



# ANNUAL

*Virtual* CONFERENCE & EXPO 2020



## Simulating Access And Patient Flow For A Cardiovascular ICU

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# CHEPS

**M** | CHEPS

**Rx**

A prescription  
to address  
system  
complexity  
in healthcare

INNOVATING  
HEALTHCARE  
DELIVERY

FOSTERING  
LEARNING

BUILDING  
COMMUNITY



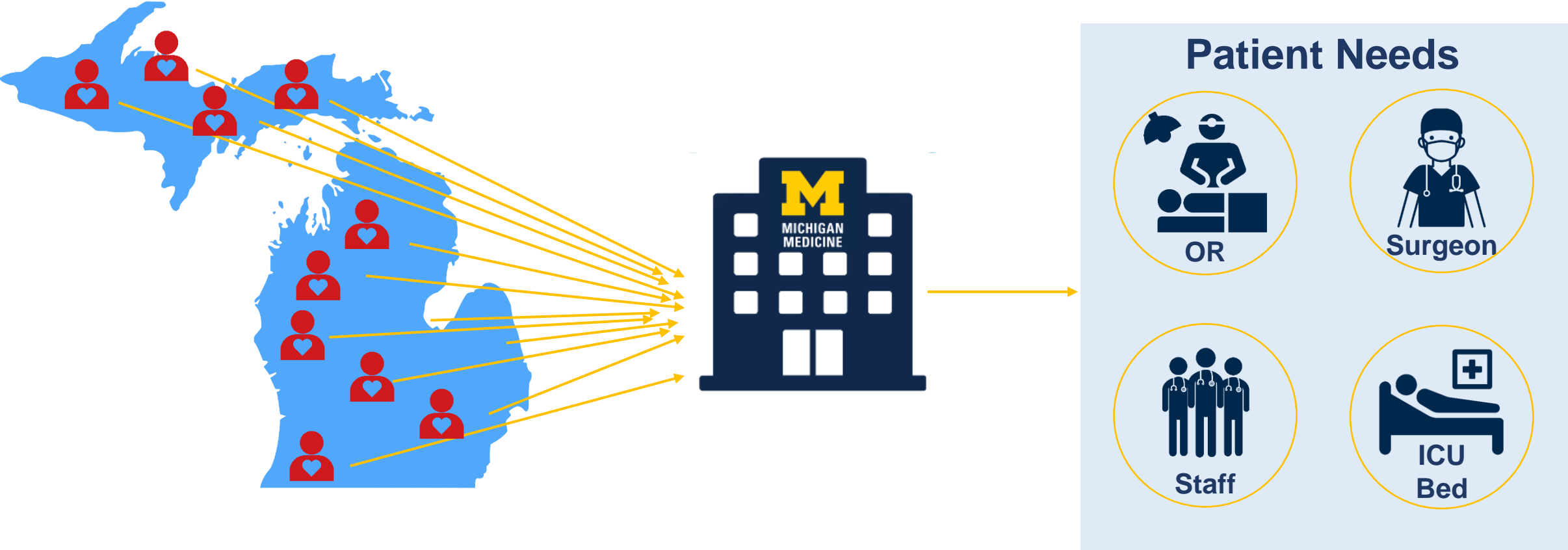
**POSITIVE IMPACT THROUGH...**

**Research**  
**Education**  
**Implementation**  
**Outreach**  
**Dissemination**

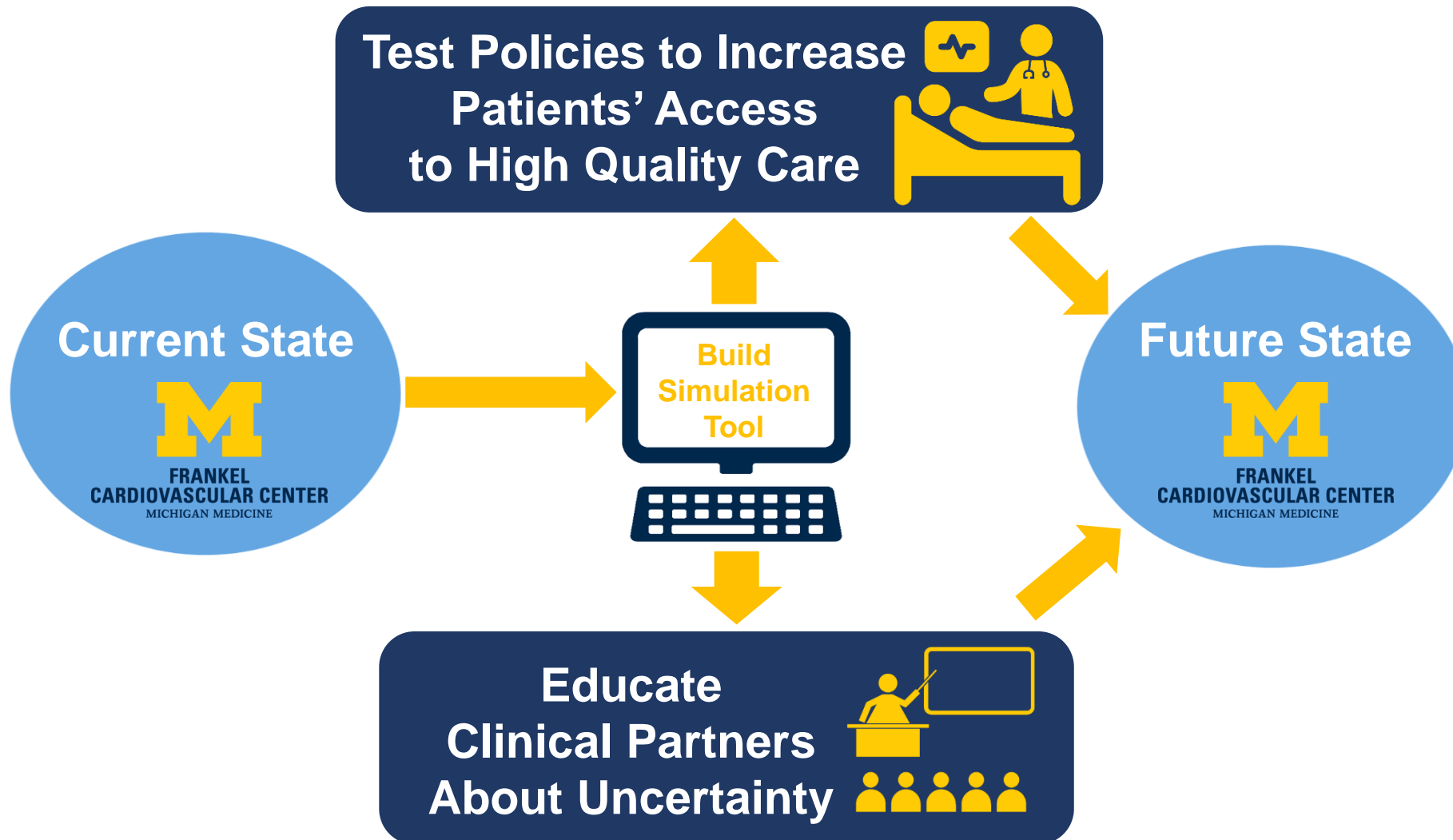
# OUTLINE

- Background
- Simulation Framework
- Analyses
- Future Research

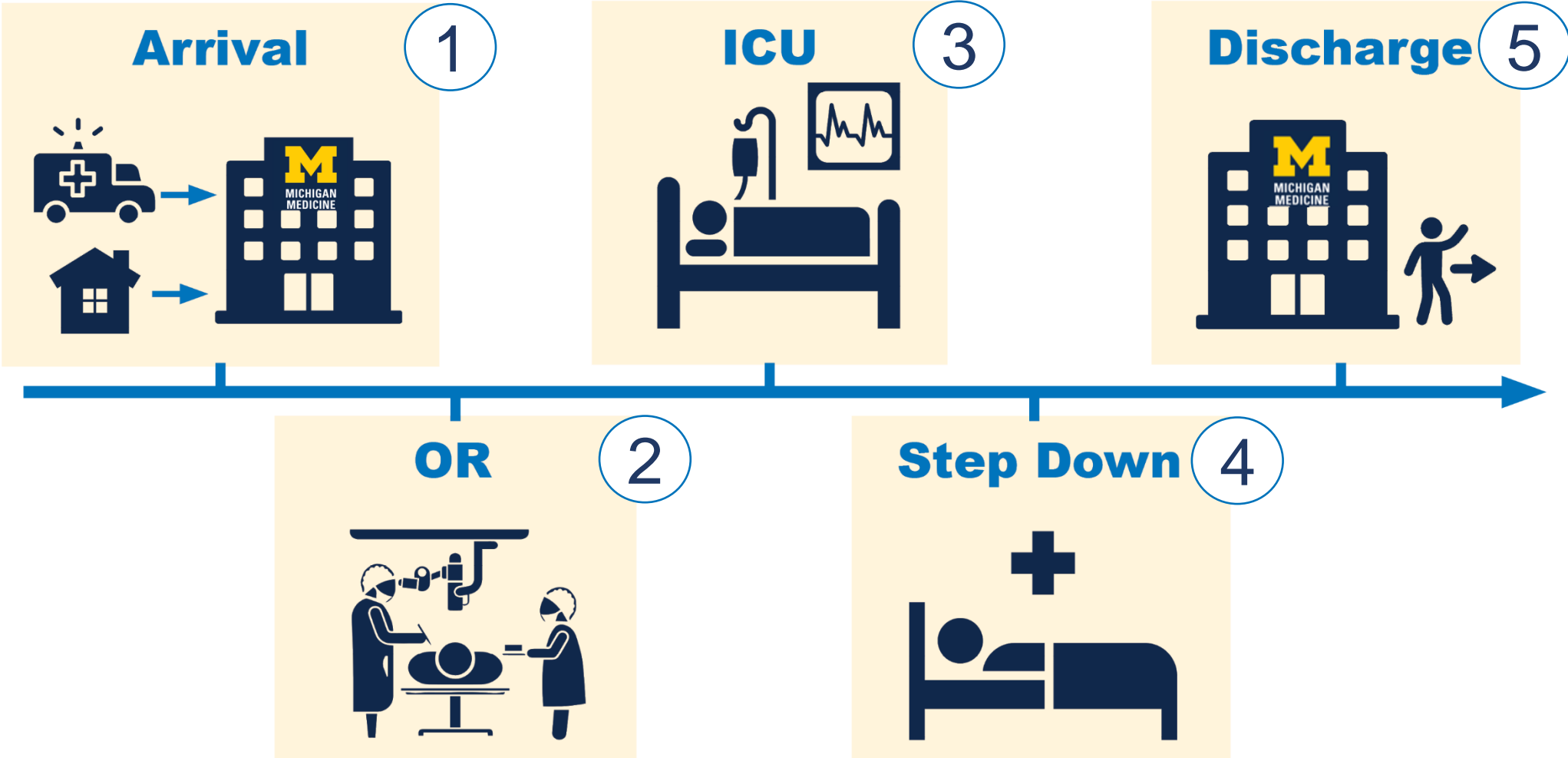
# BACKGROUND



# HOW SIMULATION CAN HELP



# PATIENT FLOW





# SIMULATION - INPUT

## Fixed input:

- Bed count per unit
- Time horizon: 1 year
- Number of replications: 1000
- Bounce back probability: determined value calculated from electronic health record data

## Variable input:

- Arrival rate: exponential distribution
- LOS in ICU and SDn: geometric distribution



# SIMULATION - INPUT

**Arrival rate:** depends on day of week (different days of the week have different arrival rates)

## LOS in ICU and SDn (ICU-first Patients):

- For patient  $X_i$ , we set  $ICULOS_i^j$  to represent his LOS of  $j$ th ICU visit
- We set  $SDLOS_i^j$  to represent his LOS of  $j$ th SDn visit
- Since the patient starts from ICU, whether he bounces back or not, he will visit ICU and SDn the same number of times
- $N$  represents the number of patients
- $M_i$  represents how many times patient  $i$  visits ICU/SDn.
- Then, we calculate:

$$ICULOS_1 = \frac{1}{N} \sum_{j=1}^N ICULOS_i^1, ICULOS_2 = \frac{1}{N * (\sum M_i)} \sum_{j=1}^N \sum_{i=2}^{M_i} ICULOS_i^j$$
$$SDLOS_1 = \frac{1}{N} \sum_{j=1}^N SDLOS_i^1, SDLOS_2 = \frac{1}{N * (\sum M_i)} \sum_{j=1}^N \sum_{i=2}^{M_i} SDLOS_i^j$$

- This means we separate patients' first ICU/SDn stay and the all remaining ICU/SDn stays

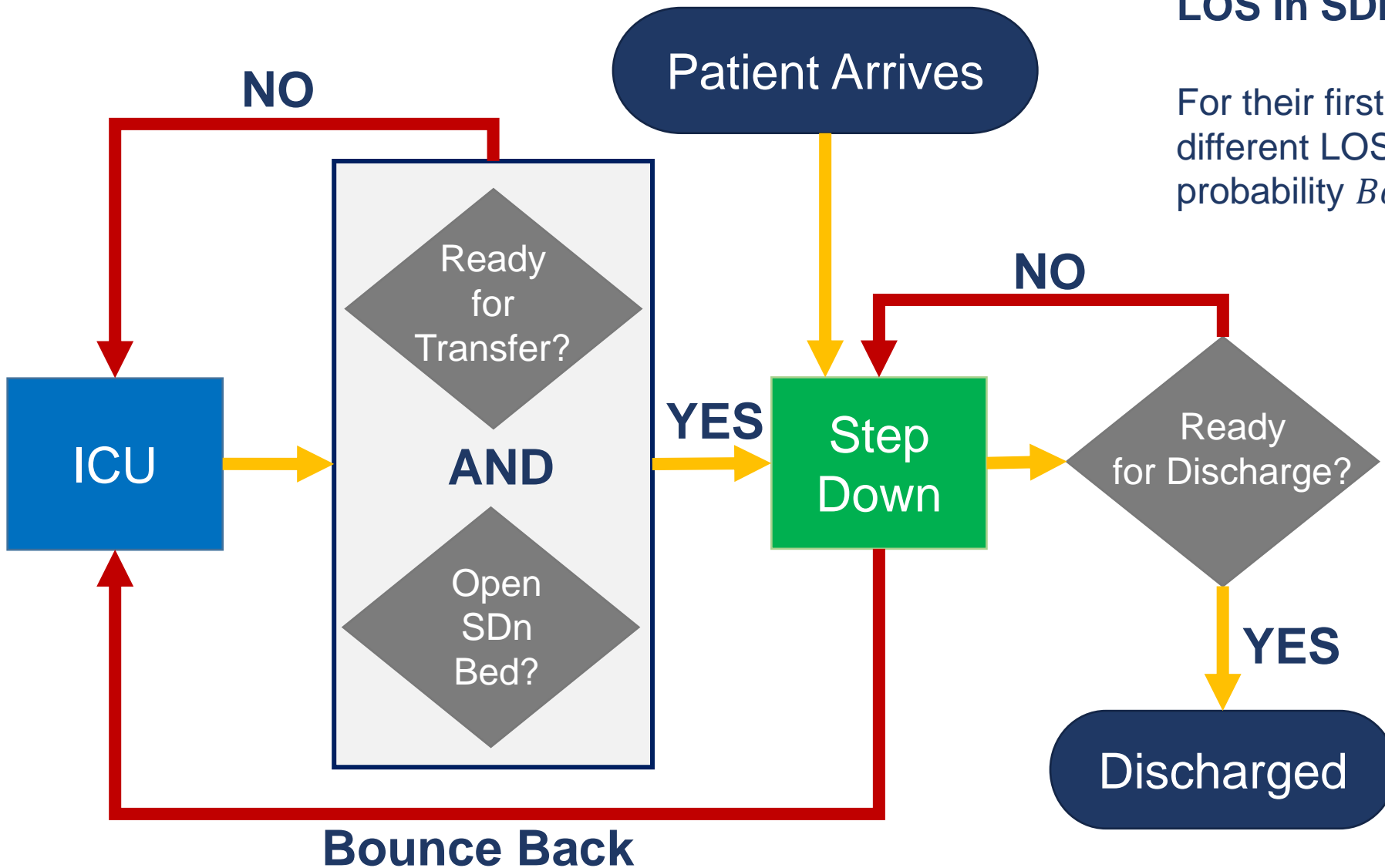
# SIMULATION - INPUT

## Bounce Back Probability

- 2 patient groups
  - LOS longer than median
  - LOS shorter than median
- Bounce Back probability used depends on LOS of the most recent ICU stay
  - $BounceBack_1$  for patients whose LOS of their most recent ICU visit is longer than the median
  - $BounceBack_2$  for patients whose LOS of their most recent ICU visit is below the median

$$BounceBack_1 > BounceBack_2$$

# SIMULATION - INPUT

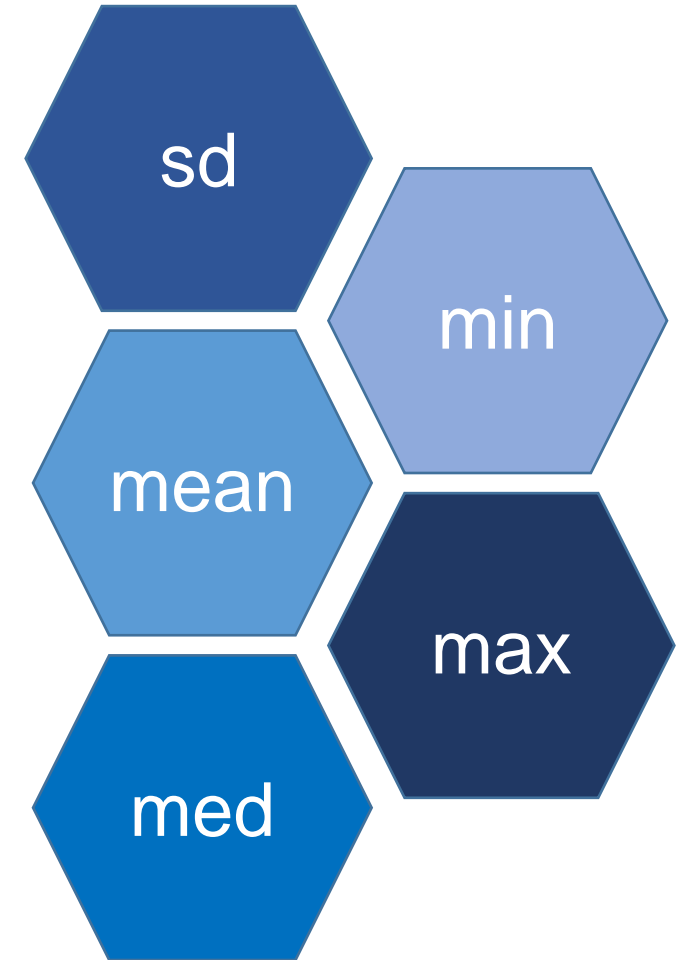


## LOS in SDn: (SDn-first patients)

For their first SDn visit, they have different LOS  $LOS_{SD}$  and bounce back probability  $BounceBack_{SD}$ .

# SIMULATION - METRICS

Number of...	
Patient Arrivals	
Accepted Patients	
Denied Patients	
ICU	Step Down (SDn)
<ul style="list-style-type: none"> <li>• Patient LOS</li> <li>• Unnecessary days in an ICU bed (SDn status)</li> <li>• Bed Utilization</li> </ul>	<ul style="list-style-type: none"> <li>• Patient LOS</li> <li>• Unnecessary days in a SDn bed (ICU status)</li> <li>• Bed Utilization</li> </ul>



# ANALYSES

## Analysis 1

How many beds we need in ICU

## Analysis 2

How many beds we need in SDn

## Analysis 3

How bounce back influences the denial rate

# BASE CASE PARAMETERS

- 1 Patient Type
- Arrival Rate vs. Day of Week

Day of Week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Arrival Rate (patients/hour)	0.237	0.281	0.245	0.231	0.243	0.090	0.080

- Time Horizon: 1 year
- Replications of simulation: 1000
- ICU-first patients (72.3%)

Parameters	$ICULOS_1$	$ICULOS_2$	$SDLOS_1$	$SDLOS_2$	$BounceBack_1$	$BounceBack_2$
Value	3.64 days	6.29 days	4.29 days	5.33 days	15.2%	10.8%

- SD-first patients (27.7%)

Parameters	$LOS_{SD}$	$BounceBack_{SD}$
Value	3.45 days	12.4%

# ANALYSIS 1 – HOW MANY BEDS IN ICU

Set 1000 SDn beds to avoid bottleneck from ICU to SDn.

Allocated ICU Beds	28	30	32	34
Annual Patient Arrival	1784	1784	1785	1783
<b>Patients Denied</b>	<b>8.67%</b>	<b>7.12%</b>	<b>5.92%</b>	<b>4.91%</b>
ICU Average LOS ICU Status	3.94	4.02	3.98	4.01
<b>ICU Average LOS SDn Status</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>
SDn Average LOS	6.03	6.05	6.02	5.99
<b>ICU Beds Utilization</b>	<b>81.93%</b>	<b>80.92%</b>	<b>79.92%</b>	<b>78.81%</b>

Acceptable level of patients denied: 5%

Acceptable level of ICU beds utilization: 75%

# ANALYSIS 2 – HOW MANY BEDS IN SDn

Set 34 ICU beds to avoid bottleneck from ICU to SDn.

Allocated SDn Beds	34	42	50	58	62
Annual Patient Arrival	1785	1781	1784	1786	1784
<b>Patients Denied</b>	<b>11.91%</b>	<b>8.54%</b>	<b>5.77%</b>	<b>5.13%</b>	<b>5.00%</b>
ICU Average LOS ICU Status	4.34	4.27	4.21	4.20	4.20
<b>ICU Average LOS SDn Status</b>	<b>0.54</b>	<b>0.44</b>	<b>0.37</b>	<b>0.36</b>	<b>0.36</b>
SDn Average LOS	5.81	5.93	5.98	5.99	6.00
<b>SDn Beds Utilization</b>	<b>79.84</b>	<b>73.08</b>	<b>61.73%</b>	<b>53.88%</b>	<b>50.56%</b>

Acceptable level of patients denied: 5%



# ANALYSIS 3 – INFLUENCE OF BB

Set 34 ICU beds and 50 SDn beds.

<b>BounceBack Probability 1</b>	<b>10.8%</b>	<b>12.8%</b>	<b>14.8%</b>	<b>16.8%</b>
<b>BounceBack Probability 2</b>	<b>15.2%</b>	<b>17.2%</b>	<b>19.2%</b>	<b>21.2%</b>
Annual Patient Arrival	1784	1784	1785	1786
<b>Patients Denied</b>	<b>5.69%</b>	<b>7.48%</b>	<b>9.93%</b>	<b>13.41%</b>
ICU Average LOS ICU Status	4.21	4.26	4.31	4.39
<b>ICU Average LOS SDn Status</b>	<b>0.37</b>	<b>0.42</b>	<b>0.48</b>	<b>0.59</b>
SDn Average LOS	5.99	6.25	6.52	6.78
<b>ICU Beds Utilization</b>	<b>78.77%</b>	<b>79.92%</b>	<b>80.76%</b>	<b>81.44%</b>
<b>SDn Beds Utilization</b>	<b>61.77%</b>	<b>66.87%</b>	<b>72.69%</b>	<b>78.45%</b>

# TAKEAWAYS

1. The benefits of adding ICU/SDn beds will plateau after a certain point as after this threshold, the marginal benefits of lowering the percentage of patients denied will be outweighed by the drawbacks of low bed utilization.
2. Even a small amount of uncertainty (change of bounce back probability) in the hospital system has a significant impact on patient flow.

# FUTURE RESEARCH

1. Add elective surgery process to the model which may influence the arrival rate
2. Use the simulation to help make better decisions about accepting transfers and arranging elective surgeries

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