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Digital Divides: K-12 Student Profiles and Online Learning

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Abstract: Online learning for primary and secondary students has expanded significantly in the United States during the last two decades. In addition to the sustained growth of online learning, many schools and districts used online learning to respond to the coronavirus pandemic. As school leaders and policymakers move more students into online courses, they need information about which students succeed and struggle online. We examine the relationship between student traits and academic success in a statewide online learning program. We find that students identified with specific exceptionalities, students who identify as male, students from disadvantaged socioeconomic backgrounds, and students from cities or fringe rural areas were more likely to struggle in their online courses. This information comes at a vital time as school leaders seek to determine the effects of widespread online learning, make decisions about the support students will need after the pandemic ends, and develop the best online learning approaches when in-person schooling returns.

Keywords: K-12 online learning; online courses; special education; coronavirus; geography

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Brechas digitales: Perfiles de estudiantes K-12 y aprendizaje en línea

Resumen: El aprendizaje en línea para estudiantes de primaria y secundaria se ha expandido significativamente en los Estados Unidos durante las últimas dos décadas. Además del crecimiento sostenido del aprendizaje en línea, muchas escuelas y distritos utilizaron el aprendizaje en línea para responder a la pandemia del coronavirus. Los líderes escolares y los legisladores mueven a más estudiantes a cursos en línea, necesitan información sobre qué estudiantes tienen éxito y luchan en línea. Examinamos la relación entre los rasgos de los estudiantes y el éxito académico en un programa de aprendizaje en línea a nivel estatal. Encontramos que los estudiantes identificados con excepcionalidades específicas, los estudiantes que se identificaron como hombres, los estudiantes de entornos socioeconómicos desfavorecidos y los estudiantes de ciudades o áreas rurales marginales tenían más probabilidades de tener dificultades en sus cursos en línea. Esta información llega en un momento vital cuando los líderes escolares buscan determinar los efectos del aprendizaje en línea generalizado, tomar decisiones sobre el apoyo que los estudiantes necesitarán después de que termine la pandemia y desarrollar los mejores enfoques de aprendizaje en línea cuando regrese la educación presencial.

Palabras-clave: Aprendizaje en línea K-12; cursos online; educación especial; coronavirus; geografía

Divisões digitais: Perfis de alunos do ensino fundamental e médio e aprendizagem online

Resumo: O aprendizado online para alunos do ensino fundamental e médio se expandiu significativamente nos Estados Unidos durante as últimas duas décadas. Além do crescimento sustentado do aprendizado online, muitas escolas e distritos usaram o aprendizado online para responder à pandemia do coronavírus. À medida que os líderes escolares e formuladores de políticas movem mais alunos para os cursos online, eles precisam de informações sobre quais alunos são bem-sucedidos e têm dificuldades online. Examinamos a relação entre as características dos alunos e o sucesso acadêmico em um programa de aprendizado online em todo o estado. Descobrimos que alunos identificados com excepcionalidades específicas, alunos que se identificam como homens, alunos de origens socioeconômicas desfavorecidas e alunos de cidades ou áreas rurais periféricas eram mais propensos a ter dificuldades em seus cursos online. Essas informações chegam em um momento vital, enquanto os líderes escolares buscam determinar os efeitos do aprendizado online generalizado, tomam decisões sobre o apoio que os alunos precisarão após o fim da pandemia e desenvolvam as melhores abordagens de aprendizado online quando a escola presencial retornar.

Palavras-chave: Aprendizagem online K-12; Cursos online; Educação especial; coronavírus; geografia

Digital Divides: K-12 Student Profiles and Online Learning

In March of 2020, the global community faced an unprecedented health crisis. As the novel coronavirus spread, governments worldwide prohibited millions of K-12 school children from learning in their school buildings for several months. These circumstances left districts and parents scrambling to determine the best way to educate their children. According to nationwide tracking of 82 school districts across the United States, many districts moved to remote instruction to provide curriculum, instruction, and progress monitoring online (Dusseault & Pillow, 2020). This tracking of districts includes a small sample, but it reflects that districts rapidly scaled their online learning use during the pandemic.

The purpose of this article is to consider how student profiles relate to academic performance in K-12 online learning. It is too soon to measure data and explore the consequences of online learning for students amidst the coronavirus pandemic (and unclear if such data will ever be available). Therefore, we instead examine robust data on a statewide online program that previously scaled to fill educational programming gaps for other reasons, mainly staffing issues, credit recovery, and geographic isolation. These unique data allow us to consider students' profiles based on several traits: exceptionality, socioeconomic status, gender, and the geographic classification of their home school district.

We consider the implications of our findings for students who were forced to enroll in online learning during the coronavirus pandemic. While the conditions were different with a heightened level of stressors and exogenous factors, the data from our sample allow us to make reasonable estimations as to who will need educational interventions upon return to face-to-face classrooms. To achieve these goals, we examine a statewide online program in the southeast of the United States. We ask the questions: What student traits relate to K-12 students scoring lower in their online courses? What student characteristics relate to students being more likely to have below a 70 average?

In the remainder of this article, we first discuss past research in K-12 online learning, showing the need for understandings of student profiles and performance. Next, we describe features of the statewide online program that we study, including why students enroll and how teaching and learning are managed. Then, we describe methods and findings. We conclude with implications and how school leaders and policymakers could use our research as they reopen their buildings, including how to think about online learning placements moving forward once the coronavirus pandemic ends.

We do not intend to make comparisons of quality between online learning to traditional classrooms. We believe online education is here to stay and will continue to shape teaching and learning in schools. As the coronavirus pandemic shows, sometimes there are situations in which there are no other learning options for students. With this in mind, we examine data from a state where students participated in online classes for various reasons, including a substantial share of students who took online courses based on circumstances out of their control. We do not argue who should and who should not be learning online because there are situations where students do not have a choice. Instead, we provide information on who may need more support during the online learning process or after their need for online learning ends.

A Brief Overview of Online Learning Research

K-12 online course attendance has grown from limited use at the turn of the 21st century with hundreds of students enrolling in thousands of courses, to hundreds of thousands of students enrolling in a million or more courses within a decade, to now uncounted (likely exceedingly high)

numbers of students enrolling, at least for a brief time, online because of a pandemic (DLC, 2019; Dusseault & Pillow, 2020). Despite this growth, research initially struggled to keep pace, but studies in recent years have investigated the efficacy of online learning and how students fare (Mann & Baker, 2017; Woodworth et al., 2015). Some quantitative studies focus on academic performance in K-12 online schools, but there are many unanswered questions (Means et al., 2014). One of the key questions that previous research has sought to understand is how students fare in various online settings compared to face-to-face environments.

The most robust research on full-time K-12 online schools' performance compared to brick-and-mortar schools focuses on online schools that operate under the charter governance structure. Early studies show mixed results depending on school context, student population, and study design (Cavanaugh, 2009). As this research has expanded, findings consistently show negative performance in cyber charters compared to traditional schools, including statistically significant lower learning growth rates in cyber charters as measured on statewide tests (Ahn & McEachin, 2017; Woodworth et al., 2015). However, if students persist in online schools, their performance improves over time (Lueken et al., 2015).

In addition to these analyses, a group of researchers for the National Education Policy Center (NEPC) has tracked K-12 online and blended learning trends for many years. The latest NEPC report at the time of writing this article is Molnar et al. (2019), and one of the chapters of the reports was reframed into an academic article for *Education Policy Analysis Archives* (Gulosino & Miron, 2017). The NEPC reports have advanced the field in providing knowledge on general challenges related to forms of online and blended learning. The researchers of the NEPC reports show concerning trends. These trends include a lack of oversight and a lack of effectiveness of online programs.

Studies on supplementary K-12 online learning settings have used sophisticated analyses and raised questions on the effectiveness of online learning compared to face-to-face courses. Researchers in one study conducted a randomized control trial to examine success rates in online versus face-to-face in Algebra 1 credit recovery classes. This study shows scores were lower in virtual environments (Heppen et al., 2017). Other studies using quasi-experimental and inferential methods show lower scores for students in virtual settings (Heissel, 2016). Relatedly, some studies use randomized control trial techniques in postsecondary education settings. These studies at times found no discernible effects related to modality, and sometimes adverse effects of online courses on student performance (Bowen et al., 2014; Figlio et al., 2013; Hart et al., 2018; Xu & Jaggars, 2011).

Despite past studies showing adverse effects in various online settings compared to face-to-face options (full-time and supplementary), a recent study used a fixed-effect model to analyze performance and persistence in high school online courses (Hart et al., 2019). The study shows that students in online courses, both first-timers and re-takers, were more likely to pass than students in face-to-face versions of the course. These results are consistent across different subgroups of students. These results raise the possibility that online courses are improving, and there is a need for continued research on learning in online environments.

One clear gap in this research, both in investigations of supplementary and full-time online settings, is that researchers tend to compare online learning to face-to-face learning. This strategy becomes an issue when online learning may be the only option for students for various reasons, such as a global pandemic. We take a different approach to performance than seen in past research. Instead of analyzing whether students perform better or worse in online settings, we analyze students within online courses and identify characteristics associated with students who struggle. Our rationale is that, at least for a brief time following the global pandemic, school leaders and policymakers need to know which students were likely to struggle while they were away from their buildings because there were no comparable face-to-face options.

There are good reasons to consider student background in a study of online learning performance. Students differ in the support they have at home for online learning. For example, working-class or low-income families have less flexibility to monitor online learning progress. Additionally, some studies explain the diversity of student needs and how they interact with online programs in unique ways. Students with exceptionalities have needs not met in online settings (Basham et al., 2015; Rice & Carter, 2015). Students from marginalized backgrounds or isolated geographic locations may face unique challenges in online schools, especially since it is unclear how equity and diversity unfold in online spaces (Mann, 2019). Course content may have subtle racial signals or biases, like what was found in other educational tools (Kranzler et al., 1999). Based on these concerns about the effect of online learning across different populations of students and the context of mass enrollment into online learning during the global pandemic, it is imperative to learn more about students' traits and how they relate to struggles in online classes.

Three Digital Divide Levels and Their Relationship to Educational Access

We conceptualize the study through a common organizing framework for issues related to the diffusion of technology: the digital divide. The Organization for Economic Cooperation and Development defines the digital divide as “the gap between individuals, households, businesses and geographic areas at different socioeconomic levels with regard both to their opportunities to access ICT and to their use of the Internet” (OECD, 2001, p. 32). This term organizes our interpretations of findings. It forces us to ask how the implementation of online learning programs leads to equitable outcomes for members across marginalized and minoritized groups of students. Scholars have long studied how education relates to the digital divide and call for understanding the digital divide across social and cultural characteristics of individuals (Clark & Gorski, 2002; Cruz-Jesus et al., 2016). A digital divide conceptual framework justifies examining educational outputs based on race and other characteristics (Clark & Gorski, 2002). Additionally, scholars have shown discrepancies in students' digital competencies with exceptionalities (Wu et al., 2014). This research motivates us to consider how students with exceptionalities fare in their online courses.

There are three components or levels to the digital divide: access, skills, and use. The early research on the digital divide focused on the first level, which is access and infrastructure. This research examined the tools, such as broadband access and hardware, available to individuals and how this availability differed for marginalized and minoritized people. For example, to determine the extent to which a digital divide exists in the United States, one group of scholars showed how regional variability and the size of technology sectors relate to those regions' socio-demographic characteristics (Azari & Pick, 2005). The first-level argument is still relevant, especially as researchers recently reconceptualized the first level to consider material needs as a digital divide issue (Van Deursen & Van Dijk, 2019).

Researchers added to these understandings through examining the second level of the digital divide. Scholars looking at the second level consider the inequitable distribution of skills and knowledge, or competencies, as a component of unequal opportunities related to technology (Peña-López, 2010). Scholars of the second level also consider related issues linked to technology use, such as behavioral and motivational characteristics and the traits of individuals (Areepattamannil & Khine, 2017). If individuals have not mastered the skills and competencies needed to gain from technology, then the expansion of infrastructure and hardware is not enough to close the digital divide (Ferro et al., 2011).

Scholars are now moving to the third level of the digital divide, discussing who gains the most from the utilization of online tools and how these advantages differ not only based on infrastructure and competencies but also through use patterns (Ragnedda & Kreitem, 2018). The

third-level digital divide merges the intersection of online and offline social conditions. Scholars focusing on this level suggest that there are various services and opportunities available on the internet. A third-level digital divide emerges if individuals use these tools in ways that perpetuate unequal offline conditions for marginalized and minoritized groups (Van Deursen & Helsner, 2015). The third-level digital divide becomes especially important as individuals blur the line between their online and offline lives.

Educational equity relates to all three levels of the digital divide. The first-level digital divide influences education because students cannot learn without the appropriate tools. The second-level digital divide influences education because students with ineffective online skills will not learn course material. The third-level digital divide influences education because even if students have adequate access and skills but are still not learning, there exists a divide based on use patterns. At all levels, the goals of an equitable education system are not met.

In our discussion, we consider what our findings mean concerning the different levels of the digital divide. We argue that online programs cannot fully achieve their goals unless they address all three levels of the digital divide. This means our study's conceptual goal is to consider how the levels of the digital divide emerge based on student traits ranging from socioeconomic to ability differences. As revealed later in the article, we show a digital divide can still exist in programs even with widespread first-level access. Educational equity goals are not achieved unless students from differing backgrounds learn at similar rates in online settings. These learning rates are the product of all levels, not just the first, of the digital divide.

Context: A Statewide Online Program

This research analyzes Statewide Online Program (or SOP, which is the pseudonym used here). SOP began in 2004 with the purpose of serving rural school children across an entire southeastern state. At the time, approximately one-third of the state's children lived in rural communities and attended school districts with staff capacity issues. These capacity issues included providing certain classes to students and attracting and hiring highly qualified teachers. Originally, SOP was designed as an online supplement so that students could enroll in their traditional public school while taking state-provided online courses in content areas not offered in their home school district. The scope of SOP has expanded and now serves students in every school district in the state, and students may take courses based on a variety of reasons and personal preferences. Current SOP student enrollments range from 7th to 12th grade; however, most are at the high school level and take classes to fulfill high school graduation requirements. Some students even fulfill all their educational responsibilities full time with SOP.

SOP is divided into regions, with each school being supported by one of three centers. These 'Support Centers' assist in hiring and monitoring online teachers, enrolling students in classes, and assisting schools as they implement the SOP program. One of the three support centers is also responsible for developing and disseminating courses. Each regional support center is funded through a line item in the state education budget. SOP classes predominately are delivered in an asynchronous manner (more than 95% of the course are asynchronous); however, a few classes (American Sign Language, Floral Design, Forestry, and some sections of Spanish) are taught synchronously using video conference equipment. Since SOP is a state-funded program, students can enroll in Advanced Placement (AP), elective, and other courses to which they may not otherwise have access. There is no cost to the student or their school district for enrollment.

All content for SOP courses is developed and taught by state-certified teachers. The SOP teachers represent a culturally diverse background that ranges from three to almost 40 years of teaching experience. Teachers may have one to several course sections at a given time, but are

limited in the number of students that they teach. Full-time teachers can have 150 students on their class rosters, while part-time teachers can have a maximum of 60 students.

SOP courses are standardized through the creation of a master course which is loaded into a learning management system (LMS). Individual sections of each course are created from the master course, allowing the SOP program to ensure that each course is delivered with fidelity. Teachers may supplement content and have personalized pedagogical online practices that influence how well students perform with the standardized material. However, the courses are structured in ways where students' experiences are consistent, including assessments.

The most popular SOP courses are foreign language and health courses. For example, in the 2017 calendar year, nearly 13% of all enrollments were in a health class, and 28% of all enrollments were in a foreign language. The rest of the courses were split along various subject areas. This distribution shows that SOP is mainly used for schools with difficulty finding teachers in specific content areas (especially foreign languages). Another use of the program is for students to either retake courses from the school year or take higher-level courses that their districts do not offer. A small number of students even use SOP to take courses full time to pursue talents outside of the school setting, such as in sports or acting.

The SOP program has served a diverse array of students. More than 27,000 students took more than 55,000 classes in 2017 alone. These students range in demographic and geographic backgrounds, offering a substantial set of students who can help us understand the composition of students who succeed and struggle in this type of educational setting.

Methods and Data

Data

Data come from the National Center for Education Statistics (NCES) and the state department of education (SDE) that funds SOP. SDE collects data on SOP course enrollment, student performance and activity, teacher activity, and student demographics. These demographic data include exceptionality status, free and reduced lunch status, reported race, reported gender identity (reported in the dataset only as male or female) and sending school district. The SDE store these data in an electronic database and shared them with researchers as part of a data-sharing agreement with the researchers' university. The data reflect enrollments that spanned annual years 2016, 2017, and 2018 (ending in the 2018 fall semester). The data are reported annually, which is different than typical education studies that report school years. We pulled data from all courses available each year, as students enroll in classes during the school year and the summer.

We merged data from the NCES to the students' home districts. Based on a district identifying code, we identified information about each student's home district. The primary variable from the NCES data was the district's locale, as we wanted to determine a geographic proxy for each student. The description of the geographic locale designations is listed in Table 1, as the NCES uses a combination of size, distance from urban clusters, and other census definitions when classifying districts. Based on the rationale to examine students' locale based on their district, we dropped students from the dataset who were enrolled in the online program from a non-district organization. These only included 51 students out of the more than 60,000 students in the dataset. The rest were attending school in a state school district and were using the SOP program as a supplement.

Table 1*NCES Classifications of Geographic Locale*

Designation	Description
City – Large	Territory inside an Urbanized Area and inside a Principal City with population of 250,000 or more.
City – Midsize	Territory inside an Urbanized Area and inside a Principal City with population less than 250,000 and greater than or equal to 100,000.
City – Small	Territory inside an Urbanized Area and inside a Principal City with population less than 100,000.
Suburban – Large	Territory outside a Principal City and inside an Urbanized Area with population of 250,000 or more.
Suburban – Midsize	Territory outside a Principal City and inside an Urbanized Area with population less than 250,000 and greater than or equal to 100,000.
Suburban – Small	Territory outside a Principal City and inside an Urbanized Area with population less than 100,000.
Town – Fringe	Territory inside an Urban Cluster that is less than or equal to 10 miles from an Urbanized Area.
Town – Distant	Territory inside an Urban Cluster that is more than 10 miles and less than or equal to 35 miles from an Urbanized Area.
Town – Remote	Territory inside an Urban Cluster that is more than 35 miles from an Urbanized Area.
Rural – Fringe	Census-defined rural territory that is less than or equal to 5 miles from an Urbanized Area, as well as rural territory that is less than or equal to 2.5 miles from an Urban Cluster.
Rural – Distant	Census-defined rural territory that is more than 5 miles but less than or equal to 25 miles from an Urbanized Area, as well as rural territory that is more than 2.5 miles but less than or equal to 10 miles from an Urban Cluster.
Rural – Remote	Census-defined rural territory that is more than 25 miles from an Urbanized Area and more than 10 miles from an Urban Cluster.

Note. Descriptions from the NCES user manual:

https://nces.ed.gov/programs/EDGE/docs/NCES_LOCALE_USERSMANUAL_2016012.pdf

The combined dataset includes 62,910 student cases and 111,665 courses delivered (averaging 1.775 courses per student). Most students (61.4%) took one course during the data period, and 12.3% took two courses. This distribution means 83.7% of students took only one or two courses. This pattern reflects the program’s goal to be a supplement. A few students (0.5%) took more than 10 courses and used online learning as their full-time educational option.

Student Sample vs. Statewide Population

As shown in Table 2, the composition of students enrolling in the SOP program was similar, but not identical, to the student demographic composition of the state. The differences likely relate to the fact that the SOP’s goal is to provide online programming primarily to rural students who would not previously have access to course content without an online option, shifting the SOP demographic data to reflect certain rural regions more than in statewide data. More than 34% of the students in the SOP dataset live in rural districts, while only about 20% of the state’s students live in

rural districts. The SOP dataset also skews more female, white, and economically advantaged than the rest of the state. The dataset includes student classifications by exceptionality status, which is a variable we do not have access to at the state level, so we have no point of comparison.

A limitation to the data is there are no reported Hispanic students in the SOP dataset in some years and only a few hundred in other years. This lack of reporting occurs for reasons we were not able to determine. We communicated these issues with the data provider and could only determine that there were reporting issues with the data, and we could not remedy these reporting issues. Many Hispanic students were likely reported as white students in the dataset, and thus our results based on race may merge white and Hispanic students. While this is an issue, we feel confident reporting the results, but with a caveat on the reporting issue. Hispanic students comprise less than 8.5% of the statewide student population during the time analyzed, and we did not focus our interpretations of results based on reported race or ethnicity.

Table 2

Statewide Student Demographics Compared to SOP Student Demographics

	Statewide Student Population, 2018-19	% Statewide Student Pop.	SOP Dataset, 2017-19	% SOP Dataset
Total	739,716		62,910	
Free Lunch	407,040	55.03%	26,102	41.49%
Reduced Lunch	44,789	6.05%	3,084	4.90%
Male	379,760	51.34%	28,952	46.02%
Female	359,956	48.66%	33,958	53.98%
Am. In./AK Natv.	6,918	0.94%	1,795	2.85%
Asian or Pac. Islander	10,887	1.47%	976	1.55%
Black	240,190	32.47%	18,659	29.66%
White	401,066	54.22%	40,910	65.03%
Other Racial Designation	80,655	10.90%	571	0.91%
City: Mid-size	140,729	19.02%	3,392	5.39%
City: Small	64,782	8.76%	3,269	5.20%
Suburb: Large	160,433	21.69%	6,739	10.71%
Suburb: Mid-size	18,709	2.53%	541	0.86%
Suburb: Small	16,031	2.17%	1,850	2.94%
Town: Fringe	10,040	1.36%	2,344	3.73%
Town: Distant	71,834	9.71%	8,697	13.82%
Town: Remote	5,168	0.70%	483	0.77%
Rural: Fringe	75,450	10.20%	6,794	10.80%
Rural: Distant	144,880	19.59%	21,538	34.24%
Rural: Remote	31,660	4.28%	7,180	11.41%
No exceptionality			45,471	72.28%
Autism			286	0.45%
Emotional Disturbance			120	0.19%
Gifted			10,517	16.72%

Table 2 cont.*Statewide Student Demographics Compared to SOP Student Demographics*

	Statewide Student Population, 2018-19	% Statewide Student Pop.	SOP Dataset, 2017-19	% SOP Dataset
Hearing Impairment			68	0.11%
Multiple Disabilities			8	0.01%
Orthopedic Impairment			32	0.05%
Other Health Impairment			647	1.03%
Specific Learning Disabilities			2,649	4.21%
Speech & Lang. Impairment			3,070	4.88%
Traumatic Brain Injury			19	0.03%
Visual			23	0.04%

Note. The “Other Racial Designation” category statewide disaggregated shows 62,089 (8.39% statewide) Hispanic students, 881 (0.12% statewide) Hawaiian Native/Pacific Islander students, and 17,685 (2.39% statewide) Two or More Race students. The reason for collapsing these categories is that there were small populations of these students represented in the SOP database (571 combined total). These omissions occur for reporting issues not correctable by the researchers.

While we report the race and ethnicity data results in the findings, we do not focus on them in the discussion. We made this decision based on the reporting issues and also because when students return to their face-to-face settings once the pandemic ends, they likely will be returning to schools that are mostly racially homogeneous, an unfortunate reality of the demographic makeup of schools in the United States (Reardon & Owens, 2014). As such, racial data are less helpful to practitioners than other student covariates in the context of this data. However, we concede this is a limitation to the study and we strongly encourage the field to continue examining online course performance as it relates to racial identity.

Dependent Variables

The first outcome measure is the average of a student’s scores in their online learning class(es). This score is equivalent to their “online school GPA” to determine how a student, on average, performs in their online class(es) overall. These scores are on a 0–100 scale. The covariates can be understood as how many more points a student scores than a reference group (for example, females scored, on average, about 8 points higher than male students, as shown in the following findings section).

The second outcome measure is a binary measure of students scoring lower than a “C” (below an average of 70) in their online courses. This measure provides a straightforward interpretation for policymakers and is consistent with a recent study that uses a similar measure when determining online student success (Hart et al., 2019). This outcome variable allows us to change the statistical analysis from linear regression to a logistic regression, which adds robustness to the findings.

Independent Variables

As shown in Table 2, there are several traits we examined when considering scores in online courses. We focused our analysis on a category in the data called “exceptionality.” The districts report this variable with accuracy due to federal law requiring schools to report and monitor students with exceptionalities. We report findings related to exceptionalities first due to past concerns raised about students with exceptionalities and needs not being met in online settings (Basham et al., 2015; Rice & Carter, 2015).

We also included student traits such as economic status, gender, race, and geographic location. The economic status variable we used was free and reduced-price lunch for students, which is a proxy indicating the financial resources. The sending school district reported race and gender with self-reported information by students and families. We could not confirm these covariates’ accuracy, as students may identify their gender or race differently than what the district reports. As mentioned, race and ethnicity variables had irregularities, such as very few Hispanic students reported in the dataset and small numbers of students from several racial groups such as Hawaiian Native/Pacific Islander students and Two or More Race students. We collapsed these categories into an “Other Racial Designation” variable and acknowledge this as a limitation to our analysis.

Analytic Methods

We use two primary analytic techniques to understand the relationship between online learning mean score (or online school GPA) and student traits. All models use statistically required reference groups across each student trait (the reference categories are no exceptionality, no FRL, female, white, and large suburb). For the first analysis, to account for the nature of the nested data, we use a three-level model (students nested within schools, and schools nested within districts) analyzing students’ average test scores (Raudenbush & Bryk, 2002):

$$Score_{ijk} = \beta_0 + \mathbf{ST}_{ijk}\mathbf{B}_1 + \mathbf{DI}_k\mathbf{B}_2 + r_k + u_{jk} + \varepsilon_{ijk},$$

Where $Score_{ijk}$ represents the average test score for student i in school j within district k ; β_0 is the intercept; \mathbf{ST}_{ijk} is a row vector of student background characteristics including SES, gender, race, and exceptionality; \mathbf{DI}_k is a row vector of district location dummy variables; r_k and u_{jk} are the district-level and school-level random effects, respectively; and ε_{ijk} is the student-level error term.

The second analytic technique we use is a three-level logistic regression model for understanding the likelihood a student trait associated with a student having an average score of 70 or lower (Raudenbush & Bryk, 2002):

$$\log \left[\frac{P(Y_{ijk}=1)}{1-P(Y_{ijk}=1)} \right] = \beta_0 + \mathbf{ST}_{ijk}\mathbf{B}_1 + \mathbf{DI}_k\mathbf{B}_2 + r_k + u_{jk},$$

In this model, Y_{ijk} is a binary indicator coded as one if the average score for student i in school j within district k is less than 70 and coded as zero if the average score is equal or greater than 70; β_0 is the intercept; \mathbf{ST}_{ijk} is a row vector of student background characteristics including SES, gender, race, and exceptionality; \mathbf{DI}_k is a row vector of district location dummy variables; r_k and u_{jk} are the district-level and school-level random effects, respectively. We report the logit coefficients as odds ratios for ease of interpretation.

Analytic Limitations

There are limitations based on the available data and methodological choices (in addition to data limitations mentioned earlier). The first limitation is that there are aspects to the scenario presented in this study that may not represent the nature of online learning nationwide. The state at focus is a rural state with no students classified as attending school in a large city. Large cities like New York and Los Angeles might have differences when compared to the findings presented here. Also, the reasons for students enrolling in the SOP program are different than students enrolling in online learning due to the circumstances based on the coronavirus pandemic. The next limitation is we do not know the students' previous experience with online learning, nor do we know their prior academic achievement. It would help to control for these student traits, but data reflecting these traits were not available to us. Another limitation is that there may be some confounding variables that influence the findings. These include teacher quality and experience with online teaching and student variables such as internet cost, bandwidth, and stability. Since most of courses were asynchronous, we believe these factors are somewhat mitigated, but they present an area for future research. A final limitation is we took an aggregate measure of student performance. This measure can be understood as their SOP final average (akin to a high school GPA). This measure does not account for the nature of the class(es) the students took. We made this choice because providing a general score is the most useful in the scenario currently facing our society, where many students are taking multiple courses online during the pandemic.

School leaders should use these findings as a starting point rather than an endpoint. Our findings allow us to understand the composition of students who succeed and struggle in the online learning experience of SOP. These findings help inform policymakers in the state. Additionally, policymakers in other settings may use the findings as they begin to consider how they overlap with their settings.

Results

Table 3

Statewide Student Performance in SOP Online Courses by Student Traits

Variable	Multi-level Regression	Multi-level Logit
Autism	-0.67 (1.44)	0.84 (0.11)
Emotional Disturbance	-14.41*** (2.68)	2.60*** (0.59)
Gifted	8.72*** (0.24)	0.49*** (0.01)
Hearing Impairment	1.06 (3.28)	0.59* (0.16)
Multiple Disabilities	0.03 (11.46)	1.66 (1.31)
Orthopedic Impairment	-11.84** (4.35)	1.26 (0.48)
Other Health Impairment	-12.60*** (1.40)	2.11*** (0.19)

Table 3 cont.*Statewide Student Performance in SOP Online Courses by Student Traits*

Variable	Multi-level Regression	Multi-level Logit
Specific Learning Disabilities	-9.83*** (0.71)	2.02*** (0.09)
Speech & Language Impairment	0.63 (0.34)	0.97 (0.04)
Traumatic Brain Injury	-7.41 (5.41)	1.70 (0.85)
Visual Impairment	-4.06 (3.58)	0.86 (0.39)
<i>(Reference No Exceptionality Reported)</i>		
Free	-8.23*** (0.44)	1.92*** (0.04)
Reduced	-4.15*** (0.46)	1.43*** (0.06)
<i>(Reference Non-FRL)</i>		
Male	-7.70*** (0.46)	1.86*** (0.03)
<i>(Reference Female)</i>		
American Indian/Alaskan Native	1.88* (0.87)	0.88* (0.05)
Asian	10.42*** (0.79)	0.46*** (0.04)
Black	-3.45*** (0.30)	1.28*** (0.03)
Other Racial Designation	-1.85 (1.01)	1.11 (0.10)
<i>(Reference White)</i>		
City: Mid-size	-7.11*** (1.51)	1.47*** (0.07)
City: Small	1.40 (1.49)	0.86** (0.04)
Suburb: Mid-size	-1.90 (2.43)	1.07 (0.11)
Suburb: Small	4.15*** (0.74)	0.79*** (0.05)
Town: Fringe	5.90*** (0.85)	0.70*** (0.04)

Table 3 cont.*Statewide Student Performance in SOP Online Courses by Student Traits*

Variable	Multi-level Regression	Multi-level Logit
Town: Distant	2.62** (0.94)	0.86*** (0.03)
Town: Remote	7.82*** (1.05)	0.58*** (0.06)
Rural: Fringe	-3.18** (1.22)	1.34*** (0.06)
Rural: Distant	2.74** (0.85)	0.88*** (0.03)
Rural: Remote	2.86*** (0.64)	0.92 (0.04)
Location-Missing	0.88 (5.18)	0.94 (0.33)
<i>(Reference Large Suburb)</i>		
Intercept	70.49*** (0.74)	N/A
Pseudo R ²	0.11	0.12
N ⁺	60,008	60,008

Note. Exponentiated coefficients; standard errors are in parentheses and * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. +Students with no scores reported were dropped from the dataset; this accounted for 2,902 students or about 4.61%. Pseudo R² was calculated as the square of the Pearson correlation coefficients between the outcome and the fitted value.

Exceptionality

The reference group for exceptionality was students labeled without an exceptionality. As shown in Table 3, students identified with autism, hearing impairments, multiple disabilities, speech and language impairments, traumatic brain injuries, and visual impairments did not have statistically different scores than students without exceptionalities. Gifted students scored 8.72 points higher than students without exceptionalities. Students identified with emotional disturbance scored 14.41 points lower, orthopedic impairments scored 11.84 points lower, other health impairments scored 12.01 points lower, and specific learning disabilities scored 9.83 points lower than students without exceptionalities.

The logit models show similar trends as the multi-level regression models. Students without an exceptionality designation were the comparison group. Gifted students were less likely to have an average below 70; students with emotional disturbance were 2.6 times more likely to score below 70; students with other health impairments were 2.11 times more likely to score below 70; and students with specific learning disabilities were 2.02 times more likely to score below 70. These likelihoods were all the highest among any of the categories in the dataset, emphasizing the need to consider the special needs of students with exceptionalities as they participate in online courses.

Free and Reduced Lunch

Compared to students who receive neither free nor reduced lunch, students who receive these benefits fared significantly worse in online courses. Students who were identified as receiving free lunch scored an average of 8.23 points lower in their online courses, while students receiving reduced lunch scored an average of 4.15 points lower.

The logit models show that compared to students without free or reduced lunch, students with free lunch were 1.92 times more likely to have an average of below 70, and students with reduced lunch were 1.43 times more likely to have an average of below 70.

Males and Females

Students reported in the dataset as male performed significantly worse than students in the dataset reported as female. Male students, on average, scored 7.70 points lower than female students. The logit models reveal that male students were 1.86 times more likely to have an average of below 70 in their online classes than female students.

Geographic Location

There were differences in scores based on geographic location. The reference was the large suburb category because it contained the most students of all geographic classifications. Compared to students from large suburbs, students from small suburbs scored 4.15 points higher, town fringe students scored 5.90 points higher, town distant students scored 2.62 points higher, town remote students scored 7.82 points higher, rural distant students scored 2.74 points higher, and rural remote 2.86 points higher. Meanwhile, students from mid-size cities (there were no large cities in the dataset) scored 7.11 points lower, and students from rural fringe districts scored 3.18 points lower.

In the logit models, when compared to large suburban districts, students from mid-size cities and rural fringe were more likely to score below a 70 in their online courses. Students from small cities, small suburbs, town fringe, town distant, town remote, and rural distant, were all less likely to score below 70.

Race

There were differences in online course performance among students across racial identities, but these results come with limitations, as mentioned in the methods. Compared to white students, black students scored 3.45 points lower and Asian students scored more than 10 points higher. In the logit models, black students were 1.28 times more likely, and Asian students were less likely than white students to score below 70.

Discussion and Conclusion

The findings reveal three themes related to the issues we raised in the first half of the article. First, the findings expand on the academic conversation about the digital divide. Second, if our findings persist during widespread online learning during the pandemic, then administrators will have to account for the emergent difficulties that relate to all levels of the digital divide. School administrators may need to establish learning mitigation strategies even if they adequately provided infrastructure and tools for students to learn online. Student access and skills development is not enough to assure that online learning unfolds in an equal and equitable manner. Third, as online education continues in a post-pandemic world, leaders should consider digital divide issues in future online learning placements.

This knowledge expands on past research because previous studies examine online learning compared to face-to-face instruction (Ahn & McEachin, 2017; Woodworth et al., 2015). We analyze

students only enrolled in an online setting. The sample is a subset of pre-pandemic students who needed or decided to use online learning to access courses they would not have had otherwise or courses they used for credit recovery in districts that did not have staffing in the summer. The sample of students we analyze is not the same as the sample of students forced to remain at home due to the coronavirus pandemic. These differences are an important note of caution, but we hope our findings are instructive to the pandemic reality. Additionally, our results come with a limitation in that they are not value-added. They may represent similar patterns seen in face-to-face settings. School administrators may look at these results and determine that the students struggling in online courses are the same students who struggle face-to-face.

Despite the cautions, our results show patterns related to student learning in the program we analyzed. The program achieved its goals because it provided infrastructure and course content across geographic boundaries in ways not available before online learning. However, the results presented here suggest that despite the spread of access in terms of course content, other levels of the digital divide created unequal learning outcomes.

It is challenging to extrapolate from our dataset what is causing the levels of digital divide. These could be a product of unidentified first-level divides such as lack of available resources. They could also be undetected differences in skills that are challenging to capture through our data. They could also be differences in use patterns leading to differences in grades. Some of our findings give us clues that suggest a combination of these issues are at play.

Third-level divides are a product of multiple forces, including first and second-level divides. Van Deursen & Van Dijk (2019) show us that the resources students require are not only technological, but also other materials and forms of sustenance. We can not identify precisely who has a lack of access to these types of resources, but our data allow us to consider these issues. For example, low-income students as measured by free and reduced lunch status, and students from minoritized and vulnerable backgrounds, score lower than students with more advantages. While we cannot know for sure the reason for this outcome gap without more research, the finding captures a concern about material need and its effect on digital divides.

Our geographic data paint an uneven picture of results as they relate to online programming. Some students in particular geographic locations score lower than other students in the dataset, including those in rural fringe and mid-size cities. These areas should have fewer connectivity issues, which reinforces that the first-level digital divide is complex. To be sure first-level divides are mitigated, each leader in their context should closely examine these issues and determine if students in their areas have the materials and resources to thrive in an online setting. We know from our research that those most disadvantaged economically struggle in online courses. Future research can detect if this is directly because of a first-level digital divide.

In addition to the first level of the digital divide, administrators must account for the second and third levels. The second level suggests that differences in skills lead to unequal access to online learning (Areepattamannil & Khine, 2017; Ferro et al., 2011; Peña-López, 2010). Scholars have also shown discrepancies in skills in relationship to students with exceptionalities (Wu et al., 2014). We find evidence to support this past work. This means that leaders should think about if their students have the resources to succeed and *also* if they have the skills and abilities to succeed. Leaders should consider modification and intervention strategies to help alleviate the second-level divide, especially for students with exceptionalities.

While there is a third-level digital divide evident through considering student results, there also may be clear indicators that how online tools are used may, in some cases, help drive these trends. For example, we find a relationship between reported gender identity and online learning outcomes. Students across gender backgrounds, on aggregate, likely have similar rates of other traits that relate to use patterns. This understanding suggests that the systematic differences in

performance based on gender likely also relate to other patterns, such as how online learning is used. While IT skills may reflect a gender gap, we believe a better interpretation is that there is probably a use and engagement differential pattern in online spaces.

Overall, these findings add complexity about how online learning relates to digital divides. We find evidence to suggest that school leaders need to consider three key features when deciding if their students have actual opportunities in online courses: access, skills, and use. Implementing material improvements and physical resources is the first step in providing access to online courses. The second is to enhance the skills of individuals. The third is to ensure all students are using the platform appropriately to learn the course content. School leaders will need to continue to consider these issues as the number of online students increases.

These understandings come at a critical time as America's students were forced to go online due to the coronavirus pandemic. Based on our findings, school leaders will have students they need to monitor upon return to face-to-face instruction following the pandemic. Of course, many students will be impacted by the pandemic and will likely not receive the type of education they would have had if the pandemic had not occurred. However, the pandemic will likely affect some students' academic trajectory more than others. Additionally, administrators will continue to make challenging online learning placement decisions after the pandemic in which they weigh students' personal needs with considerations of academically appropriate environments.

Understanding the profile of students who struggled in the SOP online environment help identify appropriate past and future placements. Past research raised concerns about students' needs from diverse backgrounds, especially those identified with an exceptionality (Basham et al., 2015; Rice & Carter, 2015). Our findings elevate those concerns because we show students identified with certain exceptionalities were most likely to struggle. We also show students who identify as male, students from disadvantaged socioeconomic backgrounds, and students from cities or fringe rural areas were more likely to struggle than those students without these backgrounds. School leaders should consider identifying if they have students with these traits in their settings. They should assess if these students experienced challenges in their online environments and then provide them with remediation.

We hope this information will help leaders and policymakers determine the students who may need extra support upon return to the classroom, especially in situations where students have no choice but to use online learning based on their circumstances. Currently, this includes many students due to the current global pandemic. In a post-pandemic world, we expect administrators to continue working with students and families to decide if they should enroll in online courses or stay in face-to-face courses.

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