Lachlan Bassi 22975276

Abstract:

The aim of this analysis is to examine a diabetes dataset using quality control methods and control charts to assess whether the patient's blood sugar levels are under control. The dataset consists of blood sugar measurements at different times of the day over a period of 26 days. Control charts, including X-bar, R, S, and Cp charts, are employed to evaluate the process's statistical control and capability. The specified limits for blood sugar levels are defined as $3 \leq B \leq 8$.

The dataset used in this analysis contains null values, and four distinct approaches were employed to handle these null values: replacing them with the daily mean, replacing them with the time of day mean, ignoring them, and removing the null values. The majority of the analysis results indicate that the process is out of control and not capable of meeting the desired specifications. However, the most successful approach, conducted in part 4, involved ignoring null values and grouping the data by time of day instead of by day. This approach produced control chart results that suggest the process is in control. However, despite being in control, the process is still deemed not capable due to a Cp value that falls below the desired threshold of 1.0.

Based on the findings, it can be concluded that while the blood sugar levels may or may not be in statistical control, they definitely do not consistently meet the specified limits. This suggests the need for improvements in managing blood sugar levels to ensure they fall within the desired range.

To address these findings, recommendations include consistent monitoring, health education, lifestyle modifications, and regular check-ups. These measures aim to optimize blood sugar control, enhance patients' health conditions, and improve their overall quality of life.

This analysis contributes valuable insights into understanding and managing blood sugar fluctuations among diabetic patients, facilitating better disease management and improved patient outcomes.

Introduction

Diabetes mellitus [1] is a chronic metabolic disorder characterized by elevated blood sugar levels (hyperglycemia) due to the body's inability to produce or effectively utilize insulin. It is a global health concern with significant implications for individuals and healthcare systems worldwide. Effective management of blood sugar levels is crucial in preventing complications and maintaining overall health in diabetic patients. This paper aims to explore the daily fluctuations in blood sugar levels among diabetics and its relevance to disease management.

Diabetes and Blood Sugar Control:

Maintaining optimal blood sugar control is essential for individuals with diabetes. Chronically elevated blood sugar levels can lead to a variety of long-term complications [2], including cardiovascular disease, kidney damage, neuropathy, and retinopathy. Conversely, excessively low blood sugar levels (hypoglycemia) can result in immediate health risks and impaired cognitive function.

Diabetic individuals face the challenge of managing blood sugar levels within a narrow range. Factors such as diet, physical activity, medication adherence, stress, and individual variability can influence blood sugar fluctuations [3]. To develop effective disease management strategies, it is crucial to understand the patterns and variations in blood sugar levels experienced by diabetics.

Daily Fluctuations in Blood Sugar Levels:

Studies have shown that blood sugar levels tend to be highest after meals, especially if the meal contains a significant amount of carbohydrates [4]. This postprandial increase in blood sugar is regulated by the release of insulin, which facilitates glucose uptake by cells.

Furthermore, diabetics may experience a phenomenon known as the dawn phenomenon or the Somogyi effect [5]. The dawn phenomenon refers to the natural increase in blood sugar levels that occurs in the early morning hours due to hormonal changes. The Somogyi effect, on the other hand, describes a rebound rise in blood sugar levels following episodes of nocturnal hypoglycemia. These fluctuations can be challenging to manage, requiring adjustments in medication, diet, and lifestyle choices.

The Role of Continuous Glucose Monitoring (CGM):

Advancements in technology have led to the development of continuous glucose monitoring (CGM) systems [6] that provide real-time data on blood sugar levels. CGM devices offer diabetic patients the ability to monitor their blood sugar continuously throughout the day, providing valuable insights into fluctuations and trends.

The article [7] highlights the benefits of CGM in improving blood sugar control and reducing the risk of complications. CGM data can be used to identify patterns, detect episodes of hypoglycemia or hyperglycemia, and guide treatment adjustments. By understanding the daily variations in blood sugar levels, healthcare professionals can tailor individualized management plans to optimise diabetes control.

The dataset provided includes blood sugar measurements taken at different times of the day (morning, lunch, dinner, and evening) over a period of 26 days. However, it is worth noting that the dataset contains some null values, indicating missing measurements at certain time points. These null values will require appropriate methods for handling missing data during the analysis.

To assess whether the patients' blood sugar levels fall within the desired control range of 3-8, control charts will be employed. Control charts provide a visual representation of data over time and help determine if a process is in a state of statistical control. Specifically, X-bar, r chart, s chart, and cp chart will be utilized for the analysis.

Methodology

The provided data set consists of numerous null values and the data set is limited in size only containing 26 rows. Because of this, the method in which the null values are to be handled will have a significant impact on the results of the analysis and so multiple methods of handling the null data were employed and compared.

The first method used to handle null values involved replacing them with the mean of the respective column. This method provides a way to estimate missing values based on the average measurement for each corresponding time interval – (morning, lunch, dinner, and evening).

The second method entailed removing rows containing null values from the dataset. By eliminating these rows, the analysis focuses solely on complete data points, allowing for a more precise evaluation of the remaining measurements but it does result in a much smaller data set for analysis.

The third method employed was to replace null values with the daily average. In this approach, the missing values are filled in using the average of the available measurements from the same day. This method takes into account the trend observed on the specific day and offers an estimation based on the existing data points.

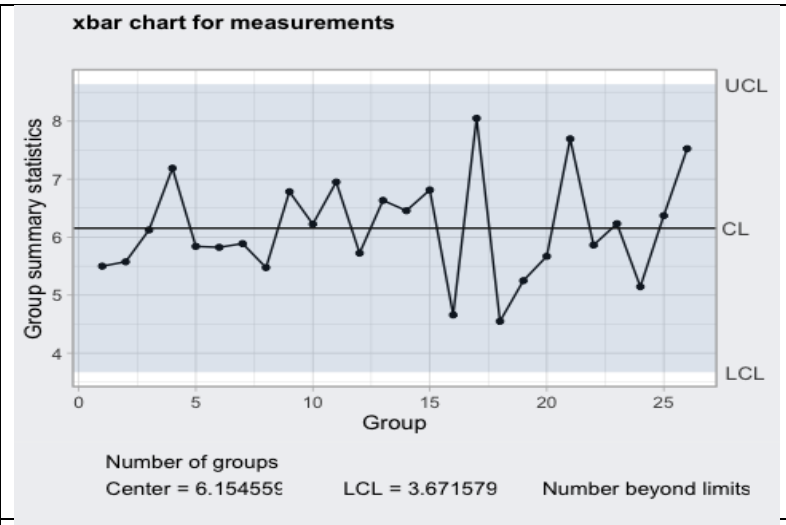
Lastly, the fourth method involved grouping the data by time of day rather than by day. This approach analyzes control charts separately for each time interval (morning, lunch, dinner, and evening) without manipulating or removing null values. The nulls in this case are left in the dataset and are disregarded during the analysis.

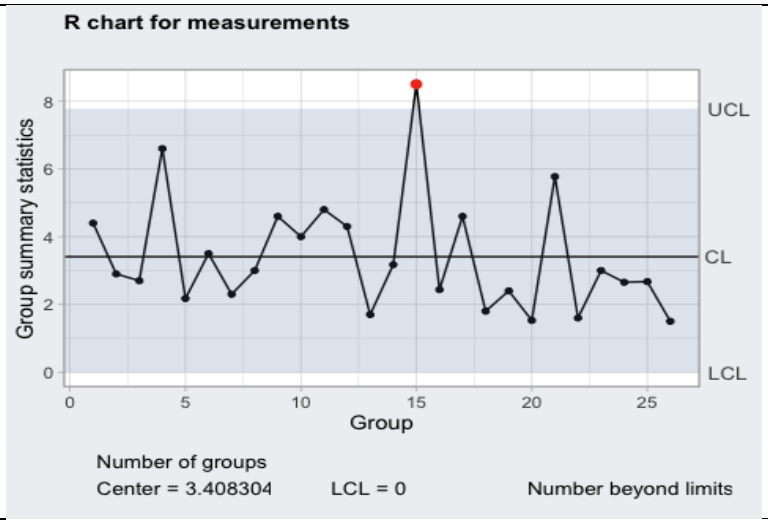
Following the handling of null values, control charts including x-bar, r charts, s charts, and cp charts are generated. These charts are used to evaluate whether the blood sugar levels of the patients fall within statistical control. The x-bar chart assesses the average blood sugar levels, the r chart evaluates the range or variability within each time interval, the s chart examines the standard deviation, and the cp chart assesses process capability against the specified control range of 3-8.

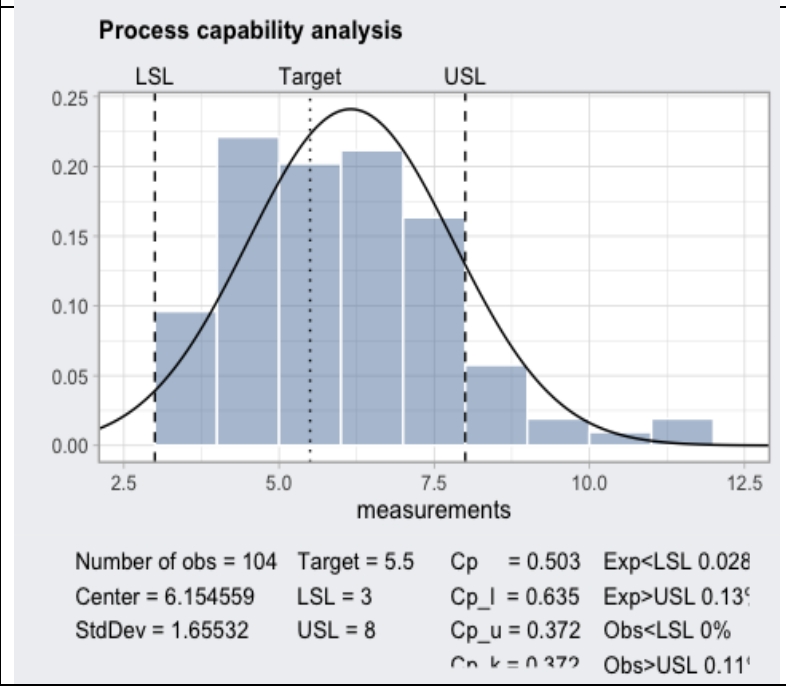
Results

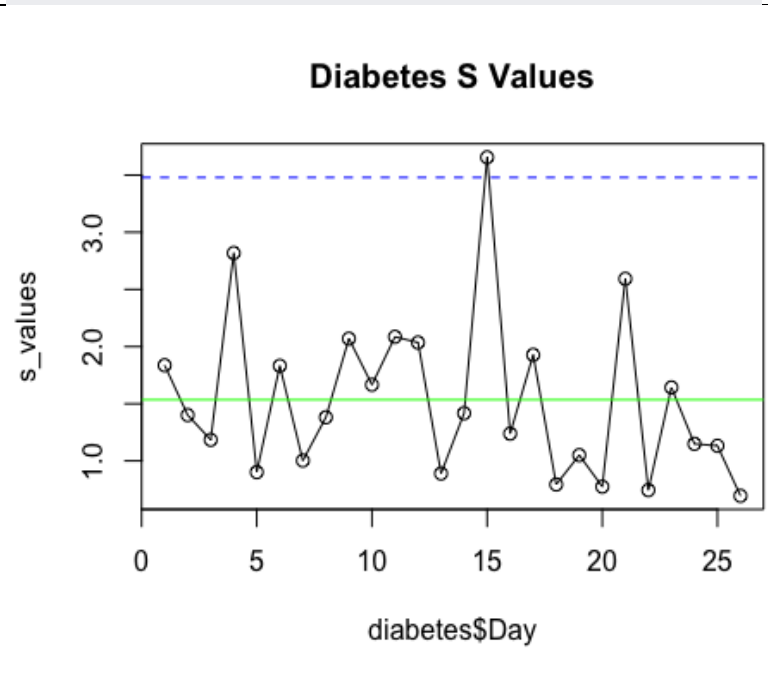
Part 1: Replacing nulls with Mean values

Figure 1









When analysing the graphs for replacing the nulls with the mean values for each column (figure 1) the following observations can be made.

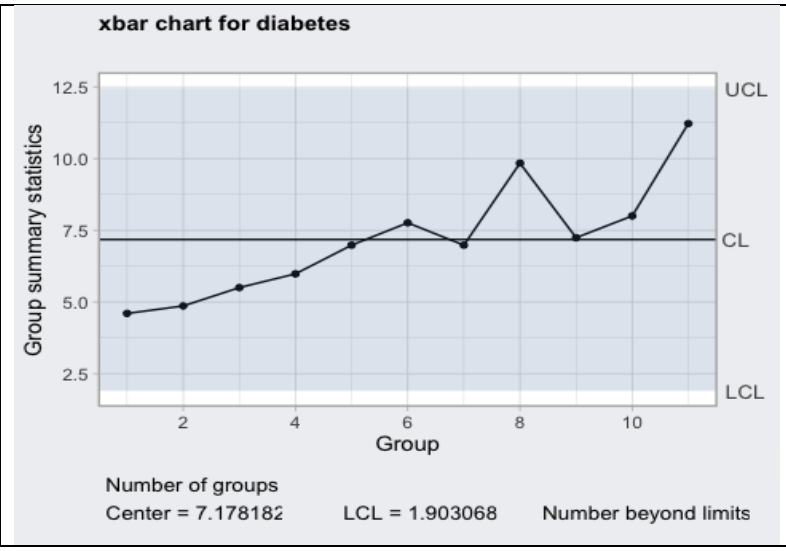
Firstly, the xbar chart seems to indicate the process is in control with all values falling within the upper and lower control limits. However, in group 15 for the R chart there is a violation of the upper control limit signalling the process it out of control.

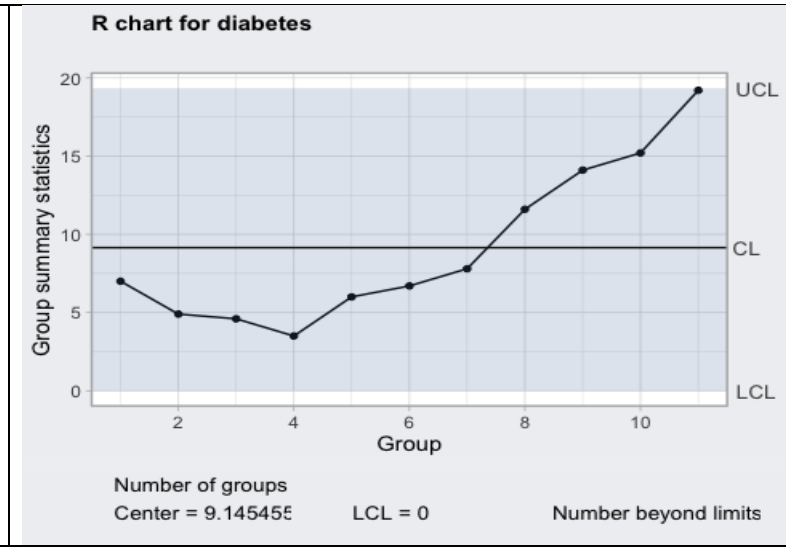
The analysis of the Process Capability Chart reveals important insights regarding the process's capability to meet specification limits. The Cp value of 0.503 indicates that the process is not capable of consistently producing results within the desired limits, even if it were perfectly centered. Additionally, the Cp_U value of 0.372 suggests that the process is closer to the upper specification limit, while the Cp_L value of 0.635 indicates relative proximity to the lower specification limit. The equality between Cp_k and Cp_U further emphasizes that the upper control limit imposes a more significant constraint on the process. With a Cp_m value of 0.468, it is evident that improvements are required to enhance the process's capability and ensure consistent results within the desired range.

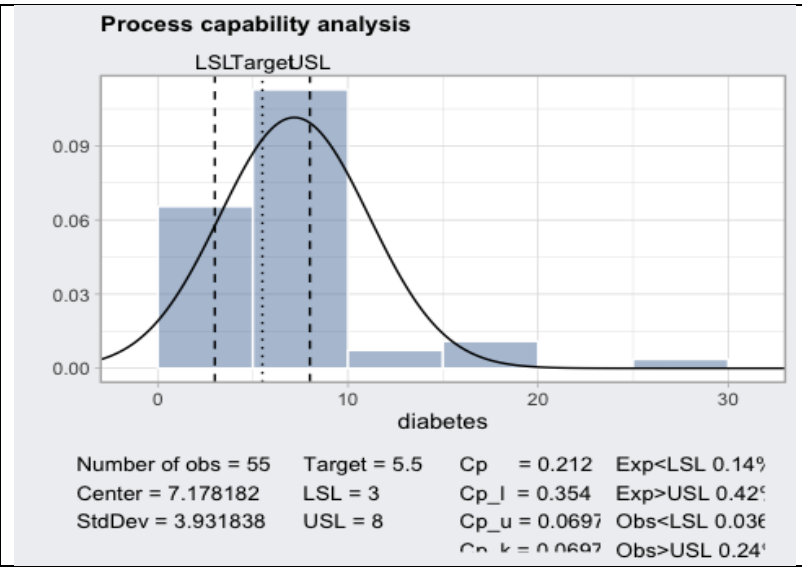
Next when analysing the S chart, like the R chart shows the process is out of control on the 15th day. Overall, when replacing the null values with the mean of the columns it produces a process which is out of control.

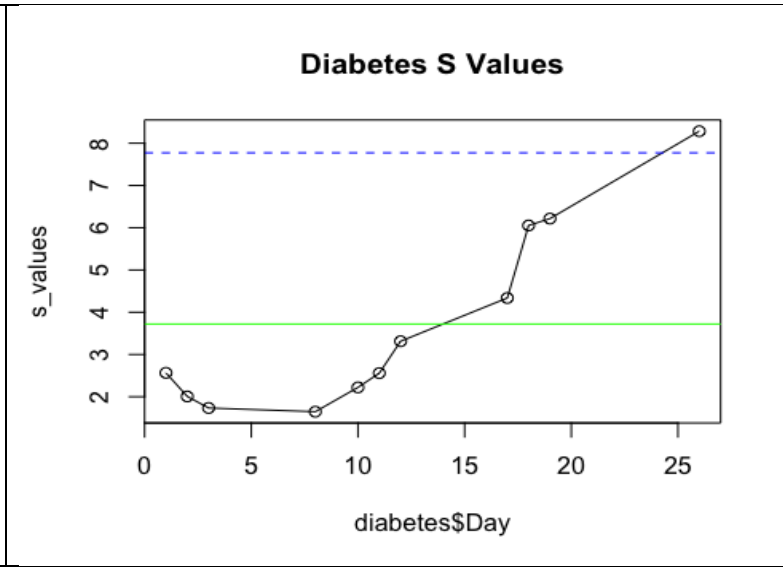
Part 2 Removing rows with na values

Figure 2









When removing the rows with na values (figure 2) only 11 rows remain. The X-bar and R charts suggest that the process is in control, as all recorded values fall within the upper and lower control limits.

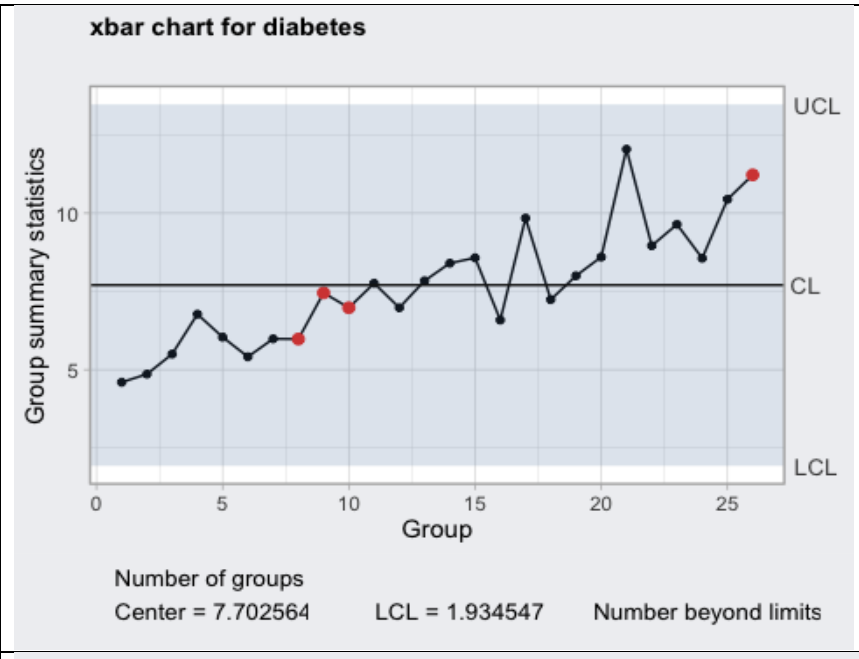
However, when looking at the S chart it reveals a violation of the upper limit on the 26th day, which signals that the process could be out of control. This discrepancy between the R and S charts could be due to the different methods sensitivity to the variability in the data.

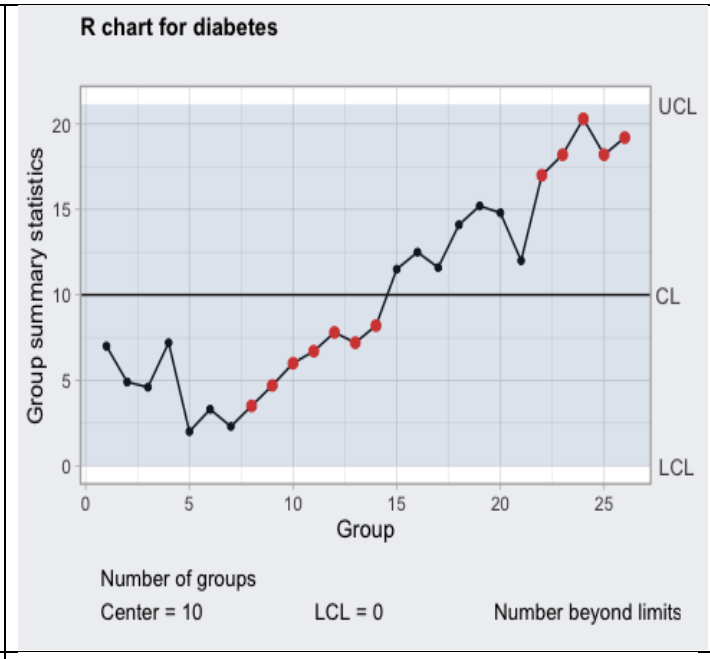
The Process Capability analysis reveals that the process is out of control and exhibits significant issues related to process variability. This is indicated by the low Cp value of 0.212, suggesting that the process is not capable of producing output within the specified limits even if perfectly centered. The Cpm value of 0.1949 further emphasizes poor performance relative to the target variable, highlighting challenges with process accuracy. Additionally, the Cp_L, Cp_U, and Cp_k values of 0.354 and 0.0697 indicate that the process is falling below the desired capability, both in terms of the lower and upper specification limits.

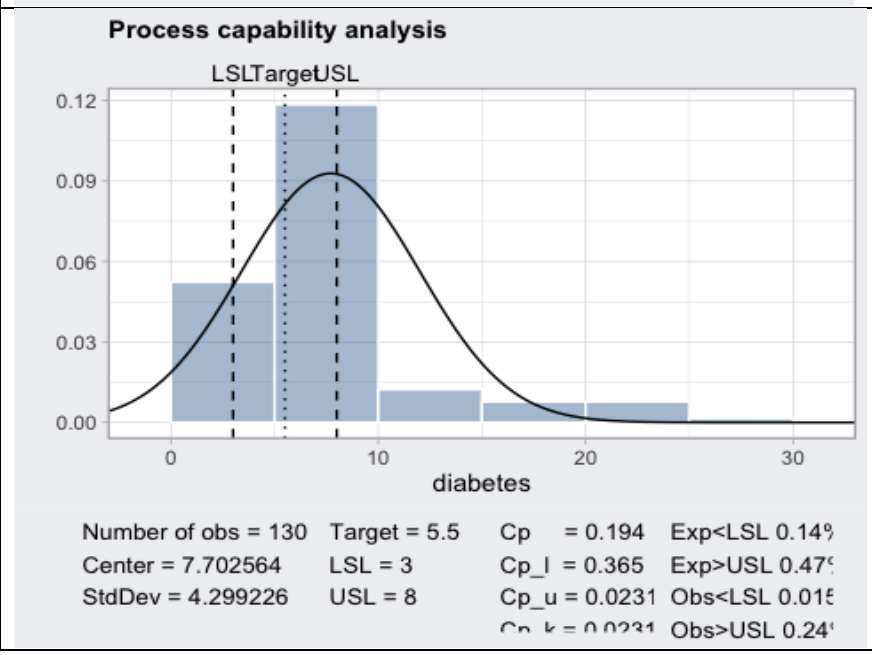
In sum, while the average behavior of the process seems stable based on the X-bar and R charts, both the S chart and Cp values raise concerns about the process control, capability and performance. This implies that the process might not be entirely in control due to significant variability and a poor alignment with the target specifications.

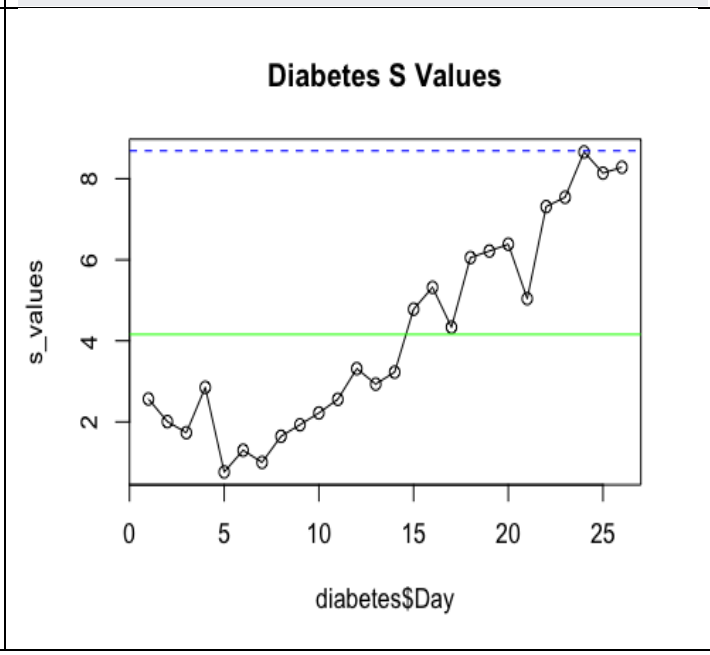
Part 3 Row Means

Figure 3









When addressing missing values in the dataset by employing row means (figure 3), both X-bar and R charts display all points within the defined upper and lower control limits. Yet, a number of these points are highlighted in red, pointing towards non-random patterns or variations within the process. This is most likely due to the method adopted to handle missing values - substituting nulls with row means. In instances where multiple values are absent in a row, this approach can lead to a series of identical replacements, potentially injecting a bias into the dataset.

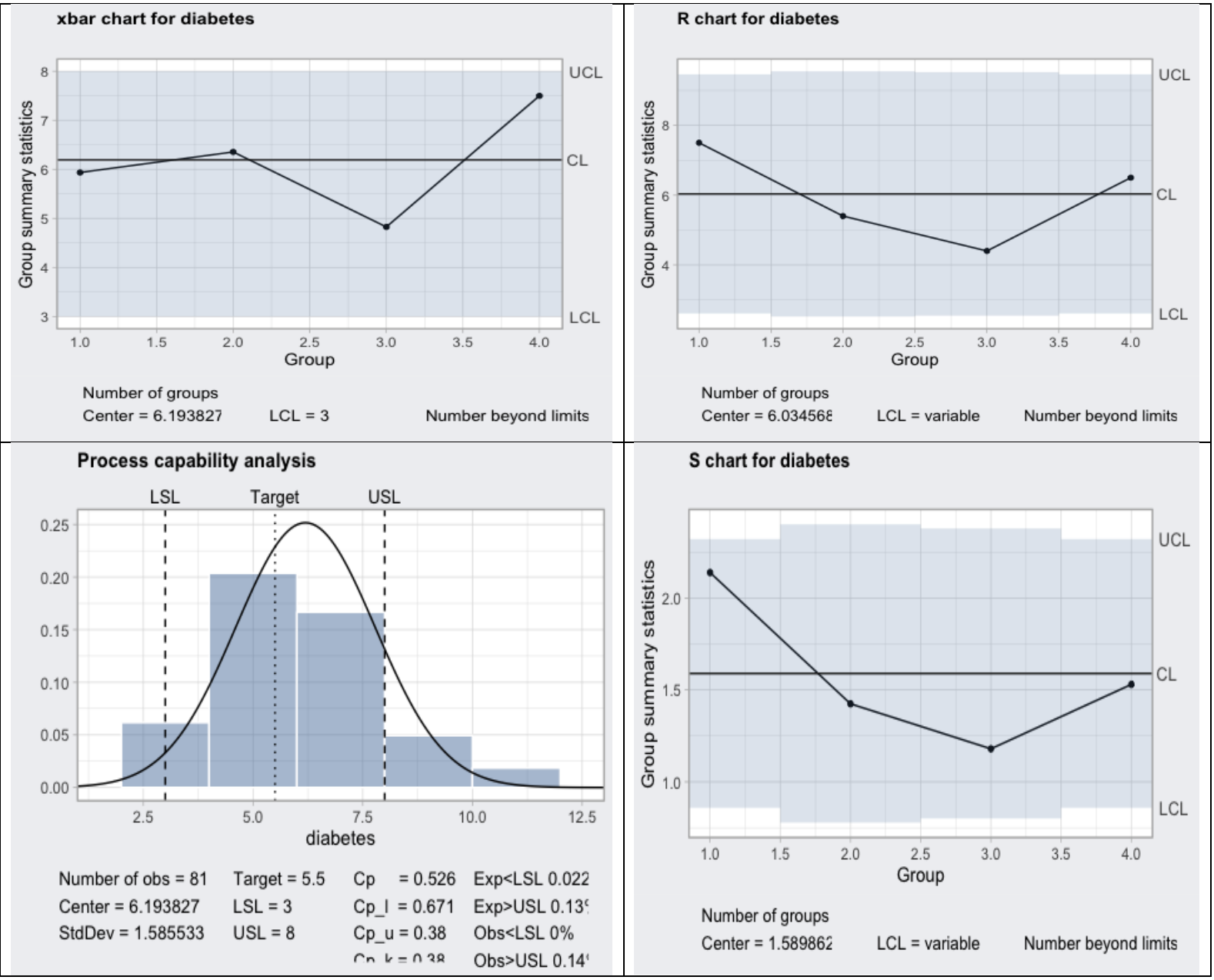
While the S chart adheres to the upper limit and initially suggests a controlled process, the interpretation of process capability indices tells a different story. The Cp value sits at 0.194, below

the commonly accepted threshold of 1.0, indicating a process that does not meet specification limits and hence is out of control. Similarly, the Cpm is also below 1.0, at 0.173, further supporting the conclusion that the process performance relative to the target is subpar, indicating that the process is not operating as intended. Additionally, the Cp_u and Cp_k values of 0.0231 and the Cp_L value of 0.365 further reinforce the notion that the process is not operating as intended.

The combination of these charts indicates that, despite the initial impressions from the S chart, the process is not under control. The strategy for handling missing data could be a contributing factor to these inconsistent findings.

Part 4 Time of Day Analysis

Figure 4



The analysis from the S, R, and X-bar charts all seem to depict a process in control, with all points consistently falling within the established upper and lower control limits. This suggests the process is well regulated and consistent, providing initial evidence of its control.

However, the Cp chart paints a starkly different picture. A Cp value of 0.526 is recorded, which falls significantly below the desired benchmark of 1.0. This indicates that the process is not capable of producing results within the specification limits even if it were perfectly centered, thereby suggesting that the process is, in fact, out of control. Similarly, the Cp_U and Cp_k value of 0.38 both fall below 1, providing additional evidence that the process is not operating within acceptable limits. The Cp_I value of 0.671, although greater than the other Cp indices, is still below 1, signaling that the process is closer to the upper specification limit.

This discrepancy between the control charts (S, R, and X-bar) and the process capability indices (Cp, Cp_U, Cp_k, Cp_I) underlines an important point: even though a process may be in control (consistent), it may still not be capable (meeting specifications). These results point to the necessity for both statistical control and capability in a process.

Discussion

The conducted analysis of blood sugar levels for a span of 26 days paints a concerning picture of the patient's health, suggesting a lack of control over the blood sugar levels. The dataset has been handled in various ways to account for null variables: replacing with the daily mean, replacing with the time of day mean, ignoring, and removing the null values. Regardless of the method used, the overarching conclusion from all four methodologies indicates a process that is out of control.

While the method in part 4, hint at a control within the S chart, R chart, and X-Bar chart, the Cp charts from all four methods paint a contrary picture. The Cp values across all methods fell below the standard threshold of 1, pointing towards an inadequate process capability.

This means that on one hand, the fact that the process is "in control" suggests that the person's blood sugar levels are consistent and stable. This can be viewed as a positive aspect, indicating that the individual's blood sugar levels are within a manageable range and not exhibiting extreme fluctuations.

On the other hand, the process being "not capable" indicates that the blood sugar levels may not consistently meet the desired specification limits or targets. This suggests that there may be room for improvement in terms of achieving more optimal blood sugar control.

In this context, it is essential to consult with healthcare professionals or diabetes specialists to assess the specific blood sugar targets and individual circumstances. They can provide guidance on optimizing blood sugar management strategies, such as adjusting medication, implementing lifestyle modifications, or enhancing dietary choices.

Both Cp_L and Cp_U for all four Cp charts fell below 1 indicating that blood sugar levels consistently fell under and above the limit meaning there were episodes of both hypoglycemia (low blood sugar) and hyperglycemia (high blood sugar) occurring.

Given these findings, the following recommendations are proposed:

Consistent Monitoring: Blood sugar readings should be taken more consistently. This will allow for a more accurate picture of the patient's blood sugar control. Inconsistent readings can potentially skew the data and may contribute to a lack of control over the blood sugar process.

Health education: Educating patients with diabetes about knowledge scores, reducing weight, improving blood glucose levels, and promoting healthy behaviours was shown to improve Glucose levels in diabetics [3].

Lifestyle Modifications: Healthy lifestyle habits such as regular exercise, maintaining a balanced diet, and ensuring adequate sleep can also significantly influence blood sugar control. In the article [8] it was found that a combination of dietary modifications and physical exercise provides benefits for patients blood sugar levels with diabetes.

Regular Check-ups: Regular appointments with healthcare providers can ensure early detection of any issues and appropriate interventions can be provided in a timely manner and has also been seen to significantly improve blood sugar control for patients [9].

This analysis and these recommendations aim to help establish a better blood sugar control process, thereby improving the patient's health condition and quality of life.

References

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[3] Mohamed SA. Effect of lifestyle intervention on health behaviors, weight and blood glucose level among patients with diabetes mellitus. Journal of Nursing Education and Practice. 2014 Dec 1;4(12):75.].

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[8] Kaplan RM, Hartwell SL, Wilson DK, Wallace JP. Effects of diet and exercise interventions on control and quality of life in non-insulin-dependent diabetes mellitus. Journal of general internal medicine. 1987 Jul;2(4):220-8.]

[9] Greenfield S, Kaplan SH, Ware JE, Yano EM, Frank HJ. Patients' participation in medical care: effects on blood sugar control and quality of life in diabetes. Journal of general internal medicine. 1988 Sep;3:448-57.

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ExamStatLearningInference

2023-05-24

PCA, S, R, XBAR

```
# Load required libraries
library(readxl)
library(qcc)

## Loading required package: ggplot2

## Package 'qcc' version 3.0
## Type 'citation("qcc")' for citing this R package in publications.

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

library(spc)
library(factoextra)

## Welcome! Want to learn more? See two factoextra-related books at https:
//goo.gl/ve3WBa

library(zoo)

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

library(tidyr)
```

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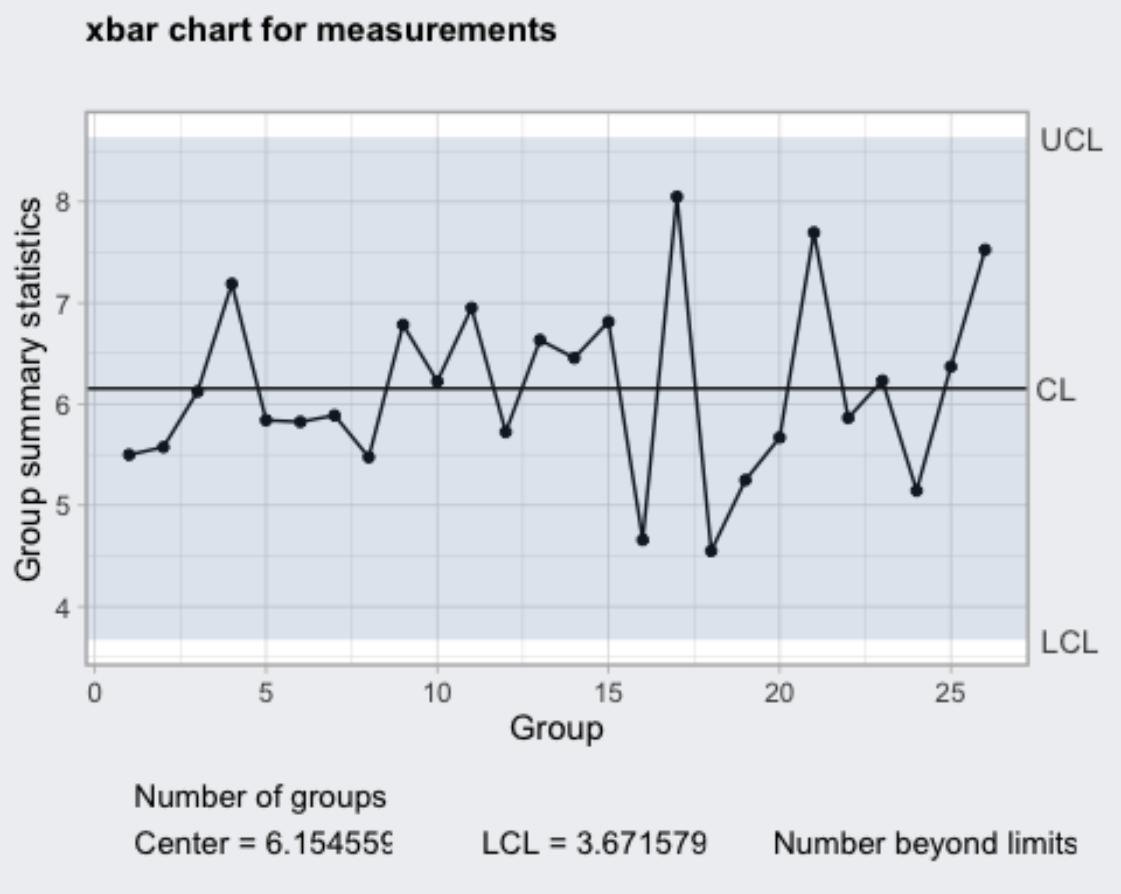
```
# Read the data from Excel file
diabetes <- read_excel("Exam-Diabetes.xlsx")
```

Part 1 Replacing nulls with mean

```
# Read the data from Excel file
diabetes <- read_excel("Exam-Diabetes.xlsx")

# Use mutate_all() to apply a function to all columns
# Use ifelse() to replace NA with mean (ignoring NA) of the column
diabetes <- diabetes %>% mutate_all(~ifelse(is.na(.), mean(., na.rm = TRUE
), .))
```

Part 1 b) Creating Xbar and R charts

```
# Define specification limits
USL <- 8  # upper spec limit
LSL <- 3  # lower spec limit

# Select the relevant columns for analysis (e.g., Morning, Lunch, Dinner,
Evening)
measurements <- diabetes[, c("Morning", "Lunch", "Dinner", "Evening")]

# Convert the measurements data frame to a matrix
measurements <- as.matrix(measurements)

# Remove rows with NA values
measurements <- na.omit(measurements)

# Compute the mean for each column (X-Bar Chart)
xbar_chart <- qcc(measurements, type = "xbar")

# Compute the range for each column (Range Chart)
range_chart <- qcc(measurements, type = "R")

plot(xbar_chart)
```




```
plot(range_chart)
```

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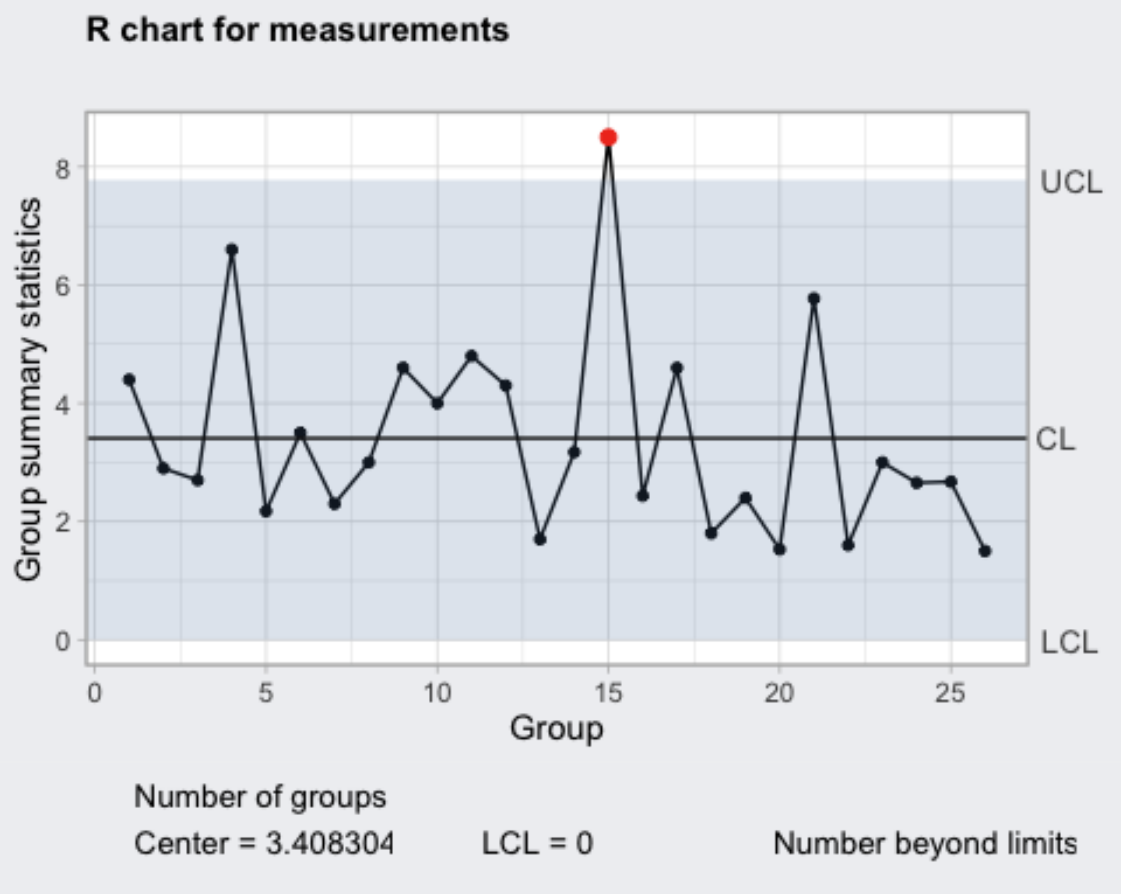


Part 1 c) Creating PC chart

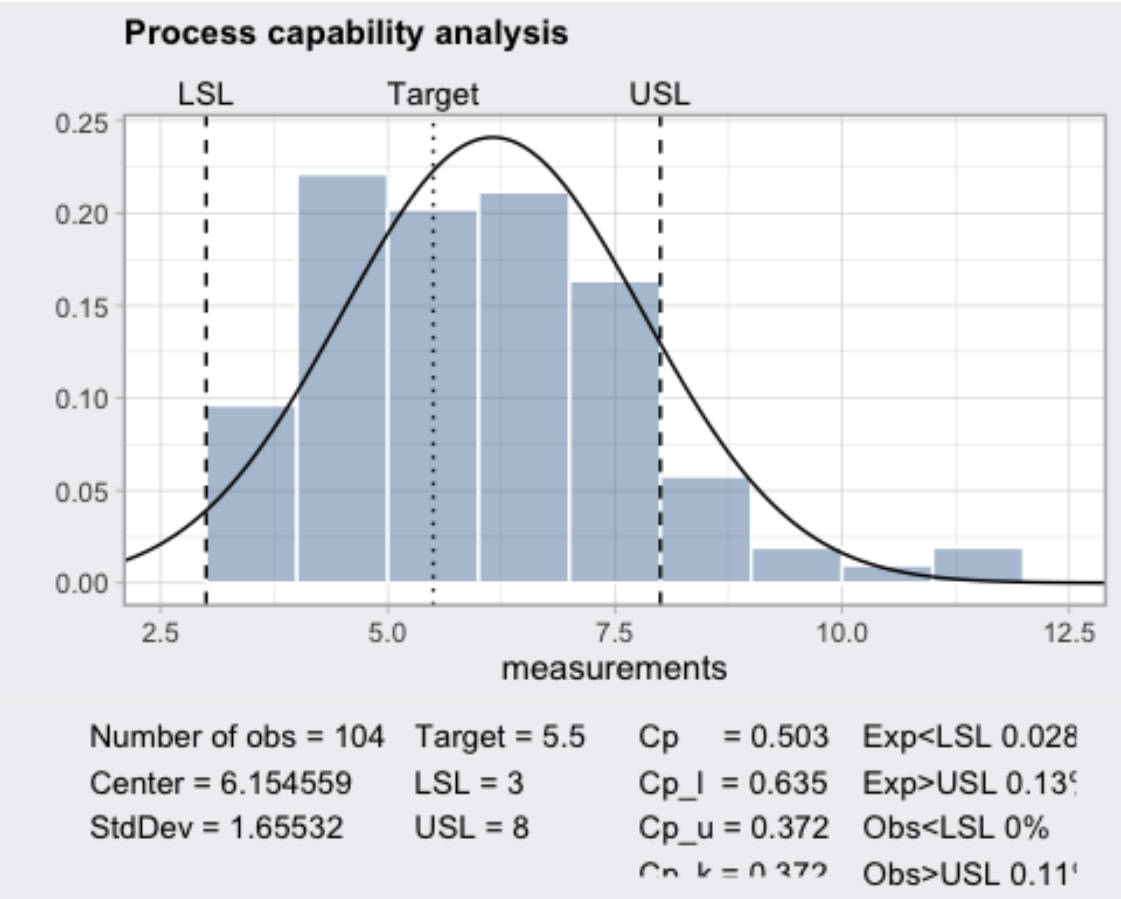
```
# Define specification limits
USL <- 8  # upper spec limit
LSL <- 3  # lower spec limit

# Compute process capability
pc <- processCapability(xbar_chart, spec.limits = c(LSL, USL))

# Print the process capability
print(pc)
```

```
## ── Process Capability Analysis ──────────────────
##
## Number of obs = 104          Target = 5.5
## Center        = 6.154559     LSL    = 3
## StdDev        = 1.65532      USL    = 8
##
## Capability indices  Value   2.5%  97.5%
##               Cp    0.503  0.435  0.572
##               Cp_l  0.635  0.545  0.726
##               Cp_u  0.372  0.303  0.440
##               Cp_k  0.372  0.290  0.453
##               Cpm   0.468  0.400  0.536
##
## Exp<LSL 0.028%    Obs<LSL 0%
## Exp>USL 0.13%     Obs>USL 0.11%
```

```
plot(pc)
```



Part 1 d) Creating S chart

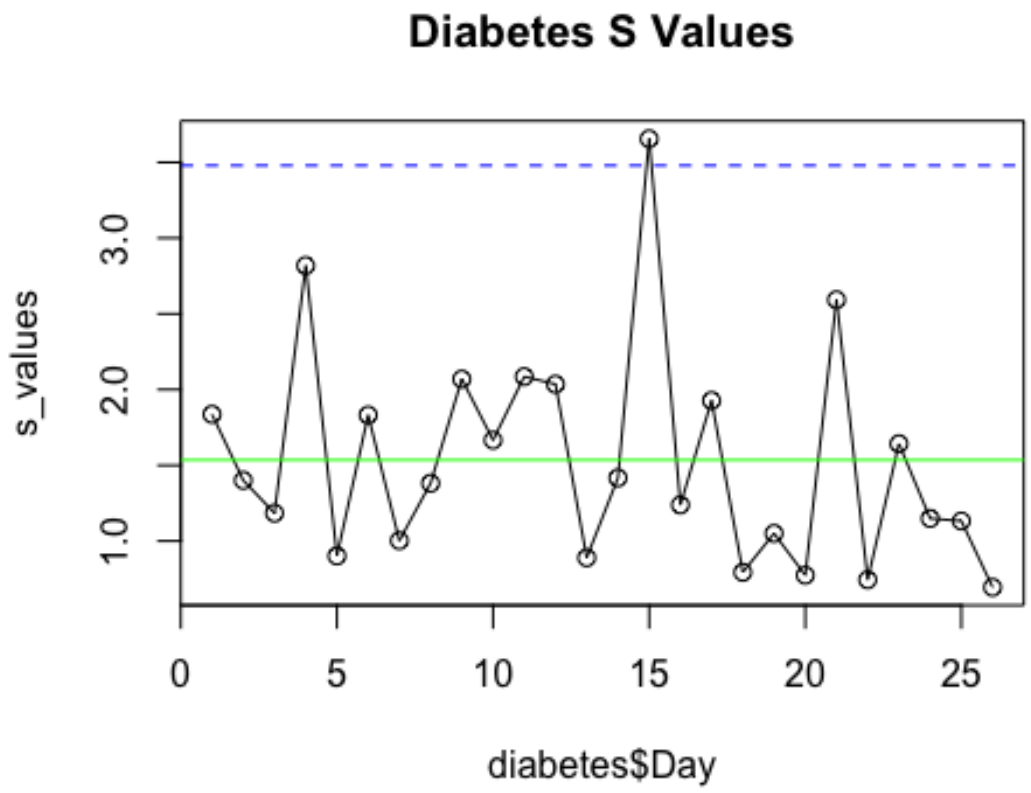
```
# Calculate and plot the S values of the new data
(s_obj <- qcc(measurements, type="S"))

## ── Quality Control Chart ────────────────────────
##
## Chart type                 = S
## Data (phase I)             = measurements
## Number of groups           = 26
## Group sample size          = 4
## Center of group statistics = 1.535304
## Standard deviation         = 1.666422
##
## Control limits at nsigmas  = 3
##  LCL      UCL
##    0 3.479071

s_center <- s_obj$center
s_std_dev <- s_obj$std.dev

s_values <- apply(measurements, 1, sd)
plot(s_values ~ diabetes$Day, type = "o", ylim = c(min(s_values), max(s_va
lues)), main = "Diabetes S Values")
abline(h = s_center, col = "green")
```

```
abline(h = s_obj$limits[1], col = "blue", lty = 2)
abline(h = s_obj$limits[2], col = "blue", lty = 2)
```



Part 2 Removing na values

```
diabetes <- read_excel("Exam-Diabetes.xlsx")
```

Part 2 b) Creating Xbar and R charts

```
diabetes <- na.omit(diabetes)
measurements = diabetes[, c("Morning", "Lunch", "Dinner", "Evening")]
# Convert the measurements data frame to a matrix
measurements <- as.matrix(diabetes)

# Compute the mean for each column (X-Bar Chart)
xbar_chart <- qcc(diabetes, type = "xbar")

# Compute the range for each column (Range Chart)
range_chart <- qcc(diabetes, type = "R")

plot(xbar_chart)
```

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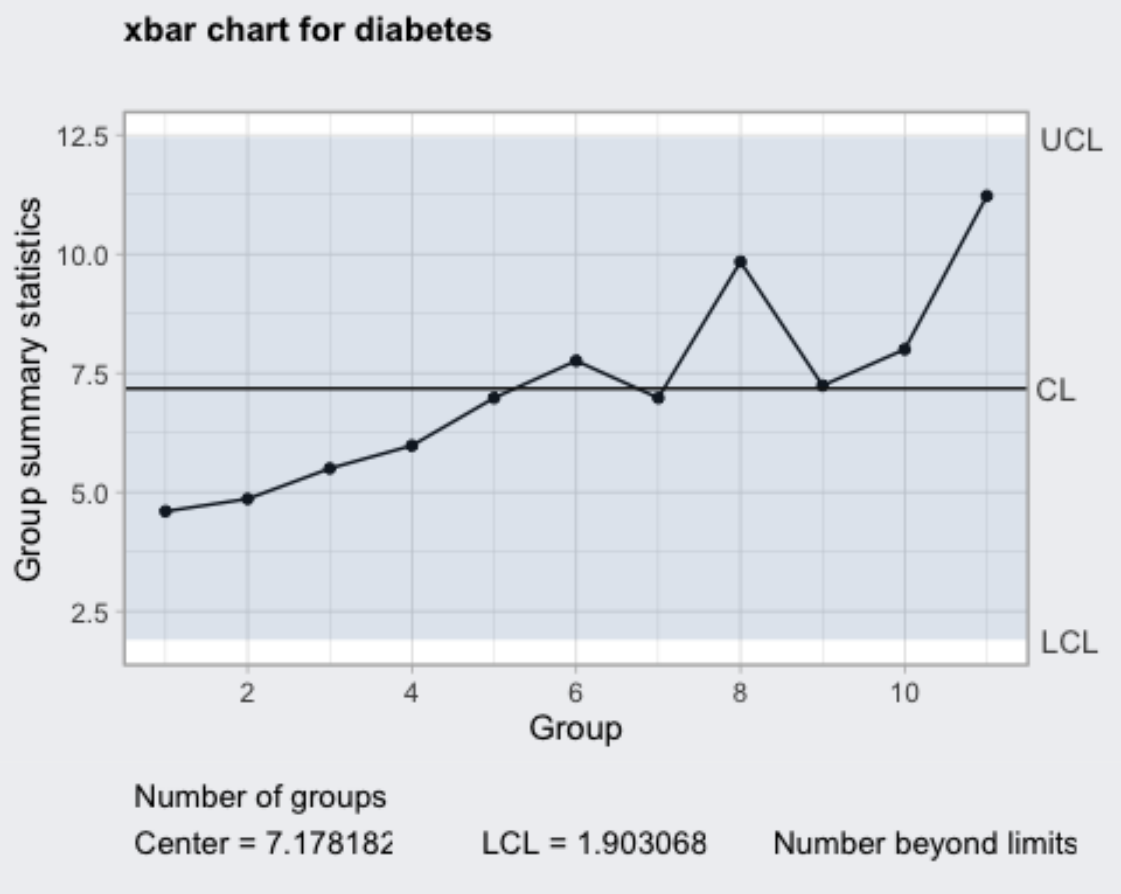


```
plot(range_chart)
```

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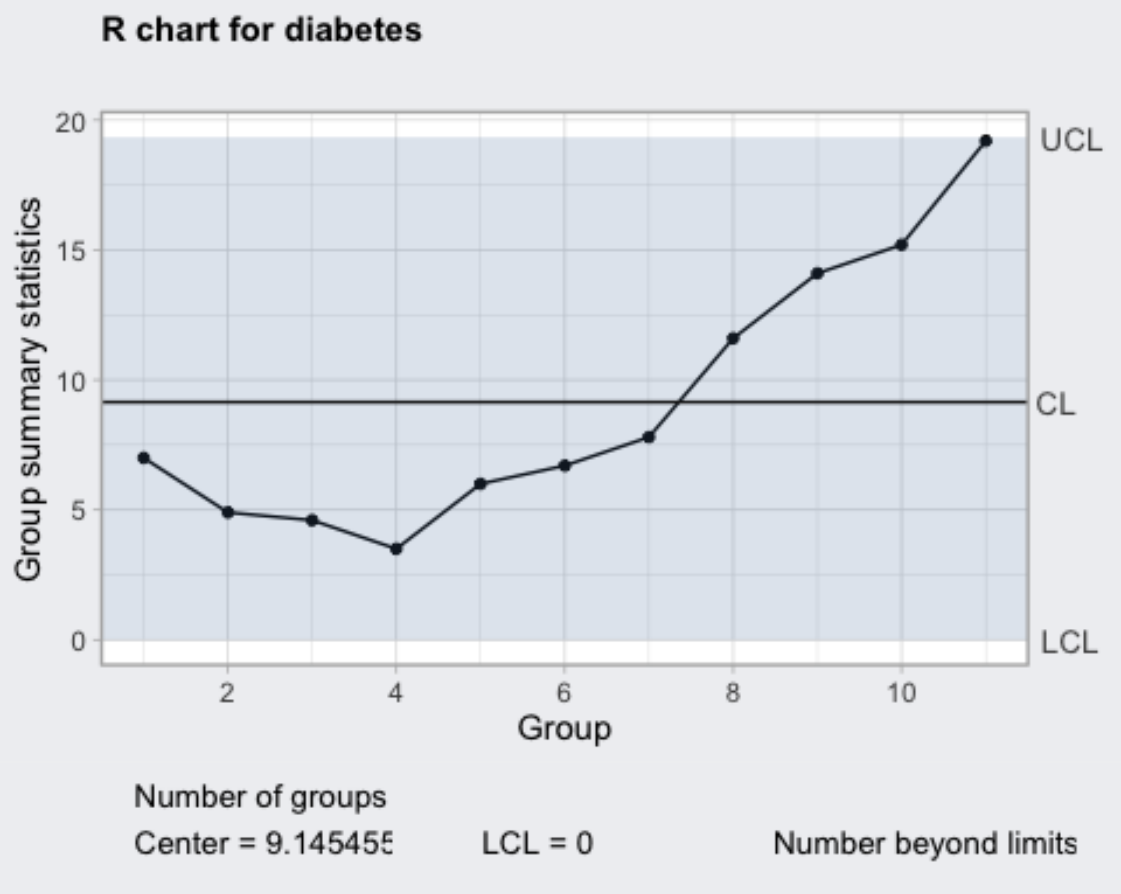


Part 2 c) PC chart

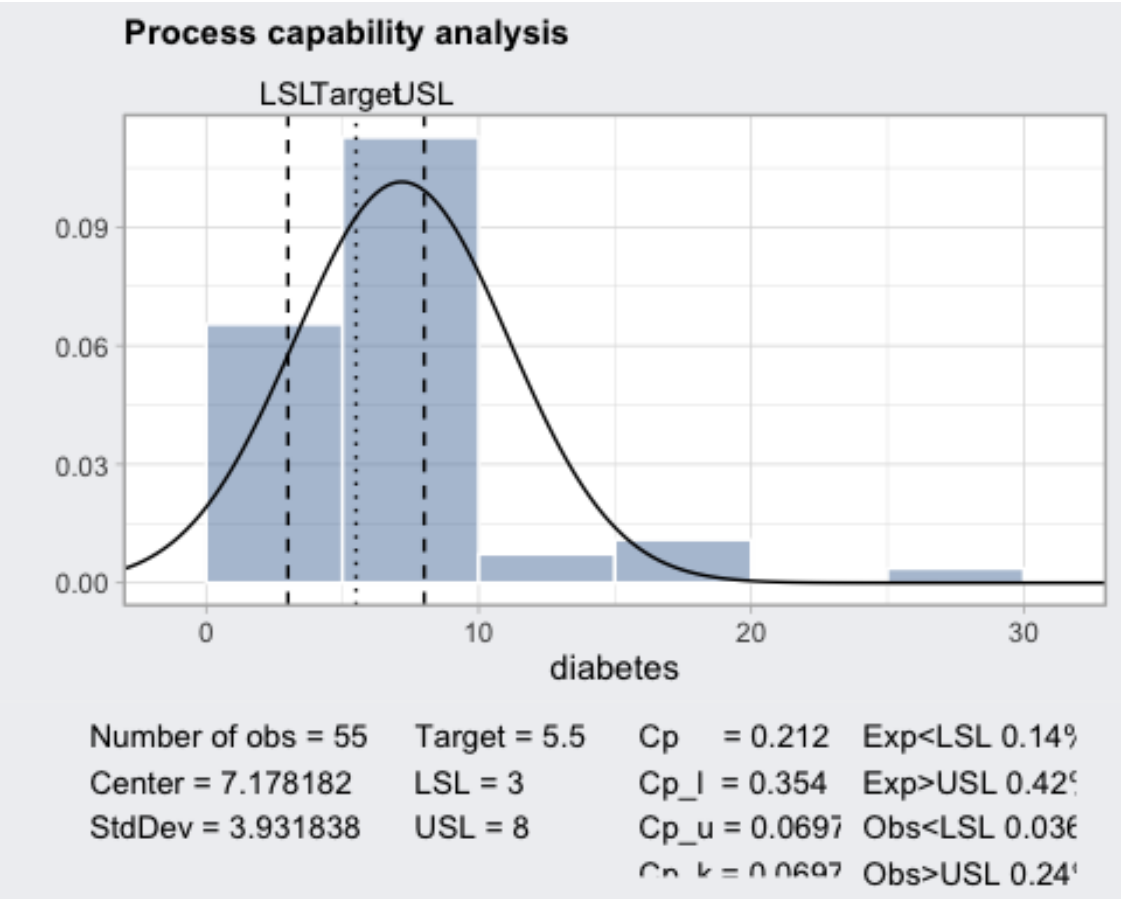
```
# Define specification limits
USL <- 8  # upper spec limit
LSL <- 3  # lower spec limit

# Compute process capability
pc <- processCapability(xbar_chart, spec.limits = c(LSL, USL))

# Print the process capability
print(pc)
```

```
## ── Process Capability Analysis ──────────────────
##
## Number of obs = 55           Target = 5.5
## Center        = 7.178182     LSL    = 3
## StdDev        = 3.931838     USL    = 8
##
## Capability indices   Value      2.5%  97.5%
##                Cp    0.2119   0.17206  0.252
##                Cp_l  0.3542   0.26143  0.447
##                Cp_u  0.0697  -0.00508  0.144
##                Cp_k  0.0697  -0.01940  0.159
##                Cpm   0.1949   0.15589  0.234
##
## Exp<LSL 0.14%     Obs<LSL 0.036%
## Exp>USL 0.42%     Obs>USL 0.24%
```

```
plot(pc)
```



Part 2 d) S chart

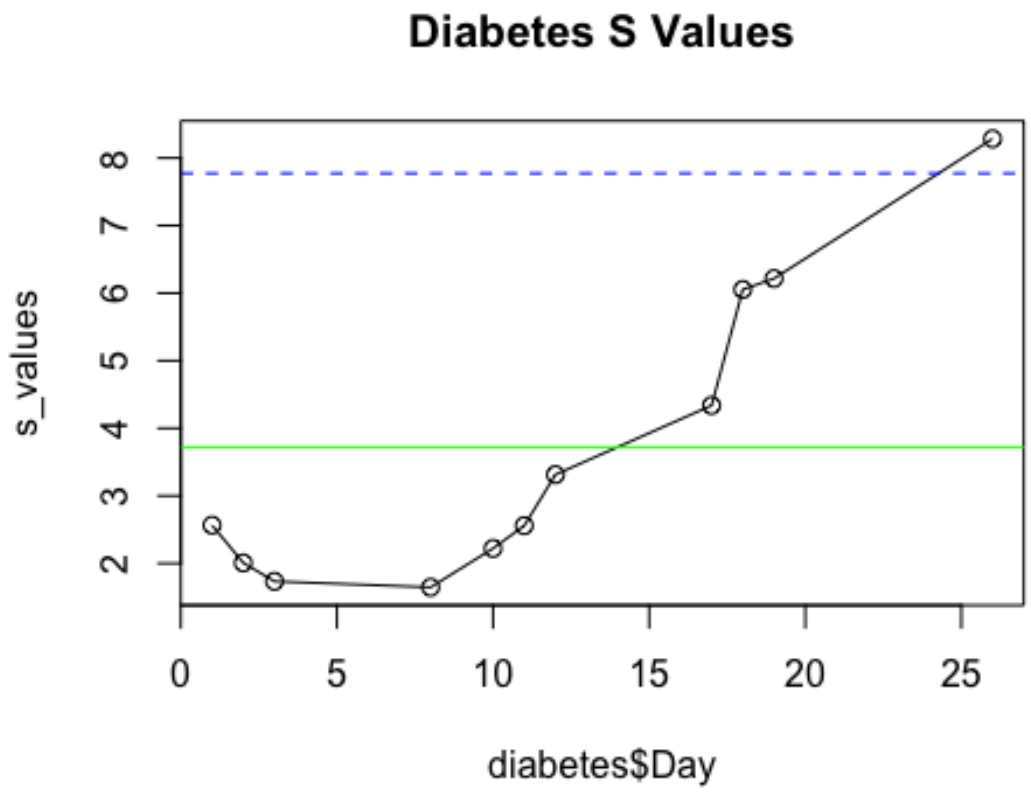
```
# Calculate and plot the S values of the new data
(s_obj <- qcc(measurements, type="S"))

## ── Quality Control Chart ────────────────────────
##
## Chart type                  = S
## Data (phase I)              = measurements
## Number of groups            = 11
## Group sample size           = 5
## Center of group statistics = 3.721347
## Standard deviation          = 3.958941
##
## Control limits at nsigmas  = 3
##  LCL      UCL
##    0 7.773886

s_center <- s_obj$center
s_std_dev <- s_obj$std.dev

s_values <- apply(measurements, 1, sd)
plot(s_values ~ diabetes$Day, type = "o", ylim = c(min(s_values), max(s_va
lues)), main = "Diabetes S Values")
abline(h = s_center, col = "green")
```

```
abline(h = s_obj$limits[1], col = "blue", lty = 2)
abline(h = s_obj$limits[2], col = "blue", lty = 2)
```



Part 3 Forward Fill

```
diabetes <- read_excel("Exam-Diabetes.xlsx")

diabetes <- na.locf(diabetes)
```

Part 3 b) xbar and range chart

```
diabetes <- na.omit(diabetes)
measurements = diabetes[, c("Morning", "Lunch", "Dinner", "Evening")]
# Convert the measurements data frame to a matrix
measurements <- as.matrix(diabetes)

# Compute the mean for each column (X-Bar Chart)
xbar_chart <- qcc(diabetes, type = "xbar")

# Compute the range for each column (Range Chart)
range_chart <- qcc(diabetes, type = "R")

plot(xbar_chart)
```

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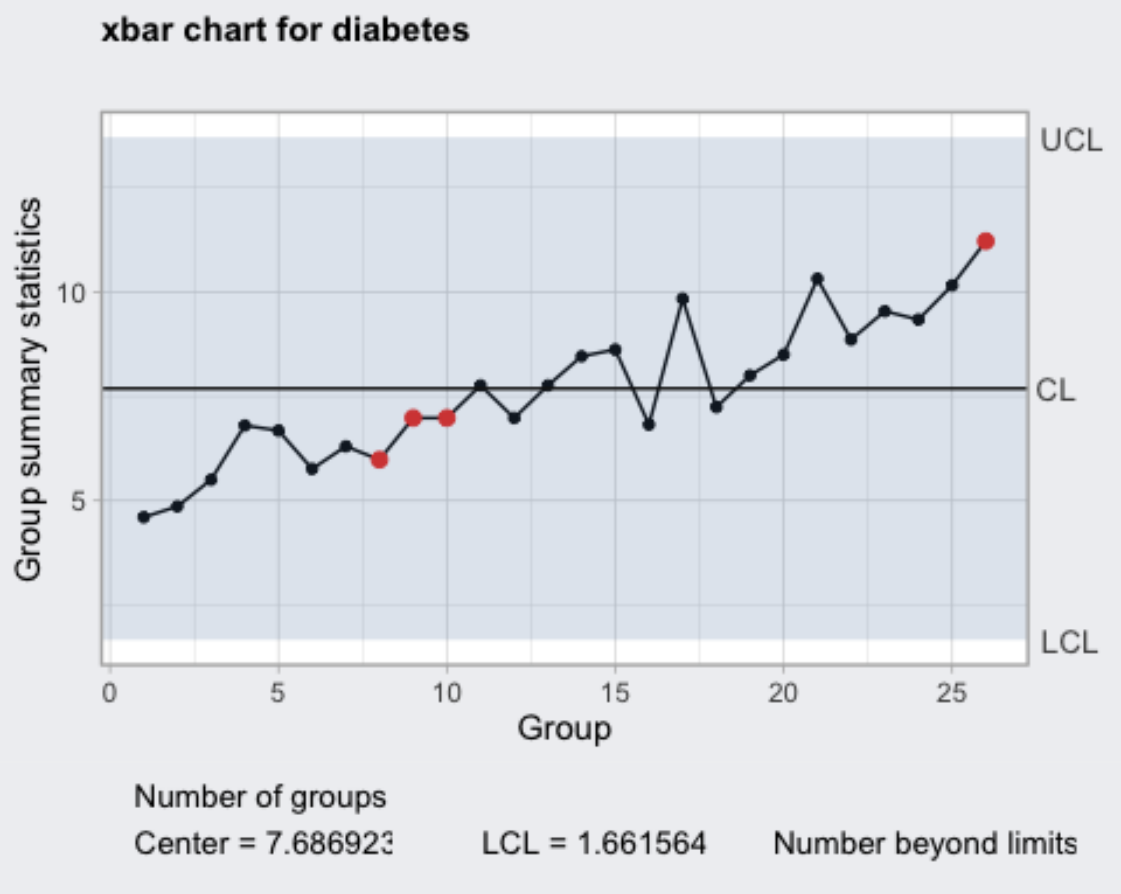


```
plot(range_chart)
```

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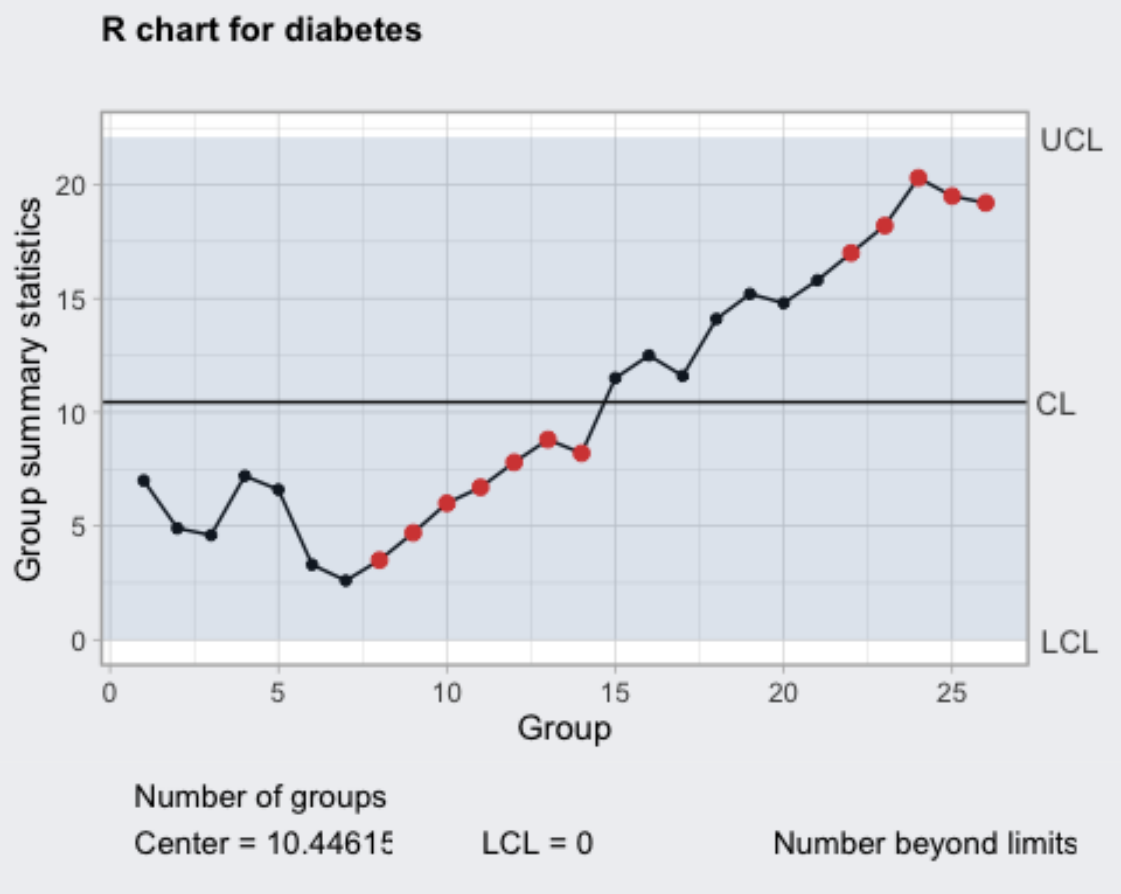
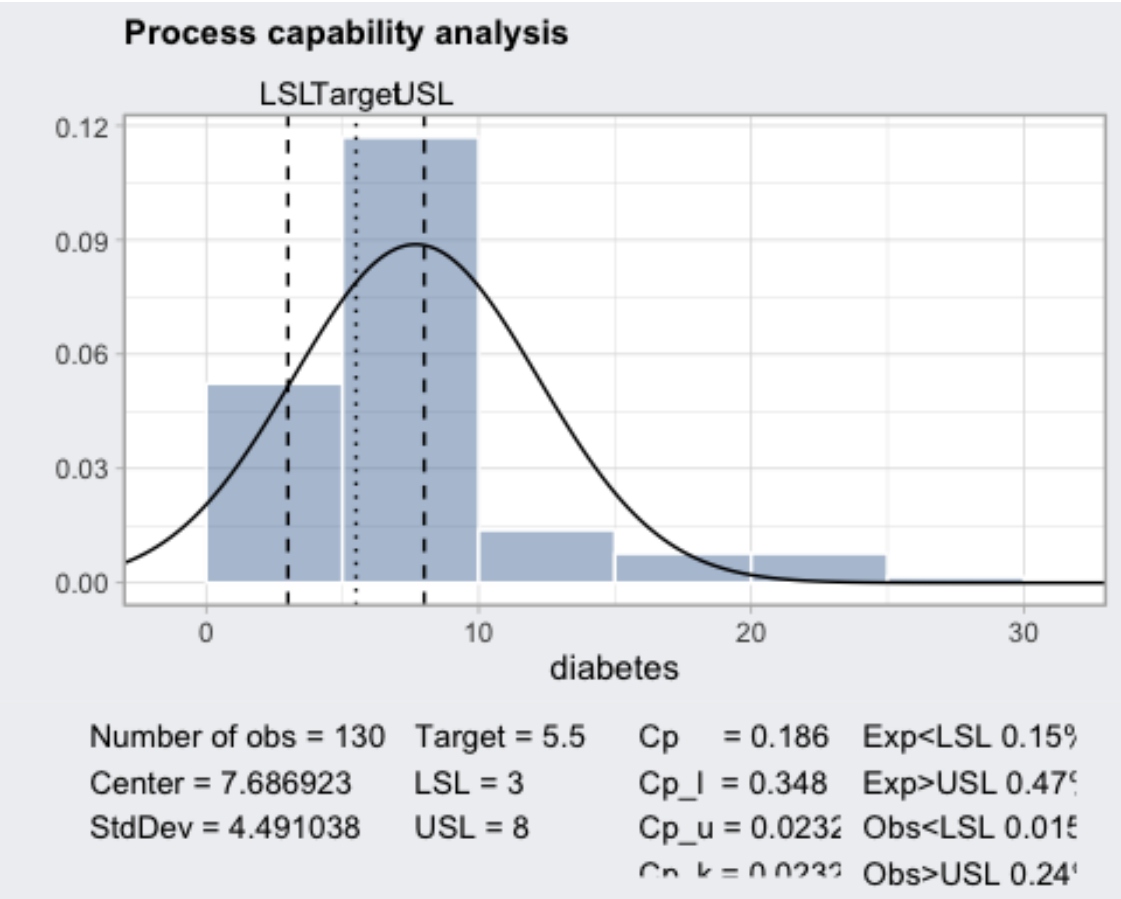


Part 3 c) PC chart

```
# Define specification limits
USL <- 8  # upper spec limit
LSL <- 3  # lower spec limit

# Compute process capability
pc <- processCapability(xbar_chart, spec.limits = c(LSL, USL))

# Print the process capability
print(pc)
```

```
## ── Process Capability Analysis ──────────────────
##
## Number of obs = 130          Target = 5.5
## Center        = 7.686923     LSL    = 3
## StdDev        = 4.491038     USL    = 8
##
## Capability indices   Value     2.5%   97.5%
##                Cp    0.1856   0.1629  0.2082
##                Cp_l  0.3479   0.2880  0.4077
##                Cp_u  0.0232  -0.0249  0.0714
##                Cp_k  0.0232  -0.0341  0.0806
##                Cpm   0.1668   0.1447  0.1889
##
## Exp<LSL 0.15%     Obs<LSL 0.015%
## Exp>USL 0.47%     Obs>USL 0.24%
```

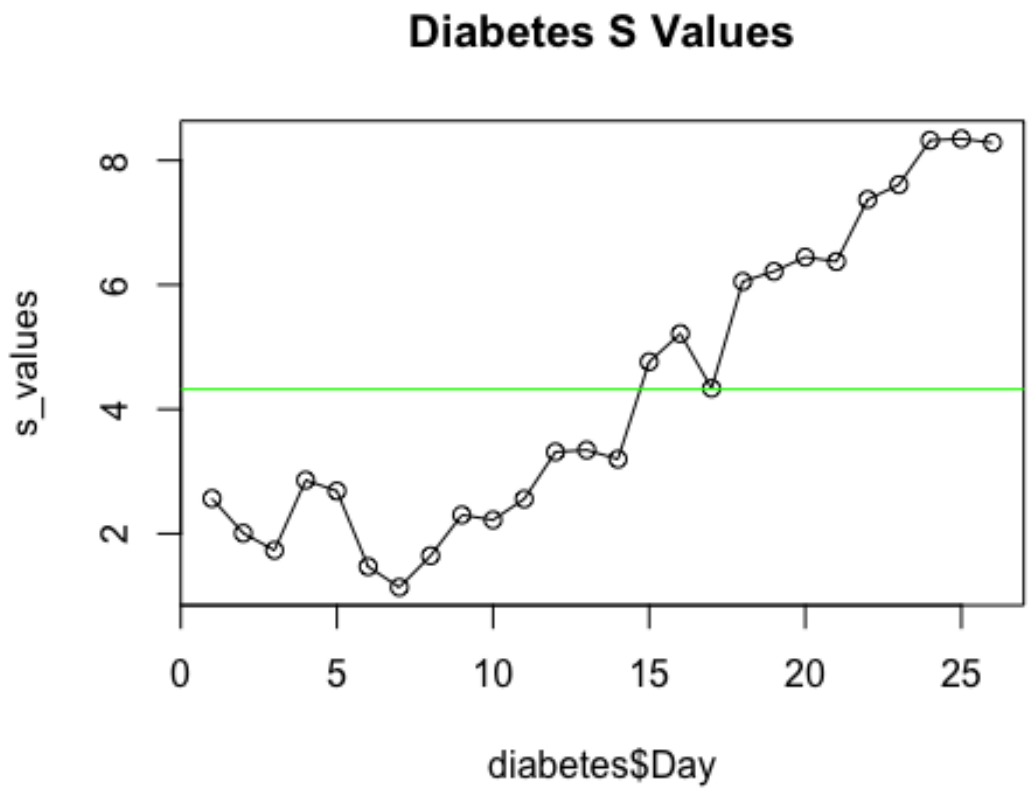
```
plot(pc)
```



Part 3 d) S chart

```
# Calculate and plot the S values of the new data
(s_obj <- qcc(measurements, type="S"))

## ── Quality Control Chart ────────────────────────
##
## Chart type                  = S
## Data (phase I)              = measurements
## Number of groups            = 26
## Group sample size           = 5
## Center of group statistics = 4.322354
## Standard deviation          = 4.598319
##
## Control limits at nsigmas   = 3
##  LCL      UCL
##    0 9.029388

s_center <- s_obj$center
s_std_dev <- s_obj$std.dev

s_values <- apply(measurements, 1, sd)
plot(s_values ~ diabetes$Day, type = "o", ylim = c(min(s_values), max(s_va
lues)), main = "Diabetes S Values")
abline(h = s_center, col = "green")
```

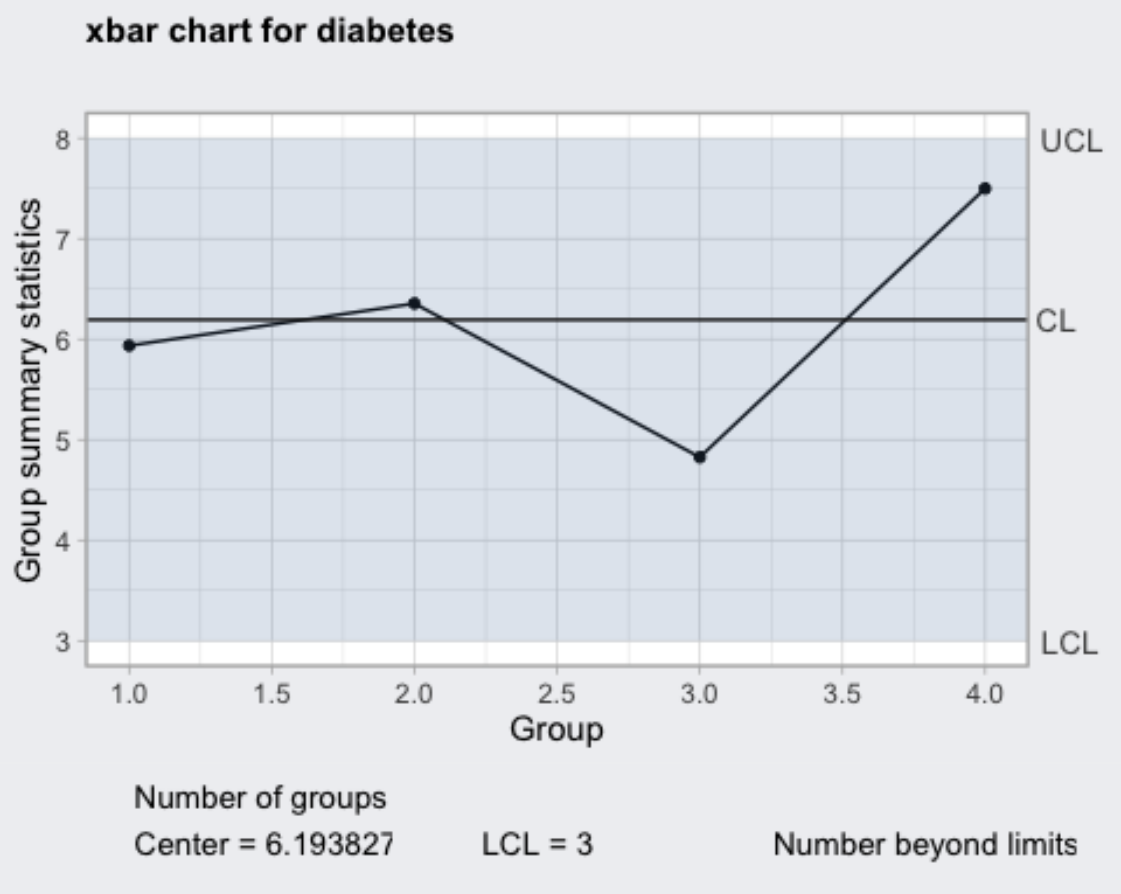
```
abline(h = s_obj$limits[1], col = "blue", lty = 2)
abline(h = s_obj$limits[2], col = "blue", lty = 2)
```



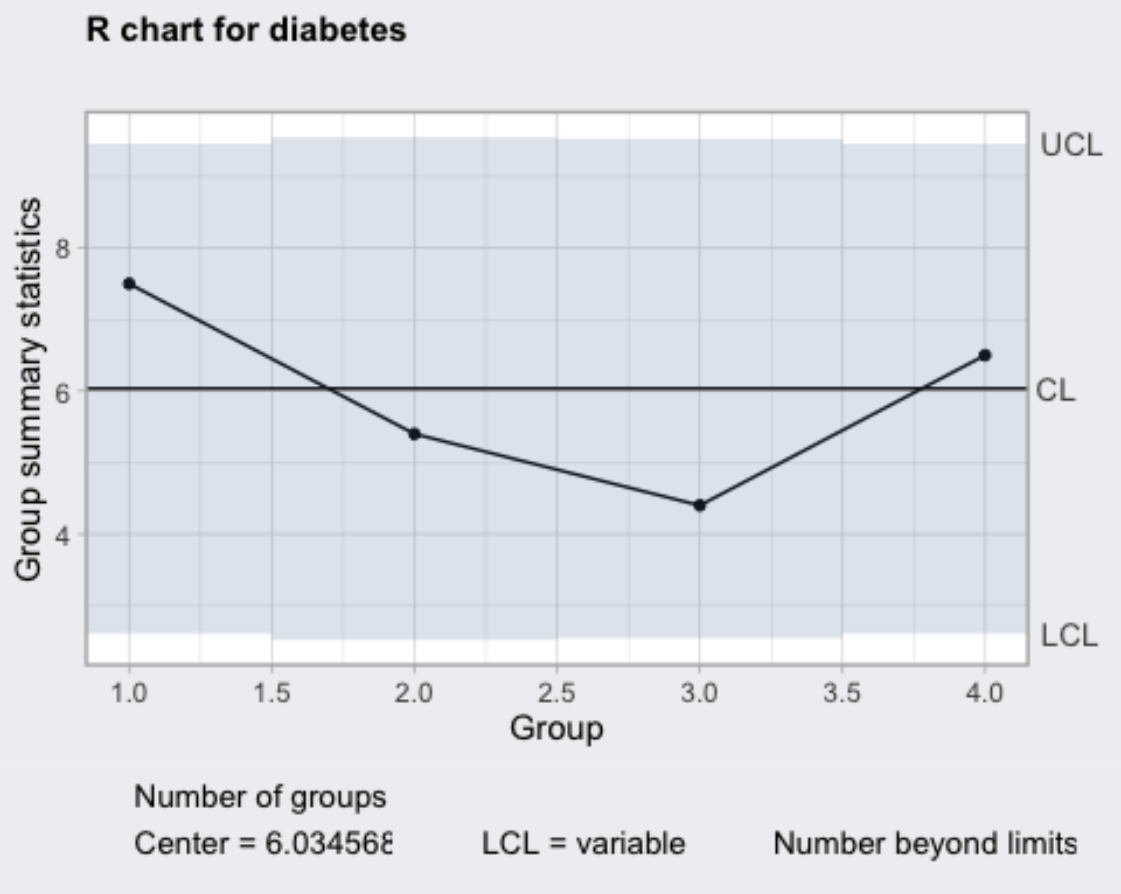
Part 4 Converting data to Long

```
# Read the data from Excel file
diabetes <- read_excel("Exam-Diabetes.xlsx")

# Convert to long format
diabetes_long <- diabetes %>%
  pivot_longer(cols = -Day, names_to = "TimeOfDay", values_to = "BloodSuga
r")

# Check the result


#group by time of day
diabetes <- qccGroups(data = diabetes_long, BloodSugar, TimeOfDay)

# Plot X-bar
control_chart <- qcc(diabetes, type = "xbar", plot = TRUE, limits = c(3, 8
))

# Plot X-bar and R chart
process_control <- qcc(diabetes, type = "R", plot = TRUE)

# Plot X-bar and S chart
process_control_s <- qcc(diabetes, type = "S", plot = TRUE)
```

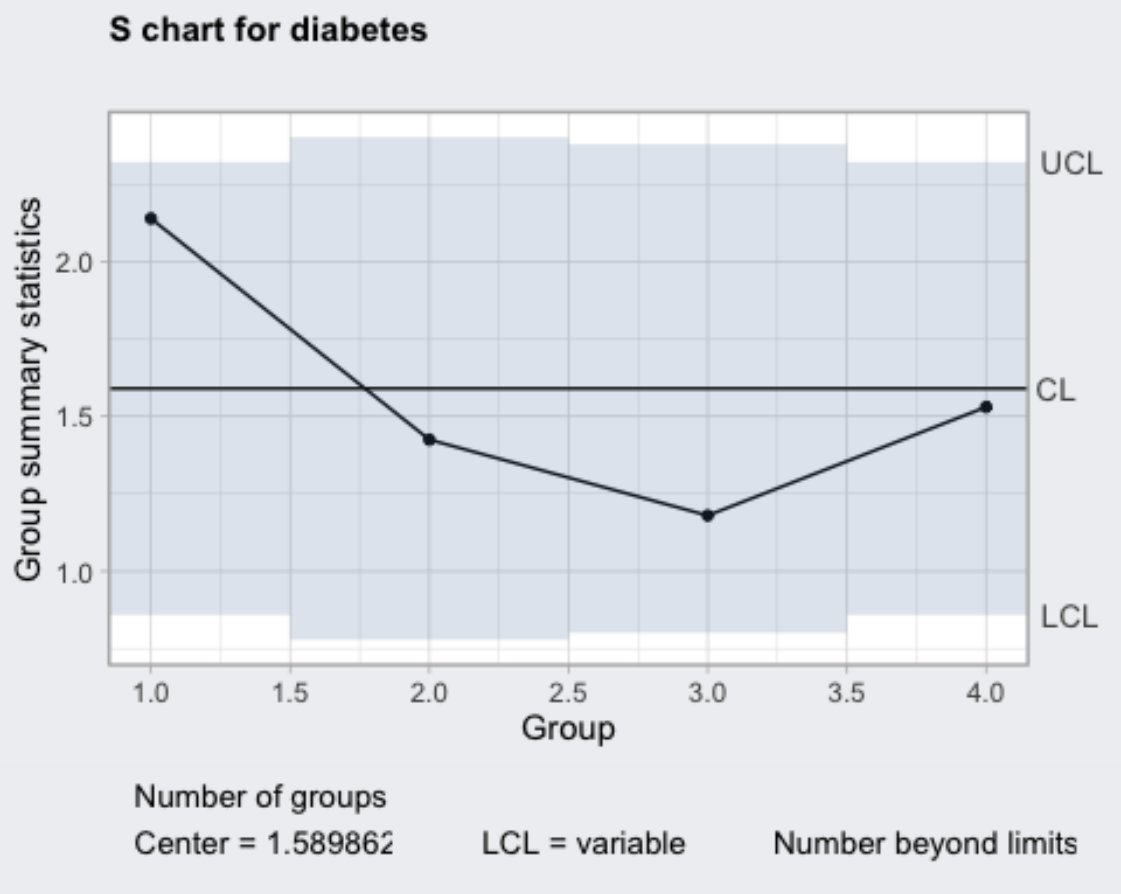
```
plot(control_chart)
```




```
plot(process_control)
```




```
plot(process_control_s)
```




```r
# Define specification limits
USL <- 8  # upper spec limit
LSL <- 3  # lower spec limit

# Compute process capability
pc <- processCapability(control_chart, spec.limits = c(LSL, USL))

# Print the process capability
print(pc)
```

```
## ── Process Capability Analysis ──────────────────
##
## Number of obs = 81           Target = 5.5
## Center        = 6.193827     LSL    = 3
## StdDev        = 1.585533     USL    = 8
##
## Capability indices  Value   2.5%  97.5%
##               Cp    0.526  0.444  0.607
##               Cp_l  0.671  0.565  0.778
##               Cp_u  0.380  0.301  0.458
##               Cp_k  0.380  0.286  0.473
##               Cpm   0.482  0.402  0.561
##
## Exp<LSL 0.022%    Obs<LSL 0%
## Exp>USL 0.13%     Obs>USL 0.14%
```

```r
plot(pc)
```

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