A Complex Systems Approach towards a Better Understanding of Healthcare

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(@ BHI’13, Maebashi)
Find information about the Summit on the NAE's Grand Challenges, March 2-3, 2009, in Durham, NC, organized by Duke University; the Viterbi School of Engineering at the University of Southern California; and Olin College.

Get a PDF of the Grand Challenges booklet here.

With input from people around the world — much of it on this website — an international group of leading technological thinkers were asked to

SHARE YOUR COMMENTS ON
One of these grand challenges:
- Prevent nuclear terror
- Engineer better medicines

COMMITTEE MEMBER SPOTLIGHT

WILLIAM PERRY
MICHAE AND BARBARA BERBERIAN PROFESSOR, PROFESSOR OF ENGINEERING, AND FORMER U.S. SECRETARY OF DEFENSE

William J. Perry (chair), former U.S. secretary of defense (1994-1997), is Michael and Barbara Berberian Professor, a senior fellow at the Freeman Spogli Institute for International Studies (FSI), and a member of the ...
Global Healthcare Challenge 1
Disease Surveillance/Control
Millennium Development Goals

• Eight goals are to be achieved by 2015, agreed by all 191 UN member states:
  1. Eradicate extreme poverty and hunger
  2. Achieve universal primary education
  3. Promote gender equality and empower women
  4. Reduce child mortality rates
  5. Improve maternal health
  6. Combat HIV/AIDS, malaria, and other diseases
  7. Ensure environmental sustainability
  8. Develop a global partnership for development
Malaria 2012-2013 (source WHO 2009)

- **no risk**
- **limited risk**
- **elevated risk**

- **A** Nivaquine® weekly
- **C** Malarone® or doxycycline daily; Lariam® weekly

for details: see www.itg.be
Malaria Endemic in China

I. Epidemiological profile

<table>
<thead>
<tr>
<th>Population (UN Population Division)</th>
<th>2011</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>High transmission (≥1 case per 1000 population)</td>
<td>13 500 000</td>
<td>1</td>
</tr>
<tr>
<td>Low transmission (0-1 cases per 1000 population)</td>
<td>674 000 000</td>
<td>50</td>
</tr>
<tr>
<td>Malaria-free (0 cases)</td>
<td>660 000 000</td>
<td>49</td>
</tr>
<tr>
<td>Total</td>
<td>1 347 500 000</td>
<td></td>
</tr>
</tbody>
</table>

Parasites and vectors

- Major plasmodium species: *P. falciparum* (43%), *P. vivax* (57%)
- Major anopheles species: *An. minimus, sinensis, anthropophagus, dirus*

II. Intervention policies and strategies

<table>
<thead>
<tr>
<th>Intervention</th>
<th>WHO-recommended policies/strategies</th>
<th>Yes/No</th>
<th>Year adopted</th>
</tr>
</thead>
<tbody>
<tr>
<td>ITN/LLIN</td>
<td>ITNs/LLINs distributed free of charge</td>
<td>Yes</td>
<td>2003</td>
</tr>
<tr>
<td></td>
<td>ITNs/LLINs distributed to all age groups</td>
<td>Yes</td>
<td>2000</td>
</tr>
<tr>
<td>IRS</td>
<td>IRS is recommended</td>
<td>Yes</td>
<td>2000</td>
</tr>
<tr>
<td></td>
<td>DDT is used for IRS</td>
<td>No</td>
<td>–</td>
</tr>
<tr>
<td>IPT</td>
<td>IPT used to prevent malaria during pregnancy</td>
<td>NA</td>
<td>–</td>
</tr>
<tr>
<td>Case management</td>
<td>Patients of all ages should receive diagnostic test</td>
<td>Yes</td>
<td>2000</td>
</tr>
<tr>
<td></td>
<td>RDTs used at community level</td>
<td>No</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>ACT is free for all ages in public sector</td>
<td>Yes</td>
<td>2006</td>
</tr>
<tr>
<td></td>
<td>Pre-referral treatment with recommended medicines</td>
<td>No</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Oral artemisinin-based monotherapies are not registered</td>
<td>Yes</td>
<td>2006</td>
</tr>
</tbody>
</table>

ITN: Insecticide-treated mosquito net; LLIN: Long-lasting insecticidal net; IPT: Intermittent preventive treatment; IRS: Indoor residual spraying; DDT: Dichloro-diphenyl-trichloroethane; RDT: Rapid diagnostic test; ACT: Artemisinin-based combination therapy.
Public Health Indicators

• **Transmission Patterns**
  – Temporal distribution of malaria cases (*When*)
  – Spatial distribution of malaria cases (*Where*)
  – Demographical distribution (*Who*)

• **Risk Measures**
  – Under control
  – Elimination
  – Eradication
Malaria Transmission

Three Stages

A. Exo-crythrocytic Cycle
B. Erythrocytic Cycle
C. Sporogonic Cycle

Within human body

Within mosquito
Multi-scale Impact Factors

- *Malaria transmission between human beings and vectors may be impacted by various factors at different scales.*

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Multi-level Transmission Dynamics

Macroscopic

Impact factors

Microscopic

Metapopulation

Individual
A Complex Systems Perspective

• **Coupling Relationships and Interactions**
  – Epidemiological entities: the host, the disease, and the transmission agent (e.g., mosquitoes)

• **Multi-scale impact factors**
  – Ecological, physiological, environmental, demographical, behavioral factors, and so on.

• **Multi-level Transmission Dynamics**
  – Agent-based models at the individual level
  – Homogeneous mixing models at the metapopulation level

• **Externality**
  – For example, human response (e.g., social awareness), public policies, environment (e.g., abnormal weather), etc.
What’s the Role of Computing? (e.g., computational intelligence)

1. Complex Systems Modeling
   • Discovering (and predicting) tempo-spatial transmission patterns
   • Identifying underlying interactions

2. Policy-level Decision Making
   • Active surveillance
   • Strategy planning
   • Resource deployment
   • Policy assessment
Malaria Endemic in Yunnan, China

Tempo-spatial Distribution of Malaria Cases

The number of *P. vivax* incidences of 62 towns in Yunnan, China, in 2005.

What is the underlying malaria transmission network?
Malaria Endemic in Yunnan

- **Malaria Transmission Networks**
  - How to characterize malaria transmissions from one location to another due to **human movement**?

- **Based on malaria prevalence, we can further address the following questions:**
  - How to build a spatial transmission model, taking into consideration impact factors at various scales (e.g., physiological, environmental, demographical factors)?
  - How to identify the underlying malaria transmission networks based on the constructed model and available surveillance data?
A Spatial Malaria Transmission Model

• Evaluating malaria risk for each individual town

**VCAP:** the number of *potentially infective contacts* an individual person makes, through vector population, per unit time.

**EIR:** the number of *infectious bites* received per day by a person.

**VCAP and EIR**

- \( VCAP = \frac{ma^2p^n}{-\ln(p)} \)
  - \( a \) – human biting habit
  - \( m \) – ratio of humans to mosquitoes
  - \( n \) – Sporogonic cycle length
  - \( p \) – probability of daily survival

- \( EIR(t) = \frac{c \cdot VCAP \cdot x(t)}{1 - ca \cdot x(t)/\ln(p)} \)
  - \( x(t) \) -- the proportion of infectious person at time \( t \)
  - \( c \) -- the transmission efficiency from an infectious person to an uninfected mosquito

The values of vectorial capacity of the 62 towns in Yunnan province in 2005. The values are calculated using time window size 16 days.
The **tempo-spatial surveillance data** about malaria infections can perform as *continuous inputs* to *an appropriate malaria transmission model*. Accordingly, the model will output some results, which will be treated as inputs to *a learning method*.

The surveillance data can also perform as *a training set* to the learning method. Based on the learning results, certain *parameters in the malaria transmission model* will be adjusted.
A Learning Method: Recurrent Neural Network

- Each node represents a town.
- $\beta_i$ represents the control effort of each node.
- $Z$ represents imported cases.
- $d$ is the diameter of the transportation network among 62 towns.

Objective: Inferring malaria transmission networks, i.e., $w_{ij}$.

Method: The backpropagation algorithm.
Our Results

- Using *a machine learning method* to infer underlying malaria transmission networks under different scenarios
- Classify transmission roles of individual locations

![Graph showing town IDs and proportion of self-propagation for different imported cases percentages.](image)
Fig. 4. Townships that form a community in the inferred malaria transmission network.
H1N1 Epidemic

How to avoid H1N1

- Avoid hugging, kissing and shaking hands when greeting
- Avoid touching eyes, nose or mouth with unwashed hands
- Cover your nose and mouth with a disposable tissue when coughing and sneezing
- Dispose of used tissue properly immediately after use
- Regularly wash hands with soap and water
- If you have flu-like symptoms, seek medical advice immediately
- If you have flu-like symptoms, keep a distance of at least 1 meter from other people
- If you have flu-like symptoms, stay home from work, school or crowded places

Age-specific disease infection

Spread of H1N1 influenza in Hong Kong [2].

Biological characteristics
- Genetics
- Virulence

Epidemiological indicators
- Basic reproduction R0
- Attack rate
- Prevalence/incidence

Demographical variations
- Age
- Susceptibility
- Infectivity

Social behaviors
- Contact relationships
- Response

Interventions
- Vaccination
- Social distancing
- Antiviral drugs

Effectiveness measurements
- Morbidity/mortality
- Transmission reduction
Motivation

1. Characterizing disease dynamics in a host population
2. Strategic planning for effective disease control
3. Characterizing and evaluating human responsive behaviors

1. Vaccination
2. Influenza-like disease
3. Computational approach
H1N1 Epidemic

• Age-Specific Contact Patterns
  – Disease transmissions are subject to the structure of individuals social contacts, which plays a key role in the assessment of an infection outbreak

• We aim to investigate H1N1 transmission in Hong Kong by addressing the following two specific issues:
  – How to characterize age-specific contact patterns by exploiting the demographical information of a host population (i.e., census data)?
  – How to use a computational model to predict the disease transmission patterns, at the metapopulation level?
Age-Specific Contact Patterns

a Computation of contact frequencies for every member of a household composed by two adults aged 31 and two children of 5 and 6 years old. The sum of the four contributions gives contact frequencies within this household (in red).

b Contact frequencies within a household composed of an adult aged 31 and a child aged 5.

c Assuming that these two households constitute the whole population, the frequency of household contacts that individuals of age \( \text{5} \) have with individuals aged \( \text{31} \) is given by the sum of the contributions from each household, divided by the number of individuals aged \( \text{31} \) having at least one household contact.

Individuals’ vaccination decision making -- Social Influence

- **Majority followers**
  - Social neighbors’ choices
  - Interaction relationships
  - Strength of social influence

- **Duel-perspective view**
  - Cost-benefit analysis
  - Social influence
  - Balance between them

---

**How to measure social influence?**

**Integrated Decision Making Process**

<table>
<thead>
<tr>
<th>Costs</th>
<th>Social influence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disease infection risk</td>
<td></td>
</tr>
<tr>
<td>Cost of infection</td>
<td>Neighbors' decisions</td>
</tr>
<tr>
<td>Cost of vaccination</td>
<td>Interaction closeness</td>
</tr>
</tbody>
</table>

**Modeling**

- Game theoretical analysis
  - Cost-minimized choice
- Social impact theory (SIT)
  - Formalized social opinion
I. Public Health Policies

Goals and targets
- Death reduction
- Case reduction

Intervention strategies
- Diagnosis
- Treatment
- Vector control
- Vaccination

Monitoring & evaluation
- Disease surveillance
- Anti-drug resistance
- Effectiveness & efficiency

Cooperation
- Financial support
- Political commitment
- Organizational management

II. Disease Transmission: A Complex Systems Perspective

Impact factors
- Ecological
- Environmental
- Socio-economic
- Demographical
- Behavioral
- Biological

Multi-scale
- Macroscopic
- Metapopulation
- Microscopic

Multi-level
- Individual

IV. Data-Driven Computational Intelligence

System modeling
- Predicting tempo-spatial patterns
  (Real-world study I)
- Identifying underlying interactions
  (Real-world study II)

Policy-level decision making
- Active surveillance
- Strategic planning
- Deployment
- Assessment

III. Public Health Indicators

Transmission patterns
- Temporal (when)
- Spatial (where)
- Demographical (who)

Risk measurements
- Under control
- Elimination
- Eradication

Original figure at https://www.cdc.gov/diphis/
Breaking Down Complex Systems in Public Health

In an effort to gain a more comprehensive understanding of public health issues, Columbia’s Mailman School of Public Health has recently partnered with Columbia Engineering to create a new program that will give public health students the tools to analyze the complex systems tied to important health matters. The goal of this new program is to give the public health researchers the ability to tackle public health issues the way an engineer would.

The Columbia University Systems Science Program (CUSSP) is a new curriculum-based program led by the Mailman School of Public Health’s Dean Linda Fried and Professors Sandro Galea and Roger Vaughan with the Engineering School’s Professor Garud Iyengar of the Department of Industrial Engineering and...
Global Healthcare Challenge 2
Service Performance
Health Data Initiative Strategy & Execution Plan Released and Ready for Feedback

The new Health Data Initiative Strategy & Execution Plan has been released! Check it out as it will guide and measure the open data strategy for the Department. Provide your feedback! Read more »
Provincial Wait Times by Month 2009–2010

**ELECTIVE ISOLATED CABG SURGERY**

PROVINCIAL ACCESS TARGET: 90 DAYS

DAYS

<table>
<thead>
<tr>
<th>April 09</th>
<th>May 09</th>
<th>June 09</th>
<th>July 09</th>
<th>August 09</th>
<th>September 09</th>
<th>October 09</th>
<th>November 09</th>
<th>December 09</th>
<th>January 10</th>
<th>February 10</th>
<th>March 10</th>
<th>Provincial Summary</th>
</tr>
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<tbody>
<tr>
<td></td>
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<td></td>
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<td></td>
<td></td>
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</tr>
</tbody>
</table>

MAXIMUM WAIT DAYS
90th PERCENTILE
Q3—75th PERCENTILE
MEDIAN
Q1—25th PERCENTILE
MINIMUM WAIT DAYS
LHIN: Local Hospital Integration Networks
### Research Context

- **Local Health Integration Network (LHIN) in Ontario, Canada**

<table>
<thead>
<tr>
<th>LHIN ID</th>
<th>LHIN name</th>
<th>Area ($km^2$)</th>
<th>PD (per $km^2$)</th>
<th>Boundary</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Erie St. Clair</td>
<td>7323.7</td>
<td>86.1</td>
<td>Windsor, Lambton, Chatham-Kent, and Essex</td>
</tr>
<tr>
<td>2</td>
<td>South West</td>
<td>20903.5</td>
<td>43.1</td>
<td>London, Stratford, Elgin, Middlesex, Oxford, Perth, Huron, Bruce, and part of Grey</td>
</tr>
<tr>
<td>3</td>
<td>Waterloo Wellington</td>
<td>4746.6</td>
<td>144.6</td>
<td>Wellington, Waterloo, Guelph, and part of Grey</td>
</tr>
<tr>
<td>4</td>
<td>Hamilton Niagara</td>
<td>6473.0</td>
<td>203.3</td>
<td>Hamilton, Niagara, Haldimand, Brant, and parts of Halton and Norfolk</td>
</tr>
<tr>
<td></td>
<td>Haldimand Brant</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Central West</td>
<td>2590.0</td>
<td>285.7</td>
<td>Dufferin, parts of Peel, York, and Toronto</td>
</tr>
<tr>
<td>6</td>
<td>Mississauga Halton</td>
<td>1053.7</td>
<td>956.7</td>
<td>Mississauga, parts of Toronto, Peel, and Halton</td>
</tr>
<tr>
<td>7</td>
<td>Toronto Central</td>
<td>192.0</td>
<td>5678.9</td>
<td>A large part of Toronto</td>
</tr>
<tr>
<td>8</td>
<td>Central</td>
<td>2730.5</td>
<td>561.3</td>
<td>Parts of Toronto, York, and Simcoe</td>
</tr>
<tr>
<td>9</td>
<td>Central East</td>
<td>15274.1</td>
<td>93.8</td>
<td>Durham, Kawartha Lakes, Haliburton Highlands, Heterborough, parts of Northumberland, and Toronto</td>
</tr>
<tr>
<td>10</td>
<td>South East</td>
<td>17887.2</td>
<td>26.1</td>
<td>Kingston, Hastings, Lennox and Addington, Prince Edward, and Frontenac</td>
</tr>
<tr>
<td>11</td>
<td>Champlain</td>
<td>1763.1</td>
<td>65.1</td>
<td>Ottawa, Renfrew, Prescott and Russell, Stormont, and Dundas and Glengarry</td>
</tr>
<tr>
<td>12</td>
<td>North Simcoe Muskoka</td>
<td>8372.3</td>
<td>50.5</td>
<td>Muskoka, parts of Simcoe and Grey</td>
</tr>
<tr>
<td>13</td>
<td>North East</td>
<td>395576.7</td>
<td>1.4</td>
<td>Nipissing, Parry Sound, Sudbury, Algoma, Cochrane, and part of Kenora</td>
</tr>
<tr>
<td>14</td>
<td>North West</td>
<td>406819.6</td>
<td>0.6</td>
<td>Thunder Bay, Rainy River, and most of Kenora</td>
</tr>
</tbody>
</table>

PD: population density.
About our LHIN

What is a LHIN

The Erie St. Clair Local Health Integration Network is one of 14 Local Health Integration Networks (LHINs) that have been established and launched in Ontario.

LHINs are community-based, non-profit organizations funded by the Ministry of Health and Long-Term Care to plan, fund and coordinate services delivered by:

- Hospitals
- Long-Term Care Homes
- Community Care Access Centre (CCAC)
- Community Support Service Agencies
- Mental Health and Addictions Agencies
- Community Health Centres (CHCs)

Erie St. Clair LHIN services the regions of Chatham-Kent, Sarnia/Lambton and Windsor/Essex which includes over 649,000 people and supports an annual budget of over $900 million for our local health care services.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Budget (Million)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospitals</td>
<td>$672.7</td>
</tr>
<tr>
<td>Long-Term Care</td>
<td>$179.9</td>
</tr>
<tr>
<td>Community Care Access Centre</td>
<td>$121.4</td>
</tr>
<tr>
<td>Mental Health Agencies</td>
<td>$31.2</td>
</tr>
<tr>
<td>Community Health Centres</td>
<td>$24.1</td>
</tr>
<tr>
<td>Community Support Services</td>
<td>$17.3</td>
</tr>
</tbody>
</table>
### Data

- A summary of data and abbreviations

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Measures</th>
<th>Abb. of surgery</th>
<th>Profile of surgery (per month)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demand</strong></td>
<td>Average number of Arrivals, monthly*</td>
<td>SA</td>
<td>82</td>
</tr>
<tr>
<td><strong>Capacity</strong></td>
<td>Number of physicians, yearly†</td>
<td>SC</td>
<td>7</td>
</tr>
<tr>
<td><strong>Throughput</strong></td>
<td>Average number of completed cases, monthly *</td>
<td>ST</td>
<td>83</td>
</tr>
<tr>
<td><strong>Wait time</strong></td>
<td>Median wait for urgent/semi-urgent/elective patient*</td>
<td>SUM/SSM/SEM</td>
<td>3/6/19</td>
</tr>
<tr>
<td></td>
<td>90th percentile wait for urgent/semi-urgent/elective patient*</td>
<td>SUN/SSN/SEN</td>
<td>11/31/49</td>
</tr>
<tr>
<td></td>
<td>Queue length*</td>
<td>SQ</td>
<td>58</td>
</tr>
</tbody>
</table>

**Data source:**

* Cardiac care network of Ontario, [https://www.ccn.on.ca](https://www.ccn.on.ca)

† Ontario physician human resources data centre. [https://www.ophrdc.org/Home.aspx](https://www.ophrdc.org/Home.aspx)

Data

- A summary of data from individual hospitals

<table>
<thead>
<tr>
<th>Hospital</th>
<th>SA</th>
<th>SC</th>
<th>ST</th>
<th>SUM</th>
<th>SUN</th>
<th>SSM</th>
<th>SSN</th>
<th>SEM</th>
<th>SEN</th>
<th>SQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>London HSC</td>
<td>115</td>
<td>8</td>
<td>120</td>
<td>2</td>
<td>7</td>
<td>6</td>
<td>29</td>
<td>15</td>
<td>49</td>
<td>76</td>
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<tr>
<td>St. Mary’s General Hospital, Kitchener</td>
<td>111</td>
<td>8</td>
<td>113</td>
<td>2</td>
<td>8</td>
<td>6</td>
<td>29</td>
<td>15</td>
<td>50</td>
<td>71</td>
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<tr>
<td>Hamilton HSC</td>
<td>105</td>
<td>8</td>
<td>107</td>
<td>2</td>
<td>8</td>
<td>5</td>
<td>29</td>
<td>14</td>
<td>49</td>
<td>65</td>
</tr>
<tr>
<td>Trillium HC, Mississauga</td>
<td>100</td>
<td>8</td>
<td>101</td>
<td>2</td>
<td>7</td>
<td>5</td>
<td>29</td>
<td>14</td>
<td>48</td>
<td>61</td>
</tr>
<tr>
<td>St. Michael’s Hospital, Toronto</td>
<td>91</td>
<td>7</td>
<td>94</td>
<td>1</td>
<td>7</td>
<td>5</td>
<td>30</td>
<td>13</td>
<td>48</td>
<td>55</td>
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<td>Sunnybrook Health Sciences Centre</td>
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<td>7</td>
<td>88</td>
<td>1</td>
<td>10</td>
<td>5</td>
<td>31</td>
<td>15</td>
<td>50</td>
<td>51</td>
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<tr>
<td>University Health Network, Toronto</td>
<td>81</td>
<td>7</td>
<td>82</td>
<td>1</td>
<td>10</td>
<td>5</td>
<td>32</td>
<td>15</td>
<td>51</td>
<td>48</td>
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<tr>
<td>Southlake Regional HC, Newmarket</td>
<td>73</td>
<td>7</td>
<td>74</td>
<td>1</td>
<td>10</td>
<td>5</td>
<td>31</td>
<td>16</td>
<td>51</td>
<td>43</td>
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<td>Kingston General Hospital</td>
<td>64</td>
<td>7</td>
<td>67</td>
<td>1</td>
<td>9</td>
<td>4</td>
<td>30</td>
<td>17</td>
<td>49</td>
<td>37</td>
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<tr>
<td>University of Ottawa Heart Institute</td>
<td>59</td>
<td>6</td>
<td>60</td>
<td>1</td>
<td>10</td>
<td>4</td>
<td>29</td>
<td>16</td>
<td>48</td>
<td>32</td>
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<tr>
<td>Hôpital Régional de Sudbury</td>
<td>52</td>
<td>6</td>
<td>53</td>
<td>1</td>
<td>10</td>
<td>4</td>
<td>31</td>
<td>17</td>
<td>48</td>
<td>28</td>
</tr>
</tbody>
</table>
Self-Organized Regularities in the Cardiac Care System?

- **Dynamically-changing arrivals**

- **Dynamically-changing median wait time**

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)
A Complex Systems Perspective

Important Issues

- **Wait Time Dynamics**
  - Capacity
  - Management (scheduler) strategies
  - Cross-unit wait time cascade effects

- **Patient Arrival Dynamics**
  - Population profiles → “Latent” patients
  - Environmental factors → “Latent” patients
  - Patient decision making (profile, environmental factors) → Patient arrivals

An open, complex health care system
The Complexity of Wait Time Management

Research Question 1
- Cardiac Care System
  - Wait Time Dynamics
    - Hospital Characteristics
      - Capacity
      - Scheduler Strategies
    - Others?
      - Coupling Units Effects
        - Cross-unit Wait Time Relationship
  - Wait Time Control
    - Hospital Characteristics Improvement
      - Resource Allocation or Reallocation Strategies
      - Adaptive Scheduler Strategies
    - Optimizing Coupling Units Effects
      - Cross-unit Wait Time Cascade Effects

Research Question 2
- Environment
  - Cardiac Disease Morbidity Dynamics
    - Personal Profile
      - Age
      - Ethnicity
      - Living Habit
    - Environmental Exposures
      - Temperature
      - Env. Tobacco Smoking
      - ...
  - Healthy Population
    - Latent Cardiac Patients

Research Question 3
- Service Utilization Behavior
  - Personal Profile
    - Age
    - Ethnicity
    - Service Utilization Habit
  - Decision Making
    - Perceived Risk of Disease
    - Service Accessibility
    - Service Capacity
  - Latent Cardiac Patients
    - Cardiac Patients

Research Question 4
Question: Can we observe any direct and moderating effects of geodemographic profiles on service utilization (patient arrivals)?

- Research hypotheses
Data

- Data Source
  - 11 CCN hospitals (2004-07): Cardiac Care Network of Ontario
  - Geodemography data for LHINs: 2006 Census of Canada
- 47 cities/towns (no. population>40,000)

Sample hospitals in Ontario, Canada
Sample cities in Ontario, Canada
Method

• Structural Equation Modeling (SEM)\textsuperscript{[Byrne, 09]}
  – A second-generation statistic technique

• Features of SEM\textsuperscript{[Gefen,00]}
  – Structural: To validate the assumed causation among a set of dependent and independent constructs
  – Measurement: To evaluate the loadings of observed items on their expected latent variables

• Partial-least-squares based SEM\textsuperscript{[Gefen,00]} vs. Covariance based SEM
  – Efficient to examine the significance of the relationships of constructs
  – More suited for predictive applications and theory building

Self-Organized Regularities in the Cardiac Care System (1)

(Statistical regularities?)

- month-to-month arrival variations
- month-to-month absolute variations for median wait time

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)
Self-Organized Regularities in the Cardiac Care System (2)
(Spatial patterns?)

- Patient flow distribution

![Heatmap showing patient flow distribution across LHINs]

- Function classification for LHINs

![Graph showing accessibility levels for different LHINs]

How to understand such emergent self-organized regularities?

Self-Organized Regularities in the Cardiac Care System (3) (Tempo-spatial patterns?)

- Dynamically-changing arrivals

- Dynamically-changing median wait time

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)
Question: How to understand the emergent self-organized regularities?

**Scope**
What factors, variables, processes, and hierarchical levels are relevant, and hence should be investigated and modeled?

**Emergence**
- How to model and simulate the self-organizing healthcare systems?
- How do these self-organized regularities emerge from simulated self-organizing process?

**Heterogeneity**
How to capture the heterogeneity of patients and hospitals in modeling and simulation?

**Challenge**
How to model, simulate, reproduce, and explain?

**Solution**
Modeling and simulating dynamically-changing patient arrivals and wait time in a complex cardiac surgery system based on AOC

**Interactions**
What are the interrelationships or local feedback loops among the impact factors and variables?
Modeling Method: **Autonomy-Oriented Computing**

- **Steps in AOC modeling:**
  1. **Real-world observations:** Self-organized regularities/patterns in a real system
  2. **Identify and design entities:** Synthetic behaviors, impact factors, local feedback loops, and an environment where entities reside
  3. **Modeled system observations:** Self-organized regularities/patterns emerging from the modeled system
  4. **Validation:** Behaviors of the system vs. the real-world counterpart
  5. **Explanation:** Explaining the regularities/patterns with the “white-box” model

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AOC-Based Model (1)

- **Entity identification**

- Hospital selection by a cardiac surgery patient

![Diagram showing patient flow and wait time information flow]

- **Entities**
  - Patient
  - GP
  - Hospital

- 93% population in Ontario have GP
  - [Link](http://www.health.gov.on.ca/en/news/release/2012/may/nr_20120507_1.aspx)
- GP is the “gatekeeper” for referrals to cardiac surgery [Chan99]

[http://www.ices.on.ca/webpage.cfm?site_id=1&org_id=67&morg_id=0&gsec_id=0&item_id=1390&type=atlas](http://www.ices.on.ca/webpage.cfm?site_id=1&org_id=67&morg_id=0&gsec_id=0&item_id=1390&type=atlas)
AOC-Based Model (2)

- Major impact factor identification

- Multi-attribute analysis

Identified factors for patient hospital-selection behaviors

- Driving distance
- Hospital resourcefulness (No. Physicians)
- Wait time


AOC-Based Model (3)

- Major impact factor identification
  - For hospital service adjustment: Accumulated arrivals

- Supporting observations:
  - Linear positive relationship between accumulated arrivals and throughput
  - Correlation between patient arrivals and throughput: 0.896** (p<0.001)

Data source: Cardiac Care Network of Ontario (accessed these data in February 2011)
AOC-Based Model (4)

- **Two local feedback loops**
AOC-Based Model (5)

- **Environment E**: maintains information (e.g., distance, hospital resourcefulness, wait time) for patients and GPs

- **Definition 1**: City-Hospital Network $CH = (C, H, D)$, where $C(N) = \{c_i\} (i \in [1, N])$ and $H(M) = \{h_j\} (j \in [1, M])$ are two node sets, $H \cap C = \emptyset$; $D = \{d_{ij}\} (i \in [1, N], j \in [1, M])$ is a set of weighted edges.

- **Entity General Physician (GP)**: makes hospital selection decisions on behalf of patients based on hospital-selection behavior rules

- **Entity Patient**: records the information (e.g., profile, join in and exit time for services) for an individual patient

- **Entity Hospital**: provides cardiac surgery services based on an M/M/1 queueing model and service adjustment behavior rules
AOC-Based Model (6)

- **Stylized facts:**
  - (1) Distance ↓ → arrival probability ↑
  - (2) No. physicians ↑ → arrival probability ↑
  - (3) Wait time ↓ → arrival probability ↑
  - (4) A large proportion (>70%) of patients do not know wait time information for hospitals [CCN05]

- **Behavior rules for patient-GP hospital selection**
  - **DHW-rule:**
    \[
    a_{ij,\tau} = p \cdot f(d_{ij}) \cdot f(s_j) \cdot f(w_{j,\tau})
    \]
    \[
    f(d_{ij}) = \frac{d'_{ij}}{\sum_{h_k \in H} d'_{ik}}
    \]
    \[
    f(s_j) = \frac{s_j^{\alpha_s}}{\sum_{h_k \in H} s_k^{\alpha_s}}
    \]
    \[
    d'_{ij} = \frac{\sum_{h_k \in H} s_k^{\alpha_s}}{d_i^{\alpha_s}}
    \]
    \[
    f(w_{j,\tau}) = \frac{\sum_{h_k \in H} w_{k,\tau}^{\alpha_w}}{w_j^{\alpha_w}}
    \]

- **Behavior rules for hospital service-rate adjustment**
  - **DH-rule:**
    \[
    \tilde{\mu}_{j,\tau} = \left( \frac{a_j A_{j,\tau-1}}{A_j} + b_j \right) \cdot \bar{\mu}_j
    \]

- **Parameters**
  - Driving time from city i to hospital j
  - No. physicians in hospital j
  - Reference wait time for hospital j at time step τ
  - Arrival probability of patients in city i to hospital j at time step τ
  - Accumulative patient arrivals, i.e., queue length, of hospital j at the end of week
  - Mean patient arrivals in a week
  - Mean service rate in a week
AOC-CSS Model-Based Simulation

- Simulated cities: 47 cities/towns with population >40,000 in 2006
- Simulated hospitals: 11 hospitals in Ontario providing cardiac surgery services
- Driving time estimation: Google map

- Simulation settings:
  - \( p \): cities in LHINs 5-9 and LHIN 12: 0.2
  - cities in LHINs 1-4, 10-11, 13-14: 0.1
- Estimated parameter values from empirical data :
  - Distance power: 3.5
  - Physician power: 1
  - Wait time power: 1
- Simulation runs: 1000

High service accessibility
Low service accessibility
Results (1)

- **Statistical regularities** as observed from simulation
  - month-to-month *arrival variations*

**Normal distribution** (passed the Kolmogorov-Smirnov test)

- **Real**
  - Mean: 0.0004
  - SD: 0.226

- **Simulation**
  - Mean: -0.0013
  - SD: 0.232

Distributions of simulated and real-world arrival variations
Results (2)

- **Statistical regularities** as observed from simulation

  - month-to-month **absolute variations of median wait time**

  ![Power law distribution](image)

  Distribution of simulated absolute variations of median wait time

  Distributions of simulated and real-world absolute variations of median wait time
Results (3)

- Temporal patterns of patient arrivals in 11 hospitals
Results (4)

- Temporal patterns of **median wait time** in 11 hospitals
Results (5)

- Accessibilities of LHINs: **real-world** vs. **simulation**

![Graph showing the accessibilities of LHINs in real-world vs. simulation](image)
Results (6): Explaining Tempo-Spatial Patterns

**Time 2:**
- ✓ H4, H6↑ (wait time ↓ <20)
- ✓ H5, H7↓ (wait time ↓ >20)

**Time 3:**
- ✓ H4, H6 ↓ ↑
- ✓ H5, H7 ↑ ↓

**Time 4:**
- ✓ H4, H7 ↑ ↓
- ✓ H6 ↓ ↑
- ✓ H5 ↑

**Time 5:**
- ✓ H4 ↑ ↓
- ✓ H6 ↓ ↑
- ✓ H5, H7 ↑
FoCAS ‘Best Paper Award’ @ CoSMoS 2013

FoCAS supported a Best Paper Award at the 6th Complex Systems Modelling and Simulation Workshop (CoSMOS 2013), University of Milano-Bicocca, Italy 1st – 5th July.

The winner of the FoCAS award for best CAS paper at CoSMoS 2013 was:

Li Tao, Jiming Liu: Understanding Self-Organized Regularities: AOC-Based Modeling of Complex Healthcare Systems

Abstract: A healthcare system, as a well-recognized complex system, exhibits certain types of self-organized regularities, such as the statistical distribution of wait-time variations. What remains to be a challenge in understanding a complex healthcare system is how to model and characterize emergent self-organized regularities by taking into account the underlying individual-level behavior (e.g., patient hospital selection...
Conclusion

• Real-world healthcare problems involve interactions among impact factors at multiple levels and scales

• Two challenges in Global Healthcare:
  1. How diseases spread (at a metapopulation level)
  2. Why services vary (with self-organizing behaviors)

• Complex systems modeling will play an important role in evidence-based healthcare (e.g., decision support)
Credits:

- Past students: Benyun Shi, Xia Shang, Li Tao & Xiaofei Yang
- National Institute of Parasitic Diseases (NIPD), China CDC
- Centre for Health Protection (CHP), Hong Kong SAR

References (Health Informatics):

- Xia, S., and Liu, J., A computational approach to characterizing the impact of social influence on individuals’ vaccination decision making. *PLoS ONE.*