USING PREDICTION TO IMPROVE PATIENT FLOW IN A HEALTH CARE DELIVERY CHAIN

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6/26-28/2011

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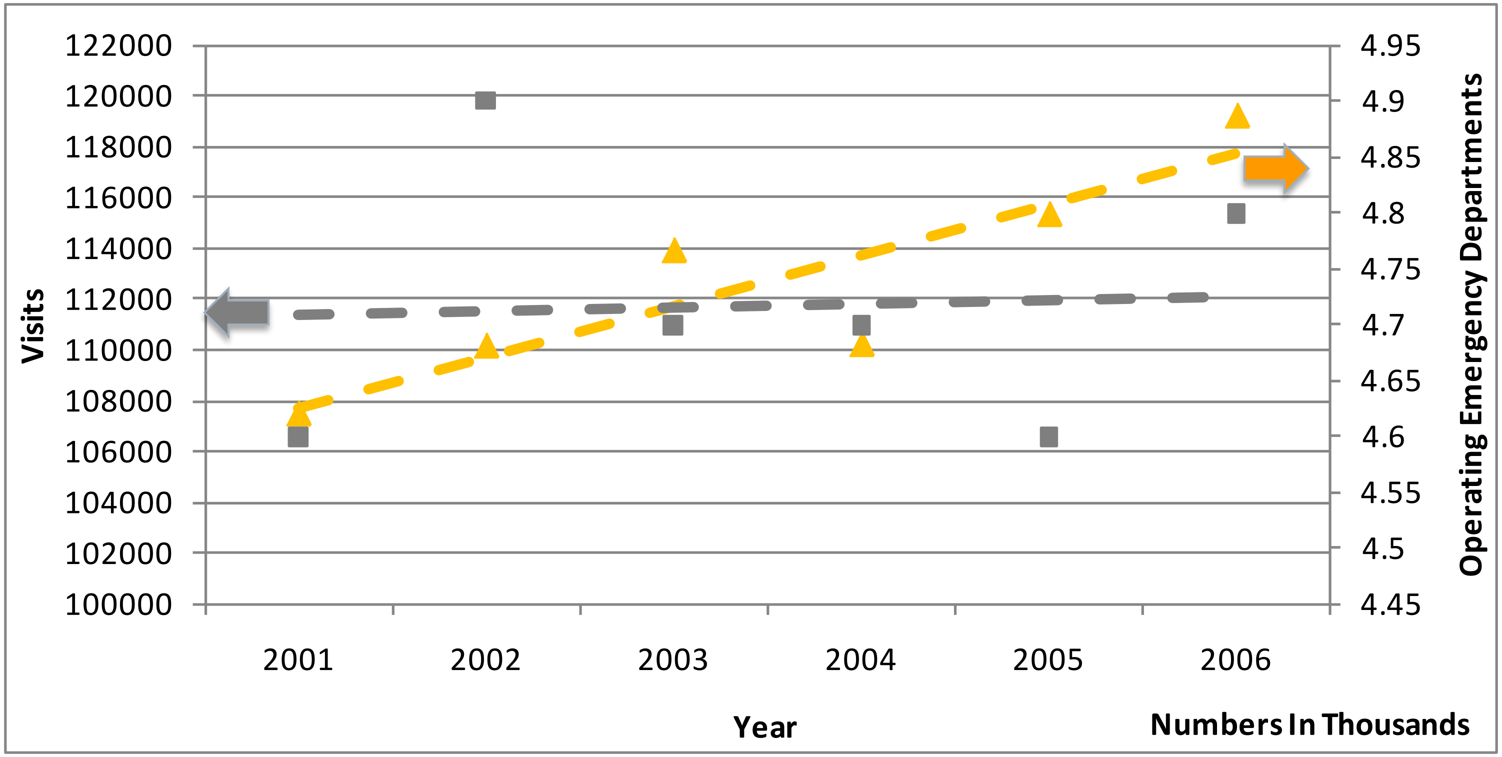
Outline

- Statement of the problem
  - Context
  - Motivation
- Expert opinion prediction experiment
- Statistical prediction development
- Moving forward

The Emergency Department Problem

- **Emergency Department are the "Safety Net" of our Health Care System [Fields 1999]**
  - Open 24/7, accessible, conspicuous in the community
  - "The Emergency Medical Treatment and Active Labor Act (EMTALA) mandates …who presents to a hospital ED must receive a medical screening examination …be offered treatment to stabilize that condition…" [Asplin 2006]

- **Emergency Department Bed / Visit Ratio decreasing** **[Nawar 2007, GAO 2009].**



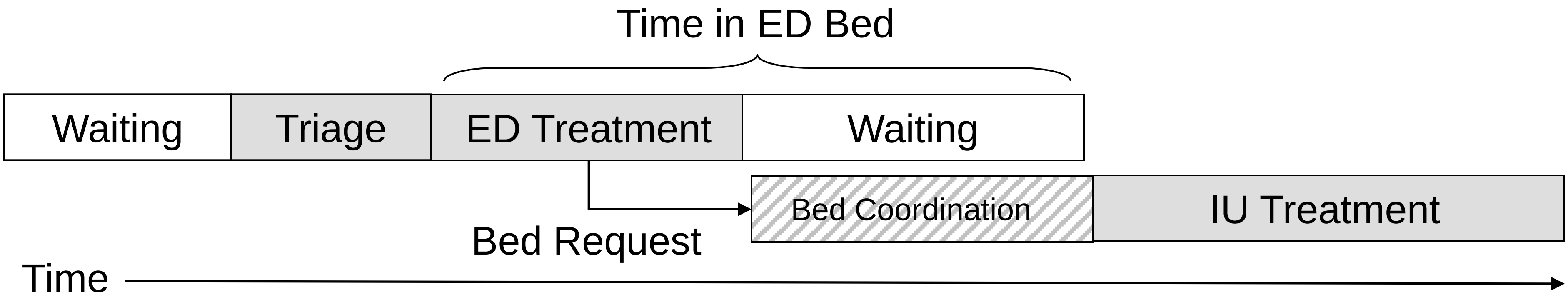
Solutions?

- Technology
  - New treatment technologies
  - Electronic medical records
  - Nurses with PDAs
  - More accurate tests

- Management
  - Lean/Six Sigma
  - Reimbursement schemes
  - Consolidation of resources

- Policy
  - Insurance policy ("Obama" Care)
  - Hospital regulation (Collective Bargaining)
  - Equality vs. equity issues (Taxing "Cadillac" Care)

Quality is connected to flow

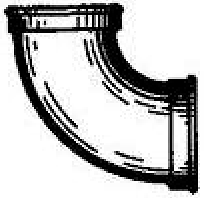


- **The Problem:**
  - Admitted patients occupy emergency resources, delaying access to new patients

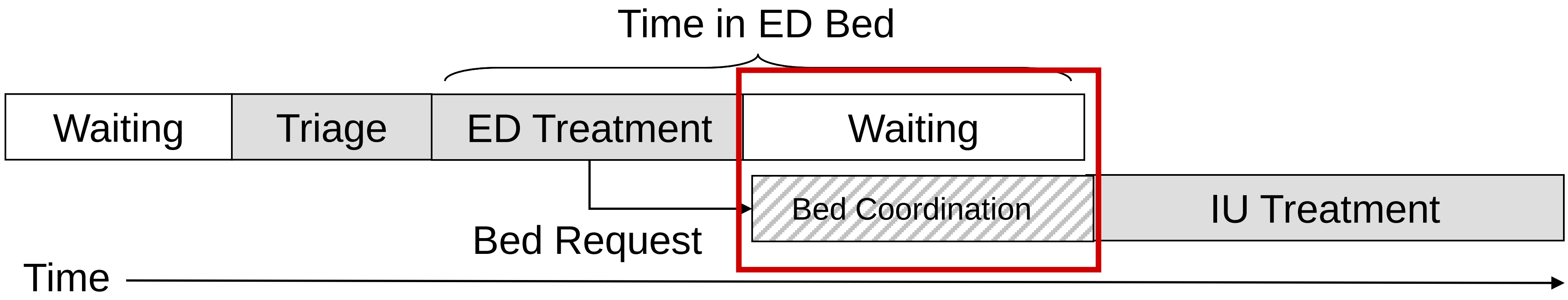
- **Quality is based on speed to and through treatment:**
  [Graff 2002, Bernstein 2009, Horwitz 2010]

  - Ambulance Diversion [Asplin 2003]
  - Patients who Leave without Being Seen [Baker 1991, Weiss 2005, Asaro 2007]
  - Exposure to Safety Risks [Trzeciak 2003]
  - Diagnosis and Admission of Critically Ill [Cowan 2005, Clark 2007]
  - Time to Antibiotics for Patients with Pneumonia [Fee 2007, Pines 2007]
  - Time to ECG and Balloon Inflation [Braunwald 2002, Antman 2004, Diercks 2007]
  - Time to Pain Assessment and Analgesic [Hwang 2008, Pines 2008]

Faucet Model



Quality is connected to flow

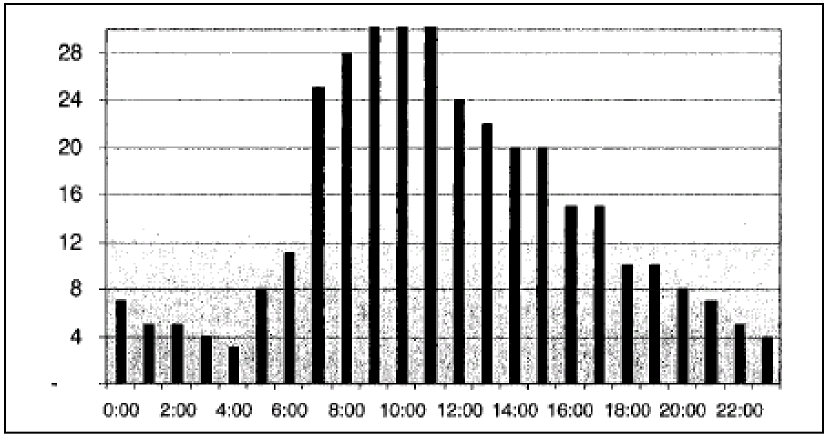


- **Inpatient Unit Bed Availability is a Severe Bottleneck**
  - "The inability to transfer emergency patients to inpatient beds was the condition reported most often as contributing to going on diversion…" [US GAO 2003]
  - "Inability to transfer emergency patients to inpatient beds as the single most important factor contributing to crowding." [Olshaker 2006]

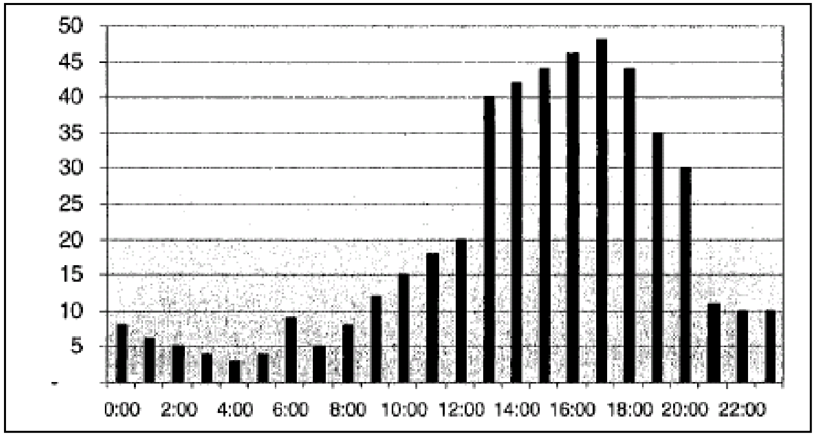
Relevant output focused solutions

- **Direct admission based on emergency physician decision rather than consult** [Howell 2004]
- **Cancelling elective surgeries during busy days** [ACEP 2008]
- **Regular updates of emergency department performance on inpatient side** [Howell 2008]
- **Hallway admissions** [ACEP 2008, Viccellio 2009]
- **Bed management programs with Hospital Bed Coordinators** [Moskop 2009]
- **Discharge by noon** [Rubino 2007, ACEP 2008]

Typical Hospital Admission Demand



Typical Hospital Discharge Rate

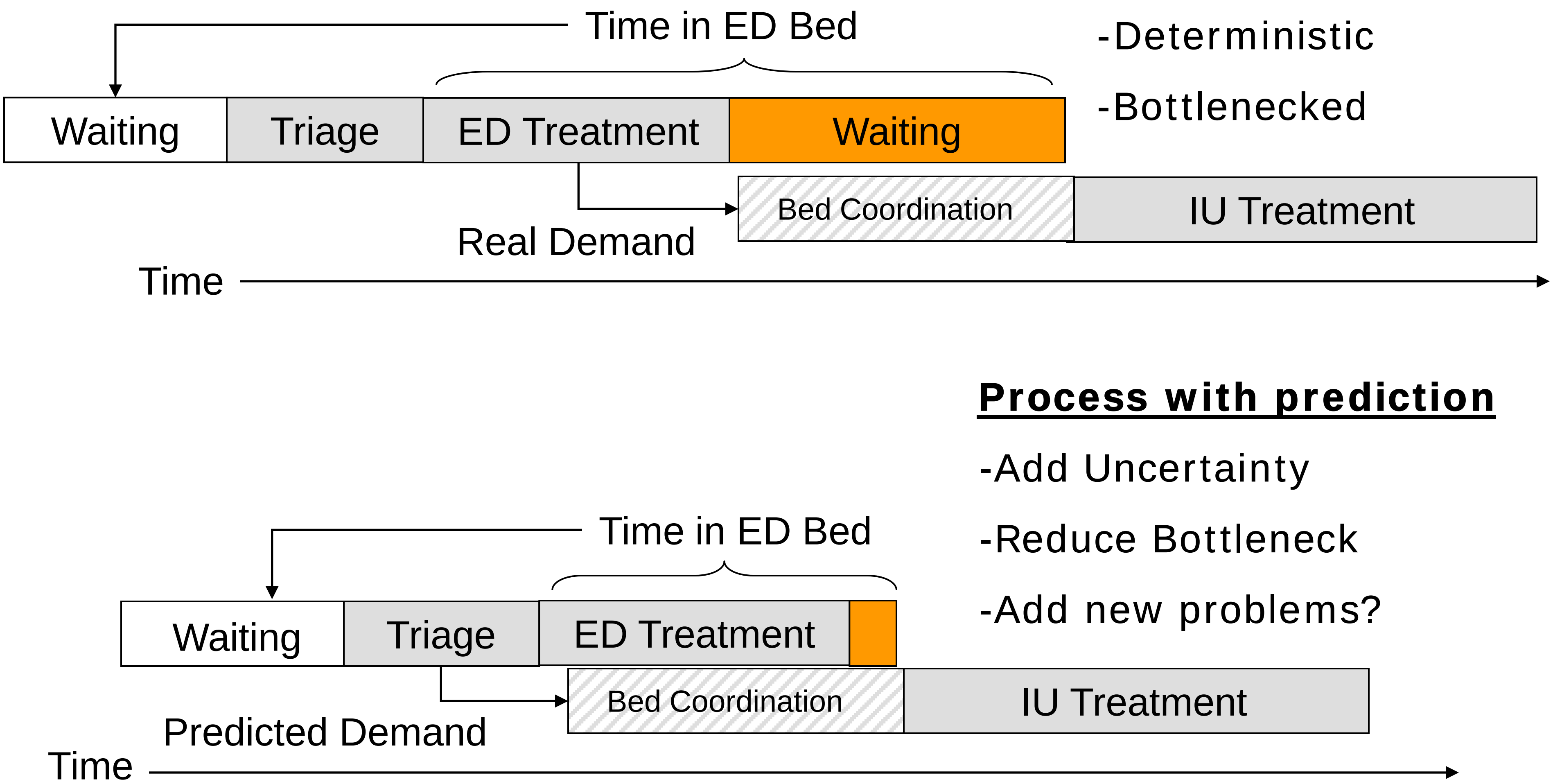


[Williams 2006]

What is missing?

- **"If one can predict earlier in the course of an evaluation whether the patient will likely be admitted, then one may improve timeliness of inpatient placement or discharge planning." [Yen 2007]**
- Echoes sentiments of "Crossing the Quality Chasm" [IOM 2001] and emphasized by GAO report [US GAO 2009]
- Concept has been used in other fields (production management, inventory management, etc.)

Prediction based approach



Current Process

-Deterministic

-Bottlenecked

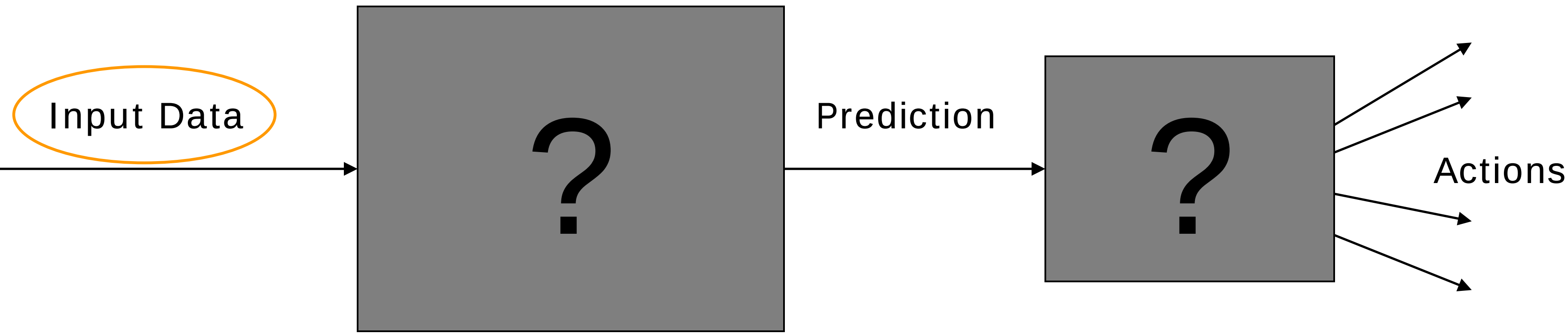
Process with prediction

-Add Uncertainty

-Reduce Bottleneck

-Add new problems?

Uncertainty and Decision Models



- Other studies claim that if we can make predictions we can drive actions.
- The goal of this study is to explore whether those predictions are even possible and what they would look like

Experiment Description

VHA West Roxbury -
Emergency Department

Place patient label here

Patient Flow Prediction Quality Improvement Project Form

Prediction 1. Please predict total time between when the patient is triaged and the decision to admit or discharge is made: (Please circle or check one time block)

- ❑ 0-29min ❑ 30-59 min ❑ 60-89min
- ❑ 90-119min ❑ 120-239min ❑ > 240min

Prediction 2. How likely is it that the patient will need admission to the hospital?

- ❑ Definitely Yes (95-100%)
- ❑ Highly Likely (75-94%)
- ❑ Likely (50-74%)
- ❑ Unlikely (25-49%)
- ❑ Highly Unlikely (5-24%)
- ❑ Definitely No (0-4%)

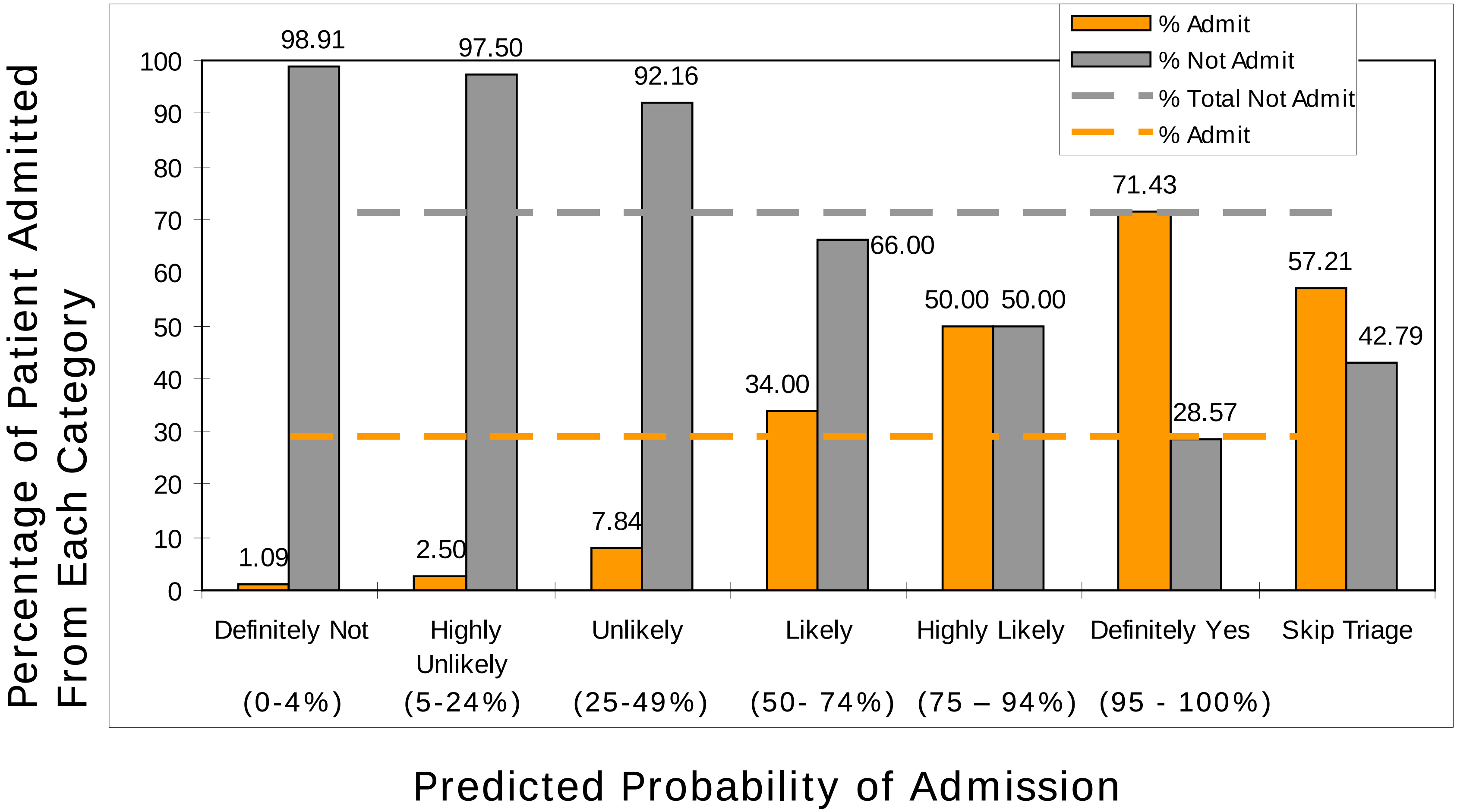
- Nurses given form with triage materials for each patient.
- Attach patient label
- Format designed for understandability and ease of selection.

MIT ESD Massachusetts Institute of Technology Engineering Systems Division

LAI MIT LEAN ADVANCEMENT INITIATIVE

VERC New England

Results of Admit Prediction



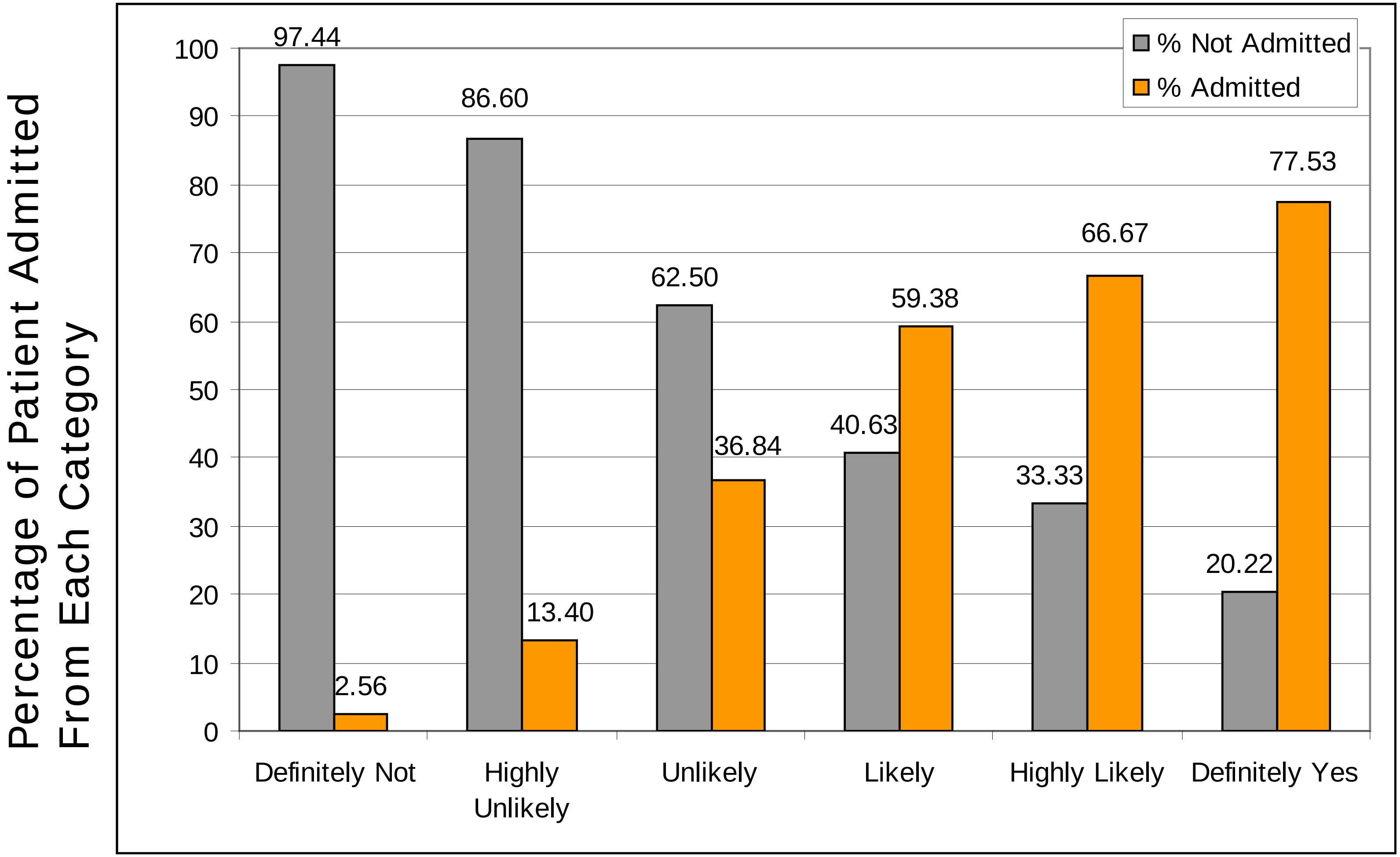
Naïve Bayesian Approach – VHA Boston West Roxbury

Naïve Bayes Approach

- Total 32% chance of admit, but can Bayes Theorem do better?
  - Try 3 Patient factors: F1-Urgent/Non, F2-Male/Female, F3-Over/Under 65
  - $$P[Admit|Factors] = \frac{P[F1|Admit]*P[F2|Admit]*P[F3|Admit]*P[Admit]}{P[Factors]}$$
  - Urgent over 65 year old male has a 61% chance of admit
  - Non-Urgent under 65 year old female has a 1.3% chance of admit

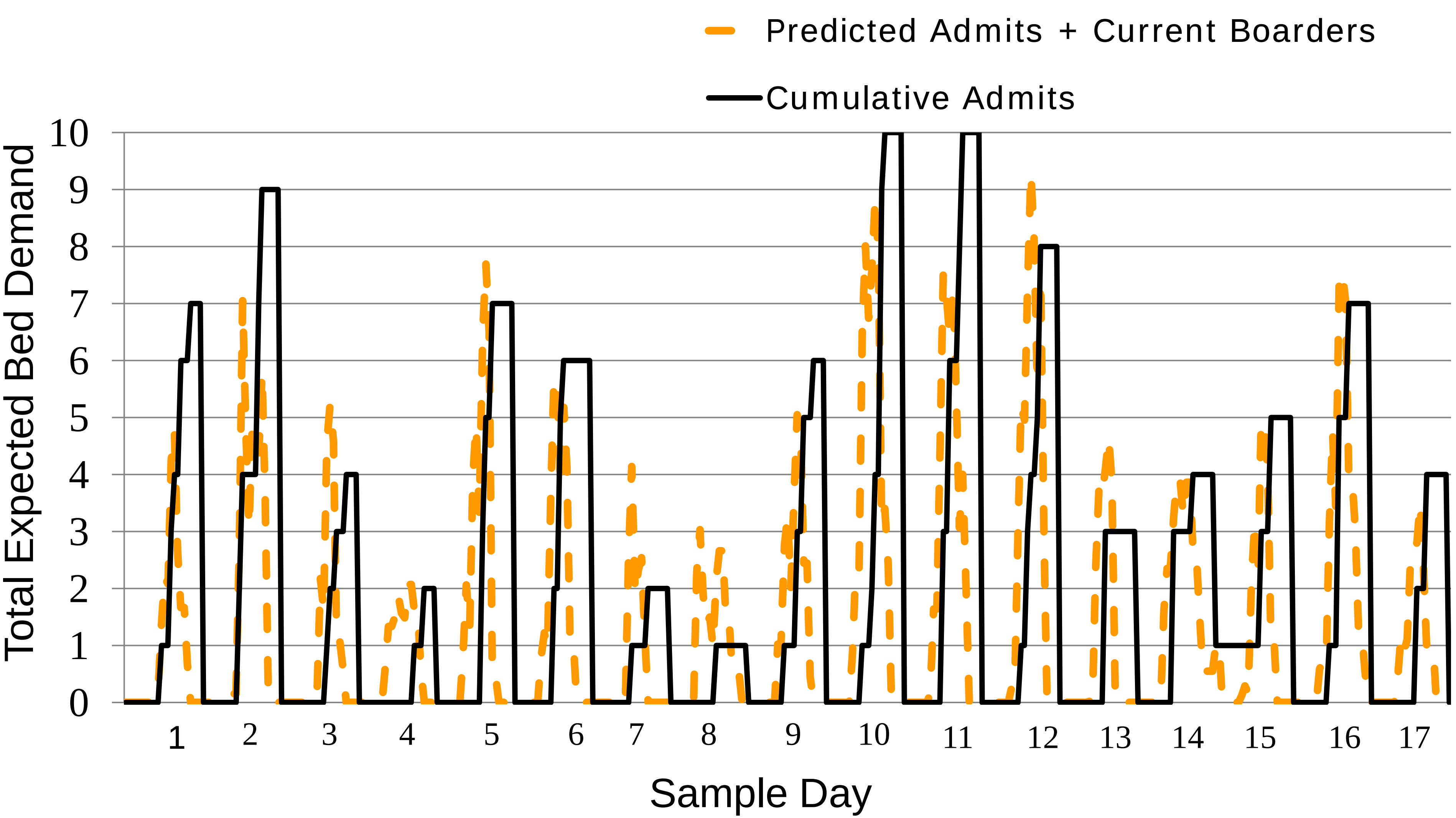
Best Fit Prediction Scheme – VA Bayes

- Complaint + Arrival Mode + Age



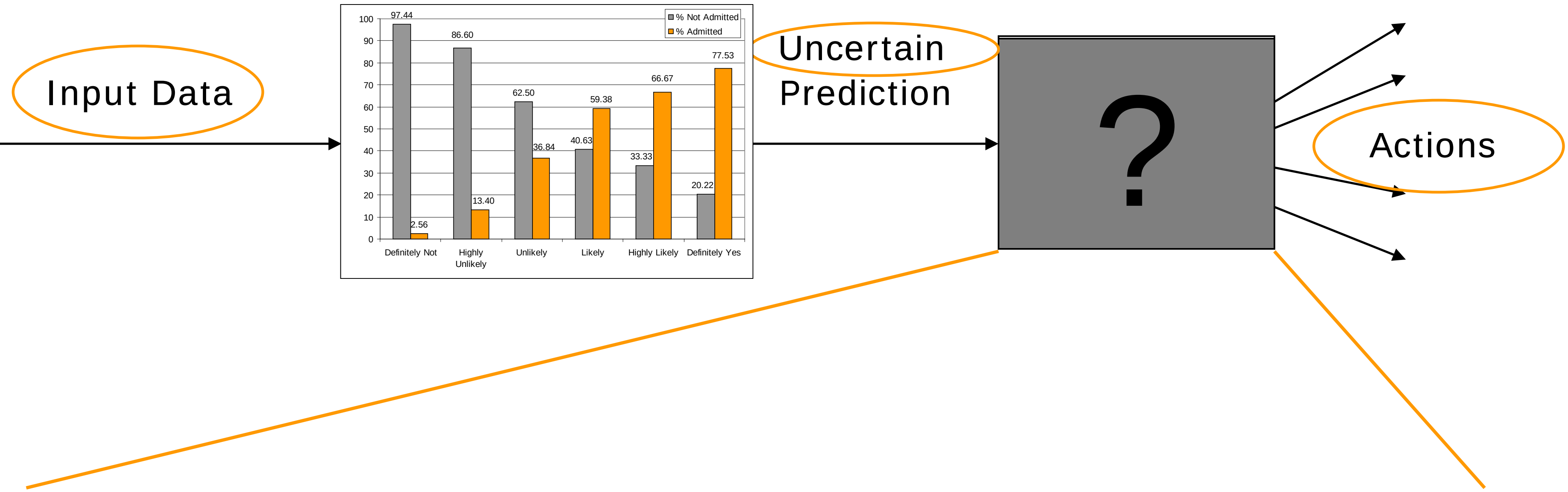
Predicted Probability of Admission

Hours of Warning



Moving Forward

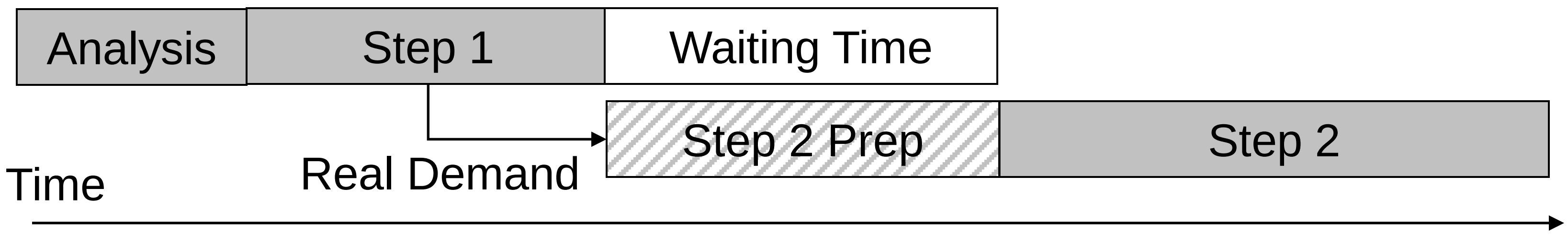
Uncertainty and Decision Models



- **Models to optimize magnitude and mix of stakeholder actions given uncertain information**
  - Resources reallocation a algorithm
  - Protocols may be needed to increase consistency of individual decisions
  - Algorithms or heuristics to suggest the highest impact elective cancelations
  - Model for defining “need to work faster”
- **Can develop multiple Predictive model/Control method combinations**

Context for methodological contribution

- **Broad Problem: Improving flow (rate, variability, wait times) between two steps in a Health Delivery Chain.**

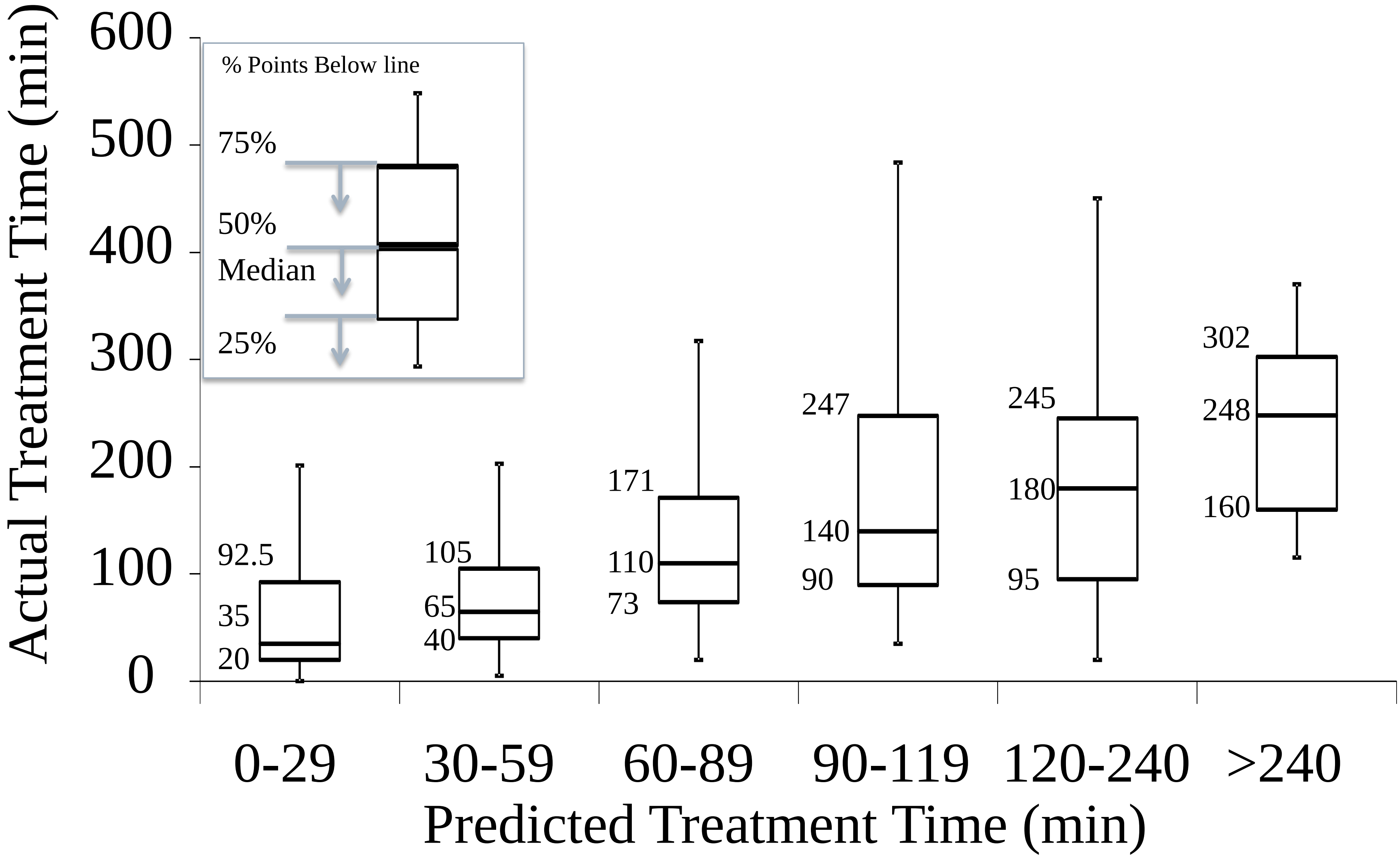


- **Occurs in multiple scenarios:**

In Department Level	Doctor Exam	Testing (Ex. CT Scan, XRay, Blood Test, etc.)
Cross Department Level	Emergency Department	Inpatient Unit
	Inpatient Unit	Long Term Stay
Cross Organizational Level	Generalist	Specialist

Backup

Results Time Prediction



Comparison of Predictors

	Method	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value
VA Test	Expert - Triage	55.66	86.98	48.11	97.45
VA Bayes 1	Naïve Bayes	53.48	91.41	71.94	82.67
VA Bayes 2	Naïve Bayes	94.09	70.11	56.27	96.67
Leegon 2005	Bayesian Network	90	71	56	95
Arslanian-Engoren 2004	Expert - Triage	57	59	68	56
Clesham 2008	Expert - EMS	71.7	77		
Levine 2006	Expert - EMS	62		59	
Walsh 2004	Neural Netowork	78	82	68	89
Sadeghi 2006	Expert - Triage	64	48	52	61
	Bayesian Network	90	25	51	75

Conclusion

- **Motivation –** Emergency department flow/quality
- **Method –** Prediction with expert opinion and statistical methods
- **Expected Merit –** Show that predictions can be made and the data is in a useable format
- **Expected Impact –** Method for approaching flow improvement in a health care delivery chain
- **Academic Contribution –** Addition to methodologies for controlling service systems

Does the Input Side Matter?

- "In addition, data now exist to suggest that low-acuity patients with nonurgent conditions contribute little, if at all, to the problems of crowding and ambulance diversion [13]. Nor does lack of insurance seem to be a powerful driver of ED usage: a 2003 report noted that two thirds of the increase in ED visits between 1996 and 1997 and 2000 and 2001 was accounted for by patients with private insurance or Medicare [14]." Bernstein 2006

- "Low-complexity ED patients are associated with a negligible increase in ED length of stay and time to first physician contact for other ED patients. Reducing the number of low-complexity ED patients is unlikely to reduce waiting times for other patients or lessen crowding." [Schull 2007]

Prediction in Health Care

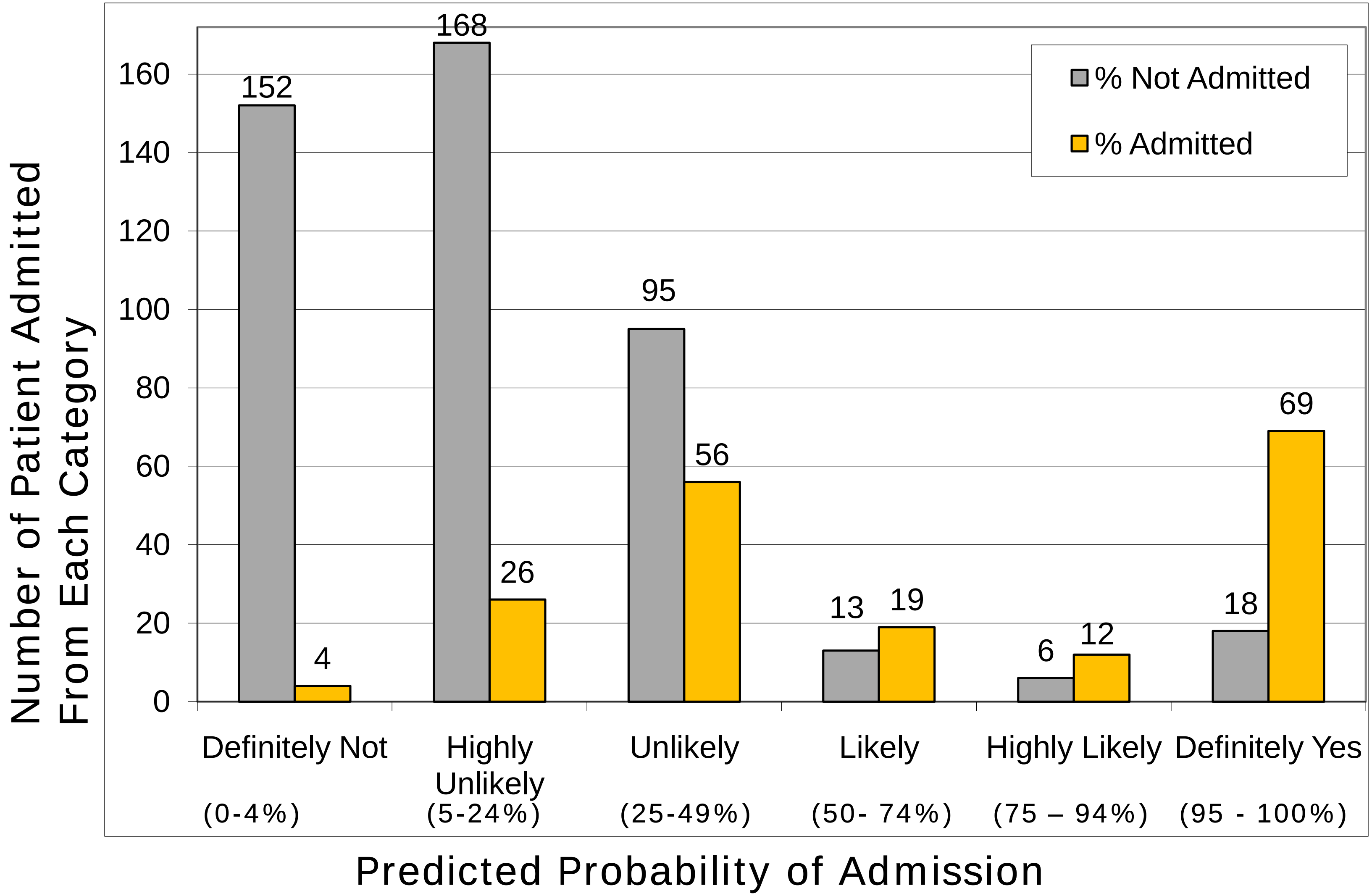
Paper	Prediction and Use	Method
Meehl 1954	Clinical vs. Statistical Prediction – "The clinical-actuarial debate." Predict behavior of mental health patients	Actuarial Prediction – (Bayesian Like Approach)
Robinson 1966	LOS of Surgery Patients for Improved Scheduling	Statistical Classification, Expert Prediction
Gustafson 1968	LOS of Hospital Patients using direct point estimates and probability distribution estimates. Bayesian Model Performed Best. Suggest use for staffing decisions.	Subjective Expert Point Estimate, Multiple Linear Regression, Historical Mean, Expert Personal Probability Estimate, Bayes' Theorem
Gustafson 1971	Diagnosis of Thyroid Disease	Bayesian Predictor
Vandankumar 1980	Discharges and LOS for Occupancy goals	Conditional Probability based on age, source of admission, physician, historical distributions and current LOS.
Long 1989	Looking at symptoms to diagnose heart disease	Probabilistic Causal Network
Glaski 1993	Predicting LOS and Future Treatment requirements of Stroke Patients for resource planning.	Multiple Linear Regression
Hamilton 1994	Diagnosing biopsy specimens given uncertainty	Bayesian Belief Network
Szolovits 1995	General discussion of dealing with uncertainty in heath care decisions	"Idiot Bayes" formulation
Fine 1997	Identify Low Risk Pneumonia Patients	Heuristic Chart (age, history, physical exam, tests)

Roxbury Specifics

- Inpatient Unit
  - Approx 35-50 medicine residents,
  - Evenly distributed 5 floor teams, 2 Cardiology teams, 1 MICU team.
  - 1 Senior resident per floor
  - ~5 nurses per floor
- Emergency Department
  - 12 Beds
  - 7 Emergency Department Physicians + Residents
  - ~10-15 Nurses
  - 2 Physician Assistants
- Administrative
  - Unknown Cleaning Crew Count
  - 1 Bed Coordinator, 2 substitutes

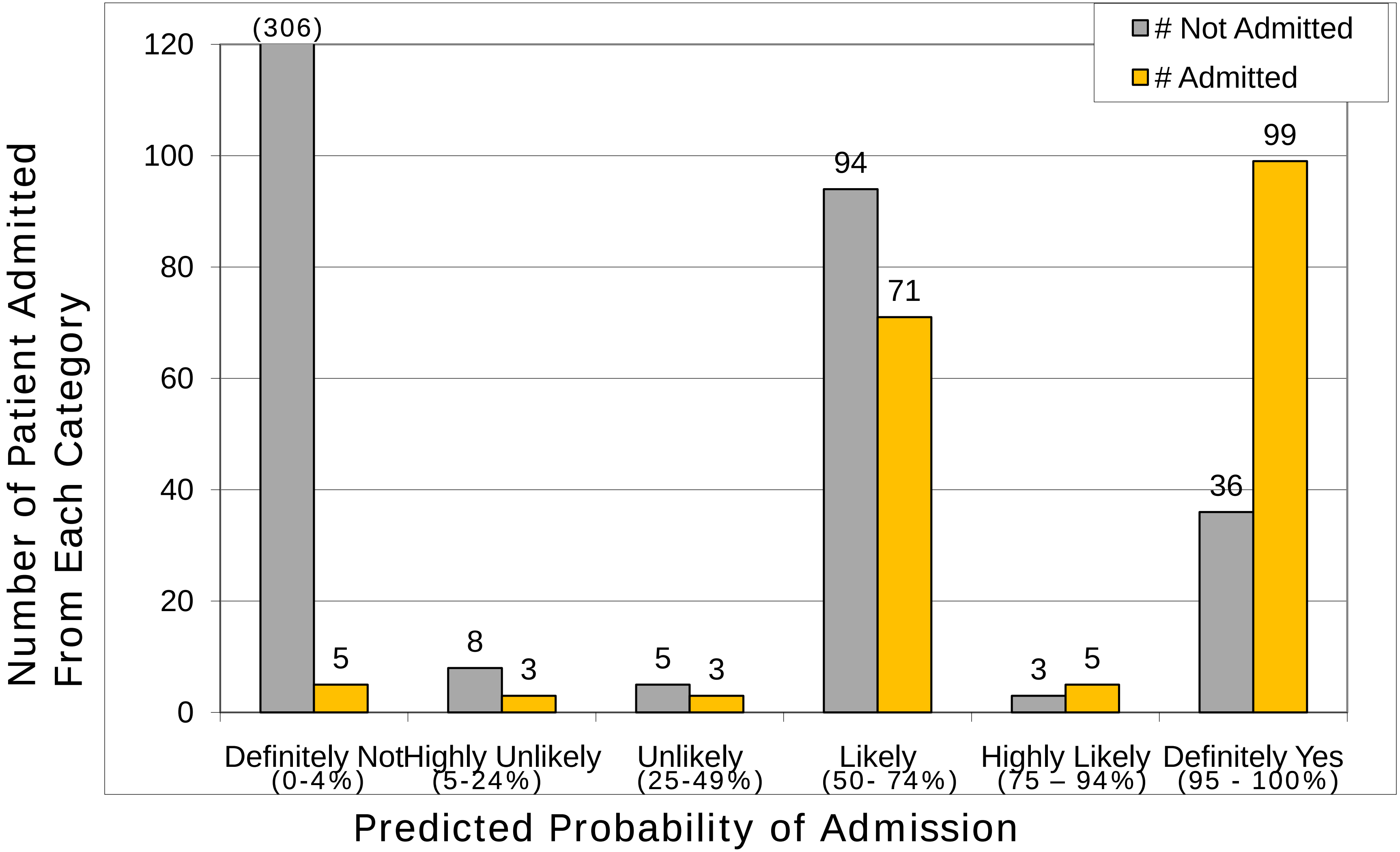
Best Fit Prediction Scheme

- Complaint + Arrival Mode + Age



Best Fit Prediction Scheme

- Urgency + Location + Arrival Mode + Age

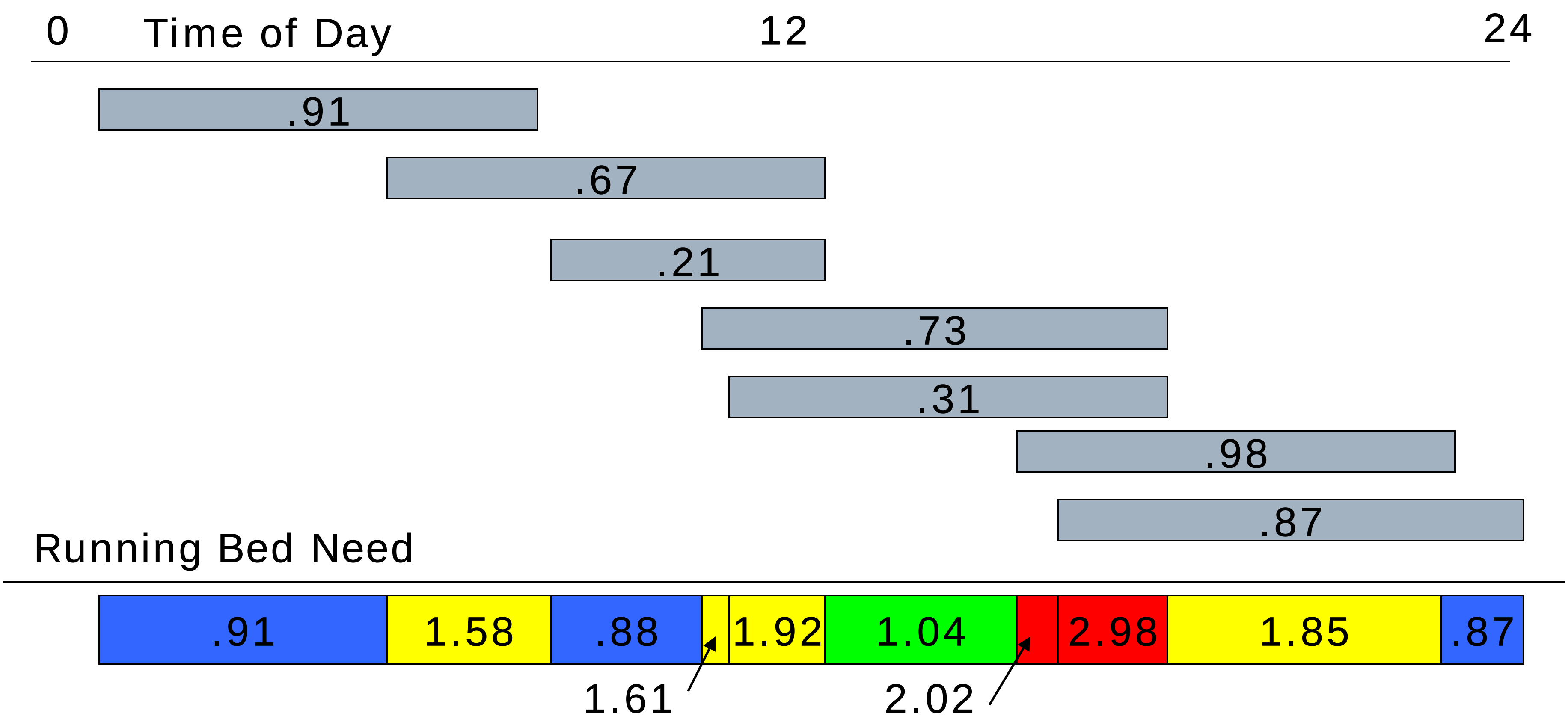


Excel Tool in Triage

		P Factor given admit	P Factor	P Admit
What is the primary compliant	Abdominal Pain	0.064698	0.045574	0.482705
Urgency	Non-Emergent	0.017815	0.401622	0.015082
Mode	Ambulatory	0.404076	0.679466	0.202211
ER or FT	FT	0.011244	0.376342	0.010159
Age	30	0.013352	0.046745	0.097124
Joint Probability				
	Complaint + Urgency + Mode	0.012733		

How will the outputs be used?

- Assume Prediction Results are a distribution and a running bed need score is kept
  - Emergency Department Crowding Index - knowledge of problem simply causes people to work harder [Bernstein 2003, Epstein 2006, Hoot 2009]



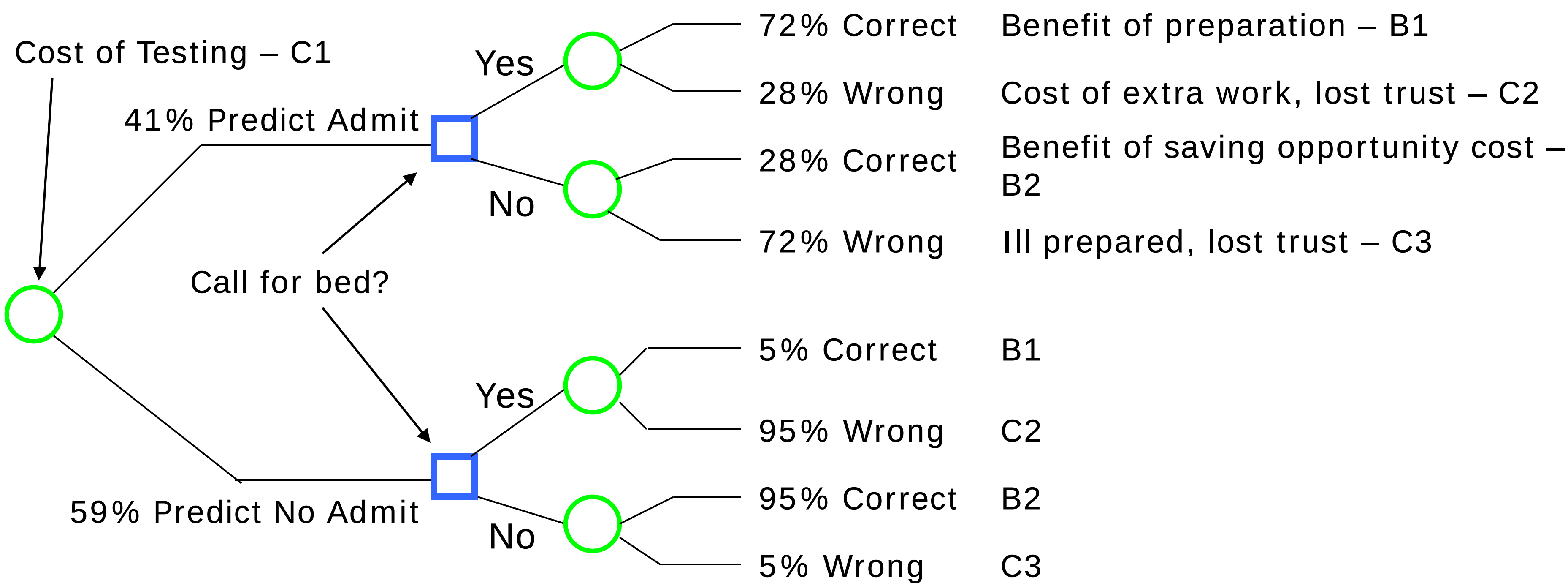
Newsvendor Model

- F(Q) = Probability that demand is less than or equal to Q
- Co = Cost of over reacting
- Cu = Cost of under reacting
- $Co \times F(Q) = Cu \times (1-F(Q))$

- $F(Q) = Cu/(Co + Cu)$

Uncertainty and Decision Models

- System Study: Yes/No admit from triage to bed coordinator.
- Method Selection: Neural Network [Walsh 2004]
- Tool showed 17% Type 1 error and 9% Type 2 error, VA West Roxbury Admits 32% of Emergency Department Patients



Threats to validity

- **Internal Validity**
  - Multiple treatment inference - VA Culture of Improvement
  - Maturation – people must adapt to new methods
  - Experimental mortality - Resident Rotations
  - Diffusion of treatments – Other VA hospitals may hear of effort and try to copy, which could influence the control groups
  - Staff cooperation

- **External Validity**

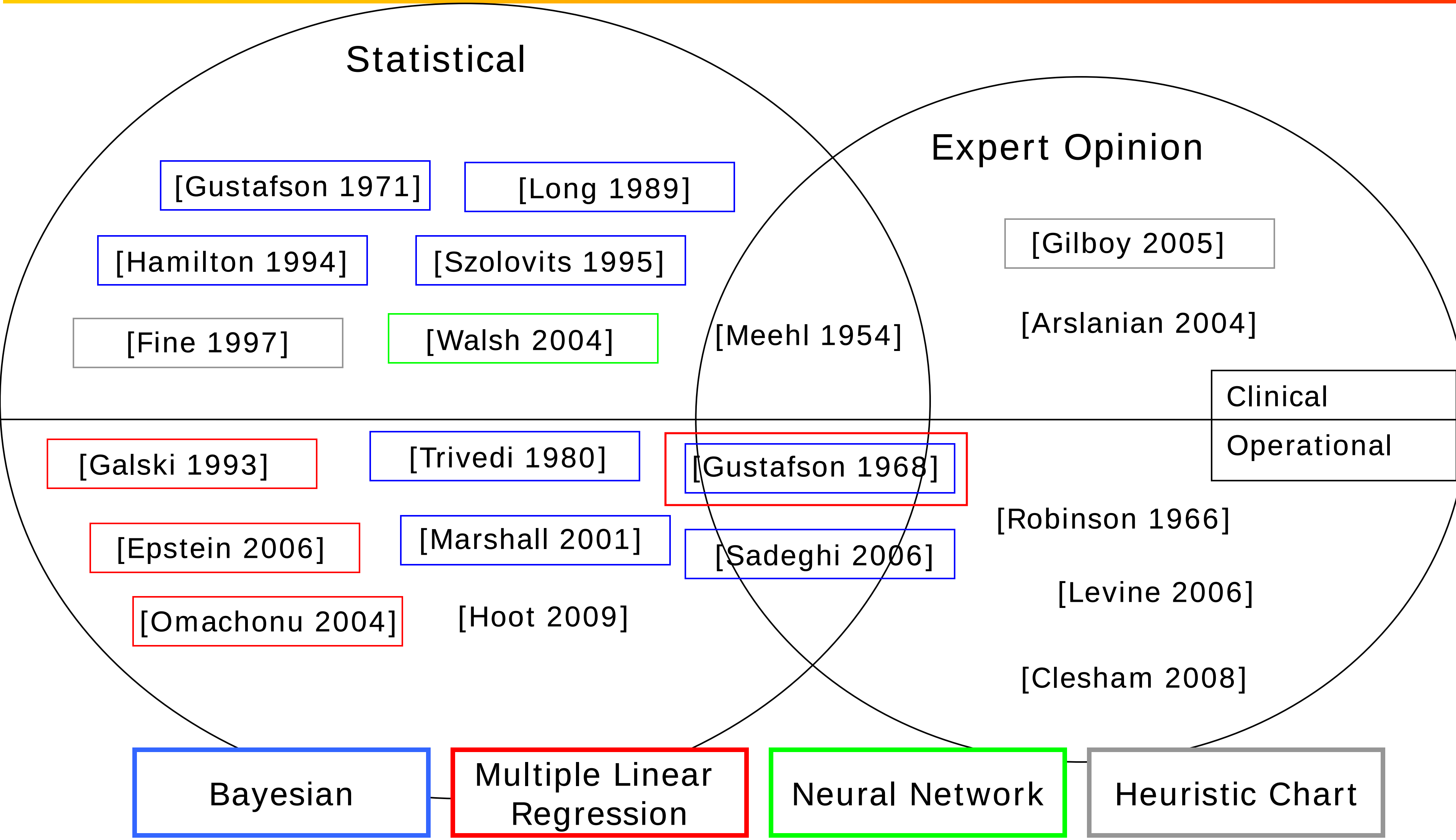
  Reactive effects of Experimental Arrangements – VA:
  - Payment/incentive structure
  - Emergency physician admission decision
  - Use of a bed coordinator
  - Distinct patient population
  - Extensive information technology system

R^2 Top 10 Results Compared to Expert

Run	1	2	Total
ACM	0.926488	0.850683	0.913728
CDU	0.851244	0.831173	0.844403
ACD	0.836273	0.806958	0.838433
ADL	0.862539	0.792481	0.836905
CD	0.709309	0.951622	0.834079
CLU	0.814925	0.826705	0.825613
D	0.80964	0.794007	0.823712
ADLU	0.804364	0.719036	0.81761
LM	0.799189	0.412601	0.815498
ACDL	0.828979	0.758435	0.814307

A – Age
C – Complaint
D – Doctor
L – Location
M – Mode
U - Urgency

Predictive Methods In Health Care



Other Options: Fuzzy Logic? Advanced Bayesian Methods?

Long history of solutions to emergency department flow

Input	Throughput	Output
-Simulation - adding registration staffing [McGuire 1994] -Triage protocols for specific tests [Kirtland 1995] -Doctors at triage discharge patients to a separate acute care unit [Kelen 2001, ACEP 2008] -Insurance policies to increase use of primary care [Richardson 2002] -Geographic diversion coordination [Wilson 2004, Patel 2006, US GAO 2009] -Physician directed ambulance destination control program [Shah 2006] -Reducing "frequent flyer" visits through education [Michelen 2006] -Direct to room when emergency department is not full [Bertoty 2007]	-Queuing theory for optimal staffing [Vassilacopoulos 1985, Green 2006] -Fast Track for low acuity patients [Meislin 1988, Rubino 2007, ACEP 2008] -Assign takt times to parts of the emergency department [McGuire 1994] -Simulation for optimal staffing [Rossetti 1999, Samaha 2003] -Mini-laboratory in the emergency department [Lee-Lewandrowski 2003] -Electronic tracking board [Boger 2003] -Emergency department crowding indexes [Bernstein 2003] -Online analytical processing to improve real time manager decisions [Gordon 2004] -In room registration [Gorelick 2005, ACEP 2008] -Lean process mapping [King 2006, Graban 2008, Dickson 2009] - Layout improvements [Miro 2007]	-Post treatment buffers [McGuire 1994, ACEP 2008] -Queuing models for optimal hospital bed levels [Green 2001, de Bruin 2007] -Prepare patient for non-hospital alternative care [Moss 2002] -Transition team of nurses to watch boarding patients and free up emergency department doctors for new patients [Ganapathy 2003] **-Direct admission based on emergency physician decision rather than consult [Howell 2004]** -Increase post emergency department care capacity (ICU cardiac units etc.) [McConnell 2005, Levin 2008] **-Discharge by noon [Rubino 2007, ACEP 2008]** -Scheduling of elective and surgical patients [ACEP 2008] **-Cancelling elective surgeries during busy days [ACEP 2008]** **-Regular updates of emergency department performance on inpatient side [Howell 2008]** **-Hallway admissions [ACEP 2008, Viccellio 2009]** **-Bed management programs with Hospital Bed Coordinators [Moskop 2009]**