Clinical Decision Support Today & Tomorrow

What does the future have for us?

Mark Ansermino: University of British Columbia, Vancouver Canada
Potential conflict of interest

- Canadian Society of Anesthesiologists
- Michael Smith Foundation
- NSERC
- CIHR
- Research Draeger Medical
- Consultant GE Medical
Phases of *Innovation*

- It will never work
- It worked in animals but will never work in humans
- It worked in a small selected group of patients
- It worked in a large group but required special expertise or is too expensive
- Of course it works. I came up with the idea but did not bother to publish it.
Delivery of FastanII main backing store for the 418/III. Capacity 132MB.
London Hospital 1970
Who wants clinical decision support?

- Do you use clinical decision support?
- Do you want clinical decision support?
- Why do you want clinical decision support?
What is decision support?
Clinical Decision Support

- **Clinical Decision Support** is a clinical system, document, application or process that helps health professionals make clinical decisions to enhance patient care.
Decision support in clinical monitoring

- Alerting
- Reminding
- Suggesting
- Critiquing
- Interpreting
- Diagnosing
- Predicting
- Doing!
What are we good at?

Your job is secure!

- Value judgments
- High complexity
- Adaptation to context
- High reliability
- Interdependence
What can we do better?

- Cognitive bias
- Information overload
- Changing habits
- Repetitive tasks
- Attention prioritization
- Multiple simultaneous tasks
Diagnostic Error

• 40 000 to 80 000 US hospital deaths result from misdiagnosis annually
• 9% TIA’s missed
• 5% MI’s missed

• Preoperative antibiotics

• These are NOT bad people…

“The greatest obstacle to knowledge is not ignorance, it is the illusion of knowledge”

- Daniel Boorstein
Adverse Anecdote

- Level IV evidence
- Last bad experience
- Expert opinion

Choice (Decision) Blindness

(Johansson, 2000)
Two Minds when making decisions

<table>
<thead>
<tr>
<th>System 1</th>
<th>System 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intuition</td>
<td>Reasoning</td>
</tr>
<tr>
<td>Fast</td>
<td>Slow</td>
</tr>
<tr>
<td>Parallel</td>
<td>Serial</td>
</tr>
<tr>
<td>Automatic</td>
<td>Controlled</td>
</tr>
<tr>
<td>Effortless</td>
<td>Effortful</td>
</tr>
<tr>
<td>Associative</td>
<td>Rule Governed</td>
</tr>
<tr>
<td>Emotional</td>
<td>Neutral</td>
</tr>
<tr>
<td>Slow learning</td>
<td>Flexible</td>
</tr>
</tbody>
</table>

Cognitive Bias
Heuristics and Biases

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- **Representativeness heuristic**
  - insensitive to base rate/prior probabilities
  - strong inference from small sample
  - confuse ‘normal’ and ‘rare’ events

- **Availability heuristic**

- **Anchoring and adjustment**

- **Decision framing**
Heuristics and Biases

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

• Representativeness heuristic
• Availability heuristic
  – swayed by information that is vivid, well-publicized, or recent
  – correlate events if close together
• Anchoring and adjustment
• Decision framing
Heuristics and Biases

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
- Availability heuristic
- Anchoring and adjustment
  - depends on starting value
  - inadequate adjustment
- Decision framing

Cognitive Bias
Heuristics and Biases

Heuristics are used to reduce mental effort in decision making, but they may lead to systematic biases or errors in judgment.

- Representativeness heuristic
- Availability heuristic
- Anchoring and adjustment
- Decision framing
  - prospect theory

Decision making is not rational?
Unrecognized limitations

The unrecognized limits of professional skill help explain why experts are often overconfident.

Statistical algorithms greatly outdo humans in noisy environments for two reasons: they are more likely than human judges to detect weakly valid cues and much more likely to maintain a modest level of accuracy by using such cues consistently.

Daniel Kahneman
### Detecting changes – Real Time

<table>
<thead>
<tr>
<th></th>
<th>PPV</th>
<th>Sensitivity</th>
<th>% Detected</th>
</tr>
</thead>
<tbody>
<tr>
<td>HR</td>
<td>0.75</td>
<td>0.60</td>
<td>59.54</td>
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<tr>
<td>NIBPmean</td>
<td>0.60</td>
<td>0.63</td>
<td>63.33</td>
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<tr>
<td>SpO2</td>
<td>1.00</td>
<td>0.06</td>
<td>6.25</td>
</tr>
<tr>
<td>ETCO2</td>
<td>0.74</td>
<td>0.13</td>
<td>12.85</td>
</tr>
<tr>
<td>MVexp</td>
<td>0.55</td>
<td>0.11</td>
<td>11.17</td>
</tr>
<tr>
<td>RR(CO2)</td>
<td>1.00</td>
<td>0.01</td>
<td>0.94</td>
</tr>
<tr>
<td>TOTAL</td>
<td>0.64</td>
<td>0.10</td>
<td>9.54</td>
</tr>
</tbody>
</table>

PPV – positive predictive value

How do we make decisions?

Special Article

Defining rules for the identification of critical ventilatory events

[Définition de règles pour identifier les événements respiratoires critiques]

J. Mark Ansermino FRCPC, Maryam Dosani BSc, Erica Amari BA, Peter T. Choi MD FRCPC MSc,
Stephan K. W. Schwarz MD PhD FRCPC

What has changed in healthcare?

Information

What will change healthcare?
The Human Factor

- CO2, Capnogram, O2, Agent, N2O, O2 consumption
- CO, PCWP, SVR, LVSWI
- EEG index, EEG, EMG
- SpO2, Plethysmograph, Respiratory variation
- HR, ECG shape, ST, T, PR
- BP, CVP, Temperature

Change ??

Drugs

Fluids

Perturbation

Attention ability

Cognitive Bias

Information Overload
Human Vigilance Over Time

The most precious resource is human vigilance.

Cognitive Bias

Information Overload
The Expert System (sensor)

History
- Visual
- Auditory
- Tactile
- Automatic

Prediction

Filter
- (Remove noise)

Extract Features
- (Average, Trend, Max, Min)

Expert Knowledge
- (Guidelines, Consensus, Rules)

Data Fusion
- (Sensors and knowledge)

Add Facts
- (Unmeasured information)

Human Interface

Outputs
- System Models
  - Neural
  - Bayesian
  - Fuzzy
  - Linear
  - Non-linear

Inputs

Cognitive Bias

Information Overload
The Expert System (outcome)

Output

Add facts (Unmeasured information)

Data Fusion

Expert Knowledge (Guidelines, Consensus, Rules)

Extract Features (Average, Trend, Max, Min)

Filter (Clean data)

Data

Inputs

System Models

Neural
Bayesian
Fuzzy
Linear
Non linear

Outcomes

Prediction

Cognitive Bias

Information Overload
Medicine Based Evidence

• **Comparative Effectiveness Research**
  – clinically relevant issues
  – who and where were the patients
  – what and why were the treatments
  – when and how were the outcomes
  – assessment of validity and generalizability considered together and denoted as accuracy
Context Specific Monitoring

Look at the trend!!
Adaptive feature extraction

Measured signal value

True signal value

Signal noise

Inter patient and intraoperative variation
Adaptive feature extraction II

Original Signal

Adaptive Kalman Filter

\( Q_0 \quad R_0 \)

Denoised Signal

\( Q_k \quad R_k \)

Slope

EWMA & DLM Forecasting

\( N \)

Signal Block

Target Value

Limits

Average Slope of Current Block

Sensitivity Control \( \sigma \)

Adaptive Local CUSUM

Change Points

State Representation

Cognitive Bias

Information Overload
Limit Based Alarms

Heart Rate

Heart rate (bpm)

Time (sec)

Upper Alarm Limit

Lower Alarm Limit
Change Point Detection - BP
Automated ‘change point’ detection

- Dependant on full history of the process
- Weighted towards more recent data
- Statistical features continuously updated
- Adaptable to individual patient
- Comparable to visual trend
### Results - Offline

Performance of iAssist compared to post hoc clinician review

<table>
<thead>
<tr>
<th>Parameter</th>
<th>PPV</th>
<th>Events</th>
<th>Missed</th>
<th>Events/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>HR</td>
<td>0.92</td>
<td>297.00</td>
<td>33.00</td>
<td>4.36</td>
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<tr>
<td>NIBPmean</td>
<td>0.94</td>
<td>137.00</td>
<td>10.00</td>
<td>2.01</td>
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<tr>
<td>SpO2</td>
<td>0.98</td>
<td>50.00</td>
<td>0.00</td>
<td>0.73</td>
</tr>
<tr>
<td>ETCO2</td>
<td>0.74</td>
<td>249.00</td>
<td>20.00</td>
<td>3.66</td>
</tr>
<tr>
<td>MVexp</td>
<td>0.90</td>
<td>230.00</td>
<td>16.00</td>
<td>3.38</td>
</tr>
<tr>
<td>RR(CO2)</td>
<td>0.84</td>
<td>128.00</td>
<td>12.00</td>
<td>1.88</td>
</tr>
<tr>
<td>TOTAL</td>
<td>0.87</td>
<td>1091.00</td>
<td>91.00</td>
<td>16.02</td>
</tr>
</tbody>
</table>

PPV - positive predictive value

Results – On line

Classification of change points per hour of anaesthesia.

15 staff
38 cases
103 min
22.8 /case
61% significant
7% artefacts

iKnow

Production rules for everyone!
Types of Knowledge

• **Explicit knowledge**
  – Can be articulated into formal language, readily transmitted to others, easily be processed by a computer.

• **Tacit knowledge**
  – Intangible factors embedded in individual experience, such as personal beliefs, and perspective (intuition). Hard to articulate with formal language (hard, but not impossible).
iKnow – knowledge authoring tool

**List of possible inputs:**
- Static representations
  - Heart rate
  - Blood pressure
  - Minute ventilation
  - Respiratory rate
  - Electrocautery activated
- Dynamic representations
  - Heart rate increasing
  - Minute ventilation decreasing
  - Mean blood pressure 10 min
  - Heart rate variability
  - Systolic pressure variation

**Rules:**
If ... then

and ... or
greater than... less than

**List of possible outputs:**
- Hypotension
- Light anesthesia
- Bronchospasm
- Circuit leak
- Circuit disconnect
- Anesthetic overdose
- Myocardial ischemia
- Hyperthermia
- Pulmonary embolism
- Main stem intubation
- Anaphylaxis

ISO/IEEE 11073

Snowmed
Patterns
Demographic
- Age
- Weight
- ASA
- Procedure

Measurement
- Heart rate
- Blood pressure

Deviation

Change point

OUTCOME
- Hypotension
- Light anesthesia
- Bronchospasm
- Anaphylaxis
- Hypercarbia

RULES

If .... Then

Real time inference engine

Just in time information

Expert Knowledge
<table>
<thead>
<tr>
<th>Start</th>
<th>End</th>
<th>Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td>11:49:34</td>
<td>11:49:34</td>
<td>Tachycardia</td>
</tr>
<tr>
<td>11:45:59</td>
<td>11:46:39</td>
<td>Hypertension</td>
</tr>
<tr>
<td>11:45:29</td>
<td>11:46:04</td>
<td>Tachycardia</td>
</tr>
<tr>
<td>11:40:24</td>
<td>11:42:19</td>
<td>BP Decrease</td>
</tr>
<tr>
<td>11:32:29</td>
<td>11:32:39</td>
<td>Tachycardia</td>
</tr>
</tbody>
</table>

**Explanation for Tachycardia**

- **Tachycardia (infant only)**
  - Infant (only) at 11:49:34
  - Age >= 0.083 and <= 0.999
  - HR >= 140.0 and <= 250.0 [20 sec]
  - HR = 145.0

**Outcome:** Tachycardia

**Description:**

Heart rate is fast
iKnow Information

Knowledge Authoring Tool

iKnow is a tool for building a knowledge base for physiological monitoring. Expert knowledge about physiological monitoring, such as used in anesthesia or the intensive care unit, is encoded into a set of rules. These rules are used in real time by the inference engine of an expert system. iKnow is designed to be easy to use and avoid the need for a knowledge engineer for rule creation. The rules are run in real time against inputs from clinical monitoring devices.

iKnow can create a custom list of rules representing the individual clinician’s knowledge or developed collaboratively by an institution or professional organization to standardize group knowledge.

The software generates programming code in a rule-based expert system language called JBoss Rules. The set of rules are then run, in real time at the patient’s bedside, against data generated by physiological monitors. Included within the iKnow program is a testing sub-application which allows a user to test the rules output against data in an Excel file. The data in this Excel file can be edited to force the rules to fire.

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Automation is the ultimate decision support!
Thanks for listening....

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