thead>
<tr>
<th>Metric</th>
<th>Lowest</th>
<th>OECD Average</th>
<th>Australia</th>
<th>Highest</th>
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</thead>
<tbody>
<tr>
<td>Health care expenditure (total spending per person, USD PPP)</td>
<td>1,080</td>
<td>4,003</td>
<td>4,708</td>
<td>9,892</td>
</tr>
<tr>
<td>Practising doctors (per 1,000 population)</td>
<td>1.8</td>
<td>3.4</td>
<td>3.5</td>
<td>6.3</td>
</tr>
<tr>
<td>Practising nurses (per 1,000 population)</td>
<td>2.0</td>
<td>9.0</td>
<td>11.5</td>
<td>18.0</td>
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<tr>
<td>Hospital beds (per 1,000 population)</td>
<td>1.5</td>
<td>3.8</td>
<td>4.7</td>
<td>13.2</td>
</tr>
</tbody>
</table>

USD PPP = United States dollars purchasing power parities.
Motivation: Australian Patients are at Risk
Motivation: The Crisis of Competing Priorities

- Patient Wait Times
- Ambulances at Door
- Surgery Waiting Lists
- Resources
- Budget

ED admissions
Elective surgery

Technological Wave
KPI
KPI
KPI

Ageing Population
KPI

Burden Of Disease
KPI

Patient Satisfaction
KPI

Staffing
KPI

Shrinking Budgets
KPI

KPI
KPI
KPI
Fixing Overcrowding: Why Does it Matter?

Aims:
• Improving public hospital performance through efficiency improvements
• Hospital avoidance and risk monitoring
• Creating an evidence base to support policy and decision making

Science Areas:
• Visualisation
• Statistical Modelling
• Machine Learning
• Stochastic Optimisation
• Distributed Constraint Reasoning
• Discrete Event Simulation
Hospital Crowding: The Magic Fixes

• Better Capacity Management
  • 85% occupancy delivers optimum patient flow
  • Higher levels result in increased patient risk and regular overcrowding
  • Is 85% a one size fits all?
• How do I manage my hospital capacity?
• How unsafe is my crowded hospital?

• Early Discharge
  • Early discharge should help ease crowding.
  • Can we quantify the impact of Early Discharge?
  • What happens if overcrowding delays Discharge?
Case Study 1: Capacity Management

Q > How full can I run my Hospital at before Capacity Crisis?

ED, Admission & Discharge vs occupancy

3 key choke points - performance declines:
- A - Admission/discharge surge
- B - ED overwhelmed
- C - Admissions overwhelmed

Overcrowding affects:
✓ Access Block
✓ ED Length of Stay (Inpatients)
✓ Inpatient Length of Stay
✓ Inpatient Admissions from ED
☒ ED Length of Stay (not admitted)

Case Study 1: Capacity Management

Q > Do we see this trend across hospitals of all sizes?

YES ... but at different levels

Group 1 (Large hospitals):
- Choke Point A: 86%
- Choke Point B: 90%
- Choke Point C: 94%

Group 2 (Mid-size hospitals):
- Choke Point A: 90%
- Choke Point B: 96%
- Choke Point C: 101%

Group 3 (Small hospitals):
- Choke Point A: 98%
- Choke Point B: 102%
- Choke Point C: 106%
Case Study 2: Discharge Timing

Q > Can we quantify the impact of Early Discharge?
Q > What happens if overcrowding delays Discharge?

2 Hour Early Discharge (all 23 Hospitals):

- Average Occupancy reduced from 93.7% to 91.6%.
- Maximum Occupancy reduced from 110.8% to 106.1%.
- Time spent above 95% occupancy reduced from 34.7% to 21.5%.

Looking Further into Discharge Timing

Q > How does this affect my KPIs?
Q > How can I operationalise this?

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>50% of patients to be discharged by 10am, 80% by 12pm and 100% by 2pm.</td>
</tr>
<tr>
<td>2</td>
<td>35% of patients to be discharged by 11am, 70% by 2pm and 100% by 5pm.</td>
</tr>
<tr>
<td>3</td>
<td>50% of patients to be discharged by 11am, 70% by 2pm and 100% by 5pm.</td>
</tr>
<tr>
<td>4</td>
<td>80% of patients to be discharged by 11am.</td>
</tr>
<tr>
<td>5</td>
<td>40% of patients to be discharged by 10am, 70% by 2pm, 90% by 5pm and 100% by 10pm.</td>
</tr>
<tr>
<td>6</td>
<td>Select the same patients as for Scenario 5 but change only the emergency discharge times, leaving elective patient discharge times unchanged.</td>
</tr>
<tr>
<td>7</td>
<td>Select the same patients as for Scenario 3 but change only the emergency discharge times, leaving elective patient discharge times unchanged.</td>
</tr>
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</table>

Looking Further into Discharge Timing

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Scenario Description</th>
<th>NEAT Performance</th>
<th>Ave Bed Occupancy</th>
<th>Ave Inpatient LOS</th>
<th>Ave wait for Inpatient Bed - ED</th>
<th>Ave wait for Inpatient Bed - All</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>50% by 10am, 80% by 12pm, 100% by 2pm.</td>
<td>+16.1%</td>
<td>-1.5%</td>
<td>-1.7%</td>
<td>-25.5%</td>
<td>-24.2%</td>
</tr>
<tr>
<td>2</td>
<td>35% by 11am, 70% by 2pm, 100% by 5pm.</td>
<td>+5.7%</td>
<td>-0.2%</td>
<td>-0.3%</td>
<td>-6%</td>
<td>-5.7%</td>
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<tr>
<td>3</td>
<td>50% by 11am, 70% by 2pm, 100% by 5pm.</td>
<td>+9.4%</td>
<td>-0.5%</td>
<td>-0.5%</td>
<td>-11.8%</td>
<td>-10.5%</td>
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<tr>
<td>4</td>
<td>80% by 11am.</td>
<td>+16.2%</td>
<td>-1.5%</td>
<td>-1.6%</td>
<td>-24.9%</td>
<td>-23.5%</td>
</tr>
<tr>
<td>5</td>
<td>40% by 10am, 70% by 2pm, 90% by 5pm, 100% by 10pm.</td>
<td>+7.3%</td>
<td>-0.3%</td>
<td>-0.4%</td>
<td>-8.6%</td>
<td>-7.7%</td>
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<tr>
<td>6</td>
<td>Same as Scenario 5 but ED only</td>
<td>+6.9%</td>
<td>-0.2%</td>
<td>-0.3%</td>
<td>-7.3%</td>
<td>-6.4%</td>
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<tr>
<td>7</td>
<td>Same as Scenario 1 but ED only</td>
<td>+15.7%</td>
<td>-1.2%</td>
<td>-1.3%</td>
<td>-22.7%</td>
<td>-20.5%</td>
</tr>
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</table>

% change as compared to baseline

Case Study 3: Predicting Demand

- Forms a regular component of daily bed management across major QLD public hospitals
- Licensed in Australia and overseas
- Estimated to deliver $23 million (direct), and $250m (indirect) in productivity gains per annum
- Several awards related to efficiency and effectiveness

References:
- Boyle J, Ireland D, Webster F, O’Sullivan K, Predicting Demand for Hospital Capacity Planning, Conf Proc IEEE Biomedical and Health Informatics. 2016: 328-331
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Case Study 3: Making it Work

WHO?
- Bed manager, after hours co-ordinator, hospital executive, hospital executive on-call, Director ED, Director Medicine, Director Surgery, decision support services

WHY?
- Inform managers (nursing and medical) re expected admissions and discharges so they have information to work proactively

HOW?
- PAPT Software and PAPT Procedure Manual: guide to assist communication processes with in-built ‘triggers’ to inform decision making (planning and functioning)

WHEN?
- Daily and Weekly

References:
- Boyle J, Ireland D, Webster F, O’Sullivan K, Predicting Demand for Hospital Capacity Planning, Conf Proc IEEE Biomedical and Health Informatics. 2016: 328-331

Related Content:
- **Daily Admissions and Discharges (DADs) Summary: Toowoomba Hospital**
- **Daily Admissions and Discharges (DADs) Management Process Flow Chart: Monday to Friday, Toowoomba Hospital**

- Bed Manager to input info for DADs report (from handover, EDs, ECHO, SAPIIT, Daily Status Report & PAPT) and generate daily expectations and identify if any TRIGGERS & ACTIONS required.
- Bed Manager to mitigate actions as required:
  - If Trigger 1 - investigate immediately;
  - If Trigger 2, 3 or 4 - investigate following discussion at 0900 bed manager meeting.

- Bed Manager to attend MAPU morning & present:
  - (i) Actual ED presentations, hospital admissions and discharges statistics from previous day (derived from handover report);
  - (ii) Predicted ED presentations, hospital admissions and discharges statistics for current-day (derived from PAPT);
  - (iii) Expected booked elective admissions, transfers in from other hospitals, transfers out of Toowoomba Hospital for current day (derived from handover and status report);
  - (iv) Current foreseeable barrier;
  - (v) Brief discussion for solutions/actions to take at 0900 Bed Management Meeting.

- Bed Manager to attend 0900 Bed Management Meeting (with NMs) and present:
  - (i) Actual ED presentations, hospital admissions and discharges statistics from previous day (derived from handover report);
  - (ii) Predicted ED presentations, hospital admissions and discharges statistics for current-day (derived from PAPT);
  - (iii) Expected booked elective admissions, transfers in from other hospitals, transfers out of Toowoomba Hospital for current day (derived from handover and status report);
  - (iv) Current foreseeable barrier;
  - (v) Solutions/actions to be imitated as discussed from 0800 MAPU morning;
  - (vi) Brief discussion for additional solutions/actions to be implemented and circulated.

Admin. Officer to attend 0900 Bed Management Meeting and:
- (i) Documents a) occupancy trends light status as per Toowoomba Hospital Daily Bed Management & Capacity Early Warning Response System in DADs information, c) proposed actions & responsible parties and d) timelines for actions to be imitated.
- (ii) Derivative info (via email) to Toowoomba Hospital Status Report Group.

eg E-Mail Message:
**SUBJECT:** Daily Admissions and Discharges (DADs) expected activity and Action Plan for today
**MESSAGE:** e.g.
WHO?
• Bed manager, after hours co-ordinator, hospital executive, hospital executive on-call, Director ED, Director Medicine, Director Surgery, decision support services

WHY?
• Inform managers (nursing and medical) re expected admissions and discharges so they have information to work proactively

HOW?
• PAPT Software and PAPT Procedure Manual: guide to assist communication processes with in-built ‘triggers’ to inform decision making (planning and functioning)

WHEN?
• Daily and Weekly

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Case Study 4: Evidence Driven KPIs

- First study to deliver evidence driven targets for public hospital ED patient flow
- Directly translated into government policy
- Several awards and endorsements
- Replicated in several other states, and in the UK

The National Emergency Access Target (NEAT)
“By 31 Dec 2015, 90% of all patients will physically leave the Emergency Department (ED) within 4 hours”

Sullivan C, Staib A, Khanna S, et al. The National Emergency Access Target (NEAT) and the 4-hour rule: time to review the target, Medical Journal of Australia 2016 May 16;204(9):354
Case Study 4 : Evidence Driven KPIs

Methodology :

• Focus on Emergency Admissions only (i.e. eHSMR)

• Exclude Palliative Care and Short Stay

• Develop several predictive models for eHSMR calculation

• Model relationship between NEAT Compliance and eHSMR

• Check for confounding effect of palliative care and short stay

No robust evidence regarding a clinically significant mortality benefit above this threshold

Sullivan C, Staib A, Khanna S, et al. The National Emergency Access Target (NEAT) and the 4-hour rule: time to review the target, Medical Journal of Australia 2016 May 16;204(9):354
Case Study 5: Risk Stratification for Hospital Avoidance

Acute Care Setting

Predictive Algorithm Driven Risk Stratification to inform in-hospital care and discharge planning

24 Month trial at Queensland Metropolitan Hospital commenced April 2018

Explainable Machine Learning employed to help interpret risk scores

Primary Care Setting

Predictive Algorithm Driven Risk Stratification to inform recruitment across up to 200 GP Practices and Aboriginal Health Services started Dec 2017

Algorithm published in Nature Scientific Reports and made publicly available through Department of Health

Patient Cohort Coverage
• 2 hospitals from a lower socio-economic area in Queensland
• Include surrounding hospitals
• All Queensland hospitals

Admissions of Interest
(Performance measured as Area under the ROC curve)
• All admissions : 80-95%
• All except dialysis admissions : 65-78%
• Emergency admissions : 50-68%
• What else do we remove ?

Response Variable
• 28 days Vs 30 days
• Readmission Vs Emergency Readmission Vs Representation to ED Vs Either

<table>
<thead>
<tr>
<th>Diagnosis Code Block</th>
<th>Description</th>
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<tbody>
<tr>
<td>E11*</td>
<td>Type 2 Diabetes Mellitus</td>
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<tr>
<td>I25*</td>
<td>Chronic Ischaemic Heart Disease</td>
</tr>
<tr>
<td>I50*</td>
<td>Heart Failure</td>
</tr>
<tr>
<td>I60*</td>
<td>Subarachnoid Haemorrhage</td>
</tr>
<tr>
<td>I61*</td>
<td>Intracerebral Haemorrhage</td>
</tr>
<tr>
<td>I62*</td>
<td>Other Nontraumatic Intracranial Haemorrhage</td>
</tr>
<tr>
<td>I63*</td>
<td>Cerebral Infarction</td>
</tr>
<tr>
<td>I64*</td>
<td>Stroke, Not Specified as Haemorrhage or Infarction</td>
</tr>
<tr>
<td>J44*</td>
<td>Other Chronic Obstructive Pulmonary Disease</td>
</tr>
<tr>
<td>J45*</td>
<td>Asthma</td>
</tr>
<tr>
<td>J46*</td>
<td>Status Asthmatic</td>
</tr>
<tr>
<td>N18*</td>
<td>Chronic Kidney Failure</td>
</tr>
<tr>
<td>Z49*</td>
<td>Care Involving Dialysis</td>
</tr>
</tbody>
</table>
Case Study 5: Background Work in Risk Stratification

Cohort: Statewide data for all patients who presented at the original 2 hospitals with at least one Chronic Disease admission over 5 years

- Exclusions:
  - Routine admissions
  - Obstetric admissions
  - Index admissions
  - Episodes resulting in inpatient death

- 4 Response Variables:
  - RA30 - Readmitted within 30 days
  - RA30E - Readmitted within 30 days through ED
  - RP30 - Represented to ED within 30 days
  - RU30 - Return to hospital within 30 days

- 3 Algorithms
  - Generalised Estimating Equations (GEE)
  - Artificial Neural Networks (ANN)
  - Random Forests (RF)

Case Study 5: Risk Stratification in Acute Care

• To develop, implement and evaluate a web-based risk stratification algorithm that can be used in-hospital to identify chronic disease patients with a high risk of re-hospitalisation.

• What are we predicting
  • Unplanned re-admission within 30 days of discharge from hospital
  • Unplanned ED re-presentation within 30 days of discharge from hospital

• Timeline

<table>
<thead>
<tr>
<th>Trial</th>
<th>Apr 2018 to Mar 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluation</td>
<td>Apr 2020 to Jun 2020</td>
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</tbody>
</table>

Chronic Disease Patient Admitted to Hospital

Risk Score generated overnight

Next morning

Risk score used by care teams for appropriate interventions and care/discharge planning
Case Study 5: Risk Stratification in Acute Care

Patient Cohort:

Patients who, over a 5 year period, as an Emergency or Admitted Patient:
- Attended Logan Hospital, and
- Had at least one Chronic Disease visit (any QLD hospital)

Data Used for Modelling & Validation:

- Emergency Data (EDIS/FirstNet)
- Inpatient Data (QHAPDC/ePADT)
- Mortality Data (Death Registry)
- Pharmacy dispensing information (eLMS)
- Pathology test results (AUSLAB)

Predictor Variables in Final Models:

- Patients stays in previous 180 days
- ED presentations in previous 180 days
- Marital status
- Age
- Indigenous status
- SEIFA
- Admission source
- Admission unit
- Care type
- Elective status
- Planned same day status
- Binary flags for routine dialysis
- Number of medication records
- Binary flags for medication
- Binary flags for abnormal pathology results
Case Study 5: Risk Stratification in Primary Care

CSIRO Predictive Risk Model (PRM) embedded within Risk Stratification Tool developed by Precedence Health Care

PRM algorithm predicts the probability of emergency admission or potentially preventable hospitalisation within one year on GP cohort

Eligible patients invited for clinical assessment using HARP questionnaire and assigned to a population tier based on complexity.

Algorithm published in Nature Scientific Reports

Open source implementation of algorithm freely available for use
Case Study 5: Statistical Approach Employed

Modelling Techniques
• Logistic regression
• Naïve Bayes
• Neural Nets
• Random Forests
• Generalised Boosting
• Ensemble approaches - model averaging, model “stacking”, etc.
• Survival Modelling (Cox Proportional Hazards Model)

Model Validation
• Models compared and validated using the area under the ROC curve (AUC)
Case Study 5: Understanding Model Performance

Calibration Plot for RA30 Model

Predicted Probability of Hospitalisation within 1 Year by Age

Key
- Predicted
- Predicted (smoothed)
- Observed (smoothed)
### Case Study 5: Web-Based Decision Support

#### Overview

<table>
<thead>
<tr>
<th>Patient</th>
<th>LHR</th>
<th>Admission Date</th>
<th>Last Discharge Date</th>
<th>Age</th>
<th>Ward</th>
<th>ED 31 days</th>
<th>LOS 180 days</th>
<th>Floatmat RISK</th>
<th>ED RISK</th>
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### Case Study 5: Web-Based Decision Support

#### Overview

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- **Today All**
- **Last 7 Days All**
- **ED ≥ 5 in last 31 days**
- **AGE less than 18**
- **Interpreter Required**
- **Diabetes**
Case Study 5: Explainable Machine Learning to Support Care Planning

Influence of inpatient RISK Factors

- **Stays**: 6 stays (180 days)
- **ED Visits**: 15 visits (180 days)
- **Age**: 36 years old
- **Abnormal Patho...**
Case Study 5: Explainable Machine Learning to Support Care Planning

Influence of inpatient RISK Factors

- **Stays**: 6 stays (180 days)
- **Age**: 74 years old
- **Unit CARD**: 3 visits (180 days)
- **ED Visits**: 3 visits (180 days)
Health System Analytics: Talk to us About

Health System Productivity & Efficiency

- Predicting patients presenting the health system
- Demand modelling and simulation to identify bottlenecks/overcrowding
- Bed configurations for current and future demand
- Winter bed planning
- Optimisation of surgery scheduling & utilisation
- Syndromic surveillance
- Patient deterioration and vital sign monitoring

Hospital Avoidance

- Risk stratification to reducing readmissions and preventable hospitalisations
- Statistical machine learning to combat the burden of chronic disease
- Automation of care planning in a leaning health system

Evidence Based Healthcare Delivery

- Evidence driven workflow and health system KPIs
- Informing policy around proposed changes such as after hours healthcare delivery
- Understanding the drivers of evidence-based practices into routine health care
- Evaluation of care models and measuring translation of evidence to practice
Questions?

For more information, please contact:

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Senior Principal Research Scientist
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  e  Sankalp.Khanna@csiro.au
  w  www.aehrc.com

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VAHI Annual Forum 2019
4-7pm, Thursday 19 September

Quality and safety in Victorian health services – is it improving?

Upcoming VAHI events