The Immediate Impact of the COVID-19 Pandemic on Young Adolescent Relationships with Family Members

Abstract
To better understand the social aftermath of COVID-19 pandemic, we conducted a case study to (1) determine whether the pandemic negatively affected an adolescent's relationship with their family members during the social distancing period (October-December 2020), and (2) identify main contributing factors to elucidate guidelines or suggestions for family members to build and maintain healthy relationships with their adolescent children. Using Wave 4 of a longitudinal survey study from two school districts in the U.S. Northeast consisting of 968 students from 6th-9th grade, we ran a binary logistic regression model and found the best first-order model to ensure ease of interpretability. Fitted with the logit-linked AIC-stepwise procedure with an AUC value of 0.78 and F-measure 0.44, we found that English being the main language spoken at home, both parents living at home, and stricter parenting were main contributing factors of a negative change in the adolescent-family relationship.

1. Background and Significance

Although adolescents were generally at a lower risk of serious health complications from COVID-19, spending extensive time in isolation during the pandemic may impact their social skills and sense of identity [1]. During a pandemic, family is an especially important sphere of social interactions for adolescents, as most family members stay at home. Research has shown that intermediate or poor relationships with family members is correlated with a higher likelihood of premature death in adolescents [2] whereas positive relationships with lower likelihood of depression throughout adulthood [3]. Thus, understanding how the adolescents' relationship with their family members changed throughout the recent pandemic is important and interesting. It may elucidate suggestions for parents to build healthy relationships with their adolescent children. As such, our research questions are: did the pandemic negatively affect the teenagers' relationship with their family members? If so, what were the main contributing factors?

2. Data

2.1 Data Description

Our data set is from an ongoing longitudinal survey study conducted by the Youth, Media & Wellbeing (YMW) Lab at the Wellesley Centers for Women [4]. Our sample consisted of students in 6th–9th grade in two school districts in Northeastern United States (n=968) with a mean age of 13.02 (SD = 1.43) [5]. We used 26 survey questions and two demographic variables from Wave 4 of the study and extracted 135 variables, collected during the in-person days during the COVID-19 social distancing period (October 2020 - December 2020).

2.2 Data Cleaning and Trimming

The initial survey data contained 135 columns and 968 rows, with missing values in multiple fields. However, we did not impute these missing values due to ethical concerns regarding some predictors (e.g. "queer" or "mood.score"). Instead, the data cleaning process involved (1) recoding the response variable, (2) recoding predictor variables, and (3) removing columns and rows that were missing too many fields.

Our response variable was the survey question: "Since the beginning of social distancing due to Covid-19, has the quality of relationships between you and your family members changed?" It originally had five ordinal categories (1: "A lot worse , 2: "A little worse", 3: "About the same"', 4: "A little better", 5: "A lot better") but was recoded it into a binary categorical variable (1: "relationship worsened", 0: "relationship did not worsen"). We noted an imbalance in this newly coded response, as 83.8% of observations held a value of 0.

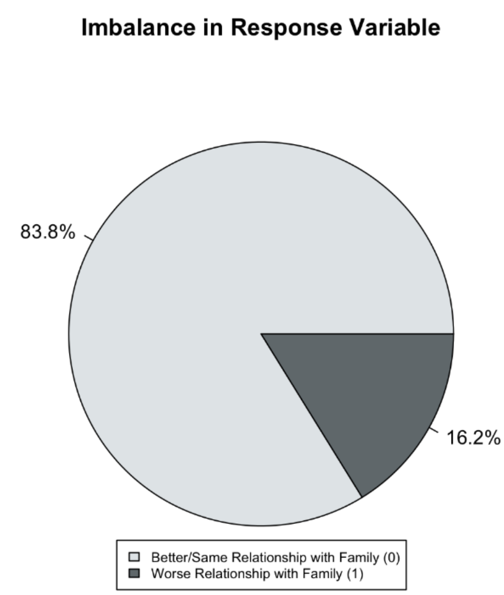


Figure 1. Imbalance in Response Variable

We recoded the remaining variables with the objective of (1) combining similar survey questions under one variable for easier interpretation and (2) reducing the feature space. The recoding process did sacrifice some information contained in the original data but yielded cleaner and more interpretable predictors.

In the recoded data, 335 out of 968 observations contained at least one missing value, so first, we removed rows missing the response variable. Next, we removed columns that were missing in at least 10% of the rows. Finally, we also removed the remaining rows that still contained missing values. These 3 steps removed a total of 89 (~9.19%) rows and 12 columns. The final clean data contained 879 rows and 26 columns, which still provided sufficient statistical power and predictors with which to fit a regression model.

3. Methods and Results

3.1 Model Fitting

We checked for multicollinearity among our predictors using variance inflation factors (VIF) (threshold=10) for quantitative and Cramér's V (threshold=0.3) for categorical predictors. Two pairs of predictors, `momed.hs` (whether mom completed high school) and `momed.college` (whether mom completed college) and `phone.limit1` (whether there is a limit of when adolescent can use their phone) and `phone.limit2` (whether there is a limit for how long adolescent can use their phone). We eliminated `momed.hs` and `phone.limit2` as they were less correlated with the response within the correlated pair.

Next, we found our two candidate models using the stepwise procedure which include logit link using backward AIC stepwise procedure (**Table 1, Model 1**) and logit link using backward BIC stepwise procedure (**Table 1, Model 2**). Model 1 has eight distinct predictor variables while Model 2 has three distinct predictor variables. We observe that Model 2 is nested in Model 1 (**Table 1**).

Table 1. Stepwise Variable Selection

Procedure	home.lang	both.parents	rel.parents	phone.own	parmon3	phone.teach	iep	hisp
AIC	✓	✓	✓	✓	✓	✓	✓	✓
BIC			✓	✓	✓			

3.2 Model Evaluation and Selection

A graphical evaluation using the ROC curve (**Appendix 6.2**) indicated that the AIC model (AUC=0.782) performs marginally better than the BIC model (AUC=0.769). Since the BIC model was more parsimonious, we conducted a more thorough performance analysis to verify that the AIC model, indeed, performed significantly better with its additional predictors.

Due to the aforementioned imbalance in the response variable, a conventional discriminatory threshold of 0.5 to convert the predicted probabilities did not yield the best classification performance. We found an alternative threshold value for each of the two models based on the F-measure, which combines precision and recall, to optimize overall model performance. Rather, the AIC model performed optimally at a threshold of 0.25 and the BIC model at a threshold of 0.20 based on the results from k-fold cross-validation (k=10). With these new thresholds, both models fit the data as well as a saturated model but the AIC model performed in every performance metric except BIC and sensitivity (**Table 2**).

Table 2. Performance Metrics with Optimized CV Thresholds

Evaluation Method	Stepwise AIC (threshold=0.25)	Stepwise BIC (threshold=0.20)
AIC	**665.99**	677.33
BIC	709.00	**696.44**
AUC	**0.782**	0.769
Accuracy	**0.802**	0.758
Sensitivity	0.495	**0.547**
Specificity	**0.859**	0.797
Precision	**0.404**	0.339
F-measure	**0.445**	0.418
LR Test for goodness-of-fit	p-val ≈ 1	p-val ≈ 1

As a final verdict, we conducted a likelihood ratio test comparing the two nested models (AIC vs. BIC model). This test yielded a p-value of ~0.001 and concluded that the AIC model, indeed, had a significantly better fit than the BIC model. Further model refinement upon the AIC model was considered but found to be insignificant in performance improvement.

3.3 Model Diagnostics and Interpretation

Due to how we defined our response variable, the interpretation of our model can be counterintuitive If an estimated coefficient is positive, it indicates that the corresponding predictor actually worsened that relationship. Most predictors included in our model yielded expected patterns, but some offered more interesting insight (**Table 3**). Notably, if English was the main language spoken at home, the odds of having a worse relationship with family members was 1.70 times greater than if not. Also, if both parents lived in the same household, the odds were 1.64 times greater than not having both parents live in the same household.

Table 3. Interpretation of Significant Predictors

Predictor	Est. Coefficient	Est. Odds	Associated Question
home.lang	0.529	1.698	Is English the main language spoken at home?
both.parents	0.491	1.635	Do both parents live in the same home?
rel.parents	-0.314	0.730	Relationship with parents (higher is stronger relationship).
phone.own	-0.917	0.379	Do you own a phone?
parmon3	0.434	1.545	My parents have taken away my cell phone or internet use.
phone.teach	-0.533	0.587	My parents taught me about social media.
iep	-0.416	0.660	I have an Individualized Educational Plan (IEP) or need special assistance during the school day.
hisp	-0.561	0.570	I am of Hispanic origin.

Visual assessment of our residual plots identified a few outlying observations but no notable spike in the delta deviance plot. Thus, we found no influential observations and proceeded without removing any data points.

4. Conclusion

4.1 Discussion

Our final model suggests that the eight diverse predictors found in Table 2 are particularly interesting in answering our research question (**Table 3**). The binary categorical predictors were if English was the main language spoken at home, both parents lived in the same home, the teenager owned a phone, parents had taken away cell phone or internet use, parents taught them about social media, having an IEP, and being of Hispanic origin. The quantitative variable was the self-evaluation of relationship with parents, with a larger number indicating a stronger relationship.

4.2 Model Limitations

Due to data ethics, we chose to not impute any of our data but lost ~9.2% of our data set. Our main concern lies with the nature of our variables as imputation for variables such as `mood.score` (a quantitative score calculated from the CESD-10 Depression Scale questions) would mean imputing whether an adolescent had no, mild, moderate, or severe depression symptoms. However, even after trimming, our data had enough statistical power to produce significant results due to the large number of observations.

4.3 Future Considerations

Given that the focus of our case study is on model interpretation rather than prediction, we decided to find the best first-order model, as interaction and higher-order terms are not desirable for interpretation purposes. We were limited by our large feature space but would like to use all-subset variable selection in the future if domain knowledge can help reduce the feature space further. Additionally, we would like to perform time series data analysis across all five waves of the current dataset (rather than only Wave 4) in order to study the patterns over time, which might help us explain the more unintuitive interpretations from our current model.

5. References

[1] Volkin, S. (2020, May 11). The impact of the COVID-19 pandemic on adolescents. The Hub. Retrieved November 22, 2022, from https://hub.jhu.edu/2020/05/11/covid-19-and-adolescents/

[2] Chen, P and Mullan Harris, H. Association of positive family relationships with mental health trajectories from adolescence to midlife. JAMA Pediatrics.2019. doi:10.1001/jamapediatrics.2019.3336

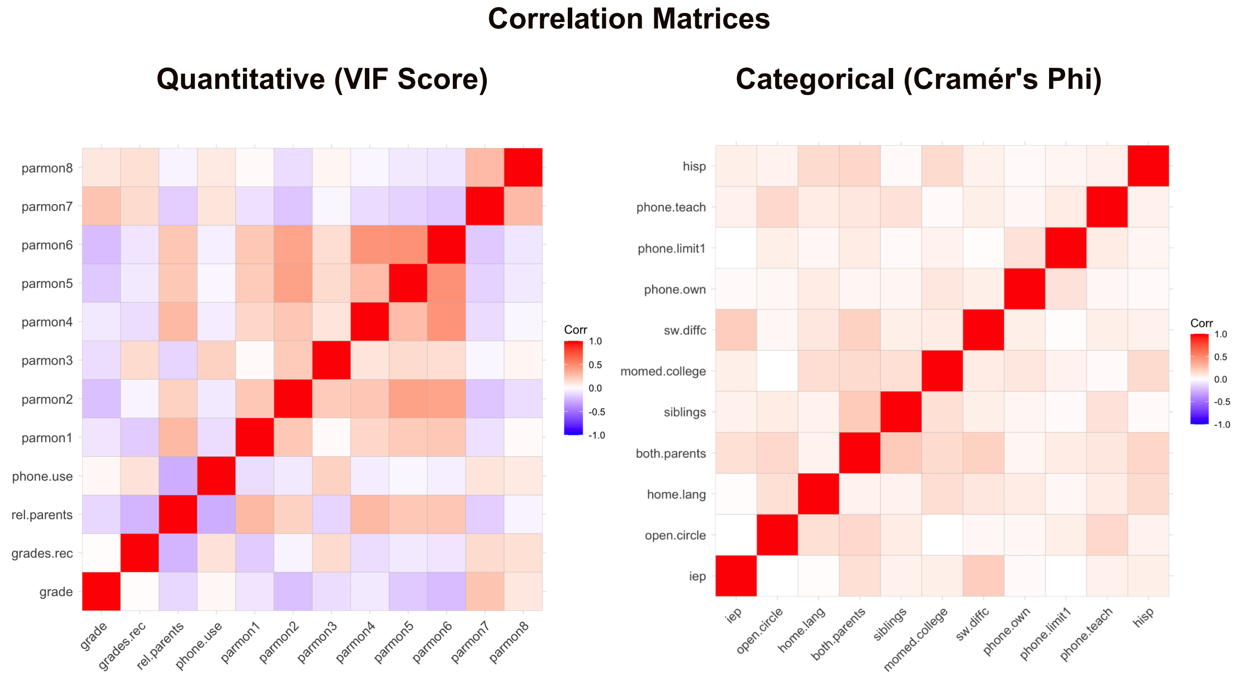
[3] Alm, S., Brolin Låftman, S., & Bohman, H. (2019). Poor Family Relationships in Adolescence and the Risk of Premature Death: Findings from the Stockholm Birth Cohort Study. International journal of environmental research and public health, 16(10), 1690. https://doi.org/10.3390/ijerph16101690

[4] Charmaraman, L. (2018). Early Adolescent Social Technology Use and Parental Monitoring: Implications for Psychosocial and Behavioral Health. Youth, Media & Wellbeing Research Lab. https://www.wcwonline.org/Active-Projects/early-adolescents-social-technology-use

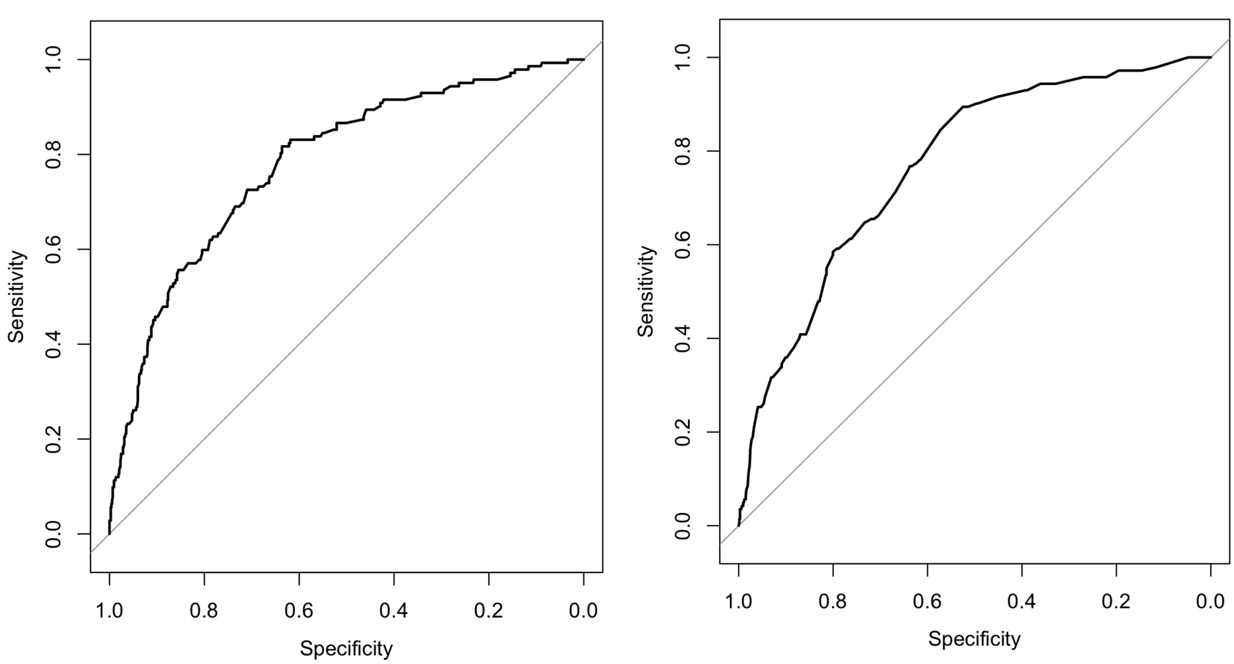
[5] Charmaraman, L., Lynch, A. D., Richer, A. M., & Zhai, E. (2022). Examining early adolescent positive and negative social technology behaviors and wellbeing during the COVID-19 pandemic. Technology, Mind, & Behavior, 3(1). https://doi.org/10.1037/tmb0000062

6. Appendix

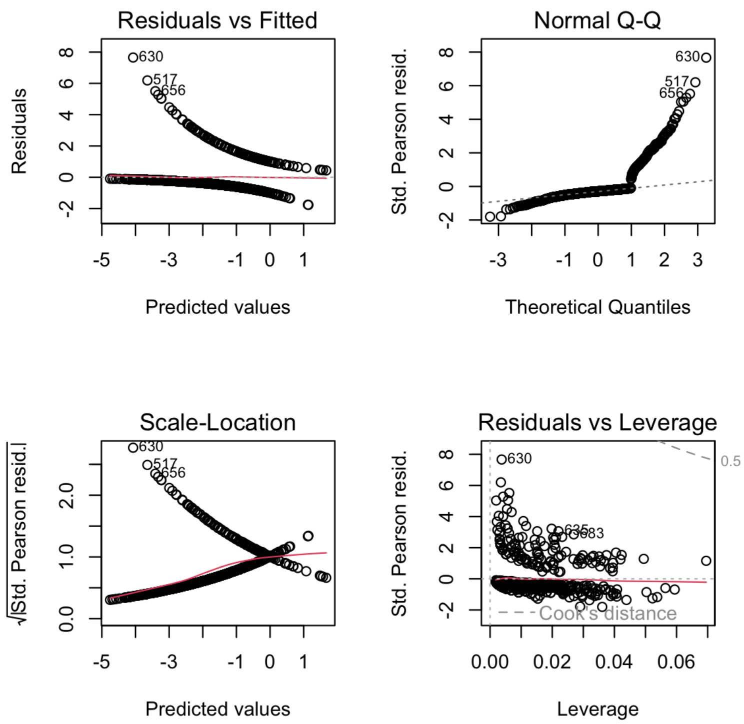
6.1 Correlation Matrices



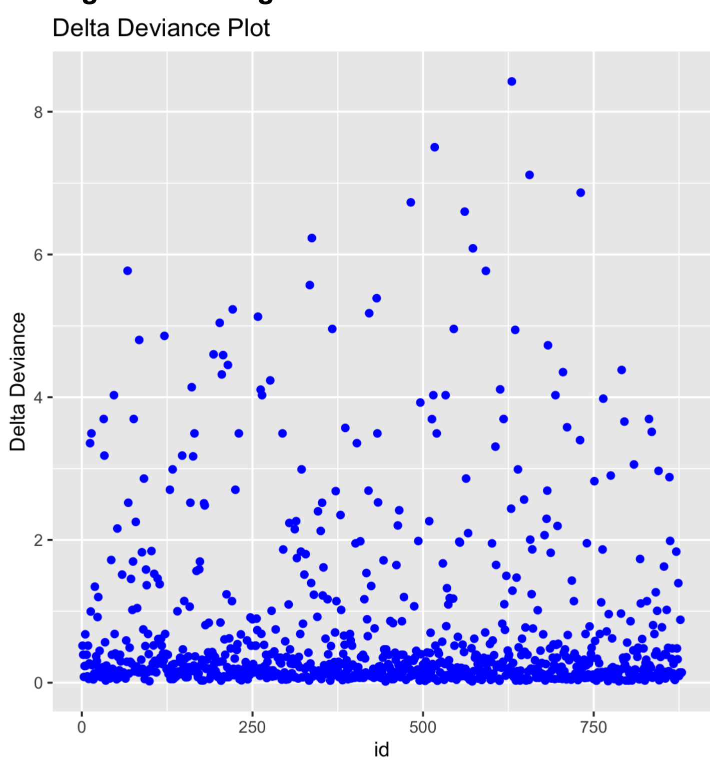
6.2 ROC Curves of Stepwise AIC model (left) and Stepwise BIC model (right)



6.3 Regression Diagnostics with Residual Plots



6.4 Regression Diagnostics with Delta Deviance Plot



6.5 Final Model Summary Table

Table 5. Model Summary

Predictor	Estimated Coefficient	Standard Error	z-value	p-value	Significance
Intercept	2.670	0.716	3.728	0.000193	***
home.lang	0.529	0.276	1.921	0.0548	.
both.parents	0.491	0.247	1.994	0.0462	*
rel.parents	-0.314	0.036	-8.655	$<$ 2e-16	***
phone.own	-0.917	0.33	-2.943	0.00326	**
parmon3	0.435	0.095	4.553	5.29e-06	***
phone.teach	-0.533	0.217	-2.451	0.0142	*
iep	-0.416	0.297	-1.399	0.162	
hisp	-0.561	0.323	-1.739	0.0821	.