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ORIGINAL ARTICLE

Student access to technology at home and learning hours during COVID-19 in the U.S

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Abstract

Studies have shown that the digital divide affects students' educational achievement across racial and ethnic groups. In light of this, the study investigates the effect of technology access at home on student learning hours during the COVID-19 pandemic and across racial and ethnic groups in the U.S. The Household Pulse Surveys (HPS), conducted by the United States Census Bureau and administered from August 19, 2020, to March 29, 2021, were used for the analysis. We compute a composite index of technology access using the principal component analysis (PCA). And for the empirical model, the study employed a Tobit regression model. The result shows that the estimated index of technology access based on PCA for the whole sample is about 0.92, indicating a higher level of access. However, the breakdown by race/ethnicity shows an average of about 0.93, 0.89, 0.90, 0.94, and 0.89 for students representing White, Black, Hispanic, Asia, and other races, respectively. This means the intensity at which households in the sample have access to technology is higher among the Asian and White students, followed by Hispanic, Black, and other races in that order. The estimated effect of technology access on the student learning hours during COVID-19 based on the Tobit regression model shows about a 3.1 unit points increase over the whole sample. And further analysis reveals variation at which access to the technology impacts learning hours across race and ethnicity groups. For example, we find that access to technology significantly increased learning hours by about 3.5, 1.6, 2.2, and 3.4 unit points among White, Black, Hispanic, and Asian students, respectively. The observed differing effect of access to technology on learning hours further highlights the racial disparities in American society's digital divide, which reveal how access to technology disproportionately impacts student learning hours during the COVID-19 pandemic across race and ethnicity.

Keywords Computer · Internet · Learning hours · COVID-19 · USA

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1 Introduction

The COVID-19 pandemic has caused one of the most significant disruptions to education in history following the stay-at-home order implemented by most countries to curb the spread of the virus and protect public health in 2020. As a result, over 1.5 billion students worldwide were affected by country-wide school closures (Marcus, 2020; Ovide, 2020; Weise, 2020). And many schools quickly transitioned from traditional face-to-face instruction to distance learning to ensure learning continues during school closures across the globe (OECD, 2020). Unfortunately, the move from formal face-to-face instruction to online education has played against students who do not have access to computers and the internet, which is a challenge in remote learning, especially in low-income families. Simply put, access to information and communication technology (ICT) became required for students to participate effectively in the learning process during the COVID-19 pandemic-led economic shutdown.

The adverse consequences of school interruption on student learning, safety, health, and well-being have been documented in the literature (see Liu, 2021). For example, pandemic-led school closures impede the continuity of learning during COVID-19 and increase the number of students at risk of not returning to school (UNESCO, 2020). The nationwide school closures also raise concerns about missing children cases— those who have not enrolled in school because of the pandemic (Ogundari, 2022). Azevedo et al. (2020) also note that school closures have generated global learning losses valued at more than US 10 trillion dollars.

In the United States, most schools were forced to transition to online distance learning, which requires access to an internet connection and a computer at home. Although before the COVID-19 pandemic, the available data showed that 15%, 8%, and 5% of U.S. households with school-age children did not have access to high-speed internet based on 2015, 2016, and 2019 Census Bureau data (Anderson & Perrin, 2018; National Center for Education Statistics, 2022). Anderson & Perrin (2018) also reveal that the overall share of households with school-age children lacking a high-speed internet connection in 2015 Census Bureau data is comparable to that obtained in 2013 Census data. In addition, most of these households are low-income. The data further show that 10%, 25%, 23%, and 5% of White, Black, Hispanic, and Asian households with children ages 6 to 17 years old did not have a high-speed internet connection at home in the U.S. Also, one in four Black teens has difficulty completing assignments due to a lack of access to technology. These data highlight the existing digital divide across the U.S. sub-population before the pandemic, as not all families have access to the internet and computer in the same way.[1]

One way the differing degree of access to computer and internet resources shows up in education during the COVID-19 pandemic is through a lack of synchronous communications and interaction between students and teachers and homework gaps.[2] For example, synchronous communication and interaction during online classes provide teachers with potential feedback and support to students during COVID-19 (Fabriz et al., 2021). As for the homework gaps, students without access to a computer and the internet are most likely to miss valuable learning time since homework and learning

[1] Lake & Makori (2020) defined the digital divide as the inability of the students to do schoolwork at home due to lack of internet and or computer.

[2] The homework gap is the difficulty students experience completing homework when they lack ICT access at home compared to those with access.

activities during online classes require these resources (Auxier & Anderson, 2020). Vogels et al. (2020) note that in a survey of U.S adults conducted April 7–12, 2020, about one-third (36%) say it is at least somewhat likely their children will not be able to complete schoolwork because they did not have access to a computer at home to help in their studies. Also, a study by the U.S. Department of Education revealed that student access to computers and modems increased the amount of time spent on educational activities outside schools, including a desire to learn, critical thinking, and writing skills (U.S. Department of Education, 1996). Anderson and Perrin (2018) note that 17% of teens in 2015 Census Bureau data say they often cannot complete a homework assignment because they do not have reliable access to a computer or internet connection at home. In addition, NEA (2020) report shows that the rates of digital access are lower for students of color and students from lower-income households.

Because of the existing digital divide, parents, members of the community, and policymakers are concerned about how children will receive the same level of education on their own at home when not all students have the same access to computers and internet resources during the COVID-19 pandemic in the U.S (Vogels et al., 2020). And to address this concern, nearly 48% of the school district in the U.S. with the highest concentration of low-income families indicated they planned to distribute computer and wifi hotspots to the student during the COVID-19 pandemic (Lake & Makori, 2020). Also, 59% of adults with children at home enrolled in school in the 2019–2020 academic year reported that computers were provided by their school or district (NCES, 2021). This percentage is higher for those with lower 2019 household income, ranging from 68% for adults below $25,000 to 50% for adults with household incomes increasing over $150,000. But despite the assistance from schools and districts across the U.S., socioeconomic inequalities in students' access to a computer and the internet still exist (NCES 2021).

UNESCO (2018) defined equity in education as achieving quality outcomes by ensuring all students have the best possible opportunities to grow into their full potential. And the disparities in access to computers and broadband for different subpopulations have made access to ICT a critical indicator of education equity (Moore et al., 2018). As noted by NEA (2020), the digital divide affects educational achievement across race and ethnic groups in the U.S. Accordingly, large inequality in access to ICT can obstruct the continuity of the learning process (Liu, 2021). Hence, understanding how access to computers and the internet impacts student learning hours during the COVID-19 pandemic and across races and ethnic groups is crucial to the ongoing discussion on the digital divide in the American educational system. The present study aims to answer the research questions below.

RQ1 What effect does access to technology have on student learning hours during the COVID-19 pandemic?

RQ2 Are there differences in the effect of technology access on student learning hours across races/ethnicity during the COVID-19 pandemic?

Arising from the research question, we believe this study is critical because it provides insights into how access to the technology impacts student learning hours during the COVID-19 pandemic. It also offers insights into whether disparities in internet and computer access at home impact learning hours differently by race and ethnic groups during the COVID-19 pandemic. Our findings show that access to technology increased student learning hours significantly by about 3.1 unit points based on the entire sample. The study also reveals that access to technology significantly increased learning hours by about 3.5, 1.6, 2.2, and 3.4 unit points among White, Black, Hispanic, and Asian students, respectively. And given this, we believe the finding highlights the racial disparities in the digital divide in American society, which reveal how access to technology disproportionately impacts student learning hours during the COVID-19 pandemic across race and ethnicity.

Despite the proliferation of the literature on the effect of technology on educational attainment or learning worldwide with mixed results (e.g., Aguirre et al., 2021; Sanchis-Guarner et al., 2021; Dettling et al., 2018; Fairlie et al., 2010; Harter & Harter, 2004; Cairlie & Robinson 2013), there is little empirical work in the context of COVID-19 pandemic. The present study contributes to the sparse literature on the effect of technology access on student learning hours, focusing on the COVID-19 pandemic. And to the best of our knowledge, this is the first study that attempts to provide insights into how technology access impact student learning hours during the pandemic in the United States.

The remainder of the paper is structured as follows. Section 2 provides the data sources and description. Section 3 highlights the estimation strategy, while Sect. 4 focuses on the results and discussion. Finally, the concluding remarks are presented in Sect. 5.

2 The data sources and description

The study employed the Household Pulse Surveys (HPS) conducted by the United States Census Bureau and administered from August 19, 2020, to March 29, 2021. The HPS covers all 50 U.S. states, the District of Columbia, and U.S. territories. Our study focuses on phase 2 and 3 data collected between 2020 and 21, with 5 biweekly data in phase 2 from August 19 to October 26, 2020, and 10 biweekly data in phase 3 from October 28, 2020, to March 29, 2021.[3] Hence, our final sample has an 885,590 sample size. HPS was conducted online using a questionnaire administered via the online survey Qualtrics as the data collection platform and publicly available at https://www.census.gov/programs-surveys/household-pulse-survey/datasets.html.

The questionnaire covers employment status, food security, physical and mental health, access to healthcare, housing, and educational disruption during the pandemic. The present study's focus is educational disruption, which covers computer and internet availability at home, student learning hours per week, and virtual learning experiences.[4] The HPS also covers household income levels, marital status, gender, educational levels, and age of household head (constructed using birth year provided in HPS and survey year), the number of children and adults, ethnicity/race, and regions where they reside. The HPS offers supplement weights for the individual and household to represent the sample nationally. However, we use a household weight so that the estimate reflects the share of the household.

[3] Phase 2 spanning Aug. 19–31 2020, Sept. 21–14 2020, Sept. 16–28; 2020, Sept. 30-Oct. 12 2020, and Oct. 14–26 2020. Phase 3 spanning Oct. 28-Nov.9 2020, Nov.11–23 2020, Nov.25-Dec.7 2020, Dec.9–21 2020, Jan. 6–18 2021, Jan. 20-Feb.1 2021, Feb. 3–15 2021, Feb. 17-March 1 2021, March 3–15 2021, and March 17–29 2021.

[4] The class of computer includes the following types: desktop, laptop, tablet or other portable wireless computers.

Table 1 Summary statistics of the variables

	Full sample	White	Black	Hispanic	Asian	Other races
	Mean or % [SD]	Mean or % [SD]	Mean or % [SD]	Mean or % [SD]	Mean or % [SD]	Mean or % [SD]
Tech_index	0.9360 [0.1359]	0.9391 [0.1315]	0.9169 [0.1519]	0.9161 [0.1532]	0.9539 [0.1086]	0.9028 [0.1751]
# Days of virtual class per week						
None	14.15	13.56	16.22	17.00	14,20	16.23
1 day	4.77	4.78	4.54	4.46	4.45	5.40
2–3 days	18.45	19.02	17.37	15.85	13.91	18.35
4 or more days	62.62	62.64	61.86	62.70	67.44	59.92
HH income levels						
< 25,000	13.16	10.07	26.44	19.82	7.58	20.02
25,000–34,999	10.62	9.21	17.32	16.14	8.12	14.44
35,000–49,999	11.67	11.00	14.80	16.59	9.04	14.83
50,000–74,999	16.38	16.96	15.22	18.35	11.55	16.49
75,000–99,999	12.93	13.90	9.42	10.29	11.07	11.12
100,000–149,999	17.06	18.94	9.58	10.40	19.54	12.94
150,000–199,999	8.13	8.94	3.80	4.29	11.80	5.00
200,000 & above	10.05	10.86	3.43	4.11	21.31	5.15
Age of HH head	42.56 [10.90]	42.69 [10.76]	42.00 [11.38]	40.51 [11.26]	43.23 [10.11]	41.71 [11.93]
Gender of HH head						
Male	43.54	45.17	33.93	43.55	48.69	41.08
Female	56.46	54	66.07	56.45	51.31	58.92
Ethnicity						
Hispanic	18.95					
Non-Hispanic	81.05					
Races						
White	74.66					
Black	13.89					
Asian	5.76					

Table 1 (continued)

	Full sample Mean or % [SD]	White Mean or % [SD]	Black Mean or % [SD]	Hispanic Mean or % [SD]	Asian Mean or % [SD]	Other races Mean or % [SD]
Other races	6.70					
Education of the HH head						
< High school	2.25	2.05	1.82	7.24	2.08	5.53
Some high school	5.64	5.17	7.06	12.89	5.22	8.19
High school/GED	26.72	26.69	30.61	32.40	14.26	29.79
Some colleges/In progress	20.42	20.26	23.91	19.99	11.74	22.43
Associate degree	10.69	10.72	11.47	9.50	7.61	11.40
Bachelor degree	18.19	10.09	12.54	10.61	26.51	12.88
Postgraduate degree	16.09	16.03	12.59	7.37	32.59	9.78
Marital status						
Married	64.97	68.95	43.64	60.21	78.19	54.11
Single	35.03	31.05	56.36	39.79	21.81	45.89
Number of children in the HH	1.97 [0.99]	1.97 [0.98]	2.02 [1.07]	2.09 [1.06]	1.85 [0.58]	2,08 [1.09]
Number of adults	2.29 [0.96]	2.28 [0.91]	2.18 [1.05]	2.53 [1.12]	2.49 [1.05]	2.45 [1.19]
Food security status of the HH						
Food secure	44.30	41.15	58.52	56.88	35.62	56.90
Not food secure	55.70	58.85	41.48	43.12	64.38	43.10
The region where HH is located						
Northeast	16.68	16.41	16.84	14.05	22.30	14.49
South	37.61	35.43	57.48	37.49	24.08	31.99
Midwest	22.04	24.30	16.76	9.75	12.92	16.04
West	23.67	23.87	8.92	38.71	40.69	37.48
Sample size	225,732	180,244	18,790	26,035	13,514	13,184

HH Household

Summary statistics of the variables taken as determinants of students' learning hours are presented in Table 1. Table 2 shows the distribution of students' weekly learning hours during the COVID-19 pandemic, taken as the dependent variable. The disaggregation of the tables by race and ethnicity reveals that the reported summary statistics vary in many variables.

3 Estimation strategy

3.1 Index of technology access using principal component analysis (PCA)

Originally the households in the sample were asked to assess the availability of computers and internet at home using a 5-point Likert scale (e.g., never, rarely, sometimes, usually, and always) reported in Table 3. And we employed principal component analysis (PCA) to generate a composite index of technology access using the 5-point Likert scale. The PCA is a technique that allows a considerable number of variables or a reduction in the dimensions of variables to compute composite indices while retaining as much information (Hardle & Simar, 2015; Ram, 1982). The PCA calculates an uncorrelated set of variables called principal components, ordered so that the first few principally composed factors preserve most of the variations present in the original variables (Hardle & Simar, 2015). Hence, the f-th factor index based on the PCA can be specified below:

$$y_{fi} = \sum_{k=1}^{K} \varnothing_{fk} Z_{fi} \tag{1}$$

where y_{fi} is the value of each principal component f for the i-th respondents; Z_i is the household response to a 5-point Likert scale question summarized in Table 3 for computer

Table 2 Distribution of learning hours per week during the COVID-19 pandemic

Number of hours learning per week	Full Sample Frequency [%]	White Frequency [%]	Black Frequency [%]	Hispanic Frequency [%]	Asian Frequency [%]	Other Races Frequency [%]
< 1 [Zeros]	36,366 [16.11]	30,912 [17.15]	2501 [13.31]	3760 [14.44]	1449 [10.72]	2000 [15.17]
1.00–4.99	62,145 [27.53]	48,214 [26.75]	5971 [31.78]	7657 [29.41]	3599 [26.63]	3714 [28.17]
5.00–9.99	50,253 [22.62]	39,141 [2172]	4674 [24.87]	6466 [24.84]	3045 [22.53]	2982 [22.62]
10.00–14.99	27,733 [12.28]	22,873 [12.69]	1983 [10.55]	2719 [10.44]	1839 [13.61]	1359 [10.31]
15.00–19.99	11,475 [5.08]	9422 [5.23]	822 [4.37]	1102 [4.23]	692 [5.12]	652 [4.95]
20.00–24.99	14,724 [6.52]	11,802 [6.55]	952 [5.07]	1445 [5.55]	1235 [9.14]	926 [7.02]
25.00–29.99	5133 [2.27]	4001 [2.22]	444 [2.36]	495 [1.90]	354 [2.62]	316 [2.40]
30.00–34.99	6558 [2.91]	5084 [2.82]	536 [2.85]	778 [2.99]	474 [3.51]	453 [3.44]
> 34.99	11,345 [5.03]	8795 [4.88]	907 [4.83]	1613 [6.20]	827 [6,12]	782 [5.93]
Average [Std. Dev]	10.65 [9.98]	10.57 [9.86]	10.19 [9.97]	10.68 [10.39]	11.72 [10.68]	11.18 [10.59]

and internet availability at home, which ranges from 1 to 5 with 1 for never available, 2 for rarely available, 3 for some time available, 4 for usually available, and 5 for always available; $\varnothing_k$ is the regression coefficient that is the eigenvector of the covariance matrix between the variables (Z_i) representing households' 5 points scale responses.

Because in PCA, the value of each component in Eq. 1 is negative for some households in the sample, we transformed these components to be positive. A similar transformation has been used in previous studies, including the work of Izraelov and Silber (2019) and Asbahi et al. (2019). The transformed component employed to generate a composite index of technology (internet and computer) access at home can be defined as,

$$\text{Tech\_Index} = \frac{y_{fi} - \text{Min}(y_{fi})}{\text{Max}\left(y_{fi}\right) - \text{Min}(y_{fi})} \tag{2}$$

The transformation means the computed indices of technology access at home range from 0 to 1, with 0 indicating lack of technology access and 1 suggesting access to technology at home.

3.2 Empirical model

The study employed a theoretical framework similar to the education production function, defined as a technical relationship between input and output (Ogundari, 2021). The output in the present study is the students' learning hours, while the input is the index of technology access and other potential confounding factors considered in the study. But the dependent variable is censored, as shown in Table 2, which thus follows a mixed distribution with a probability mass at zero and a continuous distribution for values greater than zero (Amore & Murtinu, 2021). This type of data exhibits a corner solution problem when a person chooses not to do something in favor of another activity (Sanchez-Penalver, 2019). Some households reported zero learning hours per week, which guides the choice of the Tobit model in the present study. The ordinary least square (OLS) is considered biased because ignoring censoring in OLS translates into a lower regression line slope and an inflated intercept (Maddala, 1983).

Therefore, we employed a Tobit regression model to estimate the effect of the internet and computer access denoted by the generated technology index on student learning hours

Table 3 Cross-tabulation of household response to a computer (COMAVAIL) and internet (INTRNTAVAIL) availability

	Responses	Internet availability				
		Never	Rarely	Sometimes	Usually	Always
Computer availability	Never	626 [0.27]	150 [0.07]	123 [0.05]	92 [0.04]	355 [0.16]
	Rarely	160 [0.07]	580 [0.26]	464 [0.21]	411 [0.18]	569 [0.25]
	Sometimes	110 [0.05]	439 [0.19]	2696 [1.19]	2637 [1.17]	2469 [1.09]
	Usually	66 [0.03]	232 [0.10]	1937 [0.86]	14,607 [6.47]	10,967 [4.86]
	Always	150 [0.07]	292 [0.13]	2091 [0.93]	17,116 [7.58]	166,393 [73.71]

The figure in parentheses represents the percentage during the COVID-19 pandemic while controlling for other potential confounding factors such as household demographic and economic characteristics as specified below:

$$L_i^* = \tau_0 + \omega Tech\_Index_i + \sum_{J=1}^{J} \beta_j X_{ji} + \varepsilon_i \quad (3)$$

with $L = L^*$ if $L^* > 0$, and $L = 0$, and $L = 0$ otherwise

where L is the observed learning hours, and L^* is the latent variable; $Tech\_Index_i$ is the indicator of internet and computer access in the -th household X_{ji}; is the vector of confounding variables with the potential to impact learning hours; τ_0, ω, and β_j are parameters to be estimated; ε_i is the error terms of the regression assumed to follow a normal distribution ($\varepsilon \sim N[0;\sigma^2]$).

We estimated the parameters of Eq. 3 using the Stata command *nehurdle* with a robust heteroskedasticity Tobit regression model written by Sanchez-Penalver (2019).

4 Results and discussion

4.1 Index of computer and internet access: distribution across race and ethnicity

Before discussing the composite index of computer and internet or technology access at home, we present a cross-tabulation of household responses to a 5-point Likert scale assessment of computer and internet access at home in the HPS in Table 3. This is the ordinal measure of household assessment of computer and internet availability at home employed in the survey. The table shows that 73.71% of the households always have access to computers and an internet connection at home. To put it simply, about three-quarters of the households in the sample always had access to computer and internet connections during the COVID-19 pandemic. We also find that 0.27% never have access to computers and internet connections at home.

To further understand the association between household response to a computer (COMAVAIL) and internet (INTRNAVAIL) availability in the sample, we employed the Pearson Chi-square and correlation coefficient tests. And the result is presented in Table 4. The Pearson test shown in the second row of the table rejects the null hypothesis of independence between COMAVAIL and INTRNAVAIL with a p value of 0.000. Similarly, the estimated correlation coefficient between COMAVAIL and INTRNAVAIL in the third row of the table is about 0.6 and significant at a 5% level, which means that household response to COMAVAIL is closely associated with their response to INTRNAVAIL at home. With evidence of a significant association between household computer (COMAVAIL) and internet (INTRNAVAIL) access at home, we employ principal component analysis (PCA) to compute a composite index of technology access at home, which is presented in Table 5. The indices range from 0 to 1, with 0 translating to lack of technology (computer and internet connection), while 1 indicates access at home. Alternatively, the index between 0 and 1 shows the degree to which households have access to technology.

Column 1 of Table 5 shows the distribution of the composite index of access to technology, which is about 0.92 for the whole sample, indicating a higher level of access judging by the estimated index size, with about 85% of the households having an index of 0.80 and

Table 4 Test of association between household response to a computer (COMAVAIL) and internet (INTRNTAVAIL) availability

Test	Statistics	Results
Pearson test of independence between COMAVAIL and INTRNTAVAIL	Chi-square	0.0000 (*p* value)
The correlation coefficient between COMAVAIL and INTRNTAVAIL	Pairwise	0.5992*

*Indicates significance at a 5% level

above.[5] The disaggregation of the index by race/ethnicity in columns 2–5 shows an average of about 0.93, 0.89, 0.90, 0.94, and 0.89 for students representing White, Black, Hispanic, Asian, and other races. Respectively the table also shows that about 85%, 81%, 80%, 80%, and 78% of the households have an index of 0.80 and above. The implication is that the level at which students in the sample access technology is higher among Asians, followed by White, Hispanic, Black, and other races in that order. A literature review shows that a similar finding based on the ordinal measure was obtained using American Community Survey 2015–2019 by Kwakye et al. (2021). The authors found that Asian households have access to high-speed internet at home, followed by White, Black, and Hispanic households. Supporting this view, Bacher-Hicks et al. (2021) also revealed stark evidence of the education digital divide in the U.S. during the COVID-19 lockdown period.

4.2 The effect of computer and internet access on learning hours

The first row of Table 6 presents the estimated effect of computer and internet access denoted by Technology_Index on the students' learning hours during COVID-19 for full sample. Thus, consistent with the first research questions, the result shows that access to technology increased student learning hours by about 3.1 unit points at a 5% significance level for the entire sample, which translates to a 28% increase over an average of 10.6 h of learning reported in Table 2.[6] This shows that access to technology at home can improve the quality of education and student attainment, promote self-learning, and develop new skills, as noted by Bulman and Fairlie (2016). Also, access to technology induces student productivity and time spent on homework and other educational activities to improve their problem-solving and critical thinking (Hanımoğlu, 2018; Ganimian, 2020).

A literature review shows that studies in developed and developing countries produce similar outcomes. For example, Aguirre et al. (2021) found evidence that computers and the internet at home positively impacted English language performance in Columbia. Sanchis-Guarner et al. (2021) found that increasing broadband speed by 1Mbps increases test scores by 1.37 percentiles ranks in the UK. Similarly, Dettling et al. (2018) used data from the U.S. and found that students with broadband access in their postal codes performed better on the SAT. According to Fairlie et al. (2010), students with computers at home have better educational outcomes, including high school graduation rates in the U.S. Although, some research found no significant effects of technology on academic achievement (see for details: Harter & Harter, 2004; Cristia et al., 2017; Fairlie & Robinson, 2013).

[5] An average index of 0.80 and above can be judged as evidence of higher access when considering how correlation coefficient, Gini coefficients, human development index, and other popular indices are often interpreted in the literature.

[6] Computed as (3.1/10.6)*100 = 28%.

Table 5 Distribution of the computed index of technology availability

Ranges	Full sample Frequency [%]	White Frequency [%]	Black Frequency [%]	Hispanic Frequency [%]	Asian Frequency [%]	Other races Frequency [%]
< 0.60	6654 [2.95]	4507 [2.69]	876 [4.67]	1071 [4.61]	183 [1.35]	764 [8.22]
0.60–0.69	5435 [2.41]	4159 [2.31]	620 [3.30]	878 [3.38]	211 [1.56]	447 [3.39]
0.70–0.79	19,167 [8.49]	14,913 [8.09]	1963 [10.44]	2987 [11.47]	1023 [7.57]	1590 [10.23]
0.80–0.89	28,083 [12.44]	22,432 [12.44]	2429 [12.93]	3617 [13.39]	1416 [10.48]	1806 [13.10]
> 0.89	166,393 [73.71]	134,233 [74.47]	12,902 [68.66]	17,482 [67.15]	10,681 [79.04]	8577 [65.06]
Average	0.9208	0.9262	0.8967	0.9019	0.9447	0.8906

Also consistent with the second research question on whether there are differences in the effect of technology access on student learning hours across race/ethnicity during the COVID-19 pandemic, the analysis by race/ethnicity is presented in columns 2–6 of Table 6. The results show that access to technology significantly increased student learning hours by about 3.5, 1.6, 2.2, and 3.4 unit points at a 5% significance level among White, Black, Hispanic, and Asian students, respectively. These results translate to about 33%, 16%, 21%, and 29% increase in learning hours among students from White, Black, Hispanic, and Asian households when using the average hour of learning reported in Table 2 as the baseline.[7] This, however, is not surprising given that 10%, 25%, 23%, and 5% of White, Black, Hispanic, and Asian households with children ages 6–17 years old did not have a high-speed internet connection at home in the U.S (Anderson & Perrin, 2018). And socioeconomic inequalities have been linked to students' home computers and internet access, especially income and poverty levels (NCES 2021; Mubarak et al., 2020).

The observed differing effect of access to technology on learning hours further highlights the racial inequity in the digital divide in American society, which reveal how access to technology disproportionately impacts student learning hours during the COVID-19 pandemic across race and ethnicity. And the existing digital divide has also raised concerns among parents and members of the community on how children will receive the same level of education on their own at home when not all students have the same access to computers and internet resources during the COVID-19 pandemic in the U.S (Vogels et al., 2020). Supporting this view, Schaeffer (2021) notes that 46% of parents in the survey of U.S adults conducted on April 12–18, 2021, with low-income whose children's schools closed amid COVID-19 said their child faced technology obstacles compared with 31% of parents with midrange incomes and 18% of the parent with high incomes while learning at home during the pandemic.

Hence, we believe policies that expand internet connectivity and provide computers for students to use at home for learning purposes, especially students of color, should be considered important in promoting education equity in the U.S. This, however, includes policies that prioritize investment in broadband connectivity to address affordability and broadband speed and student access to a computer at home for different subpopulations to ensure

[7] Computed respectively with White: (3.5/10.57)*100 = 33%; Black: (1.6/10.19)*100 = 16%; Hispanic: (2.2/10.68)*100 = 21%; Asian: (3.4/11.72)*100 = 29%.

Table 6 Average mean effect of the determinants of learning hours during the COVID-19 pandemic in the U.S

Variables	Full sample	White	Black	Hispanic	Asian	Other races
	Coefficient [Std. Err]	Coefficient [Std. Err]	Coefficient [Std. Err]	Coefficient [Std. Err]]	Coefficient [Std. Err]	Coefficient [Std. Err]
Tech_index	3.0665***	3.5019***	1.6197***	2.1924***	3.4156***	1.8448
	[0.3154]	[0.3421]	[0.8146]	[0.8302]	[1.4665]	[1.1406]
# Days of virtual class						
1 day	2.2629***	2.5228***	1.1988***	0.6845	1.7252**	2.3832***
	[0.2019]	[0.2289]	[0.6166]	[0.4571]	[0.7897]	[0.7878]
2–3 days	3.3558***	3.7955***	1.8761***	2.5912***	2.3340***	2.2577***
	[0.1428]	[0.1660]	[0.3989]	[0.3959]	[0.5155]	[0.4932]
4 or more days	2.2221***	2.3557***	1.5631***	2.5409***	2.6044***	2.3939***
	[0.1252]	[0.1448]	[0.3559]	[0.3429]	[0.4161]	[0.4834]
HH income levels						
25,000–34,999	0.0602	−0.1666	0.5078	−0.3599	0.7061	−0.3405
	[0.1815]	[0.2389]	[0.3673]	[0.3741]	[0.8948]	[0.4761]
35,000–49,999	0.5250***	0.2183	0.9470	0.5549	−0.2892	1.2991*
	[0.1927]	[0.2447]	[0.3743]	[0.4611]	[0.8771]	[0.6861]
50,000–74,999	0.4067**	0.0401	1.0778***	0.1239	0.1301	0.8736
	[0.1716]	[0.2159]	[0.3717]	[0.4033]	[0.8236]	[0.5544]
75,000–99,999	0.2902	−0.1030	0.9325	−0.0102	0.4550	0.8311
	[0.1811]	[0.2135]	[0.5868]	[0.4242]	[0.8169]	[0.6292]
100,000–149,999	0.4696***	0.0565	1.3161***	-0.1339	0.8477	0.8323
	[0.1741]	[0.2130]	[0.4920]	[0.4001]	[0.8090]	[0.5508]
150,000–199,999	0.9655***	0.4730**	2.0843***	0.7341	1.1072	2.9332***
	[0.2057]	[0.2455]	[0.6359]	[0.5651]	[0.8993]	[0.7259]
200,000 & above	0.9752	0.5779***	1.4761***	0.7598	1.2691	1.1943
	[0.1969]	[0.2364]	[0.5927]	[0.5536]	[0.8241]	[0.8321]
Age of HH head	0.0333***	0.0371***	0.0061	0.0349***	0.0345**	0.0411**
	[0.0043]	[0.0048]	[0.0108]	[0.0118]	[0.0169]	[0.0179]
Gender (Male)	1.2381***	1.2381***	1.8905***	1.0637***	1.3802***	0.6353*
	[0.0838]	[0.0048]	[0.2857]	[0.2461]	[0.2810]	[0.3539]
Ethnicity (Hispanic)	0.4035***	1.1997***				
	[0.1230]	[0.0943]				
Races						
Black	0.2917**					
	[0.1246]					
Asian	1.4395***					
	[0.1480]					
Other races	0.5833***					
	[0.1716]					
Education of the HH head						
Some high school	−0.2363	−0.5061	0.5129	−0.9566	1.7090	−0.4543
	[0.4563]	[0.5630]	[1.1643]	[0.6425]	[1.4399]	[1.2709]
High school/GED	−0.0607	−0.4951	1.0366	−0.4555	2.0009*	−0.4859
	[0.3979]	[0.4859]	[1.0377]	[0.5674]	[1.1404]	[1.1297]
Some colleges/in progress	0.5931	0.0685	2.1118**	0.3285	2.1460**	0.2353
	[0.3916]	[0.4792]	[1.0333]	[0.5555]	[1.0809]	[1.1141]
Associate degree	0.3781	-0.1041	1.8189*	0.5037	1.7658	0.0981
	[0.3969]	[0.4848]	[1.0474]	[0.5947]	[1.1343]	[1.1428]

Table 6 (continued)

Variables	Full sample	White	Black	Hispanic	Asian	Other races
	Coefficient [Std. Err]	Coefficient [Std. Err]	Coefficient [Std. Err]	Coefficient [Std. Err]]	Coefficient [Std. Err]	Coefficient [Std. Err]
Bachelor degree	0.3946 [0.3929]	−0.1287 [0.4802]	2.4091** [1.0514]	0.0885 [0.5696]	1.6634 [1.0684]	-0.2963 [1.1282]
Postgraduate degree	0.8602*** [0.3961]	0.2113 [0.4827]	2.6573*** [1.0631]	0.6656 [0.5919]	2.8719*** [1.0908]	0.5013 [1.1797]
Marital status (Married)	−0.3520*** [0.0989]	−0.3696*** [0.1151]	−0.3680 [0.2594]	0.2259 [0.2564]	−0.8158** [0.4156]	0.0179 [0.3664]
Number of children	0.4612*** [0.0457]	0.5784*** [0.0538]	0.1943* [0.1080]	0.4106*** [0.1304]	0.2679 [0.2019]	0.2429 [0.1605]
Number of adults	0.1232*** [0.0450]	0.2430*** [0.0539]	−0.1514 [0.1125]	0.0431 [0.0976]	0.0644 [0.1420]	−0.0361 [0.1458]
HH food security status	1.1432*** [0.0894]	1.1511*** [0.1043]	1.1984*** [0.2288]	1.2725*** [0.2432]	0.7476** [0.3325]	0.9199*** [0.3664]
Region						
South	0.5870*** [0.1143]	0.6225*** [0.1324]	0.4561 [0.2848]	0.9379*** [0.3069]	0.5436 [0.4252]	0.3446 [0.5615]
Midwest	0.2773** [0.1180]	0.1380 [0.1298]	0.8928*** [0.3566]	0.7310** [0.3504]	0.9355* [0.4836]	0.0666 [0.6162]
West	0.7149*** [0.1181]	0.8231*** [0.1342]	0.4059 [0.4129]	0.7484*** [0.2802]	0.8753** [0.3920]	−0.1357 [0.5367]

HH Household

that every student in America can learn from a distance. The return on such investment is arguably very high (OECD, 2016). And such policies should center on increasing funding for subsidized broadband connectivity by expanding the existing affordable programs, such as the Federal Communications Commission Lifeline Program, designed to provide subsidies for telephone and internet services to eligible low-income households in the U.S. The good news is that the U.S. Congress recently passed an infrastructure bill with broadband funding of about $65 billion, aiming to bridge the digital divide through broadband deployment to un and under-observed areas.

In addition to expanding broadband connectivity, policies that support the provision of computer devices for students to use at home for learning are also essential in narrowing the digital divide in the U.S. Schaeffer (2021) notes that an increasing share of U.S. adults said that K-12 schools and districts are responsible for providing all students with laptops or tablet computers to help them complete their schoolwork at home during the pandemic. The available data show that nearly 48% of the school district in the U.S. with the highest concentration of low-income families indicated they planned to distribute computer and wifi hotspots to the student during the COVID-19 pandemic (Lake & Makori, 2020). In addition, the California Department of Education, through a private nonprofit called California Dedicated to Education Foundation, launched Bridge the Digital Divide Fund to raise money to buy computers for students in the state during the COVID-19 pandemic (Johnson and Willis, 2021). And the authors also note that hundreds of thousands of students are still estimated to be without computers at home, mainly from Spanish-speaking families in the state. A similar program or scheme to help children from less privileged families access computers and the internet, known as NEU PC Plus Programme, was also introduced in Singapore (for details, see Infocomm Media Development Authority, 2022).

Given this, we believe more states and school districts need to earmark funds to support the distribution of computer devices to students in their states and districts to narrow the digital divide in the country effectively. This is because the efforts to provide equitable access to technology are fundamental to creating a sustainable global future and economic growth (Bulman & Fairlie, 2016). For example, access to reliable internet is a strong predictor of economic opportunity, resulting in more than 875,000 additional jobs and $186 billion more in economic output in 2019 in the U.S. (Deloitte, 2021). And in the context of education, student access to computers and modems increased the amount of time spent on educational activities outside schools, including a desire to learn, critical thinking, and writing skills (U.S. Department of Education, 1996). On the other hand, students without access to a computer and the internet will most likely miss valuable learning time since homework and other learning activities require these resources during online classes (Auxier & Anderson, 2020).

4.3 The effects of other control variables on student learning hours

While this is not the present study's focus, we also discuss the effect of other potential drivers of students' learning hours considered and presented in Table 6. Specifically, we find that learning hours increased significantly among students who participated in virtual learning relative to those who did not participate in virtual learning for the pooled sample. Other results show that household heads' income, age, and gender (male) are significant determinants of student hours of learning. Students' hours of learning vary significantly across races and ethnic groups, with students in white households reporting higher learning hours than black, Asian, and other races. Hispanic students reported lower learning hours compared to non-Hispanic students. Also, students in married households reported lower learning hours than those in single households, while students' learning hours increased as children and adults increased. Students in food-secure households reported higher learning hours than those in food-insecure households. However, students in the South, Midwest, and West reported higher learning hours than those in the Northwest part of the United States.

But across the races and ethnic groups, students' learning hours significantly increased as students participated in virtual learning. Also, hours of learning increased among white and black households within higher-income groups. At the same time, the effect of income on learning hours is insignificant among Asian, Hispanic, and other races. In addition, students with aged and male-headed households have higher hours of learning across all races/ethnicity. Thus, except for black households, the education of household heads is an insignificant driver of the students' learning hours. Except for students from White households, marital status (married), the number of kids and adults are insignificant drivers of learning hours. In addition, we find that students in food-secure households have higher learning hours than food-insecure households across all races and ethnicities.

Regarding regional differences, we find that students in white households in the South and West have higher learning hours than those in the northeast. In comparison, students in black families in Midwest have higher learning hours than those in the northeast. Similarly, students in Hispanic households in the South, Midwest, and West have higher learning hours than those in the Northwest. And students in Asian households in Midwest and West have higher learning hours than those in the Northwest.

These results show that variations in learning hours are associated with disparities in households' socioeconomic and demographic composition. Thus, supporting the widespread view that education outcomes are inequitable in the American education system (Darling-Hammond, 1998; Garcia & Weiss, 2017).

5 Concluding remarks

The digital divide among students during COVID-19 has been a concern to the parents, members of the community, and policymakers on how children will receive the same level of education on their own at home when not all students have the same access to computers and the internet resources in the U.S. In light of this, the study investigates the effect of technology access at home on students' learning hours and across race and ethnic groups during the COVID-19 pandemic in the United States. The study employed the Household Pulse Surveys (HPS) conducted by the United States Census Bureau and administered from August 19, 2020, to March 29, 2021. Because the HPS assesses the availability of computers and the internet at home using a 5-point Likert scale measure, we employ principal component analysis (PCA) to compute a composite index of technology access. Subsequently, the study uses a Tobit regression model as an empirical model because student hours of learning are censored in the HPS.

The estimated index of technology access based on PCA reveals a higher degree of access across the whole sample. And the breakdown by race/ethnicity shows the intensity at which families in the sample access technology, which is much higher among Asians, followed by White, Hispanic, Black, and other races. Also, the determinant of learning hours during COVID-19 based on the estimated Tobit regression model shows that access to technology increased learning hours significantly by about 3.1 unit points for the entire sample. The analysis also reveals that access to the technology significantly increased learning hours by about 3.5, 1.6, 2.2, and 3.4 unit points among White, Black, Hispanic, and Asian students, respectively. The observed differing effect of access to technology on the students' learning hours further highlights the racial disparities in American society's digital divide, which reveal how access to technology disproportionately impacts student learning hours during the COVID-19 pandemic across race and ethnicity. Because a disproportionate share of those who lack access to reliable internet connections and computers are Black and Hispanic and low-income households in the U.S. (Lake and Makori, 2020), the results underscore the urgent need for a national effort to close these gaps.

In summary, this study provides insights into how access to technology impacts students' learning hours differently across races and ethnicity during the COVID-19 pandemic in the U.S. In light of this, we believe policymakers need to prioritize policies that address the digital divide in education as part of the ongoing efforts to strengthen education equity in the country. Therefore, investment in broadband connectivity and access to a computer at home for students from different subpopulations are important to ensure that every student in America can learn from a distance. In addition, such investment help equip every student with the ability to learn at home in preparation for the next pandemic, extended personal sicknesses, and regional natural disasters, such as hurricanes and extended snow days in the United States.

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Declarations

Conflict of interest The author has no conflicts of interest to declare that are relevant to the content of this article.

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