CSE 6242 Final Report: COVID 19 and the Digital Divide in U.S. Education

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ABSTRACT

Our goal is to explore and visualize the changes in the digital divide in United States education over the course of the COVID Pandemic using the U.S. Census Household Pulse Survey data.

1 INTRODUCTION

The digital divide constitutes unequal access to digital technology among socioeconomic groups. Since being defined by Lloyd Morrisett in the mid-1990's (Roblyer et. al., 2013), the topic has been researched extensively (Ragnedda, 2017). It has taken on renewed urgency since the COVID pandemic reshaped societies worldwide and the Internet became an essential part of life in what has been called the digital surge (De' et. al. 2020).

2 PROBLEM DEFINITION

Our goal is to explore and visualize the digital divide, specifically the impact of different combinations of factors on the amount of live virtual contact students had with teachers during the COVID Pandemic using the U.S. Census Household Pulse Survey data.

3 LITERATURE SURVEY

The effect of the digital divide on education is an important strain in these discussions because of its potential long term effect on economics (Delalibera Ferreria, 2019) and the quality of life for future generations (Sanguyo et. al., 2019). Digital resources are essential for students facing school closures to continue their education. Researchers in the Philippines (Gocotano et. al., 2021) and Pakistan (Akram et. al. 2021) have used surveys to look at the challenges of online education during the COVID pandemic for students and teachers in countries with scarce digital resources. In Russia, they looked at the effects of online learning during the pandemic on student engagement at the post-secondary level (Bylieva et. al., 2021; Pesha et. al., 2020).

In the United States, researchers have also investigated the intersection of education and the digital divide during COVID. At the university level, researchers have studied how the quick transition to online classes led to a "pandemic of busywork", less student satisfaction, and lower performance outcomes (Motz et. al., 2020). They have also shown how community-building educational technology can promote student engagement and teaching best practices online (Berry, 2019). At the lower-school level, researchers investigated school districts' attempts to bridge the digital divide (Lai Widmar, 2020) and predict student online engagement (Domina et. al., 2021). Others have looked at how teachers fostered a sense of care via digital communication during the crisis to keep struggling students engaged (Miller, 2021) and the effects of the pandemic on the type and quality of distance learning provided to vulnerable populations (Robinson, et. al., 2020). Finally, one group of researchers used geographical, real-time Google search data to measure the digital divide using search terms as metrics and found that households in areas with higher incomes and better Internet access were more likely to be searching for homeschooling resources during the period of school closures (Bacher-Hicks et. al., 2021).

4 PROPOSED METHOD

4.1 Intuition and Innovation

The studies cited in the literature survey are important in their own right and further the research in their own narrow fields of interest. However, a thorough search of the literature fails to turn up any nationwide studies that are based on high quality data looking at the digital divide beyond Fall 2020. Given that a year has passed since then, the conclusions drawn from these studies will be partial and inferential. There are several publicly available interactive dashboards that attempt to look at the digital divide during the pandemic, but none do a fully effective job (PRB, 2018; U.S. Census Bureau, 2021; LearnPlatform, 2020). A few of these relied on limited data that could not be used to draw nationwide conclusions and covered until December 2020 at the latest. In addition, most of the literature and existing visualizations focused on either or both internet and computer access. The goal of our project is to improve upon the existing 'state of the art' by using more recent and longer - term data to explore the digital divide beyond outcomes that have already been visualized. The number of days per week students had live contact with a teacher was chosen because it encompasses access to the internet and devices while also giving further information about the type of learning the student experienced. Further, the visualization allows the user to explore how different factors in combination impacted students' learning experiences.

Table 1: List of Innovations

1	Used 6 months more data than previous research (making it first study to examine a full school year)
2	Investigated live virtual contact with teachers while most visualizations focus on access to computers / internet.
3	Dashboard allows users to investigate effect of different combinations of variables, rather than a single factor at a time.

4.2 Description of Approach

4.2.1 ***Data Cleaning.*** The Household Pulse Survey data consists of biweekly, online surveys conducted by the U.S. Census Bureau on the impact of the Covid-19 pandemic in the United States. The data is made available as CSV files for each biweekly survey, so Python was used to merge the data to a single 3 gigabyte file. Some questions changed in different phases of the survey, so only variables that were consistent through weeks 13 - 33 (corresponding to the 10 months between August 19, 2020 and June 23, 2021) were selected for the initial investigation. These dates were chosen because they corresponded to a full school year, the data was consistently biweekly from week 13 onwards and the chosen outcome variable (SCHLHRS) had a different response format before week 13. The race and ethnicity variables were combined into one where 'Hispanic' included anyone who identified as Hispanic and the other factors included anyone who identified as that race but not also as Hispanic. Variables missing more than 5% of their values were removed. The missing values for the remaining variables were imputed with R's mice package. Ordinal regression was used to predict the missing values of ordinal variables and linear regression was used for continuous variables. Data points with non-responses for SCHLHRS were removed.

4.2.2 ***Ordinal Regression Model.*** The end goal was to build an ordinal logistic regression model that could be used to predict and visualize the number of days of live virtual contact students had with teachers during the 2020-2021 school year as represented by the response variable, SCHLHRS. It would have been possible to simply compute percent of totals, but we wanted to identify the combinations of factors that were most predictive of live contact.

For the first phase of our project (leading up to the user survey), we selected RACE_ETHNICITY, INCOME, and INTRNTAVAIL (internet availability) as our model's predictors because these were identified as important factors in the digital divide in our literature survey. To build the model we used the MASS library from R. We also limited our model to three predictors at this stage to keep the visualization simple for the user. For this initial model, all levels of the categorical variables were significant for the income and computer availability predictors. Since a few categories for race and ethnicity were not significant, we performed a likelihood ratio test to check if the model was better with or without them. The result of the test was significant, meaning race and ethnicity did improve the model, so we kept all three original predictors. After collecting the user survey feedback, we evaluated the possibility of adding one more variable (see Experiment Design and Evaluation section for more details). The final ordinal regression model had 4 categorical predictors: RACE_ ETHNICITY, INCOME, INTRNTAVAIL, and COMPAVAIL (computer availability). For the estimated coefficients and p - values, please see Appendix B.

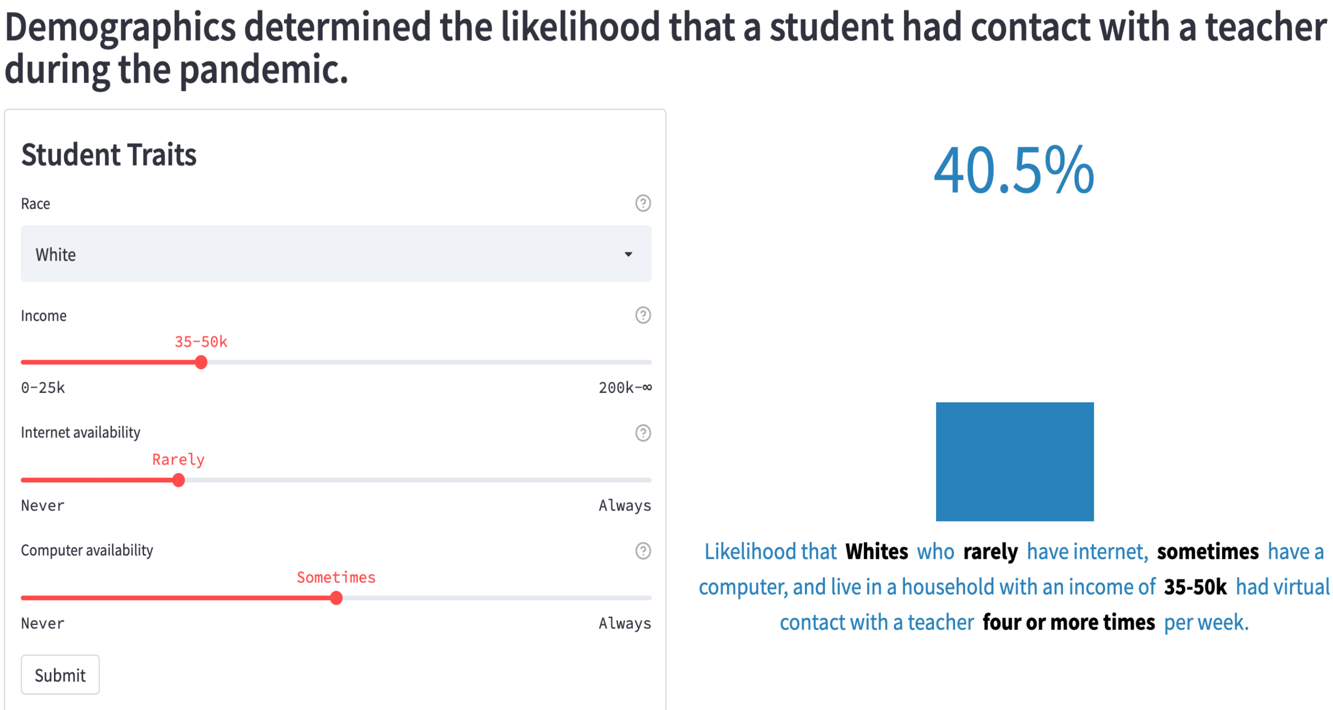

Figure 1: Visualization (Final Version)

4.2.3 ***The Visualization.*** The visualization was created using Streamlit. Streamlit is a Python web framework, similar to Flask, which is designed specifically for data driven applications. The goal of the visualization is to demonstrate in an instantly coherent way how the independent variables correlate with the probability that segments of the population receive four days of virtual live instruction per week. When designing the first version of the dashboard, we speculated that a comparison between likelihoods for subsets of respondents and the overall population would be immediately understandable. In order to highlight the comparison, we added visual cues: two differently colored human figures separated by the abbreviation, "vs." A dropdown menu and sliders, which were located at the bottom of the screen and corresponded to the model's three features, allowed users to adjust the variables. As they did, the probabilities over the head of the target figure at the left of the screen changed. For example, if a user selected Hispanic, 50-75K, with internet access sometimes, 70.1% probability appeared above the left figure. The figure on the right of the screen represented the likelihood for the whole population for comparison. The probabilities were separated into quartiles and could be selected with a button. The hypothesis was that lay users as well as experts would gain a deeper, intuitive understanding of the digital divide during the COVID pandemic by experimenting with the dashboard.

Based on the users' responses to the first version of the dashboard (see the user survey section for details), we determined that simplifying the dashboard and adding an additional factor should be our main goals. We simplified the visualization in four ways. First, we fit the tool inside the browser window so scrolling was unnecessary. Second, we removed the quartiles for comparison. They were not needed and confused users. Third, we added dynamic text, which changed as users selected factors in order to explain what the changes meant. For example, when the user selected the factors Hispanic, 50-75K, with internet and computer access sometimes, then the following phrase would appear below the visualization: "Likelihood that Hispanics who sometimes have internet, sometimes have a computer, and live in a household with an income of 50-75k had virtual contact with a teacher four or more times per week." Lastly, we simplified the dashboard headline and labels to make them more impactful and understandable so that it was clear our focus was on the experiences of specific groups of people as opposed to broader trends. These changes reduced the visual clutter, increased the impact, and improved the ease of use compared to the previous version of the application. In addition to simplifying the dashboard, we added a feature, computer availability. The majority of users surveyed indicated an extra factor would improve the tool. We chose computer availability because our model indicated it was one of the most important factors. We feel confident that these changes improve the coherency and immediacy of the visualization.

5 EXPERIMENT DESIGN AND EVALUATION

5.0.1 ***User Survey.*** To evaluate and improve our visualization tool, a survey was deployed in order to get user feedback on the user interface and to test whether the visualization is simple and easy to use. We also wanted to see whether the output from our model was properly expressed in the visualization and if the user preferred more or less variables presented in the tool. A link to the dashboard was provided with the survey. This allowed users to view and interact with the visualization. A few questions targeted user background (age, education, computer use, etc.) to provide information on the demographic of individuals taking the survey. (See Appendix A for the survey questions).

The survey was deployed on reddit under the Survey4Survey community, a survey exchange page. This social platform was chosen because of its diverse users, i.e. different levels of education, occupations, geographic location, etc., and quick response rates. A 1-5 format was used for most questions with 1 being strongly disagree and 5 being strongly agree. When asked if they understood what was being presented in the dashboard, 55% answered above 3, 30% answered 3, and 15% answered below 3. When asked if the dashboard was easy to use, 55% answered above 3, 30% answered 3, and 15% answered below 3. When asked if the dashboard could be improved, 55% answered above 3, 40% answered 3, and 5% answered below 3. These questions seem to indicate that users understood the dashboard, but when asked a question to test their understanding of the dashboard, 52.6% answered incorrectly and 26.3% answered that the dashboard did not make sense, which contradicted the responses to the previous questions. The survey also showed that 55.6% of individuals wanted more factors included in the dashboard.

Feedback for improvements was asked in the survey. Users noted that the quartile comparison was confusing. Users also wanted more clarity and explanation on how to use the dashboard. Bugs and delays in the buttons of the dashboard were pointed out as well. The results of the survey were used to determine necessary changes to improve our model and visualization. (See the visualization section for a discussion of the changes.)

5.0.2 ***Evaluating the Model.*** For the first phase of our project, as mentioned above, we built a model with just 3 predictors to ensure the design of our tool was simple for our users. We chose the 3 based on our literature survey and these were RACE_ETHNICITY, INCOME, and INTRNTAVAIL (internet availability). According to our user survey, more than half of respondents preferred more variables (55.6%) The next preference was to keep the original 3 variables (38.9% of responses). Based on this feedback, we decided to keep our original 3 predictors and test out adding one more variable to improve the model. We evaluated the models based on the following: checking assumptions for ordinal logistic regression, accuracy, likelihood ratio test, and AIC.

To ensure it was appropriate to use ordinal logistic regression, we checked that the necessary assumptions were met. An ordinal logistic regression model was chosen because the outcome variable SCHLHRS was ordinal; participants indicated whether their children had 0, 1, 2-3, or 4+ days of teacher contact per week. Each data point is independent because each time point in the survey used an independent, randomly sampled set of participants (U.S. Census). To ensure multicollinearity was not an issue, we created a correlation matrix and determined that all predictors had correlations of less than 0.8. It was not necessary to determine if the predictors were linearly related with the log odds of the outcome because the variables were all categorical. Lastly, the sample size is large as SCHLHRS had over 300,000 responses.

Next, we divided our data into training, validation and test sets for evaluation purposes. We trained 5 models for comparison and evaluation purposes. This consisted of the model we used at the user survey phase and 4 more models each with one of four variables added: COMPAVAIL (computer availability), THHLD_NUMKID (number of kids in household), EEDUC (educational attainment of adult completing survey), and CURFOODSUF (food sufficiency). We were considering adding one of these variables because they seemed relevant based on our literature review and they were also present in the same weeks as our outcome variable SCHLHRS. After we built all the models, we had 5 models in total to compare:

- M1: SCHLHRS ~ RACE_ETHNICITY+INCOME+INTRNTAVAIL (original)
- M2: SCHLHRS ~ RACE_ETHNICITY+INCOME+INRNTAVAIL+COMPAVAIL
- M3: SCHLHRS ~ RACE_ETHNICITY+INCOME+INRNTAVAIL+CURFOODSUF
- M4: SCHLHRS ~ RACE_ETHNICITY+INCOME+INRNTAVAIL+EEDUC
- M5: SCHLHRS ~ RACE_ETHNICITY+INCOME+INRNTAVAIL+THHLD_NUMKID

Using the validation dataset, we generated predicted outcomes and calculated the accuracy for each of the five models. Model M3 had the highest accuracy (0.61968). However, all 5 models have a very similar level of accuracy, differing by less than .001. The models have a similar accuracy level because they mostly predict the outcome "4" for SCHLHRS, since this is the most common outcome for that variable across the full data set. The models assign values based on the highest probability. "4" = 4 or more days of virtual contact. 62.3% of the full data set has the value of "4" for SCHLHRS. This matches up with the models' accuracy levels of the models, which were all near 0.62. Given that accuracy is more of a reflection of how much the most common value is present in the sample in this case, accuracy is a limited way to evaluate our models. Furthermore, our visualization tool uses predicted probabilities for the outcomes, rather than the predicted outcomes themselves.

To supplement our evaluation, we also used the Likelihood Ratio Test (Wilks Test) to compare the goodness of fit of the 4 variable models relative to the original model with 3 variables. The likelihood ratio test compares the goodness of fit of two nested models, meaning a fuller model with the same but also additional variables is compared to the nested model with just the base variables. The null hypothesis is that both models are equally good while the alternative hypothesis is that the full model fits the data better. In total, we perform 4 tests comparing each of M2-M5 with M1. All 4 were statistically significant with p values of 2.2e-16, suggesting that we can reject the null hypothesis and that adding a fourth variable (any of these 4) provides a better fit than just using the 3 variables from M1. To further compare the different models, we pulled the AIC scores from the model summary tables. AIC estimates prediction error and can be used to evaluate the relative quality of models where lower scores are better. M2 had the lowest AIC score of 455403.7.

Model	Accuracy	Likelihood Ratio Test (p-value)	AIC
M1	0.6194905	N/A	456260.5
M2	0.6195950	2.2e-16	455403.7
M3	0.6196786	2.2e-16	455917.0
M4	0.6195532	2.2e-16	455775.2
M5	0.6196159	2.2e-16	455864.6

Figure 2: Summary of Model Evaluations

We selected model 2 because it significantly improved upon model 1 based on the likelihood ratio test and had the lowest AIC score. The accuracy levels were too similar to include in the decision and, as mentioned previously, that information may be less useful in this case anyway. Our final model had significant coefficients for every variable at every level except RACE_ETHNICITY (see Appendix B). We previously confirmed that RACE_ ETHNICITY was worth including in the model based on a Likelihood Ratio Test. When we did a final review of the selected model using the test data, we calculated an accuracy of 0.621, which was similar to the numbers we saw using the validation set.

6 CONCLUSION

Our tool provides policy makers and educators a more complete understanding of the factors that influenced students' access to digital education during the COVID pandemic beyond obvious explanations like internet and computer availability. The visualization allows users to explore specific combinations of the factors affecting the disparities in virtual education and gain a deeper understanding of students' learning experiences during the 2020-2021 school year.

6.1 Distribution of Team Effort

All team members have contributed a similar amount of effort for the work completed.

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8 APPENDIX A - USER SURVEY

1.How old are you?
◯ Under 18
◯ 18 - 24
◯ 25 - 34
◯ 35 - 44
◯ 45 - 54
◯ 55 - 64
◯ Above 64

2.What is the highest degree or level of education you have completed?
◯ Less than high school
◯ High school graduate or equivalent
◯ Associate's degree
◯ Bachelor's degree
◯ Graduate degree

3. I am proficient with a computer.
◯ Strongly disagree
◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

4. Do you own a computer?
◯ Yes
◯ No

5. How many hours per week do you spend on a computer?
◯ Less than 10 hours
◯ 10 - 20 hours
◯ 20 - 30 hours
◯ 30 - 40 hours
◯ More than 40 hours

6. I use data visualization tools frequently.
◯ Strongly disagree
◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

Use the dashboard (linked below) to answer the following questions:

7. I understand what is being presented in the dashboard.
◯ Strongly disagree
◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

8. The dashboard is easy to use.
◯ Strongly disagree
◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

9. I could explain to someone else what is being presented in the dashboard.
◯ Strongly disagree
◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

10. According to the dashboard, how many days of live schooling does a student who is Black, comes from a 50K income household and sometimes has access to internet receive?

11. Based on the dashboard, an individual belonging to a minority group:
◯ Increases the amount of live school days received per week.
◯ Decreases the amount of live school days received per week.
◯ I cannot tell from the dashboard.

12. Based on the dashboard, the digital divide is:
◯ Greater than expected.
◯ Less than expected.
◯ About what I expected.

13. I would have preferred if the dashboard explored:
◯ More factors.
◯ Less factors.
◯ No other factors. The 3 selected are very informative.

14. The dashboard could be improved.
◯ Strongly disagree

◯ Disagree
◯ Neutral
◯ Agree
◯ Strongly Agree

15. What do you like about the dashboard?

16. What do you dislike about the dashboard?

17. What changes would you make to improve the dashboard?

9 APPENDIX B - COEFFICIENTS AND P-VALUES FOR THE FINAL ORDINAL REGRESSION MODEL

There are many coefficients because our 4 predictors are categorical variables, so the model creates a dummy variable for each level of each one. The last 3 rows refer to the intercepts.

	Estimate	Std. Error	z value	Pr(>|z|)
RACE_ETHNICITYBlack	-0.07992	0.023931	-3.3396	0.000839***
RACE_ETHNICITYHispanic	-0.01254	0.022344	-0.5611	0.574715
RACE_ETHNICITYOther	-0.15064	0.027155	-5.5474	2.90E-08***
RACE_ETHNICITYWhite	-0.05933	0.018944	-3.1321	0.001736**
INCOME2	0.048202	0.021384	2.2542	0.024186*
INCOME3	0.112763	0.020328	5.5471	2.90E-08***
INCOME4	0.181497	0.018523	9.7984	< 2.2e-16***
INCOME5	0.260318	0.01893	13.7513	< 2.2e-16***
INCOME6	0.330268	0.018008	18.3398	< 2.2e-16***
INCOME7	0.385161	0.02029	18.9824	< 2.2e-16***
INCOME8	0.527731	0.019492	27.0735	< 2.2e-16***
INTRNTAVAIL2	-0.10596	0.01295	-8.1816	2.80E-16***
INTRNTAVAIL3	-0.22347	0.024804	-9.0096	< 2.2e-16***
INTRNTAVAIL4	-0.3753	0.048673	-7.7107	1.25E-14***
INTRNTAVAIL5	-0.27627	0.066263	-4.1692	3.06E-05***
COMPAVAIL2	-0.31846	0.013819	-23.0451	< 2.2e-16***
COMPAVAIL3	-0.456	0.023496	-19.4073	< 2.2e-16***
COMPAVAIL4	-0.51663	0.044589	-11.5865	< 2.2e-16***
COMPAVAIL5	-0.66941	0.060054	-11.1468	< 2.2e-16***
1|2	-1.55797	0.024291	-64.1376	< 2.2e-16***
2|3	-1.24914	0.024181	-51.6575	< 2.2e-16***
3|4	-0.39314	0.024026	-16.3632	< 2.2e-16***