Improving Outpatient Flow in a Chemotherapy Infusion Center

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Agenda

- The Team
- Cancer Background
- Infusion Overview
- Project Initiatives
  - Infusion
  - Pharmacy
  - Phlebotomy

The Team

Hassan Abbas	Nursing Student
Jeremy Castaing, Ph.D Candidate	Industrial and Operations Engineering
Ajaay Chandrasekaran	Computer Science Student
Chhavi Chaudhry	Industrial and Operations Engineering Student
Amy Cohn, Ph.D.	Associate Director, CHEPS
Diane Drago	Patient & Family Advisory Board (PFAB)
Marian Grace Boxer, MD	Professor, Internal Med., Hematology/Oncology
Corinne Hardecki, RN	Clinical Care Coordinator, Infusion
Madalina Jiga	Nursing Student
Jennifer Mathie	Supervisor, Department of Pathology
Jonathon McCormick	Industrial and Operations Engineering

The Team

Carol McMahon, RN	Nurse Supervisor, Infusion
Harry Neusius	Manager, Department of Pathology
Donald Richardson, Ph.D Pre-Candidate	Industrial and Operations Engineering
Stephanie See, RN	Nursing Graduate
Renee Stoklosa	Associate Supervisor, Department of Pathology
Brooke Szymanski, RN	Nursing Graduate
Irene Turkewycz, RN	Nurse Manager, Infusion
Carolina Typaldos, MHSA	Operations Manager, Infusion
Alon Zadok Weizer, MD, MS	Medical Director, UMCCC
Jonathan Zhou	Pre-Medical Student

Cancer Statistics

- Second leading cause of death in the United States
- In 2016, there will be an estimated 1,685,210 new cancer cases diagnosed and 595,690 cancer deaths in the US.
- Increased outpatient demand at Infusions Centers
  - Increased patient waiting times
  - Overworked staff

Source:
American Cancer Society (2016) http://www.cancer.org

U of M Comprehensive Cancer Center

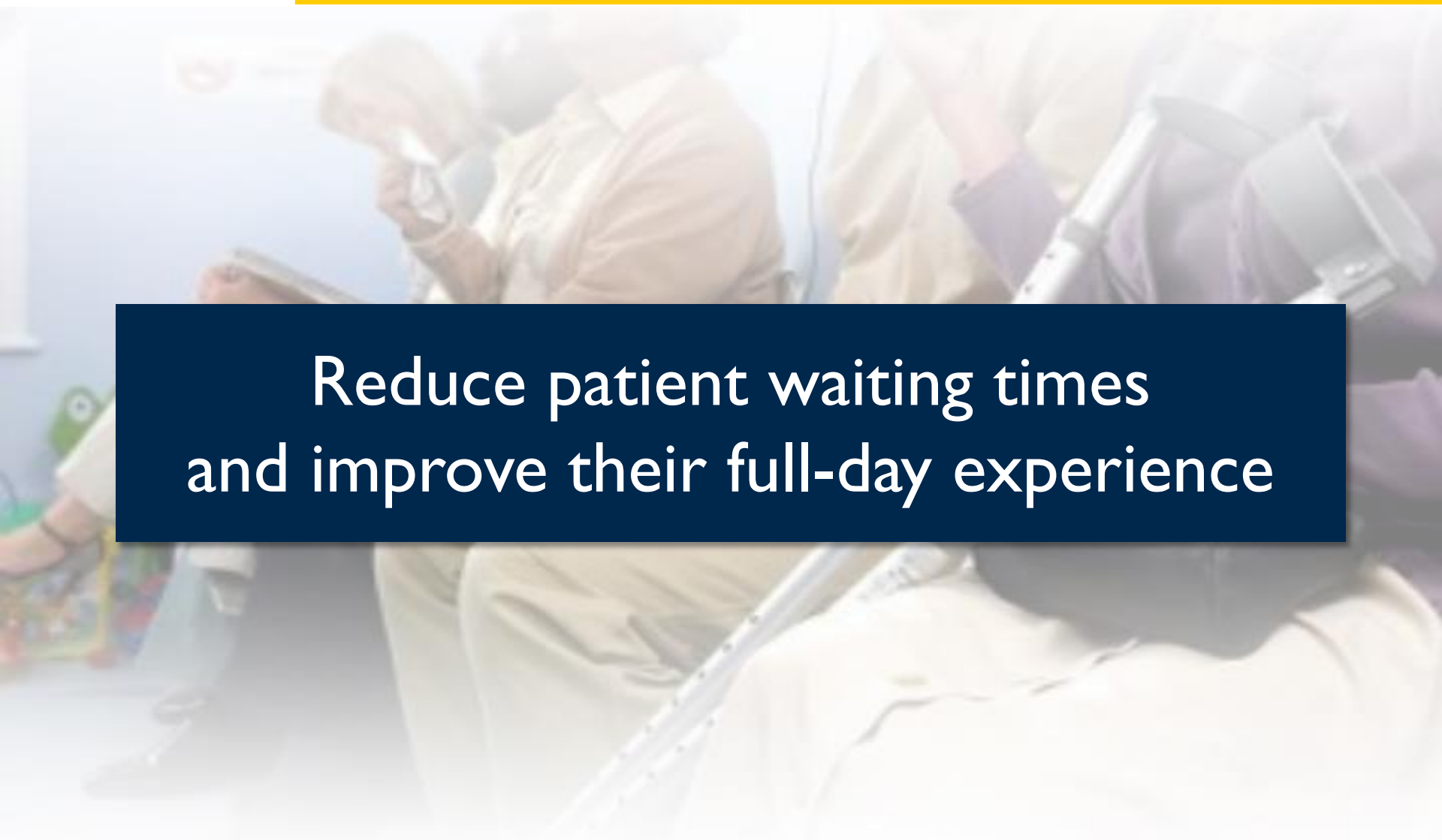
– In 2015, over 50% of outpatient visits in the UMCCC resulted in chemotherapy infusion treatments:

  - 97,147 outpatient visits
  - 58,419 infusion treatments

– Variable infusion treatment times (30 min – 8 hr)

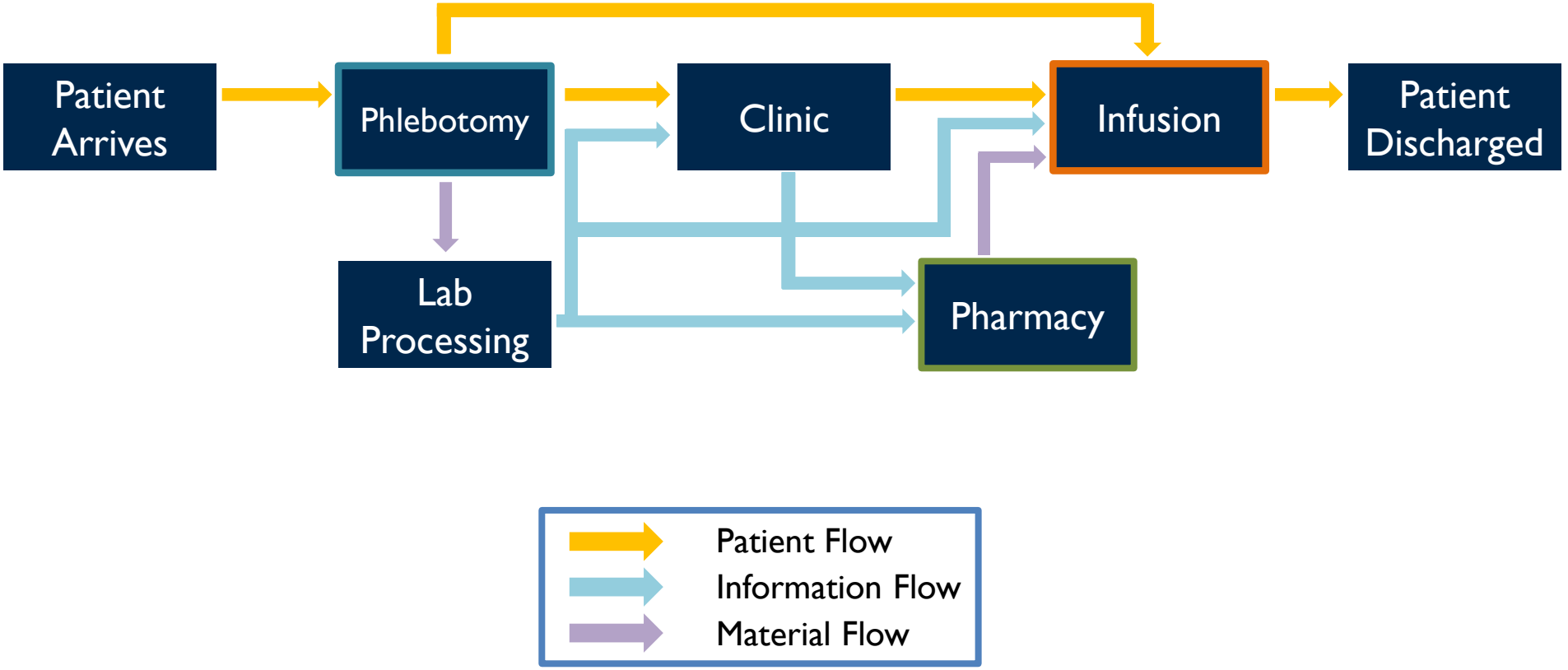
Source:
U of M Comprehensive Cancer Center (2016)
http://www.mcancer.org

Our Goal



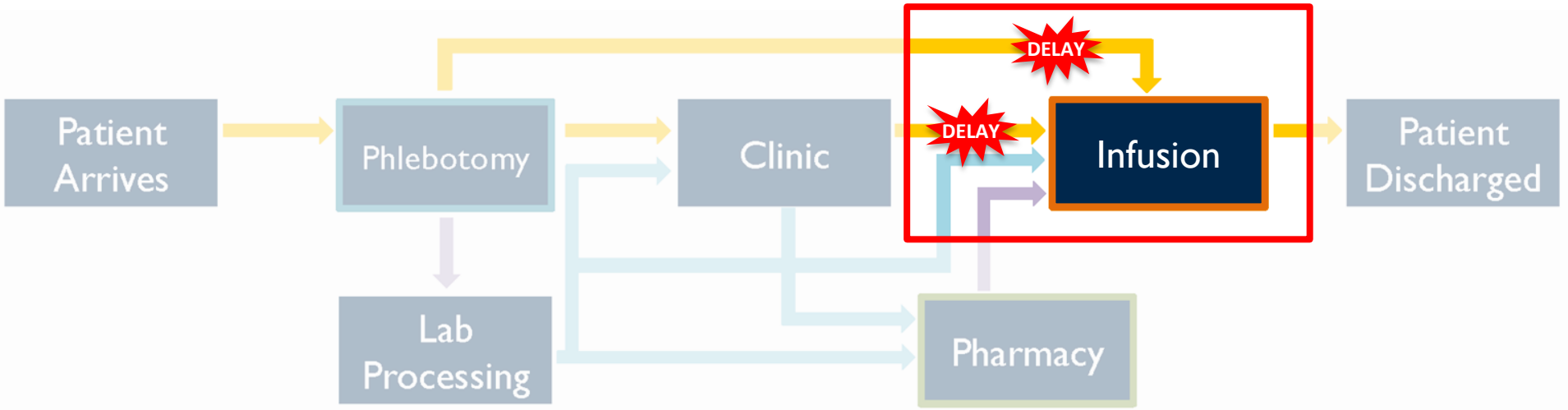
Reduce patient waiting times
and improve their full-day experience

Infusion Overview



Chemotherapy Infusion

On average, patients wait **~45 minutes** after arrival at infusion until they are seated in a chair.



Project Initiative:

Improved Scheduling of Infusion Patients

Chemotherapy Infusion

Improved Scheduling of Infusion Patients:

1) Stochastic Optimization

Castaing, J., Cohn, A., & Denton, B. (2015). Stochastic Programming Approach to Reduce Patient Wait Times and Overtime in an Outpatient Infusion Center (Working Paper)

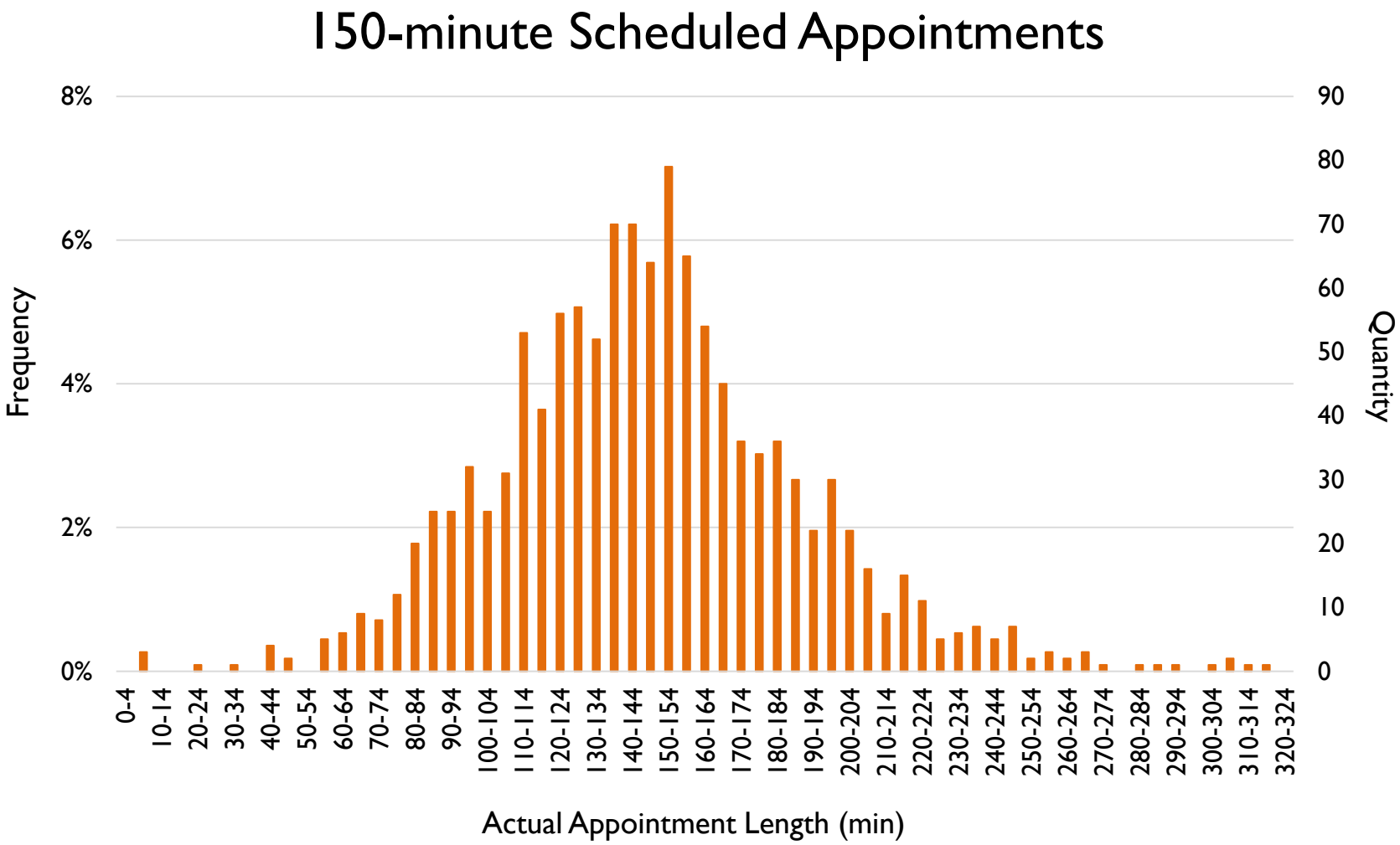
- Allow extra time for highly variable treatments and appointments in the middle of the day

Chemotherapy Infusion

Acuity Model

- Motivation:
  - Appointment lengths highly variable, even within appointment types
  - Increases wait time, staff overtime, end of day

Chemotherapy Infusion



Chemotherapy Infusion

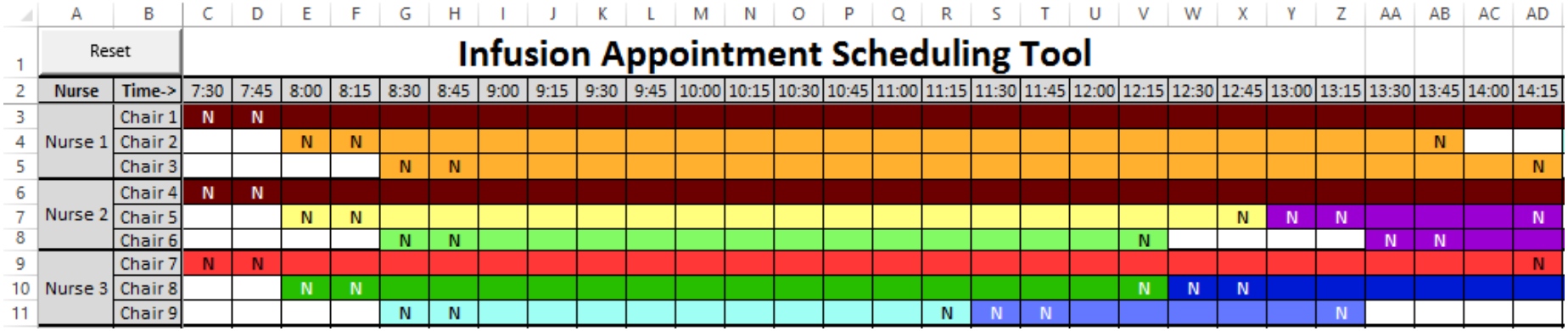
Acuity Model

- What factors contribute to actual appointment lengths?
  - Age, Sex, Treatment Type, Treatment Cycle, etc.
- Use regression techniques to better estimate slot lengths

Chemotherapy Infusion

Appointment Templating

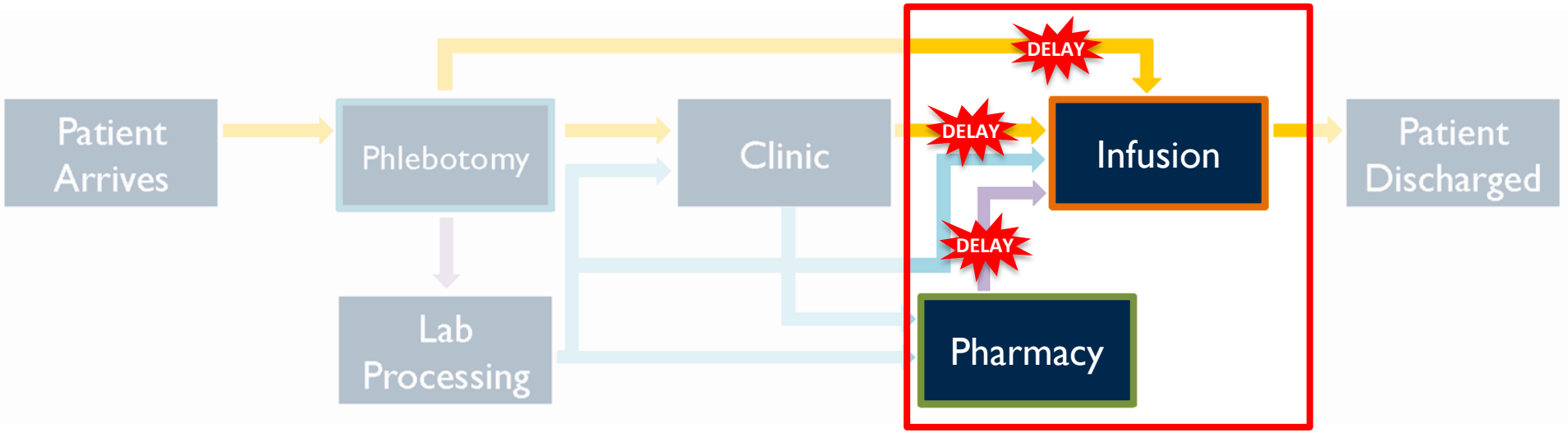
- Use Excel tool to test different scheduling algorithms
- Consulting directly with Cancer Center to ensure schedule feasibility



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD
1	Reset		Infusion Appointment Scheduling Tool																											
2	Nurse	Time->	7:30	7:45	8:00	8:15	8:30	8:45	9:00	9:15	9:30	9:45	10:00	10:15	10:30	10:45	11:00	11:15	11:30	11:45	12:00	12:15	12:30	12:45	13:00	13:15	13:30	13:45	14:00	14:15
3	Nurse 1	Chair 1	N	N																										
4		Chair 2			N	N																						N		
5		Chair 3					N	N																						N
6	Nurse 2	Chair 4	N	N																										
7		Chair 5			N	N																		N	N	N				N
8		Chair 6					N	N														N					N	N		
9	Nurse 3	Chair 7	N	N																										N
10		Chair 8			N	N																N	N	N						
11		Chair 9					N	N										N	N	N						N				

Pharmacy

Drugs not being ready could delay a patient's appointment.



Project Initiative:

Pre-mixing Drugs

Pharmacy

Pre-mixing Drugs:

- Pharmacy prepares drugs for infusion
  - Some are very expensive
  - Risk of waste
- Currently have a fixed list of drugs they are willing to pre-mix
  - Based on cost and common use
  - 2 hour window

Pharmacy

Pre-mixing Drugs:

- "Pre-mixing" may help improve patient waiting times/workload balance

- Evaluate trade-offs of improved wait/workload vs. risk of drug waste

Current Deferrals/No Shows

– Data from August 2014 to March 2015

- 13,138 total infusion appointments
- ~2000 patients
- 12.8% of appoints are same day deferrals/no shows
- 47% of patients have same day deferrals/no shows

Probability of Wasting a Drug (Cont.)

– Can depend on various factors.

- age
- sex
- treatment
- type of cancer
- deferral history
- etc.

Pre-mix Model Formulation

- Integer Programming Model
  - Objective: Max E[Reward] – E[Waste Cost]
  - Constraints
    - Drugs must be completed in 2 hour window
    - Only make finite number of drugs
    - No preemptions allowed

Pharmacy Sample

- Suppose we have patients scheduled to receive 15 different drugs.
- Each with variable mixing times

Drug	Hang by	Price	Currently pre-mixed	Treatment for
Carboplatin	12 hrs	2.52	Yes	Cancer of the ovaries, head, and neck
Paclitaxel	12 hrs	4.10	Yes	Cancer in the lungs, ovary, or breast
Cyclophosphamide	12 hrs	879.00	Yes	Leukemia and lymphomas, and nephrotic syndrome
Folotyn	12 hrs	4637.21	No	T-cell lymphoma
Adcetris	12 hrs	6516.00	No	Treats Hodgkin's lymphoma and systemic anaplastic large cell lymphoma

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Pre-mix Model Results

Drugs	Cost	Scen. I
A	$1.61	I
B	$2.52	I
C	$4.10	2
D	$6.80	I
E	$16.56	—
F	$83.40	—
G	$91.54	I
H	$155.56	I
I	$367.02	—
J	$698.60	—
K	$879.00	—
L	$1,158.84	—
M	$2,389.39	—
N	$4,637.21	—
O	$6,516.00	—
TOTAL	—	7

Parameters

- 2 doses for each drugs
- Drug mixing time variable for all drugs
- Patient Probability of deferral variable for all drugs

Pre-mix Model Results

Drugs	Cost	Scen. 1	Scen. 2
A	$1.61	1	1
B	$2.52	1	1
C	$4.10	2	1
D	$6.80	1	1
E	$16.56	—	1
F	$83.40	—	—
G	$91.54	1	1
H	$155.56	1	1
I	$367.02	—	—
J	$698.60	—	—
K	$879.00	—	—
L	$1,158.84	—	—
M	$2,389.39	—	—
N	$4,637.21	—	—
O	$6,516.00	—	1
TOTAL	—	7	8

Changed Parameters

- Inverse probabilities to cost of drug

Pre-mix Model Results

Drugs	Cost	Scen. 1	Scen. 2	Scen. 3
A	$1.61	1	1	—
B	$2.52	1	1	—
C	$4.10	2	1	1
D	$6.80	1	1	1
E	$16.56	—	1	—
F	$83.40	—	—	—
G	$91.54	1	1	1
H	$155.56	1	1	—
I	$367.02	—	—	1
J	$698.60	—	—	1
K	$879.00	—	—	1
L	$1,158.84	—	—	—
M	$2,389.39	—	—	—
N	$4,637.21	—	—	—
O	$6,516.00	—	1	—
TOTAL	—	7	8	6

Changed Parameters

- 2 doses for lower cost drugs 3-5 for higher cost drugs
- Patient Probability of deferral variable for all drugs

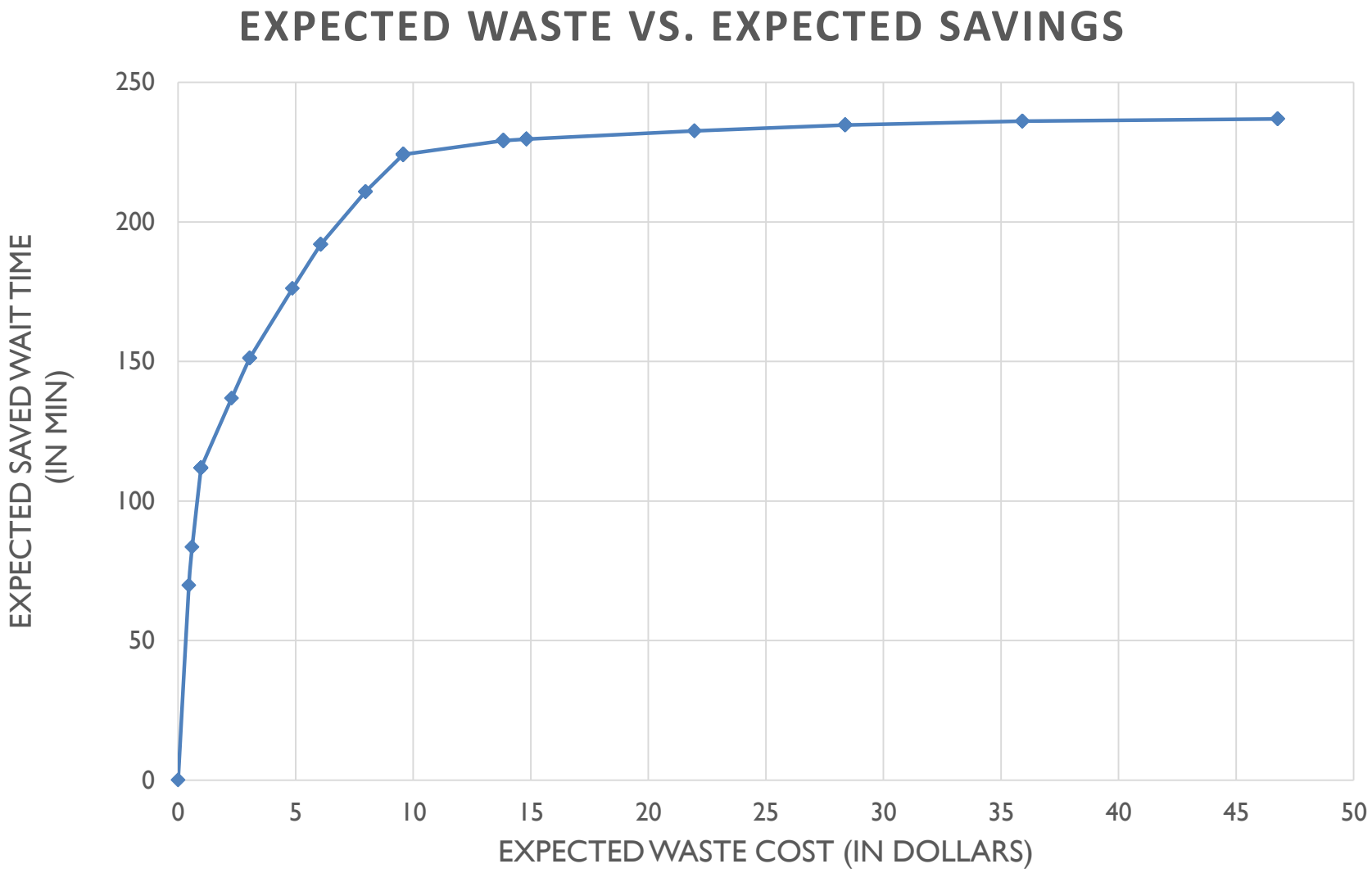
Pre-mix Model Results

Drugs	Cost	Scen. 1	Scen. 2	Scen. 3	Scen. 4
A	$1.61	1	1	—	—
B	$2.52	1	1	—	—
C	$4.10	2	1	1	—
D	$6.80	1	1	1	—
E	$16.56	—	1	—	—
F	$83.40	—	—	—	—
G	$91.54	1	1	1	—
H	$155.56	1	1	—	—
I	$367.02	—	—	1	2
J	$698.60	—	—	1	1
K	$879.00	—	—	1	1
L	$1,158.84	—	—	—	—
M	$2,389.39	—	—	—	2
N	$4,637.21	—	—	—	1
O	$6,516.00	—	1	—	—
TOTAL	—	7	8	6	7

Changed Parameters

- 2 doses for lower cost drugs 3-5 for higher cost drugs
- Inverse probabilities to cost of drug

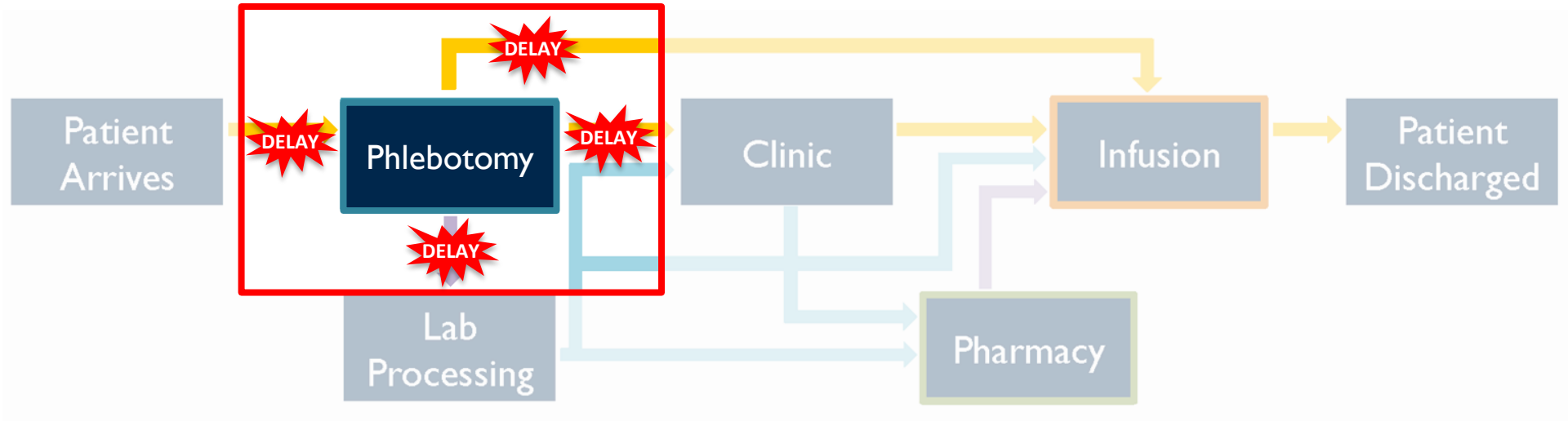
Pareto Curve: Scenario 2



Phlebotomy

Lab results needed:

- by **provider** before clinic appointment to assess patient
- by **pharmacy** to initiate drug preparation



Project Initiative:

Phlebotomy Process Analysis

Phlebotomy

Discrete Event Simulation Model

- Developed in C++
- **Event Queue**
  - Initialized with patient arrivals and phlebotomist schedule
  - Events are created and added to queue during simulation
  - Events in the queue complete in order (priority queue)
- While there are still events in the queue, continue completing them

Phlebotomy

Discrete Event Simulation Model

- Three (3) main event types, each corresponding to an availability queue:
  - **Patient Available for Check-In**
  - **Patient Available for Blood Draw**
  - **Phlebotomist Available**
- As events occur, they are either completed or added to one of the availability queues

Simulation Design

Event Queue

Event Type	Participant ID	Time
PatientAvailCI	3948	7:03:42
PatientAvailCI	2084	7:06:12
PhlebAvail	0962	7:15:00
PatientAvailCI	5541	7:16:09
PatientAvailCI	8737	7:20:33

PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time

Simulation Design

Event Queue

Event Type	Participant ID	Time
PatientAvailCI	3948	7:03:42
PatientAvailCI	2084	7:06:12
PhlebAvail	0962	7:15:00
PatientAvailCI	5541	7:16:09
PatientAvailCI	8737	7:20:33

PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time

Simulation Design

Event Queue

Event Type	Participant ID	Time
PatientAvailCl	2084	7:06:12
PhlebAvail	0962	7:15:00
PatientAvailCl	5541	7:16:09
PatientAvailCl	8737	7:20:33

PhlebAvail Queue

Participant ID	Time

PatientAvailCl Queue

Participant ID	Time
3948	7:03:42

Simulation Design

Event Queue

Event Type	Participant ID	Time
PatientAvailCl	2084	7:06:12
PhlebAvail	0962	7:15:00
PatientAvailCl	5541	7:16:09
PatientAvailCl	8737	7:20:33

PhlebAvail Queue

Participant ID	Time

PatientAvailCl Queue

Participant ID	Time
3948	7:03:42

Simulation Design

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Event Type	Participant ID	Time
PhlebAvail	0962	7:15:00
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PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time
3948	7:03:42
2084	7:06:12

Simulation Design

Event Queue

Event Type	Participant ID	Time
PhlebAvail	0962	7:15:00
PatientAvailCI	5541	7:16:09
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PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time
3948	7:03:42
2084	7:06:12

Simulation Design

Event Queue

Event Type	Participant ID	Time
PhlebAvail	0962	7:15:00
PatientAvailCI	5541	7:16:09
PatientAvailCI	8737	7:20:33

Generate Service Time: 2 minutes 51 seconds

PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time
3948	7:03:42
2084	7:06:12

Simulation Design

Event Queue

Event Type	Participant ID	Time
PatientAvailCI	5541	7:16:09
PatientAvailCI	8737	7:20:33
PatientAvailBD	3948	7:17:51
PhlebAvail	0962	7:17:51

PhlebAvail Queue

Participant ID	Time

PatientAvailCI Queue

Participant ID	Time
2084	7:06:12

Table-Top Simulation

- Hands-on activity
- Engage the whole team
- Educational component
- Verification
- Brainstorm alternatives

Future Work

Improved Scheduling of Infusion Patients:

- Acuity Model – Implement regression to identify key factors that contribute to appointment length
- Templating Model – Use historical data to predict future demand each day

Pre-mixing Drugs:

- Develop dynamic model to find an optimal drug-mixing schedule throughout the day
  - Updates as we observe patient deferrals

Discrete Event Simulation Model:

- Continued improvement towards representing current state
- Verification with clinicians and validation against data
- Evaluate potential alternative workflows

Thank you!

QUESTIONS?

CONTACT INFORMATION:

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Amy Cohn – amycohn@umich.edu

Appendix

- Phlebotomy – 253 patients per day
- Clinic (7 Total) – 311 patients per day
- Infusion:
  - Total of 51 infusion chairs
  - 123 patients per day
  - 20% of infusion appointments are coupled

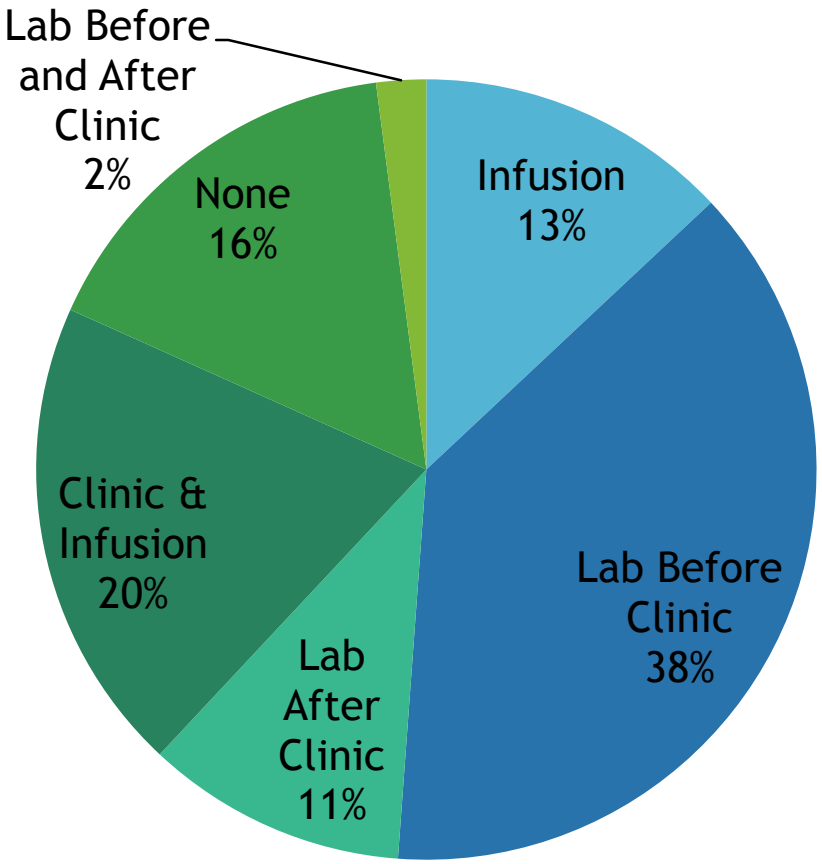
Alternative Workflow A

Workflow A	
Description	Split current check-in process in two
Pros	More patient interaction at check-in and no interruptions at order consolidation
Cons	Additional space, change in layout, more hand-offs

Alternative Workflow B

Workflow B	
Description	Order review and blood draw in the same area
Pros	2x verification and interaction with patient, fewer hand-offs
Cons	Additional space and equipment/computers

Appendix



Cancer Center Lab Patient Population
Data Source: May & June 2014 Appointment Data (10,850 patients)

Appendix

- Phlebotomy Staff Schedule

		630	700	730	800	830	900	930	1000	1030	1100
Totals do not include the Associate Supervisor		2	10	12	13	13	13	17	17	17	16
	Front Desk	-2	-3	-3	-3	-3	-2	-2	-2	-2	-2
	Greeter		-1	-1	-1	-1	-1	-1	-1	-1	
	Clinic Sweep				-1				-1		
	Breaks/Lunches					-1	-2	-2	-2	-2	-3
	Part Time/Day Off		-1	-1	-1	-1	-1	-1	-1	-1	-1
	Available to Draw	**0**	**5**	**7**	**7**	**7**	**7**	**11**	**10**	**11**	**10**

1130	1200	1230	1300	1330	1400	1430	1500	1530	1600	1630	1700	1730
16	15	15	15	15	15	15	14	7	5	4	4	4
-2	-2	-2	-2	-2	-2	-2	-2	-2	-1	-1	-1	-1
	-1				-1				-1			
-3	-3	-2	-3	-4	-2	-2	-2	-2				
-1	-1	-1	-1	-1	-1	-1						
10	**8**	**10**	**9**	**8**	**9**	**10**	**10**	**3**	**3**	**3**	**3**	**3**

Model Description

Sets

D: set of drugs d (e.g. 50 mg of Taxotere)

Variables

$x_{nt}^{d} = \begin{cases} 1 \\ 0 \end{cases}$ if we start mixing the *n*th dose of drug *d* at time *t*
otherwise

$y_{n}^{d} = \begin{cases} 1 \\ 0 \end{cases}$ If we don't mix the *n*th dose of drug *d*
otherwise

$z_{nt}^{d} = \begin{cases} 1 \\ 0 \end{cases}$ if we are mixing the *n*th dose of drug *d* at time *t*
otherwise

Objective

- We first define our Expected Waste cost of a drug with the following:

$$E_n^d[\text{waste cost}] = c_d P_d(n) \qquad E_n^d[\text{Reward}] = p_d \Delta_d [1 - P_d(n)]$$

- Then we maximize the difference between Projected Savings and Expected Waste

$$\textbf{\textit{maximize}} \sum_d \sum_n \sum_t \left(\alpha E_n^d[\text{Reward}] - (1-\alpha) E_n^d[\text{waste cost}]\right) * x_{nt}^d ,$$

Parameters

Δ_d: the reward or savings for mixing drug *d*

T: the total time units for the pre-mix period

c_d: the cost of drug *d*

p_d the time it takes to mix drug *d*

N_d: the number of doses needed for each drug *d based on* schedule of patients

C: pre-mix capacity for any pre-mix period

M: a very large number

Constraints

$$\sum_t x_{nt}^d + y_n^d = 1 \qquad \forall d, n$$

$$\sum_t z_{nt}^d + p_d * y_n^d = p_d \qquad \forall d, n$$

$$y_n^d \leq y_{n+1}^d \qquad \forall d, n = 1, \dots, N_d - 1$$

$$\sum_t t x_{nt}^d \leq \sum_t t x_{(n+1)t}^d + M * y_{n+1}^d \qquad \forall d, n$$

$$\sum_d \sum_n z_{nt}^d \leq C \qquad \forall t$$

$$x_{nt}^d \leq z_{n(t+i)}^d \qquad \forall d, n, t = 1 \dots (T - p_d + 1), i = 0 \dots (p_d - 1)$$

Parameters

- Δ_d: the reward or savings for mixing drug *d*
- T: the total time units for the pre-mix period
- c_d: the cost of drug *d*
- p_d: the time it takes to mix drug *d*
- N_d: the number of doses needed for each drug based *d based on* schedule of patients
- C: pre-mix capacity for any pre-mix period
- M: a very large number

Variables

$x_{nt}^d \in \{1,0\}$ $\quad \forall\, d \in D, n = 1 \dots N_d, t = 1 \dots (T - p_d + 1)$

$y_n^d \in \{1,0\}$ $\quad \forall\, d \in D, n = 1 \dots N_d$

$z_{nt}^d \in \{1,0\}$ $\quad \forall\, d \in D, n = 1 \dots N_d, t = 1 \dots \mathrm{T}$