

Debriefing Trends in Pediatric Emergency Room Fellows

Parvathi Meyyappan

Commissioned by Alexandria Georgadarellis, Shiva Zhargam, and Brielle Stanton
On behalf of UNC Chapel Hill and Yale University

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Advisors: Dr. Marron, Dr. Haaland, 2022-2023 Consulting Class

Abstract

Resuscitations of critically ill patients in the pediatric emergency room can result in abnormal stress responses in the medical team. Post-resuscitation debriefs can be valuable in helping analyze what happened, help with maintenance of morale, and optimize pediatric emergency room care. Through a survey sent out to pediatric emergency departments in North America, this report attempts to describe the current landscape of debrief training experiences and procedures to help determine standards and formal education practices for post-resuscitation cases. This report aims to assess the relationship between pediatric emergency room fellows' resiliency, burnout, and career satisfaction and debriefing practices in each department to better understand if debriefing can help support the medical team. The analysis resulted in three statistically significant relationships. There's a significant relationship between formal debrief training and actual debrief experiences, another between formal debrief training and the number of debrief styles encountered by the fellow, and lastly there's a relationship between the number of debrief styles a fellow has used and comfort in facilitating debriefs. Further, this report finds moderately strong regressions to predict fellows career burnout, resiliency, and career satisfaction. Unfortunately, data limitations in terms of sample size and multicollinearity hindered the strength of conclusions.

Section 1. Introduction

Resuscitation in the pediatric emergency department (PED) is usually a series of interventions conducted by a trained team in efforts to restore and/or support vital functions in a critically ill patient. Due to the complexity of the resuscitation process sometimes patient care is not always performed optimally. Literature concerning the optimization of team performance suggests that debriefing critical incidents can optimize team performance and help protect and support the medical team that are exposed to critical incidents by minimizing the abnormal stress response.¹

During a debriefing, health care teams re-examine the clinical encounter to discuss individual and team performance, identify errors, and develop performance improvement strategies via reflective learning processes.² Anecdotally, fellows and providers perceive the need for debriefing in the emergency room. Health care teams that have attended the debriefs often rate the experience as "valuable", "helpful", and a "morale maintenance". Despite these anecdotes and endorsements, this educational intervention is still relatively novel in medicine. Few institutions have formal guidelines and standards on team debriefing after critical incidents, such as a failed resuscitation.³

The client sent out surveys to PEDs across the country to measure debriefing standards and practices among pediatric emergency room fellows and program directors. The client's primary goal is to describe the current landscape of debrief training experiences, determine standards for debriefing sessions, and measure formal education pertaining to debriefs among Pediatric Emergency Medicine (PEM) fellows in the United States. We studied this by looking at the association between variables of interest such as fellow's comfort level, training experience, debriefing standards, formal education in debriefing, career satisfaction, career burnout, and resiliency. The client's secondary goal was to be able to predict burnout, career satisfaction, and

resiliency among PEM fellows using the demographic and debriefing-based variables measured in the survey.

This report is structured as follows: Section 2 describes the datasets, data processing methods, and variable transformations. Section 3 contains the methods and results regarding the associations between certain variables of interest and discusses the regression methods and results of those models that best predict career satisfaction, burnout, and resiliency. Lastly, Section 4 is the appendix and contains analysis, results, graphs, and tables that are not directly pertinent to the conclusions.

Section 2. Data

2.1 Survey Specifics

There are two Qualtrics surveys that were emailed out to all the pediatric emergency medicine program directors in the country, one for the PEM fellows and one for the PEM fellowship program directors. Ninety-three fellows filled out the survey as well as 53 program directors.

The survey sent to the program directors had 9 questions.

- How many fellows were sent the survey?
- Geographic region of the department
- Whether there is formal debrief training?
 - If yes: Who oversees the curriculum? What debriefing styles and tools are included in the curriculum?
- How satisfied are you with current curriculum?
- Are you interested in a formalized debriefing outline?
 - If so, what are you most interested in seeing?

This report focuses on the survey sent to the pediatric emergency medicine fellows and their responses. This survey had 27 questions collecting information about how debriefs are conducted in their department, how often they're conducted, personal satisfaction with the debriefs, career satisfaction, burnout, and resiliency as well as demographic data. These variables are more clearly defined in Table 1.

Table 1: Variables collected, associated question numbers and type of response collected in the survey sent out to PED's

Variable	Variable Type	Associated questions in the Survey
Frequency of participating and leading debriefs after a resuscitative event	Integer between 0 and 100	1,2
Simulated number of debriefs(that the respondent has led or participated in)	Integer	3,4
Clinical number of debriefs(that the respondent has led or participated in)	Integer	5,6
Comfort in conducting debrief	Ordinal 1 to 4	7

Which debrief styles have you heard of and use as a facilitator?	Checkbox (6/8 options)	8,10
Which debrief tools have you heard of and use as a facilitator?	Checkbox (8/9 options)	9,11
Preference among individual or group debriefs or both	Individual, Group, both regardless of situation, both depending on situation	12
Whether they've been trained on debriefing		13
Which style/tools they've been trained on and when	Checkbox (11x3)	14
Barriers to conducting debriefs	Checkbox (11x1)	15
Does the respondent want formalized debriefing curriculum?	Yes or No	16
What specifically would they like to see in the curriculum?	Open ended	17
Satisfaction with the debrief training	Ordinal 1 to 5	18
Resiliency from setbacks	Ordinal 1 to 5	19.1 – 19.6
Career satisfaction	Ordinal 1 to 5	19.7
Burnout frequency	Ordinal 1 to 7	20
What year of fellowship they are in?	1 to 4	21
Type of residency	Peds, EM, PEM	22
Geographic region	NE, South, Midwest, West, Canada, other	23
Age range	Open ended	24
Gender identity	M, F, NB, Trans, Other, Prefer not to answer	25
Race	Asian, Black, Native American, Hawaiian or Pacific Islander, White, Other, Prefer not to answer	26
Hispanic or Latino?	Yes, No, Prefer not to answer	27

Given the main objectives from this survey we can determine the broader variables of interest. To measure the broader variables of interest, we used exploratory data analysis (EDA) to combine and transform the variables to measure:

- career satisfaction
- burnout
- resiliency
- whether debriefs are used (clinically or in training)
- personal training experience in debriefing
- styles/tools of debriefing used
- years of training

3.2 Data Transformations

Many of the survey questions were written in a check all that apply format. Based on the literature there are 2 ways to deal with multiple responses: One is to create an indicator for each possible option that takes values 0 if it was chosen or 1 otherwise. The second way is to treat each grouping of options as a choice. For example, if there are 3 checkbox options: a, b, and c. The first approach would have 3 indicator variables: one for whether they chose option a, option b, and option c. The second approach would be one variable with 8 possible values: chose none of the options, just a, just b, just c, all 3 options, a & b, b & c, and a & c.

For this analysis I decided to proceed with the first method of creating indicators for each possible option since most of the survey questions with checkbox responses had more than 7 possible options and the latter method would result in far too many groupings especially considering the size of our dataset. The creation of indicator variables was used for questions 8 through 11, 14, and 15 on the survey (refer to Table 1 to see what those questions are measuring).

Some key variables in the analysis was measuring the amount of debrief training and experience the respondent has, these were in questions 3 through 6 in the survey:

3. How many simulated debriefs have you participated in during residency and fellowship?
4. How many simulated debriefs have you led during residency and fellowship?
5. How many debriefs have you participated in during residency and fellowship?
6. How many have you led during residency and fellowship?

The responses to these four questions are shown in Figure 1 as histograms. A histogram shows the distribution of the survey question's responses. It shows the frequency at each response option. Histograms often classify data into various "bins" or "range groups" and count how many data points belong to each of those bins.

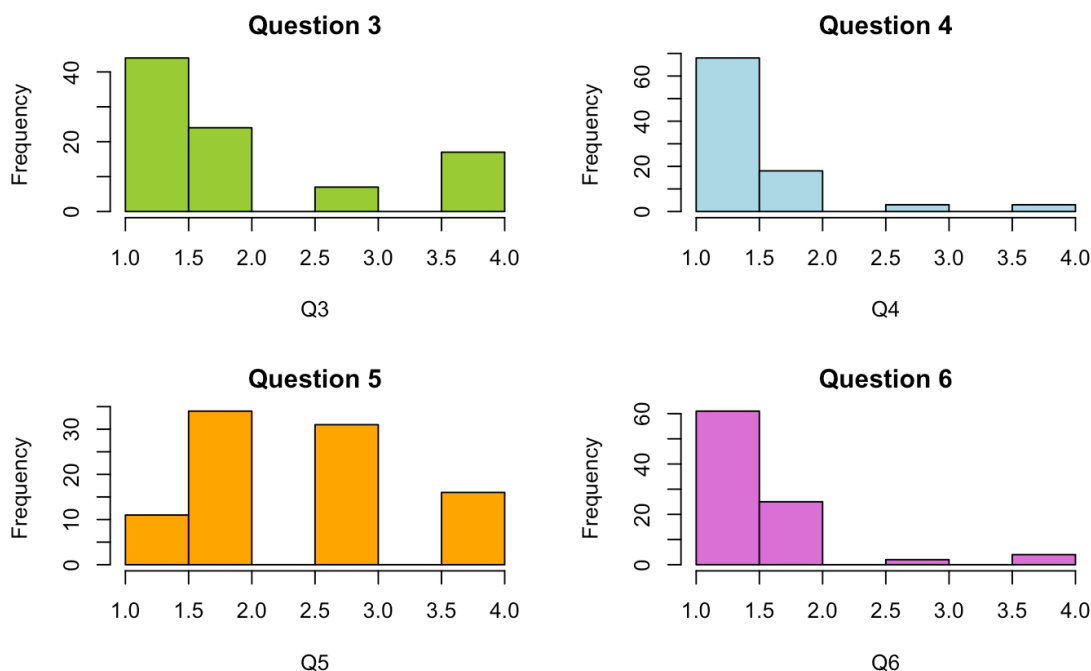


Figure 1: Histograms of the responses to questions 3 through 6 on the survey asking about participation and leadership of debriefs both clinically and in simulation.

Looking at the histograms we can see that the histograms for Q4 and Q6 are identical: fellows have led similar levels of debriefs in a training and clinical setting. Questions 3 and 5 are what I thought were most important to the association analysis we're conducting. Thus, I decided to take the average for each respondent of their participation in debriefs, clinically, and in training. This is a value between 1 to 4:

- 1 means 0-1 debriefs
- 2 means 2 – 5 debriefs
- 3 means 6 – 10 debriefs
- 4 means more than 11 debriefs

After the simple transformation figure 2 shows what the resulting histograms looked like.

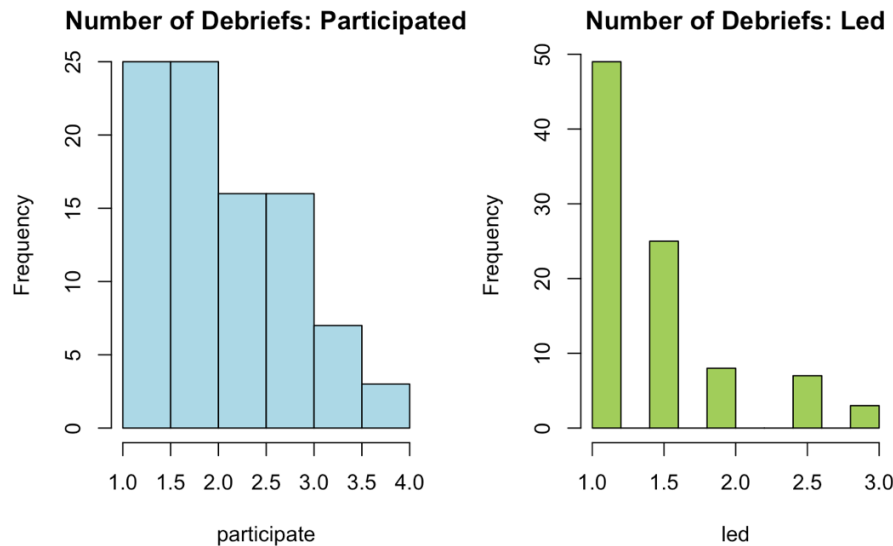


Figure 2: After transformation which combined clinical, and practice debriefs to get an average number of debriefs pediatric emergency room fellows led or participate in.

Another variable that was measured across a few survey questions was resiliency. There were 6 survey questions measuring the respondent's resiliency each asking them a score ranging between 1: strongly disagree to 5: strongly agree. The survey questions were written such that 3 of the 6 questions response had a direct relationship with resiliency: strongly agree meant the respondent was more resilient where the other 3 questions had an inverse relationship: lower scores/disagreement meant the respondent had higher resilience. Thus, I transformed the latter group so all 6 questions values were in the format: a higher score meant more resilience in the respondent. I then took the sum of these scores so that resiliency of the respondent was a score out of 30 where a lower score implied lower resilience. Figure 3 shows the histogram or the distribution of the composite resiliency score.

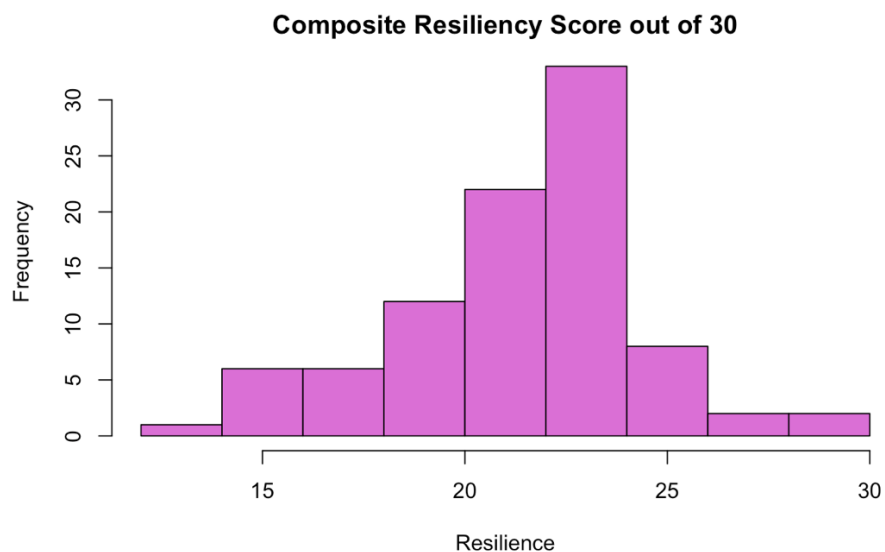


Figure 3: The distribution of the composite resiliency scores out of 30: most fellows rank themselves between a score of 20 and 25.

The other variable that required transformation was debriefing standards. There were 5 questions measuring this:

1. Which debriefing styles have you heard of?
2. Which debriefing tools have you heard of?
3. Which debriefing styles have you used?
4. Which debriefing tools have you used?
5. Do you prefer individual, group, or both debriefing methods?

For the first 4 of these questions, I created indicator variables to handle the checkbox style responses and then summed the indicator variables to create variables that measured how many debriefing tools and styles the respondent has heard of and used. For the first part of analysis that looked at associations among variables I summed up the indicator variable to create 4 variables:

1. Number of debriefing styles the respondent has heard of
2. Number of debriefing tools the respondent has heard of
3. Number of debrief styles they've used as a facilitator
4. Number of debrief tools they've used as a facilitator

So I used the count of styles/tools instead of the specific styles/tools for the first part of the analysis.

Section 3. Methods and Results

The analysis is split into 2 major parts: one that looks at the associations between certain variables of interest and a second part that conducts regression analysis to determine which variable are important in predicting career burnout, satisfaction, and resiliency.

3.1 Association and Correlations

To study the associations between certain variables I used a few different methods. First, I used contingency tables to explore the relationship between various categorical variables. They provide a basic picture of the interrelation between two variables and can help find interactions between them. It's an easy way to see the frequency distribution of the variables.

To help visualize the contingency tables, I included mosaic plots. Mosaic plots to help visualize the contingency table. A mosaic plot is a special type of stacked bar chart. For two variables, the width of the columns is proportional to the number of observations in each level of the variable plotted on the horizontal axis. The vertical length of the bars is proportional to the number of observations in the second variable within each level of the first variable. Mosaic plots help show relationships and give a visual way to compare groups.

Next, I looked at chi square tests of independence. This test checks whether two variables are likely to be related or not. Given counts for two categorical variables, this test tells us whether a relationship between the two variables is plausible or not. The test is set up on the hypothesis that the two variables of interest are independent and the alternate hypothesis that they are not

independent. After running the test, if the p-value is less than our significance level of 0.05 then we can say reject the null hypothesis and say that there is sufficient evidence that the two variables are not independent or equivalently that there is a relationship between the 2 variables. We want to prove the latter point, that there is significant evidence that the variables are not independent and that there is a relationship between them. To verify these results, I support the Chi square test of independence with Fisher's exact test. In practice Fisher's tests are used for smaller sample sizes and we have 92 respondents for the fellow's survey, so it's a good choice. The test is useful for categorical data that result from classifying objects in two different ways; it is used to examine the significance of the association (contingency) between the two kinds of classification.

There were 7 sets of associations the clients were interested in:

1. The relationship between training experience and comfort
2. The relationship between training experience and formal education
3. The relationship between standards and formal education
4. The relationship between standards and comfort
5. Comfort vs burnout, satisfaction, resiliency
6. Formal education vs burnout, satisfaction, resiliency
7. Years of training vs burnout, satisfaction, resiliency

Many of the associations were not significant according to the Fisher exact test and the chi square test of independence. There were a few pairs that were statistically significant at an 0.05 alpha value.

The variables measuring whether the respondent has been trained in conducting debriefs and formal education in debriefs, clinically and in simulations, had statistically significant values indicating that these variables are not independent and that there is a statistically significant relationship between these variables.

Table 2: Contingency table between debrief participation and whether a respondent had formal training in conducting debriefs.

	Whether the Respondent has had Formal Training in Conducting Debriefs?			
		Yes	No	Unsure
Average Number of Debriefs that the respondent has participated	0 – 1	0	7	0
	2 – 5	14	42	3
	6 – 10	9	4	3
	11+	5	5	0

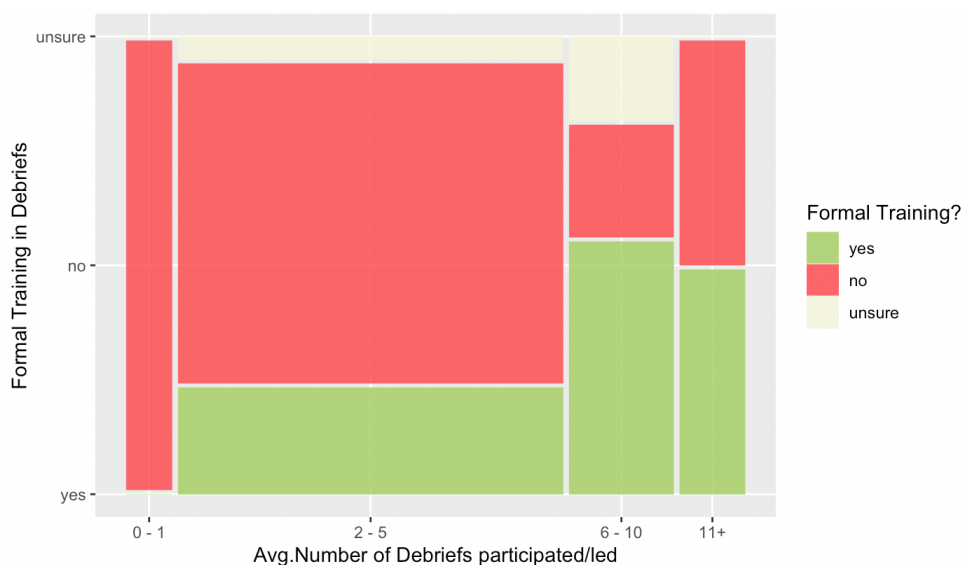


Figure 4: Mosaic plot showing the direct relationship between the average number of debriefs a resident has participated in/led and the formal training the resident has been through

In Table 2 and Figure 4 you can see the contingency table and visualize it with the mosaic plot. This relationship is fairly expected: if PEM fellows have been formally trained in debriefs then they are more likely to participate and facilitate debriefs in their programs. Whether or not there is causality here isn't determinable but rather that there is a significant relationship between the two variables. The chi square test resulted in a p-value of 0.0045 and the Fisher exact test resulted in a p-value of 0.0034. Both tests are strongly significant at alpha level 0.05.

Another significant association was that between certain questions measuring standards and the formal education of the respondent. Standards were measured through 5 different questions that have been mentioned earlier in this report. The relationship between whether the respondent had formal training in debriefs and the number of debrief styles the respondent has heard of.

Table 3: Contingency table between debrief styles exposure and formal training in conducting debriefs

Number of debrief styles the respondent has heard of	Whether the Respondent has had Formal Training in Conducting Debriefs?			
		Yes	No	Unsure
0		0	2	0
1		0	3	0
2		1	19	1
3		9	23	4
4		18	11	1

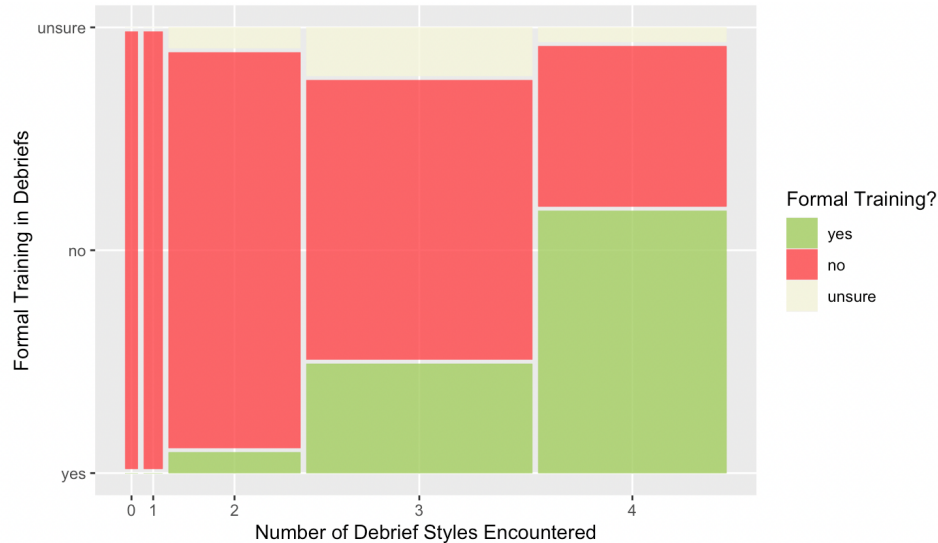


Figure 5: Mosaic plot visualizing the relationship between the number of debrief styles the respondents have heard of and whether they have had formal training in conducting debriefs.

In Figure 5, we can see that as the number of debrief styles the respondent has heard of increases there is a larger proportion of respondents that have received formal training in debriefs. This is an expected correlation between the variables and makes sense intuitively. The chi square test resulted in a p-value of 0.0023 and the fisher exact test resulted in a p-value of 0.00058. Both tests are strongly significant at alpha level 0.05.

The last significant relationship found in the analysis was that between debriefs styles used by facilitators and comfortability facilitating debriefs.

Table 4: Contingency table between number of debrief styles used by facilitators and the comfort in facilitating debriefs

Number of debrief styles used as a facilitator	Comfort facilitating and conducting debriefs				
		Very Uncomfortable	Uncomfortable	Comfortable	Very Comfortable
0		4	11	1	0
1		6	10	12	3
2		2	4	9	2
3		1	5	10	2
4		0	2	6	0
5		0	0	1	1

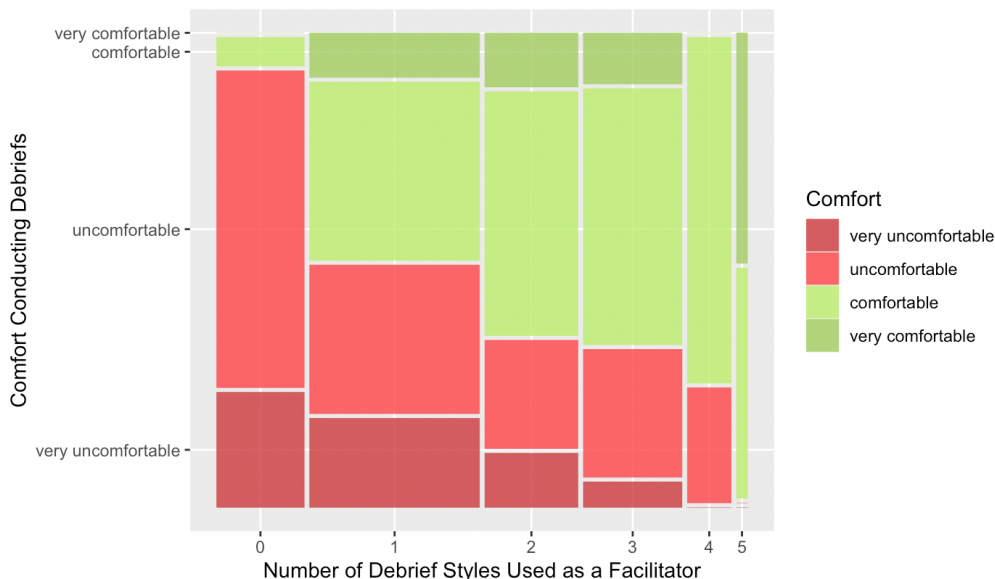


Figure 6: There's a clear dependence between the number of debrief styles used as a facilitator and the fellows' comfort conducting debriefs.

In Figure 6, there are two possible interpretations: One is that as the number of debrief styles used by the facilitator increases so does their comfort in conducting debriefs. Or, as fellows become more comfortable conducting debriefs, they use more debrief styles. The chi square test resulted in a p-value of 0.037 and the fisher exact test could not be conducted since the workspace was too small or equivalently the dataset did not have enough respondents in each pair of responses to the 2 questions.

There could be many more significant relationships or correlations between variables of interest but given the number of categories on these variables and 92 respondents the sample size isn't quite large enough to find correlation or relationships that aren't apparent or ones that can be easily assumed. If there were more respondents, I think this could change the number of significant relationships.

3.2 Regression Analysis

One of the goals of the regression analysis was to find which variables were useful and significant in predicting respondent resiliency. Thus, I tried many models predicting resiliency using most of the other variables collected in the survey. Despite there being 27 questions in the survey I had 64 predictor variables since many of the checkbox style variables were split into a few indicator variables so we could see if specific selections were important. But since we had 64 variables, dimensionality reduction was super useful. After trying various linear regressions, LASSO, ridge, principal components regression, and partial least squares regression, the two models with the best results were a basic linear model resulting from a stepwise selection and a LASSO regression.

To determine the “best” model I used R^2 and Akaike information criterion (AIC). R^2 shows how well terms (data points) fit a curve or line. Adjusted R^2 also indicates how well terms fit a curve or line but adjusts for the number of terms in a model. If you add more and more useless variables to a model, adjusted r-squared will decrease. If you add more useful variables, adjusted r-squared will increase. AIC is used to compare different possible models and determine which one is the best fit for the data. AIC is calculated from:

- the number of independent variables used to build the model.
- the maximum likelihood estimates of the model (how well the model reproduces the data).

The best-fit model according to AIC is the one that explains the greatest amount of variation using the fewest possible independent variables. The AIC scores for each model attempted is shown in table 5. We want a model with a low AIC score.

Table 5: AIC scores of models attempted in predicting resiliency.

Model	Adjusted R^2	AIC
Full Linear Regression	0.7044	41.17
Reduced Linear Regression	0.8343	29.21
Principal Components Regression	0.6011	39.6569
Partial Least Squares Regression (Latent Variable)	0.9216	-10.4156
Lasso	0.4056667	-322.9049
Ridge	0.3796697	1057.118

In statistics and machine learning, Lasso (least absolute shrinkage and selection operator; also Lasso) is a regression analysis method that performs both variable selection, and regularization in order to enhance the prediction accuracy and interpretability of the resulting statistical model.

One well performing model, based on R^2 , was the partial least squares regression. This model. Partial Least Squares regression is based on linear transition from a large number of original descriptors to a new variable space based on small number of orthogonal factors (latent variables). In other words, factors are mutually independent (orthogonal) linear combinations of original descriptors. This model is a lot harder to interpret or understand how the changes in statistically significant variables affect the response variable or resiliency. As a result, I focus more on the reduced linear regression and the Lasso Regression.

Although the linear model has a fairly low AIC it may not be the best model. It has many predictors which can really contribute to overfitting. Often a simpler model, like the LASSO model might be preferred to a complicated linear model. We can see the significant predictors in both models (linear regression and Lasso) in appendix section 1. We can interpret these coefficients as the increase or decrease in a respondent’s resiliency score (out of 30) for a one unit increase in that variable. For example, the first row, Q2 represents the frequency of participation in debriefs: With statistical significance, as the frequency of participation increases

by one unit the resiliency score of the respondent decreases by 0.08 according to the linear model.

In the linear model, notable variables that can have major increases or decreases (> 3 or < -3) in a respondent's resiliency score are:

- the number of simulated debriefs that the respondent led
- whether or not the respondent has heard of cold debriefs
- used cold, informal, or group debriefs
- whether or not the respondent has heard of discern tool
- used the stop or reflect tools
- whether they've been trained on how to conduct a debrief
- if they've received training in how to conduct group debriefs
- the barriers of lack of participation or interest in debriefs
- the type of residency completed

In the LASSO model, notable variables (coefficients > 3 or < -3) are:

- whether as a facilitator they've used the discern debrief tool
- whether they've been trained in the reflect tool

The coefficients are smaller for the LASSO regression since the aim of Lasso regression is to perform variable selection or push coefficients of variables to zero. Thus, it makes sense that there are fewer largely significant variables in the Lasso regression.

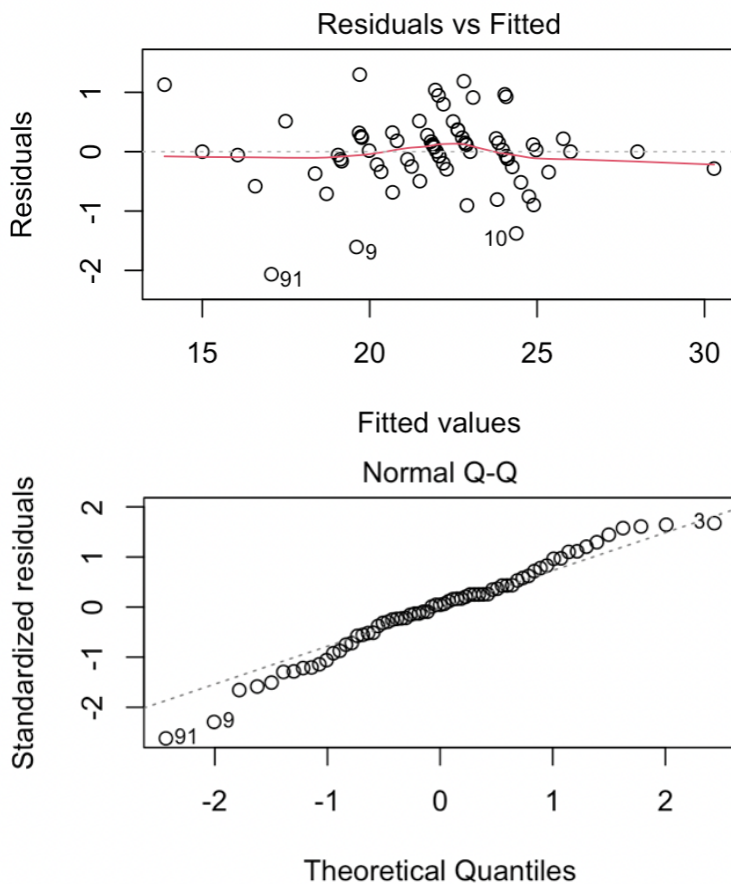


Figure 6: Diagnostic plots of predicting resiliency using a reduced linear model. The top plot shows that there are not apparent patterns in the residuals – which implies the model is well suited to the data. The second plot is a QQ plot which measures the normality of the residuals – in this case our model's residuals are normally distributed.

Another major goal of the regression analysis was to predict career satisfaction and to predict burnout. Career satisfaction was measured as an ordinal variable, values ranging from 1 to 5, where 1 was low and 5 was high. Similarly, burnout is an ordinal variable with 7 possible values measuring how often the respondent feels burnout, ranging from never to everyday.

Since both career satisfaction and burnout are ordinal, we decided to proceed with ordinal logistic regression. Both ordinal models ran into pretty major issues. The first models with all the predictors worked and resulted in a model with coefficients and high AIC scores as seen in table 6. This high AIC could be due to overfitting but variable selection for this model proved difficult. Due to the multicollinearity in the dataset the Hessian had many NA and infinite values making it difficult to find p-values or significance levels of each predictor. This in turn affected the ability to get rid of insignificant predictors and find the best model with fewest predictors. These coefficients and AIC values are shown in the appendix sections 2 and 3.

Table 6: AIC scores for the relevant models in predicting burnout and career satisfaction.

	Model	AIC
Predicting Fellow Burnout	Multinomial Logistic Regression	402.0001
	Ordinal Logistic Regression	1171.256
Predicting Career Satisfaction	Multinomial Logistic Regression	744.0001
	Ordinal Logistic Regression	3759.905

Even though our response variables of career satisfaction and burnout are ordinal, I attempted a multinomial logistic regression which is usually used for nominal variables. The data we have satisfies the assumptions for this model and thus it was able to perform without hiccups. The coefficients and p-values of these models are attached in the appendix. In regressing to predict career satisfaction, no single predictor was significant in predicting across the 3 groups with at least 4 respondents in it (career satisfaction levels 3, 4, 5). The nominal logistic regression predicting burnout had 3 significant predictor variables:

- Q10_4: whether the respondent had used cold debriefs as a facilitator,
- Q10_7: if the respondent was not sure about which debriefing style they used, and
- Q11_6: whether the respondent used the info tool when conducting debriefs.

In context, these variables contain no apparent relevant information except for the cold debriefs. Earlier analysis also found that to be a useful predictor.

3.3 Brief Conclusion

The correlation and association analysis resulted in 3 significant relationships. The first was between respondents training experience (clinically and in simulations) and whether they've had formal debrief training. We found that these variables are not independent and that there may not necessarily be a causal link. The second significant relationship was between the types of debrief

style fellows had heard of and whether they've had formal debrief training. This one is a straightforward link: respondents who've had formal training have heard of more debrief styles. The last significant relationship was between the debriefing styles used by fellows when they facilitate debriefs and they're comfort conducting debriefs. The direction of causality is certain. It could be that as fellows get more comfortable leading debriefs, they use more debriefing styles and tools. Or that as fellows use more debriefing styles and tools, they get more comfortable facilitating debriefs. There may be more important relationships between the variables of interest but due to the size of the dataset and the nature of the categorical variables, it's more difficult to establish statistical significance.

The regression analysis aimed to predict three variables: resiliency, career satisfaction, and burnout. Given the large number of predictor variables, the LASSO regression proved to be beneficial in predicting resiliency and only required 14 predictors in comparison to the potentially overfitted reduced liner regression that require 25 predictors. The LASSO regression did not have a very high R^2 value in comparison to the linear regression, but it was far more simplified. Prediction of the ordinal variables burnout and career satisfaction proved to be more difficult. Given the multicollinearity and the smaller sample size it was difficult to get a well fitted ordinal regression model. Instead, nominal logistic regression models sufficed and resulted in an lower AIC scores in comparison to the ordinal logistic regression. With more responses and fewer checkboxes or categories for certain question there's potential for stronger results and conclusions in the future.

Section 4. Appendix

Section 4.1 Significant Coefficients

Coefficients of the statistically significant regressors at alpha level 0.05 from the two best performing models in predicting resiliency

Significant Regressors	Reduced Linear Model	LASSO
Q2	-0.08334	---
Q3	-1.35497	---
Q4	3.08558	---
Q6	1.56824	---
Q7	1.43447	---
Q8_3	---	0.8184352
Q8_4	3.95069	0.2474154
Q9_1	-2.77287	-0.6920640
Q9_2	5.63212	---
Q10_1	-3.59468	---
Q10_2	-2.33840	---
Q10_4	-3.53216	-0.6471547
Q10_7	-3.79016	-0.1918247
Q11_1	-4.40472	---
Q11_2	---	4.3189981
Q11_4	6.65746	---
Q12	1.44309	---
Q13	3.75984	0.7698816
Q14_1	6.49127	---
Q14_7	9.51531	---
Q14_8	---	-3.2718979
Q15_4	---	-0.2542182
Q15_6	1.80425	-0.3119607
Q15_8	-4.44762	---
Q15_9	3.40320	---
Q16	-2.67907	---
Q18_1	2.02462	---
Q20	---	-0.1189630
Q22	6.92491	1.2284738
Q23	---	0.1986752
Q25	2.35195	---
Adjusted R- squared	0.7795	0.35685

Section 4.2 Models predicting career satisfaction

Predicting Career Satisfaction Ordinal Regression Output:


```

4 -1.2186461 3.495703 -1.097466 -0.6543538 -10.7039466 -12.633463 2.935266
5 0.3031252 -3.630508 -8.107218 -7.7323372 9.6435400 5.341865 -4.480843
    Q14_5    Q14_6    Q14_7    Q14_8    Q14_9    Q14_10    Q14_11    Q15_1
3 -6.445334 1.703928 -6.648947 0.1947029 -0.6358059 -0.2158571 1.919785 -1.6615493
4 -2.526121 5.086036 1.080936 2.5043022 -0.9525585 1.1489882 3.937048 1.3466879
5 8.430542 -9.560993 4.018100 -2.6205476 1.6201781 -2.3832987 -7.177694 -0.6992849
    Q15_2    Q15_3    Q15_4    Q15_5    Q15_6    Q15_7    Q15_8
3 3.0076312 7.8277124 -5.205783 -5.343378 1.164737 -0.7142965 -7.422957
4 -0.3538670 -0.5981836 -7.548318 0.817012 17.474038 -4.5087036 17.120914
5 0.8760132 -3.6012407 3.803093 7.202948 -12.560351 9.0949056 -11.345792
    Q15_9    Q16    Q18_1    Q20_12    Q20_13    Q20_14    Q20_15
3 6.526190 -11.012379 -2.730903e+00 -4.2054222 4.034973 2.9653941 4.071981
4 -15.600664 13.576341 5.297404e-01 1.7848948 8.729391 -0.4087068 2.045787
5 6.560171 -2.902306 2.855216e-05 0.1915328 -13.524603 -5.5638691 -3.643017
    Q20_16    Q20_17    Q20_2    Q21    Q22    Q23    Q24
3 0.2116015 -0.3524264 -0.329214 2.8346108 -4.006338 -3.254480 0.5684865
4 -12.3274223 4.2439232 -2.585790 -3.3893937 1.674473 -1.887560 -1.4217879
5 6.5209428 -1.9756333 -5.408621 0.6329115 2.222468 -1.316791 -1.0620912
    Q25    Q26    Q27    Q19_res
3 -6.706669 2.2085218 0.2948737 0.7622351
4 3.809286 -1.4778000 0.3738330 1.6940263
5 -7.029312 -0.0920255 -0.4510619 4.2169811

```

Residual Deviance: 0.0001030712

AIC: 402.0001

Section 4.3 Models predicting fellow burnout

Predicting Burnout Ordinal Regression Output:

Call:

```
polr(formula = Q20_1 ~ ., data = no.na.df, Hess = TRUE)
```

Coefficients:

```

    Q1_1    Q2_1    Q3    Q4    Q5    Q6
Q7_1    Q8_1    Q8_2    Q8_3    Q9_3    Q9_4    Q9_5
-0.3639685 1.2004071 21.1984902 -43.7432856 -34.7607014 1.9068883 -
49.6115330 -108.2919736 -38.3571093 49.2297185
    Q8_4    Q9_1    Q9_2    Q9_3    Q9_4    Q9_5
Q9_6    Q10_1    Q10_2    Q10_3    Q11_1    Q11_2    Q11_3
-43.8715899 6.9790483 -234.2125225 -43.1279704 88.6991689 -139.2352563 -
99.2569613 74.0643661 33.6352238 -24.0041384
    Q10_4    Q10_5    Q10_7    Q11_1    Q11_2    Q11_3
Q11_4    Q11_5    Q11_6    Q11_8    Q14_3    Q14_4
41.0599388 96.1914266 44.6294311 167.8513504 -24.8433588 23.9537790 -
248.1603436 100.5083318 239.3852645 -28.8484195
    Q12    Q13    Q14_1    Q14_2    Q14_3    Q14_4
Q14_5    Q14_6    Q14_7    Q14_8    Q15_4    Q15_5    Q15_6
-34.0701198 -4.7122356 40.2667503 128.7386936 21.6582164 -25.2731227 -
228.3514676 159.6589525 -133.0536477 177.0530745
    Q14_9    Q15_2    Q15_3    Q15_4    Q15_5    Q15_6
Q15_7    Q15_8    Q15_9    Q16    Q19_7.L    Q19_7.Q    Q19_7.C    Q20_2    Q21
134.3871843 21.4606050 27.8449796 23.7656248 -14.8224696 -36.4761781
10.8832283 9.1603106 -53.4368248 22.2416505
    Q18_1    Q19_7.L    Q19_7.Q    Q19_7.C    Q20_2    Q21
Q22    Q23    Q24    Q25
-60.4507511 -764.3787692 606.7860556 -293.2357402 19.4260822 17.3899342 -
98.4865421 -6.6813898 25.6321251 -109.4629652
    Q26    Q27    Q19_res
1.5835496 -45.0102608 25.2326573

```

Intercepts:

1|2 2|3 3|4 4|5 5|6 6|7
 384.5458 385.6698 386.5186 387.2944 388.0264 388.9834

Residual Deviance: 3621.905

AIC: 3759.905

Predicting Burnout Nominal Logistic Regression Output:

Call:

multinom(formula = Q20_1 ~ ., data = df)

Coefficients:

	(Intercept)	Q1_1	Q2_1	Q3	Q4	Q5	Q6
2	4.09700752	-0.31332192	-0.2637749	0.50024907	-4.5117729	13.542201	12.707691
3	7.24259297	-0.17293174	-0.1058546	6.34640463	-7.0562012	-2.523799	2.724293
4	-7.73228924	0.29960973	0.1441313	0.08714584	13.3805268	1.176261	-2.934415
5	0.01000248	-0.22617403	-0.1516244	-2.75727720	-0.5547071	10.938293	-2.777969
6	-0.49823780	0.03370745	-0.1525004	-2.88128428	3.8784885	6.738773	-5.344233
7	-0.20065727	-0.04721666	-0.2371865	-1.53632981	0.8022413	1.419612	9.586306
	Q7_1	Q8_1	Q8_2	Q8_3	Q8_4	Q9_1	Q9_2
2	3.35619708	10.2469521	-18.7560032	-5.3688997	19.640940	-3.896931	2.3804957
3	-12.45086437	1.2491862	6.7460993	13.0264358	-8.772024	-7.967646	3.3133627
4	-0.10500595	-6.5827819	2.1758938	-6.8506227	6.467387	-3.587507	-9.0133920
5	-4.05185508	-4.1218946	-0.2497451	-7.5794533	-6.710776	3.297103	1.0724247
6	9.95297440	1.7355426	1.7462288	8.8500257	-1.477758	5.488585	0.5322639
7	-0.05627126	-0.3412383	0.2625857	-0.7161986	5.928847	4.404198	4.8438587
	Q9_3	Q9_4	Q9_5	Q9_6	Q10_1	Q10_2	Q10_3
2	0.9701869	6.884237	-9.624039	2.0329351	-2.1542216	6.9701254	-7.461331
3	2.4566734	-3.608582	-5.608753	-6.3068939	14.1456217	12.4115550	17.231407
4	-23.4626836	1.553854	-8.410675	-3.4421880	8.2556422	-6.6495171	6.427598
5	22.6269854	-1.792424	18.670631	7.3701751	2.5713830	-1.3196483	-1.505541
6	-2.1359174	-3.077826	4.135526	2.4200467	-5.0142770	0.6242858	-2.960433
7	1.1265152	-1.295837	1.587171	-0.4315611	0.5495917	-0.3178059	1.228494
	Q10_4	Q10_5	Q10_7	Q11_1	Q11_2	Q11_3	Q11_4
2	-4.467254	-0.5630694	-16.2336427	-13.7780151	2.5129137	5.1066495	-6.334628
3	-6.105948	8.6120447	11.0309056	20.4994503	-8.9231275	4.5656701	12.528491
4	12.190002	-7.0575666	9.5290992	-12.0743590	-2.2168200	-6.0367649	12.932267
5	1.697499	12.4998226	0.4260421	2.1985276	9.1501849	-1.4498380	-13.428176
6	-2.823613	2.1888897	-10.2700635	4.5374363	2.4402580	0.1657471	-2.783803
7	1.725150	-1.8452131	-0.5404274	-0.2461835	-0.8779135	-0.3462293	-3.266588
	Q11_5	Q11_6	Q11_8	Q12	Q13	Q14_1	Q14_2
2	-2.417184	5.5507080	0.2353797	-4.31092462	2.320875	6.3286194	-11.07926083
3	-5.279499	0.7378980	17.3973477	-3.06380763	2.675339	9.1635792	10.02052375
4	1.098218	-4.9835055	-10.6644947	-3.57779839	3.714620	-5.0222078	7.15639717
5	7.005990	-0.5007668	3.6811100	0.03438536	1.785163	-2.4690496	-2.73636061
6	-1.166266	1.3329618	-8.2445284	1.78733676	-7.073283	-0.4432323	-0.71086114
7	1.724624	-0.8705438	-2.9538274	-1.56171861	-1.086559	-0.4314459	-0.07094768
	Q14_3	Q14_4	Q14_5	Q14_6	Q14_7	Q14_8	Q14_9
2	13.3523817	-13.2524660	-3.7000705	2.0837652	2.3913169	3.3565038	-4.9265451
3	-5.7015003	12.8189337	9.6038632	-1.3544320	0.9915854	-4.6564756	-3.9136788
4	-1.7402810	8.2728368	-15.1636657	-0.7186780	-4.7358212	5.3472433	6.7410488
5	0.6865656	1.7455540	-0.1347053	0.2331951	-0.3911815	-0.2884333	2.4030306
6	-4.8116333	-7.2778354	9.1759251	2.1473848	2.3573224	-1.5576104	-0.9820663
7	0.1960642	0.4896801	-0.1414940	-0.7580267	0.1475711	-0.8891818	1.5092811
	Q14_10	Q14_11	Q15_1	Q15_2	Q15_3	Q15_4	Q15_5
2	5.5507080	-3.4669428	4.09700752	-11.0941260	4.5325586	-3.6886789	-8.1089449
3	0.7378980	-2.0923300	7.24259297	-4.1793408	-14.0654274	-3.6780612	15.2349233
4	-4.9835055	4.2648275	-7.73228924	0.1279727	-9.4950992	10.6067113	-0.7410974
5	-0.5007668	0.7339618	0.01000248	5.6731766	-5.3389480	-8.1137653	-10.5057671
6	1.3329618	0.8144230	-0.49823780	3.2003832	9.4685803	3.4124021	5.4607333

```

7 -0.8705438  0.1125171 -0.20065727  2.2163627  0.2641832 -0.5872956 -0.4648303
   Q15_6      Q15_7      Q15_8      Q15_9      Q16      Q18_1      Q19_7
2 18.1415487  0.7881444  4.169849 -12.358679 -19.5204545 13.7030593  6.271560
3 -7.6191717  3.2455559 -4.117606 11.645540  3.3210757  9.5393259 -6.492712
4  0.9981234 -9.2347234  6.120391  6.794485 -10.4737272 -6.1876866 -8.894121
5 -0.2034203 -4.8711022  1.708475  8.350922 14.6501775 -6.1767292  1.509258
6 -6.9245560  5.7931897  1.799208 -8.699390  0.8408094 -6.8234757 -3.686690
7  0.5309030  0.7581206  1.714717 -1.279487  0.7563724 -0.4085946 -2.238823
   Q20_2      Q21      Q22      Q23      Q24      Q25      Q26
2 -4.084379 -6.680601 -3.650700 -5.0887060 -2.48196624  7.804957  1.2563190
3  5.595300 16.262341  8.949078  5.1772289 -0.10932136 -1.282550  2.3214044
4  8.357301  9.589244 -13.579051  2.7714384 -1.58901985  8.930847  9.4217658
5  8.710244  9.527429  2.698567 -1.8918424  0.56461220 -5.923509 -4.9158909
6  7.685927  8.218959 -2.833242 -2.7751722  0.21071632 -4.108730 -3.6113623
7  5.381112  2.453540 -1.395483 -0.4851236 -0.05831714 -2.912613 -0.8391101
   Q27      Q19_res
2 14.4906217  0.1338626
3 -11.7449196 -2.5835615
4 -7.2063450  1.7501828
5  4.3065864 -1.7369239
6  0.5234787 -0.8360131
7  0.4718391 -0.5715868

```

Residual Deviance: 0.0001045434

AIC: 744.0001

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