

Impacts of Patients' Parents Virtually Attending the Rounds on Rounding Time

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Abstract

There are three different ways of patients' parents to attend the rounds at UNC Children's hospital – physically attending in person, virtually attending via Skype and not attending. The goal of this statistical analysis is to analyze the effects of virtually attending on rounding versus the other two ways of attending the rounds on rounding time. What the analysis found is that virtually attending the rounds significantly increased the rounding time compared to not attending, while it did not change the rounding time significantly compared to physically attending. To reach this conclusion, regression analysis and multiple variable selection methods were used.

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1. Introduction

Patient rounds are an important part of the patient care process. During the rounds, various disciplines come together to discuss the patient's health condition and coordinate care. Pediatric patients' parents are encouraged to physically attend the rounds since it tends to make communication easier and help resolve potential problems faster. However, due to issues such as time conflicts, some parents may not be able to physically attend the rounds. In order to deal with this difficulty, UNC Children's Hospital implemented a program that allows pediatric patients' parents to virtually attend the rounds via Skype. This study checks if this newly introduced way of virtually attending the rounds significantly changed the rounding time compared to not attending and compared to physically attending.

The structure of the rest of the report is as follows. Section 2 summarizes the data used, including some initial exploration. Section 3 states the model methodologies and results. Section 4 gives a summary of the analysis and suggestions for future work to be done on the topic.

2. Data Structure

The data used in this study contains 210 observations of 13 variables. Each of the 210 observations represents an encounter of a cardiac patient rounding at UNC Hospital. The names and descriptions of the 13 variables are shown in the table below:

Variable Name	Variable Description
Time	Rounding time (in seconds) of the encounter
Patient_Identifying_Number	Numbers that identifies each patient
Heart	If the patient's issue was a heart defect of some type
ECMO/CRRT	If Extracorporeal membrane oxygenation (ECMO) or Continuous renal replacement therapy (CRRT) was used for the patient
Intubated/trach dependent	If the patient was intubated/trach dependent
Presenter	The presenter of the round (0: Fellow, 1: Resident, 2: Medical Student)
Specialist_present	If a specialist in heart disease attended the round
Length_of_stay	Duration (in days) for the patient stayed in the hospital
Age	Age of the patient
PRISM IV	Pediatric risk of mortality level
PIM_2_severity_score	Pediatric index of mortality (PIM) 2 severity score
Language	Language that the patient's parents speak (0: Non-English speaking, 1: English Speaking)
Family_present	Ways of patients' parents attending the rounds: (0: not attending, 1: physically attending, 2: virtually attending).

Table 1: Variables used in the study and their description

Note that this study focuses on the relationship between the dependent variable (Time) and one particular independent variable (Family_present). Specifically, two problems were examined:

1. If the rounding time significantly differs when parents did not attend the rounds compared with when parents virtually attended the rounds
2. If the rounding time significantly differs when parents physically attended the rounds compared with when parents virtually attended the rounds

Therefore, it makes sense to first extract two sub-datasets from the original dataset based on the value of the "Family_present" variable:

1. One sub-dataset (174 observation) that only contains the data where the "Family_present" variable value is 0 (not attending) and 2 (virtually attending). Hereinafter referred to as "sub-dataset 1".
2. The other sub-dataset (94 observations) that only contains the data where the "Family_present" variable value is 1 (physically attending) and 2 (virtually attending). Hereinafter referred to as "sub-dataset 2".

3. Data Analysis and Modeling

3.1 Box-Cox Transformation for Multiple Linear Regression

The first model methodology tried was the multiple linear regression. Note that one patient might have multiple encounters, and all variables are measured for each encounter instead of each patient. A natural first step was to take the “Time” variable (the rounding time of each encounter) as response and the rest of the variables, except for “Patient_Identifying_Number”, as predictors. Before actually fitting the regression model, we first did some exploratory work on the “Time” variable in order to check potential issues such as skewness. The analysis was firstly done for the sub-dataset 1 (not attending versus virtually attending).

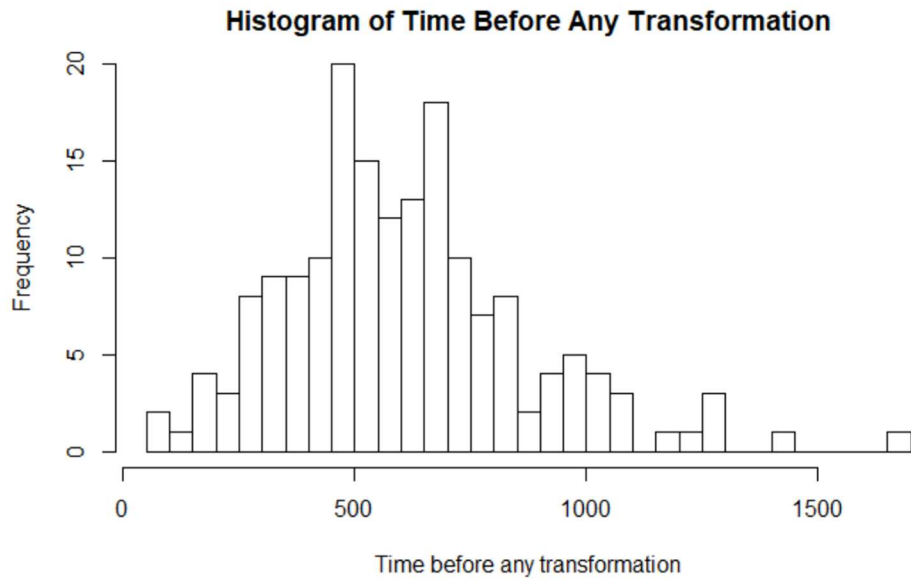


Figure 1: Histogram of "Time" to check potential issues: right-skewness was found

The figure above is the histogram for the “Time” variable for sub-dataset 1. The x-axis is the rounding time in seconds, while the y-axis is the number of encounters whose rounding time falls into the corresponding time slots. It is clear to see that the mean of this variable is larger than its median, suggesting that its distribution is right-skewed. This issue of skewness led us to try the Box-Cox transformation, which is a statistical method to transform the non-normal response variable into a normal shape.

For situations in which the response variable Y is known to be positive, the Box-Cox transformation can be expressed as:

$$Y_i^\lambda = \begin{cases} \frac{(Y_i^\lambda - 1)}{\lambda}, & \lambda \neq 0 \\ \log(Y_i), & \lambda = 0 \end{cases}$$

where λ is a parameter that controls the scale of transformation. Using the “boxcox” function in the “MASS” package in R, the optimal λ value is determined to be 0.5. In this situation, the Box-Cox Transformation is equivalent to the square-root transformation. The figure below shows the comparison between the “Time” variable before and after the Box-Cox transformation.

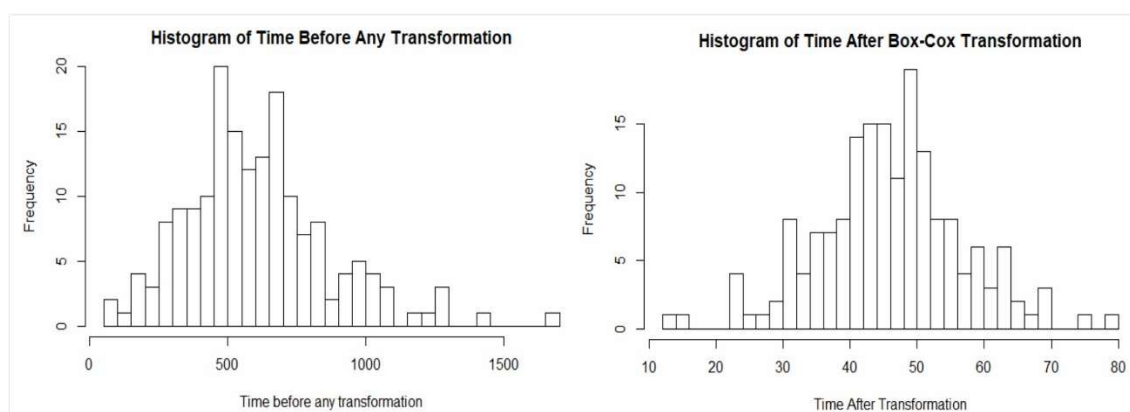


Figure 2: Before and after taking the Box-Cox transformation on “Time”: skewness was alleviated

The right plot in the above figure is the histogram of “Time” after taking the Box-Cox transformation. It is more like a “normal” shape compared to the situation before any transformation, which is shown in the left part of the above figure.

This Box-Cox transformation could also help us to hold one of the important assumptions of the multiple linear regression – the regression residuals should be normally distributed. Normal Q-Q (quantile-quantile) plot is a graphical method for comparing a probability distribution with normal distribution. We used it to check if the Box-Cox transformation did improve the normality of the regression residuals.

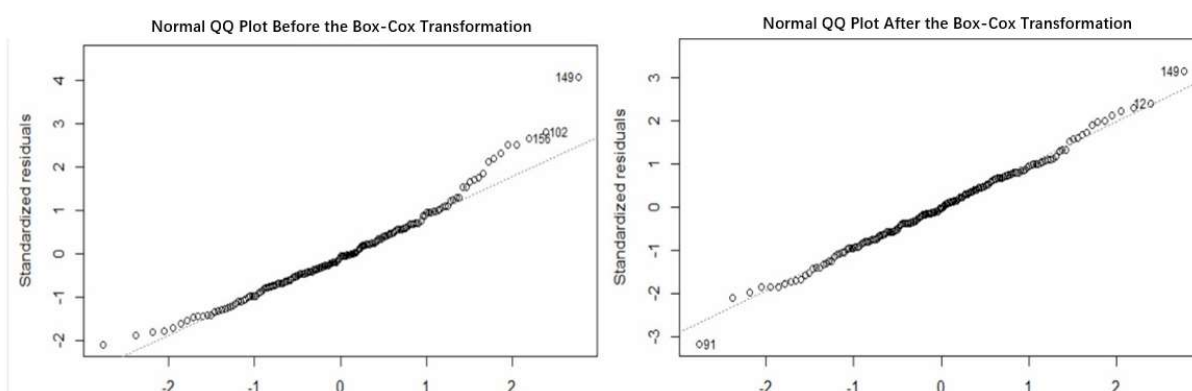


Figure 3: Comparison between normal Q-Q plots for regression residuals: normality was improved

As shown in the figure above, the right plot is the normal Q-Q plot for the regression residuals where the response variable “Time” was first transformed, while the left plot is the one where no transformation was conducted at first. The points in the right plot are more aligned with the straight line, suggesting that the regression residuals are more likely to be normally distributed than the situation where there was no transformation at first.

Next, similar data exploration and transformation were conducted for the sub-dataset 2, where the “Family_present” variable value is 1 (physically attending) and 2 (virtually attending). Here, the optimal Box-Cox transformation parameter λ was calculated as 0.4. We thought about let λ to be 0.5 as in our discussion for sub-dataset 1 in order to keep good interpretability since that was equivalent to the squared-root transformation. However, λ being 0.5 resulted in the regression residuals not normally distributed. Therefore, we kept the optimal λ value as 0.4.

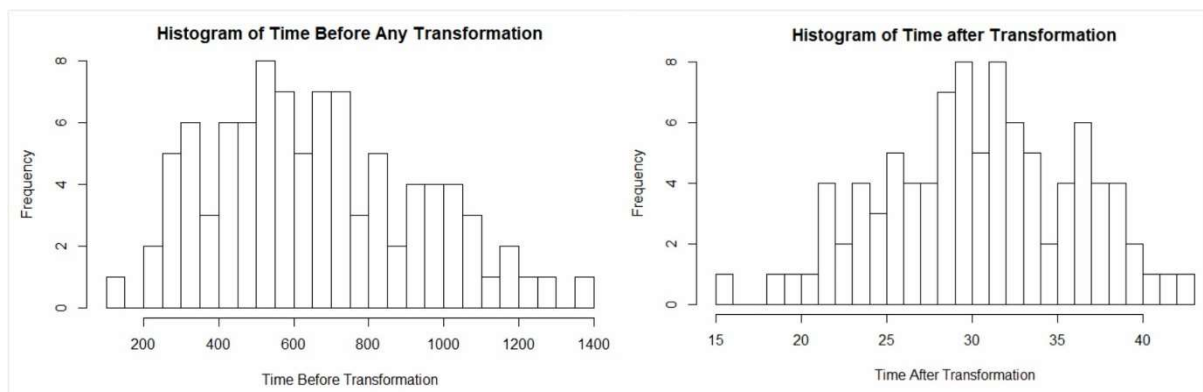


Figure 4: Before and after taking the Box-Cox transformation on “Time” for sub-dataset 2: skewness was alleviated

Similarly, the above figure shows the histograms for the “Time” variable before (the left plot) and after (the right plot) the Box-Cox transformation. Again, the Box-Cox transformation helped to make the response variable more like a normal shape. Moreover, the figure below showed that the normality for the regression residuals was also improved after the Box-Cox transformation.

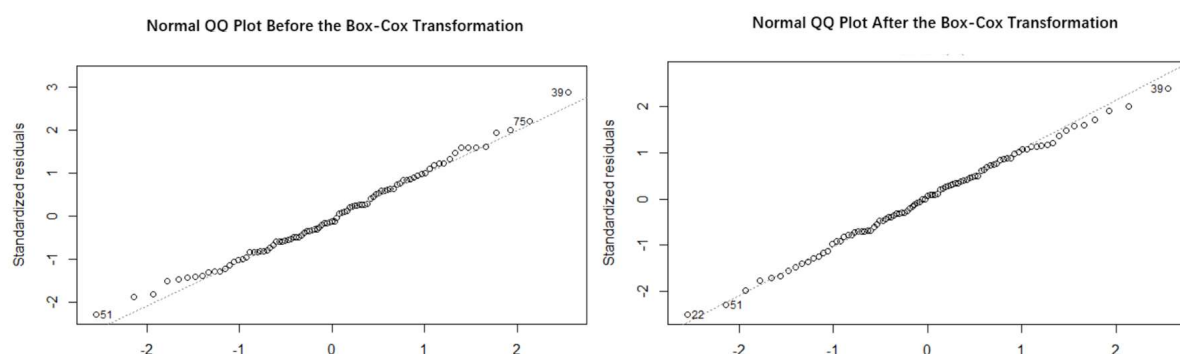


Figure 5 Comparison between normal Q-Q plots for regression residuals: normality was improved

All in all, for both sub-dataset 1 and sub-dataset 2, the Box-Cox transformation helped us to alleviate the skewness issue for the response variable and to better hold the regression residual normality assumption for the multiple linear regression. Therefore, the Box-Cox transformation was applied for both sub-datasets.

3.2 Variable Selection for the Multiple Linear Regression

One of the important assumptions for the multiple linear regression is that the predictors should have no or little collinearity. Otherwise, it will cause issues like multicollinearity. In regression, multicollinearity occurs when the model includes multiple predictors that are correlated not only to the response variable, but also to each other. In other words, it results when you have predictors that are redundant. In this study, multiple variable selection methods with different selection criteria were applied to alleviate this multicollinearity issue (discussed in Section 3.2.1 to 3.2.5). In the meantime, we can check if the variable of interest, “Family_present”, is redundant or not by seeing if it would be removed during the variable selection process. Note that all the selection methods were first applied to sub-dataset 1 (not attending versus virtually attending).

3.2.1 Forward Selection with the AIC as criterion

Forward selection is one of the variable selection methods that begins with no predictors in the model. We then add predictors (if any) whose inclusion gives the most statistically significant improvement of the fit measured based on a pre-determined selection criterion. We repeat this process until the addition of new predictors no longer improves the model to a statistically significant extent.

First, the Akaike information criterion (AIC) was chosen as the selection criterion. AIC, developed with a foundation in information theory, is a widely used criterion for selecting among nested statistical models. Mathematically, the AIC value can be calculated as follows:

$$AIC = 2k - 2\ln(\hat{L})$$

where k is the number of predictors in the model plus the intercept, and \hat{L} is maximum value of the likelihood function for the model. Given a set of candidate models, the preferred model is the one with the minimum AIC value.

After applying the forward selection with the AIC as criterion, the final model contains the following predictors:

Predictors in the final model	P-value
Intubated.trach.dependent	6.19e ⁻¹⁰
Heart	0.005
Specialist_present	0.024
Presenter	0.030
Family_present	0.041
Age	0.047

Table 2: Predictors in the final model after forward selection with the AIC as criterion

The p-value is used in the context of null hypothesis testing in order to quantify the idea of statistical significance of evidence. Here, if the p-value for a certain predictor is less than 0.05, we reject the null hypothesis that the coefficient for that predictor is 0, meaning that the predictor is statistically significant to explain the change for the response variable. The smaller the p value is, the more significant the predictor is.

Note that the “Family_present” variable showed up in the final model and the corresponding p-value is 0.041. This suggests that there is a significant effect on rounding time depending on whether patients’ parents virtually attend the rounds or do not attend the rounds. However, the “Family_present” variable is not as significant as some other variable, such as “Intubated.trach.dependent” (if the patient is intubated/trach dependent), whose corresponding p-value is extremely small.

3.2.2 Forward Selection with the BIC as criterion

Besides the AIC, the Bayesian information criterion (BIC) is also a widely used variable selection criterion. The BIC value is calculated as:

$$BIC = \ln(n)k - 2\ln(\hat{L})$$

where k is the number of predictors in the model plus the intercept, \hat{L} is maximum value of the likelihood function for the model, and n is the number of observations.

We applied the forward selection method with the BIC as criterion, the following table contains predictors that showed up in the final model:

Predictors in the final model	P-value
Intubated.trach.dependent	4.55e ⁻¹⁰
Specialist_present	0.003
Heart	0.023

Table 3: Predictors in the final model after using forward selection with the BIC as criterion

Note that the “Family_present” variable did not show up in the final model, indicating that there is not a significant effect on rounding time depending on whether patients’ parents virtually attend the rounds or do not attend the rounds based on this specific model selection method and criterion. Comparing the results shown in Section 3.2.1, we infer that the “Family_present” variable was excluded because that the BIC is a stricter model selection criterion. Only variables that are very significant would be left in the final model, such as “Intubated.trach.dependent”, “Specialist_present” and “Heart”. This result, again, shows that the “Family_present” variable was not as significant as those three variables.

3.2.3 Backward Selection with the AIC as criterion

Besides forward selection, backward selection is also a popular variable selection method. With backward selection, all candidate predictors are entered into the equation first. We then take out predictors whose removal gives the most statistically insignificant deterioration of the model fit, determined based on a chosen selection criterion. We repeat this process until no further predictors can be deleted without a statistically significant loss of fit.

After applying the backward selection with the AIC as criterion, the final model contained the following predictors:

Predictors in the final model	P-value
Intubated.trach.dependent	6.19e ⁻¹⁰
Heart	0.005
Specialist_present	0.024
Presenter	0.030
Family_present	0.041
Age	0.047

Table 4: Predictors in the final model after using backward selection with the AIC as criterion

We can see that in this case, the predictor of our interests, “Family_present”, did show up in the final model, indicating that it is statistically significant using this model selection method. However, the “Family_present” variable is not as significant as some other variables, such as “Intubated.trach.dependent”, whose p-value is very small.

3.2.4 Backward Selection with the BIC as criterion

Next, we applied backward selection with the BIC as criterion. The final model contained the following predictors:

Predictors in the final model	P-value
Intubated.trach.dependent	4.55e ⁻¹⁰
Specialist_present	0.003
Heart	0.023

Table 5: Predictors in the final model after using backward selection with the BIC as criterion

Note that the predictor of interest, “Family_present”, did not show up in the final model. Again, the main reason for this is that the BIC is a stricter model selection criterion, which removes the predictors that are not very significant away from the final model. Note that some predictors, such as “Intubated.trach.dependent” is still very significant base on their extremely small p-value, even though using this stricter variable selection method.

3.2.5 LASSO

The Least absolute shrinkage and selection operator (LASSO) is another widely used variable selection method. It can be viewed as an extension of the Ordinary Least Squares (OLS) regression, which chooses the regression coefficients that minimize the difference between the observed Y's and the estimated Y's. To reduce model complexity, LASSO introduces a new parameter λ that controls the small coefficient estimates to be 0. The goal of the LASSO is to find:

$$\operatorname{argmin}_{\beta \in \mathcal{R}^p} \sum_{i=1}^n \left(Y_i - \sum_{j=1}^p X_{ij} \beta_j \right)^2 + \lambda \sum_{j=1}^p |\beta_j|$$

Here, Y_i 's are the observed values of the response, X_{ij} 's are the observed values of the predictors, β_j 's are the regression coefficients we want to estimate, and λ is a tuning parameter that controls the amount of shrinkage.

In order to find the optimal λ , a list of λ values are tested and the optimal λ was chosen using 10-fold cross-validation.

The list of λ values that were tested are:

$$\lambda = 10^x, \quad \text{where } x = -2, -1.9, -1.8, \dots, 1.8, 1.9, 2$$

To find the optimal λ value using 10-fold cross-validation, the following steps were taken:

1. Randomly split the dataset into 10 groups
2. Given a λ value, for each unique group:
 - 2.1 Take the group as the test data
 - 2.2 Take the remaining groups as the training data

- 2.3 Fit a LASSO regression model using the training data. Use “Time” as response and all other variables as predictors
- 2.4 Calculate the test error using the test data
3. Calculate the average test error for that λ over all 10 groups
4. Repeat step 2 & 3 for all candidate λ values and the one that results in the lowest average test error is optimal

After applying the 10-fold cross-validation, the optimal λ value was calculated as 0.1. We then used the whole sub-dataset 1 (“not attending versus virtually attending”) to find the regression coefficients. The “Time” variable was used as response and all other variables were used as predictors. The predictors in the final model are those whose corresponding regression coefficient estimates were not zero.

In sum, the final model contains the following predictors:

Predictors in the final model	P-value
Intubated.trach.dependent	6.19e ⁻¹⁰
Heart	0.005
Specialist_present	0.024
Presenter	0.030
Family_present	0.041
Age	0.047

Table 6: Predictors in the final model after using LASSO

Note that the p-value for the predictor of interest, “Family_present”, is less than 0.05 after using LASSO, suggesting that it is statistically significant. However, it is not as significant as some other predictors, such as “Intubated.trach.dependent”, whose p-value is extremely small.

3.2.6 Summary

The table below shows a summary of the predictors’ presence in the final models after applying the above selection methods and criteria. A predictor with a check mark means that it was statistically significant using the corresponding selection method, while one with a cross mark means that it was not statistically significant.

Selection Methods Predictors	Forward Selection with AIC	Forward Selection with BIC	Backward Selection with AIC	Backward Selection with BIC	LASSO
Heart	✓	✓	✓	✓	✓
ECMO/CRRT	✗	✗	✗	✗	✗
Intubated.trach.dependent	✓	✓	✓	✓	✓
Presenter	✓	✗	✓	✗	✓
Specialist_present	✓	✓	✓	✓	✓
Length_of_stay	✗	✗	✗	✗	✗
Age	✓	✗	✓	✗	✓
PRISM IV	✗	✗	✗	✗	✗
PIM_2_severity_score	✗	✗	✗	✗	✗
Language	✗	✗	✗	✗	✗
Family_present	✓	✗	✓	✗	✓

Table 7: Summary of the predictors' presence in the final models

Note that the predictor of interest, “Family_present”, showed up in the final models 3 out of 5 times. The two models within which it did not show up were selected using the BIC as criterion. Consider the fact that the BIC is a stricter model selection criterion and “Family_present” was not removed in all other situations. We conclude that compared with parents not attending, virtually attending the rounds did have a significant effect on the rounding time. However, the “Family_present” variable was not as significant as some other variables which showed up in the final models 5 out of 5 times. Those variables and the potential reasons why they are significant are discussed below:

- “Heart” (If the patient’s issue is a heart defect of some type): we infer that having a heart defect is a more severe health condition that leads to longer rounding time
- “Intubated/trach dependent” (If the patient is intubated/trach dependent): we think that intubated/trach dependent tends to make regular communication much slower, which may result in longer rounds
- “Specialist_present” (If a specialist in heart disease attends the round): we infer that specialist in heart disease tends to provide more information about the patient condition during the rounds, which may cause longer rounding time.

Next, we want to get an idea about how the rounding time will change when virtually attend the rounds compared with when they do not attend. We can achieve it by checking the coefficient estimate and confidence interval for the predictor of interest, “Family_present”. As shown in the table above, all three final models within which “Family_present” variable presents, have same variables left: “Heart”, “Intubated/trach dependent”, “Presenter”, “Specialist_present” and “Family_present”. If we use these significant variables as predictors and use the “Time” variable as response, the following coefficient estimation and confidence interval for the “Family_present” variable are calculate as below:

Predictor of Interest	Coefficient Estimation	95% Confidence Interval
Family_present	6.655	[1.142, 16.737]

Table 8: Coefficient estimation and 95% confidence interval for the predictor of interest

As shown in the table above, the regression coefficient estimation for the “Family_present” variable is 6.655. Recall that we let the value of “Family_present” to be 1 for parents virtually attending the rounds while to be 0 for not attending. This coefficient estimate suggests that parents virtually attending the rounds tended to increase the rounding time by 6.655 seconds on average, compared to not attending. The confidence interval shown in the right part of the above table suggests that, we are 95% confident that the increase of time by introducing the new way of virtually attending the rounds compared with not attending is between 1.142 seconds and 16.737 seconds.

3.2.7 Variable Selection for the Sub-dataset 2

Similarly, we applied the five variable selection methods described in Section 3.2.1 to Section 3.2.5 to the sub-dataset 2, where the “Family_present” variable is 1 (physically attending) or 2 (virtually attending). Below is a summary table for the predictors’ presence in the final models:

Selection Methods Predictors	Forward Selection with AIC	Forward Selection with BIC	Backward Selection with AIC	Backward Selection with BIC	LASSO
Heart	✗	✗	✗	✗	✗
ECMO/CRRT	✓	✓	✓	✓	✓
Intubated.trach.dependent	✓	✓	✓	✓	✓
Presenter	✓	✓	✓	✓	✓
Specialist_present	✗	✗	✗	✗	✗
Length_of_stay	✓	✓	✓	✗	✓
Age	✓	✗	✗	✓	✓
PRISM IV	✗	✗	✗	✗	✓
PIM_2_severity_score	✗	✗	✗	✗	✗
Language	✗	✗	✗	✗	✗
Family_present	✗	✗	✗	✗	✗

Table 9: Summary of the predictors’ presence in the final models using dataset2

Note that the predictor of interest, “Family_present”, did not show up in the final models 5 out of 5 times. We conclude that parents physically versus virtually attending the rounds did not have significant effects on the rounding time.

For other predictors, we note that there is no obvious pattern for their significant level compared with the results we got using sub-dataset 1. For example:

- The “Intubated.trach.dependent” (if the patient is intubated/trach dependent”) variable was significant 5 out of 5 times either we use sub-dataset 1 or 2
- The “Heart” (If the patient’s issue was a heart defect of some type) variable is significant 5 out of 5 times when we use sub-dataset 1, but 0 out of 5 times when we use sub-dataset 2
- The “ECMO/CRRT” (If Extracorporeal membrane oxygenation (ECMO) or Continuous renal replacement therapy (CRRT) was used for the patient) variable is not significant 5 out of 5 times when we use sub-dataset 1, but is significant all times when we use sub-dataset 2

Therefore, it is hard for us to see the reason why these variables are significant or not just based on their actual meanings and observed values. Also, since this is an observational study, where researchers simply collect data for certain factors based on what is seen, there may be more important factors which were not recorded. Further analysis, such as randomized controlled trial, can be done in the future to test the effectiveness for certain variables.

4. Conclusion

In summary, we conclude that rounding time was significantly higher in cases where parents attended the rounds virtually compared to not attending at all. However, rounding time was not significantly impacted in cases where parents attended the rounds in-person versus attending them virtually. We infer that virtually attending the rounds provided opportunities for patients’ parents, like in physically attending cases, to raise questions and get more information during the rounds.

In this study, we mainly used multiple linear regression as our model methodology. In the future, Three-Way ANOVA can also be leveraged to solve the problems and evidence the conclusion we drew. Moreover, as mentioned in Section 3.2.7, randomized controlled trial can also be applied to further study the effectiveness for certain variables.

Note that we also have survey data about satisfaction ratings related to patients’ parents virtually attending the rounds. The surveys were answered by physicians in the hospital after they attended the virtual family centered rounds. However, due to some defects in experimental design, only limited statistical analysis could be done (see Appendix A). Some improvements for the experimental design (see Appendix A) could be done in the future to further prove the conclusion we have drawn.

Appendix A

Discussion about the survey data

As mentioned in Section 4, we have some survey data about the newly introduced way to attend the rounds virtually. The survey questions were answered by the physicians after they attended the rounds. All the questions were listed in the table below:

Survey Questions
Q1: What type of physician are you?
Q2: How many years have you worked in the PICU?
Q3: Overall, virtual family centered rounds are? (1: Not helpful; 2: Somewhat helpful; 3: Very helpful)
Q4: Compared to having no family present at the bedside, how do you feel virtual communication encounters have impacted your communication with the patient families? (-5 ~ -1: Negatively impact; 0: No impact; 1 ~ 5: Positively impact)
Q5: Has virtual family centered rounds affected your ability to provide good care to your patients? (-5 ~ -1: Negatively impact; 0: No impact; 1 ~ 5: Positively impact)
Q6: Please indicate the overall level of disruption you experienced as a result of this encounter. (0: No disruption; 1 ~ 9: Moderate disruption; 10: Very disruptive)
Q7: Please indicate your overall satisfaction with virtual family centered rounds (0: Not satisfied at all; 1 ~ 9: Moderate satisfied; 10: Completely satisfied).
Q8: Did you have any technical issues with the virtual communication?

Table 10 Survey questions answered by the physicians after they attended the rounds

First, we took a look at the average ratings for the questions. Below is a summary for what we found that might be useful:

- The average rating for Q3 was 2.531, and all the answers were 2 or 3. It suggests that physicians thought that virtual family centered rounds were helpful.
- All the ratings for Q4 were positive and the average was 3.531, indicating that physicians felt that virtual family centered rounds had positive impact on communications.
- The average rating for Q5 was 2.219, suggesting that physicians thought that virtual family centered rounds positively affected their ability to provide good care. Also note that some physicians' answers for this question were 0, meaning that they did not feel any additional effects were there.
- Though some ratings for Q6 were 0, most of the answers were greater than 0, meaning that many physicians thought that this newly introduced way of attending the rounds also brought some disruption.
- All ratings for Q7 were between 1 and 9 and the average was 7.563. It suggests that physicians were moderately satisfied by this way of virtually attending the rounds.

- According to the answers to Q8, physicians had technical problems in 5 out of 32 cases.

In summary, physicians had an overall positive experience after introducing a way for patients' parents to attend rounds virtually. However, note that the survey questions were answered by physicians only after they attended the virtual family centered rounds, therefore limited statistical analysis could be done. In the future, if these same questions could be asked after each way of attending the rounds, like not attending, physically attending and virtually attending, more statistical analysis, such as Analysis of Variance (ANOVA), could be done to get more convincing results.