

My title*

My subtitle if needed

First author

Another author

February 11, 2024

First sentence. Second sentence. Third sentence. Fourth sentence.

1 Introduction

The COVID-19 pandemic has profoundly disrupted education systems worldwide, compelling schools and districts across the United States to rapidly adapt their learning models. In 2020 and 2021, educational institutions faced unprecedented challenges, transitioning between in-person, hybrid, and virtual learning models in response to evolving public health guidelines and infection rates. This shift has brought into sharp focus the need to understand the implications of these various schooling models on educational outcomes.

This paper delves into a comprehensive analysis across 11 U.S. states, examining the relationship between different schooling models and their impact on student enrollment and staffing patterns. The unique dataset compiled for this study encompasses a variety of metrics, including total enrollment, in-person and virtual attendance, as well as staff count across different learning models. By analyzing data from kindergarten to 12th grade, this study provides a granular view of how the pandemic has reshaped the educational landscape across these states.

Our findings reveal significant variations in how states have navigated the challenges posed by the pandemic, with notable differences in the adoption of in-person, hybrid, and virtual learning models. We observe that these variations are not only reflective of public health policies but also indicate broader socio-economic and demographic influences. For instance, preliminary analysis suggests that shifts to virtual learning correlate with changes in student enrollment, raising questions about equity and access in education during these challenging times.

*Code and data are available at: [LINK](#).

The remainder of the paper is structured as follows: Section 2 provides a detailed overview of the data and methodology employed in this study. Section 3 presents an in-depth analysis of the schooling models across the 11 states, offering insights into the trends and patterns observed in the data. Section 4 discusses the key findings, exploring the implications of these schooling models on educational outcomes. Finally, Section 5 concludes with a reflection on the study’s findings, limitations, and potential directions for future research in this critical area of educational policy.

The remainder of this paper is structured as follows. Section 2....

2 Data

Some of our data is of penguins (Figure 1), from Horst, Hill, and Gorman (2020).

Proportional Comparison of Learning Models in US States

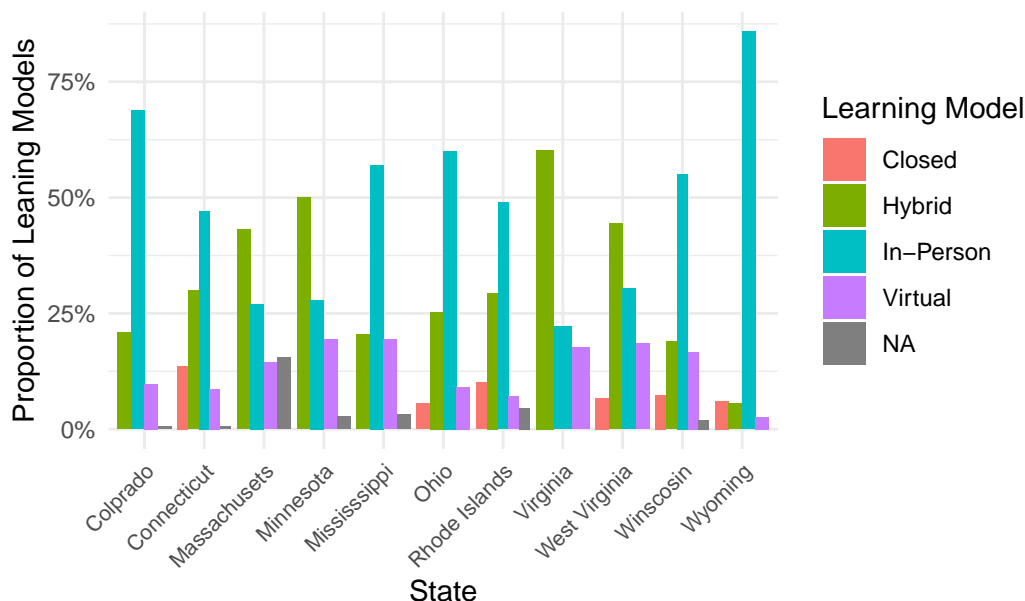


Figure 1: Bills of penguins

Talk more about it., SURE

And also planes (?@fig-planes). (You can change the height and width, but don’t worry about doing that until you have finished every other aspect of the paper - Quarto will try to make it look nice and the defaults usually work well once you have enough text.)

Talk way more about it.

State	Avg. Share In-person	Avg. Share Virtual	Avg. Share Hybrid	Avg. Participation	Avg. Pass Rate
CO	65.68918	10.285258	24.02556	95.11431	36.03400
CT	55.21059	6.625613	31.45075	98.68581	59.33747
MA	33.46283	9.333824	57.20335	100.00000	53.69718
MN	35.23909	8.302583	56.45833	96.34993	56.35686
MS	56.80734	17.653758	25.53891	100.00000	72.84675
OH	63.31093	9.349329	26.61283	99.66106	69.27725
RI	54.77593	5.261545	34.39462	98.90301	41.80093
VA	16.28958	27.904606	55.80582	99.35298	76.24432
WI	68.29115	5.583664	17.70248	99.04207	44.79036
WV	31.84275	16.216216	48.20639	94.10710	40.05973
WY	85.46875	2.395833	5.62500	99.68056	55.27684

Figure 2: Relationship between wing length and width

State	Avg. Share In-person	Avg. Share Virtual	Avg. Share Hybrid	Avg. Participation	Avg. Pass Rate
CO	63.66436	10.832368	25.50328	81.01494	32.31432
CT	55.20204	6.625613	31.45931	93.31494	50.27606
MA	33.46283	9.333824	57.20335	95.58099	43.86268
MN	35.40717	8.277188	56.31564	87.20716	46.03220
MS	56.64420	17.999144	25.35666	97.00386	59.95366
OH	63.30790	9.319841	26.64837	97.11603	58.88783
RI	54.77593	5.261545	34.39462	90.82130	34.79347
VA	16.28958	27.904606	55.80582	84.78617	54.15240
WI	68.29115	5.583664	17.70248	95.61564	38.65995
WV	31.84275	16.216216	48.20639	87.97907	32.07227
WY	85.46875	2.395833	5.62500	97.16042	51.90012

Figure 3: Relationship between wing length and width

3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in [Appendix B](#).

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$y_i | \mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$

$$\mu_i = \alpha + \beta_i + \gamma_i \tag{2}$$

$$\alpha \sim \text{Normal}(0, 2.5) \tag{3}$$

$$\beta \sim \text{Normal}(0, 2.5) \tag{4}$$

$$\gamma \sim \text{Normal}(0, 2.5) \tag{5}$$

$$\sigma \sim \text{Exponential}(1) \tag{6}$$

We run the model in R (R Core Team 2022) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular...

We can use maths by including latex between dollar signs, instance θ .

4 Results

Our results are summarized in [?@tbl-modelresults](#).

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In ?@fig-ppcheckandposteriorvsprior-1 we implement a posterior predictive check. This shows...

In ?@fig-ppcheckandposteriorvsprior-2 we compare the posterior with the prior. This shows...

References

- Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. “Rstanarm: Bayesian Applied Regression Modeling via Stan.” <https://mc-stan.org/rstanarm/>.
- Horst, Allison Marie, Alison Presmanes Hill, and Kristen B Gorman. 2020. *Palmerpenguins: Palmer Archipelago (Antarctica) Penguin Data*. <https://doi.org/10.5281/zenodo.3960218>.
- R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.