



# AI in Healthcare: Hype, Hope, and Missed Opportunities

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# Agenda

- Sample explorations with generative AI
- Purposeful AI for everyday decisions
- Improving human-computer interactions
- Next step? Purposeful AI for large levers and high stakes

# Let's Ask ChatGPT...

DischargeMonth	LoS
6/30/2020	3.041666
7/31/2020	2.833333
8/31/2020	2.875
9/30/2020	2.833333
...	
4/30/2023	2.833333
5/31/2023	2.791666
6/30/2023	3

Here is my length of stay data by month. What is my baseline performance? Has anything changed?

# The Answer...

I apologize for the inconvenience. Since I'm an AI language model, I can't directly execute code with graphics or visualizations. However, I can show you the numerical results from the code that calculates the baseline performance. Here are the results:

Baseline Average Length of Stay: 2.85  
Baseline Minimum Length of Stay: 2.67  
Baseline Maximum Length of Stay: 3.33  
Baseline Median Length of Stay: 2.83  
Baseline Standard Deviation of Length of Stay: 0.13

These results give us an overview of the baseline performance for the length of stay data. The average length of stay is approximately 2.85 months, with the minimum being 2.67 months and the maximum being 3.33 months. The median length of stay is 2.83 months, and the standard deviation is 0.13 months.

If you need to visualize the length of stay trend over time, you can use the code provided in the previous response and run it using a Python environment or IDE that supports plotting libraries like Matplotlib. This will generate a line graph displaying the trend in the length of stay over the given time period.

# Can you give me R code...

```
# Length of Stay data
los_data <- c(3.041666, 2.833333, 2.875, 2.833333, 2.791666, 2.791666, 2.791666, 2.7
2.666666, 2.75, 2.75, 2.75, 2.75, 2.875, 2.875, 2.791666, 2.75, 2.75,
2.916666, 2.75, 2.75, 2.833333, 2.916666, 3, 3.333333, 2.916666, 2.833
2.833333, 2.875, 2.916666, 2.958333, 2.958333, 2.833333, 2.791666, 3)

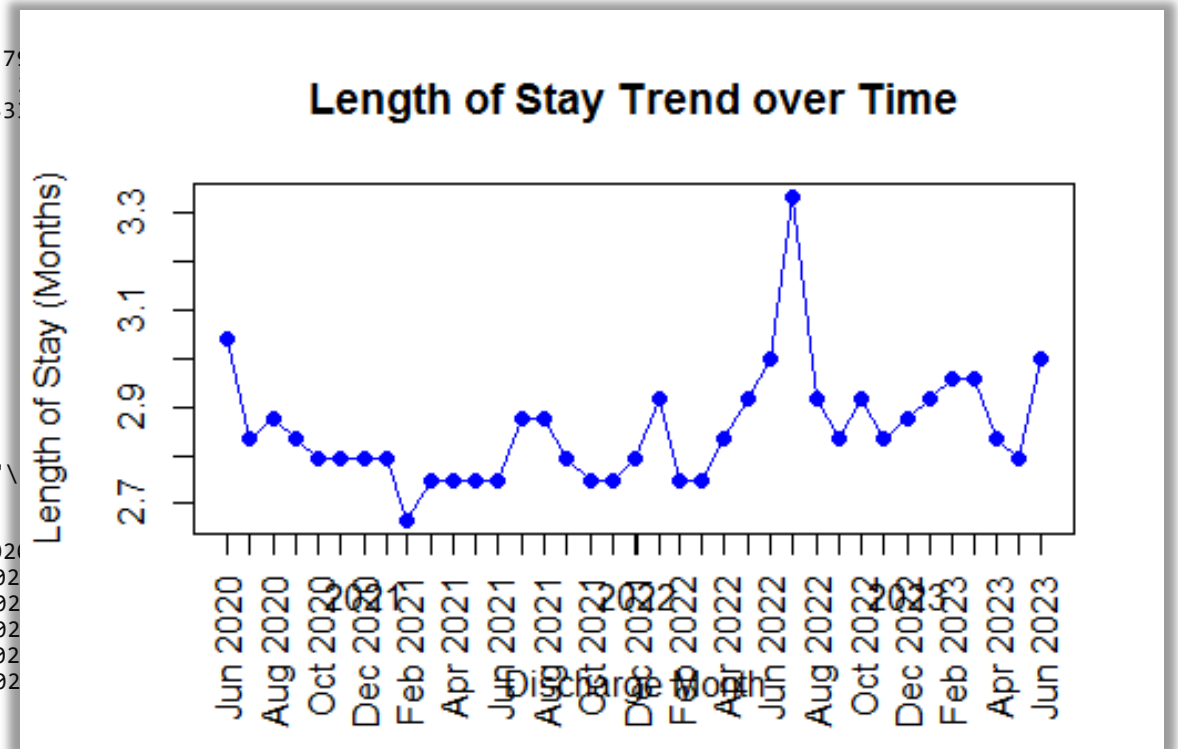
# Calculate baseline metrics
baseline_average_los <- mean(los_data)
baseline_min_los <- min(los_data)
baseline_max_los <- max(los_data)
baseline_median_los <- median(los_data)
baseline_std_los <- sd(los_data)

cat("Baseline Average Length of Stay:", round(baseline_average_los, 2), "\n")
cat("Baseline Minimum Length of Stay:", round(baseline_min_los, 2), "\n")
cat("Baseline Maximum Length of Stay:", round(baseline_max_los, 2), "\n")
cat("Baseline Median Length of Stay:", round(baseline_median_los, 2), "\n")
cat("Baseline Standard Deviation of Length of Stay:", round(baseline_std_los, 2), "\n")

# Discharge month data in MM/DD/YYYY format
discharge_months <- c('6/30/2020', '7/31/2020', '8/31/2020', '9/30/2020', '10/31/2020',
'12/31/2020', '1/31/2021', '2/28/2021', '3/31/2021', '4/30/2021',
'6/30/2021', '7/31/2021', '8/31/2021', '9/30/2021', '10/31/2021',
'12/31/2021', '1/31/2022', '2/28/2022', '3/31/2022', '4/30/2022',
'6/30/2022', '7/31/2022', '8/31/2022', '9/30/2022', '10/31/2022',
'12/31/2022', '1/31/2023', '2/28/2023', '3/31/2023', '4/30/2023',
'6/30/2023')

# Convert discharge months to Date objects
discharge_dates <- as.Date(discharge_months, format = "%m/%d/%Y")

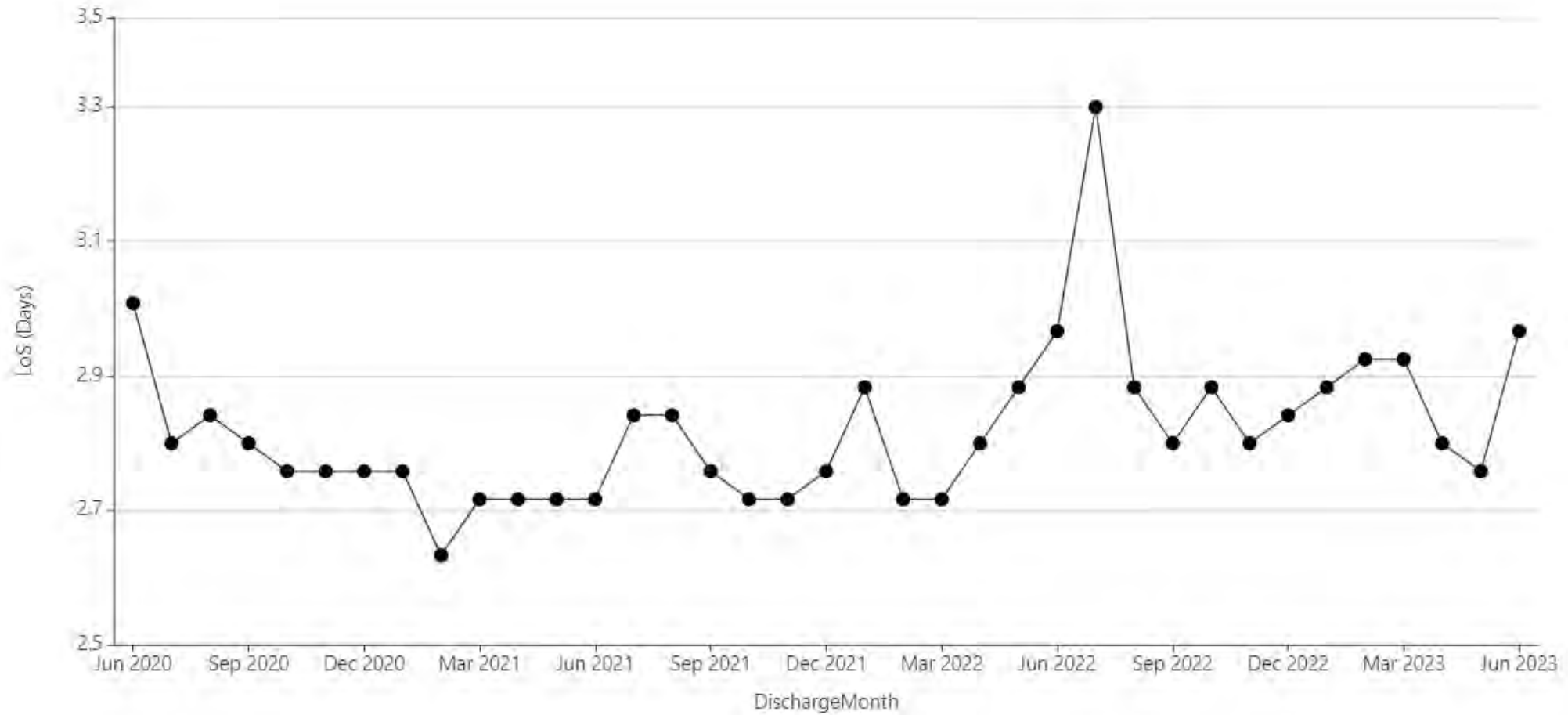
# Plot the length of stay data
plot(discharge_dates, los_data, type = "o", pch = 16, col = "blue", xlab = "Discharge Month", ylab = "Length of Stay (Months)",
main = "Length of Stay Trend over Time")
axis(1, at = discharge_dates, labels = format(discharge_dates, "%b %Y"), las = 2)
grid()
```



# Length of Stay (Days)

line chart

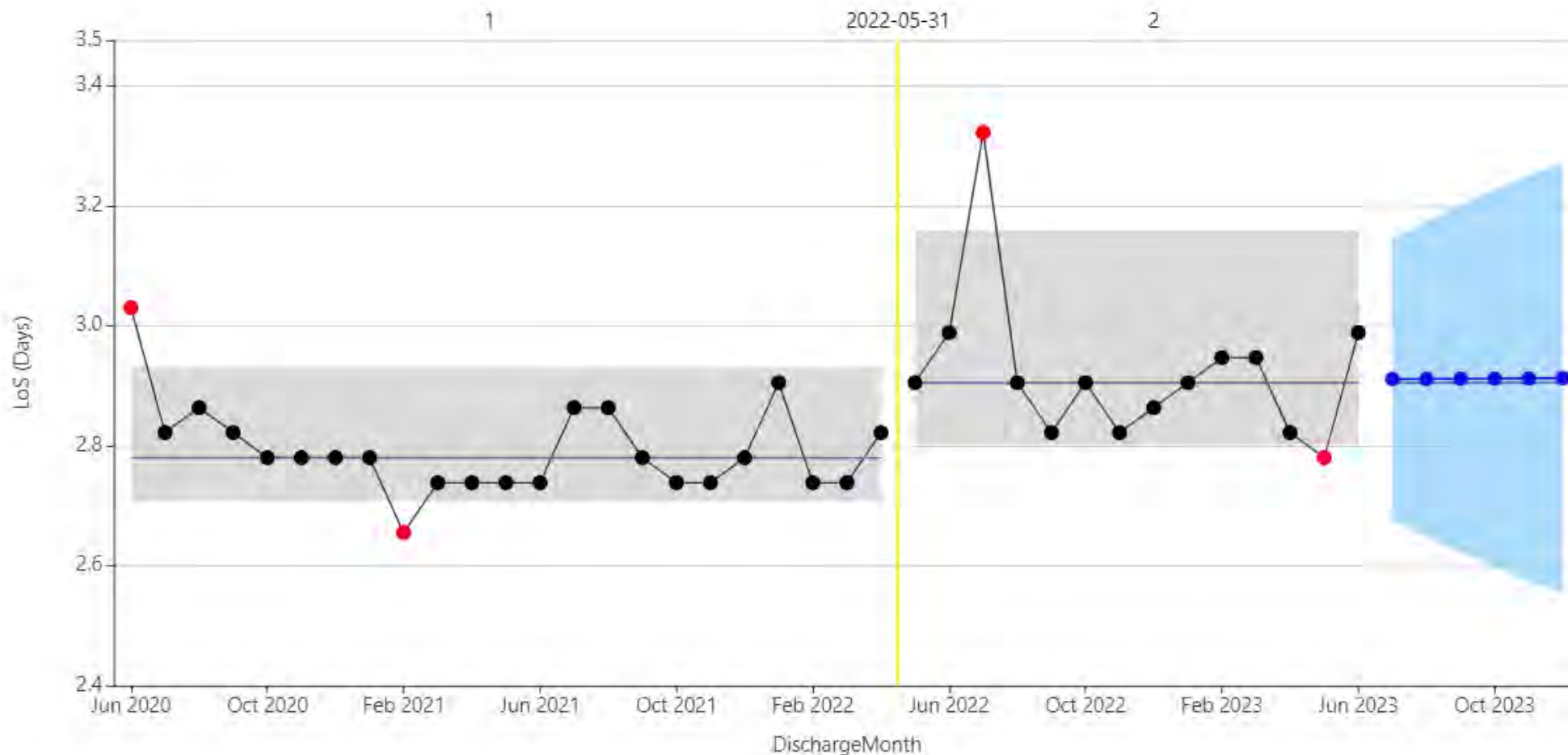
● Actual



# Length of Stay (Days)

SPC i-chart with changepoint detection & forecast

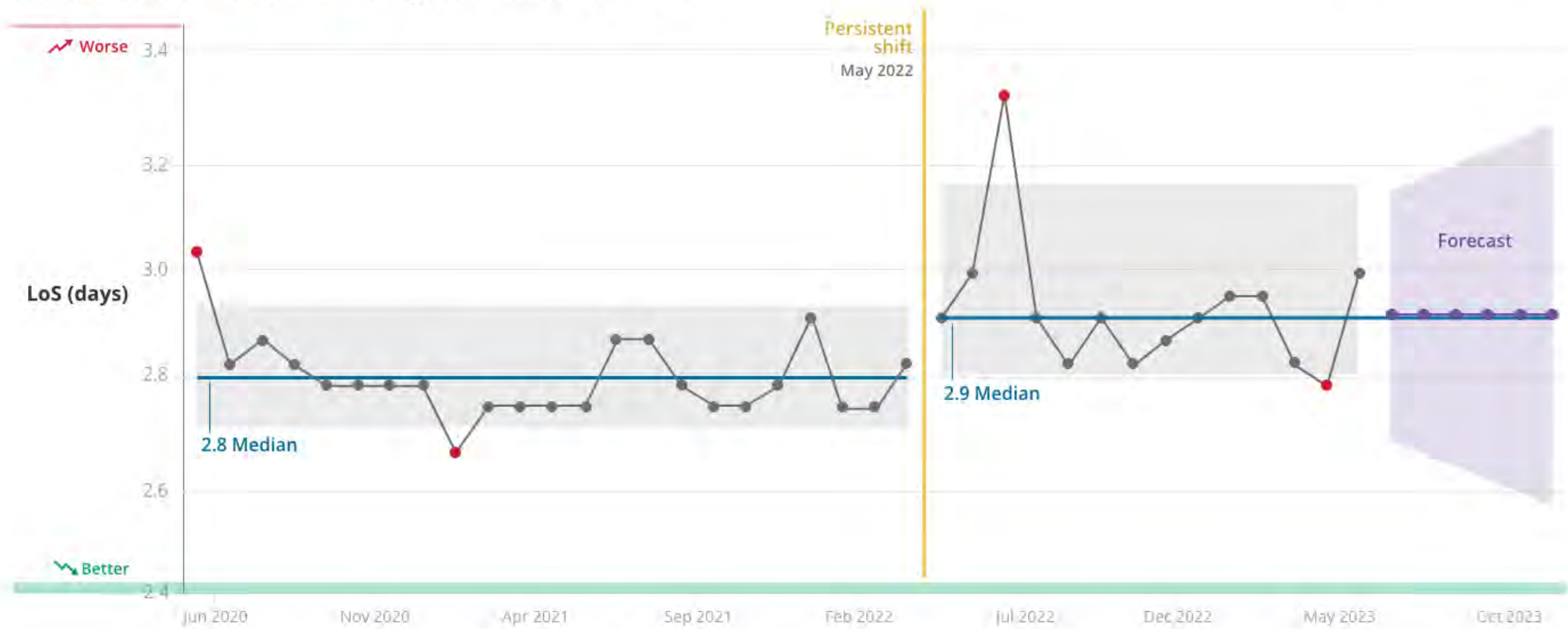
● Actual ■ Expected (median) ■ Control Limits (boot | 0.95) ● Limit violation ● Run violation ■ Detected Change ● Forecast ■ Forecast Control Limits



# Length of Stay (Days)

Statistical Process Control i-chart with change point detection & forecast

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- Actual
- Unusual point (Outside normal variation)
- Expected variation (95% confidence interval)
- Median
- Persistent shift
- Direction of improvement
- Forecasted
- Forecasted variation

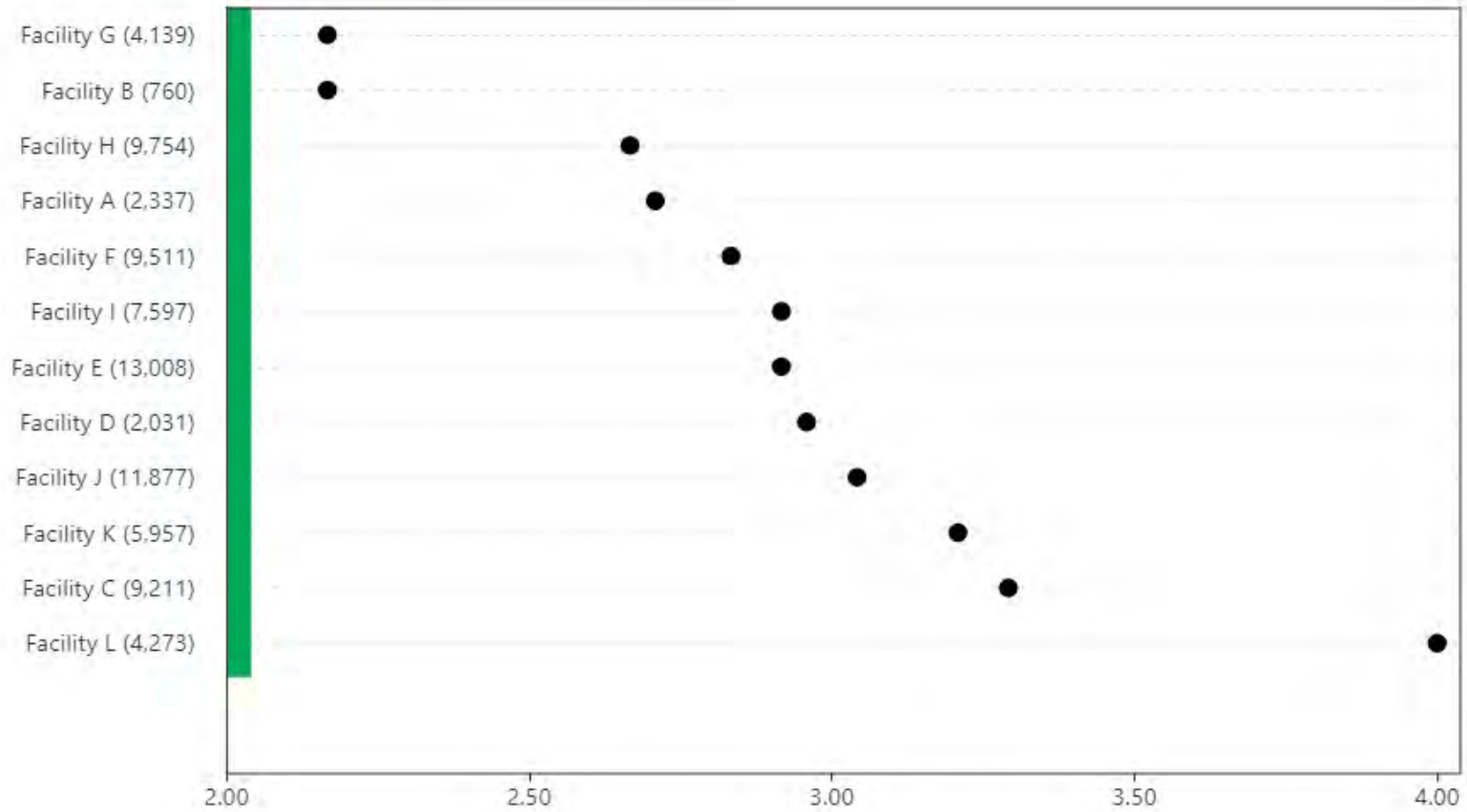


# Poll Question #3

How would you compare the current and possible new version of the charts?

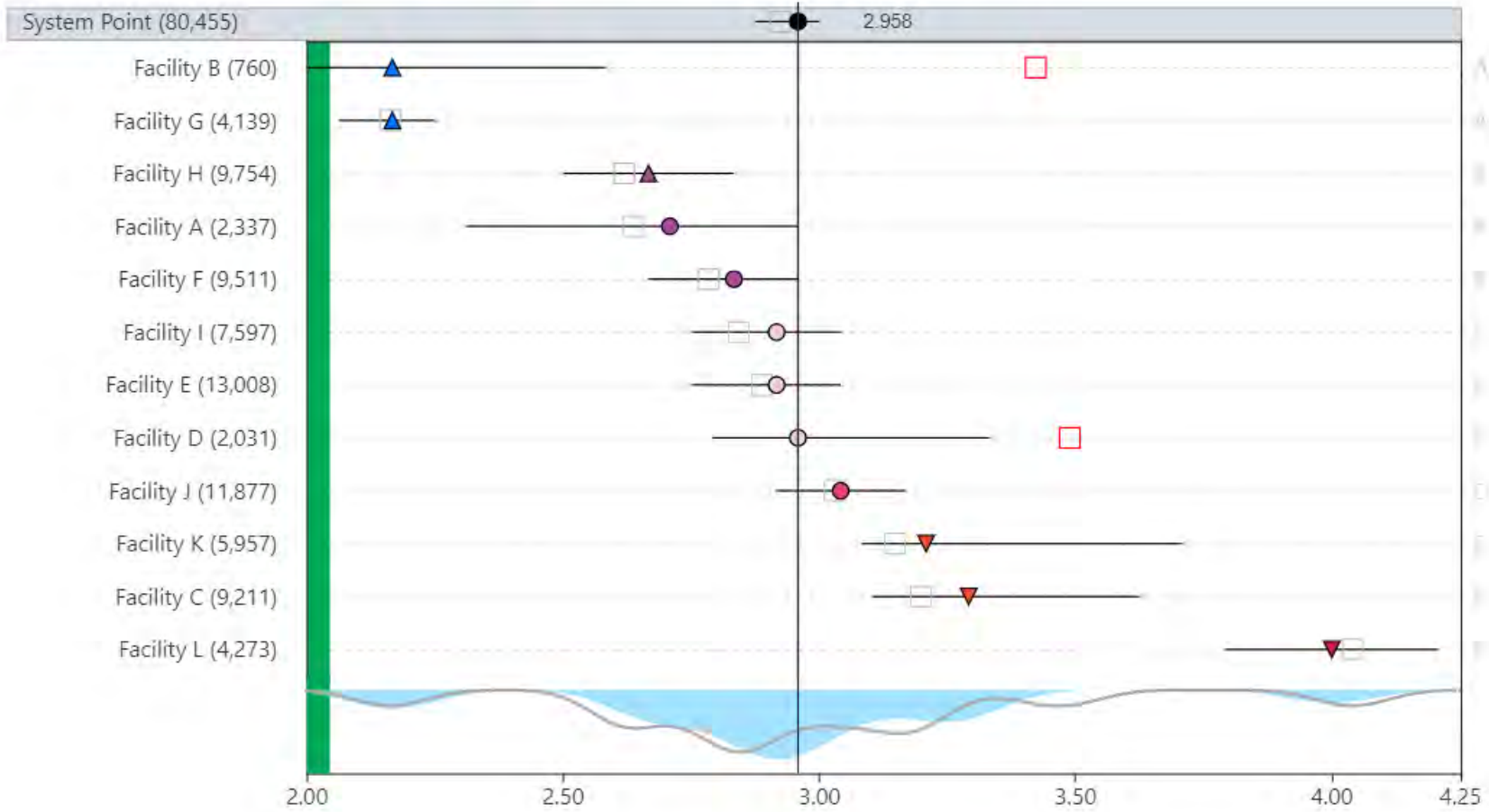
## Length of Stay (Days)

● Actual (2022-07-01 to 2023-06-30) ▼ Worse ▲ Better ■ Direction of Good



# Length of Stay (Days)

● Actual (2022-07-01 to 2023-06-30) ▼ Worse ▲ Better ■ Direction of Good □ Forecast (1-12 months) ▲ Cluster



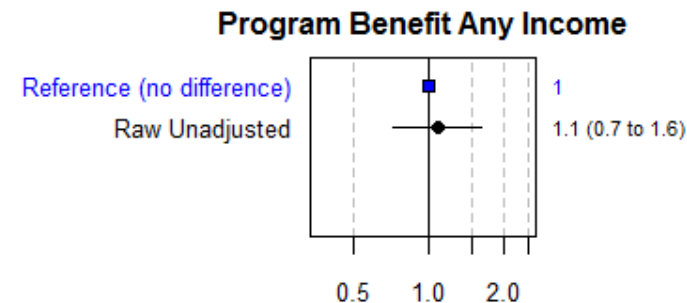
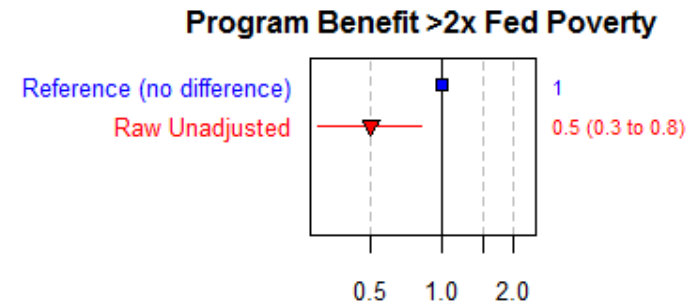
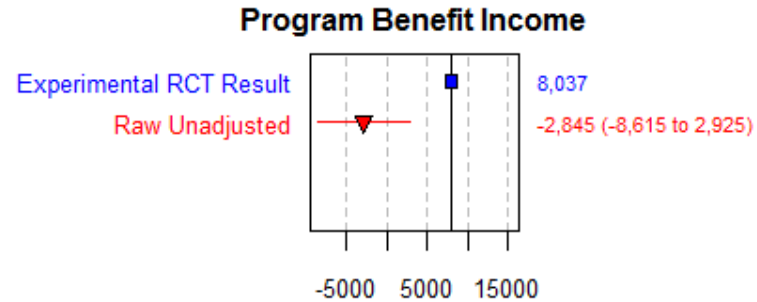
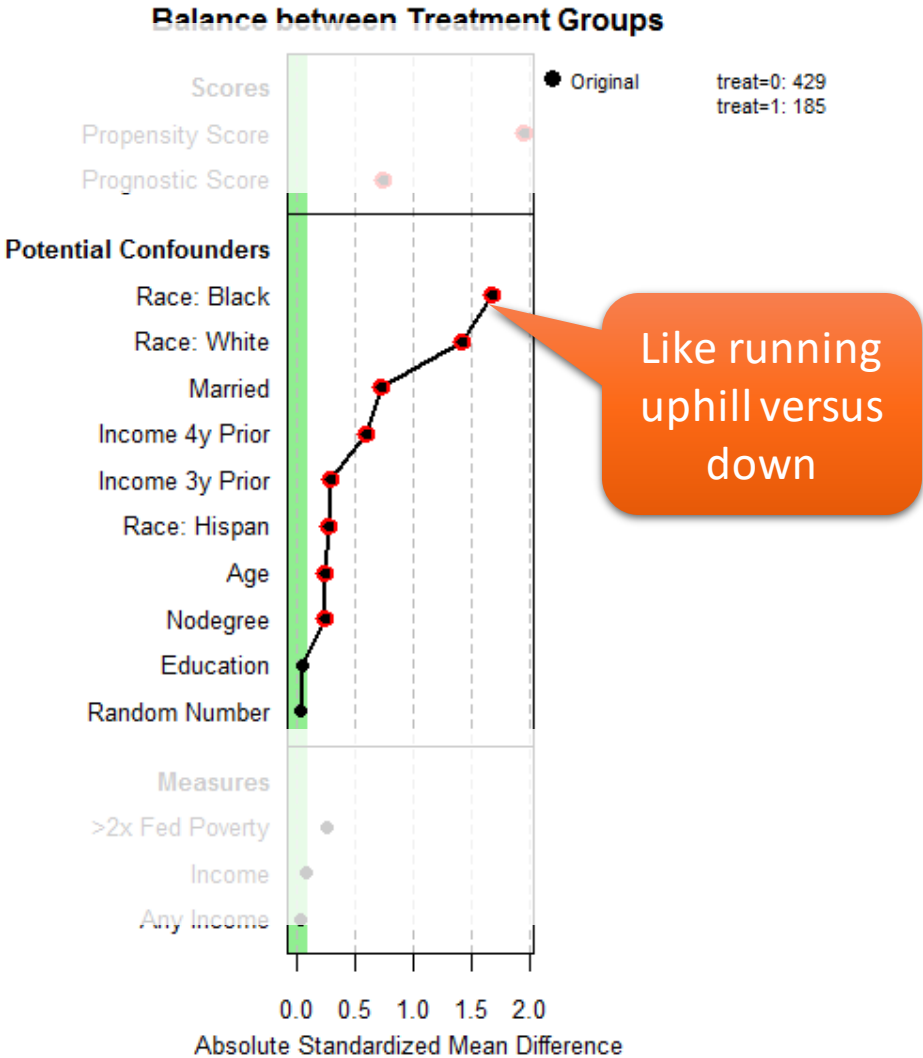
# Next step? Causal Analysis

# Large Levers, High Stakes

- Program evaluation: Should we continue/expand/alter/stop X (with a vendor)?
- Drug/device selection: Is X benefiting patients/people relative to the cost?
- Process change: How well is our innovative approach working?

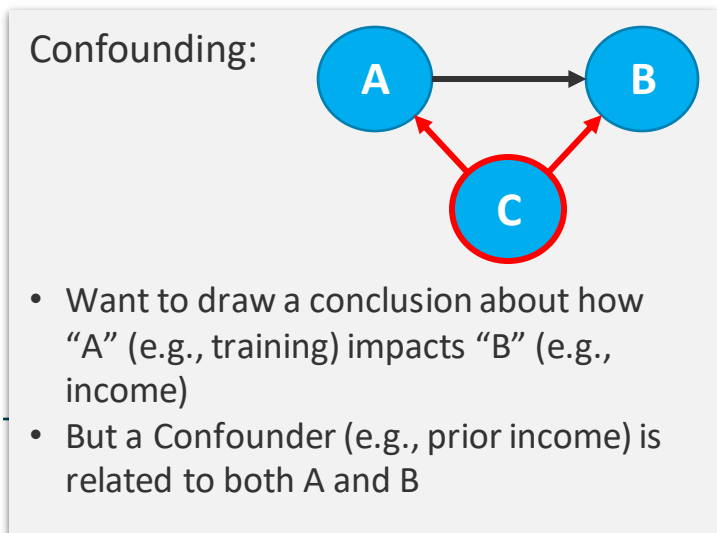
# Should we expand our work training program?

**Typical “comparison group” is not a good comparison (apples and oranges)**



Love Plot shows important “imbalances” (potential confounding):

- Both treatment group (propensity score) and outcome (prognostic score) can be predicted by other characteristics
- Important differences in race, marital status, prior income, age, an having no degree
- Small differences in education level
- Random number has no difference...as expected



# Poll Question #4

How interested are you in a follow-up session focused on causal analysis?



# Questions?

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