

## Using Bayesian network to model colonisation with Vancomycin Resistant Enterococcus (VRE)

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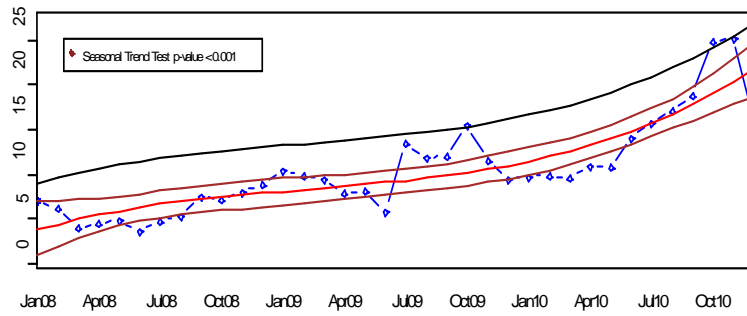
## Overview

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- Introduce the Problem
- Motivation for our approach
- Background on Bayesian networks(BN)
- BN Construction
- BN Quantification
- BN Evaluation
- Results and Conclusion

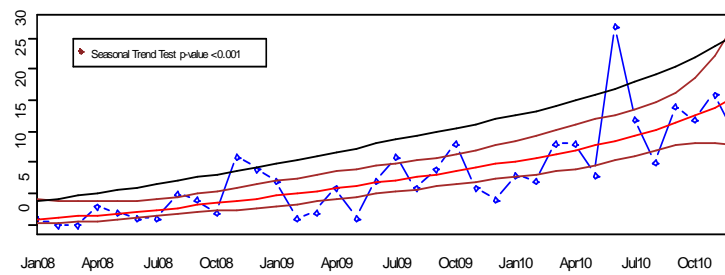
## The Problem

Prevalence of VRE at PAH.



## The Problem

Number of new VRE isolates at PAH



## Motivation for our approach

### Infections cost \$1 billion in lost bed days

**Public health**

INFECTIONS caught in hospital are costing the Australian healthcare system more than 850,000 lost bed days per year, according to a new QUT study.

Associate Professor Nick Graves, from the Institute of Health and Biomedical Innovation, said there were 175,153 cases where patients had acquired an infection during their hospital stay.

"If rates were reduced by just one per cent, then 150,158 bed days would be released for alternative uses, allowing an estimated 38,700 additional admissions annually," he said.

The results, which have been published in the Australian journal *Healthcare Infection*, calculate the economic consequences of healthcare-acquired infections arising among admissions to Australian acute care hospitals.

Professor Graves said the research

revealed there was an opportunity to improve the efficiency of the Australian healthcare system.

"Acute hospitals in Australia cannot meet current demand," he said. "Waiting lists for elective surgery and specialist outpatient appointments are lengthening in every state and territory."

Professor Graves said many infections were preventable and Australian infection control practitioners could reduce rates if they had additional resources.

"Healthcare-acquired infection rates are about five per cent of all admissions at the moment and with bed days valued at \$1005 each, the total economic burden is close to \$1 billion per annum," he said.

Professor Graves said the bulk of the costs were faced by the most populous states of New South Wales, Queensland and Victoria.

"New South Wales loses 272,844 bed days, Victoria 232,951 and Queensland 170,126," he said.



Associate Professor Nick Graves said an extra 38,600 patients could be treated each year if hospital-acquired infections were reduced by just one per cent.

"This accounts for almost 56,000 infection cases in NSW, 47,700 cases in Victoria and 34,900 cases in Queensland."

Lost bed days for other states and territories are: 80,619 for Western Australia, 72,753 for South Australia, 11,257 for Tasmania, 7,408 for Australian Capital Territory and 7079 for the Northern Territory.

"Spending more money on

infection control could reduce rates, release bed days and increase hospital throughput. This is likely to improve the efficiency of the hospital sector," he said.

Professor Graves said the next step was to investigate cost-effective ways of spending extra dollars on new and expanded research programs.

He said a national program was being undertaken to encourage

healthcare workers to wash their hands before and after touching every patient, which had the potential of being effective at reducing infection and cost-effective.

The research was funded by The Centre for Healthcare Related Infection Surveillance and Prevention.

- Sandra Hutchinson

## Motivation for our approach

- Complex and interrelated.
- Potential causes and control strategies in isolation.
- Control strategies effective when used in combination.
- Used Bayesian network model

## Motivation for our approach

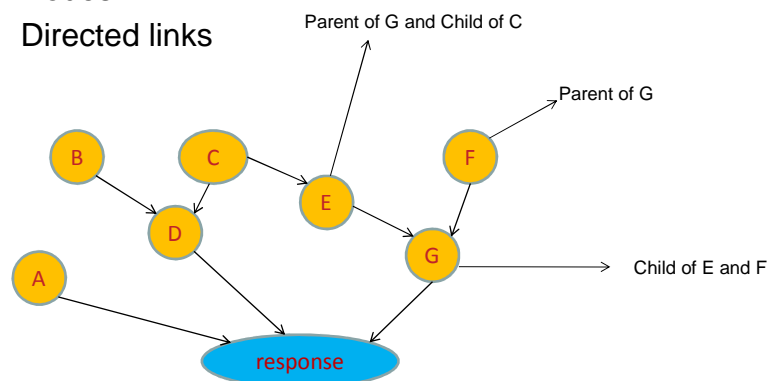
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- Multiple interacting agents
- Use of expert opinion and existing data
- Update the model as information becomes available.
- Quantify relationships using conditional probabilities.
- Identify most influential factors
- Investigate scenarios

## Background on Bayesian networks(BN)

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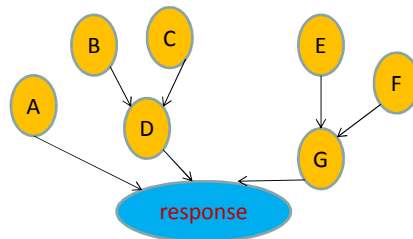
- Nodes
- Directed links



## Background on Bayesian networks(BN)

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- Underlying probabilistic framework
  - Capture uncertainty via conditional probability distributions
  - State of child depends only on states of parents



## Background on Bayesian networks(BN)

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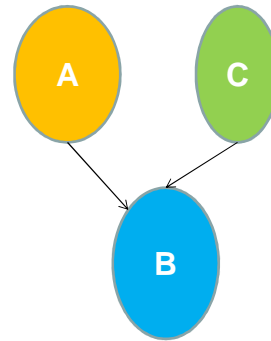
- Aims were threefold:
  - Construct a BN to describe potential risk factors associated with the outcome
  - Quantify the BN model using data from PAH
  - Evaluate the predictive ability, sensitivity, and robustness of the resultant model.

## Background on Bayesian networks(BN)

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- Conditional probability table for B

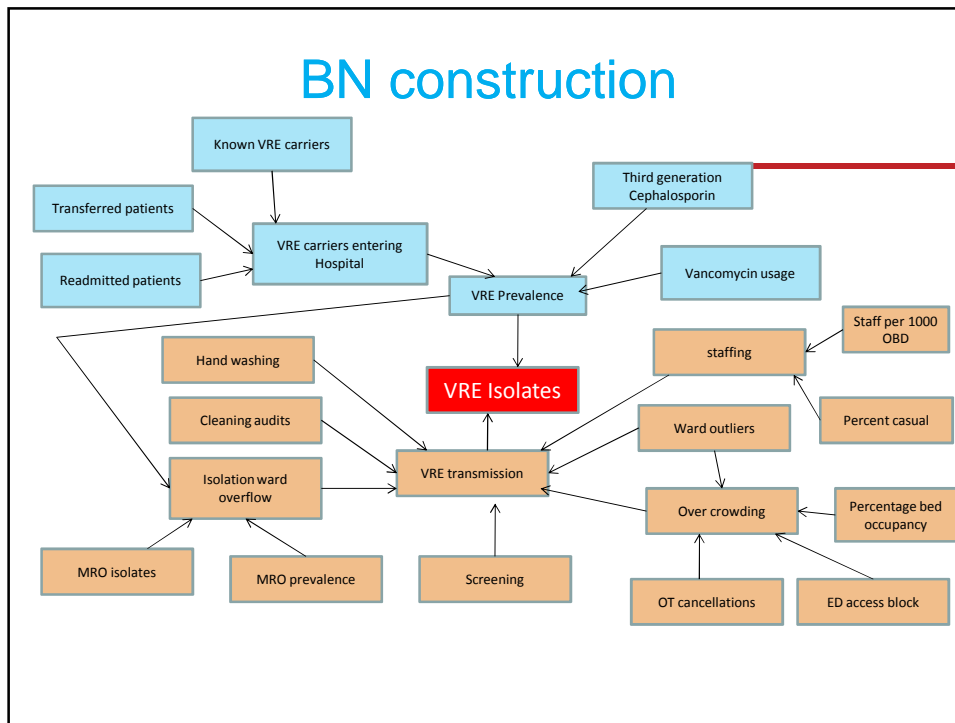
C	A	B	
		High	Normal
Satisfactory	High	0.6	0.4
	Normal	0.3	0.7
Unsatisfactory	High	0.8	0.2
	Normal	0.6	0.4



## BN construction

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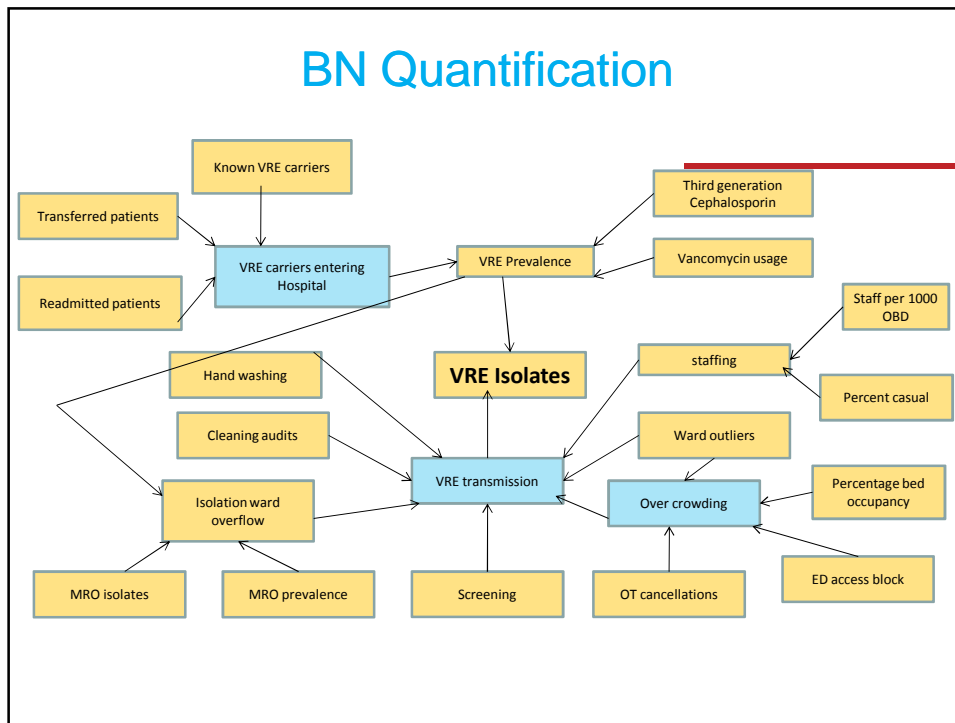
- Twenty two variables
- Medical literature and expert
- Nodes arranged in 2 major clusters.



### BN Quantification

- Used 36 months (Jan 2008 – Dec 2010) data
- Data not collected directly for three nodes
- Linear regression models
- Example:

The example diagram shows three nodes: 'Transferred patients', 'Readmitted patients', and 'Known VRE carriers'. Arrows from each of these three nodes point to a single node labeled 'VRE carriers entering Hospital'.



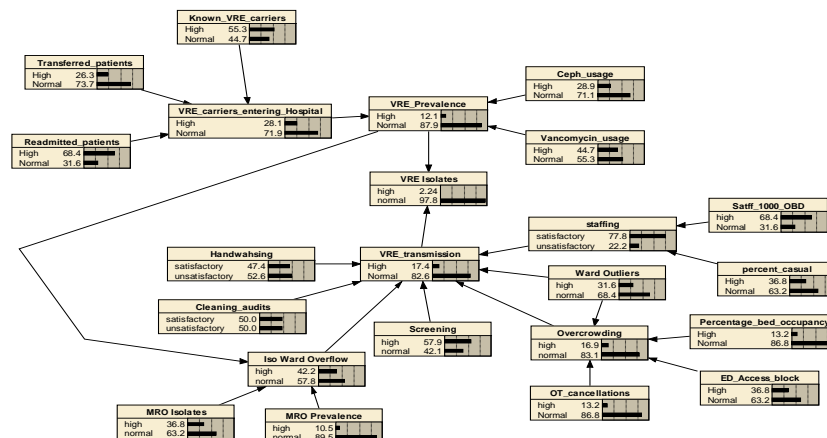
- ### BN Quantification
- Netica software
  - Variables dichotomized based on the third quartile of a subset of the 2008 data.
  - 19 dichotomized into 'high' and 'normal' levels;  
3 dichotomized into 'satisfactory' and 'unsatisfactory'.



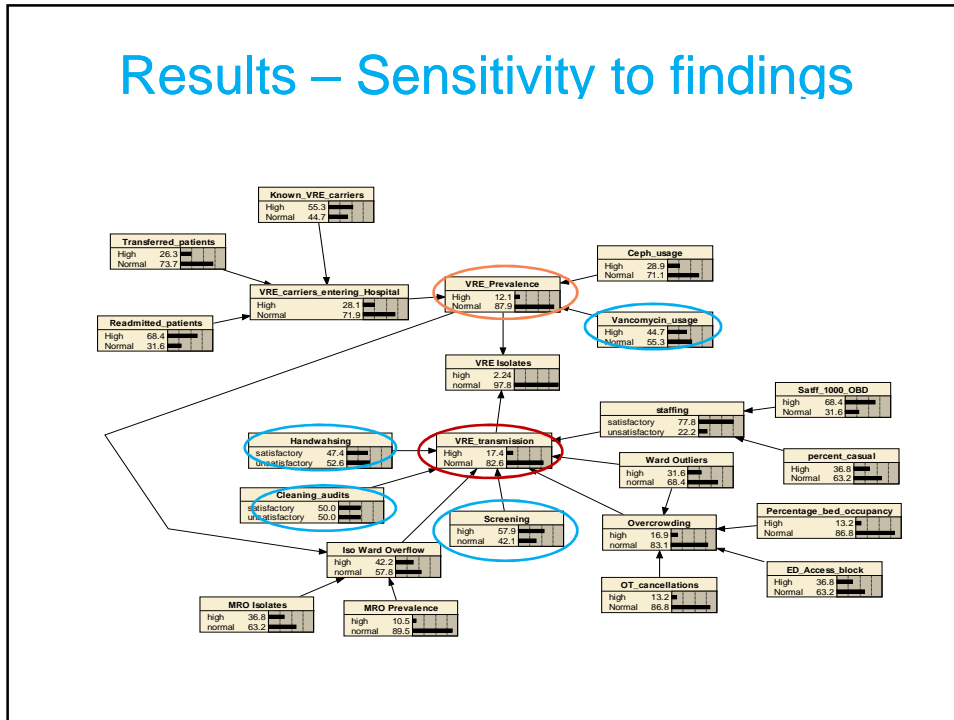
## BN Evaluation

1. The probability of high level of VRE isolates
2. Sensitivity analysis
3. Scenario analyses
4. Robustness of the model.

## Results – Baseline Probabilities



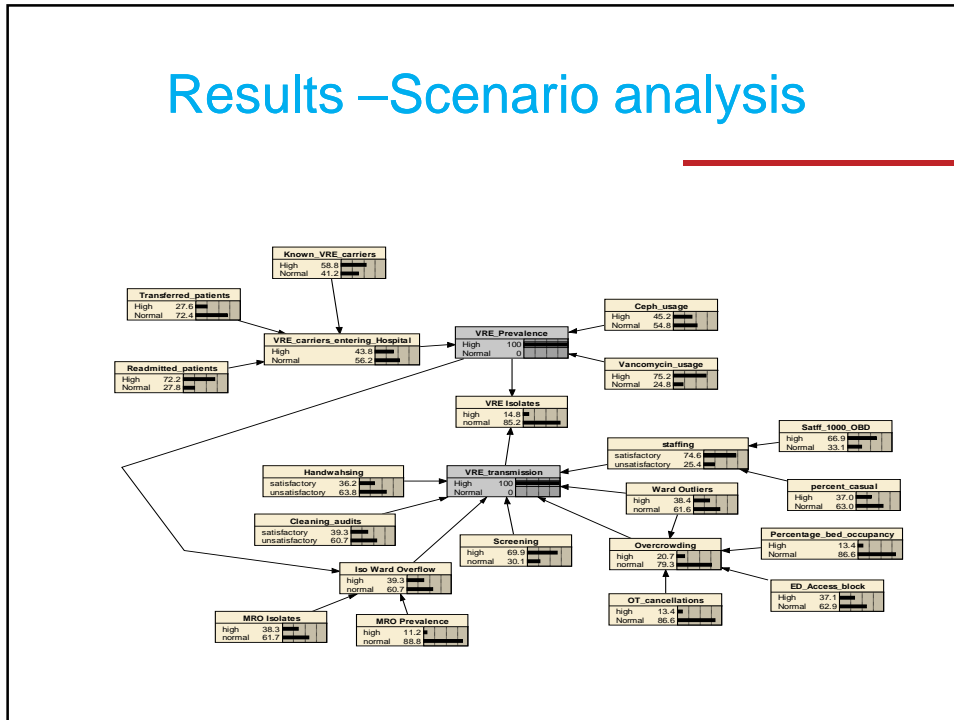
## Results – Sensitivity to findings



## Results – Sensitivity to findings

Factor	Level	Mutual information	Importance relative to VRE transmission (%)	p
New VRE isolates	-	0.15497		0.022
<b>VRE transmission</b>	<b>High</b>	<b>0.02487</b>		<b>0.174</b>
<b>VRE Prevalence</b>	<b>High</b>	<b>0.0086</b>	<b>34.6</b>	<b>0.121</b>
<b>Vancomycin usage</b>	<b>High</b>	<b>0.00064</b>	<b>2.6</b>	<b>0.447</b>
<b>Screening</b>	<b>High</b>	<b>0.00042</b>	<b>1.7</b>	<b>0.579</b>
<b>Hand washing</b>	<b>Unsatisfactory</b>	<b>0.00035</b>	<b>1.4</b>	<b>0.526</b>
<b>Cleaning audits</b>	<b>Unsatisfactory</b>	<b>0.00032</b>	<b>1.3</b>	<b>0.500</b>
Ceph. Usage	High	0.00022	0.9	0.289
VRE Carriers Entering Hospital	High	0.0002	0.8	0.281
Ward outliers	High	0.00015	0.6	0.316
Over crowding	High	0.00007	0.3	0.169
Staffing	Unsatisfactory	0.00004	0.2	0.222
Isolation ward overflow	High	0.00003	0.1	0.422
Readmitted patients	High	0.00001	0.04	0.684
Known VRE Carriers	High	0.00001	0.04	0.553
Staff per 1000 OBD	High	0.00001	0.04	0.684
MRO Isolates	High	0	0	0.368
Transferred patients	High	0	0	0.263
MRO Prevalence	High	0	0	0.105
Operating Theatre Cancellations	High	0	0	0.132
Percentage bed occupied	High	0	0	0.132
Emergency Department Access block	High	0	0	0.368
% casual	High	0	0	0.368

## Results –Scenario analysis



## Results –Scenario analysis

VRE transmission	VRE Prevalence	Probability (p)
Normal	-	<b>0.74%</b> ↓ from 2.24%
High	-	<b>9.4%</b> ↑ from 2.24%
-	Normal	<b>1.52%</b> ↓ from 2.24%
-	High	<b>7.52%</b> ↑ from 2.24%
Normal	Normal	<b>0</b> ↓ from 2.24%
Normal	High	<b>6.01%</b> ↑ from 2.24%
High	Normal	<b>8.7%</b> ↑ from 2.24%
High	High	<b>14.8%</b> ↑ from 2.24%

## Results – VRE Transmission

Factor	Level	Mutual Information	Importance relative to Screening (%)
VRE transmission	High	0.66662	
<b>Screening</b>	<b>High</b>	<b>0.00861</b>	
<b>Hand washing</b>	<b>Unsatisfactory</b>	<b>0.00717</b>	<b>83.3</b>
<b>Cleaning audits</b>	<b>Unsatisfactory</b>	<b>0.00645</b>	<b>74.9</b>
<b>Isolation ward overflow</b>	<b>High</b>	<b>0.00439</b>	<b>51.0</b>
<b>Ward outliers</b>	<b>High</b>	<b>0.00294</b>	<b>34.1</b>
Over crowding	High	0.00144	16.7
Staffing	Unsatisfactory	0.00085	9.9
Staff per 1000 OBD	High	0.00015	1.7
MRO isolates	High	0.00003	0.3
VRE prevalence	High	0.00003	0.3
MRO prevalence	High	0.00003	0.3
Percentage bed occupied	High	0.00001	0.1
OT cancellations	High	0.00001	0.1
ED Access block	High	0.00001	0.1
Percent casual	High	0	0
Vancomycin usage	High	0	0
VRE carriers entering into Hospital	High	0	0
Ceph. usage	High	0	0
Readmitted patients	High	0	0
Transferred patients	High	0	0
Known VRE carriers	High	0	0

## Results – Robustness assessment

Factor	Proportion agreement
<b>VRE transmission</b>	<b>1.00</b>
<b>VRE Prevalence</b>	<b>1.00</b>
<b>Vancomycin usage</b>	<b>0.65</b>
<b>Screening</b>	<b>0.50</b>
Hand washing	0.40
Cleaning audits	0.65
Ceph. usage	0.35
VRE Carriers Entering in Hospital	0.60
Ward Outliers	0.65
Over crowding	0.55
Staffing	0.30
Isolation ward overflow	0.20
Readmitted patients	0.50
Known VRE Carriers	0.35
Staff per 1000 OBD	0.30
Transferred patients	0.15
MRO Isolates	0.10
MRO Prevalence	0.25
Percentage bed occupancy	0.50
Operating Theatre Cancellations	0.40
Emergency Department access block	0.30
% casual	0.60

## Conclusion

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- BN is a sensible model for risk assessment of rare event.
- VRE transmission appears to be more important than VRE prevalence.
- Hand hygiene and cleaning have a relatively minor effect

## Conclusion

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- Consider some pruning of the BN structure
- Update CPTs as more data become available.
- Limitation: Mutual interdependence of prevalence and transmission

