Analytical Projects at Lucile Packard Children's Hospital Stanford

SUCCESSES, FAILURES AND OPPORTUNITIES

Margaret Brandeau

David Scheinker

Lucile Packard Children's Hospital Stanford

Stanford | ENGINEERING
Management Science & Engineering

My talk today

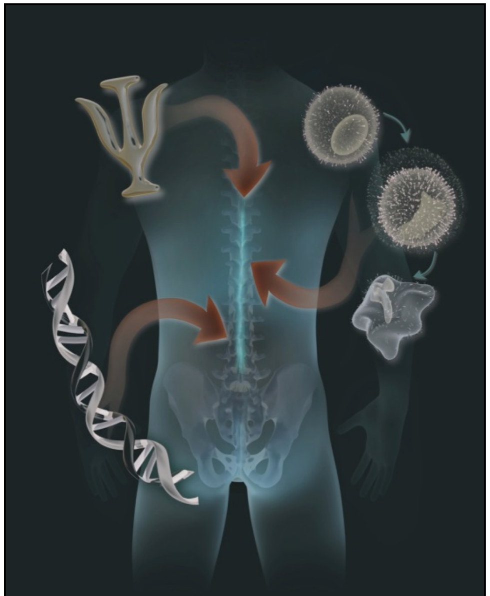
- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Lucile Packard Children's Hospital Stanford

- Pediatric academic medical center
- 360 beds
- Level 1 trauma facility
- 13,000 admissions per year
- 6,600 surgeries per year

Challenges at LPCH

~~Challenges~~ Opportunities at LPCH



CUTTING EDGE CLINICAL CARE

WASTE AND INEFFICIENCY

30 to 40 cents of every health care dollar covers costs of "overuse, underuse, misuse, duplication, system failures, poor communications and inefficiency"

Our goal:
Use practice-based evidence to empower data-driven clinical and operational decisions

OUTMODED MANAGEMENT SYSTEMS

Example: Pediatric heart surgery

SURF(ing?)

- Collaboration between LPCH, Stanford School of Medicine, and Stanford's Department of Management Science and Engineering
- Aims to facilitate the delivery of cutting-edge advances in medical care through advances in hospital operations
- Projects employ a range of analytical techniques
  - Machine learning, optimization, simulation, and statistical, probabilistic, and computational tools

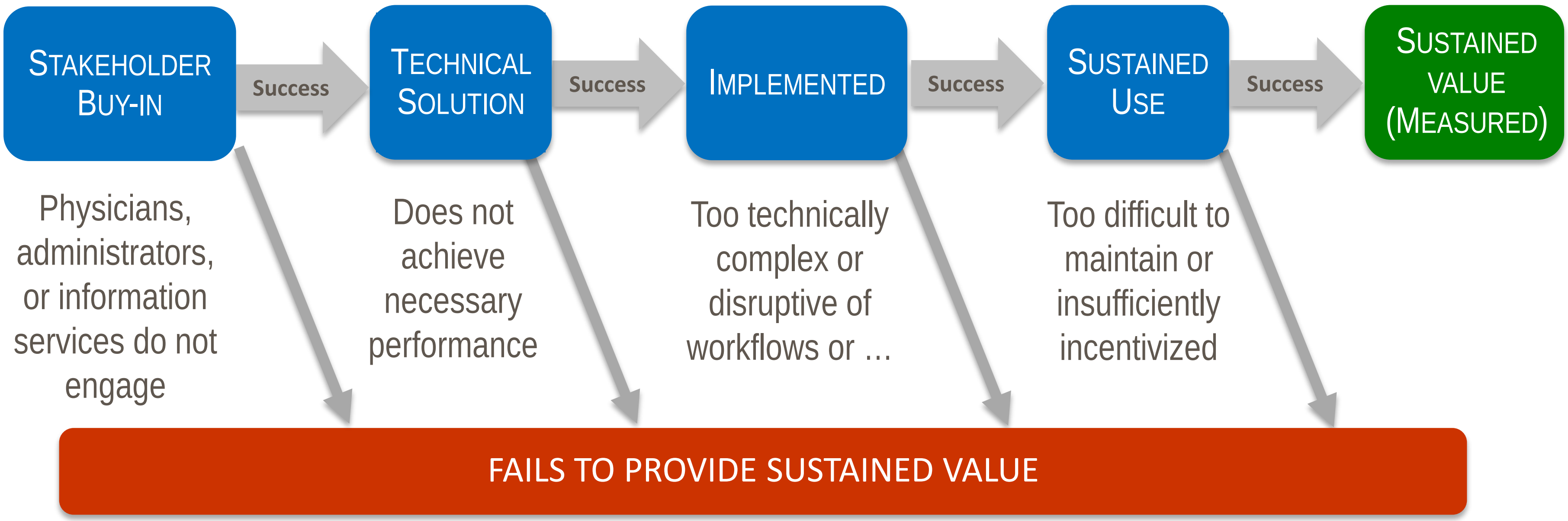
SURF projects

- All project teams include
  - Hospital analytics director (David Scheinker)
  - Clinical partner (physician or nurse)
  - Student(s) from engineering, medicine, or business school
- Some project teams include
  - Faculty member from Management Science and Engineering
- Project durations range from one quarter to several years

My talk today

- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Project success = sustained value



My talk today

- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Achieving stakeholder buy-in

- Need to create and maintain working partnership with the hospital
- We work in project teams (wide inclusion)
  - Scheinker, LPCH, MS&E faculty, students
- Project selection
  - Must match institutional priorities
  - Analytics must be able to add value

Achieving stakeholder buy-in

- Identify a small group of physicians/administrators who are passionate about analytics
- Select an initial project with a focused, technically modest goal
  - ML to predict surgery duration $\rightarrow$ operating room scheduling
- Before work begins, discuss project with a wide range of stakeholders
  - Human resources, process improvement, information services, …

My talk today

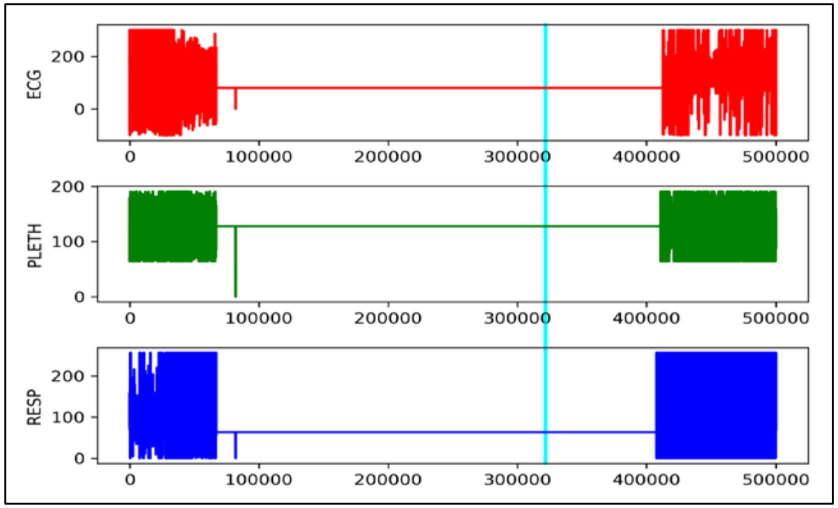
- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Identifying patients at risk of clinical decline

- Goal: Predict clinical decline from waveform data
- Clinical decline = crisis event
- Dense waveform data (125 samples/second)
- 38,000 patients over almost a decade
- 35 terabytes of data

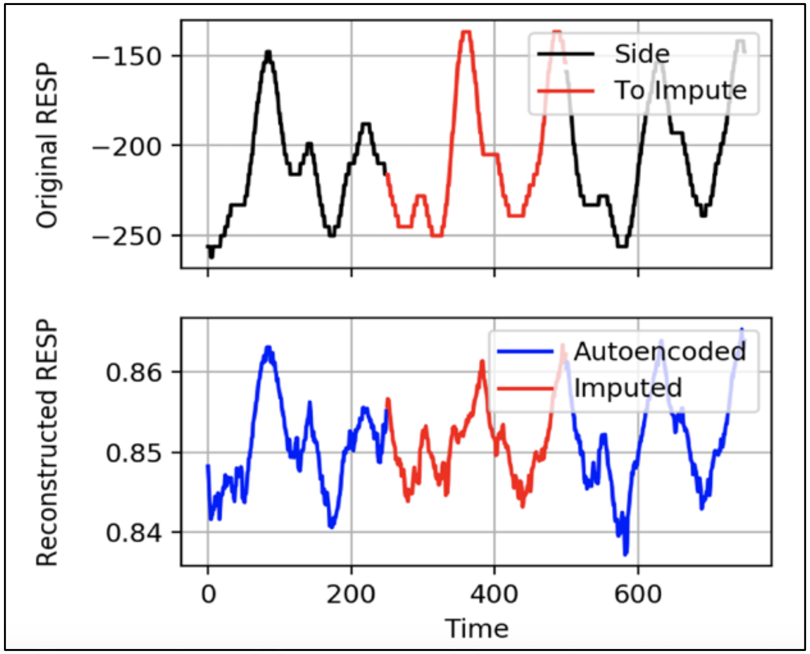
Identifying patients at risk of clinical decline

- Challenges
  - Rare events (~50 in 3 years)
  - Gaps and noise in data
  - Massive amounts of data



Identifying patients at risk of clinical decline

- New goal: Improve waveform data
- Developed a model to
  - Reconstruct missing data from patient's existing data
  - Analyze and extract information from arbitrary physiological waveforms

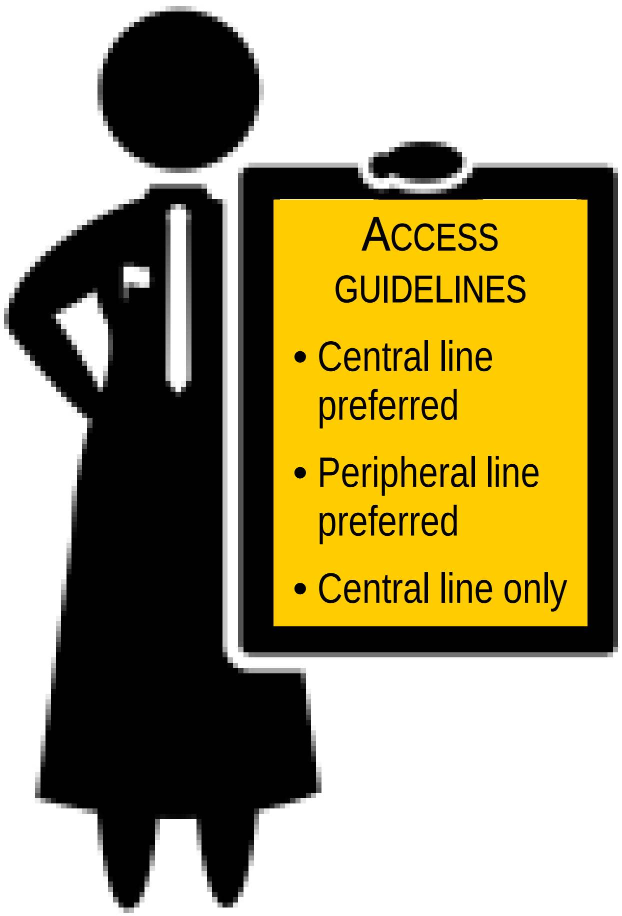


Miller et al (2018) Physiological waveform imputation of missing data using convolutional autoencoders. *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom)*.

Monitoring and reducing CLABSIs

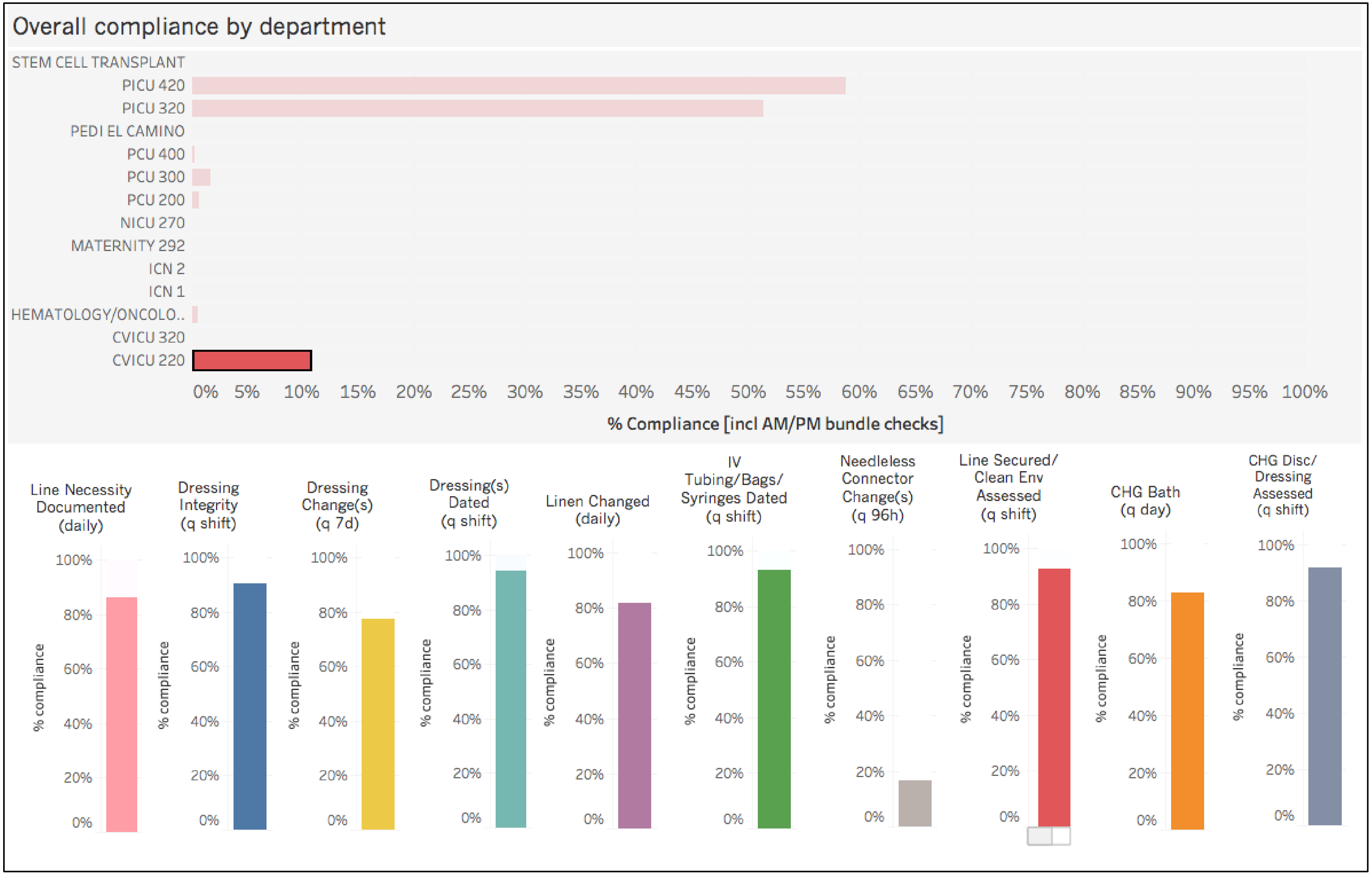
- ~~Goal: Predict CLABSIs from patient data~~
- Problem: CLABSIs are rare (.002/line-day)
- New goal: Analyze clinical practices reflected in the data

Monitoring and reducing CLABSIs



- Examined 3 years of data on central line access
- Categorized whether the access was appropriate
- Finding: Half of all access was inappropriate
- Hospital leadership had not known about this
- Clinicians were enthusiastic that a simple change could help prevent CLABSIs

Monitoring and reducing CLABSIs



Technical solution

Implemented

Sustained

My talk today

- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Scheduling surgical procedures

- Goal: Schedule surgical procedures to minimize downstream PACU congestion
- Solution approach
  - Machine learning to estimate PACU recovery times
  - Integer programming to schedule procedures
  - Simulation to demonstrate effect of new schedule

Scheduling surgical procedures

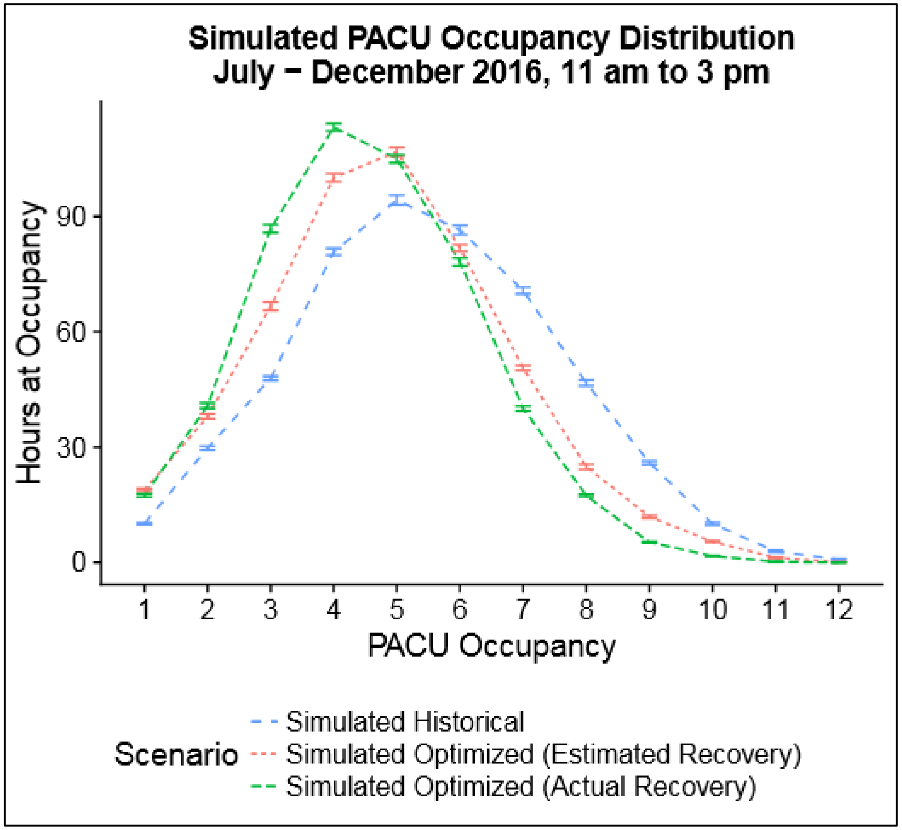
- Machine learning to predict recovery duration
- 40% accurate on tuning set

Feature	**Type**	**Importance**
Procedure type	Categorical	41%
Weight	Continuous	14%
Age	Continuous	13%
Estimated procedure length (from ML)	Continuous	6%
Scheduled post-op destination	Categorical	10%
Service	Categorical	9%
Patient class (inpatient vs. outpatient)	Categorical	4%
Sex	Binary	2%
Location (OR vs. Ambulatory Unit)	Categorical	1%
Whether a radiology case	Binary	0%

Scheduling surgical procedures

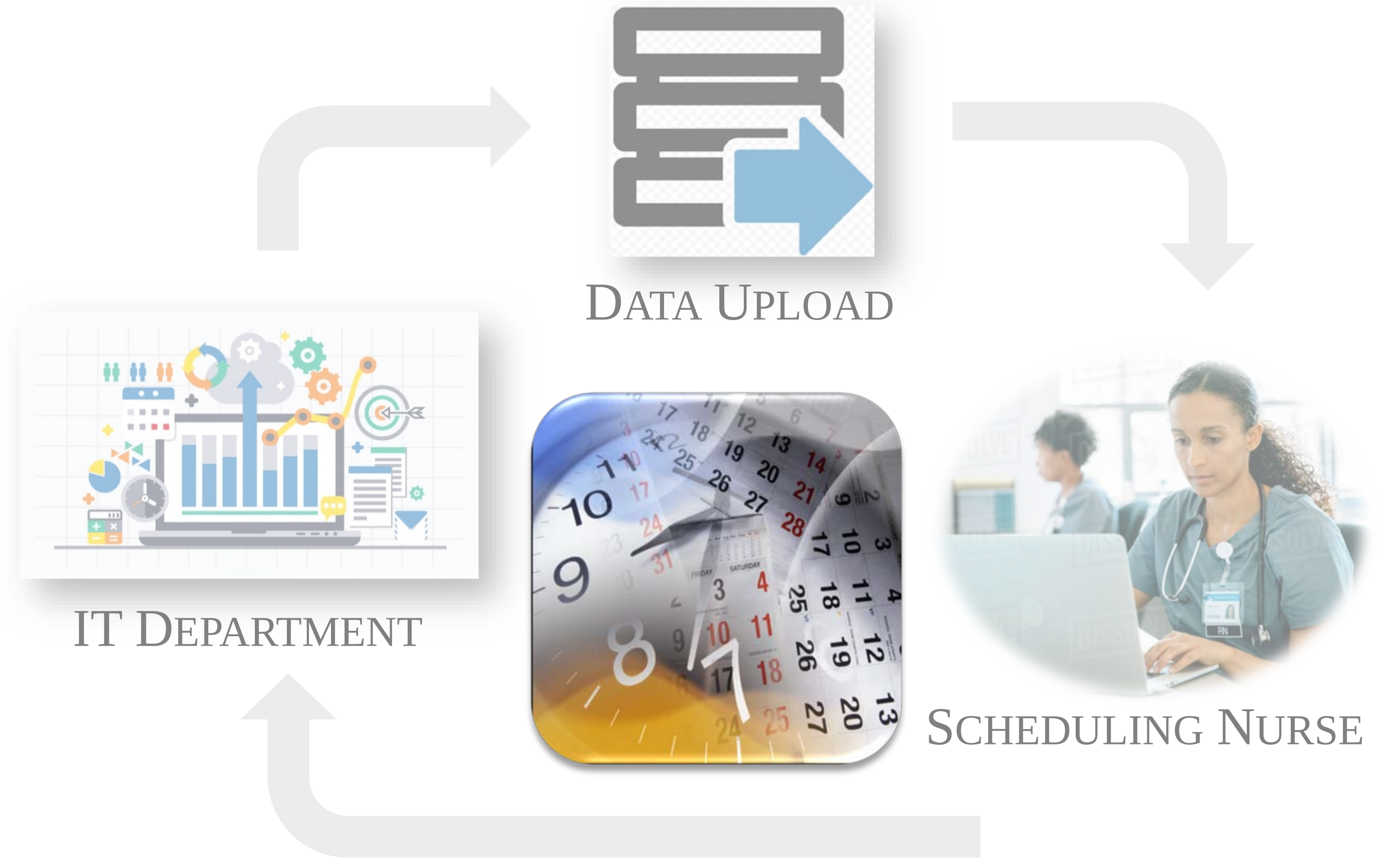
- Scheduling solved with two sequential integer programs
- First integer program
  - Schedule procedures to minimize ending time of each room, using case length estimates
- Ending times are constraints in second integer program
  - Add an extra allowable time *f* to each room
- Second integer program
  - Schedule procedures to minimize maximum PACU occupancy, using recovery time estimates

Scheduling surgical procedures



- Simulation to compare optimized to actual schedule
- Optimized schedule
  - Same operating room utilization
  - PACU holds reduced by 76%

Scheduling surgical procedures



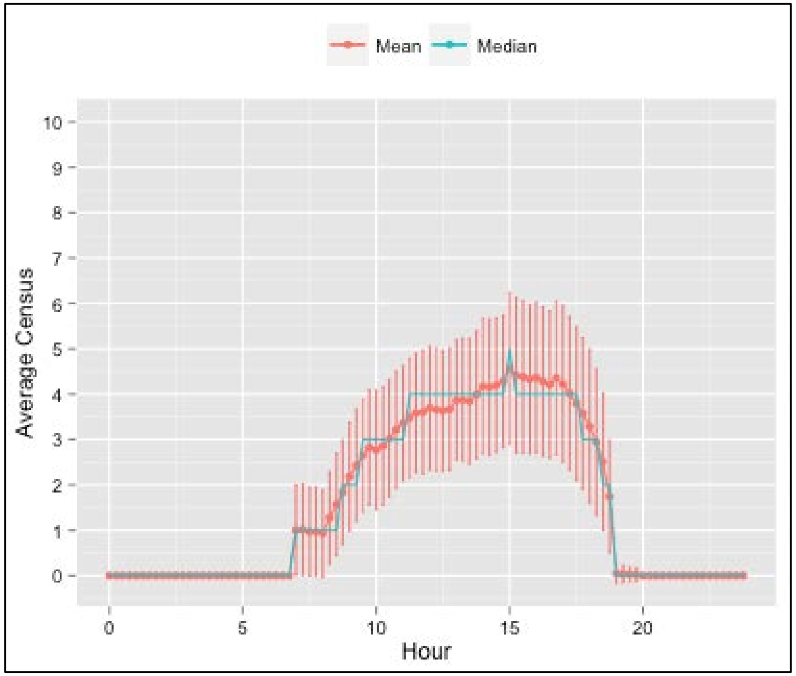
Fairley et al (2018) Improving the efficiency of the operating room environment with an optimization and machine learning model. *Healthcare Management Science*.

Infusion Center scheduling

- Goal: Create a scheduling system to
  - Maximize bed utilization (7 beds)
  - Accommodate scheduled and walk-in demand
  - Minimize patient waiting times

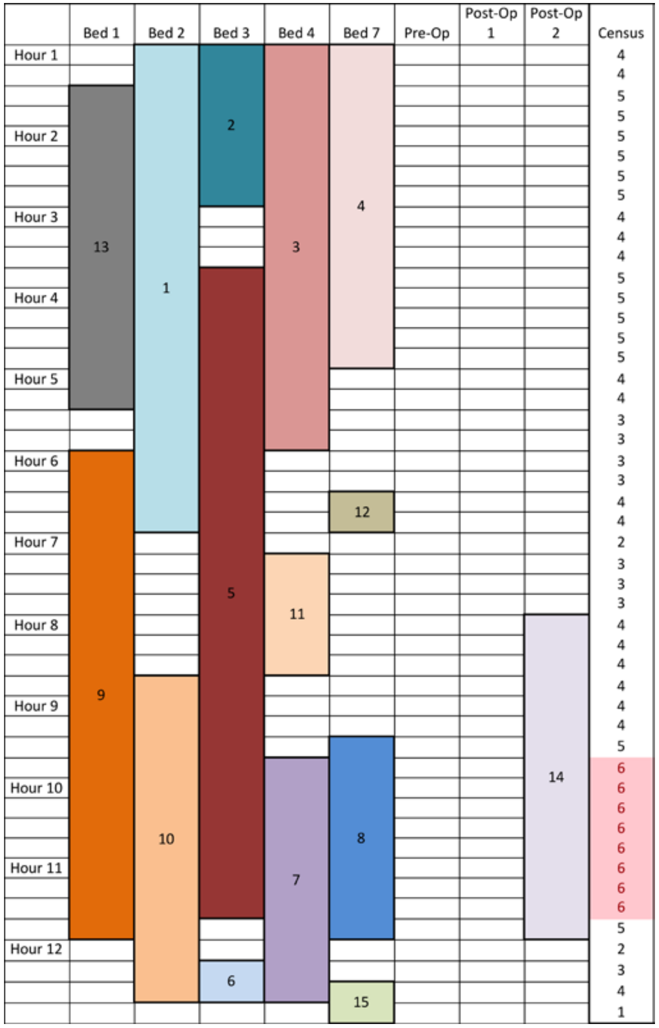
Infusion Center scheduling

- Solution approach
  - Optimization model to maximize bed utilization
  - Development of near-optimal heuristic
  - Simulation model to evaluate and revise heuristic



Infusion Center scheduling

- Implementation
  - Formalized instructions for implementing the heuristic
  - Created a paper-based flow diagram
- Ongoing use
  - Monitoring improvements in the schedule
  - Providing feedback and additional training to schedulers



Pitt et al (2020) Scheduling algorithm improves system utilization at Lucile Packard Children's Hospital Stanford infusion center. *Working paper*.

My talk today

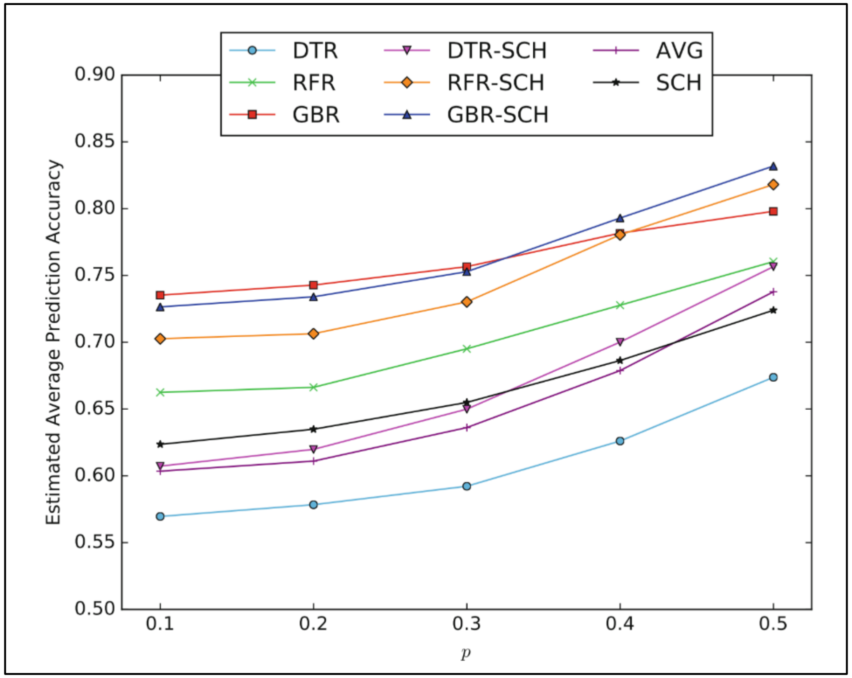
- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Predicting surgical case length

- Procedure durations estimated by busy surgeons

Predicting surgical case length

- Goal: Predict length of surgical procedures
- Considered several machine learning methods
  - Decision tree regressor, random forest, gradient boosting
  - With and without surgeon's procedure length estimate



Predicting surgical case length

- Best method was random forest
- 65% accurate on tuning set

Feature	**Type**	**Weight**
Surgeon’s estimate of procedure length	Continuous	63%
Surgeon	Categorical	9%
Procedure type	Categorical	7%
Weight	Continuous	8%
Age	Continuous	4%
Sex	Binary	4%
Patient’s physical status score	Categorical	2%
Patient class (inpatient vs. outpatient)	Categorical	1%
Location (OR vs. Ambulatory Unit)	Categorical	1%

Predicting surgical case length

- Implementation
  - Email alerts sent if ML forecast differed significantly from surgeon’s forecast
  - Forecasts reviewed manually
  - Schedule adjusted manually
- Issues
  - Significant personnel effort required
  - Many alerts were for short cases

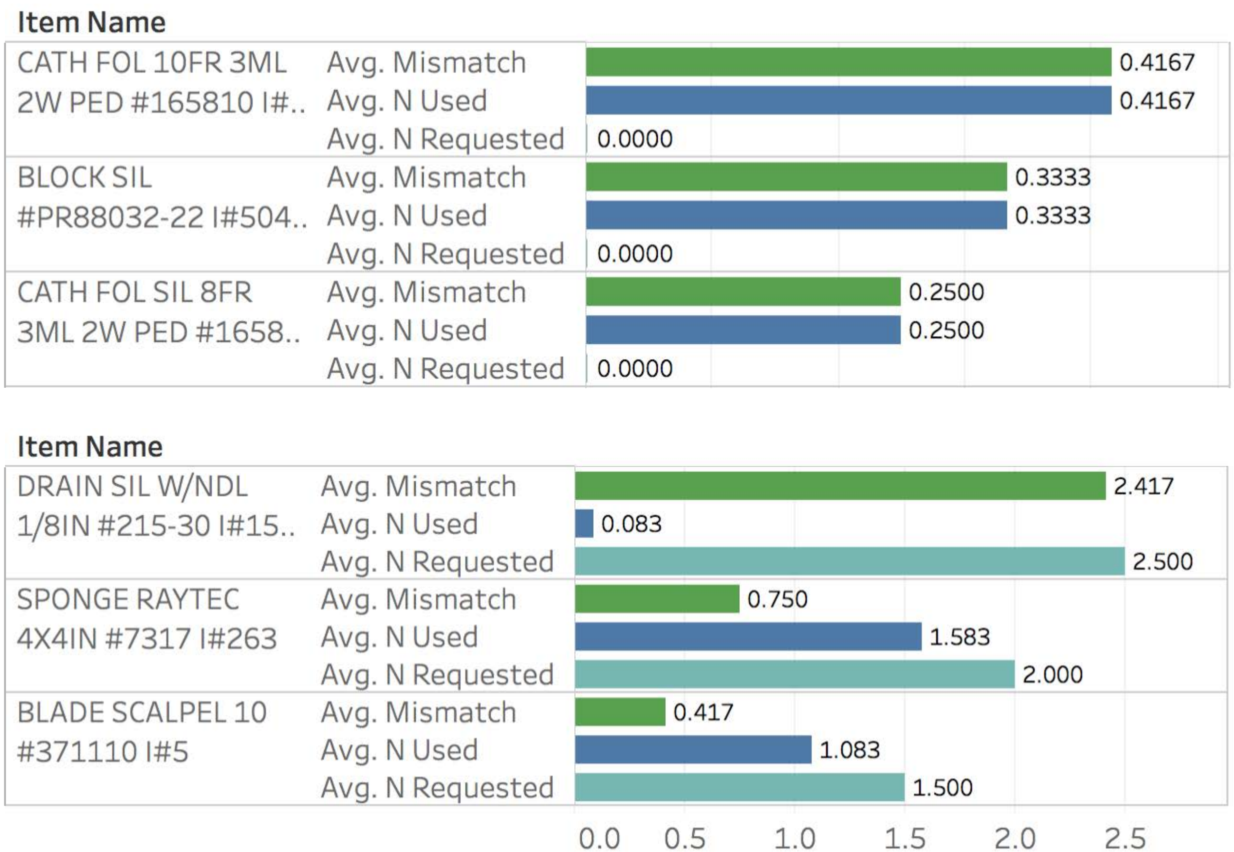
Zhou et al (2016) Detecting inaccurate predictions of pediatric surgical durations. *Data Science and Advanced Analytics (DSAA)*, 2016 IEEE International Conference

Managing surgical supplies

- Goal: Analyze operating room supply processes (preference cards)
- Impact of inaccurate cards
  - Surgical delays
  - Wasted, unused supplies
  - Supplies used but not billed for

Managing surgical supplies

- Inventory analysis using electronic health record

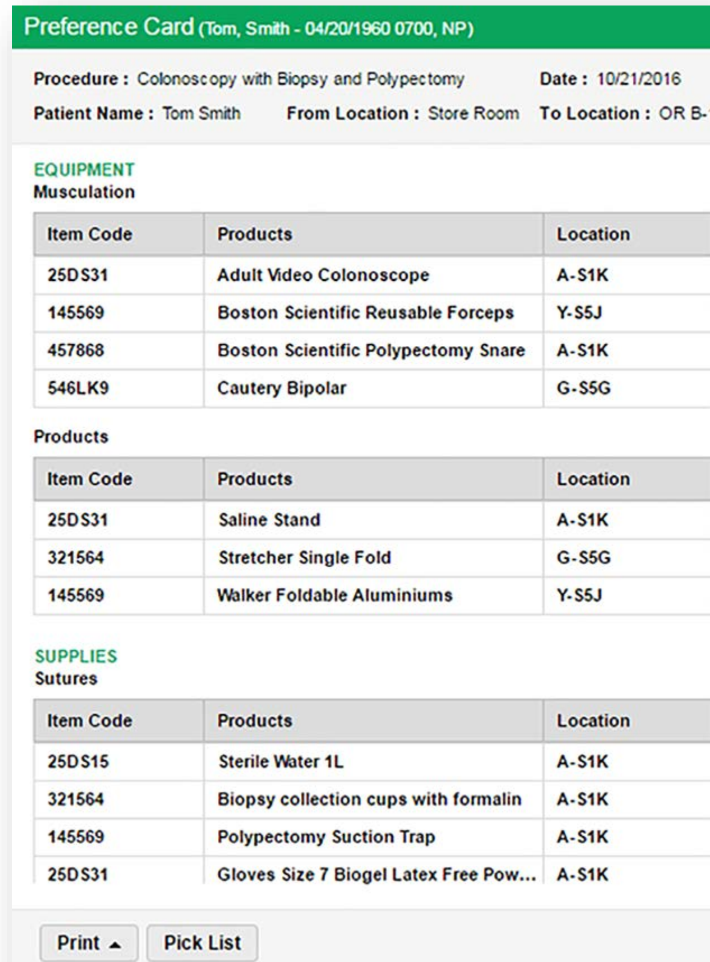


Necessary items missing from preference cards

Unnecessary items included on preference cards

Managing surgical supplies

- Fully data-driven tool using EHR
- Nurses can accept, reject, or modify changes to preference cards
- Case-controlled study
  - Average 7 items added, 5 items removed per card
  - Significant cost savings
- Sustained use



Preference Card (Tom, Smith - 04/20/1960 0700, NP)

Procedure : Colonoscopy with Biopsy and Polypectomy **Date :** 10/21/2016

Patient Name : Tom Smith **From Location :** Store Room **To Location :** OR B-1

EQUIPMENT

Musculation

Item Code	Products	Location
25DS31	Adult Video Colonoscope	A-S1K
145569	Boston Scientific Reusable Forceps	Y-S5J
457868	Boston Scientific Polypectomy Snare	A-S1K
546LK9	Cautery Bipolar	G-S5G

Products

Item Code	Products	Location
25DS31	Saline Stand	A-S1K
321564	Stretcher Single Fold	G-S5G
145569	Walker Foldable Aluminiums	Y-S5J

SUPPLIES

Sutures

Item Code	Products	Location
25DS15	Sterile Water 1L	A-S1K
321564	Biopsy collection cups with formalin	A-S1K
145569	Polypectomy Suction Trap	A-S1K
25DS31	Gloves Size 7 Biogel Latex Free Pow...	A-S1K

Print

Pick List

Scheinker et al (2020) The use of electronic health record data to optimize surgical preference cards. *Working paper*.

My talk today

- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Lessons learned

- Solving the technical problem
  - Need to choose the model(s) that fits the problem and data
  - Obtaining needed data is always a challenge (availability, quality)
  - Rare events are often orders of magnitude lower than you think
  - Must be willing to pivot (e.g., focus on understanding and then visualizing data, rather than predicting)
  - Sometimes more than one model is needed
  - Can be useful to test multiple models and pick the best one

Lessons learned

- Implementing the solution
  - Important to understand how the model will be implemented, before starting work, and involve key staff members
  - Need to choose appropriate technical partners for implementation
  - Important to disrupt as few workflows as possible
  - Need to be aware of the technical constraints of the hospital
  - Successful projects are often implemented in stages (e.g., understand data, create dashboard, optimize)

Lessons learned

- Sustaining the implementation
  - Critical to build partnerships across the hospital – at the project start
  - Successful projects align with institutional priorities
  - Continual feedback and incentives are needed
  - Automated systems have an advantage
  - One-time process redesign tends to be sustained
  - Important to be able to measure the improvements generated by a project

My talk today

- Overview of our projects at LPCH
- Successes and failures
  - Achieving stakeholder buy-in
  - Solving the technical problem
  - Implementation
  - Sustained use
- Lessons learned
- Concluding thoughts

Concluding thoughts

- Many opportunities to improve healthcare value using analytical tools
- Such tools can improve decisions about the design and delivery of healthcare
  - Exploit available data
  - Capture system complexities
  - Optimize system performance
- But … it is important that the tools be designed to achieve sustained value

Scheinker and Brandeau (2020) Implementing analytics projects in a hospital: Successes, failures and opportunities. *INFORMS Journal on Applied Analytics*.


Thank you
https://surf.stanford.edu