WHY ARE ED’S OVERCROWDED?
FINDING SOLUTIONS USING GAME THEORY AND AGENT BASED COMPUTER SIMULATION

RICHARD J HAMILTON MD
Prisoners' dilemma

<table>
<thead>
<tr>
<th></th>
<th>prisoner A</th>
<th>prisoner B</th>
</tr>
</thead>
<tbody>
<tr>
<td>confess</td>
<td>5 years</td>
<td>0 year</td>
</tr>
<tr>
<td>remain silent</td>
<td>20 years</td>
<td>20 years</td>
</tr>
</tbody>
</table>

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The El Farol Problem

60 = crowded
## ED OVERCROWDING

<table>
<thead>
<tr>
<th>Number of ED Patients and Position in line</th>
<th>net benefit</th>
<th>average position in line</th>
<th>average net benefit</th>
<th>benefit of alternative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>1</td>
<td>10</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>1.5</td>
<td>9</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>2</td>
<td>8</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>2.5</td>
<td>7</td>
<td>5</td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td>3</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>3.5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>7</td>
<td>-2</td>
<td>4</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>8</td>
<td>-4</td>
<td>4.5</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>9</td>
<td>-6</td>
<td>5</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>10</td>
<td>-8</td>
<td>5.5</td>
<td>1</td>
<td>5</td>
</tr>
</tbody>
</table>
COMPUTER BASED AGENT SIMULATION OVER MULTIPLE ITERATIONS

- Expected from ED
- Actual benefit in ED
- Actual benefit from alternative
COMPUTER BASED AGENT SIMULATION OVER MULTIPLE ITERATIONS
FINDINGS: ED OVERCROWDING IS THE EQUILIBRIUM STATE OF THE US HEALTHCARE SYSTEM

• The cause is patient preference for the ED as a source of health care (higher expectations of satisfaction from the ED over alternatives)
  • Reinforced by EMTALA

• Adding capacity has little effect on overcrowding until capacity exceeds demand

• Adding capacity attracts volume and can be a growth strategy
Machine Learning Application in the ED

G. D. Kelen, MD, FRCP(C)

Disclosure

Under a license agreement between StoCastic, LLC and the Johns Hopkins University, Dr. Levin, Hinson, Kelen, and the University are entitled to royalty distributions on technology described. Dr. Levin is a founder of StoCastic, LLC and both he and the University hold equity in the company. This arrangement has been reviewed and approved by the Johns Hopkins University in accordance with its conflict of interest policies.
Can Machine Learning Improve ESI Triage

Characteristics
- High majority of EDs in United States using
- Based on subjective judgment

Validation
- Some limited validation against hospital admission and mortality.
- Inter-rater reliability varies ($k = .46 - .91$)
- ~59% Nurse concordance with AHRQ ESI Answer Key

Severity of illness uncertain
Machine Learning Application in the ED

Self Correcting Feedback Loop

New Data In

Black Box Rules
E-Triage Algorithm

Outcomes predicted
• Critical care: in-hospital mortality, ICU admission
• Emergent surgery: in the OR within 12 hours of disposition
• Hospital Admission

Predictor variables
• Chief complaint
• Vital signs
• Demographics: age, gender
• Arrival mode: ambulance / walk-in
• Medical/surgical history
• Pain scale*
• Immunocompromised*
Rationale
Emergency Severity Index

Level 3’s: Mitigates Three...iage
Separates high-risk from low-risk Level 3’s
Uses large-scale data from ED
Built for your ED’s population, resources, and objectives
E-Triage Interface

Acuity level recommendation

Acuity assignment
Results: JHH Pre/Post E-Triage Implementation

Triage distribution changes
Filtering high- and low- risk Level ESI Level 3s

- 60% ▲ in low acuity (4-5) from 18% to 29%
- 18% ▼ mid acuity (3) from 67% to 55%
- No change in high acuity (1-2) proportion
## Results

### Level 1: Immediate Need

<table>
<thead>
<tr>
<th>Cohort Size, No. (%)</th>
<th>Nurse (pre)</th>
<th>Nurse + E-Triage (post)</th>
<th>Level 1-2: High Acuity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Daily Volume, median (IQR)</td>
<td>1206 (2.0)</td>
<td>1483 (2.5)</td>
<td>9167 (15.2)</td>
</tr>
<tr>
<td>Nurse (pre)</td>
<td>3 (2-5)</td>
<td>4 (3-5)</td>
<td>25 (21-30)</td>
</tr>
<tr>
<td>Nurse + E-Triage (post)</td>
<td>9716 (16.3)</td>
<td>27 (23-30)</td>
<td></td>
</tr>
</tbody>
</table>

### Predicted Outcomes % (95% CI)

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Level 1</th>
<th>Level 2-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical Care Outcome</td>
<td>16.5 (14.4-18.6)</td>
<td>20.3 (18.2-22.3)</td>
</tr>
<tr>
<td>In-Hospital Mortality</td>
<td>2.7 (1.8-3.7)</td>
<td>5.7 (4.5-6.9)</td>
</tr>
<tr>
<td>Intensive Care Unit Admission</td>
<td>15.9 (13.9-18.0)</td>
<td>18.3 (16.3-20.2)</td>
</tr>
<tr>
<td>Emergency Surgery</td>
<td>4.0 (2.9-5.1)</td>
<td>9.8 (8.3-11.3)</td>
</tr>
<tr>
<td>Hospitalization</td>
<td>55.8 (53.0-58.6)</td>
<td>59.3 (56.8-61.8)</td>
</tr>
</tbody>
</table>

### Secondary Outcomes % (95% CI)

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Level 1</th>
<th>Level 2-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevated Troponin</td>
<td>6.5 (5.1-7.9)</td>
<td>10.5 (8.9-12.0)</td>
</tr>
<tr>
<td>Elevated Lactate</td>
<td>16.9 (14.8-19.0)</td>
<td>23.7 (21.6-25.9)</td>
</tr>
</tbody>
</table>

### Timeliness in min, Mean (Median, IQR)

<table>
<thead>
<tr>
<th>Event</th>
<th>Level 1</th>
<th>Level 2-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arrival to Provider</td>
<td>16.6 (15.0,8.0-24.0)</td>
<td>15.5 (14.0,8.0-22.0)</td>
</tr>
<tr>
<td>Arrival to ED Departure: ICU</td>
<td>337.5 (255.0,163.0-372.0)</td>
<td>289.7 (211.0,132.0-347.0)</td>
</tr>
<tr>
<td>Arrival to ED Departure: Emergency Surgery</td>
<td>264.3 (216.0,77.0-359.0)</td>
<td>225.7 (125.0,58.0-307.0)</td>
</tr>
<tr>
<td>Arrival to Admit Decision</td>
<td>211.0 (146.0,86.0-237.0)</td>
<td>166.4 (110.0,58.0-195.0)</td>
</tr>
<tr>
<td>Boarding Time for Admitted</td>
<td>357.0 (217.0,100.0-501.0)</td>
<td>298.1 (172.0,75.0-366.0)</td>
</tr>
</tbody>
</table>

Increased detection of all outcomes and high-risk markers as high acuity (Level 1 or 2)

~140 patients per year detect as high acuity that will go on to the ICU or have emergency surgery

Improved speed to the highest-severity patients
## Results

### Total ED Population

<table>
<thead>
<tr>
<th></th>
<th>Nurse (pre)</th>
<th>Nurse + E-Triage (post)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cohort Size, No. (%)</strong></td>
<td>60112</td>
<td>59788</td>
</tr>
<tr>
<td><strong>Daily Volume, median (IQR)</strong></td>
<td>164 (152-177)</td>
<td>163 (152-175)</td>
</tr>
</tbody>
</table>

### Outcomes, % (95% CI)

- **Critical Care Outcome**: 1.9 (1.8-2.0) ▲ 2.2 (2.0-2.3)
- **In-Hospital Mortality**: 0.4 (0.3-0.4) ▲ 0.5 (0.4-0.5)
- **Intensive Care Unit Admission**: 1.7 (1.6-1.8) ▲ 1.9 (1.8-2.0)
- **Emergency Surgery, % (95% CI)**: 1.3 (1.2-1.4) ▲ 2.3 (2.0-2.3)
- **Hospitalization, % (95% CI)**: 22.6 (22.2-22.9) ▲ 23.6 (23.3-24.0)

### Secondary Outcomes, % (95% CI)

- **Elevated Troponin**: 2.3 (2.1-2.4) ▲ 2.8 (2.7-2.9)
- **Elevated Lactate**: 4.1 (4.0-4.3) ▲ 4.8 (4.7-5.0)

### Timeliness in min, Mean (Median, IQR)

- **Arrival to Provider**: 56.4 (35.0,20.0-60.0) ▼ 46.0 (36.0,20.0-61.0)
- **Arrival to ED Departure: ICU**: 520.2 (431.0,264.0-660.0) ▼ 492.7 (389.0,235.0-620.0)
- **Arrival to ED Departure: Emergency Surgery**: 657.8 (513.0,303.0-838.0) ▼ 570.1 (461.0,254.0-771.0)
- **Arrival to Admit Decision**: 466.2 (340.0,198.0-599.0) ▼ 424.3 (308.0,175.0-545.0)
- **Arrival to Discharge Decision**: 467.1 (356.0,213.0-618.0) ▼ 469.7 (365.0,216.0-616.0)
- **Boarding Time for Admitted**: 465.2 (337.0,169.0-635.0) ▲ 481.3 (339.0,158.0-686.0)

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### Observations

- **Increased illness severity across the total population over time**
  - 10 min ▼ in average wait time
- **Improved speed for critically ill patients**
  - 27 min ▼ from door to ICU
  - 88 min ▼ from door to ED departure for those having emergency surgery
  - 42 min ▼ in door to admit decision ~ 10,000+ bed-hours annually
- **No changes (sacrifices) in door to discharge times for lower acuity patients**
- **Improved speed to high-severity patients despite challenges with ▲ boarding time**
Beauty of Machine Learning Application
Data-Science in Emergency Medicine Research Program

People

Vess Vassileva-Clarke  Program Coordinator
Scott Levin, PhD  Associate Professor
Jeremiah Hinson, MD, PhD  Assistant Professor
G. D. Kelen, MD  Professor
Eili Klein, PhD  Assistant Professor
Diego Martinez, PhD  Assistant Professor
Matt Toerper  Software Engineer
Gary Lin  Post-Doc
Aria Smith, MS  Programmer Analyst

Research
Sponsors: NSF, AHRQ, NIH, CDC and Industry Partners

AHRQ Patient Safety Learning Lab on Connected Emergency Care
ED Decision Support and Systems Analyses
E-Triage (HopScore)
Acute Kidney Injury
Crowding and Policy
Opioid Use Disorder
Infectious Diseases
Modeling Transmission of HAIs
Antimicrobial Stewardship
Deployed Operations-Focused Tools
Inpatient Discharge Predictions
Outpatient No-Show Management (Home Visits)
Cath Lab Forecasting
Computer Simulation for Department Operations Planning

Eight counties; 1.8 million people; small towns & cities with rural communities. All 17 acute care hospitals partnering, with liaisons to EMS and EMA.

Funded through a grant by the Department of Health & Human Services Office of Preparedness & Emergency Operations Division of National Healthcare Preparedness Programs Grant No. HFPEP070002-01-01. Thanks to Crisis Simulations Intern.
The HCF Partnership of South Central PA

**Hospitals & Preparedness** ~635 ventilators; ~500 person ‘drug caches’; Counter-terrorism Task Force & Emergency Health System Federation; radio-communication dependency; PanFlu'07, 49% hospital beds “available”.

<table>
<thead>
<tr>
<th>Description</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital Beds</td>
<td>3,192</td>
</tr>
<tr>
<td>ICU Beds</td>
<td>393</td>
</tr>
<tr>
<td>Ped/Neonate Beds</td>
<td>254</td>
</tr>
<tr>
<td>Hosp. occupancy</td>
<td>~75%</td>
</tr>
<tr>
<td>EMS Providers</td>
<td>4,748</td>
</tr>
<tr>
<td>ED visits annual</td>
<td>621,000</td>
</tr>
</tbody>
</table>

**Kay Carmen, Exec. Comm. Chair**
South Central Pennsylvania Counterterrorism Task Force
- 8 County EMA’s
- Regional decon. teams
- 5 Hazmat teams

**Steve Lyle, Exec. Director**
- 137 EMS agencies
- 172,179 transports (’06)
- 911 dispatch
Theoretical Surge Response

Pre-incident response
Local medical response
Surge response needs
Federal disaster response

SURGE CAPABILITY
EVENT DURATION
Improved incident response

Local medical response

Federal disaster response

Surge response needs

SURGE CAPABILITY

EVENT DURATION

Theoretical Surge Response with Preparedness Interventions

Improved incident response

Local medical response

ED expansion

Hospital expansion

Alternative expansion

Regional expansion

Surge response needs

Federal disaster response

Theoretical Surge Response with Preparedness Interventions
### Increasing Emergency Care capacity

<table>
<thead>
<tr>
<th>Potential Methods for Creating Emergency Care (EC) Surge:</th>
<th>*Needs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency gains to augment, standardize care.</td>
<td>P, S</td>
</tr>
<tr>
<td>Regional synchronization of EC</td>
<td>C, R, O</td>
</tr>
<tr>
<td>Altering clinical standards of care under mass casualty circumstances.</td>
<td>R, S, C</td>
</tr>
<tr>
<td>Alternative locations for lower acuity emergency needs patients.</td>
<td>E, M, L, O, T</td>
</tr>
<tr>
<td>Existing clinics, public health, behavioral health Utilization existing hospital spaces for EC:</td>
<td>R, O</td>
</tr>
<tr>
<td>Direct transfer to OR, PACU, ICU, other Hospital parking lots, loading docks, other for initial triaging</td>
<td>P, E, M, R, C, L, O, T</td>
</tr>
<tr>
<td>Utilizing community space:</td>
<td>P, E, M, R, C, L, O, T</td>
</tr>
<tr>
<td>Schools, parks, hotels, community centers, shelters Bringing functional “medical space” to incident community</td>
<td>R, C, L, I, O, T</td>
</tr>
<tr>
<td>Portable clinics &amp; mobile hospitals Utilize home or community care for minor to modest</td>
<td>EC E, M, R, C, L, O, T</td>
</tr>
<tr>
<td>Transfer patients to other communities and hospitals</td>
<td>C, T, O</td>
</tr>
</tbody>
</table>

*Personnel (P), equipment (E), medications (M), regulations (R), treatment space (S), communications (C), support lab/xray (L), infrastructure – water/power (I), non-routine operations (O), transport (T).
“SIGNIFICANT” EVENT PROCESS DIAGRAM
6/11/08 Communication Exercise Results