Article

American Behavioral Scientist
1–22

Reprints and permissions:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/0002764218773826
journals.sagepub.com/home/abs
SAGE

Interlocking Inequalities: Digital Stratification Meets Academic Stratification

Laura Robinson[1], Øyvind Wiborg[2], and Jeremy Schulz[3]

Abstract

This article examines the effects of digital inequality in conjunction with curricular tracking on academic achievement. Capitalizing on an original survey administered to seniors (fourth-year secondary school students), our survey data (N = 972) come from a large American public high school with a predominantly disadvantaged student body. The school's elective tracking system and inadequate digital resources make for an excellent case study of the effects of a differentiated curriculum and digital inequalities on academic achievement. Multilevel random-effects and fixed-effects regression models applied to the survey data reveal the important role played by digital inequalities in shaping academic achievement as measured by GPA. As the models establish, academic achievement is positively correlated with both duration of digital experience and usage intensity regarding academically useful computing activities, even when students' curricular and class placement are taken into account. In contrast, both leisure computing and smartphone usage are negatively correlated with academic achievement as measured by GPA. Also with regard to GPA, findings show that students in the higher curricular tracks benefit more from longer durations of digital experience than do students in lower curricular tracks. These results underscore the importance of focusing attention on the ways in which digital inequalities combine with curricular tracking in shaping academic achievement.

[1]Santa Clara University, Santa Clara, CA, USA
[2]University of Oslo, Oslo, Norway
[3]University of California Berkeley, Berkeley, CA, USA

Corresponding Author:
Laura Robinson, Department of Sociology, Santa Clara University, 500 El Camino Real, Santa Clara, CA 95053, USA.
Email: laura@laurarobinson.org

Keywords
digital inequality, digital divide, curricular tracking, grade point average (GPA), academic achievement

Introduction and Goals

While digital inequalities and educational stratification both hold great interest for scholars of academic achievement, we have yet to fully understand how they interact to produce disparities in grades and other indicators of academic achievement. Studies of digital inequalities in school settings neglect to attend to the curricular stratification that figures so prominently in many educational settings, particularly in the United States. This article begins to fill this gap by examining the effects of digital inequality in conjunction with curricular tracking on academic achievement. We use original survey data drawn from a strategic case study of high school seniors attending a Title 1 or high-poverty public high school in an economically vulnerable region of California. This educational setting is ideally suited to examining the consequences of digital inequality for the academic achievement of marginalized young people coming of age in the digital age. This case study enables us to probe the intersection of digital inequality and institutional inequalities, an understudied combination in the digital inequalities and education literatures. The study thereby strengthens our grasp of academic achievement by bridging the study of an emergent form of inequality with the study of one of the most "prominent structural aspects" of educational environments already shown to affect academic achievement (Carbonaro, 2005).

The study's orienting question is "How do different forms of digital inequality intersect with the curricular stratification system in shaping the academic achievement of disadvantaged secondary school students? This research question is grounded in a larger ethnographic and interviewing study of an under-resourced secondary school (Robinson, 2014b). Analyzing survey data gathered from the school we call "Rancho Benito High," findings from the study clarify the powerful influence of digital inequality on academic achievement in several important ways.

First, we ascertain how digital inequality and curricular stratification work together to affect academic achievement among low-income students attending an under-resourced school. Second, we introduce digital experience as a predictor of offline inequalities, in this case grade point average (GPA). In so doing, we translate Helsper's (2012) theoretical concept of digital experience, conceptualized as a mediator between digital behaviors and offline outcomes, into an empirical operationalization useful as a predictor of offline outcomes. Third, we tease apart the positive impacts of academically useful computing intensity compared with the negative impacts of smartphone and leisure-computing intensity. Fourth, we introduce the concept of the *digital bind*.

Previous Studies: Digital Inequalities and Academic Achievement

A number of studies have explored the influence of digital inequality on academic achievement in elementary and secondary schools. The exemplary studies in this area tackle questions of whether the objective intensity or character of digital activities, whether mediated by Internet-enabled computers or smartphones, affects learning and academic achievement on the part of children and adolescents in formal educational settings. Disclosing associations between academic achievement and inequalities in access to computing devices, Gulek and Demirtas' (2005) study of a public middle school in California showed that participation in a school-based laptop program resulted in a measurable improvement in math and English grades among students who had previously lacked a personal computer. Another study found that among significantly disadvantaged students between the ages of 10 and 18 years, Internet use predicts an improvement in GPA after a year of home Internet use with larger benefits continuing to accrue after the 12-month point (Jackson et al., 2006). However, other studies (Becker, 2000; Judge, Puckett, & Bell, 2006) found that while computer use was positively correlated with academic achievement, frequency of use for reading was negatively correlated with achievement.

These and other studies indicate that the relationship between digital resources and academic achievement depends on the dominant type of use (Jackson et al., 2008). Studies that focus on usage intensity effects find a threshold effect on grades where, past a certain point, more intense Internet-based activity actually harms students' grades (Judge, 2005). While moderate amounts of time spent on online activities tend to boost academic achievement, excessive amounts of time yield lower GPAs (Lei & Zhao, 2007). Because this excessive computer use is typically oriented to recreation rather than study, especially if it takes place at home without adult supervision, it can consume scarce time and energy that could be channeled into schoolwork (Mesch & Talmud, 2010). At the college level, the presence of compulsory laptops in the classroom seems to depress academic achievement, particularly among less able students (Patterson & Patterson, 2017). Also, at the college level, multitasking with social media and cell phone use is also negatively associated with overall college GPA (Junco & Cotten, 2012). This also holds true for elevated levels of instant messaging that can impede learning and divert students from schoolwork (Junco & Cotten, 2011). This body of work, therefore, concludes that not all forms of Internet use are conducive to academic achievement (Nævdal, 2007).

Curricular Tracking and Academic Achievement

While digital inequalities are important, institutional stratification must also be considered as a predictor of academic achievement (Domina, Penner, & Penner, 2017). Where curricular tracking prevails, academic achievement tends to mirror students' placement within the existing hierarchy of curricular tracks. In other words, all else equal, higher tracked students typically achieve higher grades than their counterparts in lower tracks. This track effect is particularly visible in U.S. public secondary schools. Though the mandatory and rigid tracking schemes prevalent in the 1980s (Archbald & Keleher, 2008) have been phased out across the U.S. public secondary school system, elective tracking systems are still in place in many schools. Curricular tracking, whether “hard” or “soft,” has been shown to exert an independent influence on students’ grades and academic achievement.

Past research into mandatory tracking has demonstrated that sorting assignments exert both direct and indirect effects on academic achievement, even taking into account a large array of other grade-determining factors at the individual and environmental levels (Gamoran, 1992). The “track effect” (Carbonaro, 2005) operates both directly on students’ academic achievement and through the mediation of academic effort, as Carbonaro shows in an analysis of secondary data pertaining to American secondary schools. Moreover, in public U.S. secondary schools, there is evidence that students’ academic outcomes may reflect their track placements both during and prior to the period in which the outcome is measured, especially in the core subjects of English and math (Lucas & Berends, 2002). Detailed studies of tracking effects across schools suggest that placement in higher tiered tracks can accelerate learning and boost academic achievement, and the strength of this track effect can also vary across schools with different tracking structures (Gamoran, 1992; Hallinan 1994). Finally, cross-track differences are more muted in elective tracking systems whereby students formally decide their own track placement, as well as in tracking systems that channel a greater proportion of students into college-eligible programs and allow for more mobility across tracks.

Introducing the Digital Bind: Rancho Benito High as a Strategic Case Study

While they enrich our understanding of academic achievement, existing studies do not attend to several key factors. First, they do not explore the synergistic influence of curricular tracking and digital inequality on academic achievement. In contrast, our study pays attention to the stratified character of educational curricula present in many public American secondary schools. Second, they do not account for what we call the *digital bind*. To flesh out this concept, we have selected a particular field site emblematic of a “digital bind” environment. In this environment, many of the low-income students attending the school are encouraged or required to use digital resources in undertaking schoolwork, even when the school cannot assure equal access to digital resources. In this school, institutional imperatives to digitize instruction collide with a shortage of school-based computing resources, thereby translating offline and online disparities into disparities in academic outcomes. Though common, digital binds in secondary schools are still overlooked in the digital inequalities and education fields. Indeed, though much prior research has documented the effects of digital disadvantage on offline outcomes, including academic achievement, it has remained unclear how digital inequalities unfold in digital bind situations such as the one exemplified by our case study. Our setting serves as a “revelatory” case study (Yin, 1994), strategically positioned to direct attention to the academic consequences of this digital bind for students.

This digital bind proves particularly costly for those digitally disadvantaged students who find themselves in classes where they are asked to employ the Internet for information searching, for researching written assignments, and for typing up papers and exercises. In our field site, many teachers treat Internet-based resources as an indispensable "pedagogical tool" (Wainer et al., 2008). At the same time, the school's resources are insufficient to provide digital facilities for students to use software such as word processing platforms for assignments. Chronically under-resourced during the period under study, seniors at Rancho Benito High could make only a limited number of desktop computers available to the thousands of students attending the school. Teachers and students needing access to Internet-enabled computers were restricted to a handful of machines in the school's library and career center and one formal computer lab facility. Because of the intense competition for on-campus computer resources, teachers had to book the lab up to six weeks in advance if they wanted to hold a class in the lab. For roughly two hours outside the normal class day (before the first class period, during the lunch hour, and after the final class period), the computer lab was made available to individual students. Unsurprisingly, students' demand for time on the school's computers far outstripped their availability, creating long wait times and queues before and after the class day. Because of the scarcity of school-based computing resources, students lacking personal or familial digital devices were at a disadvantage. These doubly digitally disadvantaged students, therefore, found it impossible or extremely difficult to gain Internet access to carry out academic work either at home or at school.

Curricular Stratification at Rancho Benito High

Students in our case study varied greatly in both their placement within the school's curricular structure and their position within the digital inequality order. During the period under study, a system of elective tracking prevailed within multiple subject areas in the senior-year curriculum. At the time of the survey administration, the senior-year English curriculum at Rancho Benito High was organized around the college-noncollege divide. Senior-year English-language classes were grouped into four curricular tracks, only one of which (Practical English) disqualified students from matriculating at a 4-year college. Three distinct curricular tracks made students college eligible: English Literature, Expository Writing, and AP (Advanced Placement) English. Although AP English was considered the highest track, all three curricular tracks conferred college eligibility. Table 1 presents the distribution of survey respondents across the four curricular tracks. As indicated in Table 1, 29 of the 44 classes belonged to one of the three college-eligible tracks (7 AP classes, 11 Expository Writing classes, and 11 English Literature classes). In contrast, 15 of the 44 classes were designated as Practical English classes that were not considered college-eligible. In other words, 34% of the classes in which students were surveyed were in the lowest curricular track: Practical English. In contrast, 16% of the classes belonged to the highest curricular track (AP). The remaining 50% of classes belonged to the two intermediate college-eligible tracks (English Literature and Expository Writing).

Table 1. Distribution of Students Across Curricular Tracks.

		Curricular Track			
	Total	Advanced Placement	English Literature	Expository Writing	Practical English
No. of classes	44	7	11	11	15
No. of students	972	165	249	250	308

Research Hypotheses

In the course of hundreds of student interviews at Rancho Benito High, patterns emerged regarding linkages among academic achievement, digital inequality, and curricular tracking. These patterns informed the development of hypotheses that we tested by collecting and analyzing original survey data. The following analysis is thus designed to allow for the statistical testing of the four hypotheses below. Each hypothesis regards the association between academic achievement and a facet of digital inequality. Hypothesis 4 also trains attention on curricular track placement as a conditioning factor accounting for academic achievement across multiple curricular tracks.

Hypothesis 1: As the duration of digital experience at home or school or both increases, students' grades (as measured by GPA) will increase.
Hypothesis 2: As the level of usage intensity for academically useful computing increases, students' grades (as measured by GPA) will increase.
Hypothesis 3: As the level of usage intensity for smartphones and/or leisure computing decreases, students' grades (as measured by GPA) will increase.
Hypothesis 4: The higher the student's placement in a curricular track, the stronger the effect of digital experience on grades (as measured by GPA).

In the following section, we assess these hypotheses by analyzing data from our original survey with multilevel regression modeling.

Data and Methods

Our original survey was administered to four waves of high school seniors graduating from the school between 2010 and 2013. The respondent pool included 1,015 students, all of whom were in their senior year of high school when they took the survey. After removing students with missing values on any of the variables, but after the imputation of predicted numeric GPA based on self-reported letter grades in those cases where GPA is missing, we arrived at a total number of 972 cases. Of the remaining 972 students, more than 80% self-identified as Latino, though a number of these students also indicated another ethnic identity as well. Regarding parental education, more than 80% of the respondents indicated that the parent with the highest education had concluded their education without obtaining a BA or higher degree. During the years the survey was administered, Rancho Benito High was designated by the state as a Title 1 school with more than one third of the enrolled students eligible for state-subsidized lunches.

As English was the only mandatory subject for all students across all four curricular tracks, we administered our survey through the English Department with the cooperation and participation of English teachers. In administering the survey through this channel, we were able to obtain responses from students in 44 classes corresponding to all the four curricular tracks in the school's curriculum (AP, Expository Writing, English Literature, and Practical English). This mode of administration had the additional benefit of ensuring that we surveyed the entirety of each senior class or graduating cohort, as all students are required to take four years of English courses.

Survey Instrument

Our data come from an original survey designed to maximize the analytical leverage provided by the specific context of the case study, namely, a school setting with a stratified curriculum selectively incorporating digital pedagogical tools and serving a low-income student population with varying patterns of digital activity. In addition to background questions on topics such as gender and parental education, the survey included questions on academic achievement, curricular tracking, and course assignment. The survey instrument captures duration and intensity dimensions of digital inequality through questions 1) probing duration of Internet use at home and at school and 2) intensity of Internet use at home and at school. Questions also asked about the intensity of smartphone use and digital activities including e-mail, digital research for school, search engine use, social media, IM (instant messaging), and entertainment media as we detail below.

Dependent Variable: GPA

We operationalize our dependent variable, academic achievement, as measured by numeric GPA. GPA was reported by students in two ways: numeric GPA and self-reported letter grades. In the cases where the students only reported their letter grades, we predicted the students' numeric GPA based on these letter grades, so as to minimize the number of missing observations. This strategy minimized the number of missing cases as well as measurement error. Nonmissing values corresponding to these two items exhibit a high degree of correlation (Pearson's $r = .8$ for self-reported letter grades and numeric GPA). Our measure for the academic achievement variable (GPA) follows a normal distribution, with a mean of 3.01 and a standard deviation of 0.69.

Independent Variable of Theoretical Interest: Digital Experience

Digital experience is one of the primary predictors of grades in our study. While not used to predict offline inequalities, this measure has been found to predict dominant types of Internet behaviors among high-access users (van Deursen & van Dijk, 2013). Digital experience is especially well-suited for examinations of digital inequality among youths as the high school years are critical years to acquiring digital literacies and skills. There is variation in the duration of digital experience across preadolescent and adolescent age groups because they encounter the Internet at varying ages. For this reason, measuring the duration of digital experience during the senior year of high school, when students are between the ages of 17 and 19, makes good sense because a substantial proportion of Americans first gain access to the Internet between the ages of 9 and 19. Table 2 shows the age when Americans first begin to access the Internet. These figures suggest that what we could call the age of *Internet debut* varies more than many would imagine, were we only to believe popular discourses about digitally savvy elementary school-age children in the United States.

Table 2. Percentage of U.S. Population Accessing the Internet at Any Location (2013).

Age group (years)	Percentage
5-9	53%
10-15	71%
16-19	85%

Note. Adapted from the National Center for Education Statistics (2013).

In our study, digital experience is operationalized in terms of how many years the respondent has been using computer and Internet-mediated resources at both home and school, only home, and only school. To measure digital experience at both home and school, we constructed the "all digital experience" index. This measure of digital experience combines or aggregates the duration of home-based digital experience and school-based digital experience. To do so, this index relies on three components measuring the duration of school-based Internet usage together with the duration of home-based Internet usage and the duration of digital computing device ownership at home. This combined index achieves a high reliability score as well (alpha for underlying items = .77). To measure digital experience at home, we constructed the "home digital experience index." This index is constructed as the average of two survey items: duration of home-based Internet usage and duration of digital computing device ownership at home. The digital home experience index achieves a high-reliability score (alpha for underlying items = .86). To measure digital experience at school, we used a single survey question tracking the duration of Internet usage at school (not an index).

Independent Variable of Theoretical Interest: Academically Useful Computing Index

We operationalize academically useful computing in terms of usage intensity of hours per week. The index is composed of three survey items tracking e-mail activity, digital research, and search engine use for school. The academically useful computing index is constructed as the average of these three survey items. These usage types correspond closely to several types of online activities specified in the Oxford Internet Survey, namely, e-mail, school-related Internet activities, and information-seeking activities (Blank & Groselj, 2014). Our useful computing index scores well on the reliability scale (alpha for underlying items = .73).

Independent Variable of Theoretical Interest: Leisure Computing Index

We operationalize leisure computing in terms of usage intensity of hours per week. The index is built from three survey items monitoring usage of social media such as Facebook, IM, and entertainment sites such as Hulu. The leisure computing index is constructed as the average of these three survey items. It scores lower on the reliability scale (alpha for underlying survey items = .41) but serves as an important predictor variable nonetheless, because the items exhibit considerable theoretical consistency with one another.

Independent Variable of Theoretical Interest: Smartphone Usage Intensity Index

We operationalize smartphone usage in terms of usage intensity per day. The index is constructed from four survey items capturing intensity of daily texting, app use, browser use, and talking. The smartphone index is constructed of the average of these four survey items. The index scores well on the reliability scale (alpha for underlying items = .78).

Control Variables

To account for the cross-individual differences within the student respondent pool arising from individual-level attributes, we control for several potentially confounding background characteristics. We use a dummy variable for gender, and we control for parental education. We also added parental occupational status as a potential control variable, but the addition of this control variable had no effect on the results. We therefore removed this variable from the regression models presented in the article.

Two Types of Multilevel Models

Our multilevel and hierarchically structured data are composed of students nested within 44 classes nested within four curricular tracks. Curricular track can be treated as the highest order unit, class assignment as the middle-level unit, and individual student as the lower-level unit. In our main analyses, we use only two levels simultaneously: (1) individual students nested within (2) school classes. However, in some of the latter analyses, we additionally control for curricular tracks as well as using dummy variables, constituting a “third” level.

To accommodate the nested structure of our data, we utilize two different types of multilevel models: (1) a linear mixed-effects regression model assuming random intercepts (Snijders & Boskers, 1999) and (2) a fixed-effects regression model that actively controls for all-stable higher level unit variation (Allison, 2009). Both types of models gain traction on the potential selection effects following from students' placement in different curricular tracks and school classrooms.

We use both types of models to control for observable individual-level factors as well as possible selection effects associated with placement in a specific curricular track that may lead to spurious correlations between digital inequality variables and our outcome, academic achievement. In the fixed-effects models, we additionally control for student assignment to the same class. Only the fixed-effects regression model, however, controls for nonmeasured sources of spurious correlation. Such nonmeasured sources are likely present on account of students' exposure to particular peer groups, something that could influence both their digital behaviors and their academic achievement.

We designate our initial model, following Snijders and Boskers (1999), as a random-effects model. While this model can be used for both categorical and continuous dependent variables, we apply this random-effects model to a continuous dependent variable. We present a set of linear mixed-effects regression models containing both fixed predictors and random variables. To be more specific, we use a particular kind of linear mixed-effects regression model that assumes random intercepts. In our analyses, we do not put the emphasis on the random variables themselves. Rather, the main motivation is to adjust the estimates' standard errors for the nested structure. To be more conservative in this adjustment of the standard errors, we, therefore, use the lower of the two context-level variables: the student's class assignment. The two-level random-intercepts model divides the variation in the dependent variable among the different levels of the data. In the two-level structure, we nest students (j) within school classrooms (i). The equation for the random-intercepts model is given as

$$y_{ij} = \mu + \beta x_{ij} + \beta z_i + \alpha_i + \varepsilon_{ij} \tag{1}$$

In the random-intercepts model, βx_{ij} represents a set of observed student-level variables and ε_{ij} represents a random-error term applying to the student. The school class-level variables here are the represented βz_i and the random-error term α_i, which applies to the school classroom. The random errors on either level are assumed to be independent and normally distributed. The group-level variables (βz_i and α_i) are school classroom-level characteristics such as class size that do not vary across the individual students.

In an additional preliminary random-intercepts analysis, we provide a simple descriptive decomposition of the variance components according to all three levels simultaneously, using what is known as the empty model. This model accommodates the third level of hierarchical data, namely, the curricular-track level, in addition to the class and student levels. Here, we begin with an empty model, a model with no independent variables. The purpose of this model is to estimate the intraclass correlation (ICC), where the share of variation in the dependent variable is determined for each level of the analysis, namely, the student level, the classroom level, and the curricular track level.

The next type of model we employ, the so-called fixed-effects model (see Allison, 2009), handles group-level variation by actively controlling for all stable characteristics of the group-level units. We enlist this type of model to address measured, nonmeasured, and nonmeasurable sources of potentially spurious correlation. The name *fixed effects* derives from the basic estimation strategy that assigns dummy variables for each group (also known as the least square dummy variable (LSDV) approach. Instead of assuming the group-level variation to randomly vary around the group mean (as α_i in Equation 1), the variation is actively controlled through the use of either dummy variables for each group ($D\alpha_i$) or a mean-differencing technique. The latter estimation technique differences out from Equation (1) all the shared variation resulting from membership in a particular school class (Allison, 2009; Petersen, 2004; Wooldridge, 2002). The variation at the group level may be correlated in any fashion with the omitted variables at the group level in the model. Thus, a strength of the fixed-effects models is that it differences out from the equation all the shared variation resulting from membership in a particular school classroom (Allison, 2009; Petersen, 2004; Wooldridge, 2002). Because there is no variation left for curricular tracks after controlling for the school class level, this strategy simultaneously controls for class and curricular tracks.

The fixed-effects model is particularly desirable in our case because it controls for all potentially confounding attributes of the group-level units. Such confounding is easy to imagine. In one hypothetical example, a very savvy student elects to take an AP English class, and in doing so, adopts new digital behaviors and achieves high grades simply on account of exposure to a particular class environment. By contrasting this model with the random-effects model, we are able to determine to what extent our predictors of digital inequality are uncorrelated with the omitted group-level variables.

Descriptive Findings

Table 3 reports descriptive univariate statistics for the dependent and independent variables we use in the regression models. In the following sections, we examine associations between the specified dependent variable academic achievement and the main predictors of theoretical interest digital experience and the three usage intensity variables. We examine whether such correlations work independently of the students' (1) social background and gender, (2) participation in particular class environments, and finally (3) placement in particular curricular tracks. Before answering these questions, we start by decomposing the amount of variation attributable to the variables corresponding to the different levels of analysis.

Table 3. Descriptive Statistics for Variables in Models.

	Mean	Standard deviation	*N*
Dependent variables			
Academic achievement (GPA)	3.01	0.65	951
Digital experience indices			
All digital experience	4.23	1.26	958
Home digital experience	4.52	1.48	958
School digital experience	4.65	1.56	941
Background characteristics			
Parents' education (years)	10.69	4.41	972
Mother's education (years)	10.93	4.69	972
Father's education (years)	10.45	4.96	972
Gender	0.52	0.50	823[a]
Gendermiss	0.15	0.36	972
Intensity indices for usage types			
Academically useful computing index	1.82	1.14	956
Leisure computing index	1.96	1.34	957
Smartphone index	2.03	1.51	958
Curricular track			
Advanced Placement	0.17	0.38	972
Expository Writing	0.26	0.44	972
Practical English	0.32	0.47	972
English Literature	0.26	0.44	972
School class size	25.26	10.04	972
Number of school classes = 44			

[a]Missing values are set = 0 and gendermiss is included.

How Much Do Class, Track, and Individual Factors Account for Variation in GPA?

Assignment to one of the school's four curricular tracks may have consequences for the student's learning environment and thereby affect GPA. Classes and students can thus be nested within tracks in a three-level model. The three-level model reveals that significant shares of the variation in the outcome (academic achievement) can be explained in terms of differences among the four curricular tracks at the school. In Table 4, we report the share of variation attributed to each of the three levels in empty random-intercept models. The percentages in Table 4 alert us to the fact that 79% of the variation in school performance can be ascribed to characteristics of the individual students. However, we also observe that 17.9% of the variation in the outcome has to do with students' curricular assignment. In contrast, class assignment only contributes 3.1% of the variation in academic achievement. From the three-level decomposition of the variation, we see that curricular track location accounts for a larger share of the variation in the outcome than class assignment. This result makes it clear that any statistical models must account for the possible confounding effects of track assignment. The smaller share of variation due to class assignment suggests that the curricular track assignment outweighs the teachers or fellow students as a source of variation in academic achievement among the students.

Table 4. Share of Variation on Each Level for School Performance.

Level	Academic achievement (%)
Curricular track	17.9
Class assignment	3.1
Student	79.0
Total	100.0

Note. Estimations based on intraclass correlations from empty three-level random-intercept effects models. Students nested within classes (N = 44) and classes nested within curricular tracks (N = 4).

Assessing the Impact of Digital Inequality Variables

We begin by estimating the effects of the three primary digital inequality measures on academic achievement. With the multilevel regression models, we find statistically significant effects of the digital experience predictors on achievement, as illustrated in Table 5 where all models rely on standard errors clustered on the school class level. Findings are also illustrated in Figure 1, which is based on Table 5. Figure 1 shows the regression of academic achievement (GPA) on digital experience, as well as control variables. The lines illustrate the gross effects where other control variables are taken into account and gross models where only digital experience is taken into account. Here, we see the association between digital experience (at both home and school, only home, and only school) and our dependent measure, academic achievement (GPA).

Figure 1 reports predicted margins of the aggregate combined measure of digital experience at both home and school. Note that the effect size equals the effect size of the combined predictor when one sums the coefficients for digital experience at home and digital experience at school. Here, the net models are based on Models 6 and 7 in Table 5. The gross models are based on Models 1 and 7. Figure 1 also reports the net and gross models for our two disaggregated computer indices: digital experience at home and digital experience at school. In Figure 1, the gross models are based on Model 1 in Table 5, while the net models are based on Model 6 in Table 5. Across all the models, the digital experience variable has a positive effect on academic achievement (GPA). Moreover, the effect seems to be only marginally confounded through differences associated with class assignment.

As the effect of digital experience on the outcome may be confounded by students' parental education or gender, Model 2 (Table 5) therefore controls for students' parental education and gender. Model 2 indicates that neither gender nor parental education

Table 5. Results From Regression Models Predicting Academic Achievement.

	Random-effects models			Fixed-effects models			
	Gross model	Background	Type of use	Curricular track	School class	Aggregate experience	
						Gross	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Digital experience, home and school						.0833*** (.0183)	.0746** (.0221)
Digital experience, home	.0463** (.0147)	.0436** (.0164)	.0587*** (.0165)	.0485** (.0162)	.045** (.0163)		
Digital experience, school	.0395** (.0123)	.0392** (.0125)	.0373** (.0137)	.0331* (.0135)	.0309* (.013)		
Gender (ref = male)		−.000411 (.046)	−.0243 (.047)	.000118 (.0483)	−.000512 (.0496)		−.0074 (.0493)
Gender (missing)		.0187 (.0587)	.00413 (.0604)	.0272 (.0593)	.0362 (.06)		.0298 (.061)
Parents education, years (ref = mean)		.00279 (.0059)	.00341 (.0056)	.0018 (.00562)	.00194 (.00572)		.00226 (.00559)
Class size (ref = mean)		.00399 (.00434)	.00361 (.00379)	.000185 (.00211)			
Usage intensity: Academic use computing (Index)			.0782*** (.0208)	.0602** (.0201)	.0633** (.0206)		.0642** (.0203)
Usage intensity: Leisure use computing (Index)			−.0564*** (.017)	−.0458* (.0181)	−.0428* (.0174)		−.0412* (.0173)
Usage intensity: Smartphone (Index)			−.0411** (.0126)	−.0315** (.0118)	−.0289* (.0123)		−.0302* (.0124)
Advanced Placement				.647*** (.0923)			
Expository English				.372*** (.0507)			
English Literature				.42*** (.064)			
Practical English				ref.			
Constant	2.61*** (.078)	2.64*** (.0915)	2.64*** (.0842)	2.37*** (.0925)	2.69*** (.088)	2.65*** (.0791)	2.73*** (.0881)
Fixed-effects school class	No	No	No	No	No	Yes	Yes
Fixed-effects tracks	No	No	No	Yes (LSDV)	Yes	Yes	Yes
Number of classes	44	44	44	44	44	44	44
Number of students	930	930	930	930	930	930	930

Note. Standard errors in parentheses. LSDV = least square dummy variable.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

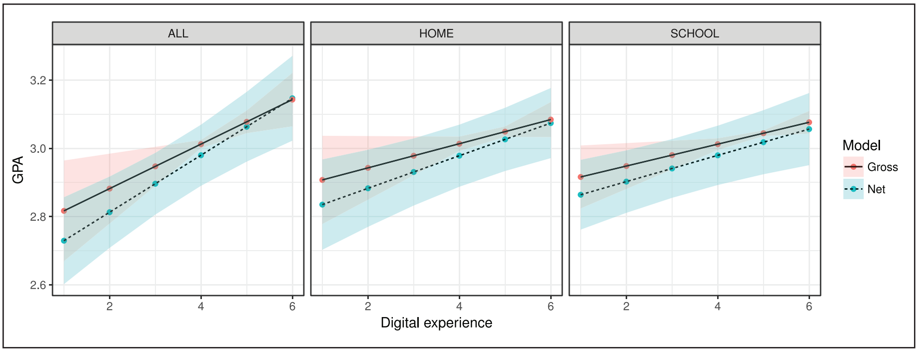

Figure 1. Gross and net effects of digital experience on academic achievement (predicted margins at the grand mean).
Note. Predicted grade point average (GPA) derived from Models 1 + 6 + 7 in Table 5. Confidence intervals set at 95% based on robust standard errors.

confounds the impact of digital experience on academic achievement. After taking into account parental education (e.g., parents' highest degree), the effect size of digital experience on academic achievement remains largely the same and retains the same level of statistical significance. From Table 5, it is also apparent that academic achievement does not vary by gender in this analysis.

Model 3 in Table 5 includes variables measuring academically useful-computing, leisure computing, and smartphone usage. When added to Model 3, the intensity of usage indices capturing smartphone usage and leisure computing correlate negatively with academic achievement. All the models indicate that the GPA of high-intensity smartphone users is lower than that of their lighter intensity counterparts, net of controls and effects due to curricular track placement. The negative effect of high-intensity smartphone usage persists, even when the effects of school class and curricular track assignment are taken into account (see Models 4, 5, and 7). As revealed by interviews with many of these same students, for this academically stratified student population, the formation of academic skills and competencies is thus promoted by longer durations of digital experience (Robinson, 2014a). Smartphone usage exhibits the opposite association with GPA: the lighter the intensity of smartphone usage, the higher the students' GPA.

Does the Digital Experience Effect Vary by Curricular Program Placement?

Model 4 in Table 5 includes dummy variables for the curricular track assignment. The dummy variables show that students enrolled in Practical English (the reference category) have the lowest GPA and the students enrolled in AP English have the highest GPA. In Figure 2, we see how students' curricular track assignments interact with the effect of digital experience on academic achievement. The interaction effects are statistically

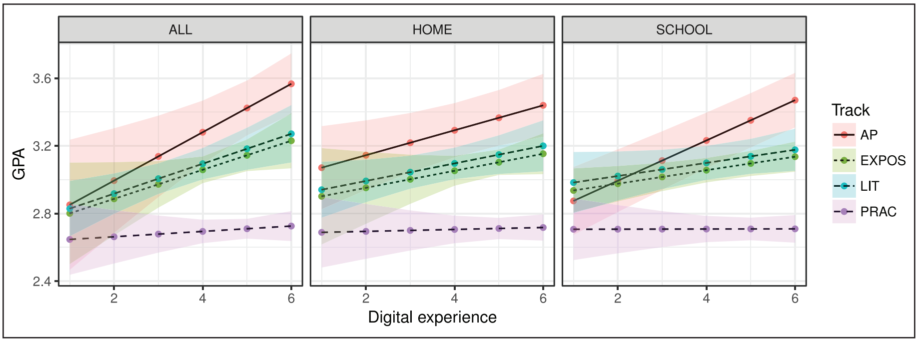

Figure 2. Academic achievement dependent on home and school digital experience for all curricular tracks net of controls (predicted margins at the grand mean).
Note. Predictions derived from random-effects models using school class as the group variable, with interactions between curricular track and digital experience variable (95% confidence intervals are included).

significant net of control variables. The coefficients for the interaction terms suggest the presence of significant differences in academic achievement across the four curricular tracks. Given the fixed-effects models using school classes in the preceding models, we opt not to show these interactions in Table 5 for the sake of clarity and simplicity.

As is evident from Figure 2, the effects of the digital duration variable on academic achievement vary according to the student's curricular track assignment. From these results, we infer that longer exposure to digital resources widens the achievement gap between students in the AP curricular track relative to students in both the intermediate curricular tracks (English Literature and Expository Writing) as well as the Practical English curricular track. Figure 2 renders evident the ways in which curricular track placement conditions the effects of digital experience on academic achievement. Figure 2 shows how academic achievement varies according to curricular track placement as a function of the duration of students' digital experiences as measured by our combined index of home and school, only home, and only school digital experience. Finally, Figure 2 also illustrates complementary results for the disaggregated measures of duration at home and at school.

It is clear from the models that curricular placement interacts with digital experience in different ways, depending on the student's track placement, particularly for the measure of digital experience at school. For the students taking classes within the college preparatory tracks (AP, English Literature, Expository Writing), the higher the student's curricular program placement, the stronger the positive effect of school-based digital experience on academic achievement, net of controls. In other words, while AP students benefit substantially from longer durations of digital experience at home and particularly at school, for the students enrolled in Practical English courses, longer durations of digital experience both at home and at school do not appear to boost their GPA to nearly the same degree. For students in Practical English, only the combination of the two forms of digital experience makes any positive difference to academic achievement, and this effect appears minimal in magnitude when compared with the other groups.

Summary of Findings

This research takes advantage of a revealing case study of a stratified digital bind environment in the form of an under-resourced public secondary school we call Rancho Benito High. This school exemplifies the digital bind as it serves largely disadvantaged students, yet it cannot provide adequate digital resources often required for school assignments. At the same time, Rancho Benito High serves as an excellent example of a stratified educational institution that channels students into distinct curricular tracks.

Our analyses find both a digital experience effect and a usage intensity effect within curricular tracks. We find that academic achievement in such an environment reflects digital stratification. The findings leave no doubt that digital disparities can be highly consequential when it comes to the academic achievement of economically insecure students who have the most to gain from educational success and the most to lose from educational failure. Where the digital bind is present for some students and where the students are characterized by predominantly economically disadvantaged backgrounds, academic achievement is codetermined by students' digital activities and their placement within curricular tracks.

Therefore, our results support all four of the hypotheses presented in the beginning of the article. As the duration of digital experience at home or school or both increases, students' grades (as measured by GPA) will increase (Hypothesis 1). Digital experience has the strongest positive effect on GPA for those students with digital experience at both home and school. The synergy achieved through the combination of duration of digital experience and multiple access-point usage-in this case home and school-pays especially high academic dividends. As the level of usage intensity for academically useful computing increases, students' grades (as measured by GPA) will increase (Hypothesis 2). The analysis also supports the third hypothesis: as the level of usage intensity for smartphones and leisure computing decreases, students' grades (as measured by GPA) will increase. All these effects persist at statistically significant levels even after fixed-effects models have been employed to eliminate the potentially confounding effects of class assignment and curricular track assignment on academic achievement. All predictors of theoretical interest are also robust to the introduction of control variables indexing the educational backgrounds of students' parents and gender.

Just as important, the presence of an interaction effect between curricular placement and digital experience supports the fourth hypothesis. The higher the student's placement in a curricular track, the stronger the effect of digital experience on grades (as measured by GPA). Students' placement in the curricular tracking system thereby conditions the relationship between academic achievement and duration of digital experience (Hypothesis 4). The highest tracked AP students gain the greatest returns in terms of GPA from extended durations of digital experience. In comparison, those students positioned in the bottom track reap negligible benefits from the same durations of digital experience. Students in the intermediate curricular tracks benefit from longer periods of digital experience, but to a far lesser extent than their AP counterparts. Thus, the largest academic dividends of digital experience are concentrated among those students enrolled in AP courses situated in the highest of the four curricular tracks.

Contributions and Implications

The analysis has advanced our understanding of both digital inequality and academic achievement along several axes. First, the study has established that digital inequalities have measurable consequences for academic achievement in a stratified digital bind environment. Digital inequality functions in tandem with curricular inequalities to structure academic achievement. Second, the article provides evidence that two key forms of digital inequality—digital experience and usage intensity for academically useful computing—are not interchangeable in their functioning or effects, given that only digital experience interacts with curricular placement. Finally, types of usage matter, as smartphone usage and leisure computing intensity have effects contrary to those of academically useful computing. This disparity mirrors the results from other studies, which alert us to the discrepancies between more class-advantaged students who use digital resources for capital-enhancing purposes guided by their teachers and parents and less class-advantaged students who tend to use the Internet more intensively for recreational and entertainment purposes (Micheli, 2015).

This study makes it clear that neither emergent nor long-standing institutional forms of inequality can be dismissed in accounts of academic achievement. Indeed, digital inequalities are implicated in academic achievement alongside curricular stratification. Since this form of achievement has long-lasting consequences for individuals' social and economic trajectories well into adulthood (French, Homer, Popivici, & Robins, 2015), digital inequalities in adolescence and childhood may, therefore, cast a long shadow. At the same time, the findings simultaneously speak directly to the foundational task at the heart of digital inequality research, namely, the identification of pathways linking specific forms of digital inequality and (dis) advantage, on the one hand, and specific outcomes, on the other hand. Indeed, the results give us grounds for some important inference about these linkages in this regard. First, it is only digital experience whose effects on academic achievement are conditioned by track placement. Academically useful computing has approximately the same positive effect on academic achievement, but it is *not* conditioned by track placement. This result reveals that long-term cumulative differences in patterns of digital activity interact with curricular tracking even when the intensity of digital activities does not.

One explanation for this pattern has to do with the cumulative character of digital skill building. It is likely, based on the extensive interviews with many of these same students, that students with more digital experience are able to develop foundational digital skills earlier than their less-experienced counterparts (Robinson, 2014b). Students who are recently introduced to digital media must master basic skills while also doing academic work. In contrast, more digitally experienced students can focus their time and energies on the academic tasks, resulting in higher levels of academic achievement. This extrapolation warrants future study through longitudinal investigations into digital skill building in such stratified digital bind environments. Indeed, this skill-building process should be examined in future work touching on phenomena other than academic achievement in which digital skill acquisition may play a crucial role. Exactly how this cumulative process of skill building works—as well as the application of those skills in different life arenas and motivating factors (Ball, Huang, Rikard, & Cotten, 2017)—are worthwhile topics for future study.

Limitations and Future Research

While it should be noted that the findings cannot be generalized to a larger population, as the data derive from a single case study, they nevertheless deserve our attention for several reasons. First, the results are based on data drawn from a hard-to-reach population of theoretical and empirical interest, namely disadvantaged young people living on the fringe of the digital world. Furthermore, the research provides a template for future studies focusing on digital bind environments analogous to the school under study, both inside and outside the educational arena. Future studies could seek to identify connections between academic and nonacademic outcomes, on the one hand, and digital and nondigital determinants, on the other hand. For example, the workplace is an environment where employment status and organizational rank, institutional markers akin to curricular track placement, could come together with various forms of digital inequality to affect job performance or compensation. Such an environment could provide fertile terrain for investigating how digital stratification orders interact with nondigital stratification orders similar to the curricular tracking system we have examined in this study.

Acknowledgments

The authors wish to thank Michael Johnston for his invaluable expertise, as well as the educators, students, and staff at Rancho Benito High who generously offered their insights.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Laura Robinson thanks the Santa Clara University Miller Center for Social Entrepreneurship, the Bannan Institute-Ignatian Center for Jesuit Education, the SCU Internal Research Grants Program, and the SCU Faculty-Student Research Assistant Award Program for funding for the project.

References

Allison, P. D. (2009). *Fixed effects regression models* (Vol. 160). Thousand Oaks, CA: Sage.

Archbald, D., & Keleher, J. (2008). Measuring conditions and consequences of tracking in the high school curriculum. *American Secondary Education*, *36*(2), 26-42.

Ball, C., Huang, K. T., Rikard, R. V., & Cotten, S. R. (2017). The emotional costs of computers: An expectancy-value theory analysis of predominantly low-socioeconomic status minority students' STEM attitudes. *Information, Communication & Society*. Advance online publication. doi:10.1080/1369118X.2017.1355403

Becker, H. J. (2000). Who's wired and who's not: Children's access to and use of computer technology. *Future of Children*, *10*(2), 44-75.

Blank, G., & Groselj, D. (2014). Dimensions of Internet use: Amount, variety, and types. *Information, Communication, & Society*, *17*, 417-435. doi:10.1080/1369118X.2014.889189

Carbonaro, W. (2005). Tracking, students' effort and academic achievement. *Sociology of Education*, *78*, 27-49.

Domina, T., Penner, A., & Penner, E. (2017). Categorical inequality: Schools as sorting machines. *Annual Review of Sociology*, *43*, 311-330. doi:10.1146/annurev-soc-060116-053354

Gamoran, A. (1992). The variable effects of high school tracking. *American Sociological Review*, *57*, 812-828. doi:10.2307/2096125

French, M. T., Homer, J., Popivici, I., & Robins, P. K. (2015). What you do in high school matters. *Eastern Economic Journal*, *41*, 370-386.

Gulek, C. J., & Demirtas, H. (2005). Learning with technology: The impact of laptop use on student achievement. *Journal of Technology, Learning, and Assessment*, *3*(2), 4-35.

Hallinan, M. (1994). School differences in tracking effects on achievement. *Social Forces*, *72*, 799-820. doi:10.1093/sf/72.3.799

Helsper, E. J. (2012). A corresponding fields theory model for the links between social and digital exclusion. *Communication Theory*, *22*, 403-426. doi:10.1111/j.1468-2885.2012.01416.x

Jackson, L. A., von Eye, A., Biocca, F. A., Barbatsis, G., Zhao, Y., & Fitzgerald, H. E. (2006). Does home Internet use influence the academic performance of low-income children? *Developmental Psychology*, *42*, 429-435. doi:10.1037/0012-1649.42.3.429

Jackson, L., Zhao, Y., Kolenic, A., Fitzgerald, H., Harold, R., & von Eye, A. (2008). Race, gender, and information technology use: The new digital divide. *CyberPsychology & Behavior*, *11*, 437-442.

Judge, S. (2005). The impact of computer technology on academic achievement of young African-American children. *Journal of Research on Childhood Education*, *20*, 91-102. doi:10.1080/02568540509594554/

Judge, S., Puckett, K., & Bell, S. (2006). Closing the digital divide: Update from the Early Childhood Longitudinal Study. *Journal of Educational Research*, *100*, 52-60.

Junco, R., & Cotten, S. (2011). Perceived academic effects of instant messaging use. *Computers & Education*, *56*, 370-378.

Junco, R., & Cotten, S. (2012). No A 4 U: The relationship between multitasking and academic performance. *Computers & Education*, *59*, 505-514.

Lei, J., & Zhao, Y. (2007). Technology use and student achievement: A longitudinal study. *Computers & Education*, *49*, 284-296. doi:10.1016/j.compedu.2005.06.013

Lucas, S. R., & Berends, M. (2002). Sociodemographic diversity, correlated achievement, and de facto tracking. *Sociology of Education*, *75*, 328-348. doi:10.2307/3090282

Mesch, G., & Talmud, I. (2010). *Wired youth: The social world of adolescence in the information age*. New York, NY: Routledge.

Micheli, M. (2015). What is new in the digital divide? Understanding Internet use by teenagers from different social backgrounds. In L. Robinson, S. R. Cotten, J. Schulz, T. M. Hale, & A. Williams (Eds.), *Communication and information technologies annual* (Vol. 10, pp. 55-87). Emerald.

National Center for Education Statistics. (2013). *Table 702.10*. Retrieved from https://nces.ed.gov/programs/digest/d15/tables/dt15_702.10.asp?current=yes
Nævdal, F. (2007). Home-PC usage and achievement in English. *Computers & Education*, *49*, 1112-1121.
Patterson, R. W., & Patterson, R. M. (2017). Computers and productivity: Evidence from laptop use in the college classroom. *Economics of Education Review*, *57*, 66-79. doi:10.1016/j.econedurev.2017.02.004
Petersen, T. (2004). Analyzing panel data: Fixed-and random-effects models. In M. Hardy & A. Bryman (Eds.), *The handbook of data analysis*. (pp. 331-346). London, England: Sage.
Robinson, L. (2014a). Endowed, Entrepreneurial, and Empowered-Strivers: Doing a lot with a lot, doing a lot with a little. *Information, Communication & Society*, *17*(5), 521-536.
Robinson, L. (2014b). Freeways, detours, and dead ends: Search journeys among disadvantaged youth. *New Media & Society*, *16*(2), 234-251.
Snijders, T. A. B., & Bosker, R. J. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. London, England: Sage.
Van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2013). The digital divide shifts to differences in usage. *New Media & Society*, *16*, 507-526. doi:10.1177/1461444813487959
Wainer, J., Dwyer, T., Dutra, R. S., Covic, A., Magalhães, V. B., Ferreira, L. R. R., . . . Claudio, K. (2008). Too much computer and Internet use is bad for your grades. *Computers & Education*, *51*, 1417-1429. doi:10.1016/j.compedu.2007.12.007
Wooldridge, J. M. (2002). *Econometric analysis of cross-section and panel data*. Cambridge: MIT Press.
Yin, R. K. (1994). *Case study research: Design and methods*. Thousand Oaks, CA: Sage.

Author Biographies

Laura Robinson is associate professor in the Department of Sociology at Santa Clara University. She earned her PhD from UCLA, where she held a Mellon Fellowship in Latin American Studies and received a Bourse d'Accueil at the École Normale Supérieure. She is a series coeditor for *Emerald Studies in Media and Communications* and previously served as the Chair of Communication, Information Technologies, and Media Sociology (formerly Communication and Information Technologies section of the American Sociological Association). Her research has earned awards from the Communication and Information Technologies section of the American Sociological Association, and the Association of Internet Researchers, and the National Communication Association International and Intercultural Communication Division. Robinson's work examines digital and informational inequalities, interaction and identity work, as well as digital media in Brazil, France, and the United States. Current multiyear study examines digital and informational inequalities. Her website is www.laurarobinson.org.

Øyvind Wiborg is an associate professor at the Department of Sociology and Human Geography, University of Oslo, and a researcher at the Center for the Study of Professions, Oslo Metropolitan University. His research is quantitative and focuses on social inequalities, with special attention to social reproduction across and within generations, within the educational system as well as the labor market. He has been a visiting scholar at the University of California, Berkeley and a senior researcher at the Nordic Institute for studies in Innovation, Research and Education.

Jeremy Schulz is a visiting scholar in residence at the Institute for the Study of Societal Issues, UC Berkeley. After earning his PhD at University of California, Berkeley, he held a National Science Foundation postdoctoral fellowship at Cornell University, served as an affiliate at the UCSD Center for Research on Gender in the Professions, and was elected as a Council Member of the American Sociological Association Section on Consumers and Consumption. He has published on a broad range of topics, including consumption, work, family, culture, and inequalities. His publications include "Talk of Work" published in *Theory and Society* and "Shifting Grounds and Evolving Battlegrounds," published in the *American Journal of Cultural Sociology*. His article "Winding Down the Workday," published in *Qualitative Sociology*, received the Shils-Coleman Award from the ASA Theory Section. His current research examines family business, wealth trajectories, indebtedness, and innovative qualitative methods. His website is www.jeremyschulz.org.