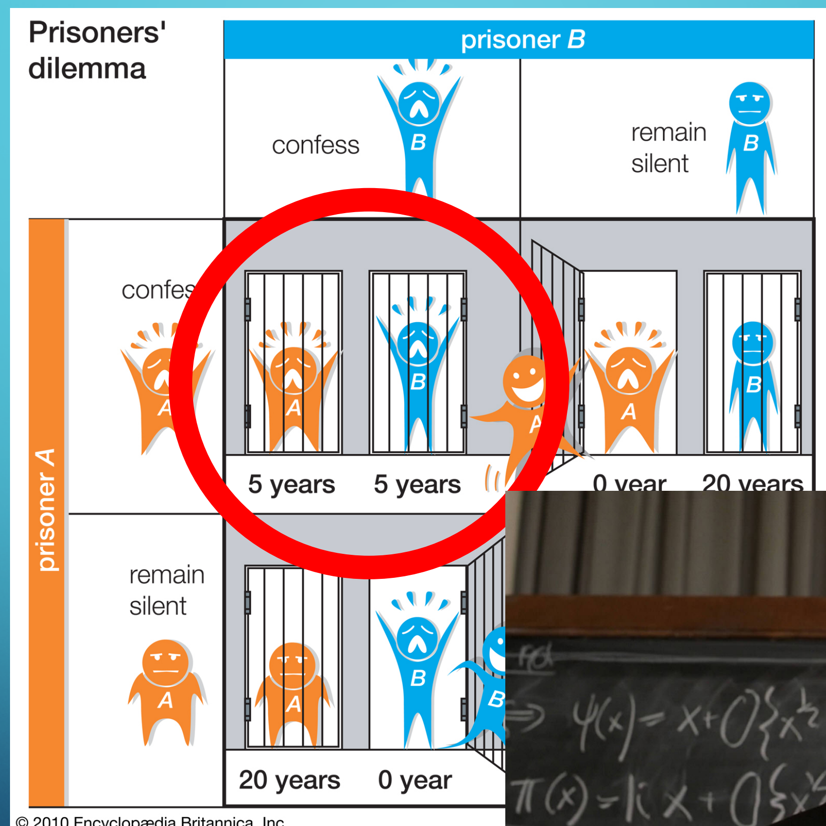
WHY ARE ED'S OVERCROWDED? FINDING SOLUTIONS USING GAME THEORY AND AGENT BASED COMPUTER SIMULATION

RICHARD J HAMILTON MD



Prisoners' dilemma
prisoner B
confess
remain silent
prisoner A
confess
remain silent
5 years
5 years
0 year
20 years
20 years
0 year
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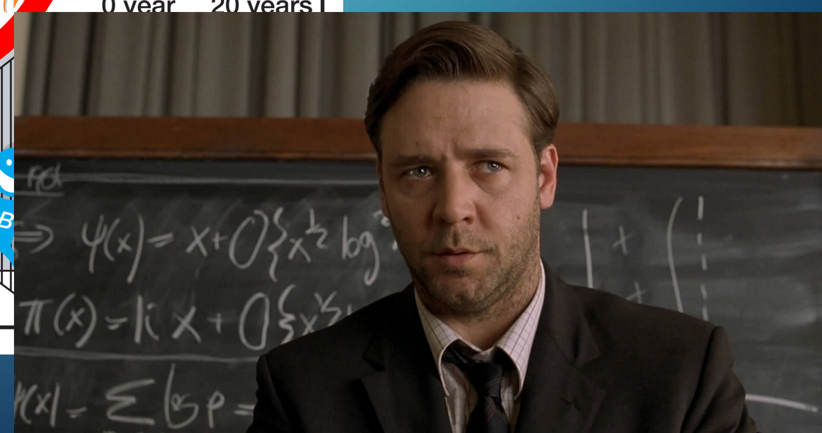
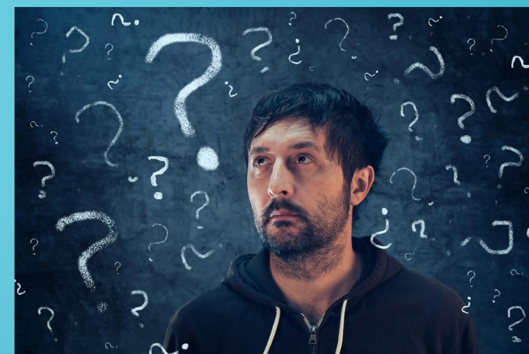



The El Farol Problem
BRAVOS TOROS



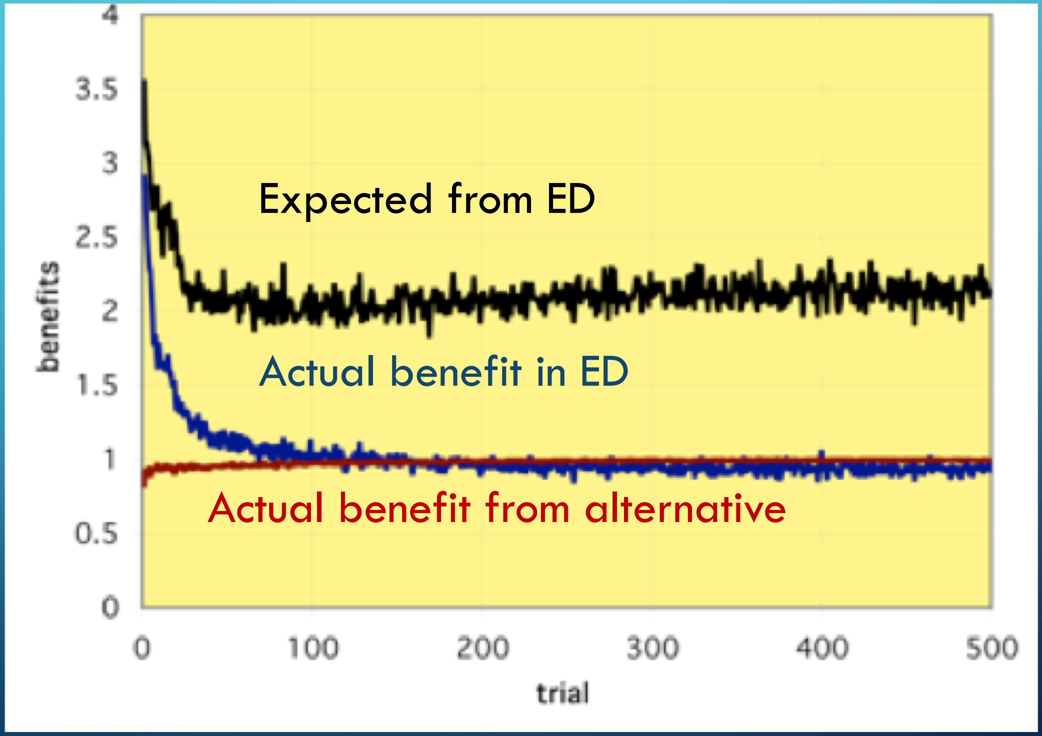
60 = crowded


Standard Normal Probabilities
Table entry for z is the area under the standard
to the left of z.
DEL
AC

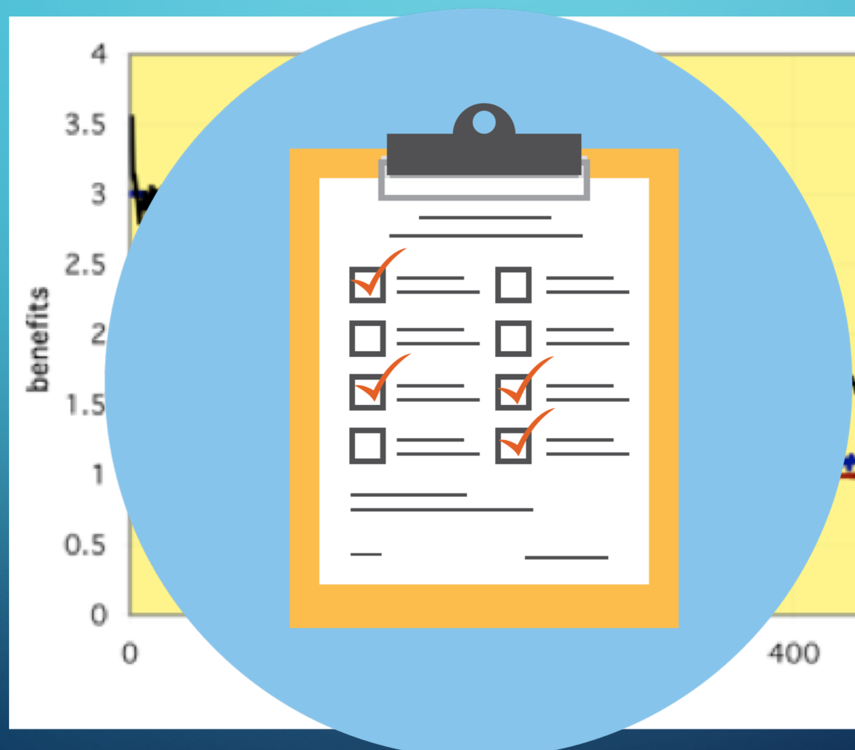
ED OVERCROWDING

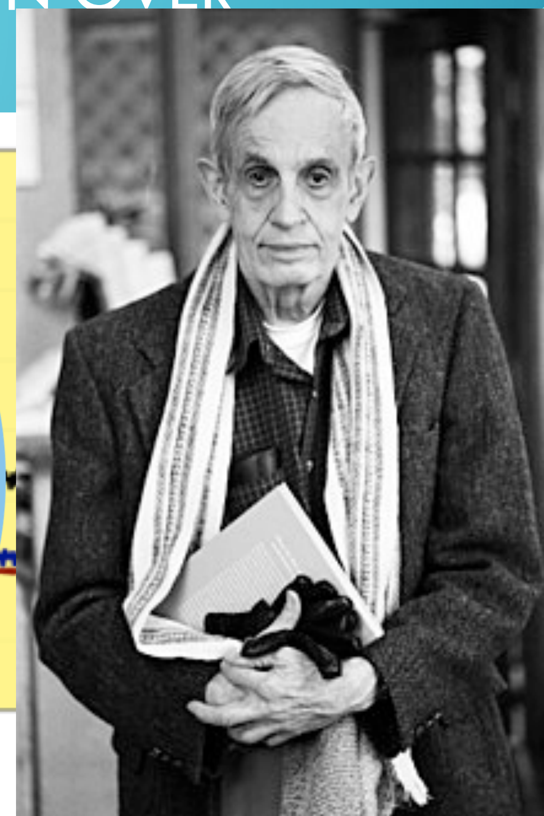
Number of ED Patients and Position in line	net benefit	average position in line	average net benefit	benefit of alternative
1	10	1	10	5
2	8	1.5	9	5
3	6	2	8	5
4	4	2.5	7	5
5	2	3	6	5
6	0	3.5	5	5
7	-2	4	4	5
8	-4	4.5	3	5
9	-6	5	2	5
10	-8	5.5	1	5

COMPUTER BASED AGENT SIMULATION OVER MULTIPLE ITERATIONS



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

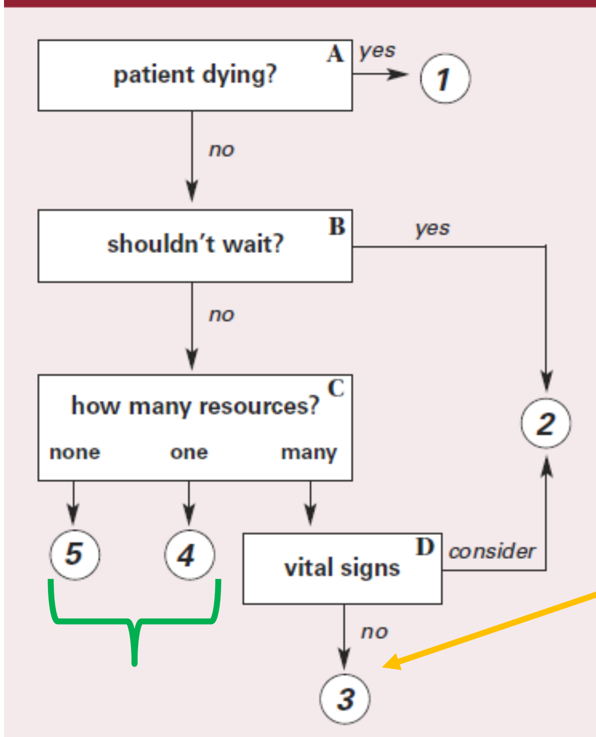
G. D. Kelen, MD, FRCP(C)

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

Figure 2-1. Emergency Severity Index Conceptual Algorithm, v. 4

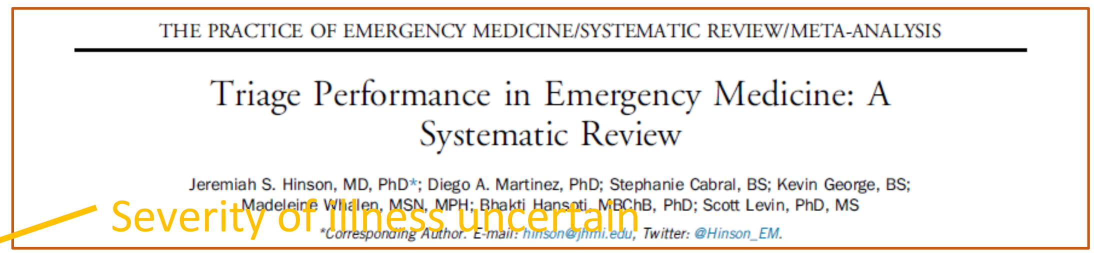


Characteristics

- 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



THE PRACTICE OF EMERGENCY MEDICINE/SYSTEMATIC REVIEW/META-ANALYSIS

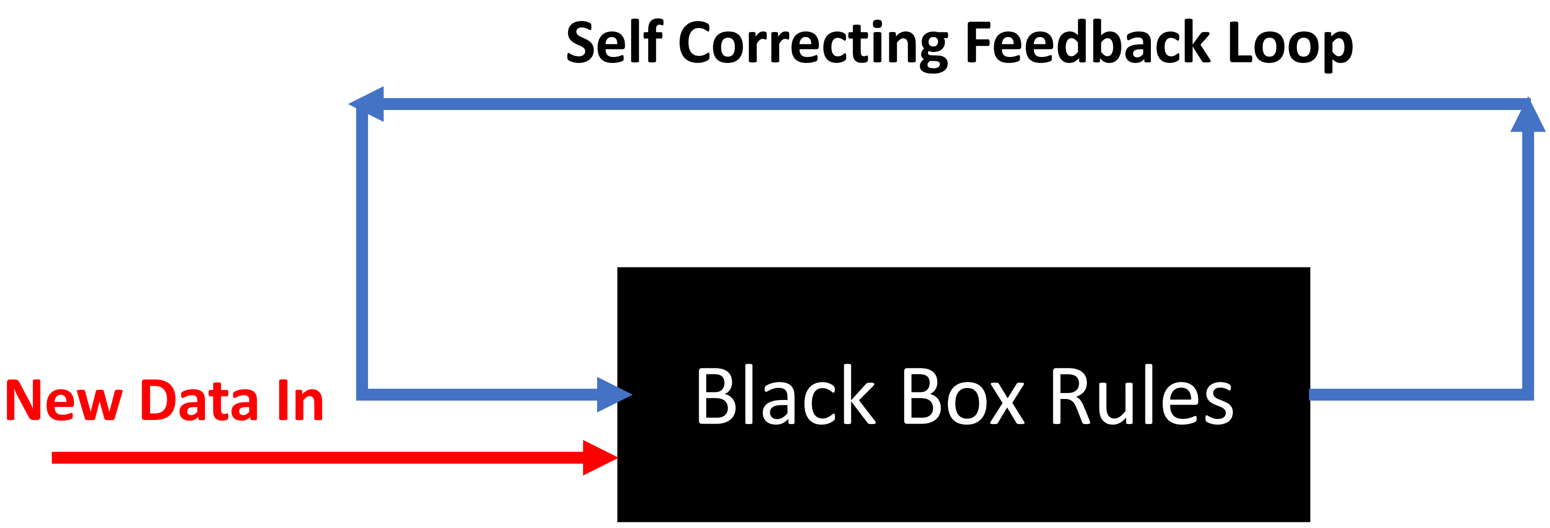
Triage Performance in Emergency Medicine: A Systematic Review

Jeremiah S. Hinson, MD, PhD*; Diego A. Martinez, PhD; Stephanie Cabral, BS; Kevin George, BS; Madeleine Whalen, MSN, MPH; Bhakti Hansoti, MBChB, PhD; Scott Levin, PhD, MS

*Corresponding Author. E-mail: hinson@jhmi.edu, Twitter: @Hinson_EM.

Severity of illness uncertain

Machine Learning Application in the ED



E-Triage Algorithm

Outcomes predicted

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

Machine Learning Algorithm

estimate risk → translate to recommendation

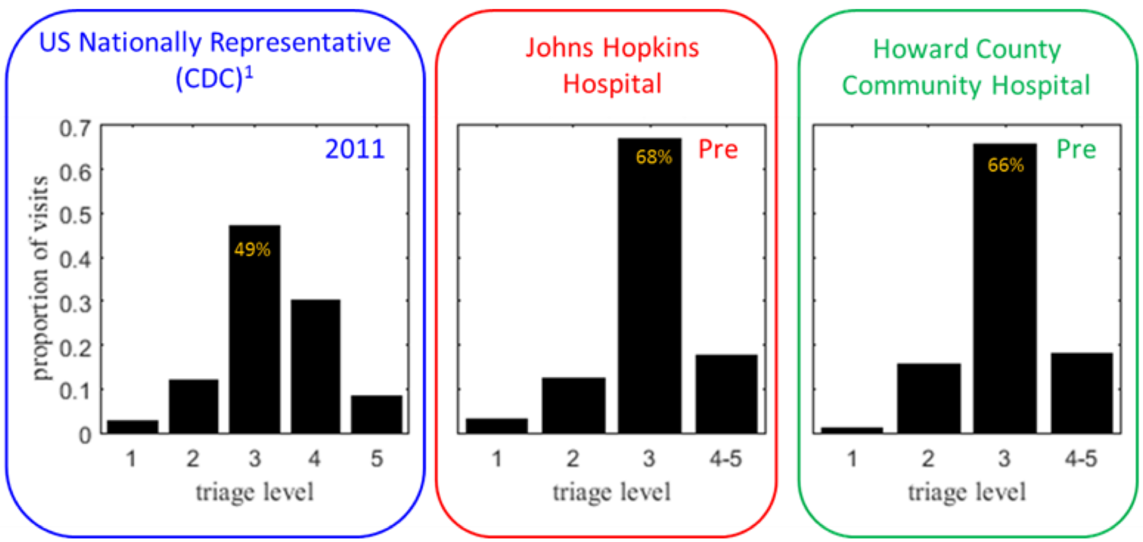
Predictor variables

- Chief complaint
- Vital signs
- Demographics: age, gender
- Arrival mode: ambulance / walk-in
- Medical/surgical history
- Pain scale*
- Immunocompromised*

Artwork by: hopkinsmedicine.org/insight

Rationale

Emergency Severity Index



E-Triage

THE PRACTICE OF EMERGENCY MEDICINE/ORIGINAL RESEARCH

Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index

Scott Levin, PhD*; Matthew Toerper, BS; Eric Hamrock, MBA; Jeremiah S. Hinson, MD, PhD; Sean Barnes, PhD; Heather Gardner, RN; Andrea Dugas, MD, PhD; Bob Linton, MD; Tom Kirsch, MD, MPH; Gabor Kelen, MD

*Corresponding Author. E-mail: slevin33@jhmi.edu.

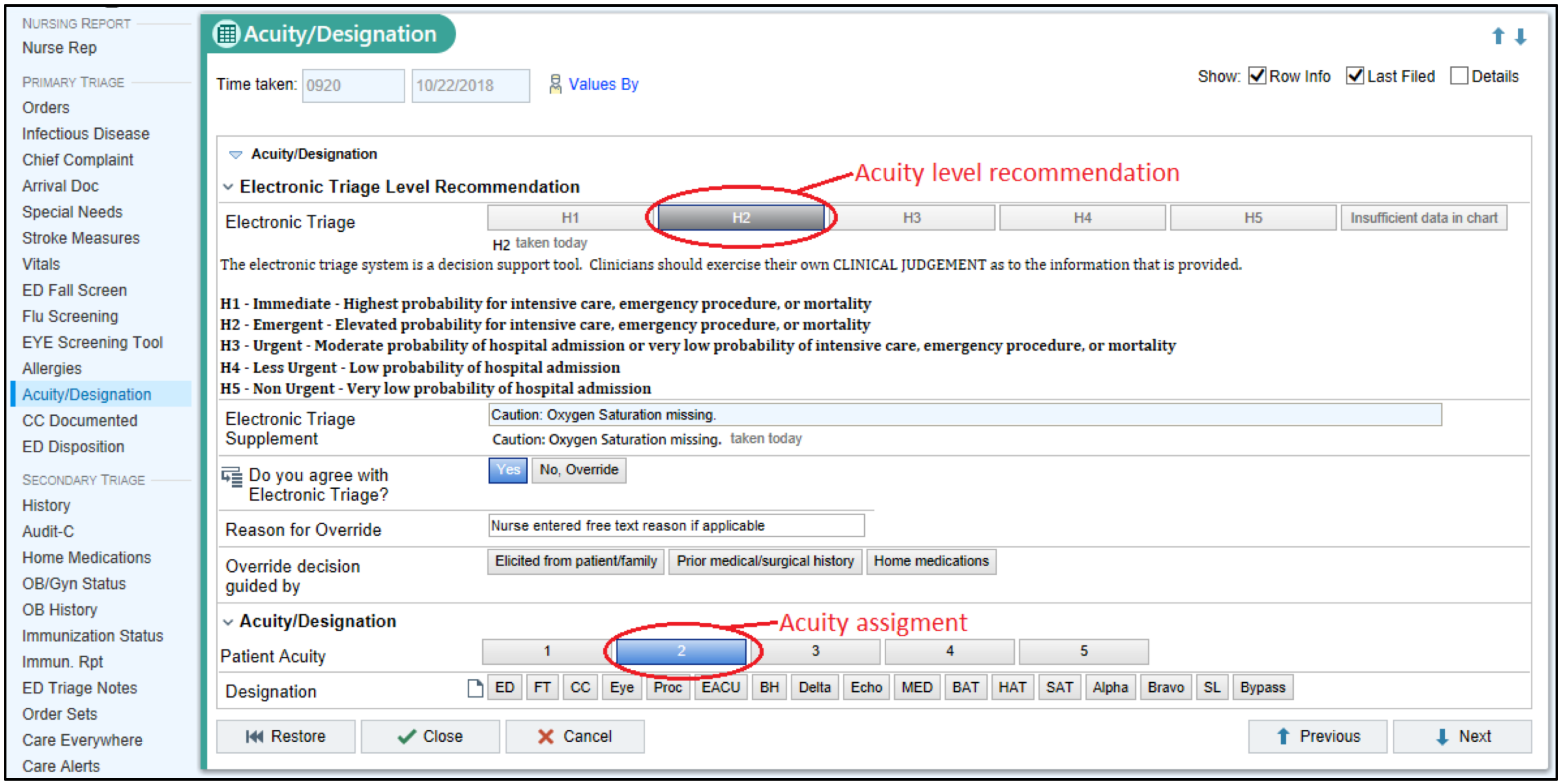
▼ Level 3's: Mitigates Three…iage

Separates high-risk from low-risk Level 3's

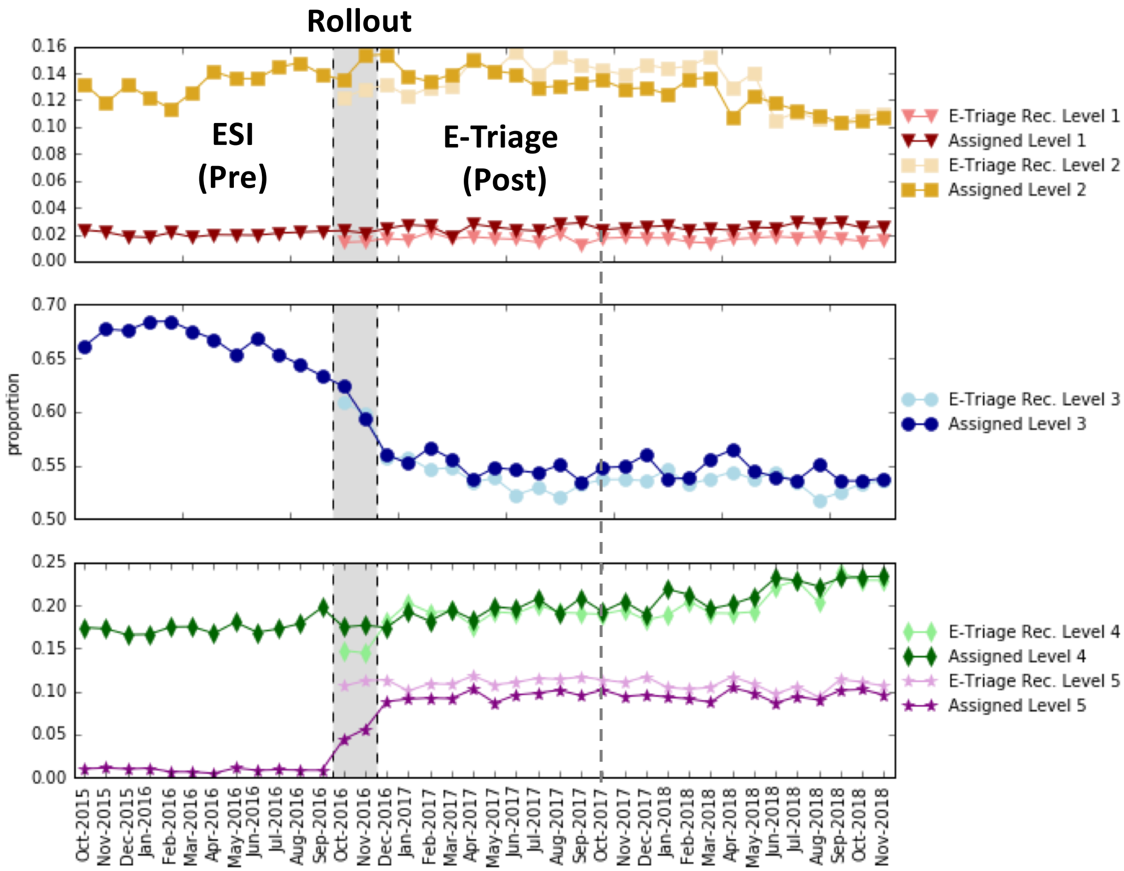
Uses large-scale data from ED

Built for your ED's population, resources, and objectives

E-Triage Interface



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		Level 1-2: High Acuity	
	Nurse (pre)	Nurse + E-Triage (post)	Nurse (pre)	Nurse + E-Triage (post)
Cohort Size, No. (%)	1206 (2.0)	1483 (2.5)	9167 (15.2)	9716 (16.3)
Daily Volume, median (IQR)	3 (2-5)	4 (3-5)	25 (21-30)	27 (23-30)
Predicted Outcomes % (95% CI)				
Critical Care Outcome	16.5 (14.4-18.6)	▲20.3 (18.2-22.3)	8.5 (8.0-9.1)	▲9.6 (9.0-10.2)
In-Hospital Mortality	2.7 (1.8-3.7)	▲5.7 (4.5-6.9)	1.6 (1.3-1.8)	▲2.3 (2.0-2.6)
Intensive Care Unit Admission	15.9 (13.9-18.0)	▲18.3 (16.3-20.2)	7.7 (7.2-8.3)	▲8.3 (7.8-8.9)
Emergency Surgery	4.0 (2.9-5.1)	▲9.8 (8.3-11.3)	2.9 (2.6-3.3)	▲5.0 (4.5-5.4)
Hospitalization	55.8 (53.0-58.6)	▲59.3 (56.8-61.8)	52.7 (51.7-53.7)	▲56.0 (55.0-56.9)
Secondary Outcomes % (95% CI)				
Elevated Troponin	6.5 (5.1-7.9)	▲10.5 (8.9-12.0)	7.0 (6.4-7.5)	▲9.0 (8.4-9.5)
Elevated Lactate	16.9 (14.8-19.0)	▲23.7 (21.6-25.9)	11.4 (10.7-12.1)	▲13.8 (13.1-14.5)
Timeliness in min, Mean (Median, IQR)				
Arrival to Provider	16.6 (15.0,8.0-24.0)	15.5 (14.0,8.0-22.0)	41.0 (27.0,16.0-48.0)	37.7 (25.0,15.0-43.0)
Arival to ED Departure: ICU	337.5 (255.0,163.0-372.0)	▼289.7 (211.0,132.0-347.0)	443.0 (367.0,228.0-553.0)	▼425.4 (332.0,203.0-535.0)
Arrival to ED Departure: Emergency Surgery	264.3 (216.0,77.0-359.0)	▼225.7 (125.0,58.0-307.0)	556.9 (367.0,189.0-648.0)	▼415.0 (297.0,137.0-569.0)
Arrival to Admit Decision	211.0 (146.0,86.0-237.0)	▼166.4 (110.0,58.0-195.0)	287.5 (210.0,132.0-335.0)	▼247.9 (186.0,112.0-295.0)
Boarding Time for Admitted	357.0 (217.0,100.0-501.0)	▼298.1 (172.0,75.0-366.0)	450.6 (325.0,158.0-603.0)	448.0 (304.0,141.0-605.0)

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	
	Nurse (pre)	Nurse + E-Triage (post)
Cohort Size, No. (%)	60112	59788
Daily Volume, median (IQR)	164 (152-177)	163 (152-175)
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)	1.8 (1.7-1.9)
Emergency Surgery, % (95% CI)	1.3 (1.2-1.4)	▲1.9 (1.8-2.0)
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)
72-Hour Return Visits for Discharged	4.8 (4.7-5.0)	4.9 (4.8-5.1)
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)
Arival 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)

No changes in volume pre/post

Increased illness severity across the total population over time

10 min ▼ in average wait time

Improved speed for critically ill patients

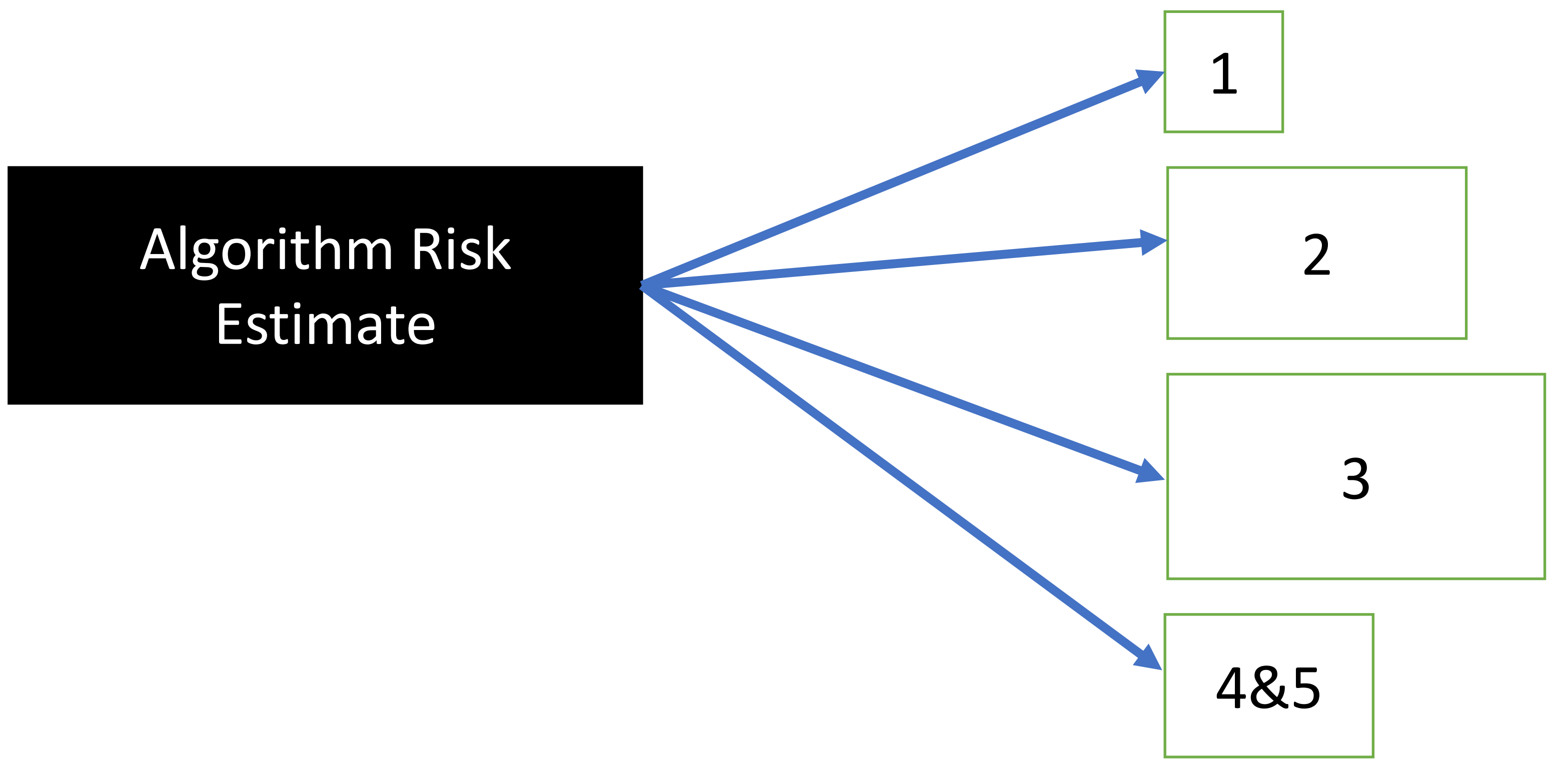
- 27 min ▼ from door to ICU
- 88 min ▼ from door to ED departure for those having emergency surgery

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

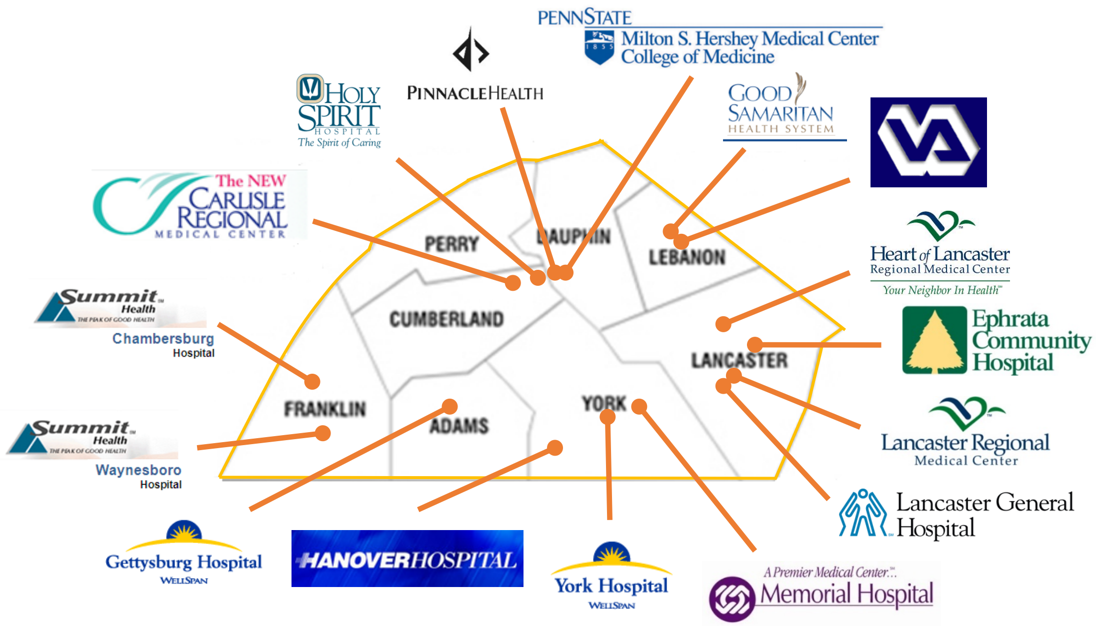
Infectious Diseases

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



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.

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

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”.

SCTF

Semper Vigilans

Kay Carmen, Exec. Comm. Chair

South Central Pennsylvania
Counterterrorism Task Force

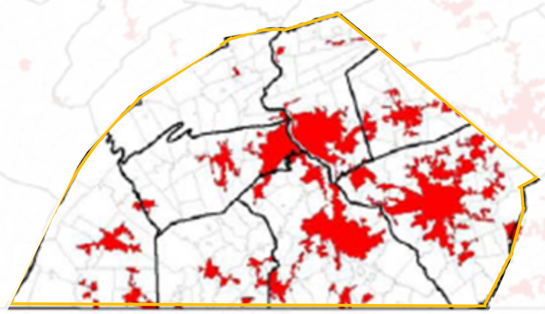
- 8 County EMA’s
- Regional decon. teams
- 5 Hazmat teams

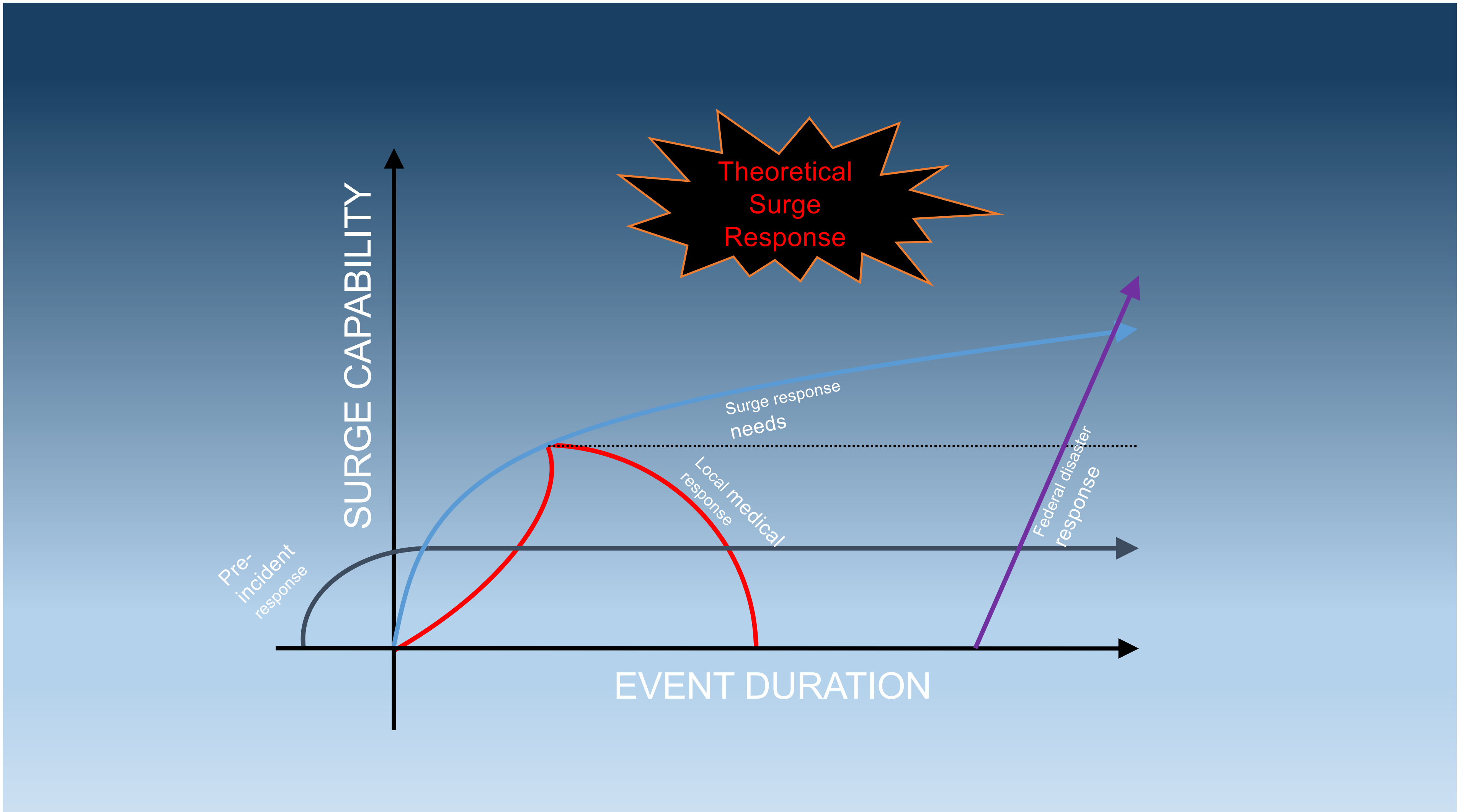
Hospital Beds	**3,192**
ICU Beds	**393**
Ped/Neonate Beds	**254**
Hosp. occupancy	**~75%**
EMS Providers	**4,748**
ED visits annual	**621,000**

Emergency Health Services Federation

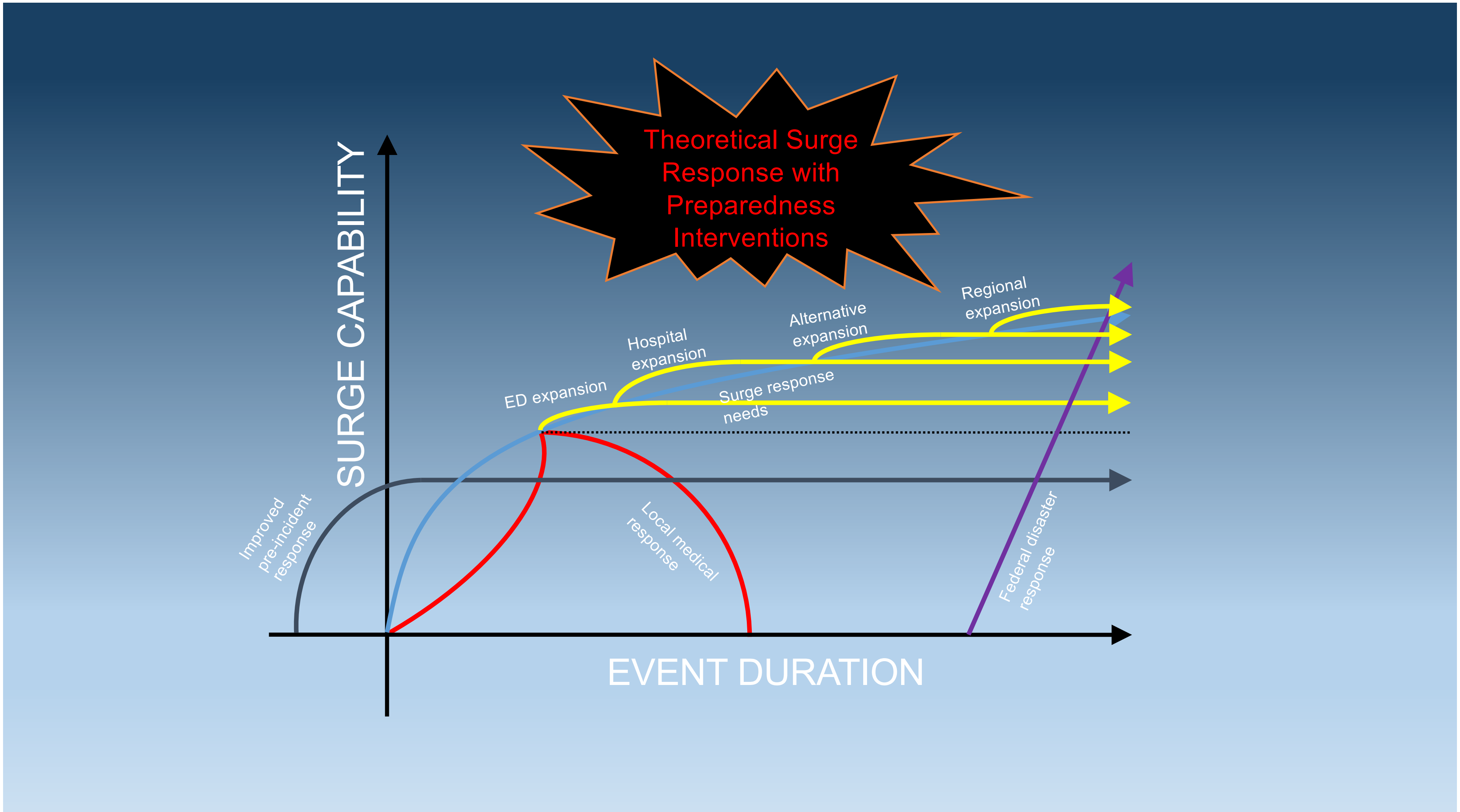
Steve Lyle, Exec. Director

- 137 EMS agencies
- 172,179 transports (’06)
- 911 dispatch





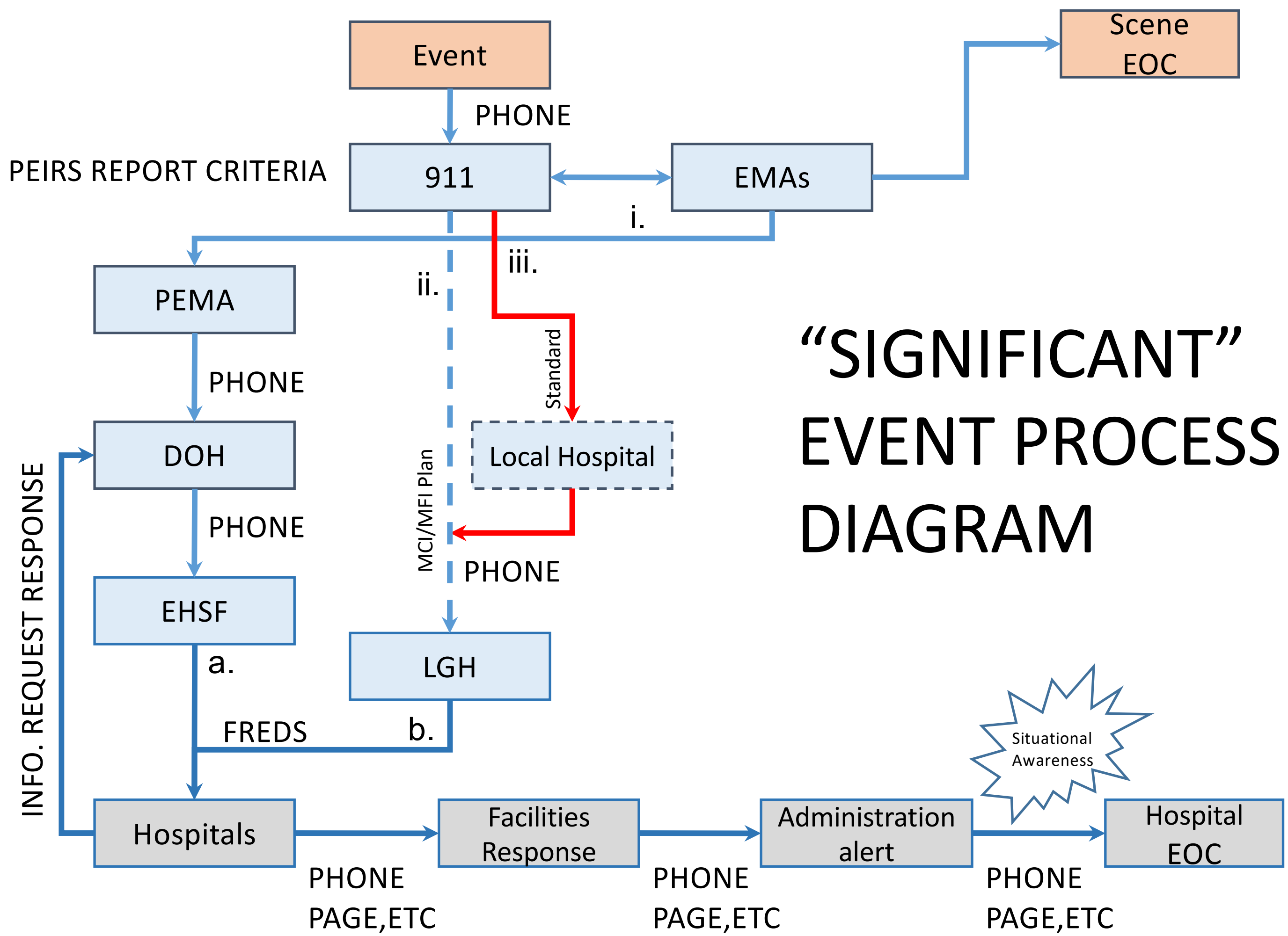
Theoretical Surge Response
SURGE CAPABILITY
EVENT DURATION
Surge response needs
Local medical response
Federal disaster response
Pre-incident response


Theoretical Surge Response with Preparedness Interventions
SURGE CAPABILITY
EVENT DURATION
Improved pre-incident response
ED expansion
Hospital expansion
Alternative expansion
Regional expansion
Surge response needs
Local medical response
Federal disaster response

Increasing Emergency Care capacity

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

*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).



Event
PHONE
Scene EOC
PEIRS REPORT CRITERIA
911
EMAs
i.
ii.
iii.
PEMA
PHONE
Standard
"SIGNIFICANT" EVENT PROCESS DIAGRAM
DOH
Local Hospital
MCI/MFI Plan
PHONE
INFO. REQUEST RESPONSE
EHSF
PHONE
a.
LGH
FREDS
b.
Situational Awareness
Hospitals
Facilities Response
Administration alert
Hospital EOC
PHONE PAGE,ETC
PHONE PAGE,ETC
PHONE PAGE,ETC

6/11/08 Communication Exercise Results