Diabetes Wound Care & Management Analysis

STAT 560 Nonparametric Statistics Midterm Report

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Exploratory Data Analysis with Power BI

Background

There are a total of 15 patients in this study for wound care and management. The data shown below is only a part of the ongoing study. Data is divided into three main sections and each contain statuses for the following information:

1. ***Wound Score, Compliance, and Goal Score***
    a. *Wound score is diagnosed at the beginning of the study.*
    b. *Compliance status is assumed to be dependent on the wound score diagnosis.*
    c. *Goal score is the sum of factors including compliance and others not listed in data here.*
2. ***Systemic***
    a. *DM (Diabetes Mellitus), exercise, diet, smoking, and meds (medication).*
3. ***Local***
    a. *Dressing changes, off-loading, skincare, edema control, and F/U (follow-up).*

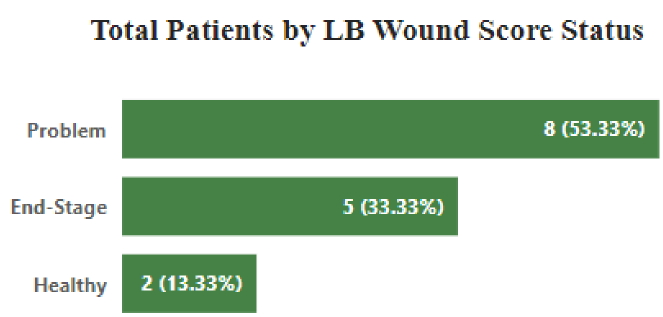
Tables and Plots with Descriptions

Wound Score, Compliance, and Goal Score

Table displays statuses from each category for all 15 patients.

Total Patients	LBWS Status	Compliance Status	Goal Score Status
1	End-Stage	Best	Best
2	Problem	Best	Best
1	Problem	Best	Good
1	End-Stage	Good	Good
1	End-Stage	OK	Good
2	Healthy	OK	Good
2	Problem	OK	Good
1	Problem	OK	OK
2	End-Stage	Worst	OK
2	Problem	Worst	Poor
15			

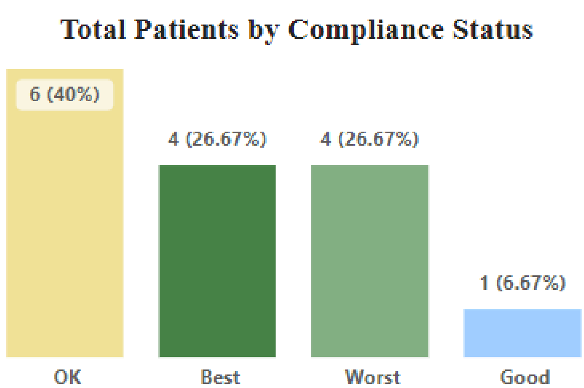
Shown are plots and their corresponding descriptions about the number of patients and percentages for each level within wound score, compliance, and goal score.



Five patients at 33.33% have a n end-stage wound score.

Eight patients at 53.33% have a problematic wound score.

Two patients at 13.33% have a healthy wound score.

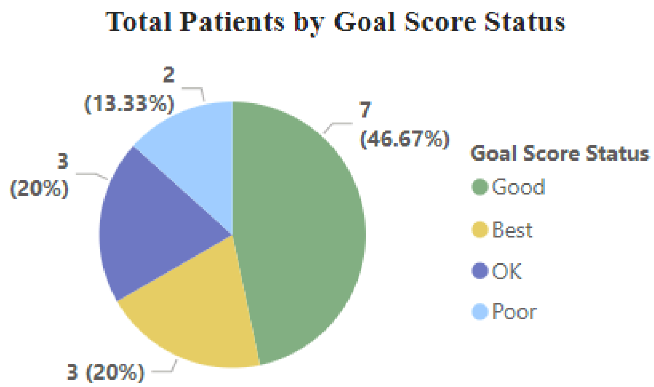


Four patients at 26.67% have the worst compliance.

Six patients at 40% have OK compliance.

One patient at 6.67% has good compliance.

Four patients at 26.67% have the best compliance.



Two patients at 13.33% have a poor goal score.

Three patients at 20% have an OK goal score.

Seven patients at 46.67% have a good goal score.

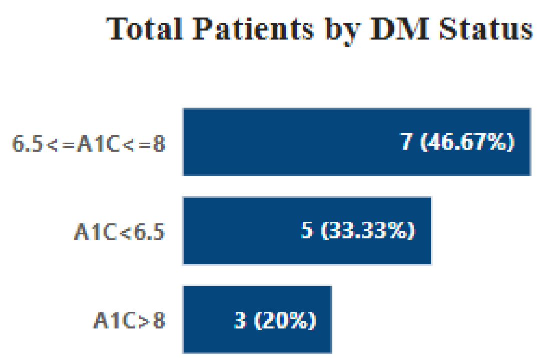
Three patients at 20% have the best goal score.

Systemic Data

Table displays statuses from each systemic category for all 15 patients.

Total Patients	DM Status	Exercise Status	Diet Status	Smoking Status	Meds Status
1	6.5<=A1C<=8	None	BMI>30	Current	Partial
2	A1C>8	None	BMI>30	Past	Partial
1	6.5<=A1C<=8	None	25<=BMI<=30	Never	Complete
1	6.5<=A1C<=8	None	BMI>30	Never	Complete
1	6.5<=A1C<=8	Some	25<=BMI<=30	Never	Complete
2	6.5<=A1C<=8	Some	BMI<25	Never	Complete
1	6.5<=A1C<=8	Some	BMI>30	Never	Complete
2	A1C<6.5	Full	BMI<25	Current	Complete
1	A1C<6.5	Full	BMI<25	Past	Complete
1	A1C<6.5	None	BMI>30	Never	Complete
1	A1C<6.5	None	BMI>30	Past	Complete
1	A1C>8	None	BMI>30	Never	Complete
15					

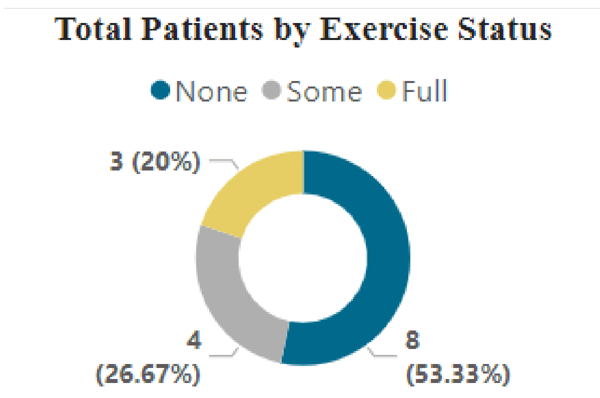
Shown are plots and their corresponding descriptions about the number of patients and percentages for each level within the status.



Five patients at 33.33% have an A1C score lower than 6.5.

Seven patients at 46.67% have an A1C score between 6.5 and 8.

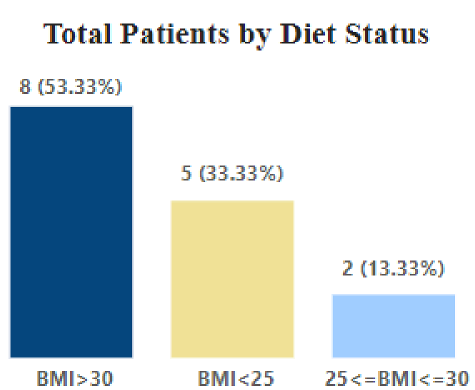
Three patients at 20% have an A1C score greater than 8.



Eight patients at 53.33% do not exercise.

Four patients at 26.67% do some exercise.

Three patients at 20% fully exercise.

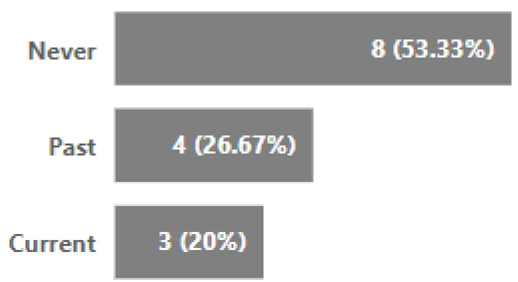


Five patients at 33.33% have a BMI score lower than 25.

Two patients at 13.33% have a BMI score between 25 and 30.

Eight patients at 53.33% have a BMI score greater than 30.

Total Patients by Smoking Status

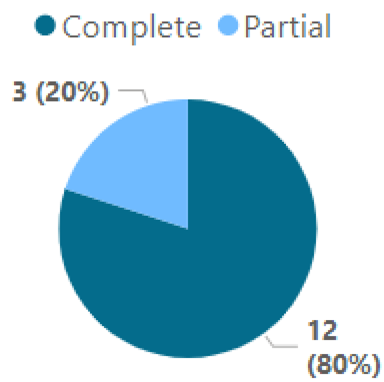


Eight patients at 53.33% have never smoked.

Four patients at 26.67% did smoke.

Three patients at 20% currently smoke.

Total Patients by Meds Status



No patients were inconsistent with taking medication.

Three patients at 20% partially take medication.

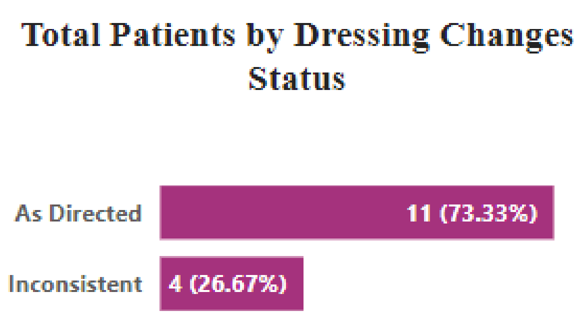
Twelve patients at 80% completely take medication.

Local Data

Table displays statuses from each local category for all 15 patients.

Total Patients	Dressing Status	Off-Load Status	Skincare Status	Edema Status	F/U Status
1	As Directed	As Directed	Healthy	1-2+	Consistent
1	As Directed	As Directed	Healthy	None	Consistent
2	As Directed	Disregard	Healthy	None	Consistent
1	As Directed	Disregard	Scaly	>2+	Inconsistent
1	As Directed	Inconsistent	Fungal	None	Consistent
1	As Directed	Inconsistent	Healthy	>2+	Consistent
2	As Directed	Inconsistent	Healthy	1-2+	Consistent
1	As Directed	Inconsistent	Scaly	>2+	Inconsistent
1	As Directed	Inconsistent	Scaly	None	Consistent
1	Inconsistent	Disregard	Fungal	>2+	Consistent
1	Inconsistent	Disregard	Scaly	1-2+	Consistent
1	Inconsistent	Disregard	Scaly	1-2+	Inconsistent
1	Inconsistent	Inconsistent	Fungal	1-2+	Disregard
15					

Shown are plots and their corresponding descriptions about the number of patients and percentages for each level within wound score, compliance, and goal score.

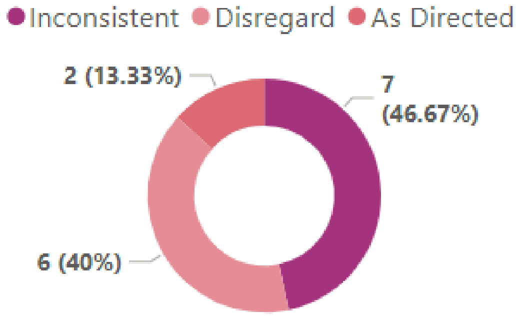


No patients disregarded changing dressings.

Four patients at 26.67% were inconsistent with changing dressings.

Eleven patients at 73.33% changed dressings as directed.

Total Patients by Off-Load Status

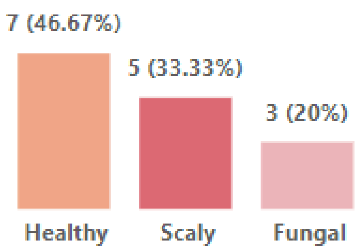


Six patients at 40% disregarded off-loading.

Seven patients at 46.67% were inconsistent with off-loading.

Two patients at 13.33% off-loaded as directed.

Total Patients by Skincare Status

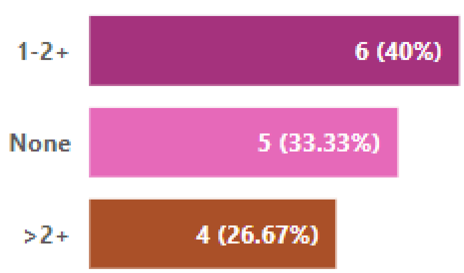


Three patients at 20% have fungal skin.

Five patients at 33.33% have scaly skin.

Seven patients at 46.67% have healthy skin.

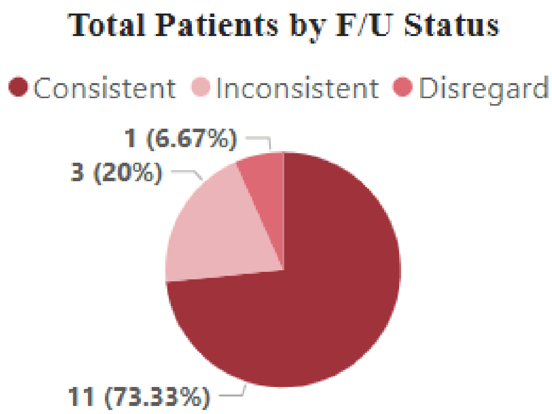
Total Patients by Edema Control Status



Five patients at 33.33% have no edema control.

Six patients at 40% have edema control of 1 to 2+.

Four patients at 26.67% have edema control of greater than 2+



One patient at 6.67% disregarded follow-up.

Three patients at 20% were inconsistent with follow-up.

Eleven patients at 73.33% are consistent with follow-up.

Statistical Methods

Kruskal-Wallis Test

Compliance for Exercise and Diet

If we separate patients based on exercise and diet, would those categories have significantly different compliance scores?

The EDCat (Exercise and Diet Category) field was created with three groups for this comparison: combined exercise and diet score less than zero, combined exercise and diet score equal to zero, and combined exercise and diet score greater than zero.

Nonparametric Approach

```
> kruskal.test(COMPLIANCE ~ as.character(EDCat), data = cmp)

        Kruskal-Wallis rank sum test

data:  COMPLIANCE by as.character(EDCat)
Kruskal-Wallis chi-squared = 5.5933, df = 2, p-value = 0.06101
```

The groups are not significantly different at the 5% level.

Parametric Approach

```
> an <- aov(cmp$COMPLIANCE ~ as.character(EDCat), data = cmp)
> shapiro.test(an$residuals)

        Shapiro-Wilk normality test

data:  an$residuals
W = 0.91922, p-value = 0.1874

> summary(an)
                    Df Sum Sq Mean Sq F value Pr(>F)
as.character(EDCat)  2  2.878  1.4389    3.79  0.053 .
Residuals           12  4.556  0.3796
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The groups are not significantly different at the 5% level.

Compliance for Local Total Categories

If we separate patients based on their Local Total, would those categories have significantly different compliance scores?

The LTotCat (Local Total Category) field was created with five groups for this comparison: local total less than -2.4, local total between -2.4 and -0.8, local total between -0.8 and 0.8, local total between 0.8 and 2.4; and local total above 2.4.

Nonparametric Approach

```
> kruskal.test(COMPLIANCE ~ as.character(LTotCat), data = cmp)

        Kruskal-Wallis rank sum test

data:  COMPLIANCE by as.character(LTotCat)
Kruskal-Wallis chi-squared = 8.1081, df = 3, p-value = 0.04383
```

The groups are significantly different at the 5% level.

<u>*Parametric Approach*</u>

```
> an <- aov(cmp$COMPLIANCE ~ as.character(LTotCat), data = cmp)
> shapiro.test(an$residuals)

        Shapiro-Wilk normality test

data:  an$residuals
W = 0.78465, p-value = 0.002352

> summary(an)
                      Df Sum Sq Mean Sq F value Pr(>F)
as.character(LTotCat)  3  4.246  1.4153   4.884 0.0214 *
Residuals             11  3.188  0.2898
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The data does not satisfy the normality assumption, so the ANOVA results are not valid.

Compliance for Systemic Total Categories

If we separate patients based on their Systemic Total, would those categories have significantly different compliance scores?

The STotCat (Systemic Total Category) field was created with five groups for this comparison: systemic total less than -2.4, systemic total between -2.4 and -0.8, systemic total between -0.8 and 0.8, systemic total between 0.8 and 2.4; and systemic total above 2.4.

<u>*Nonparametric Approach*</u>

```
> kruskal.test(COMPLIANCE ~ as.character(STotCat), data = cmp)

        Kruskal-Wallis rank sum test

data:  COMPLIANCE by as.character(STotCat)
Kruskal-Wallis chi-squared = 8.11, df = 4, p-value = 0.08763
```

The groups are not significantly different at the 5% level.

<u>*Parametric Approach*</u>

```
> an <- aov(cmp$COMPLIANCE ~ as.character(STotCat), data = cmp)
> shapiro.test(an$residuals)

        Shapiro-Wilk normality test

data:  an$residuals
W = 0.80038, p-value = 0.003717

> summary(an)
                      Df Sum Sq Mean Sq F value Pr(>F)  
as.character(STotCat)  4  4.267  1.0667   3.368 0.0543 .
Residuals             10  3.167  0.3167                 
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

The data does not satisfy the normality assumption, so the ANOVA results are not valid.

Compliance for Wound Score Categories

If we separate patients based on their Wound Category, would those categories have significantly different compliance scores?

(1) *Approach based on recommended categories:*
The PWCat (Professor's Wound Category) field was created with three groups for this comparison: wound score less than 3.5, wound score between 3.5 and 7, wound score more than 7.

<u>Nonparametric Approach</u>

```
> kruskal.test(COMPLIANCE ~ as.character(PWCat), data = cmp)

        Kruskal-Wallis rank sum test

data:  COMPLIANCE by as.character(PWCat)
Kruskal-Wallis chi-squared = 0.13288, df = 2, p-value = 0.9357
```

The groups are not significantly different at the 5% level

<u>Parametric Approach</u>

```
> an <- aov(cmp$COMPLIANCE ~ as.character(PWCat), data = cmp)
> shapiro.test(an$residuals)

        Shapiro-Wilk normality test

data:  an$residuals
W = 0.90424, p-value = 0.1105

> summary(an)
                    Df Sum Sq Mean Sq F value Pr(>F)
as.character(PWCat)  2  0.058  0.0292   0.047  0.954
Residuals           12  7.375  0.6146
```

The groups are not significantly different at the 5% level.

(2) *Approach based on our own categories:*
The WndCat (Wound Category) field was created with five groups for this comparison: wound score less than 3.2, wound score between 3.2 and 4.4, wound score between 4.4 and 5.6, wound score between 5.6 and 6.8; and wound score above 6.8.

Nonparametric Approach

```
> kruskal.test(COMPLIANCE ~ as.character(WndCat), data = cmp)

        Kruskal-Wallis rank sum test

data:  COMPLIANCE by as.character(WndCat)
Kruskal-Wallis chi-squared = 2.1078, df = 4, p-value = 0.7159
```

The groups are not significantly different at the 5% level.

Parametric Approach

```
> an <- aov(cmp$COMPLIANCE ~ as.character(WndCat), data = cmp)
> shapiro.test(an$residuals)

        Shapiro-Wilk normality test

data:  an$residuals
W = 0.94957, p-value = 0.5177

> summary(an)
                     Df Sum Sq Mean Sq F value Pr(>F)
as.character(WndCat)  4  1.100  0.2750   0.434  0.781
Residuals            10  6.333  0.6333
```

The groups are not significantly different at the 5% level

Pairwise Tests to Determine which Groups are Different

Nonparametric Approach

```
> pairwise.wilcox.test(cmp$COMPLIANCE, as.character(cmp$LTotCat), p.adjust.method = "fdr")

        Pairwise comparisons using Wilcoxon rank sum test with continuity correction

data:  cmp$COMPLIANCE and as.character(cmp$LTotCat)

  2    3    4
3 1.00 -    -
4 0.31 0.62 -
5 0.11 0.31 1.00

P value adjustment method: fdr
Warning messages:
1: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties
2: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties
3: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties
4: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties
5: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties
6: In wilcox.test.default(xi, xj, paired = paired, ...) :
  cannot compute exact p-value with ties


> dunn.test(cmp$COMPLIANCE, as.character(cmp$LTotCat), method = "by", kw=T, altp=T)
  Kruskal-Wallis rank sum test

data: x and group
Kruskal-Wallis chi-squared = 8.1081, df = 3, p-value = 0.04


                           Comparison of x by group
                              (Benjamini-Yekuteili)
Col Mean-|
Row Mean |          2          3          4
---------+--------------------------------
       3 |  -0.236508
         |     1.0000
         |
       4 |  -1.790704  -1.345973
         |     0.5391     0.6553
         |
       5 |  -2.500889  -1.699577  -0.020853
         |     0.1821     0.4371     1.0000

alpha = 0.05
Reject Ho if p <= alpha
```

The most significant difference is between group 2 and group 5, although all differences are insignificant.

Parametric Approach

```r
i <- 2
j <- 1
while(i < 5)
{
     tt <- t.test(cmp[cmp$LTotCat==(i),]$COMPLIANCE, cmp[cmp$LTotCat==(i+j),]$COMPLIANCE)

     print("Group 1  Group 2  t.test pvalue")
     print(c(i, i+j, tt$p.value))
     print("----------------------------- ")

     if(i + j < 5){j <- j + 1}
     else
     {
         i <- i + 1
         j <- 1
     }
}
```

```
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 2.000000 3.000000 0.848685
## [1] "----------------------------- "
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 2.0000000 4.0000000 0.2218725
## [1] "----------------------------- "
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 2.000000000 5.000000000 0.008577804
## [1] "----------------------------- "
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 3.0000000 4.0000000 0.2928932
## [1] "----------------------------- "
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 3.0000000 5.0000000 0.2653562
## [1] "----------------------------- "
## [1] "Group 1  Group 2  t.test pvalue"
## [1] 4 5 1
## [1] "----------------------------- "
```

The data does not satisfy the normality assumption, so the t test results are not valid.

Pearson's Correlation, Spearman's Rho, and Kendall's Tau

Wound Score vs. Compliance

Do wound score and compliance have a positive correlation?

```
```{r compliance and wound score}
# H0: compliance and wound score are mutually independent.
# H1: compliance and wound score have a positive correlation.
wound_score= c(2,4,7.5,3,6.5,2.5,5,6,5.5,8,6.5,3,4,3,3.5) #X's
compliance = c(2,1,1,0,0,1.5,2,2,1,1,2,0.5,0,1,1) #Y's
cor.test(wound_score, compliance, method="pearson", alternative="greater")
cor.test(wound_score, compliance, method="spearman", alternative="greater")

# Kendall's tau:
cor.test(wound_score, compliance, alternative="greater", method="kendall", exact=F)
```
```

```
        Pearson's product-moment correlation

data:  wound_score and compliance
t = 0.20125, df = 13, p-value = 0.4218
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 -0.3961211  1.0000000
sample estimates:
       cor
0.05573089

Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  wound_score and compliance
S = 555.79, p-value = 0.4894
alternative hypothesis: true rho is greater than 0
sample estimates:
        rho
0.007517867


        Kendall's rank correlation tau

data:  wound_score and compliance
z = 0, p-value = 0.5
alternative hypothesis: true tau is greater than 0
sample estimates:
tau
  0
```

Taking into account the wound score is diagnosed at the initial stage of the study, we will consider this the independent variable. Compliance, consequently, depends on the wound score and will be considered the dependent variable. The tests for Pearson's correlation, Spearman's rho, and Kendall's Tau all have p-values>alpha=0.05, with the lowest being p=0.4218 from Pearson's. Thus, results indicate that wound score and compliance are actually independent of each other, and we can disregard the assumption from the background section above that compliance is dependent on wound score.

Compliance vs. Goal Score

Do compliance and goal score have a positive correlation?

```
```{r compliance and goal score}
# H0: compliance and goal score are mutually independent.
# H1: compliance and goal score have a positive correlation.
compliance = c(2,1,1,0,0,1.5,2,2,1,1,2,0.5,0,1,1)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)
cor.test(compliance,goal_score,method="pearson",alternative="greater")
cor.test(compliance,goal_score,method="spearman",alternative="greater")

# Kendall's tau:
cor.test(compliance, goal_score, alternative="greater", method="kendall", exact=F)
```
```

```
        Pearson's product-moment correlation

data:  compliance and goal_score
t = 6.7196, df = 13, p-value = 7.135e-06
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.7192697 1.0000000
sample estimates:
      cor
0.8811658

Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  compliance and goal_score
S = 69.091, p-value = 9.003e-06
alternative hypothesis: true rho is greater than 0
sample estimates:
      rho
0.8766231


        Kendall's rank correlation tau

data:  compliance and goal_score
z = 3.677, p-value = 0.000118
alternative hypothesis: true tau is greater than 0
sample estimates:
      tau
0.7816961
```

Considering that compliance is a part of the goal score, we will consider this the independent variable. Goal score, consequently, will be considered the dependent variable. The tests for Pearson's correlation, Spearman's rho, and Kendall's Tau all have p-values<alpha=0.05, with the highest being p=0.000118 from Kendall's Tau. Thus, results indicate that compliance and goal score are actually positively correlated to each other.

Compliance vs. Sum Total for Systemic and Local Data

Do compliance and the sum total of the systemic and local data have a positive correlation?

```
```{r compliance and sum total of systematic/local}
# H0: compliance and sum total of systematic/local are mutually independent.
# H1: compliance and sum total of systematic/local have a positive correlation.
compliance = c(2,1,1,0,0,1.5,2,2,1,1,2,0.5,0,1,1)
sumtotal_systemic_local= c(6,0,6,-3,-5,6,3,7,4,4,8,-2,-1,-5,5)
cor.test(compliance,sumtotal_systemic_local,method="pearson",alternative="greater")
cor.test(compliance,sumtotal_systemic_local,method="spearman",alternative="greater")

# Kendall's tau:
cor.test(compliance, sumtotal_systemic_local, alternative="greater", method="kendall", exact=F)
```
```

```
        Pearson's product-moment correlation

data:  compliance and sumtotal_systemic_local
t = 4.2826, df = 13, p-value = 0.0004458
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.487896 1.000000
sample estimates:
      cor
0.7649848

Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  compliance and sumtotal_systemic_local
S = 131.11, p-value = 0.0004359
alternative hypothesis: true rho is greater than 0
sample estimates:
      rho
0.7658827


        Kendall's rank correlation tau

data:  compliance and sumtotal_systemic_local
z = 3.0959, p-value = 0.000981
alternative hypothesis: true tau is greater than 0
sample estimates:
      tau
0.6555556
```

Again, consider compliance as the independent variable and the sum total for the systemic and local data as the dependent variable. The tests for Pearson's correlation, Spearman's rho, and Kendall's Tau all have p-values<alpha=0.05, with the highest being p=0.000981 from Kendall's Tau. Thus, results indicate that compliance and the sum total for systemic and local data are positively correlated to each other.

Systemic Data Using Parametric Linear Regression and Pearson's Correlation

Within the systemic data, we can compare the lifestyles of each patient. Does exercise, diet, and smoking help get the patient a better goal score? Or is it a combination of them all together? These questions could potentially influence the patients to make better choices on their day-to day basis and can start immediately. We can report these findings to the doctor to share with the patients. We will use Kendall's tau and Pearson's method to find correlation.

Exercise

```
Family: gaussian
Link function: identity

Formula:
goal_scr ~ exercise_S

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.6071     0.6644  11.450 3.66e-08 ***
exercise_S    1.8214     0.7758   2.348   0.0354 *
---
Signif. codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =  0.244   Deviance explained = 29.8%
GCV = 6.4825  Scale est. = 5.6181    n = 15
```

Regression Output for Exercise in R

```
> cor.test(exercise, goal_score, alternative="greater", method="pearson")

        Pearson's product-moment correlation

data:  exercise and goal_score
t = 2.3477, df = 13, p-value = 0.01769
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.1364801 1.0000000
sample estimates:
      cor
0.5456496
```

Pearson's Correlation Output for Smoking in Python

Keeping in mind that the values for exercise are -1, 0, and 1 which represent no exercise, moderate exercise, and active exercise respectively. Looking at the effects and correlation between exercise and goal score, we can see that jumping 1 exercise level can increase a patient's goal score by about 1.8 using regression. Additionally, there is a positive correlation of 0.55 between exercise and goal score using Pearson's correlation. Both tests were significant with p-value<alpha=0.05.

Diet

```
Family: gaussian
Link function: identity

Formula:
goal_scr ~ diet_S

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.3548     0.5910  12.445 1.35e-08 ***
diet_S        1.7742     0.6348   2.795   0.0152 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =  0.327   Deviance explained = 37.5%
GCV = 5.7664  Scale est. = 4.9975    n = 15
```

Regression Output for Diet in R

```
> cor.test(diet, goal_score, alternative="greater", method="pearson")

        Pearson's product-moment correlation

data:  diet and goal_score
t = 2.7947, df = 13, p-value = 0.007592
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.2338755 1.0000000
sample estimates:
      cor
0.6126256
```

Pearson’s Correlation Output for Diet in Python

For our diet values, we have 1, 0, and -1 which represent BMI<25, BMI between 25 and 30 (inclusive), and BMI>30 respectively. Testing the effect and correlation between diet and goal score, we can see that jumping 1 BMI level can increase a patient's goal score by about 1.8 using regression. Additionally, there is a positive correlation of 0.61 between diet and goal score using Pearson’s correlation. Both tests were significant with p-value<alpha=0.05.

Smoking

```
Family: gaussian
Link function: identity

Formula:
goal_scr ~ smoking_S

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   6.8571     0.7863   8.721 8.59e-07 ***
smoking_S     0.4286     0.9182   0.467    0.648
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


R-sq.(adj) =  -0.0592   Deviance explained = 1.65%
GCV = 9.0786  Scale est. = 7.8681    n = 15
```

Regression Output for Smoking in R

```
> cor.test(smoking, goal_score, alternative="greater", method="pearson")

        Pearson's product-moment correlation

data:  smoking and goal_score
t = 0.46677, df = 13, p-value = 0.3242
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 -0.3325812  1.0000000
sample estimates:
      cor
0.1283881
```

Pearson’s Correlation Output for Smoking in Python

Recall that the smoking values are -1, 0, and 1 which represent current smoker, past smoker, and never smoked respectively. Testing the effect and correlation between smoking and goal score, both tests were not significant with p-value>alpha=0.05. Thus, we cannot make any statements about smoking and goal score using the tests above.

Diet and Exercise Regression

When using diet and exercise as predictor variables in a regression model, the model showed no significance at level alpha=0.05. Therefore, we check the correlation between exercise and diet and find that they are highly correlated and our findings are significant. Thus, when running regression on this data set it would be best to remove either diet or exercise to reduce multicollinearity and overfitting the model.

Regression Total

Before running all of the predictors against goal score, we will disregard total sum variables. From our findings above, we will also disregard exercise due to its high correlation with diet. Now, below is a list of our other highly correlated predictor variables that we will not include in our “big model”.

- *Cor(dressing_change_L, dm_S) = 0.74*
- *Cor(edema_control_L, diet_S) = 0.78*
- *Cor(edema_control_L, exercise_S) = 0.80*
- *Cor(dressing_change_L, meds_S) = 0.83*

Therefore, we choose to remove edema control because it is highly correlated with diet and exercise; as well as dressing change for the same reasons with dm and medications. Earlier in the report, we found that compliance has a positive correlation with goal score, so we will remove that as well.

After running that model (not shown), the p-value for dm was too high (0.9). Therefore, we removed the dm variable as the last removed variable and reached a reduced model.

```
Parametric coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      10.1457     1.5382   6.596 0.000306 ***
wound_scr         0.1607     0.2232   0.720 0.494751
diet_S            2.3811     0.5979   3.983 0.005306 **
smoking_S         1.7183     0.6953   2.472 0.042738 *
meds_S           -4.5077     1.6737  -2.693 0.030939 *
off_loading_L     1.4373     0.5723   2.512 0.040300 *
skin_toe_care_L   2.5857     0.7521   3.438 0.010867 *
F_U_app_L        -1.0385     0.7938  -1.308 0.232087
---
Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Reduced Regression Model Output for Smoking in R

We are interested in systematic variables that capture lifestyle insight. This reduced regression model output without correlated values shows that diet and smoking show significance when predicting goal score. We cautiously included local variables in our model as support variables in hopes that we would not overfit the model. This provides insight that is beneficial to the patient and the caretaker/doctor in better helping the current and future patients. The doctor can now communicate to the patient that keeping a healthy diet and not smoking can increase their goal score significantly.

Nonparametric Linear Regression with Different Correlation Tests for Systemic Data

Exercise vs. Goal Score

````
```{r LOWESS exercise and goal score}

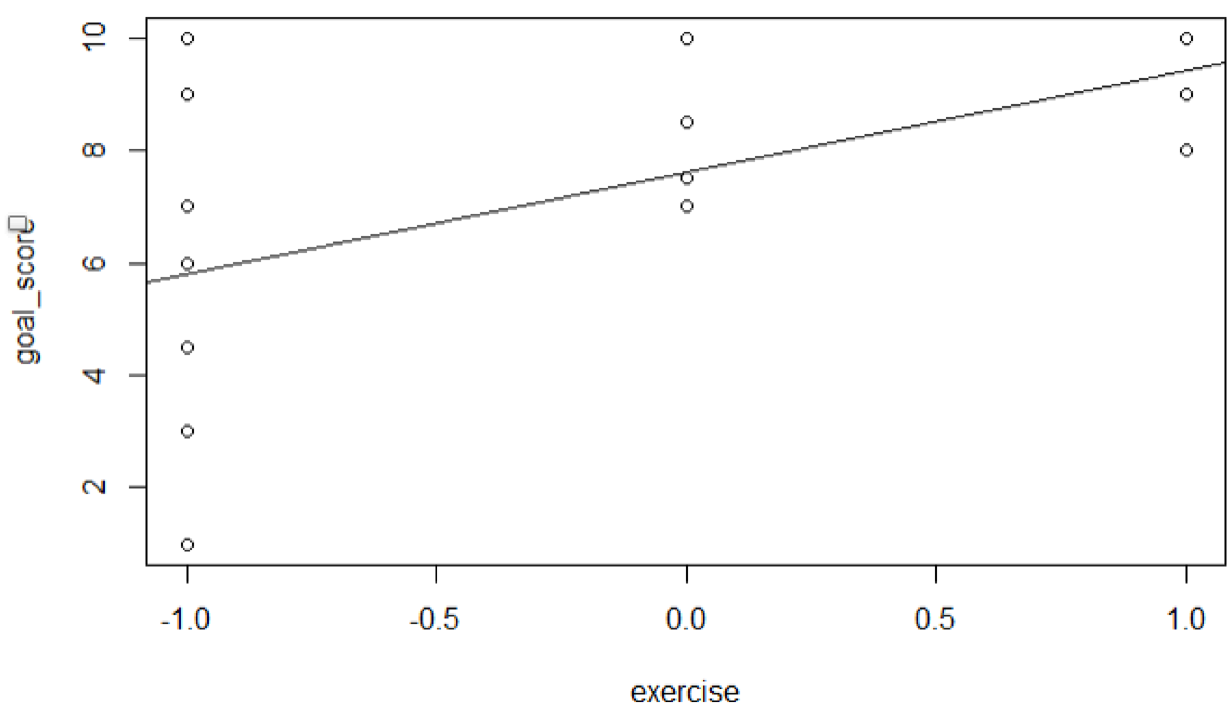
exercise = c(0,-1,1,-1,-1,0,-1,1,-1,0,1,-1,-1,-1,0)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)

plot(exercise,goal_score)
abline(lm(goal_score~exercise))

cor.test(exercise, goal_score, alternative="greater", method="spearman")
cor.test(exercise, goal_score, alternative="greater", method="kendall")

library(carData)
plot(goal_score ~ exercise, xlab="Exercise", ylab="Goal Score")

# A window including the 50 nearest x-neighbors of x_(80) (i.e., for span s = 50/102 ≈ 1/2)
lines(lowess(exercise, goal_score, f=0.5, iter=0), lwd=1, lty=2)
lines(lowess(exercise, goal_score, f=0.5, iter=3), lwd=2)
```
````



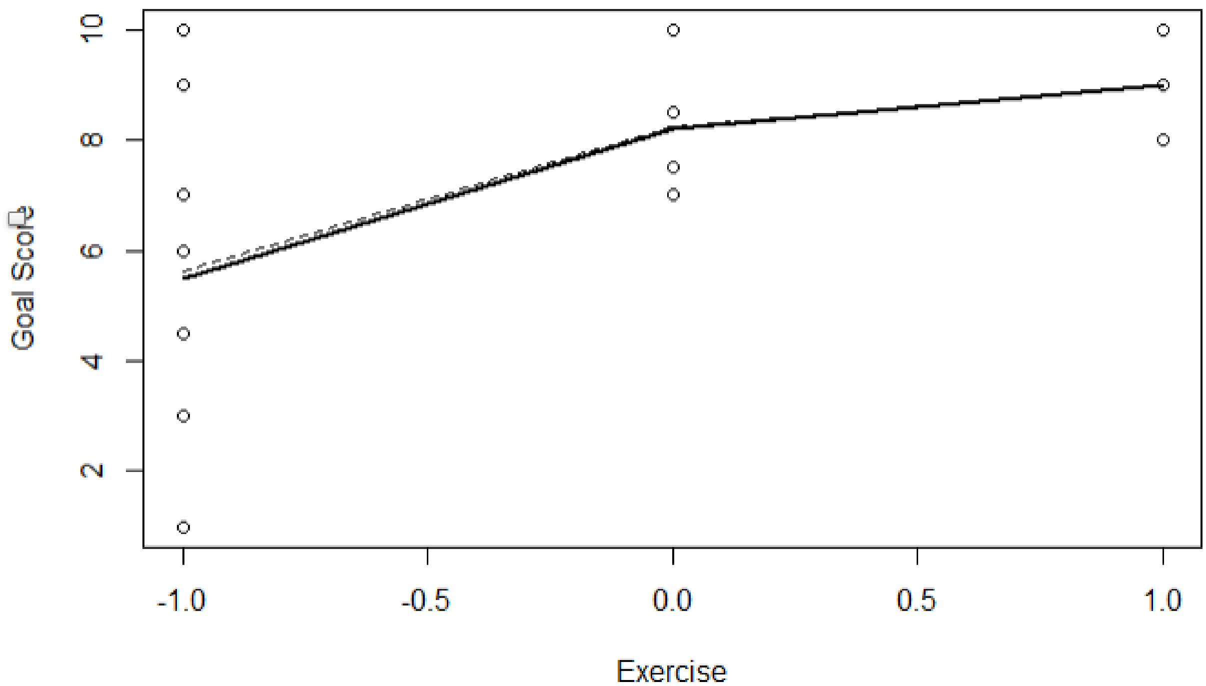

```
> cor.test(exercise, goal_score, alternative="greater", method="spearman")
Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  exercise and goal_score
S = 252.55, p-value = 0.01702
alternative hypothesis: true rho is greater than 0
sample estimates:
      rho
0.549009
```

```
Warning: Cannot compute exact p-value with ties
        Kendall's rank correlation tau

data:  goal_score and exercise
z = 2.1593, p-value = 0.01541
alternative hypothesis: true tau is greater than 0
sample estimates:
      tau
0.4753271
```

Kendall's Tau Output for Exercise in R



The comparison between the two plots for the regular linear regression versus the lowess method both show that exercise and goal score are positively correlated. However, the lowess plot details that the patients who do not exercise and who do some exercise share a faster increase in goal score than the ones who exercise fully.

This correlation is also confirmed through the different tests for Spearman's and Kendall's, where both p-values are lower than 0.05 significance level. Thus, we conclude that both exercise and goal score are positively correlated.

Diet vs. Goal Score

````
```{r LOWESS diet and goal score}

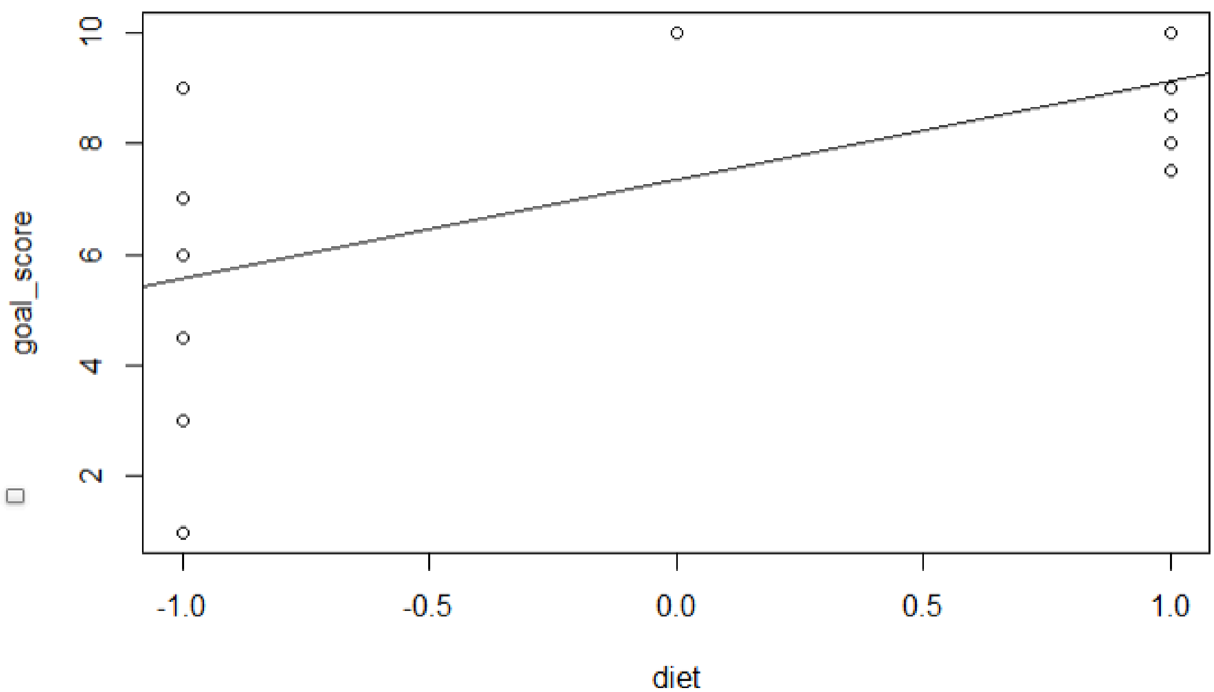
diet = c(0,-1,1,-1,-1,1,0,1,-1,-1,1,-1,-1,-1,1)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)

plot(diet,goal_score)
abline(lm(goal_score~diet))
```

```
cor.test(diet, goal_score, alternative="greater", method="spearman")
cor.test(diet, goal_score, alternative="greater", method="kendall")

library(carData)
plot(goal_score ~ diet, xlab="Diet", ylab="Goal Score")

# A window including the 50 nearest x-neighbors of x_(80) (i.e., for span s = 50/102 ≈ 1/2)
lines(lowess(diet, goal_score, f=0.5, iter=0), lwd=1, lty=2)
lines(lowess(diet, goal_score, f=0.5, iter=3), lwd=2)
```
```



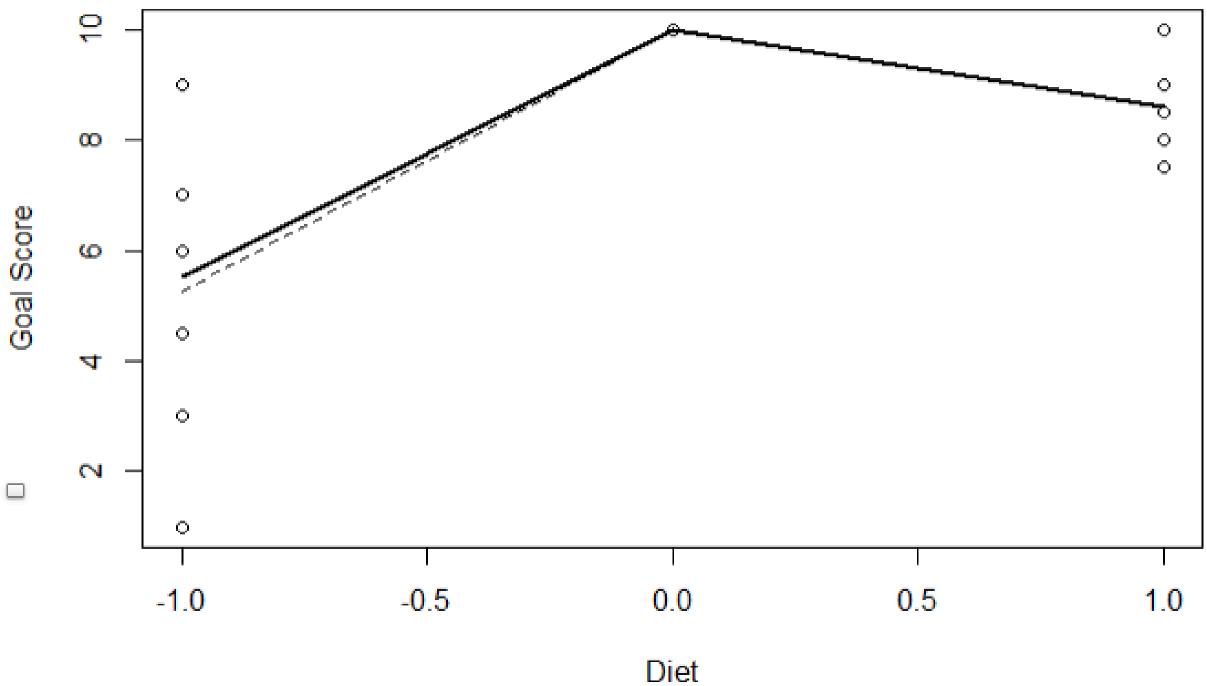

```
> cor.test(diet, goal_score, alternative="greater", method="spearman")
Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  diet and goal_score
S = 188.8, p-value = 0.003538
alternative hypothesis: true rho is greater than 0
sample estimates:
      rho
0.6628624
```

```
Warning: Cannot compute exact p-value with ties
        Kendall's rank correlation tau

data:  goal_score and diet
z = 2.2884, p-value = 0.01106
alternative hypothesis: true tau is greater than 0
sample estimates:
      tau
0.5072176
```

Correlation Output for Diet in R




*The comparison between the two plots for the regular linear regression versus the lowess method both show that diet and goal score are correlated. The first plot only shows an increase in diet score as the goal score increases, but the lowess plot details that the patients who have a BMI greater than 30 and BMI between 25 to 30 share a faster increase in goal score. The highest goal scores are for patients with a BMI from 25 to 30, but a BMI score below 25 will actually have a negative correlation.*

*This correlation is also confirmed through the different tests for Spearman's and Kendall's, where the highest p-value of 0.01106 from Kendall's is still significantly lower than alpha at the 0.05 significance level. Thus, we conclude that both diet and goal score are correlated.*

### *Smoking vs. Goal Score*

````
```{r LOWESS smoking and goal score}

smoking = c(1,1,-1,-1,0,1,1,0,1,1,-1,1,0,0,1)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)

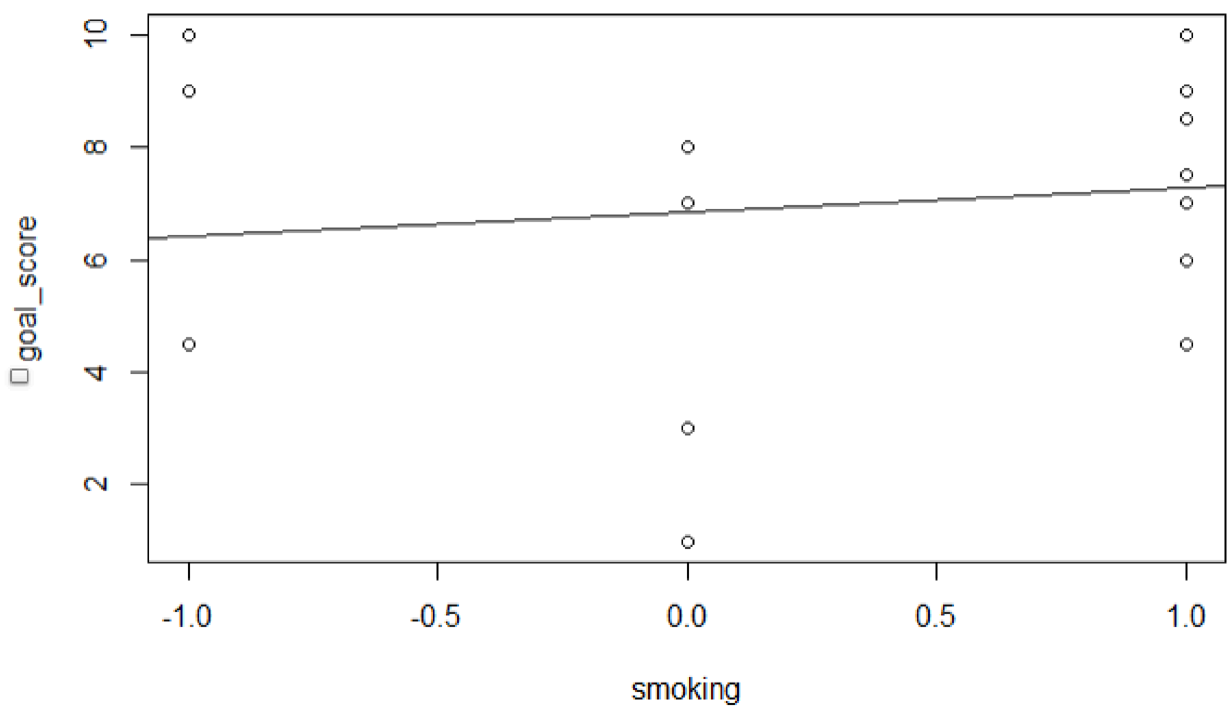
plot(smoking,goal_score)
abline(lm(goal_score~smoking))

cor.test(smoking, goal_score, alternative="greater", method="spearman")
cor.test(smoking, goal_score, alternative="greater", method="kendall")

library(carData)
plot(goal_score ~ smoking, xlab="Smoking", ylab="Goal Score")

# A window including the 50 nearest x-neighbors of x_(80) (i.e., for span s = 50/102 ≈ 1/2)
lines(lowess(smoking, goal_score, f=0.5, iter=0), lwd=1, lty=2)
lines(lowess(smoking, goal_score, f=0.5, iter=3), lwd=2)

```
````



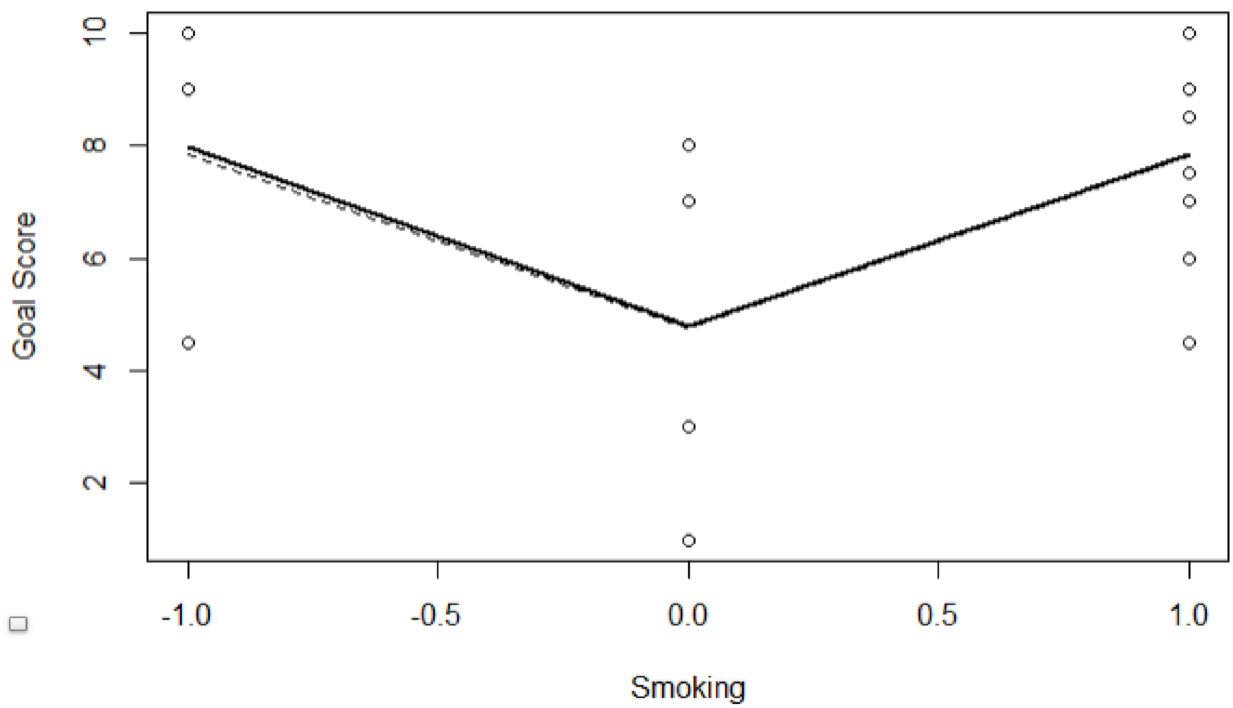

```
> cor.test(smoking, goal_score, alternative="greater", method="spearman")
Warning: Cannot compute exact p-value with ties
        Spearman's rank correlation rho

data:  smoking and goal_score
S = 485.77, p-value = 0.3188
alternative hypothesis: true rho is greater than 0
sample estimates:
      rho
0.1325535
```

```
Warning: Cannot compute exact p-value with ties
        Kendall's rank correlation tau

data:  goal_score and smok
z = 0.49831, p-value = 0.3091
alternative hypothesis: true tau is greater than 0
sample estimates:
      tau
0.1096909
```

Kendall's Correlation Output for Smoking in R



Despite comparisons between both plots indicating a possible correlation between smoking and goal score, the p-values for all the tests contradict this.

The lowest p-value of 0.3091 from Kendall's tau is still significantly higher than alpha at the 0.05 significance level, so tests conclude that smoking and goal score are mutually independent.

This is an indication it is safe to drop smoking from the full model, where goal score is the response variable.

Applying nonparametric regression with loess (not lowess) this time, the reduced model will retain at least one of the two predictors diet and exercise. This will depend on whether both these predictors are highly correlated. If so, eliminating one will eliminate multicollinearity.

Diet and Exercise Multiple Regression

```
```{r Diet and Exercise Multiple Regression}
#parameters
diet = c(0,-1,1,-1,-1,1,0,1,-1,-1,1,-1,-1,-1,1)
exercise = c(0,-1,1,-1,-1,0,-1,1,-1,0,1,-1,-1,-1,0)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)

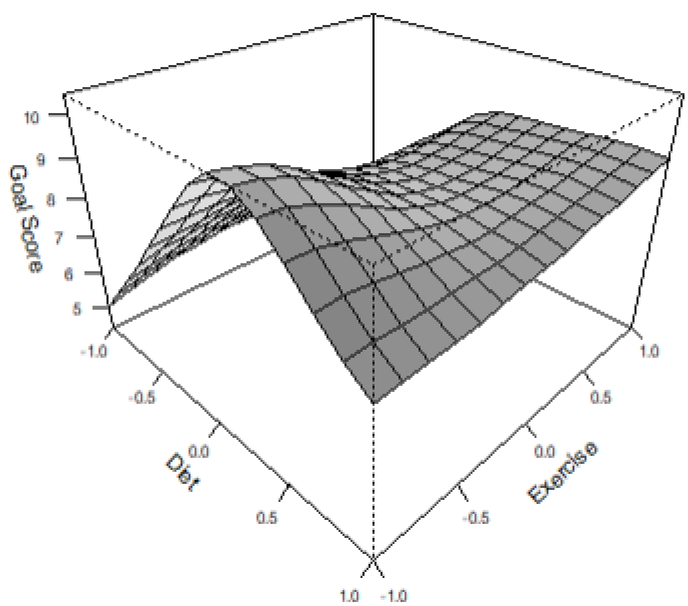
# Specifying degree=1 fits locally linear regressions
diet_exercise_reg <- loess(goal_score ~ diet + exercise, span=0.75, degree=1)
summary(diet_exercise_reg)

# Visualize the result of the regression by examining the fitted regression surface graphically
dt <- seq(min(diet), max(diet), len=15)
ex <- seq(min(exercise), max(exercise), len=15)
df1 <- expand.grid(diet=dt, exercise=ex)

fit.goal_score <- matrix(predict(diet_exercise_reg, df1), 15, 15)
persp(dt, ex, fit.goal_score, theta=45, phi=30,
      ticktype="detailed", xlab="Diet", ylab="Exercise",
      zlab="Goal Score", expand=2/3, shade=0.5, cex.axis = 0.5,
      cex.lab=.7)

# goal score has a nonlinear relationship with diet and exercise.
#particularly nonlinear with diet

```
```



From the simple regressions earlier between either exercise or diet and goal score, exercise's highest p-value=0.01769 is greater than diet's highest p-value=0.01106. This implies that diet is slightly more significant than exercise, which is confirmed in the 3D plot above, where diet is particularly correlated to goal score in a nonlinear manner.

Reduced Parametric Linear Regression Model - Python

Unlike the reduced model for the parametric linear regression above in R, the idea here is to consider all factors from both systemic and local features as potential predictors for the goal score.

Prior to applying a linear regression model, exercise and smoking were removed based on results from the correlation tests above. Predictors such as patients and the totals of anything were also removed since patients is basically an index and totals are correlated to the predictors that make up their sum total. Furthermore, the focus is on which individual predictors are correlated to the goal score, not the total of the predictors.

The correlation between compliance and goal score resulted in an extremely small p-value, implying compliance was highly correlated to goal score. When compliance was not removed prior to linear regression, it remained the only significant factor towards the end. This is due to such a significant weight attached to compliance as a predictor that all other predictors were practically insignificant in comparison. Thus, compliance was removed.

```python
import pandas as pd
import numpy as np
import statsmodels.api as sm

data=pd.read_csv('data.csv')
#-------------unimportant predictors-------------#
#remove patients since just number of people (like index)
#remove compliance since very significant and carries huge weight, would make other predictors insignificant in comparison
#remove exercise since strongly correlated to diet.
#remove smoking since not correlated to goal score
#remove totals of anything since obviously correlated to all factors
trivial_predictors=['Patient ','COMPLIANCE','Exercise','Smoking ','TOTAL (systemic)',
                    'TOTAL (local)','SumTotalSystemicLocal']
#drop trivial predictors and rows with Nan
data=data.drop(trivial_predictors,axis=1)
data=data.dropna(how='all')
data
```

	GOAL SCORE	WOUND SCORE	DM	Diet	Meds	Dressing changes	Off-loading	Skin/toenail care	Edema control	F/U Appt
0	10.0	2.0	0.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0
1	6.0	4.0	0.0	-1.0	1.0	1.0	0.0	0.0	-1.0	0.0
2	9.0	7.5	1.0	1.0	1.0	1.0	-1.0	1.0	1.0	1.0
3	4.5	3.0	0.0	-1.0	0.0	0.0	-1.0	0.0	0.0	1.0
4	3.0	6.5	-1.0	-1.0	0.0	0.0	-1.0	-1.0	-1.0	1.0
5	8.5	2.5	0.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0
6	10.0	5.0	0.0	0.0	1.0	1.0	0.0	1.0	-1.0	1.0
7	8.0	6.0	1.0	1.0	1.0	1.0	-1.0	1.0	1.0	1.0
8	9.0	5.5	1.0	-1.0	1.0	1.0	0.0	1.0	0.0	1.0
9	7.0	8.0	0.0	-1.0	1.0	1.0	0.0	1.0	0.0	1.0
10	10.0	6.5	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
11	4.5	3.0	-1.0	-1.0	1.0	0.0	-1.0	0.0	0.0	0.0
12	1.0	4.0	1.0	-1.0	1.0	1.0	-1.0	0.0	-1.0	0.0
13	7.0	3.0	-1.0	-1.0	0.0	0.0	0.0	-1.0	0.0	-1.0
14	7.5	3.5	0.0	1.0	1.0	1.0	0.0	-1.0	1.0	1.0

```python
from sklearn.model_selection import train_test_split
X=data.drop('GOAL SCORE', axis=1)
y=data['GOAL SCORE']

#split data
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2, random_state=560)

#regression with GOAL SCORE as response variable
X_train=sm.add_constant(X_train)
reg=sm.OLS(y_train,X_train).fit()
reg.summary()
```

	coef	std err	t	P>|t|	[0.025	0.975]
const	10.0245	3.968	2.526	0.086	-2.604	22.653
WOUND SCORE	-0.2034	0.480	-0.423	0.701	-1.732	1.326
DM	-1.5556	1.688	-0.921	0.425	-6.929	3.818
Diet	0.9340	1.288	0.725	0.521	-3.167	5.034
Meds	-1.2922	1.950	-0.663	0.555	-7.497	4.912
Dressing changes	-1.2922	1.950	-0.663	0.555	-7.497	4.912
Off-loading	0.9523	1.219	0.781	0.492	-2.926	4.831
Skin/toenail care	3.8661	2.077	1.861	0.160	-2.744	10.477
Edema control	0.6759	1.336	0.506	0.648	-3.576	4.928
F/U Appt	-0.5672	1.486	-0.382	0.728	-5.296	4.161

All p-values are insignificant and much larger than alpha=0.05, so backward elimination was applied to reduce dimensions by the highest p-value one at a time.

Predictors were dropped one at a time in the order of F/U Appt, Edema control, WOUND SCORE, DM, Meds and Dressing changes, and Skin/toenail care. Meds and Dressing changes were dropped simultaneously since they both had the same p-values in addition to the same coefficients, standard error, t-statistic, and confidence interval.

Variations of backward elimination were applied, which all resulted in the same final model. Such attempts included removing Smoking prior to applying linear regression and removing Smoking after. Likewise with Edema control and Dressing changes since the lack of correlation between these features and goal score was confirmed through various tests from earlier.

	coef	std err	t	P>|t|	[0.025	0.975]
const	8.0192	0.556	14.431	0.000	6.762	9.276
Diet	1.6304	0.597	2.733	0.023	0.281	2.980
Off-loading	2.2347	0.779	2.868	0.019	0.472	3.997

The final model includes only two predictors and a constant. This seems valid since the p-values for both Diet and Off-loading are less than alpha=0.05 significance level.

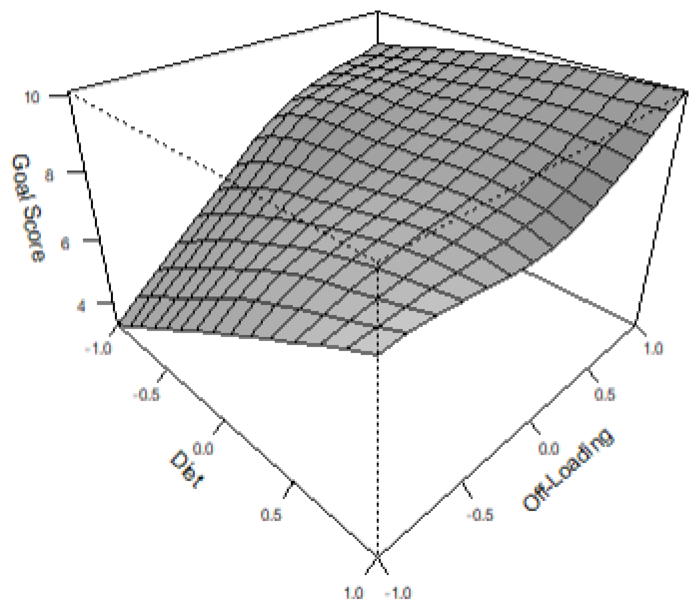
Below is a nonparametric multiple regression on Diet and Off-loading.

```
```{r Diet and Off-loading Multiple Regression}
#parameters
diet = c(0,-1,1,-1,-1,1,0,1,-1,-1,1,-1,-1,-1,1)
off_loading = c(1,0,-1,-1,-1,0,0,-1,0,0,1,-1,-1,0,0)
goal_score= c(10,6,9,4.5,3,8.5,10,8,9,7,10,4.5,1,7,7.5)

# Specifying degree=1 fits locally linear regressions
diet_offload_reg <- loess(goal_score ~ diet + off_loading, span=0.75, degree=1)
summary(diet_offload_reg)

# Visualize the result of the regression by examining the fitted regression surface graphically
dt <- seq(min(diet), max(diet), len=15)
ol <- seq(min(off_loading), max(off_loading), len=15)
df1 <- expand.grid(diet=dt, off_loading=ol)

fit.goal_score <- matrix(predict(diet_offload_reg, df1), 15, 15)
persp(dt, ol, fit.goal_score, theta=45, phi=30,
      ticktype="detailed", xlab="Diet", ylab="Off-Loading",
      zlab="Goal Score", expand=2/3, shade=0.5, cex.axis = 0.5,
      cex.lab=.7)
```



This is more linear than the previous multiple regression with diet and exercise as predictors.
```

Appendix

Power BI Query Table

Original Data

List of 15 patients and their corresponding goal score, compliance, and wound score.

	Patient	GOAL SCORE	COMPLIANCE	WOUND SCORE
1	1	10	2	2
2	2	6	1	4
3	3	9	1	7.5
4	4	4.5	0	3
5	5	3	0	6.5
6	6	8.5	1.5	2.5
7	7	10	2	5
8	8	8	2	6
9	9	9	1	5.5
10	10	7	1	8
11	11	10	2	6.5
12	12	4.5	0.5	3
13	13	1	0	4
14	14	7	1	3
15	15	7.5	1	3.5

Systemic data for 15 patients with their corresponding statuses and total per patient.

	DM	Exercise	Diet	Smoking	Meds	TOTAL (systemic)
1	0	0	0	1	1	2
2	0	-1	-1	1	1	0
3	1	1	1	-1	1	3
4	0	-1	-1	-1	0	-3
5	-1	-1	-1	0	0	-3
6	0	0	1	1	1	3
7	0	-1	0	1	1	1
8	1	1	1	0	1	4
9	1	-1	-1	1	1	1
10	0	0	-1	1	1	1
11	1	1	1	-1	1	3
12	-1	-1	-1	1	1	-1
13	1	-1	-1	0	1	0
14	-1	-1	-1	0	0	-3
15	0	0	1	1	1	3

Local data for 15 patients with their corresponding statuses and total per patient.

Last column is the sum total for both systemic and local data per patient.

	Dressing changes	Off-loading	Skin/toenail care	Edema control	F/U Appt	TOTAL (local)	SumTotalSystemicLocal
1	1	1	1	0	1	4	6
2	1	0	0	-1	0	0	0
3	1	-1	1	1	1	3	6
4	0	-1	0	0	1	0	-3
5	0	-1	-1	-1	1	-2	-5
6	1	0	0	1	1	3	6
7	1	0	1	-1	1	2	3
8	1	-1	1	1	1	3	7
9	1	0	1	0	1	3	4
10	1	0	1	0	1	3	4
11	1	1	1	1	1	5	8
12	0	-1	0	0	0	-1	-2
13	1	-1	0	-1	0	-1	-1
14	0	0	-1	0	-1	-2	-5
15	1	0	-1	1	1	2	5

Categorical Data

List of 15 patients and their corresponding Long Beach wound score, compliance, and goal score statuses.

	LBWS Status	Compliance Status	Goal Score Status
1	End-Stage	Best	Best
2	Problem	OK	OK
3	Healthy	OK	Good
4	End-Stage	Worst	OK
5	Problem	Worst	Poor
6	End-Stage	Good	Good
7	Problem	Best	Best
8	Problem	Best	Good
9	Problem	OK	Good
10	Healthy	OK	Good
11	Problem	Best	Best
12	End-Stage	Worst	OK
13	Problem	Worst	Poor
14	End-Stage	OK	Good
15	Problem	OK	Good

Systemic data for 15 patients with their corresponding statuses.

	DM Status	Exercise Status	Diet Status	Smoking Status	Meds Status	Dressing Status
1	6.5<=A1C<=8	Some	25<=BMI<=30	Never	Complete	As Directed
2	6.5<=A1C<=8	None	BMI>30	Never	Complete	As Directed
3	A1C<6.5	Full	BMI<25	Current	Complete	As Directed
4	6.5<=A1C<=8	None	BMI>30	Current	Partial	Inconsistent
5	A1C>8	None	BMI>30	Past	Partial	Inconsistent
6	6.5<=A1C<=8	Some	BMI<25	Never	Complete	As Directed
7	6.5<=A1C<=8	None	25<=BMI<=30	Never	Complete	As Directed
8	A1C<6.5	Full	BMI<25	Past	Complete	As Directed
9	A1C<6.5	None	BMI>30	Never	Complete	As Directed
10	6.5<=A1C<=8	Some	BMI>30	Never	Complete	As Directed
11	A1C<6.5	Full	BMI<25	Current	Complete	As Directed
12	A1C>8	None	BMI>30	Never	Complete	Inconsistent
13	A1C<6.5	None	BMI>30	Past	Complete	As Directed
14	A1C>8	None	BMI>30	Past	Partial	Inconsistent
15	6.5<=A1C<=8	Some	BMI<25	Never	Complete	As Directed

Local data for 15 patients with their corresponding statuses.

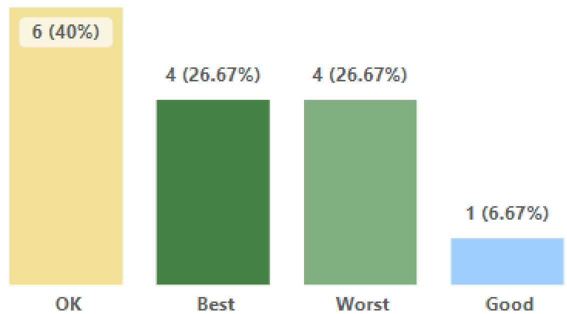
	Dressing Status	Off-Load Status	Skincare Status	Edema Status	F/U Status
1	As Directed	As Directed	Healthy	1-2+	Consistent
2	As Directed	Inconsistent	Scaly	>2+	Inconsistent
3	As Directed	Disregard	Healthy	None	Consistent
4	Inconsistent	Disregard	Scaly	1-2+	Consistent
5	Inconsistent	Disregard	Fungal	>2+	Consistent
6	As Directed	Inconsistent	Scaly	None	Consistent
7	As Directed	Inconsistent	Healthy	>2+	Consistent
8	As Directed	Disregard	Healthy	None	Consistent
9	As Directed	Inconsistent	Healthy	1-2+	Consistent
10	As Directed	Inconsistent	Healthy	1-2+	Consistent
11	As Directed	As Directed	Healthy	None	Consistent
12	Inconsistent	Disregard	Scaly	1-2+	Inconsistent
13	As Directed	Disregard	Scaly	>2+	Inconsistent
14	Inconsistent	Inconsistent	Fungal	1-2+	Disregard
15	As Directed	Inconsistent	Fungal	None	Consistent

Complete Power BI Dashboards

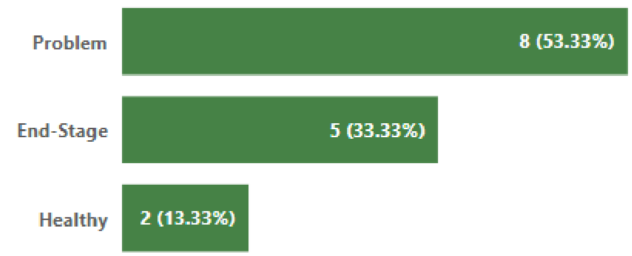
Wound Score, Compliance, Goal Score

Goal Score, Compliance, and Wound Score

Total Patients by Compliance Status

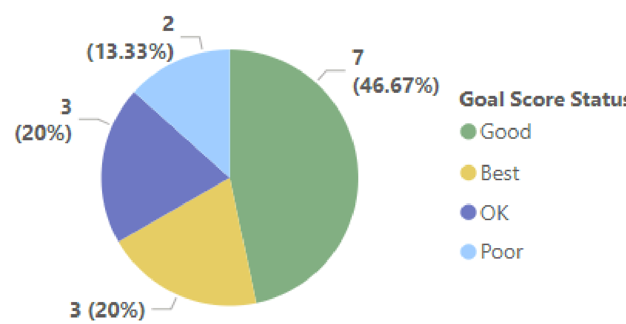


Total Patients by LB Wound Score Status



Total Patients	LBWS Status	Compliance Status	Goal Score Status
1	End-Stage	Best	Best
2	Problem	Best	Best
1	Problem	Best	Good
1	End-Stage	Good	Good
1	End-Stage	OK	Good
2	Healthy	OK	Good
2	Problem	OK	Good
1	Problem	OK	OK
2	End-Stage	Worst	OK
2	Problem	Worst	Poor
15			

Total Patients by Goal Score Status



Systemic Data

Systemic Diabetes Wound Care and Management

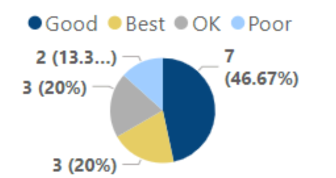
Compliance

Best	Good	OK	Worst
4	1	6	4
26.7%	6.7%	40.0%	26.7%

LB Wound Score

Healthy	Problem	End-Stage
2	8	5
13.3%	53.3%	33.3%

Goal Score Status

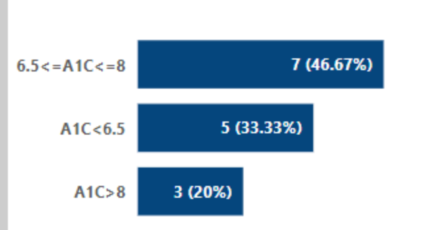


Total Patients

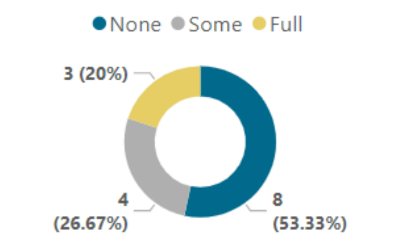
Systemic

15

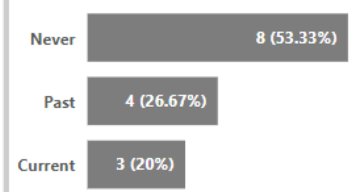
Total Patients by DM Status



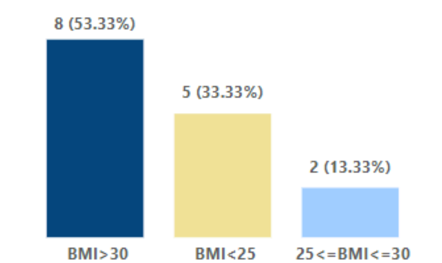
Total Patients by Exercise Status



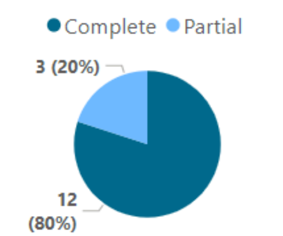
Total Patients by Smoking Status



Total Patients by Diet Status



Total Patients by Meds Status



Total Patients	DM Status	Exercise Status	Diet Status	Smoking Status	Meds Statu
1	6.5<=A1C<=8	None	BMI>30	Current	Partial
2	A1C>8	None	BMI>30	Past	Partial
1	6.5<=A1C<=8	None	25<=BMI<=30	Never	Complete
1	6.5<=A1C<=8	None	BMI>30	Never	Complete
1	6.5<=A1C<=8	Some	25<=BMI<=30	Never	Complete
2	6.5<=A1C<=8	Some	BMI<25	Never	Complete
1	6.5<=A1C<=8	Some	BMI>30	Never	Complete
2	A1C<6.5	Full	BMI<25	Current	Complete
1	A1C<6.5	Full	BMI<25	Past	Complete
1	A1C<6.5	None	BMI>30	Never	Complete
1	A1C<6.5	None	BMI>30	Past	Complete
1	A1C>8	None	BMI>30	Never	Complete
15					

Local Data

Local Diabetes Wound Care and Management

Compliance

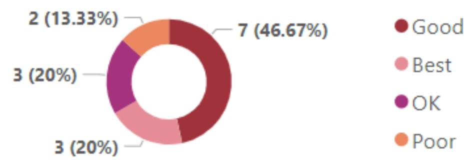
Best	Good
4	1
26.7%	6.7%

OK	Worst
6	4
40.0%	26.7%

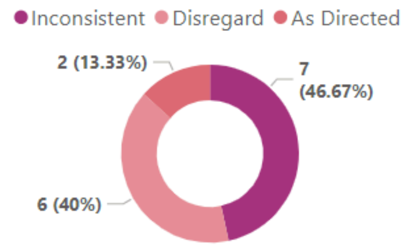
LB Wound Score

Healthy	Problem	End-Stage
2	8	5
13.3%	53.3%	33.3%

Goal Score Status



Total Patients by Off-Load Status



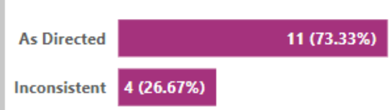
Total Patients

Local

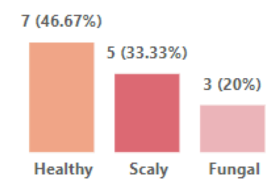
15

Total Patients	Dressing Status	Off-Load Status	Skincare Status	Edema Status	F/U Status
1	As Directed	As Directed	Healthy	1-2+	Consistent
1	As Directed	As Directed	Healthy	None	Consistent
2	As Directed	Disregard	Healthy	None	Consistent
1	As Directed	Disregard	Scaly	>2+	Inconsistent
1	As Directed	Inconsistent	Fungal	None	Consistent
1	As Directed	Inconsistent	Healthy	>2+	Consistent
2	As Directed	Inconsistent	Healthy	1-2+	Consistent
1	As Directed	Inconsistent	Scaly	>2+	Inconsistent
1	As Directed	Inconsistent	Scaly	None	Consistent
1	Inconsistent	Disregard	Fungal	>2+	Consistent
1	Inconsistent	Disregard	Scaly	1-2+	Consistent
1	Inconsistent	Disregard	Scaly	1-2+	Inconsistent
1	Inconsistent	Inconsistent	Fungal	1-2+	Disregard
15					

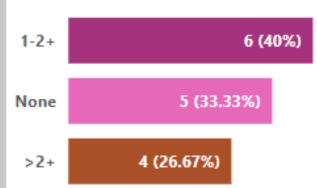
Total Patients by Dressing Changes Status



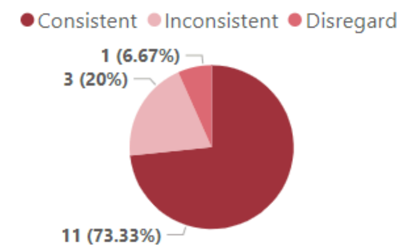
Total Patients by Skincare Status



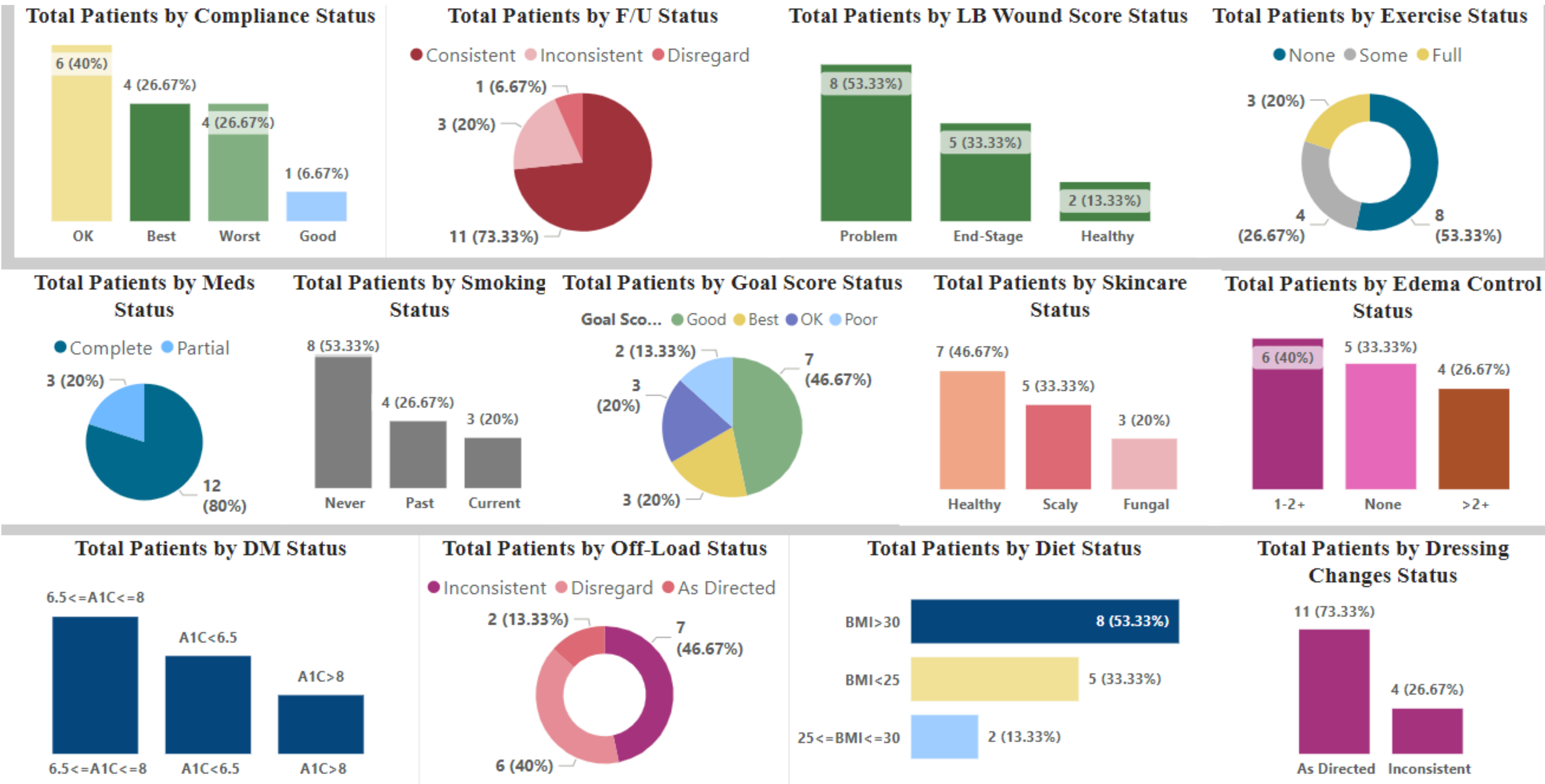
Total Patients by Edema Control Status



Total Patients by F/U Status



All Plots


Total Patients by Compliance Status
6 (40%)
4 (26.67%)
4 (26.67%)
1 (6.67%)
OK
Best
Worst
Good
Total Patients by F/U Status
Consistent
Inconsistent
Disregard
1 (6.67%)
3 (20%)
11 (73.33%)
Total Patients by LB Wound Score Status
8 (53.33%)
5 (33.33%)
2 (13.33%)
Problem
End-Stage
Healthy
Total Patients by Exercise Status
None
Some
Full
3 (20%)
4 (26.67%)
8 (53.33%)
Total Patients by Meds Status
Complete
Partial
3 (20%)
12 (80%)
Total Patients by Smoking Status
8 (53.33%)
4 (26.67%)
3 (20%)
Never
Past
Current
Total Patients by Goal Score Status
Goal Sco...
Good
Best
OK
Poor
2 (13.33%)
7 (46.67%)
3 (20%)
3 (20%)
Total Patients by Skincare Status
7 (46.67%)
5 (33.33%)
3 (20%)
Healthy
Scaly
Fungal
Total Patients by Edema Control Status
6 (40%)
5 (33.33%)
4 (26.67%)
1-2+
None
>2+
Total Patients by DM Status
6.5<=A1C<=8
A1C<6.5
A1C>8
6.5<=A1C<=8
A1C<6.5
A1C>8
Total Patients by Off-Load Status
Inconsistent
Disregard
As Directed
2 (13.33%)
7 (46.67%)
6 (40%)
Total Patients by Diet Status
BMI>30
8 (53.33%)
BMI<25
5 (33.33%)
25<=BMI<=30
2 (13.33%)
Total Patients by Dressing Changes Status
11 (73.33%)
4 (26.67%)
As Directed
Inconsistent