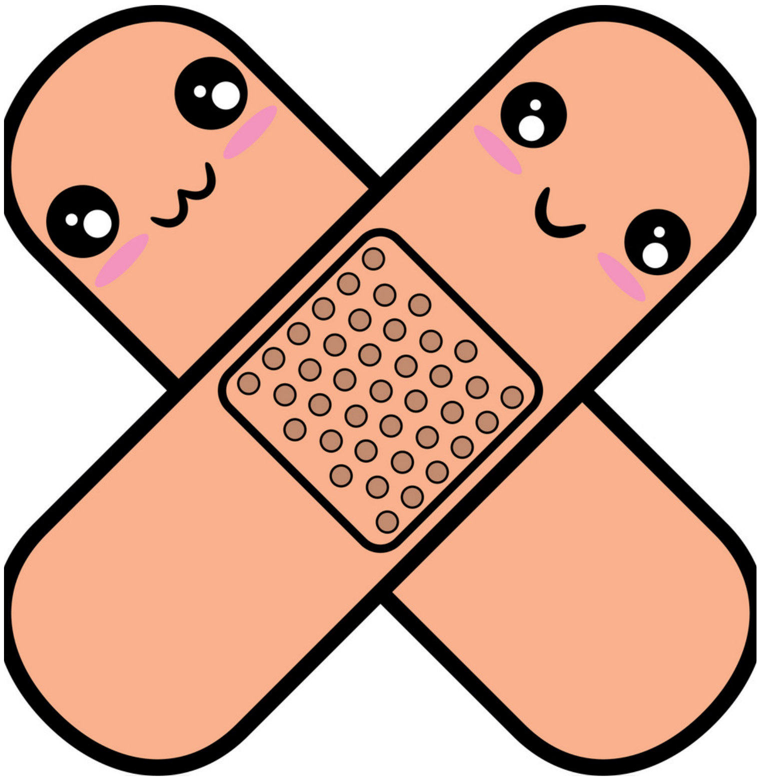
Wound Score Analysis

STAT 560 Nonparametric Statistics Final Report



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Objective

With a dataset containing clinical and demographic information for approximately 100 patients, researchers aim to delve into the wound scoring system's intricacies. This involves examining variables such as wound size, depth, and healing progress alongside patient characteristics like age, gender, and medical history. The primary objective is to understand how these factors influence wound assessment and treatment outcomes.

Furthermore, the dataset allows for the exploration of correlations between wound characteristics, patient demographics, and treatment efficacy. Understanding these relationships can inform personalized treatment approaches and contribute to the development of more effective wound management strategies tailored to individual patientneeds.

Overall, leveraging this comprehensive dataset provides valuable insights into wound assessment practices, enhances our understanding of wound healing processes, and ultimately contributes to improving patient care outcomes in clinical settings.

Data Summarization and Visualization

I. Data Cleaning

Given the raw data set, it is necessary to organize and clean it. In Excel, columns are combined with their sub-columns and column names with spaces are changed to underscores to simplify the data cleaning process. A new file is provided in the submission named *patients.csv*.

Utilizing the updated excel file in R, rows without a specific patient ID are removed. Additionally, columns that do not provide sufficient information or have less than 10 observations out of a total possibility of 96 rows are removed. Moreover, each column left is looked over to conclude whether or not it was worth keeping. Additional columns are removed based on study preference. This results in 65 columns, compared to the original 108. Some of the observations recorded are not organized into proper categories due to reasons such as spelling errors, inconsistent punctuation, and inconsistent capitalization. This is also rectified by changing equal, but mistyped, observations to the same name. The updated and final data used is provided in the submission named *clean_df.csv.*

II. Variable Summary

Patient’s wound scores are classified according to the Wagner’s Stages or UT’s Grades Wound Score Systems.

1. The patients are classified into Grade 1-5 based on Wagner’s Classification.
    a. Grade 1: Risk
    b. Grade 2: Ulcer
    c. Grade 3: Abscess
    d. Grade 4: Gangrene
    e. Grade 5: Extensive

By transforming the patient’s Wagner’s Grade Classification into similar categories of Wound Types, this allows us to conduct inter-rater reliability analysis.

a. Grade 1 - Risk
b. Grade 2 - Infection
c. Grade 3 - Infection
d. Grade 4 - Ischemia

e. Grade 5 - Both

Wagner's classification of diabetic foot ulcers

Wagner's Classification	
Grade 0	Skin intact but bony deformities lead to "foot at risk"
Grade 1	Superficial ulcer
Grade 2	Deeper, full thickness extension
Grade 3	Deep abscess formation or osteomyelitis
Grade 4	Partial Gangrene of forefoot
Grade 5	Extensive Gangrene

Table 1. Wagner's Classifications

2. The patients are also classified into one of these categories based on UTSA's classification, specifically from 1A to 3D.
   a. 1A, 2A, 3A: Risk
   b. 1B, 2B, 3B: Infection
   c. 1C, 2C, 3C: Ischemia
   d. 1D, 2D, 3D: Both

	GRADE				
STAGE		0	1	2	3
	A	Pre-ulcerative lesions No skin break	Superficial wound No penetration	Wound penetrating tendon or capsule	Wound penetrating bone or joint
	B	With infection	With infection	With infection	With infection
	C	With ischemia	With ischemia	With ischemia	With ischemia
	D	With infection and ischemia	With infection and ischemia	With infection ad ischemia	With infection and ischemia

Table 2. UT's Classification

III. Data Visualization:

i. Wound Score

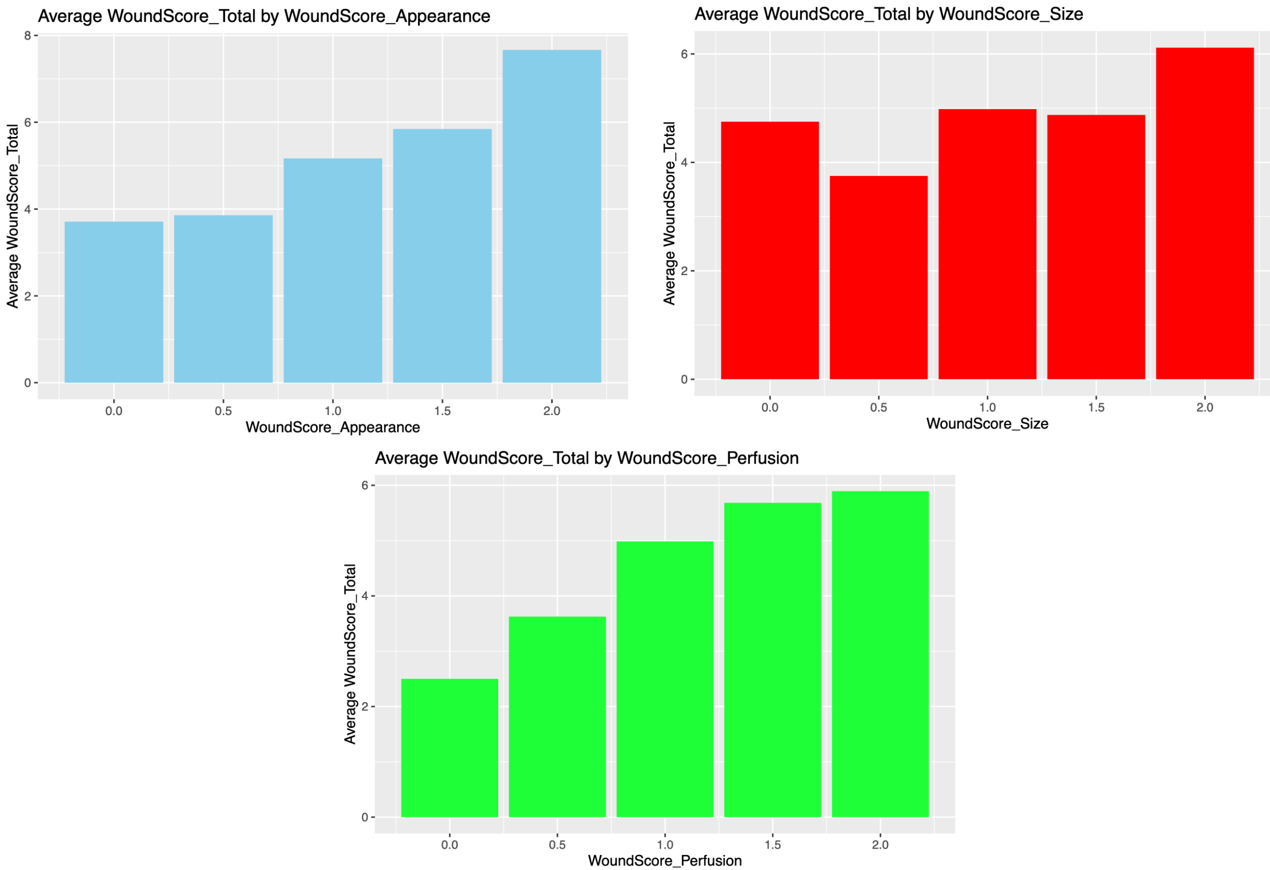

Figure 1: Histograms made in R

Looking at the sub-categories regarding wound score, it shows that wound appearance and perfusion seem to have a positive trend against total wound score. Wound size doesn't appear to have any effect on total wound score.

ii. Patient Background

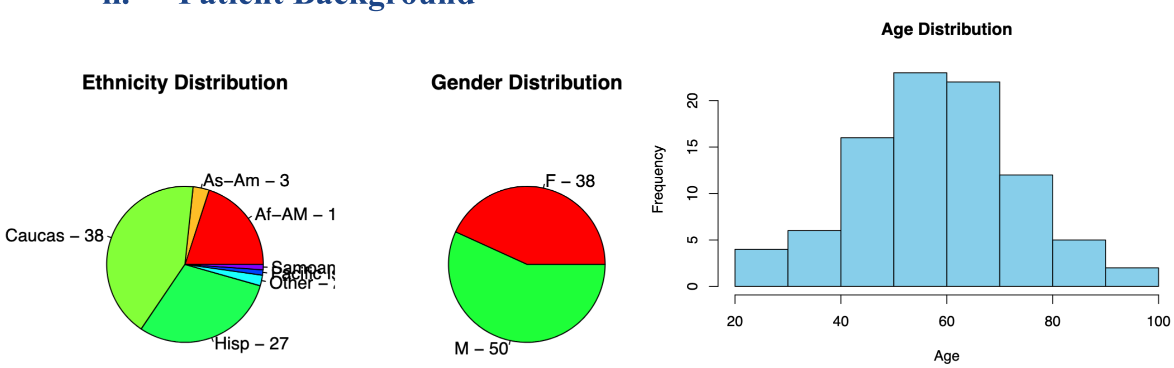

Figure 2: Graphs made in R

Checking out the distribution of the patients from whom the data was gathered from, it shows that males and females are significantly represented. A majority of the patients are either categorized as Caucasian, Mexican, and African-American. The rest are underrepresented. It is possible that the ethnicity population distribution in the locations of where the patients were found and chosen may look similar to the sample distribution. Furthermore, we cannot claim that the sample ethnicity distribution is biased, even though it appears so.

iii. Goal Score

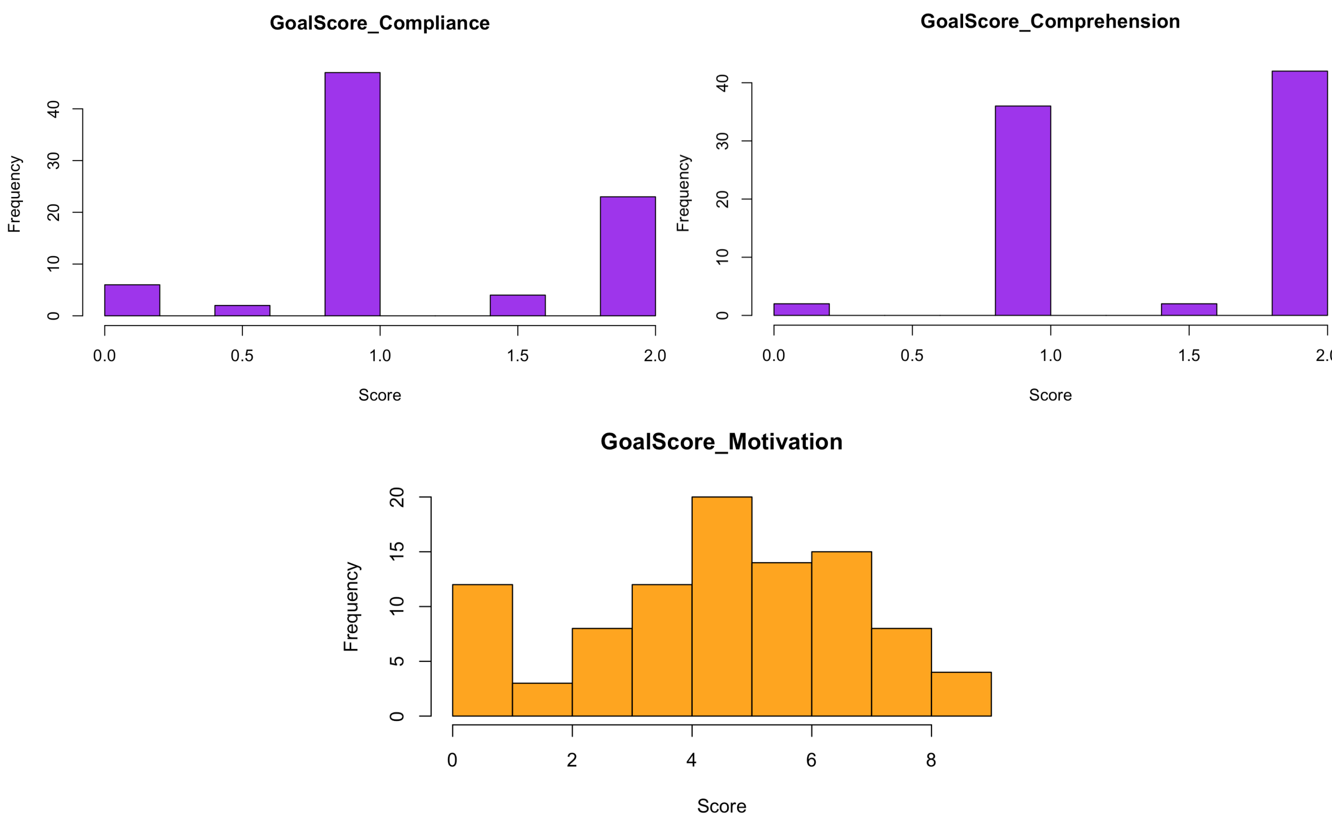

Figure 3: Histograms Made in R

Diving into goal score categories, the information suggests that compliance and comprehension score is important. Additionally, they appear highly correlated. It is apparent that there are many patients who are not completely compliant with their treatment as well as patients who do not fully understand their treatment. Patients who fail to adhere to treatment protocols or grasp the nature of their treatment may compromise the study's outcomes.

Inter-Rater Reliability Analysis

Inter-observer reliability builds insight on agreement between two or more raters. The two statistical methods that will be carried out to analyze the measurement are Weighted kappa and intraclass correlation coefficient (ICC). Inter-rater reliability of UTSA_Lavery_Grade and Wagners_Grade for the wound scores is calculated and interpreted using these methods.

I. Weighted Cohen's Kappa Calculations:

The data has two graders, and five possible grades which are considered ordinal data. Therefore, weighted kappa must be calculated to allow for partial agreement. Constructing a 5x5 contingency table for our graders of interest, the table shows the following:

		UTSA				
Wagner		**1**	**2**	**3**	**4**	**5**
	1	17	1	0	0	0
	2	2	12	12	0	0
	3	0	4	18	0	0
	4	4	1	9	0	0
	5	2	0	2	0	0

Table 3: 5x5 Contingency Table

The values in figure 4 are calculated by plugging in P_0 and P_e to the formula:

$$k = \frac{P_0 - P_e}{1 - P_e},$$

where the proportion of observed agreement is

$$P_0 = \sum_{i=1}^{k} P_{ii},$$

and the proportion of chanced agreement is

$$P_e = \sum_{i=1}^{k} P_i P_i .$$

To calculate kappa and the confidence interval for two graders in R we have,

```
library(vcd)
(res.table = Kappa(table))

#Confidence interval
confint(res.table)
```

which produces the following:

```
              value     ASE     z   Pr(>|z|)
Unweighted  0.4064 0.06536 6.218 5.032e-10
Weighted    0.4389 0.07211 6.086 1.155e-09

Kappa              lwr       upr
  Unweighted 0.2783134 0.5345208
  Weighted   0.2975571 0.5802262
```

Figure 4: Kappa Calculation/Confidence Interval

Weighted Cohen's Kappa Findings:

Here, the weighted version is for ordinal data. In our output, Cohen's kappa (k) = 0.439, which represents a fair to good strength of agreement according to Fleiss e al. (2003) classification. This is confirmed by the obtained p-value ($p < 0.0001$), indicating that our calculated kappa is significantly different from zero. Additionally, the unweighted kappa is less than the weighted kappa. This means that there are more partial agreements than total disagreement.

It is 95% confident that the true value of kappa lies in the interval (0.296, 0.58). Therefore, we are confident that the graders are not in excellent agreement.

II. FLEISS'S KAPPA Calculations

We want to compare the USTA and Wagner's Classifications to the patients' wound type classifications to assess whether the rating and grading are consistently in agreement. The data frame consists of UTSA Classification, Wagner's Grade, and Wound Type.

```
wound_class_df = df |>
  select(WoundType, Wagner_Type, USTA_Type)
head(wound_class_df,5)
```

```
##   WoundType Wagner_Type  USTA_Type
## 1      RISK   INFECTION INFECTION
## 2 INFECTION   INFECTION  ISCHEMIA
## 3      RISK   INFECTION INFECTION
## 4      BOTH   INFECTION INFECTION
## 5      RISK        BOTH      BOTH
```

```
kappam.fleiss(wound_class_df, detail = TRUE)
```

```
##  Fleiss' Kappa for m Raters
##
##  Subjects = 85
##    Raters = 3
##     Kappa = 0.0871
##
##         z = 2.3
##   p-value = 0.0216
##
##              Kappa      z          p.value
## BOTH         -0.025     -0.406     0.685
## INFECTION    0.055      0.872      0.383
## ISCHEMIA     0.094      1.495      0.135
## RISK         0.244      3.889      0.000
```

The Fleiss's Kappa for all the classifications of wound are in poor agreement with Kappa = 0.087 and p-value of 0.02. For each category, *Risk* is the one that has more positive agreement; however, it's still at a low value.

III. ICC Calculations

1. ICC for UTSA, Wagner, and Wound Types

```r
wound_class_num = df |>
  select(WoundType_Coded, Wagners_Grade, USTA_Coded)
head(wound_class_num,5)
```

```
##   WoundType_Coded Wagners_Grade USTA_Coded
## 1               1             3          2
## 2               2             3          3
## 3               1             3          2
## 4               4             2          2
## 5               1             5          4
```

```r
icc(wound_class_num, model = "twoway", type = "agreement", unit =
"single")
```

```
##  Single Score Intraclass Correlation
##
##    Model: twoway
##    Type : agreement
##
##    Subjects = 85
##    Raters = 3
##    ICC(A,1) = 0.156
##
##  F-Test, H0: r0 = 0 ; H1: r0 > 0
##   F(84,170) = 1.56 , p = 0.00757
##
##  95%-Confidence Interval for ICC Population Values:
##   0.029 < ICC < 0.299
```

There is a great disagreement between actual wound types, the Wagner's grade, and UTSA Classification. The 95% CI also shows that the wound type classifications are not in excellent agreement.

2. **ICC for UTSA and Wagner's**

```r
usta_wagner = df |>
  select(USTA_Coded,Wagners_Grade)
head(usta_wagner,5)
```

```
##   USTA_Coded Wagners_Grade
## 1          2             3
## 2          3             3
## 3          2             3
```

```
## 4        2           2
## 5        4           5
```

```
icc(usta_wagner, model = "twoway", type = "agreement", unit =
"single")
```

```
##  Single Score Intraclass Correlation
##
##   Model: twoway
##   Type : agreement
##
##   Subjects = 85
##   Raters = 2
##   ICC(A,1) = 0.383
##
##  F-Test, H0: r0 = 0 ; H1: r0 > 0
##  F(84,84.8) = 2.24 , p = 0.000132
##
##  95%-Confidence Interval for ICC Population Values:
##   0.186 < ICC < 0.55
```

There is a great disagreement between two wound type classification. The 95% CI also shows that the wound type classifications are not in excellent agreement with the highest value of 0.55.

3. ICC for Wound Types and Wagner's

```
wound_wagner = df |>
  select(WoundType_Coded,Wagners_Grade)
head(wound_wagner,5)
```

```
##   WoundType_Coded Wagners_Grade
## 1               1             3
## 2               2             3
## 3               1             3
## 4               4             2
## 5               1             5
```

```
icc(wound_wagner, model = "twoway", type = "agreement", unit =
"single")
```

```
##  Single Score Intraclass Correlation
##   Model: twoway
##   Type : agreement
##
##   Subjects = 85
##   Raters = 2
```

```
##    ICC(A,1) = 0.176
##
##   F-Test, H0: r0 = 0 ; H1: r0 > 0
##   F(84,84.5) = 1.43 , p = 0.0523
##
##   95%-Confidence Interval for ICC Population Values:
##    -0.037 < ICC < 0.374
```

There is a great disagreement between actual wound types and Wagner's grade. The 95% CI also shows that the wound type classifications are not in excellent agreement.

4. **ICC for Wound Types and UTSA**

```
wound_usta = df |>
  select(WoundType_Coded,USTA_Coded)
head(wound_usta,5)
```

```
##   WoundType_Coded USTA_Coded
## 1               1          2
## 2               2          3
## 3               1          2
## 4               4          2
## 5               1          4
```

```
icc(wound_usta, model = "twoway", type = "agreement", unit = "single")
```

```
##   Single Score Intraclass Correlation
##
##    Model: twoway
##    Type : agreement
##
##    Subjects = 96
##    Raters = 2
##    ICC(A,1) = -0.0879
##
##   F-Test, H0: r0 = 0 ; H1: r0 > 0
##   F(95,90.1) = 0.827 , p = 0.819
##
##   95%-Confidence Interval for ICC Population Values:
##    -0.268 < ICC < 0.103
```

There is a great disagreement between actual wound types and UTSA classification. The 95% CI also shows that the wound type classifications are not in excellent agreement, and the interval is worse than that of Wagner's Grades.

ICC findings and conclusion: There are disagreement between patient's wound types and each of the wound classification systems (Wagner's and UTSA's). However, Wagner's seems to be more consistent with the actual observed wound types than UTSA.

IV. Chi-squared Test

Based on the results of IRR, Chi-squared tests were also conducted to determine if there's a significant association between the patient's wound category and the grading systems.

1. Wound Types and Wagner's Grades

```
wagner_wound = table(df$WoundType,df$Wagner_Type)
wagner_wound
##              BOTH  INFECTION  ISCHEMIA    RISK
##   BOTH        3     13          2          2
##   INFECTION   6     20          8          4
##   ISCHEMIA    2      9          3          2
##   RISK        4      6          1         11

chisq.test(wagner_wound)

##
##   Pearson's Chi-squared test
##
## data:  wagner_wound
## X-squared = 19.828, df = 9, p-value = 0.01901
```

Based on the p-value above, there is a significant difference between the patient's wound type and Wagner's Grades. This could indicate some discrepancy between the patient's wound type and Wagner's Grade due to some other factors.

2. Wound Types and UTSA Classifications

```
usta_wound = table(df$WoundType,df$USTA_Type)
usta_wound

##              BOTH  INFECTION  ISCHEMIA    RISK
##   BOTH        3     10          3          1
##   INFECTION   14    13          5          2
##   ISCHEMIA    2     7           3          3
##   RISK        5     7           4          3

chisq.test(usta_wound)
##   Pearson's Chi-squared test
##
```

```
## data:  usta_wound
## X-squared = 8.4034, df = 9, p-value = 0.4941
```

Based on the p-value above that is larger than 0.05, there seems to be no significant difference in patient's wound type and USTA's Classification. The classification system seems to be consistent with the recorded wound type.

3. Wagner's and UTSA Classification

```
wagner_usta = table(df$Wagner_Type,df$USTA_Type)
wagner_usta
##                BOTH  INFECTION  ISCHEMIA     RISK
##    BOTH        4     12          6           2
##    INFECTION   0     26          2           9
##    ISCHEMIA    0     6           5           4
##    RISK        0     4           1           4
chisq.test(wagner_usta)
##   Pearson's Chi-squared test
##
## data:  wagner_usta
## X-squared = 23.365, df = 9, p-value = 0.005426
```

Based on the p-value obtained, there seems to be a significant difference between Wagner's Grades and USTA's Classification in classifying wound types

Research Development

I. Goal Score vs. Wound Score Development:

The path of research development is to test goal score total (GST) vs wound score total (WST) which will hopefully determine which goal score categories carry important information about WST. The goal of this analysis is to provide clarity on the impact of specific goal scores on wound outcomes.

Once that is complete, subsequent tests are run on goal score categories to investigate results on GST. This step aims to build insight on the subset categories that sufficiently influence achieving the best WST. In approaching this research, the objective is to uncover effects of specific medical practices that need to be prioritized by the patient and caregiver.

If there exists a high correlation between GST and WST, it poses the question that categories affecting GST have a similar effect on WST. To explore this theory, Pearson's tau (non-parametric), Kendall's tau (parametric), and Spearman's rho (parametric) calculations, used in correlation testing, are conducted as part of this investigation.

Upon completion of the correlation analysis between GST and WST, the insights gained will be used in constructing a final predictive model for wound score to ultimately determine if there is a direct relationship between sub goal categories and WST. By leveraging the identified relationships and influences between specific goal score categories and GST which is highly correlated with WST, we aim to develop a robust model that accurately predicts WST based on relevant factors. Additionally, insights learned from the correlation analysis will inform the selection of features and variables to include in the final model, ensuring its efficacy in predicting wound outcomes. Through this process of data analysis and model refinement, we strive to create a comprehensive and actionable tool that healthcare providers can utilize to optimize wound management strategies and improve patient outcomes.

The fundamental question is whether there exists a transitive correlation relationship: if sub goal categories correlates with GST, and GST correlates with WST, then sub goal categories correlates with WST and can build a regression model.

Data Investigation

I. Goal Score vs. Wound Score Investigation:

This investigation begins with the focus on the relationship between goal score and wound score. Looking closely at how GST and WST are connected, this initial analysis aims to find out which specific goal score categories are most important for understanding wound scores. By carefully examining this data, we hope to understand better how each goal score affects wound outcomes. This will help us make smarter choices when it comes to managing wounds.

```
        Pearson's product-moment correlation

data:  wound_goal$GoalScore_Total and wound_goal$WoundScore_Total
t = 24.937, df = 94, p-value < 2.2e-16
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.9057056 1.0000000
sample estimates:
      cor
0.9320335
```

Figure 5: Pearson Correlation

Pearson's product-moment correlation had the lowest p-value out of the 3 correlation tests. Data shows that GST and WST are extremely highly correlated. The 95% confidence interval lies in the range (0.906, 1). It is possible that GST and WST could be perfectly correlated.

Diving deeper into subset categories of goal score and comparing them to goal score total, we find some significant results. The categories include motivation, comprehension, compliance, support, and insight. In each test, Pearson's tau holds the best p-value. Therefore, that is the statistic that will be used. The calculations are shown below.

```
> goal <- df[, c("GoalScore_Motivation", "GoalScore_Comprehension", "GoalScore_Compliance",
"GoalScore_Support", "GoalScore_Insight", "GoalScore_Total")]
>
> ######### MOTIVATION
> cor.test(goal$GoalScore_Motivation, goal$GoalScore_Total, alternative="greater",
+          method="pearson", exact=T)

        Pearson's product-moment correlation

data:  goal$GoalScore_Motivation and goal$GoalScore_Total
t = 3.7703, df = 80, p-value = 0.0001554
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.2211791 1.0000000
sample estimates:
      cor
0.3884354

> ######### CONPREHENSION
> cor.test(goal$GoalScore_Comprehension, goal$GoalScore_Total, alternative="greater",
+          method="pearson", exact=T)

        Pearson's product-moment correlation

data:  goal$GoalScore_Comprehension and goal$GoalScore_Total
t = 2.9938, df = 80, p-value = 0.001832
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.1427232 1.0000000
sample estimates:
      cor
0.3174104
```

```
> ######### Compliance
> cor.test(goal$GoalScore_Compliance, goal$GoalScore_Total, alternative="greater",
+          method="pea", exact=T)

        Pearson's product-moment correlation

data:  goal$GoalScore_Compliance and goal$GoalScore_Total
t = 2.4423, df = 80, p-value = 0.0084
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.08450537 1.00000000
sample estimates:
      cor
0.2634088
> ######### GoalScore_Support
> cor.test(goal$GoalScore_Support, goal$GoalScore_Total, alternative="two.sided",
+          method="pearson", exact=T)

        Pearson's product-moment correlation

data:  goal$GoalScore_Support and goal$GoalScore_Total
t = 1.4942, df = 80, p-value = 0.139
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.05416602  0.36860454
sample estimates:
     cor
0.164778
> ######### GoalScore_Insight
> cor.test(goal$GoalScore_Insight, goal$GoalScore_Total, alternative="greater",
+          method="pearson", exact=T)

        Pearson's product-moment correlation

data:  goal$GoalScore_Insight and goal$GoalScore_Total
t = 1.8359, df = 80, p-value = 0.03504
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.01878282 1.00000000
sample estimates:
      cor
0.2010682
```

Figure 6: Pearson Correlation

The data shows that the only insignificant factor is support. The remaining factors are motivation, comprehension, compliance, and insight. They all have a positive correlation with goal score. These factors will be placed in a base model with WST as the outcome variable.

```
Formula:
WoundScore_Total ~ GoalScore_Motivation + GoalScore_Comprehension +
    GoalScore_Compliance + GoalScore_Insight

Parametric coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)               2.9677     0.6511   4.558 1.91e-05 ***
GoalScore_Motivation      0.7668     0.4803   1.596    0.114
GoalScore_Comprehension   0.6045     0.4786   1.263    0.210
GoalScore_Compliance      0.3059     0.3988   0.767    0.445
GoalScore_Insight        -0.3625     0.4630  -0.783    0.436
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =  0.0919   Deviance explained = 13.7%
GCV = 2.5209  Scale est. = 2.3672    n = 82
```

Figure 7: Linear Regression

The results show that there are no significant factors in the base model that includes all of the subcategories. Performing single predictor models, the following results are yielded.

```
> model2 <- gam(WoundScore_Total ~ GoalScore_Motivation, data=df)
> summary(model2)

Family: gaussian
Link function: identity

Formula:
WoundScore_Total ~ GoalScore_Motivation

Parametric coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)            3.2116     0.6242   5.145 1.87e-06 ***
GoalScore_Motivation   1.0958     0.3458   3.169  0.00217 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =    0.1   Deviance explained = 11.2%
GCV = 2.4036  Scale est. = 2.345     n = 82
```

```
> model3 <- gam(WoundScore_Total ~ GoalScore_Comprehension, data=df)
> summary(model3)

Family: gaussian
Link function: identity

Formula:
WoundScore_Total ~ GoalScore_Comprehension

Parametric coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)               3.7721     0.5041   7.483 8.27e-11 ***
GoalScore_Comprehension   0.8958     0.3161   2.834  0.00582 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =  0.0799   Deviance explained = 9.12%
GCV = 2.4586  Scale est. = 2.3986    n = 82
> model4 <- gam(WoundScore_Total ~ GoalScore_Compliance, data=df)
> summary(model4)

Family: gaussian
Link function: identity

Formula:
WoundScore_Total ~ GoalScore_Compliance

Parametric coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)            4.2355     0.4102  10.326 2.24e-16 ***
GoalScore_Compliance   0.7219     0.3048   2.368   0.0203 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =  0.0538   Deviance explained = 6.55%
GCV = 2.5281  Scale est. = 2.4664    n = 82
```

```
> model5 <- gam(WoundScore_Total ~ GoalScore_Insight, data=df)
> summary(model5)

Family: gaussian
Link function: identity

Formula:
WoundScore_Total ~ GoalScore_Insight

Parametric coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)         4.3558     0.4091  10.647   <2e-16 ***
GoalScore_Insight   0.5935     0.2888   2.055   0.0432 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =  0.0383   Deviance explained = 5.01%
GCV = 2.5697  Scale est. = 2.507     n = 82
```

Figure 8: Linear Regression

All of the models in Figure 8 show significant estimators. To determine the best model, Akaike Information Criterion (AIC) values are calculated. The AIC showed that the best fit model was with the singular predictor being motivation with the lowest AIC score of 306.57. Therefore our final model is shown below and also a part of Figure 8.

```
> model2 <- gam(WoundScore_Total ~ GoalScore_Motivation, data=df)
> summary(model2)

Family: gaussian
Link function: identity

Formula:
WoundScore_Total ~ GoalScore_Motivation

Parametric coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)            3.2116     0.6242   5.145 1.87e-06 ***
GoalScore_Motivation   1.0958     0.3458   3.169  0.00217 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1


R-sq.(adj) =    0.1   Deviance explained = 11.2%
GCV = 2.4036  Scale est. = 2.345     n = 82
```

Our analysis of all models presented in Figure 8 revealed significant estimators. To identify the optimal model among them, we employed the AIC. Our calculations demonstrated that the model featuring motivation as the singular predictor achieved the best fit. We have determined this model to be the most suitable representation of our data.

Healthcare and medical workers must prioritize patient motivation for self-care due to its profound impact on wound health outcomes. Motivated patients are more likely to actively engage in preventive measures, adhere to medication regimens, and adopt healthier lifestyle habits, leading to improved overall better wound scores. By emphasizing patient motivation, healthcare professionals can empower individuals to take charge of their health.

II. Wound Score and Other Medical Conditions

Are there differences in wound score among patients with different categories such as their initial nutrition, cardiovascular, neurological, rheumatological, renal, and pulmonary status?

```
wound_factors = df |>
  select(WoundScore_Total,Neuro_Initial,Cardio_Initial,Nutrition_Initial,
         Pulmonary_Initial,Renal_Initial,Rheuma_Initial)
head(wound_factors,5)

##   WoundScore_Total Neuro_Initial Cardio_Initial Nutrition_Initial
## 1              6.0      Impaired  Decompensated          Impaired
## 2              4.5      Impaired       Impaired     Decompensated
## 3              3.0      Impaired         Normal          Impaired
## 4              6.5        Normal         Normal            Normal
## 5              2.0      Impaired       Impaired          Impaired
##   Pulmonary_Initial Renal_Initial Rheuma_Initial
## 1            Normal      Impaired         Normal
## 2            Normal      Impaired         Normal
## 3            Normal        Normal         Normal
## 4            Normal        Normal       Impaired
## 5          Impaired        Normal         Normal

# Kruskal-Wallis Test for Neurological
wound_neuro <- kruskal.test(WoundScore_Total ~ Neuro_Initial, data = wound_fa
ctors)
print(wound_neuro)


##  Kruskal-Wallis rank sum test
##
## data:  WoundScore_Total by Neuro_Initial
## Kruskal-Wallis chi-squared = 6.9828, df = 2, p-value = 0.03046

# Kruskal-Wallis Test for Nutrition
wound_nutrition <- kruskal.test(WoundScore_Total ~ Nutrition_Initial, data =
wound_factors)
print(wound_nutrition)

##
##  Kruskal-Wallis rank sum test
```

```
##
## data:  WoundScore_Total by Nutrition_Initial
## Kruskal-Wallis chi-squared = 2.7652, df = 2, p-value = 0.2509
```

```
# Kruskal-Wallis Test for Cardiovascular
wound_cardio <- kruskal.test(WoundScore_Total ~ Cardio_Initial, data = wound_
factors)
print(wound_cardio)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  WoundScore_Total by Cardio_Initial
## Kruskal-Wallis chi-squared = 0.82693, df = 2, p-value = 0.6614
```

```
# Kruskal-Wallis Test for Cardiovascular
wound_pulmonary <- kruskal.test(WoundScore_Total ~ Pulmonary_Initial, data =
wound_factors)
print(wound_pulmonary)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  WoundScore_Total by Pulmonary_Initial
## Kruskal-Wallis chi-squared = 1.9122, df = 2, p-value = 0.3844
```

```
# Kruskal-Wallis Test for Cardiovascular
wound_rheuma <- kruskal.test(WoundScore_Total ~ Rheuma_Initial, data = wound_
factors)
print(wound_rheuma)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  WoundScore_Total by Rheuma_Initial
## Kruskal-Wallis chi-squared = 1.1499, df = 2, p-value = 0.5627
```

```
# Kruskal-Wallis Test for Cardiovascular
wound_renal <- kruskal.test(WoundScore_Total ~ Renal_Initial, data = wound_fa
ctors)
print(wound_renal)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  WoundScore_Total by Renal_Initial
## Kruskal-Wallis chi-squared = 7.963, df = 2, p-value = 0.01866
```

```
# Post-hoc analysis
post_hoc_neuro = pairwise.wilcox.test(wound_factors$WoundScore_Total, wound_f
actors$Neuro_Initial, p.adjust.method = "bonferroni")
```

Since Neurological and Renal Status seem to be statistically significant to wound score, pairwise post-hoc analysis was conducted.

```
# Result
print(post_hoc_neuro)
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correct
ion
##
## data:  wound_factors$WoundScore_Total and wound_factors$Neuro_Initial
##
##          Decompensated Impaired
## Impaired 1.00          -
## Normal   0.16          0.03
##
## P value adjustment method: bonferroni

# Post-hoc analysis
post_hoc_renal = pairwise.wilcox.test(wound_factors$WoundScore_Total, wound_f
actors$Renal_Initial, p.adjust.method = "bonferroni")

# Result
print(post_hoc_renal)

##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correct
ion
##
## data:  wound_factors$WoundScore_Total and wound_factors$Neuro_Initial
##
##          Decompensated Impaired
## Impaired 0.623          -
## Normal   0.022          0.506
##
## P value adjustment method: bonferroni
```

Conclusion

Recall the initial question whether there exists a transitive correlation relationship: if sub goal categories correlates with GST, and GST correlates with WST, then sub goal categories correlates with WST and can build a regression model. The goal score vs wound score investigation focuses on the relationship between goal score subcategories and wound score, aiming to identify key goal score categories influencing wound outcomes. Pearson’s correlation indicates a strong correlation between GST and WST. Subset analysis highlights motivation, comprehension, compliance, and insight as significant factors. AIC analysis selects motivation as the best predictor for the final model, emphasizing its importance in wound management. Healthcare workers should prioritize patient motivation for better self-care, fostering engagement and improving wound health outcomes.

The results from the Kruskal-Wallis pairwise post-hoc analysis indicating that both initial renal and neurological statuses are statistically significant in relation to wound scores. It suggests that the severity of wounds in patients is closely associated with their renal and neurological health.

The findings and information enables a more integrated approach to treating patients with wounds, particularly those with underlying renal or neurological status. These conditions can be significant predictors of wound severity and early detection lead to more personalized and proactive treatment plans. For instance, patients with poor renal function or significant neurological impairments might require more attentive wound care strategies, closer monitoring, and probably other different therapeutic approaches compared to patients without these issues.

R Code

Import Data (clean_df.csv submitted along with R file)

```
library(readr)
df <- read_csv("~/Desktop/clean_df.csv", show_col_types = FALSE)
ncol(df)
```

I. Data Visualization

i. Wound Score

Figure 1: Histograms Made in R

```
## subset data
wound_data <- df[, c("WoundScore_Appearance", "WoundScore_Size",
"WoundScore_Perfusion", "WoundScore_Total")]
## packages
library(ggplot2)
library(magrittr)
## WoundScore_Appearance
aggregate(WoundScore_Total ~ WoundScore_Appearance, wound_data,
mean) %>%
  ggplot(aes(x = WoundScore_Appearance, y = WoundScore_Total)) +
  geom_bar(stat = "identity", fill = "skyblue") +
  labs(title = "Average WoundScore_Total by
WoundScore_Appearance",
       x = "WoundScore_Appearance",
       y = "Average WoundScore_Total")
## WoundScore_Perfusion
aggregate(WoundScore_Total ~ WoundScore_Perfusion, wound_data,
mean) %>%
  ggplot(aes(x = WoundScore_Perfusion, y = WoundScore_Total)) +
  geom_bar(stat = "identity", fill = "green") +
  labs(title = "Average WoundScore_Total by
WoundScore_Perfusion",
       x = "WoundScore_Perfusion",
       y = "Average WoundScore_Total")
```

ii. Patient Background

Figure 2: Histograms Made in R

```
## subset data
patient_data <- df[, c("Age", "Ethnicity", "Gender")]
## pie chart function
```

```
create_pie_chart <- function(data, variable, title) {
  color_palette <- rainbow(length(unique(data[[variable]])))
  variable_counts <- table(data[[variable]])
  pie(variable_counts, labels = paste(names(variable_counts),
"-", variable_counts),
      col = color_palette,
      main = title)
}
## pie charts
par(mfrow=c(1, 2))  # Arrange plots in one row with three
columns
create_pie_chart(patient_data, "Ethnicity", "Ethnicity
Distribution")
create_pie_chart(patient_data, "Gender", "Gender Distribution")
## histogram for Age
hist(patient_data$Age,
     col = "skyblue",
     main = "Age Distribution",
     xlab = "Age",
     ylab = "Frequency",
     border = "black",
     breaks = 10)
```

iii. Goal Score

Figure 3: Histograms Made in R

```
hist(df$GoalScore_Compliance,
     col = "purple",
     main = "GoalScore_Compliance",
     xlab = "Score",
     ylab = "Frequency",
     border = "black",
     breaks = 10)
hist(df$GoalScore_Total,
     col = "orange",
     main = "GoalScore_Total",
     xlab = "Score",
     ylab = "Frequency",
     border = "black",
     breaks = 10)
hist(df$GoalScore_Comprehension,
     col = "purple",
```

```
    main = "GoalScore_Comprehension",
    xlab = "Score",
    ylab = "Frequency",
    border = "black",
    breaks = 10)
```

Inter-Rater Reliability Measurement

I. Weighted Cohen's Calculations

Table 3: 5x5 Table

```
cohen_data <- df[, c("Wagners_Grade", "UTSA_Lavery_Grade")]
## Get levels the same
## Change I
cohen_data$UTSA_Lavery_Grade <-
ifelse(cohen_data$UTSA_Lavery_Grade == "I", 1,
cohen_data$UTSA_Lavery_Grade)
# Change II
cohen_data$UTSA_Lavery_Grade <-
ifelse(cohen_data$UTSA_Lavery_Grade == "II", 2,
cohen_data$UTSA_Lavery_Grade)
## Change III
cohen_data$UTSA_Lavery_Grade <-
ifelse(cohen_data$UTSA_Lavery_Grade == "III", 3,
cohen_data$UTSA_Lavery_Grade)
## Calculations for Table (changing numbers to get values)
sum(cohen_data$Wagners_Grade == 5 & cohen_data$UTSA_Lavery_Grade
== 3, na.rm=TRUE)
## Table
table = as.table(rbind(
  c(17, 1, 0, 0, 0), c(2, 12, 12, 0, 0), c(0, 4, 18, 0, 0),
  c(4, 1, 9, 0, 0), c(2, 0, 2, 0, 0)))
categories = c("1", "2", "3",
                "4", "5")
dimnames(table) = list(Wagner = categories, UTSA = categories)
```

Figure 4: Kappa Calculation/Confidence Interval

```
## Compute Kappa for two raters
library(vcd)
(res.table = Kappa(table))
#Confidence interval
confint(res.table)
```

Figure 5: Pearson Correlation

```
## subset data
wound_goal<- df[, c("GoalScore_Total", "WoundScore_Total")]
# Using Pearson:
cor.test(wound_goal$GoalScore_Total,
wound_goal$WoundScore_Total, alternative="greater",
         method="pearson", exact=T)
# jonckheere.test
jonckheere.test(goal$GoalScore_Motivation, goal$GoalScore_Total,
alternative="increasing")
# Using Spearman:
cor.test(goal$GoalScore_Motivation, goal$GoalScore_Total,
alternative="greater",
         method="spearman", exact=T)
# Using kendall:
cor.test(goal$GoalScore_Motivation, goal$GoalScore_Total,
alternative="greater",
         method="kendall", exact=T)
```

Figure 6: Pearson Correlation

```
goal <- df[, c("GoalScore_Motivation",
"GoalScore_Comprehension", "GoalScore_Compliance",
"GoalScore_Support", "GoalScore_Insight", "GoalScore_Total")]
######### MOTIVATION
cor.test(goal$GoalScore_Motivation, goal$GoalScore_Total,
alternative="greater",
         method="pearson", exact=T)
######### CONPREHENSION
cor.test(goal$GoalScore_Comprehension, goal$GoalScore_Total,
alternative="greater",
         method="pearson", exact=T)
######### Compliance
cor.test(goal$GoalScore_Compliance, goal$GoalScore_Total,
alternative="greater",
         method="pea", exact=T)
######### GoalScore_Support
cor.test(goal$GoalScore_Support, goal$GoalScore_Total,
alternative="two.sided",
         method="pearson", exact=T)
######### GoalScore_Insight
```

```
cor.test(goal$GoalScore_Insight, goal$GoalScore_Total,
alternative="greater",
         method="pearson", exact=T)
```

Figure 7: Regression

```
## base model
df <- df[, c("GoalScore_Motivation", "GoalScore_Comprehension",
"GoalScore_Compliance", "GoalScore_Insight",
"WoundScore_Total")]
## non parametric regression
library(mgcv)
## Fit non-parametric regression model
model <- gam(WoundScore_Total ~
GoalScore_Motivation+GoalScore_Comprehension+
GoalScore_Compliance+GoalScore_Insight, data=df)
## Print model summary
summary(model)
```

Figure 8: Regression/AIC

```
# single predictor
model2 <- gam(WoundScore_Total ~ GoalScore_Motivation, data=df)
summary(model2)
model3 <- gam(WoundScore_Total ~ GoalScore_Comprehension,
data=df)
summary(model3)
model4 <- gam(WoundScore_Total ~ GoalScore_Compliance, data=df)
summary(model4)
model5 <- gam(WoundScore_Total ~ GoalScore_Insight, data=df)
summary(model5)
# AIC
AIC(model2)
AIC(model3)
AIC(model4)
AIC(model5)
```