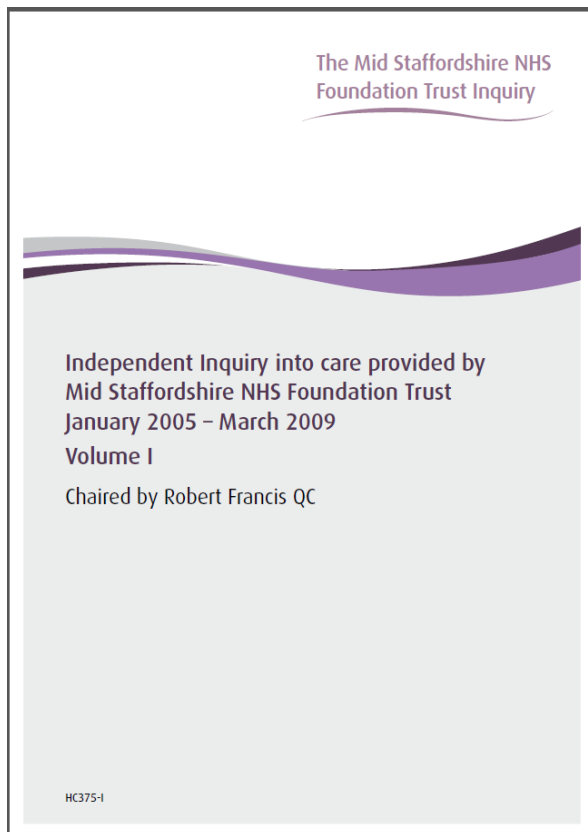


Identifying at-risk patients from clinical data

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Francis report



And many others ...

- Kennedy on Bristol
- Kennedy on c.diff
- National Audit Office
- Darzi
- National Institute for Health and Clinical Excellence 2007
- DH Comprehensive Critical Care 2000
- National Confidential Enquiry into Patient Outcome and Death
- National Patient Safety Agency
- RCPL Acute Medicine Task Force 2002 and 2004

Background

- People die in hospitals
 - [Hogan et al, BMJ Quality and Safety, 2012] study of 1000 adults who died in 10 English hospitals in 2009
 - 5% preventable (>50% chance)
 - = 12,000 per year in England

- Causes:
 - a clinician (or team of) is less competent
 - someone of sufficient expertise sees patient too late
 - the supply of clinical activity is finite

How can data and IT help?

- Operationalise the collection of data
- Operationalise the analysis of data
- Detect patterns in clinical data indicative of deterioration that clinicians might not spot
- Help clinicians manage the process of care
 - prompt some action
 - facilitate making the next step
- **Help managers**
 - monitor/compare patterns of activity
 - analyse effectiveness



Clinical data: quality (poor)

- Some data in hospitals is poor quality for analysis:
 - much not stored electronically – therefore not easily accessible
 - some stored electronically has transcription errors
 - some not recorded until days/weeks/months after the fact
 - some is an administrator's judgement (e.g. what an clinical episode is classified as for claims purposes)
 - some is a clinician's judgement (e.g. diagnosis)

Clinical data: quality (better)

- Some data is much more reliable:
 - pathology data
 - most is taken automatically from quality-controlled testing equipment
 - lab regularly quality-assured
 - most test results available in an hour
 - in Portsmouth, vital signs
 - collected regularly at the bedside using portable data entry devices (iPod touch)
 - very good user interface (reduces data entry error)
 - data available immediately
- Has to be “operational” data

Data we have used

- **Patient administrative data**
 - patient id pseudonymised
 - age, gender
 - date/time of admission and discharge
 - whether admitted as an elective or emergency case
 - whether discharged dead or alive
 - which dept(s)/ward(s) the patient was in
- **Pathology data**
 - 7 most commonly performed blood tests
- **Vital signs data**
 - 7 routinely measured physiological indicators

Model 1

***BIOCHEMISTRY AND HAEMATOLOGY
OUTCOME MODELLING (BHOM)***

Pathology data used

- The "magnificent 7" blood tests:
 - albumin
 - creatinine
 - haemoglobin
 - potassium
 - sodium
 - urea
 - white cell count
- Over 12 months, 9497 patients discharged from "general medicine"
- Outcome measured: mortality on discharge
- Method: logistic regression



The BHOM model

- $\ln (R / 1-R)=$
 - $-10.192 + (-0.013 \times \text{gender})$
 - $+ (5.712 \times \text{mode of admission})$
 - $+ (0.053 \times \text{age on admission}) + (0.018 \times \text{urea})$
 - $+ (-0.001 \times \text{Na}+) + (-0.101 \times \text{K}+)$
 - $+ (-0.047 \times \text{albumin}) + (-0.037 \times \text{haemoglobin})$
 - $+ (0.067 \times \text{white cell count}) + (0.001 \times \text{creatinine})$
 - $+ (2.744 \times \text{urea/creatinine})$

BHOM model evaluated

- Two main evaluators:
 - calibration
 - does the model reflect the distribution of risk?
 - most patients are "low" (<5%) risk
 - discrimination
 - does the model discriminate between patients who died and those who didn't?
 - AUROC ~ .76
- Key papers:
 - D R Prytherch, J S Sirl, P Schmidt, P I Featherstone, P C Weaver, G B Smith, The use of routine laboratory data to predict in-hospital death in medical admissions, *Resuscitation* 2005; 66: 203-207.
 - D.R. Prytherch, J.S. Briggs, P.C. Weaver, P. Schmidt, G.B. Smith, "Measuring clinical performance using routinely collected clinical data", *Medical Informatics and the Internet in Medicine*, vol. 30, no. 2, pp151-156, June 2005

Model 2

VITAL SIGNS MODELS (VIEWS, NEWS AND DT-EWS)

Background to vital sign modelling

- 2006-2008 KTP with *The Learning Clinic*, developers of VitalPAC
 - allows nurses to collect vital sign data at the patient's bedside
 - data immediately stored in hospital systems
 - doctors use a tablet-based interface
- Now in use at Portsmouth Hospitals Trust and about 50 other hospitals



Vital sign data used

- Another "magnificent 7", vital signs:
 - pulse
 - respiration rate
 - temperature
 - blood pressure (systolic)
 - O₂ saturation
 - supplemental oxygen
 - AVPU score (alert or not)



Application: Early warning systems

- Used widely to monitor patient deterioration
- Map each vital sign parameter onto a "score"
- Add the scores up
- If score is above a threshold, take appropriate action, e.g.
 - increase frequency of observation
 - call for a doctor
 - call for a doctor urgently
- Most EWSs based on "experience" of a single clinician or a committee of clinicians

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

*The NEWS initiative flowed from the Royal College of Physicians' NEWS Development and Implementation Group (NEWSDIG) report, and was jointly developed and funded in collaboration with the Royal College of Physicians, Royal College of Nursing, National Outreach Forum and NHS Training for Innovation

ViEWS – VitalPAC Early Warning Score

- First EWS based on large scale data
- Derived from 198,755 observation sets from 35,585 acute medical admissions
- Outcome: mortality within 24 hours
- Evaluation
 - discrimination
 - does the model discriminate between patients who died and those who didn't
 - AUROC = .888
- Superior to 33 other published EWSs
- Key paper:
 - Prytherch, David, Smith, G., Schmidt, P. and Featherstone, P. (2010) *ViEWS - Towards a national early warning score for detecting adult inpatient deterioration*. Resuscitation, 81 (8). pp. 932-937.

Methods

- Initially, trial and error to optimise discrimination
- More recently, used Decision Tree tools to develop models
 - Tessy Badriyah PhD work
 - DT-EWS
- DT is a data mining method that produces models that are feasible for humans to apply
- Key paper:
 - Badriyah, Tessy, Briggs, Jim, Meredith, Paul, Jarvis, Stuart, Schmidt, Paul E., Featherstone, Peter I., Prytherch, David and Smith, Gary B. (2014) *Decision-tree early warning score (DTEWS) validates the design of the National Early Warning Score (NEWS)*. Resuscitation, 85 (3). pp. 418-423

Impact

- Embodied into VitalPAC
 - advises nurses; alerts doctors
- Issue is where to set threshold for response
 - ~20% of obs have score of ≥ 5 (medium alert)
 - ~10% of obs have score of ≥ 7 (high alert)
 - Too low a threshold means too much work to do
 - Too high means you might be too late to save the patient
- NEWS is ViEWS adapted by the Royal College of Physicians
 - Now recommended for adoption by all hospitals
- As of 2013:
 - scheduled for adoption in about 68% of UK hospitals
 - adopted nationally in Wales
 - recommended for adoption in Ireland

Recent work

- Do we need condition-specific models?
- Is NEWS applicable to surgery as well as medicine?
- Can NEWS be simplified?

Current/future work

- Can the model be improved by adding more variables?
 - the HAVEN project
- What are the implications for nurse staffing?
 - the Missed Care project
- Are Portsmouth patients typical?
- What is the significance of trends in scores?

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<http://www.chmi.port.ac.uk/outcomes/>

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THE END