Society of Student-Run Free Clinics Annual Conference 2017

Using Analytics to Effectively Manage Student Run-Clinics

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Introduction

CRIMSON CARE COLLABORATIVE
A HARVARD MEDICAL SCHOOL STUDENT-FACULTY MEDICAL PRACTICE

A group of 6 student-run clinics providing services in: pediatrics, primary care, mental health, and dentistry

Focus on **Internal Medical Associate at Massachusetts General Hospital (CCC-IMA)**

- Adult primary care practice
- Urgent care + bridge to care
- Clinic runs every Tuesday 5 – 9 pm
- Up to 12 patients per clinic, > 300/year
- ~ 75 volunteers + faculties
- 15 Board Members + 1 faculty director

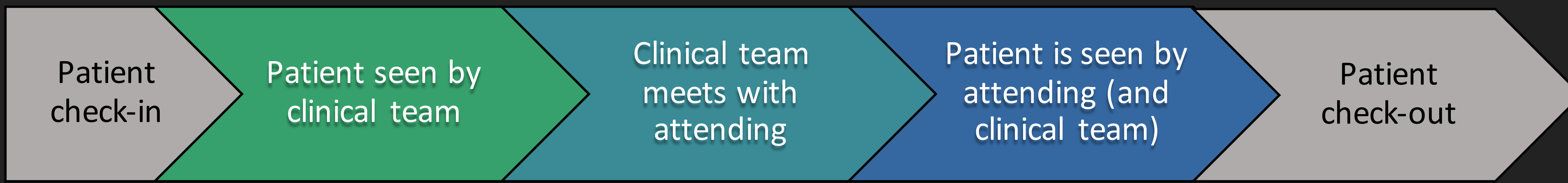
We provide **clinical service for patients** and **educational opportunities for volunteers**

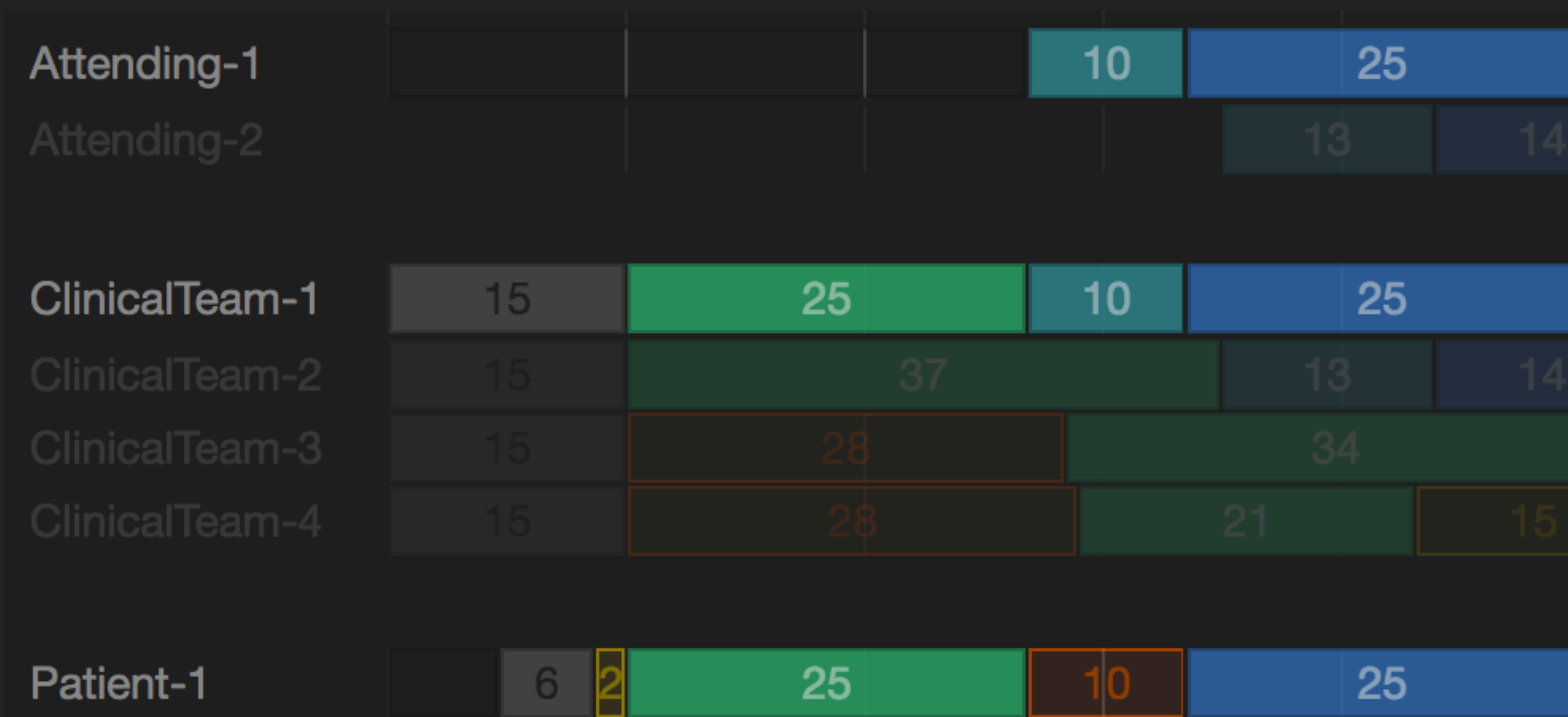
- Craft roles and responsibilities
- Design training and educational programs
- *Staffing and scheduling for clinic operations*

Objectives of this Workshop

- Learn data-driven approaches for informed policy decisions affecting clinic operations
- Use model-based simulation to analyze a real-world staffing problem
- Develop ideas on applying these concepts to your clinic
- Gain insights on how to jump-start the infrastructure for data-driven operations
- Hands-on session

A Typical Visit





Challenges in Designing Operations Policies

Patient check-in → Patient seen by clinical team → Clinical team meets with attending → Patient is seen by attending (and clinical team) → Patient check-out

Design constraints and objectives:

- Clinic must finish within 3 hours
- Minimize patient wait time
- Ensuring continuity of care

  e.g. maximizing probability of being seen by “preferred” attending/clinical team

What are some other design constraints and objectives?

Stakeholder interests relating to operations

- Volunteer
  - Accessibility
    - Patients per session
    - Time commitment
    - End time of clinic
  - Quality of experience
    - Time spent w/ attending
    - Diversity of cases seen
- Patient
  - Accessibility
    - Duration of visit
    - How soon is first appointment
  - Quality of care
    - Continuity of care
    - Waiting time

Challenges in Designing Operations Policies

A typical policy question:

Should we increase the number of clinical teams to better achieve our design objectives?

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Alice says (proponent of increase)

- More patients seen per session
- Patients will wait less
- Clinic may end earlier
- More volunteering opportunities

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Alice says (proponent of increase)

- More patients seen per session
- Patients will wait less
- Clinic may end earlier
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Bob says (against increase)

- Bottleneck may lie elsewhere (attendings)
- Patients will have to wait more
- May not have impact on duration on clinic
- Reduction in number of patients/team

Approaches to Design Operations Policies

First approach: **Conduct an experiment**

- Delayed feedback (~ months)
- Requires long-term commitment, even for small sample size
- Can only perform one experiment at a time
- Hard to preserve institutional knowledge
- Full dynamics (captures all idiosyncrasies)

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Second approach: **Model-based simulation**

Policy of Interest → Model of Clinic Dynamics → (multiple) simulated clinic sessions

↓

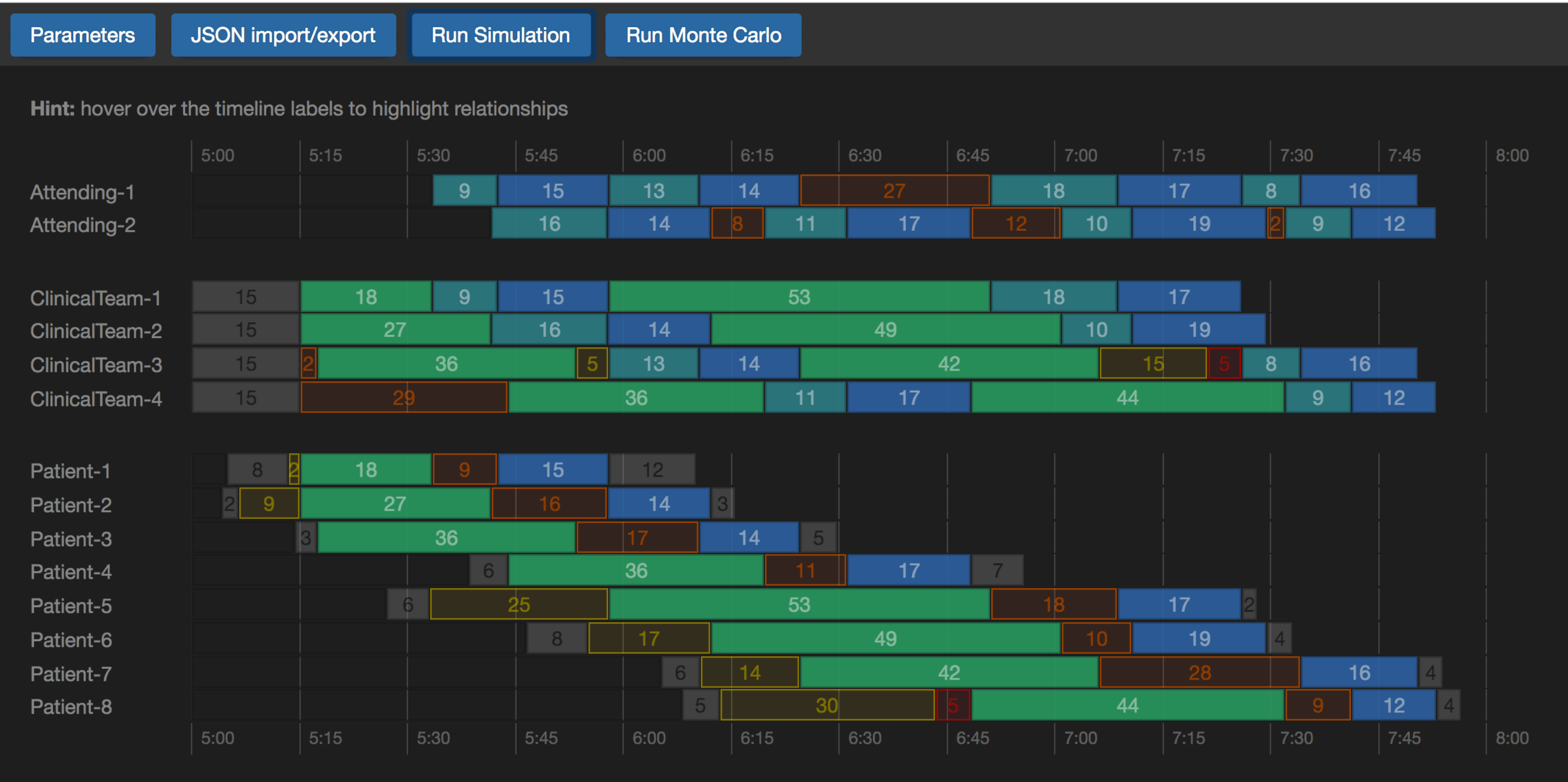
performance metrics (averages, percentiles)

- Immediate feedback for rapid iteration
- High throughput and "large" sample size
- Useful tool for training and education
- Simplified dynamics require model calibration and validation

Application Example

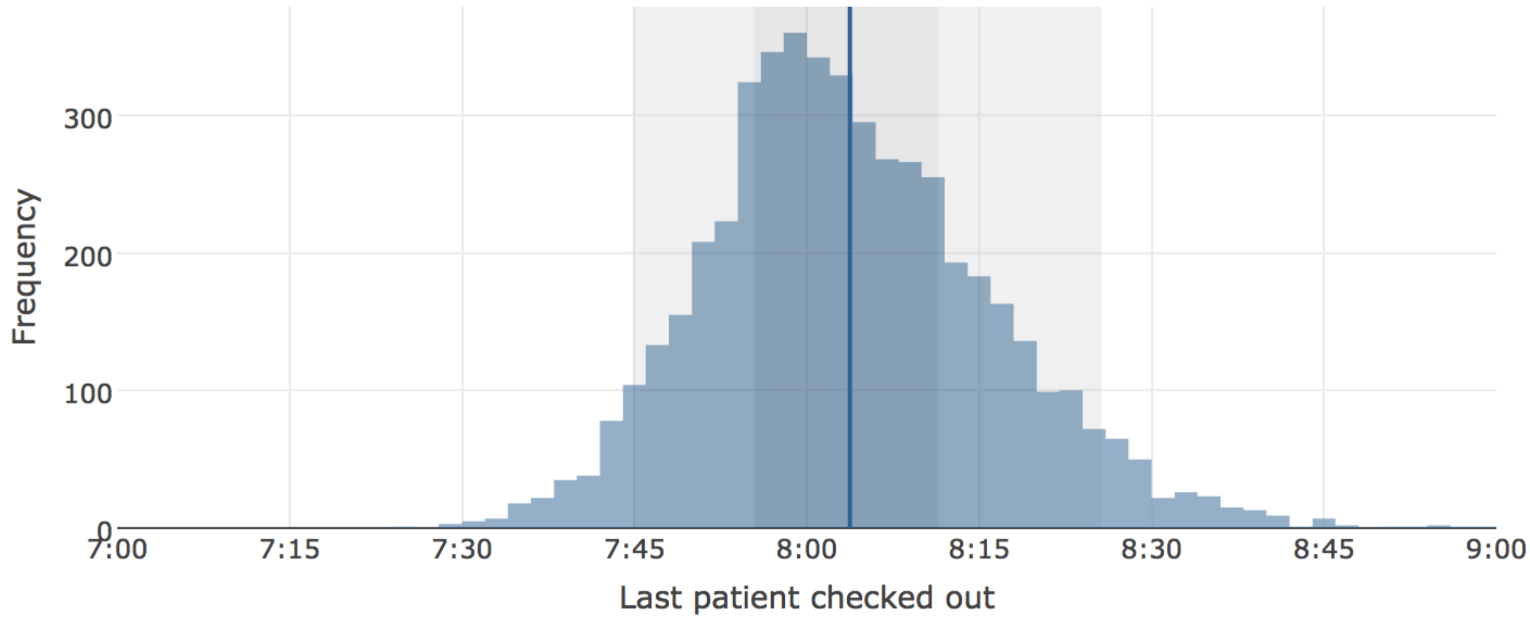
Revisit: How many teams should we have per clinic?

Live simulation demo: http://crimsoncare.github.io/ccc-ima-app

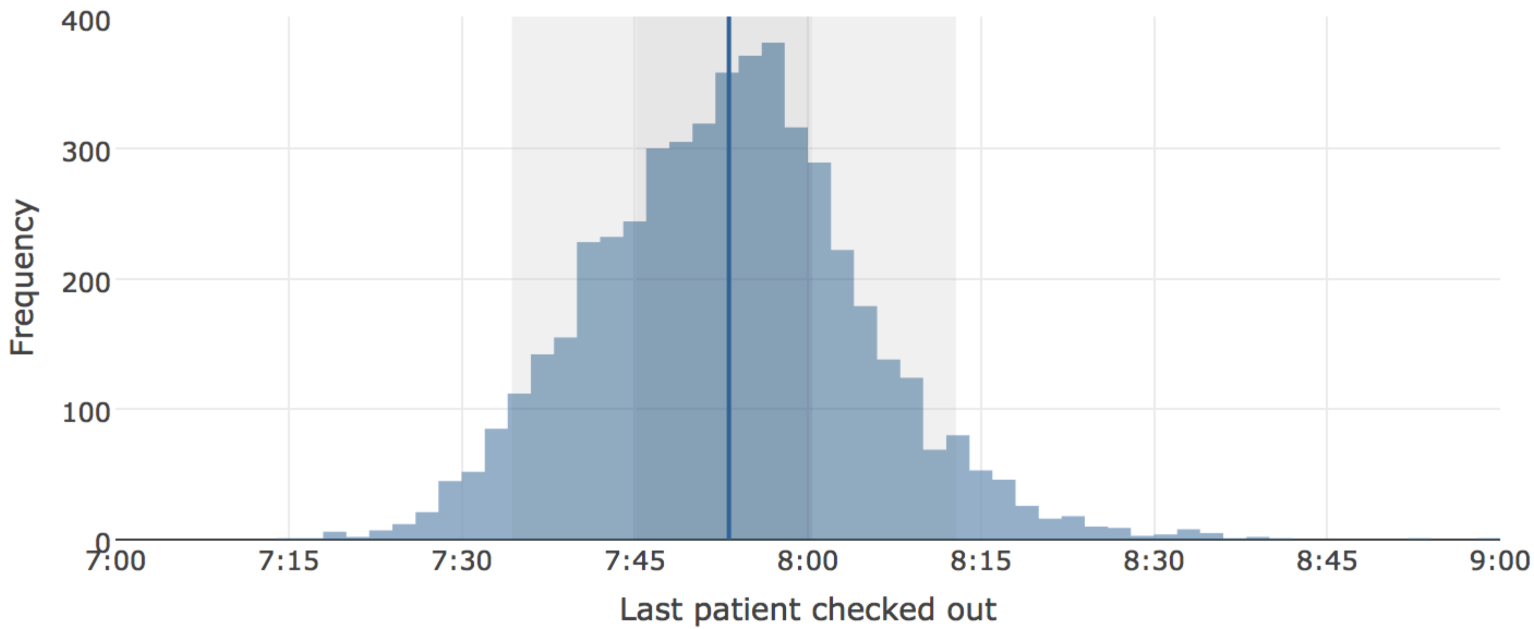


Observations: 6 vs. 4 clinical teams

4 Clinical Teams

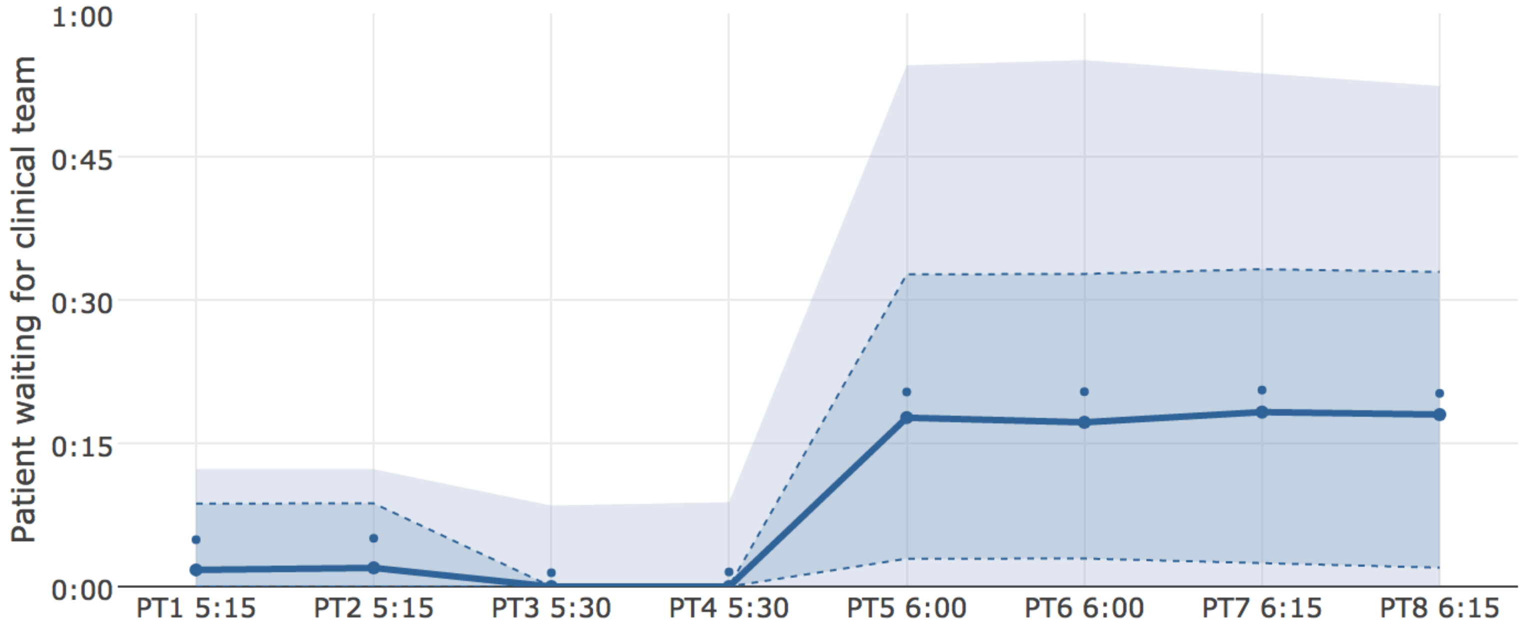


6 Clinical Teams



Observations: Patient waiting for clinical team

4 Clinical Teams



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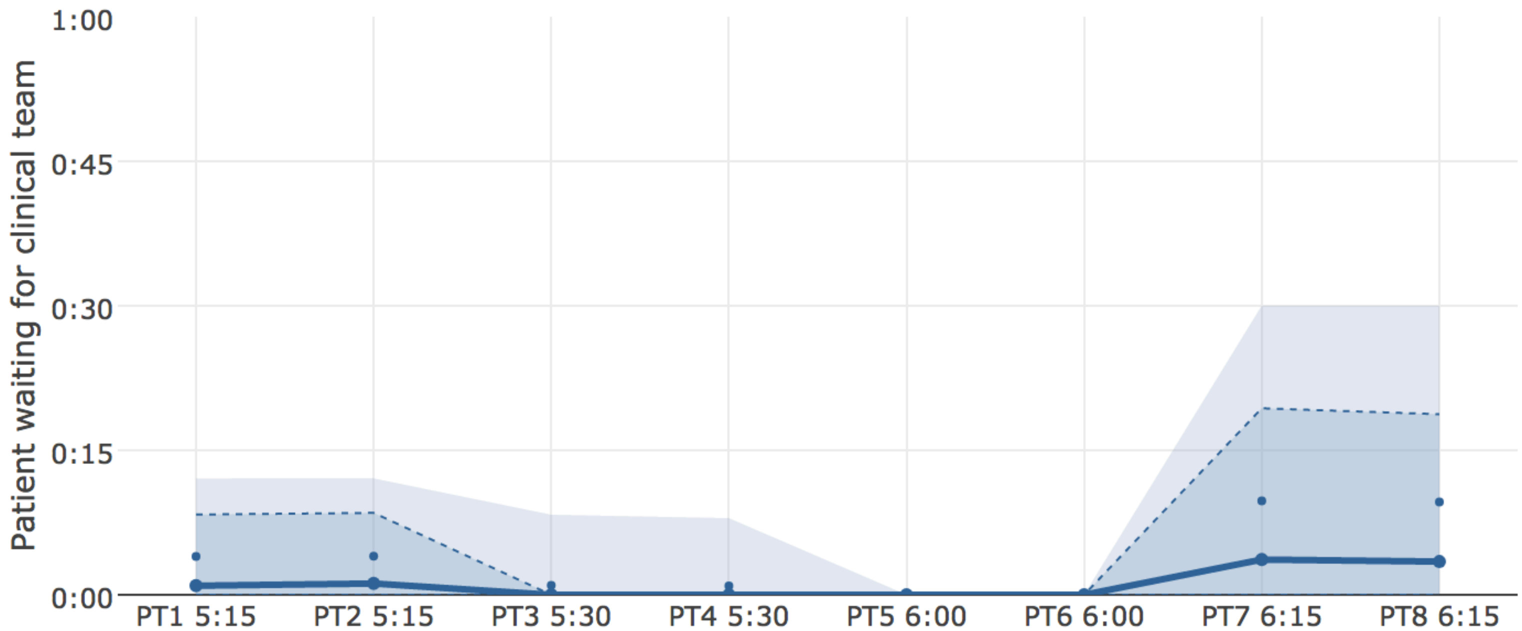
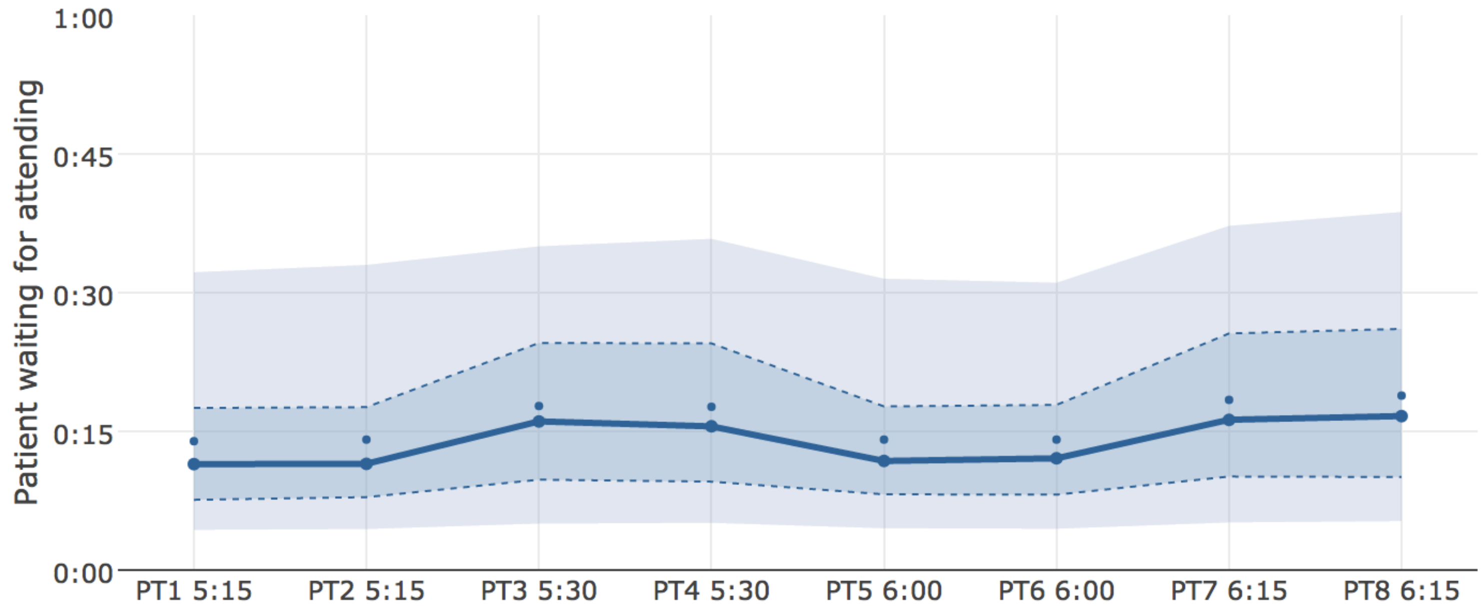
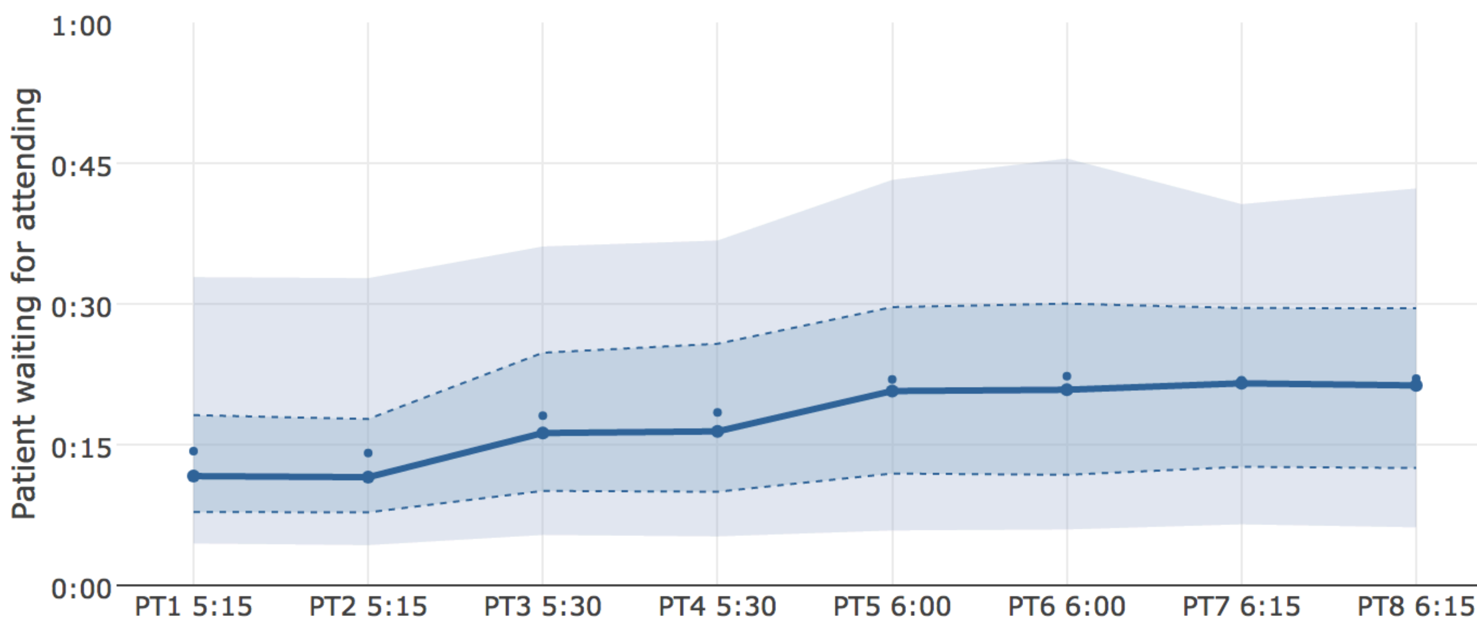


Observations: Patient waiting for attending

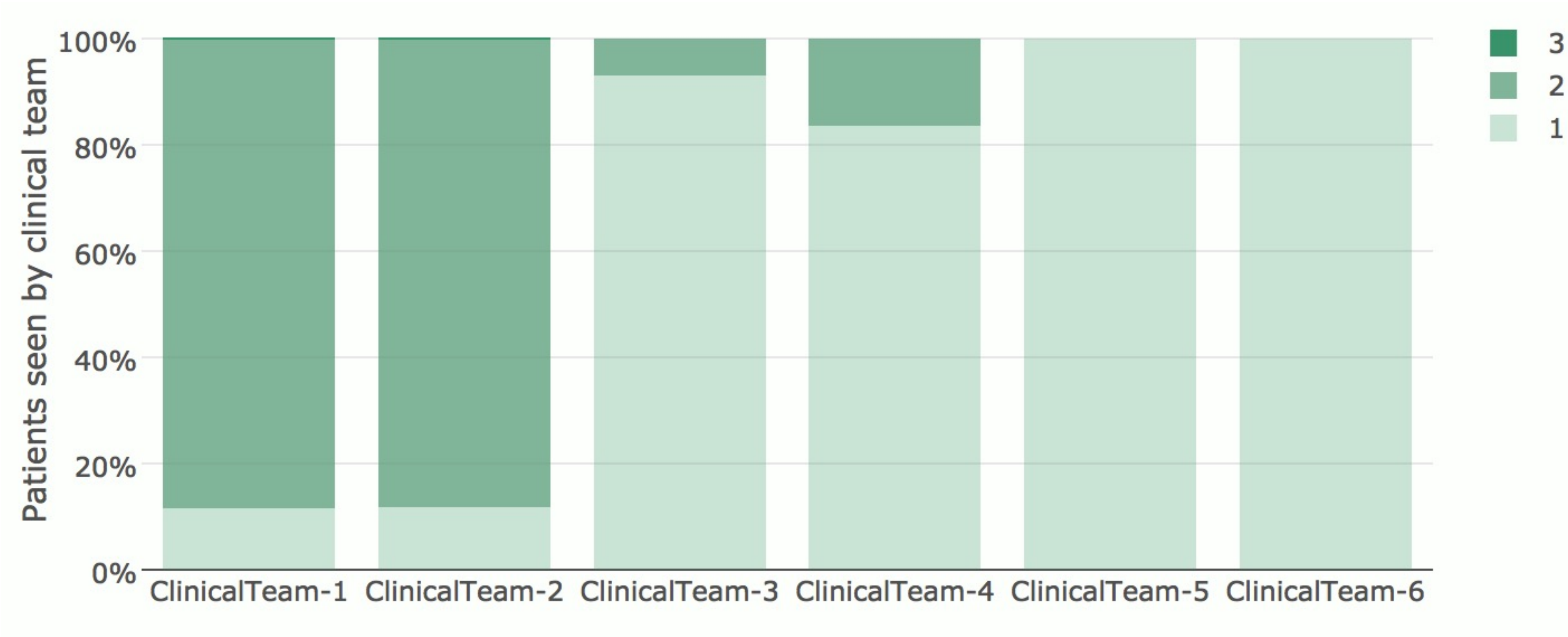
4 Clinical Teams



6 Clinical Teams



Observations



Observations:

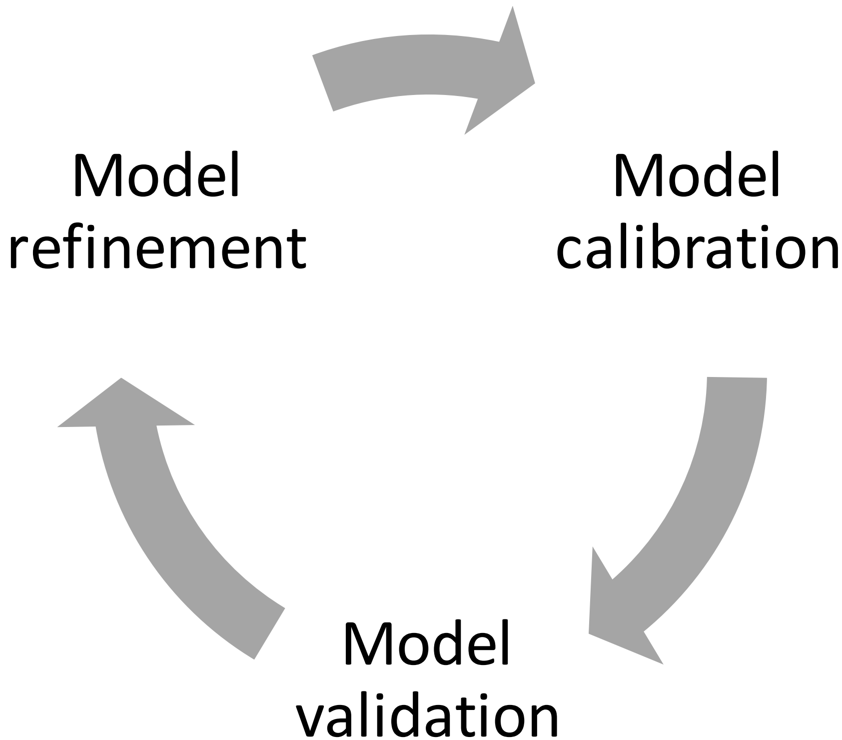
- Attending availability is the key bottleneck
  - Duration of the clinic is not significantly affected
  - Patients wait in the examination room instead of the lobby
- Patients volume limits the patient : clinical team ratio and affects volunteer experience

Approach to Modeling Clinic Dynamics

The model is based on:

- Data collected in clinic over time
- Constraints that we know the clinic has to operate under,

and is built to reflect the true dynamics of the clinic in an iterative approach:



Model Calibration

Model Calibration: find values of model parameters that result in predictions that best match the training data.

KEY IDEA: Identify model parameters, usually **intrinsic** properties (independent from the design parameters, e.g., staffing, scheduling)

Examples:

Patient	Arrival time relative to scheduled time?
Clinical team	How long do they tend spend with the patients?
Attending	How long do they tend to spend with the patients?

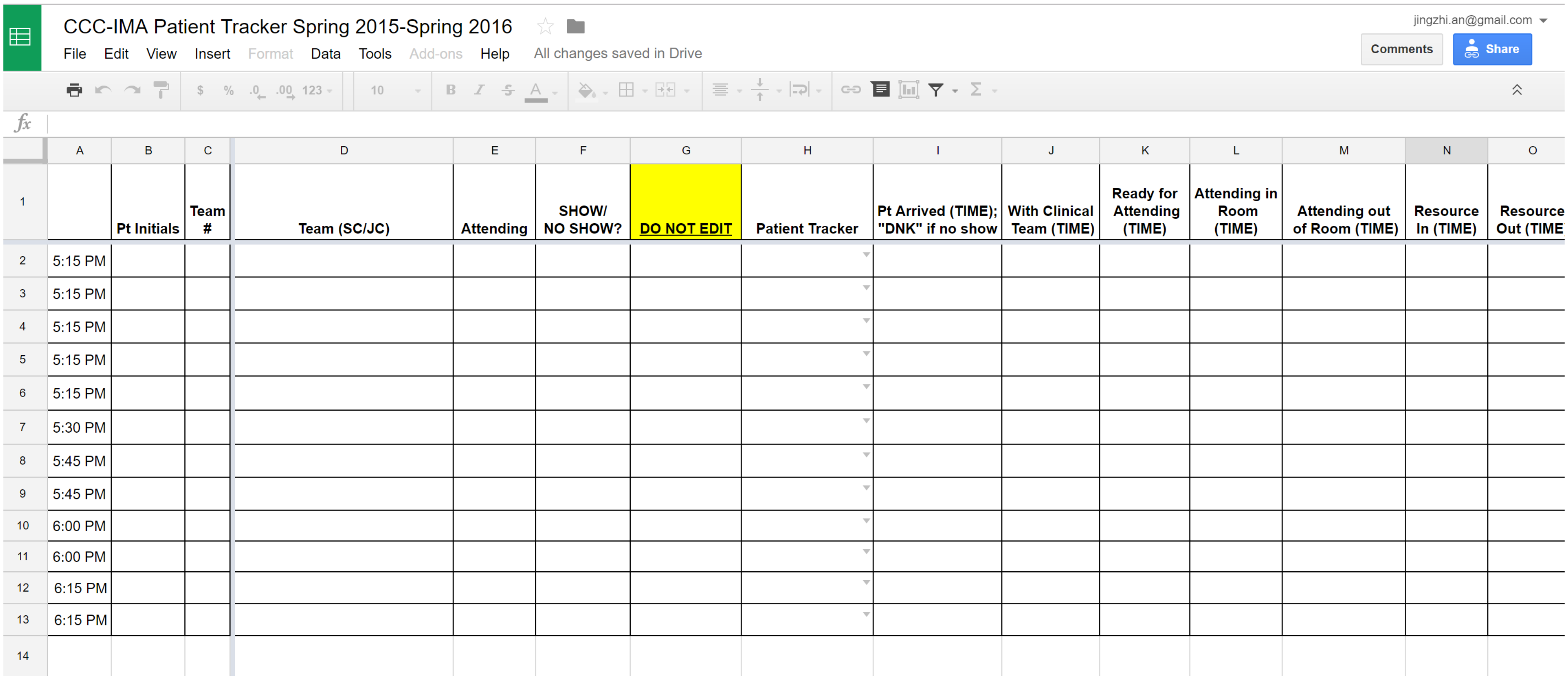
Can you name any other intrinsic properties?

How do we collect useful data?

Model Calibration – Data Collection

How we collect the data at CCC-IMA

Current - Google Spreadsheet



CCC-IMA Patient Tracker Spring 2015-Spring 2016

File Edit View Insert Format Data Tools Add-ons Help All changes saved in Drive

jingzhi.an@gmail.com

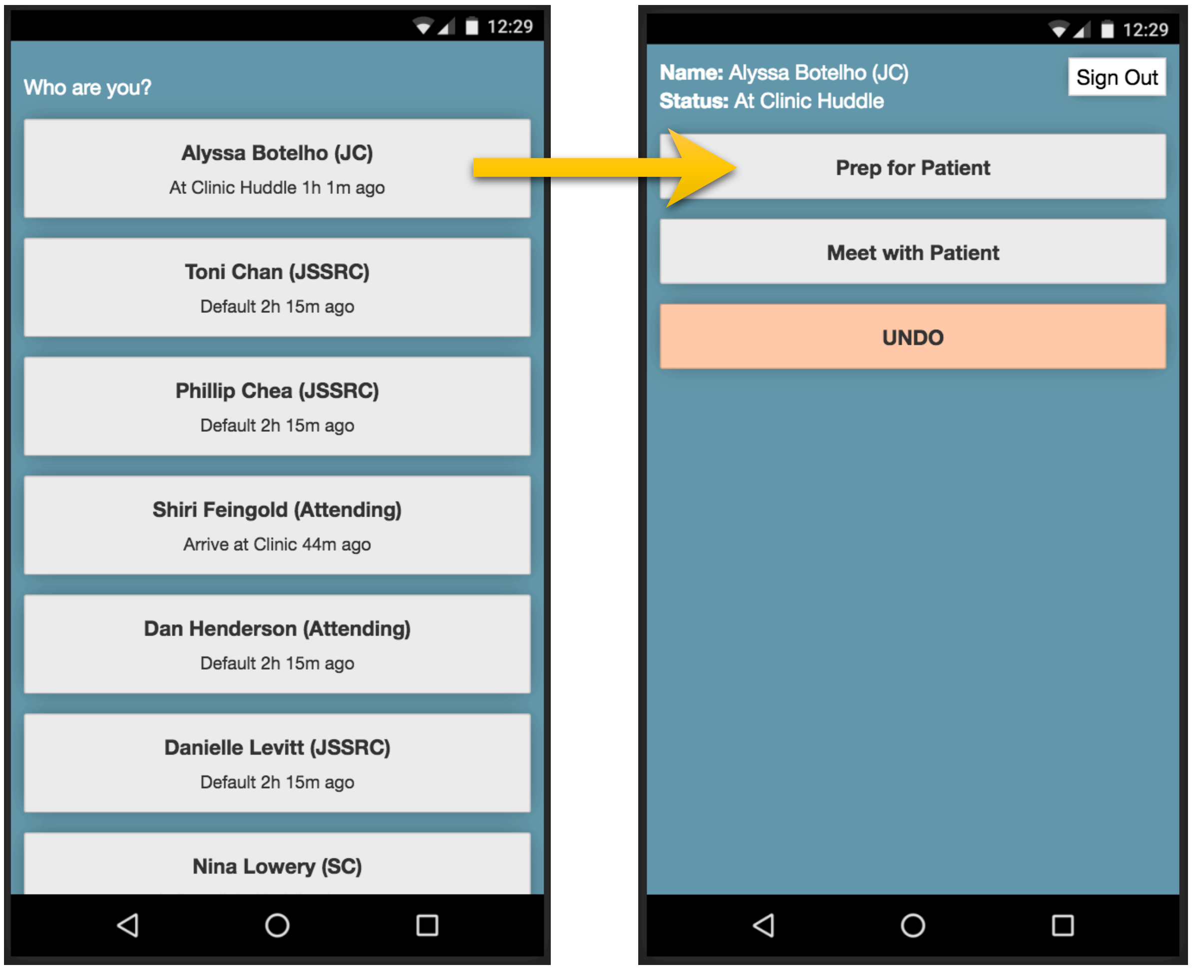
Comments Share

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1		Pt Initials	Team #	Team (SC/JC)	Attending	SHOW/ NO SHOW?	DO NOT EDIT	Patient Tracker	Pt Arrived (TIME); "DNK" if no show	With Clinical Team (TIME)	Ready for Attending (TIME)	Attending in Room (TIME)	Attending out of Room (TIME)	Resource In (TIME)	Resource Out (TIME
2	5:15 PM														
3	5:15 PM														
4	5:15 PM														
5	5:15 PM														
6	5:15 PM														
7	5:30 PM														
8	5:45 PM														
9	5:45 PM														
10	6:00 PM														
11	6:00 PM														
12	6:15 PM														
13	6:15 PM														
14															

Model Calibration – Data Collection

How we collect the data at CCC-IMA

Moving towards real-time data collection:



Chelsea Nunez (JC)

- 18:59:33 Meet with Attending
- 18:59:31 Meet with Patient
- 17:57:48 End Visit
- 17:38:56 Meet with Attending
- 17:38:54 Meet with Patient
- 17:14:21 Prep for Patient
- 17:12:10 At Clinic Huddle
- 16:00:00 Default

Katie Slusarz (JC)

- 19:47:35 End Visit
- 19:47:34 Meet with Attending
- 19:20:15 Wait for Attending
- 19:20:13 Meet with Patient
- 18:31:21 End Visit
- 18:17:57 Meet with Attending
- 18:01:45 Wait for Attending
- 17:21:33 Meet with Patient
- 17:16:50 Prep for Patient
- 17:12:29 At Clinic Huddle
- 16:00:00 Default

Model Calibration – Data Analysis

How we use the data collected to obtain model parameters

Data tracked 2015-2017

Appointment Time

Team: Attending / SC/ JC

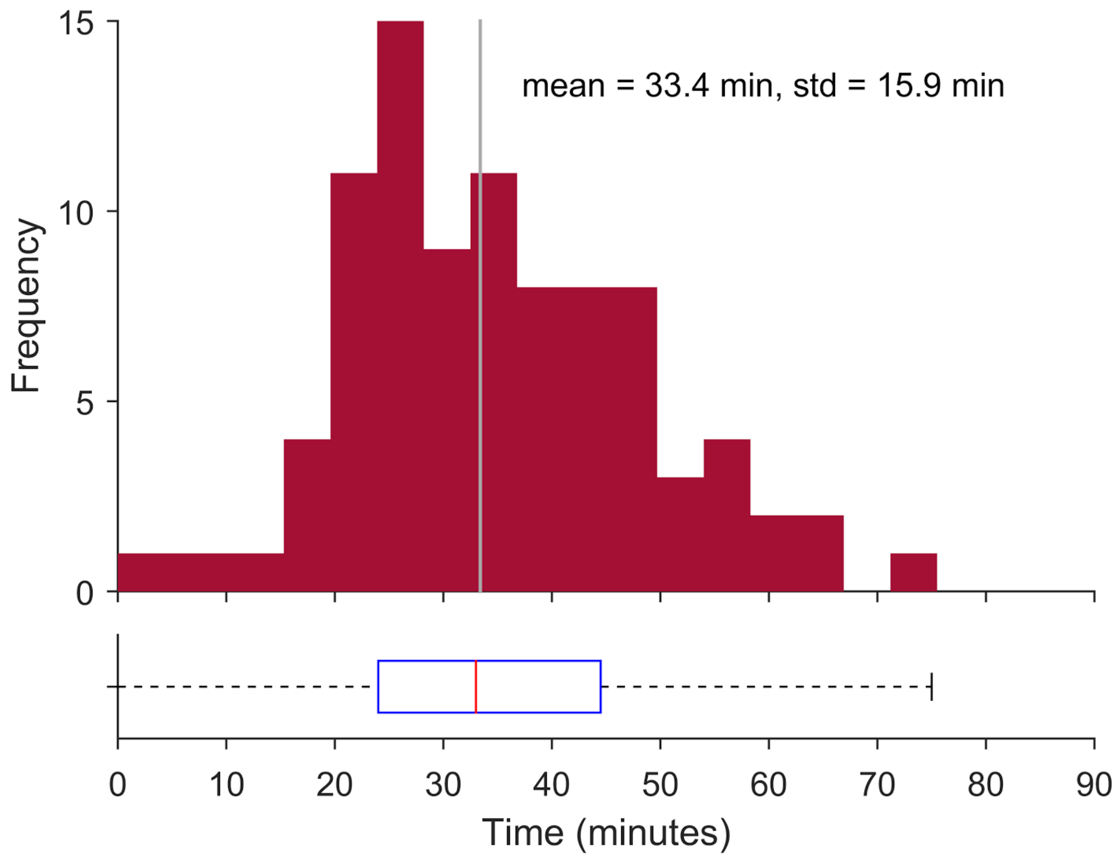
Show / No Show

Time-stamps

- Patient arrived
- With clinical team
- Ready for attending
- Attending in room
- Attending out of room
- Patient checked out
- Resource in/out*

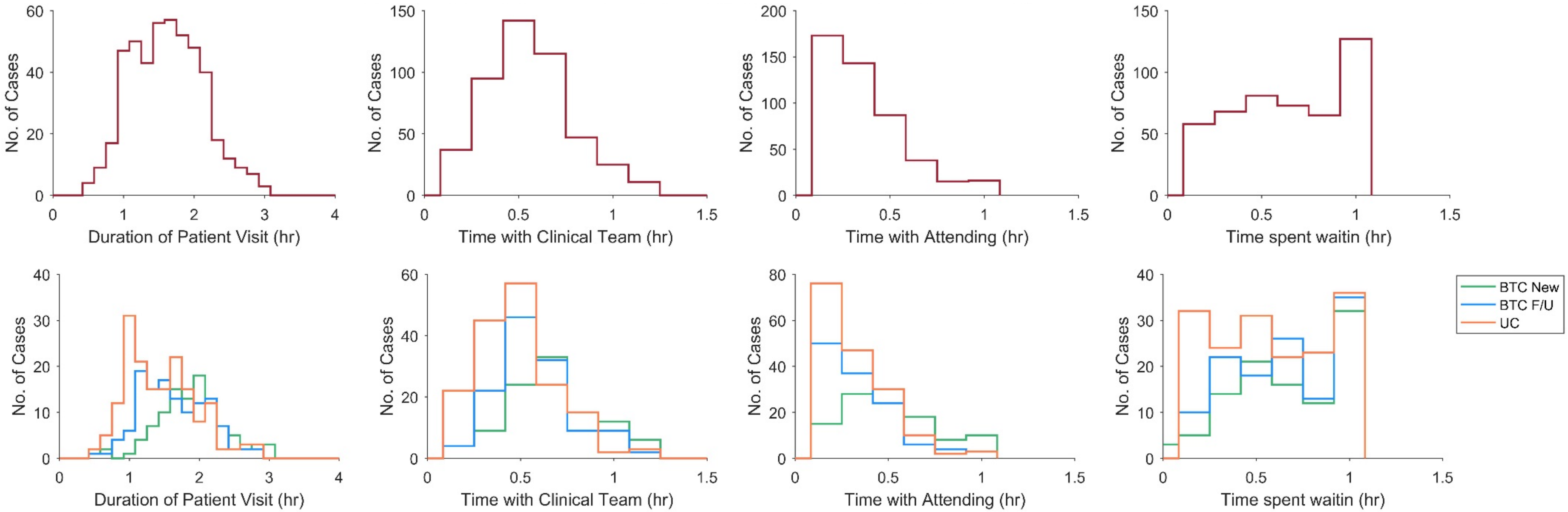
Example of parameter extraction

Clinical team time with patient



Model Calibration – Data Analysis

How we use the data collected to obtain model parameters



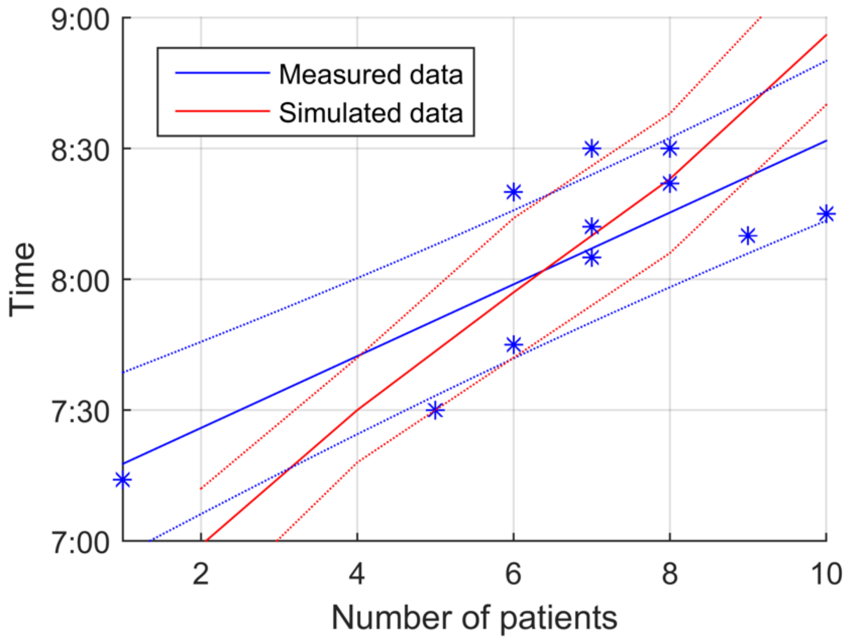
1. Visualize the distributions described by data
2. Explore characteristics of sub-groups
3. Extract summary statistics from distributions

Model Validation

Model Validation: checks the the model's representation of the real system.

Key Idea: Identify **extrinsic** (or derived) properties of the clinic

Examples: 1. When does the clinic tend to end?



2. How long do patient visits tend to take?

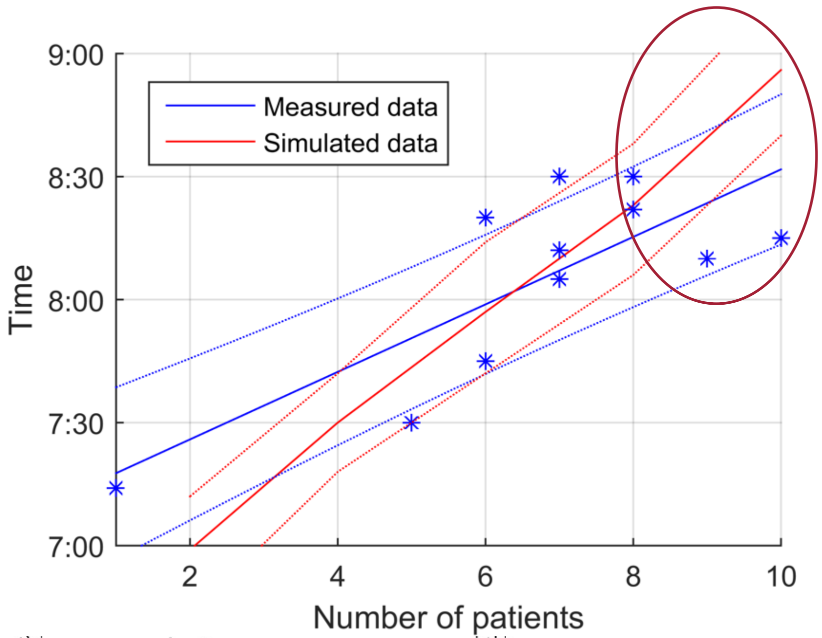
3. How long do patients, clinical teams spend waiting?

Model Refinement

Model Refinement: further improve the model accuracy

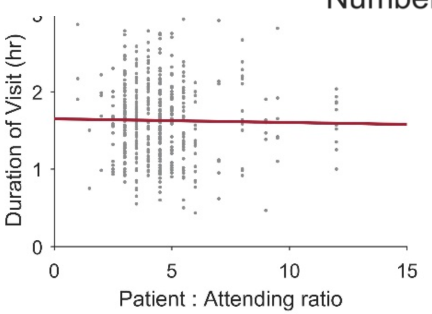
Key Idea: Identify discrepancies, look for explanation, and incorporate new dynamics

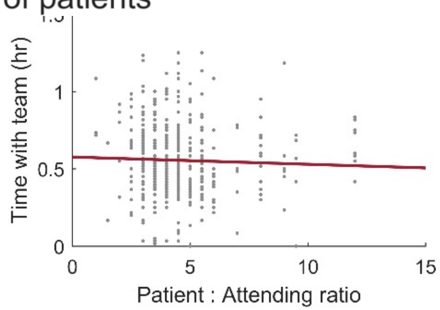
Example: Mismatch in simulated data and measured data for busier clinics

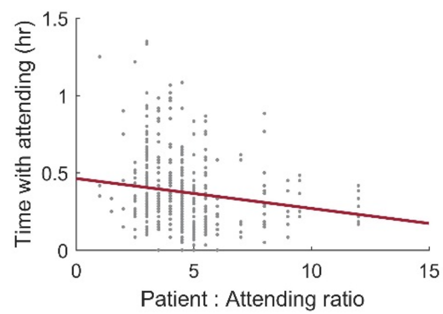


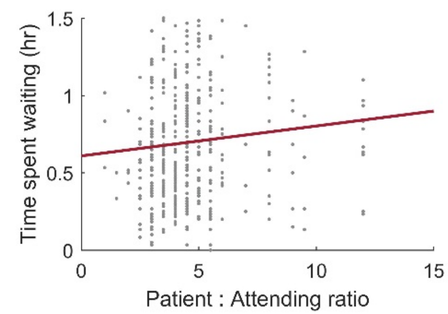
Potential causes for shorter appointments:

- Time pressure for clinicians later in session
- Increased motivation to keep to schedule
- Implement as “hurry factor”









Audience Challenge: Find optimal schedule

How can we **schedule the patients** to optimize the **end time of the clinic**? What policies will make an (positive or negative) impact?

crimsoncare.github.io/ccc-ima-sim

Conditions: 2 Attending physicians

4 Clinical Teams

8 Patients

- 3 Urgent Care (uc)
- 3 Bridge-to-Care New (btc_new)
- 2 Bridge-to-Care Follow-up (btc_fu)
  has preferred attending & team

Hints: Try different arrangements of preferred attending and team

Try different scheduled appointment times

BTC New appointments take the longest, may be beneficial to spread them out, front-load, or back-load

Take-away

- Data-driven simulation is an effective tool for making informed policy decisions
  - Enables quantitative, probabilistic thinking:

    Mean/media and **percentiles** of performance metrics

- Our model is constructed using the **calibrate** – **validate** – **refine** approach
  - Model parameters were chosen based on historical data
  - Validate model predictions against observations

- The simulation was used to explore several staffing / scheduling problems

- Getting started is straightforward:
  - Build a data collection system in your clinic
  - Code is open source: github.com/crimsoncare/ccc-ima-sim