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Laptop or Bust: How Lack of Technology Affects Student Achievement

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Abstract

Research shows that digital divides and inequalities are related to lower socioeconomic status and detrimental to social and economic capital acquisition. Other studies show that use of information and communication technologies in the classroom can lead to worse academic performance. Nevertheless, many universities require that students own or buy a laptop, and many offer financial aid for students who cannot afford to buy one. As such, laptop ownership may be crucially tied to academic performance. Based on a large data set of incoming freshmen at a large public university in the United States, this article shows that not owning a laptop is negatively associated with overall college performance, even when controlling for socioeconomic background. Whereas we find that laptop ownership is not necessarily responsible for the higher performance of individuals in our broader sample, it could be beneficial to nonowners, which has implications for university policies seeking to provide institution-wide access to laptops and for universities' broader interactions with students who do not own a laptop.

Keywords

digital divide, digital inequalities, laptops, higher education, academic performance

Introduction

There is a large body of work on whether information and communication technologies, such as mobile phones or laptops in classrooms pose a distraction to college

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students (Fayyoumi, 2014; Fried, 2008; Patterson & Patterson, 2017). Similarly, research has shown that having access to the Internet and information and communication technologies, quality and location of access, and types of devices as well as the means to maintain these devices have a strong impact on what individuals in highly connected countries, such as the United States, can and cannot do (Gonzales, 2016; Gonzales et al., 2018; Keegan Eamon, 2004; Ryan & Lewis, 2017, Van Deursen & van Dijk, 2019). As such, U.S. higher education institutions have come to recognize the importance of Wi-Fi and computers for students to succeed in their studies.

For example, Michigan State University (MSU), the source of data for this article, implemented a new requirement in Spring 2017 that "all undergraduate students [. . .] are required to have a laptop computer that can connect to the Internet" (MSU, n.d.). Previously, students were required to have any kind of computer, desktop, or laptop. Students agree to this requirement implicitly when they accept their place at the university. Financial aid for the purchase of a working laptop as well as loaners are available for students who struggle with purchasing or maintaining access to a working laptop. However, with an undergraduate student body of roughly 40,000 students, many from diverse backgrounds, it may still be the case that many students lack a working laptop, despite the options for help in purchasing and maintaining the technology. Anecdotal evidence from faculty and students indicated that each class had a handful of students who did not have a laptop available to them, which hindered participation in class and flexibility in completing homework outside of class. However, hard evidence was not available to support this claim, and research on laptops in university settings has mostly focused on uses and classroom performance (e.g., Patterson & Patterson, 2017), rather than laptop *ownership* and overall college performance. Based on a large survey of freshmen at MSU during the fall semester 2016, we examine the following questions:

Research Question 1: How many incoming freshmen at MSU did not have a laptop in 2016 and why?
Research Question 2: What were the primary demographic characteristics that were associated with laptop nonownership at MSU during the year 2016?
Research Question 3: How might laptops or laptop nonownership have affected academic performance?

Background

Digital Inequalities and Devices

Despite a shift of digital divide research from first-level divides—material access to devices and Internet connections—toward a focus on second-level divides operationalized as digital literacy, skills, and uses, and third-level divides—outcomes of Internet use—there has been a renewed focus on how first-level divides affect second- and third-level divides (Cohron, 2015; Rowsell et al., 2017). Van Deursen and van Dijk (2019) found that material access to devices and peripherals have an ongoing effect on

second- and third-level divides for residents of the Netherlands, one of the most connected countries in the world. Relatedly, Hampton et al. (2020) found that the means of access is crucial in rural Michigan, where students who only had access to the Internet using a mobile device underperformed those with a fixed connection that could support wired or wireless devices.

In addition, access does not stop at obtaining or owning a device. Devices and Internet connections have to be maintained when they are malfunctioning or stop working altogether. Technology maintenance is a factor that contributes to continuing digital divides and inequalities for marginalized and less fortunate communities (Gonzales, 2016; Gonzales et al., 2016). Considering that computer ownership and household Internet subscriptions in the United States are still strongly associated with higher income levels and are considerably higher among White and Asian American households (Ryan & Lewis, 2017), it is important to consider if and how we find similar effects among college students.

Digital Inequalities in (Higher) Education

Higher education is a specific context within which to examine digital inequalities. Most higher education institutions in the United States offer free Wi-Fi to their students[1] and facilitate education through virtual learning platforms like Blackboard or Canvas (McKenzie, 2018). This could lead to the premature assumption that because they are better connected (Dahlstrom & Bichsel, 2014; Smith et al., 2011), college students are not a group to worry about digital inequality research. However, the necessity to be able to use all these technologies to conduct schoolwork online also means that college students who are digitally disadvantaged may suffer serious consequences that are present in lower academic performance and lower digital literacy.

To combat digital inequalities at higher education institutions, some colleges trialed or instituted initiatives that provided laptops to all incoming students, as was, for instance, done at a Western Pennsylvania college in 1994 (Finn & Inman, 2004). The results were positive attitudes of students toward the initiative and a diminishing of digital divides based on gender and field of study. Cotten and Jelenewicz (2006) found that environments that provide universal access can help diminish digital divides. However, there were still differences in how college students used the universal Internet access that was provided along gender and experience with the technology. Due to these second-level divides, some scholars have argued that digital inequality initiatives in higher education must go beyond provision of laptops and other material access to also address digital skills and literacy (Peña-López, 2010). In addition to digital literacy issues, a considerable number of students struggle to maintain access to technologies. Although Gonzales et al. (2018) found that almost all students in their survey had a laptop or cell phone, 20% struggled to maintain access to technology (e.g., laptops breaking). They found that students with lower socioeconomic status and students of color were more affected and that these issues were related to a lower grade point average (GPA).

This research suggests that ownership and ability to maintain a laptop or similar technology has become a necessity in higher education. It is therefore important to understand who is least likely to be able to partake in this digital college environment and with what effects.

Benefits and Drawbacks of Digital Devices in Higher Education

Not everyone is in favor of the ever-increasing presence of laptops, tablets, and smartphones in classrooms. Anecdotal evidence in higher education institutions is ripe with stories of distracted students with adverse effects for class outcomes and exhausted faculty who feel like they have to police their students' technology use (May, 2017). This has led to some calls to ban laptops and other technologies from classrooms, with some faculty including such statements in syllabi or asking students to put away any technologies at the beginning of each class.

There is ample research on how laptops and other portable technology affect student behaviors and outcomes in classroom settings. In a university or college setting, laptop use has been shown to have both beneficial and adverse effects, depending on the type of activities that students perform during classes.[2]

For example, lecture-related smartphone activities have been found to positively affect performance and satisfaction levels (Fayyoumi, 2014; Gaudreau et al., 2014). Moreover, university students' perceptions of the usefulness of laptops for academic success have been shown to be related to how well faculty utilize technology in their classes, with most students finding laptops to be essential to their overall academic success (Demb et al., 2004).

There is, however, substantial evidence for the potential distracting nature of laptops inside and outside of the classroom. Device-based multitasking has a negative effect because it reduces student focus and limits cognitive capacity (Fayyoumi, 2014). Devices can also distract users' classroom peers (Kay & Lauricella, 2011). Studies that looked at how device use affects student outcomes in large lecture settings have found that students who used devices during class had a lower GPA (Carter et al., 2017; Lepp et al., 2014; Patterson & Patterson, 2017), and reported lower understanding of course materials (Fried, 2008).[3] Ravizza et al. (2017) found that students in an introductory psychology class at MSU, the very same university we are examining here, commonly engaged in nonacademic activities on their laptops, with time spent on such activities negatively related to performance.[4] In addition to lower academic performance, students appear to underestimate (or underreport) how much time they spend on multitasking and distracting behaviors during classes (Kraushaar & Novak, 2010).

Although the evidence for potential downsides of laptop use seems to suggest that not owning a laptop might, in fact, be better for students, we argue that laptops have become such an integral part of teaching cultures at higher education institutions that we need to examine laptop ownership and academic performance at a larger scale than the classroom setting. When technology is integrated into the classroom, not owning a laptop could leave a student at a disadvantage. In addition to classroom note-taking, a laptop allows students to do homework and research between classes and on the go.

Students who cannot afford a laptop are bound to computer labs at school or desktop computers in their (dorm) room, allowing them considerably less flexibility and time in which they can do their homework, research, and reading assignments. Thus, a recommendation to restrict classroom laptop use (Carter et al., 2017; Patterson & Patterson, 2017) is not incompatible with a finding that laptops could be beneficial to overall student outcomes. Moreover, even if laptops were not found to have positive causal effects on performance, if there is an achievement gap between laptop owners and (the relatively few) nonowners, it is worth for school officials to explore and to attempt to remedy, whether through improved technology access or by other means.

In the following section, we describe our methodology used to examine how many students are, in fact, without a laptop, who is affected, and how nonownership relates to student achievement.

Methodology

Data

In this study, we use 2016 survey data from MSU. The survey is sent to all incoming freshmen every fall semester to provide administrators with key data for identifying at-risk students early on to allow for immediate support that could boost academic retention and success.[5]

The baseline survey contains standard demographic data, including race, gender, sexual orientation, parents' education level, and financial need, along with performance related variables, such as GPA (see Table 1).

In addition, we added three questions concerning laptop ownership and usage:

1. When did you first acquire your personal laptop computer? (1 = prior to attending MSU; 2 = on enrolling; 3 = have not purchased one yet, but plan to acquire one soon; 4 = do not have a laptop, and do not have plans to acquire one)
2. If you do not own a laptop, what are the reasons that you don't own a laptop? (Select all that apply: 1 = I have a laptop; 2 = cost, for example, can't afford it and don't want to take out a loan; 3 = cost, for example, can't afford it and have exhausted all loan resources; 4 = don't need it; 5 = don't want it)
3. If you do not own a laptop, do you feel that it affects your participation in classrooms and/or assignments? (1 = yes, positively, for example, I don't get distracted in class; 2 = no effect; 3 = yes, negatively, for example, can't do certain tasks)

Unfortunately, due to the length of the survey, we were unable to add any additional questions, such as age and functionality of owned laptops and whether students were able to maintain the technology (see Gonzales et al., 2018).

A total of 8,306 students completed the survey in 2016. Out of these, 4,370 students answered our laptop-related questions. In addition to dropping students who did not

Table 1. Demographic and Performance Variables.

Demographics	
Sex	The sex that the student was assigned at birth (female, male).
Ability	Student's disability status (disabled, not disabled).
Race	The student's race (White, Black, Hispanic, Asian, other).
Sex orientation	The student's sexual orientation (heterosexual/straight, not heterosexual/straight).
First generation	Whether students are in the first generation in their family to enroll in college (yes, no).
Education of parent	The highest level of student's parent or legal guardian education (high school or less, some college/associate degree, bachelor's degree or higher, don't know).
Financial aid	The percentage of the student's financial need met through financial aid (none and no need, none with need, about 25%, about 50%, about 75% or more, don't know).
Community	Type of geographic community where student previously resided (urban, suburban, rural, other).
Performance	
GPA	The Fall 2016 end of semester GPA (between 0.0 and 4.0).

Note. GPA = grade point average. GPA was measured as the GPA reported by Michigan State University. MAP works has the ability to match individuals' GPAs to their responses. The authors received a deidentified data set, which included the GPA for fall semester 2016.

complete the laptop questions from our sample, we additionally dropped 200 observations for inconsistently answering the laptop nonownership questions. This left us with 4,170 observations, including 4,097 laptop owners and 73 nonowners. While this may appear like a negligibly low number of freshmen who do not own a laptop (1.8% of those who answered our laptop questions), our results show that the distribution of nonownership follows classic patterns of (digital) inequalities.

Table 2 presents the demographic constitution of our 4,170 student subsample and also partitions these demographics according to laptop ownership. Over half (56.7%) of participants in the sample were female (male, 41.6%), which is reasonably close to the 2016 projection of 55.2% and 44.8%, respectively, across 4-year degree granting institutions in the United States.[6] In contrast, individuals who are White (68.2%) were overrepresented in our survey data, whereas those who are Black, Hispanic, or of other racial makeup (e.g., two races) were underrepresented.[7] Moreover, only approximately 39% of individuals in our sample reported receiving at least some financial aid (with an additional 21% being uncertain), which is substantially lower than the 83.5% reported across 4-year public institutions across the United States for 2014-2015.[8]

For each variable category, the third and fourth columns of Table 2 denote the percentage of individuals in that category who owned laptops and the percentage of those who did not. Although most students owned a laptop, as in Table 2, females in our sample were more likely to be owners than males and individuals who are White or Asian were more likely to be owners than individuals who are Black, Hispanic, or

Table 2. Demographics by Laptop Ownership (%).

Category	Total	Laptop	No laptop
Gender			
Female	56.7	98.6	1.4
Male	41.6	97.7	2.3
Disability			
No	80.2	99.0	1.0
Yes	18.1	95.4	4.6
Race/ethnicity			
White	68.2	99.1	0.9
Black	6.9	95.3	4.7
Hispanic	4.3	96.3	3.7
Asian	6.5	98.9	1.1
Other	12.3	95.9	4.1
Sexual orientation			
Heterosexual/straight	83.3	98.8	1.2
Not heterosexual/straight	14.9	95.5	4.5
First generation student			
No	77.3	98.8	1.2
Yes	20.9	96.4	3.6
Parent education			
College degree (BA or higher)	73.8	99.3	0.7
Some college or associate degree	16.2	96.4	3.6
High school or less	8.4	94.7	5.3
Financial aid			
No financial aid and don't need financial aid	26.8	99.6	0.4
No financial aid but need financial aid	11.7	99.4	0.6
About 25%	11.5	98.8	1.2
About 50%	5.6	96.7	3.3
75% or more	21.3	96.5	3.5
Don't know	21.4	98.1	1.9
Community			
Urban	40.6	98.6	1.4
Suburban	17.2	96.8	3.2
Rural	32.3	99.0	1.0
Other	8.1	96.8	3.2

Note. $N = 4{,}170$; Laptop and No laptop columns represent percentage of individuals in Total column who, respectively, own or do not own a laptop.

other. Individuals who had a disability were substantially less likely to own a laptop (4.6%) in contrast to only 1% of those who did not report a disability. A similar contrast appears with regard to sexual orientation, with 4.5% of those who did not identify as heterosexual not owning a laptop in comparison with 1.2% of those who identified

as heterosexual. Consistent with previous work on digital inequalities, a higher percentage of those who identified as first-generation college students, those who had parents with relatively less education, and those who received financial aid were laptop nonowners, and individuals from urban or rural communities were less likely to own a laptop than those from suburban communities.

Statistical Methods

In the subsequent analyses, we sought to answer two questions: "What are the primary demographic characteristics that are associated with laptop nonownership?" and "How do laptops, and specifically, laptop nonownership affect academic performance?"

To answer the first question, we used logit and probit specifications to regress laptop ownership on the demographic covariates described in Table 1. The logit and probit specifications are appropriate for an analysis of which demographic background characteristics are associated with laptop ownership because the outcome variable (laptop ownership) is binary. To account for missing demographic data, we imputed data using different regression approaches that rely on data of remaining observed covariates and replaced missing values with predictive values obtained.[9]

The second question was a key motivation for undertaking this study. If laptop ownership were a significant predictor of academic performance, it would be important for school officials to be able to engage in targeted interventions to boost academic success among those who struggle to own (or maintain) a functioning laptop. Indeed, our data indicates that laptop ownership could serve as a highly useful barometer for intervention. One way analysis of variance tests of the demographic variables in Table 1 indicate that the mean Fall 2016 GPA is statistically significantly different across demographic characteristics.

Ordinarily, the number of demographic categorizations and variation within categories could make it difficult to design an intervention that selectively targets a group of individual students.[10] However, because laptop ownership is so prevalent, if laptop ownership is predictive of academic success, an intervention could focus on individuals who do not own laptops. We stress that an intervention need not imply providing access to technology unless a causal relationship between laptop ownership and academic achievement is established. Poor academic performance may, for instance, be tied to the combination of demographic characteristics that lead to laptop nonownership, and not to the lack of ownership itself. In this case, laptop nonownership serves as a predictor of poor performance, which might be ameliorated through other means.

As a preliminary measure, we used *t* tests to compare the academic performance of laptop owners and nonowners. Although all statistically significant, these tests give a biased estimate of the "average treatment effect" (ATE) of laptop ownership on performance because laptop owners and nonowners do not necessarily have comparable demographic characteristics. To correct for this bias and, in turn, to determine if laptops predict academic achievement, we use two approaches: propensity

score matching (PSM), and the inverse-probability-of-treatment-weighted (IPTW) estimator.

Unlike in a randomized experiment in which some students are given a laptop and some are not, students endogenously determine whether to purchase a laptop, a decision that is driven by their demographic background and other factors. That is, the assignment of the treatment variable is nonrandom. As a result, *t* tests seeking to determine the ATE, or alternatively, a regression of performance on laptop ownership and demographic covariates for which the correct specification is not known, might be expected to lead to biased estimates of the impact of not owning a laptop. PSM potentially allows us to reduce this bias by approximating a randomized experiment that then allows us to compare laptop owners and nonowners with similar covariate distributions.[11] Doing so enables us to gauge the association between laptop ownership and academic achievement controlling for student demographics.

PSM is a commonly used technique in the natural and social sciences (Stuart, 2010). It has also been prominently featured in education research, where it has been used to help quantify the effects of special education services (Morgan et al., 2010), to compare the educational attainment of community college transfer students relative with peers who enroll directly in a 4-year postsecondary institution (Dietrich & Lichtenberger, 2015; Melguizo et al., 2011), and to better assess the impact of skipping grades in elementary school (Kretschmann et al., 2014).

PSM proceeds as follows: In the first step, we use our previous logit (or probit) specification with imputed data to regress laptop ownership on the demographic covariates. For each individual observation, the aim is to obtain a propensity score: the predicted or conditional probability of not purchasing a laptop given pretreatment individual characteristics (from a statistical standpoint, we view treatment as not owning a laptop). The propensity score serves to aggregate the impact of all of the demographic covariates. Next, using standard matching techniques, we match laptop nonowners (treatment group) to laptop owners with similar propensity scores. This necessarily alters the control group by trimming and weighing observations to match the treatment group.[12] Finally, once each treated observation is matched to the appropriate observations in the control group, we can once again use a *t* test to compare the academic performance of laptop owners and nonowners.

We note that in comparing laptop owners with nonowners, we compute, separately, the "average treatment effect on the treated" (ATT) and the ATE. In our framework, the former gauges the impact that not having a laptop has on nonowners, whereas the latter gauges the impact of nonownership if no individual owned a laptop. As an alternative means of computing the ATE, we rely on the IPTW estimator (Robins et al., 2000). The first step proceeds the same way as PSM. However, once propensity scores are calculated, they are instead used as weights in a second-stage weighted regression of performance on the treatment and set of covariates. Unlike in an unweighted regression, the IPTW adjustment is akin to a regression in which the treatment and other covariates are independent of each other. The second-stage regression allows us to control for any remaining covariate differences across treatment assignments.

Table 3. Logistic Regression Predicting the Likelihood of Laptop Nonownership.

	B	Exp (B)
(Intercept)	−6.805	0.001***
Gender (Female)		
Male	0.692	1.997**
Disability (no)		
Yes	0.969	2.636***
Race (White)		
Black	1.007	2.738**
Hispanic	0.570	1.769
Asian	0.064	1.066
Others	0.777	2.175*
Sexual orientation (heterosexual/straight)		
Not heterosexual/straight	0.722	2.058*
First generation (no)		
Yes	−0.574	0.563
Education Parent (BA or more)		
Some college or associate degree	1.438	4.213***
High school	1.742	5.706***
Financial aid (No financial aid and don't need it)		
No financial aid but need it	0.262	1.299
About 25%	1.023	2.781
About 50%	1.827	6.216**
75% and above	1.719	5.577**
Don't know	1.122	3.071*
Community (Urban)		
Suburban	−0.237	0.789
Rural	0.595	1.812
Others	−0.237	0.789
R^2 (McFadden)		.19

Note. $N = 4{,}170$.
$^{\dagger}p < .05$. $^{*}p < .01$. $^{**}p < .001$. $^{***}p < .0001$.

Summary of Findings

Laptop Nonownership

We conducted logistic regressions to predict laptop nonownership among students in our sample. In addition to the logistic regressions, we assessed the robustness of our analyses using a probit specification. The results from that specification are very similar and hence omitted.[13] The results in Table 3 show that various sociodemographic

Table 4. Reasons for Laptop Nonownership.

Variable name	Total %
Reason for not having laptop	
Cost (e.g., can't afford it and don't want to take out a loan)	40.60
Cost (e.g., can't afford it and have exhausted all loan resources)	18.80
Don't need it (e.g., have alternative device)	24.60
Don't want it	15.90

Note. $N = 73$.

background variables are associated with laptop nonownership among college students. In our sample, those students who identified as male or not heterosexual were twice as likely to be nonowners as female students and those who identified as heterosexual, respectively. Students who reported a disability were 2.6 times more likely to be laptop nonowners than those who did not report a disability. The same is true for race: students who identified as Black were 2.7 times more likely to be laptop nonowners than Whites, and those who identified as "other" were 2.2 times more likely to be nonowners.

However, parent education and financial aid had the strongest association with laptop nonownership. Those students whose parents had a high school degree or less were 5.7 times more likely to be laptop nonowners compared with those students whose parents completed a college degree, and students whose parents attended some college (without a degree) or earned an associate degree were 4.2 times more likely to be laptop nonowners. Similarly, those students who received a lot of financial aid were more likely to be nonowners. Those who received aid covering about 50% of financial need were 6.2 times more likely to be laptop nonowners than students who did not received financial aid and did not need it. Students who received 75% or more financial aid were 5.6 times more likely to be nonowners, and those who did not know what their financial aid status were 3.1 times more likely. These results are in line with digital inequality research on general populations (Cohron, 2015; Gonzales, 2016; Reisdorf & Rhinesmith, 2018), demonstrating that despite a generally higher level of connectivity and device ownership, digital inequalities and divides play a role for college students as well—especially for those students who are socioeconomically disadvantaged and less likely to attend college in the first place.

Similar to the patterns of laptop nonownership, the reasons for not owning a laptop were consistent with those found in other digital inequality studies and literature (Helsper & Reisdorf, 2017). Almost 60% of laptop nonowners said that they could not afford it (see Table 4), whereas 25% said that they had other means of doing their work, for example, on a different kind of device, and 15% said that they did not want a laptop. In addition, more than half of the students who reported nonownership felt that this lack of a laptop had an adverse effect on their academic performance, whereas 40% felt it had no effect, and 9% felt it may even have a positive effect (see Table 5).

Table 5. Perceived Effects of Laptop Nonownership.

Variable name	Total %
Laptop affects performance	
Yes, positively (e.g., I don't get distracted in class)	8.80
No effect	39.70
Yes, negatively (e.g., I can't do certain tasks)	51.50

Note. $N = 73$.

Table 6. Matching Results for Laptop Nonownership (ATT).

	Logit	Probit	Genetic
Estimate	−0.5579	−0.3925	−0.4850
AI SE	0.1433	0.1577	0.13442
t Statistic	−3.8922	−2.4888	−3.6081
p	.0000	.0128	.0003
Original number of observations	4,170	4,170	4,170
Original number of treated observations	73	73	73
Matched number of observations	73	73	73
Matched number of observations (unweighted)	1,278	1,181	678

Note. ATT = average treatment effect on the treated. Results of *t* tests assessing the average effect of laptop nonownership on nonowners.

How Does Laptop Nonownership Affect Academic Performance

In addition to understanding the demographics of laptop nonownership and student perceptions of the effects of laptop nonownership, we sought to determine whether not having a laptop had a measurable effect on students' academic performance as measured by their fall semester GPA. As described in the methodology, we used matching (primarily PSM) and the IPTW estimator to compare performance with and without laptop ownership. Eight demographic variables were used to create propensity scores that aggregate the impact of the demographic covariates. These variables are as follows: *sex, disability, race, sexual orientation, first generation, parental education, financial aid*, and *community*.

Following the first-stage (i.e., logistic) regression, we used k:1 nearest neighbor matching according to the estimated propensity score, leaving us with 1,278 matched observations out of 4,097 initial laptop owners. Table 6 estimating the ATT indicates that based on the logit specification, not having a laptop has an (absolute) negative effect of −0.56 points (out of 4.0) on the GPA score ($p < .01$) of nonowners.[14]

To assess balance—that is, to confirm that the distributions of covariates in the treated and control groups are similar—we compared standardized differences of means in the treatment and control (the standardized bias) as well as the ratios of variances of the treatment and control groups for each level of each of our categorical

Table 7. Matching Results for Laptop Nonownership (ATE).

	Logit	Probit	Genetic
Estimate	−0.2888	−0.3199	−0.21264
AI SE	0.2052	0.2098	0.20455
t Statistic	−1.4071	−1.5249	−1.0396
p	.1593	.1273	.2985
Original number of observations	4,170	4,170	4,170
Original number of treated observations	73	73	73
Matched number of observations	4,170	4,170	4,170
Matched number of observations (unweighted)	5,944	5,964	4,976

Note. ATT = average treatment effect. Results of *t* tests assessing the average effect of laptop nonownership in general.

covariates. In all but one instance, the absolute value of the standardized bias fell below 0.23,[15] while the ratios of variances ranged between 0.80 and 2.13,[16] giving us comfort that our covariates were balanced. Nevertheless, as a robustness measure, we applied a genetic matching algorithm to reduce bias and the mean square error of the estimated treatment effect (Diamond & Sekhon, 2013).[17] This yielded an ATT of −0.49 ($p < .01$; see Table 6).

Our results indicate that after controlling for demographic characteristics, students who do not own a laptop substantially underperform their peers with a laptop. To put these results in context, to the authors' knowledge, many postsecondary institutions in the United States assign letter grades according to GPA increments of 0.3 and 0.4 for letter grades above a C− (i.e., A = 4.0, A− = 3.7, B+ = 3.3, B− = 3.0, . . .), or according to increments of 0.5 (i.e., A = 4.0, A−/B+ = 3.5, B = 3.0, . . .). As such, for instance, nonownership can be associated with the difference between as much as a B+ and an A for a corresponding laptop owner with similar demographic characteristics.

Overall, these results suggest that not owning a laptop is associated with a highly negative impact on performance of nonowners. When taken together with the survey results concerning reasons for nonownership and nonowners' perceptions of the impact of nonownership, these results seem even more distressing. In particular, that 60% of nonowners cited inability to afford a laptop as the reason for not having one is at least suggestive that ownership could be a means of remediation for such students and that lack of a laptop is a disadvantage. An additional concern is that the demographic characteristics of nonowners are associated with lower participation in higher education, meaning that such individuals are less likely to go to college (and to have made it into our survey to begin with) and also less likely to do well in college than their better-off peers (Brennan & Naidoo, 2008).

While striking, we caution that the above results do not provide insight into how laptops might have enhanced the performance of those who *do* own them. To assess the impact that ownership had on the GPAs of the broader sample, after calculating propensity scores, we instead calculated the ATE (see Table 7), while the estimates

Table 8. Covariate Balance.

	Standard bias	Variance ratio
Gender		
Female	0.0273	1.0009
Male	0.0273	1.0009
Disability		
No	0.0272	1.0081
Yes	0.0272	1.0081
Race		
White	0.0282	1.0197
Black	0.2073	0.9545
Hispanic	0.0462	1.0486
Asian	0.0685	1.3949
Others	0.1482	0.9638
Sexual orientation		
Heterosexual/straight	0.1936	1.0253
Not heterosexual/straight	0.1936	1.0253
First generation		
No	0.0547	0.9964
Yes	0.0547	0.9964
Education parent		
BA or more	0.0290	1.0156
Some college or associate degree	0.0284	1.0072
High school	0.0000	0.9757
Financial aid		
No financial aid and don't need it	0.1077	0.7989
No financial aid but need it	0.1371	2.1343
About 25%	0.1981	0.9387
About 50%	0.1742	1.8476
75% and above	0.3000	1.0104
Don't know	0.0966	1.1676
Community		
Urban	0.2317	0.9057
Suburban	0.1728	1.1144
Rural	0.1521	1.3428
Others	0.0290	1.0393

Note. $N = 4{,}170$. Balance measured based on propensity score matching with a first-stage logit specification.

have the same sign as in Table 6; they are insignificant regardless of the method used to estimate propensity scores. As an alternative, we used propensity scores as weights in a regression of GPA on laptop ownership and the remaining demographic covariates (i.e., IPTW estimation; see Table 8). Table 9 (which relies on a first-stage logit to

Table 9. IPTW Regression Predicting GPA Based on Laptop Ownership and Demographics.

	Estimate
(Intercept)	3.450***
Laptop (does not own)	−0.143
Gender (Female)	
Male	−0.106***
Disability (no)	
Yes	−0.147***
Race (White)	
Black	−0.542***
Hispanic	−0.317***
Asian	−0.078†
Others	−0.422***
Sexual orientation (heterosexual/straight)	
Not heterosexual/straight	−0.059
First generation (no)	
Yes	0.047
Education Parent (BA or more)	
Some college or associate degree	−0.227***
High school	−0.320***
Financial aid (No financial aid and don't need it)	
No financial aid but need it	−0.033
About 25%	0.006
About 50%	0.059
75% and above	−0.071†
Don't know	−0.092**
Community (Urban)	
Suburban	0.154***
Rural	0.045
Others	0.138***
$R^2 = .142$; Adjusted $R^2 = .140$	

Note. $N = 4{,}170$. IPTW = inverse-probability-of-treatment-weighted; GPA = grade point average.
†$p < .05$. *$p < .01$. **$p < .001$. ***$p < .0001$.

compute propensity scores) similarly shows that the estimated ATE of nonownership is negative (−0.14), but insignificant ($p = .066$).[18]

Thus, while we were able to find a statistically significant ATT, our data does not suffice to accurately estimate the ATE. Whereas our sample of laptop owners is sufficiently large that we could use PSM to identify owners who closely resemble each nonowner across our demographic covariates, there were insufficient nonowners in our sample resembling certain high-performing (on average) segments of laptop owners. This raises the distance between matched individuals, making it difficult to attain statistical significance.

Our IPTW results indicate that the significant predictors of a lower GPA across the broader sample turn out to be the same factors that contribute to laptop nonownership. For instance, students whose parents had a high school degree or less or those whose parents attended some college (without a degree) or earned an associate degree were predicted to earn a GPA that was, respectively, 0.32 or 0.23 lower than those whose parents completed a college degree. Male students were predicted to earn a GPA that was 0.11 lower than female students. Those who reported a disability were predicted to earn a GPA that was 0.15 lower than those who did not. Finally, students who identified as Black, Hispanic, or "other" were predicted to earn a GPA that was, respectively, 0.54, 0.32, or 0.42 lower than those who identified as White. Finally, students who lived in an urban community were predicted to earn a GPA that was 0.15 lower than students from a suburban one. The one variable that predicted laptop ownership, but was generally not a significant predictor of GPA, was financial aid.

Discussion and Conclusion

Given the wide array of findings regarding laptops and their impact on classroom performance, we set out to answer a number of questions on the extent of laptop nonownership (Research Question 1), characteristics associated with nonownership (Research Question 2), and potential effects on academic performance (Research Question 3) based on a sample of MSU freshmen in 2016.

Our findings indicate that while laptop nonownership is limited (Research Question 1), students who are already marginalized are disproportionately nonowners (Research Question 2). Although financial aid for purchasing a laptop is available at MSU, a majority of nonowners reported that they could not afford a laptop—in part, because they were under the impression that they had exhausted all loan options and, in part, because they did not want to take out additional loans. This nonownership was associated with lower academic performance (Research Question 3), and half of the students who did not own a laptop perceived nonownership as a disadvantage.

Limitations

We emphasize that while our findings suggest that nonowners may benefit from owning laptops or possibly other academic interventions, our data does not permit us to assess the impact of laptop ownership on performance in any specific university setting such as the classroom. Moreover, if nonownership is driven by unobserved demographic characteristics outside our covariates (so that our ignorability assumption is violated), then interventions should seek to take those other characteristics into account—though in this case, given the limited number of nonowners, we would advise university administrators that laptop nonownership is still a good means of identifying students who are likely to underperform.

However, our results are based on one freshmen cohort from one single university and may therefore not be generalizable to other universities and beyond the United States. Future research that adopts a broader research approach, which includes

several higher education institutions and students from various years and degree levels would be a useful next step. Finally, we note that even though we did find a significant negative relationship between laptop nonownership and GPA for nonowners, on average, our results do not imply (nor disprove) that laptops had benefited existing laptops owners—the vast majority of our sample—in the same way. Assessing this would require a cohort of laptop nonowners with greater demographic variation, or ideally, a randomized controlled trial.

Critical Discussion of Results

Our findings need to be considered further in light of (a) digital inequality research and (b) research examining the use of laptops in the classroom. Our results are in line with studies that indicate that socioeconomic background has a strong impact on Internet use and ownership of digital devices. Although students are one of the best-connected societal groups in the United States, we still find digital inequalities and divides among those students. Whereas our findings showed that those who do not have a laptop are a small group that is socioeconomically worse off than their laptop-owning peers, Gonzales et al. (2018) also showed that even among those who do own a laptop, digital inequalities persist in the form of technology maintenance. In addition to the roughly 2% at MSU do not own a laptop in our study, Gonzales et al. (2018) found in their study of college students at a Midwestern university that 20% are struggling to maintain access to crucial technologies. Taken together, this means that over one fifth of college students may not have stable access.

Thus, future researchers might seek to extend our study with more detailed data on technology maintenance. If technology maintenance problems have a similar impact on performance as does nonownership, university administrators would be well advised to take the extent of such problems in making their technology decisions and designing performance interventions. It should also be noted that in addition to material access issues, there are differences in how students utilize technologies and their digital literacy levels (Cotten & Jelenewicz, 2006; Enoch & Soker, 2006). This is especially true for nontraditional college students, who often have lower digital literacy levels and should be offered additional digital literacy training and resources (Jesnek, 2012).

There has been much debate and research on the benefits and drawbacks of laptops in the classroom, which call into question whether students who own a laptop are actually better off. A number of studies found that laptop use in classrooms can be a distraction that affects academic performance negatively (Fried, 2008; Lepp et al., 2014; Ravizza et al., 2017). However, these studies looked at specific courses and not overall academic performance across the curriculum. Laptop ownership transcends classroom use, for instance, allowing students to complete readings, assignments, and homework whenever and wherever—in breaks between classes, over lunch in the food court, at a friend's place, at the student union, or on the train or bus home. This gives flexibility that nonowners, who rely on computer labs at school or other, potentially less suitable, devices, do not have.

Implications for Higher Education Institutions

Technology is omnipresent in higher education institutions across the United States. Many college-related activities require students to use computers, laptops, and the Internet all throughout their degrees. University and college administrators and faculty cannot assume that all college students are digital natives or that all college students have the devices that allow them to do their classwork—even if it is a requirement. Those who are digitally excluded or struggling are most often also those who are already less privileged.

Our results indicate that it would be useful for higher education institutions to identify issues with technology acquisition early on and assist those students who are struggling. Although some financial aid is available for purchasing a laptop at MSU, students still struggled to obtain a laptop, as they had either exhausted their loan options or simply did not want to add to their loan burden. One option might be to offer a program that refurbishes laptops that are not used any longer by faculty and loan or give them out to those students who are struggling to obtain and maintain a laptop.

We reiterate that our findings concern laptop nonownership. Additional research is necessary to determine whether our results extend similarly to digital divides resulting from factors such as technology maintenance and digital literacy. Such research could inform educators on how to design broader and more suitably tailored interventions—for example, involving tutoring or digital literacy support—that allow them to better account for underlying factors that might affect the GPAs of socioeconomically marginalized groups.

Authors' Note

The analysis and conclusions set forth are those of the authors and do not necessarily represent the views of the Federal Communications Commission, other Commission staff members, or the U.S. Government.

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Notes

1. See, for instance, Association of College and University Housing Officers—International, State of ResNet 2019 report (https://www.acuho-i.org/resources/cid/7011?portalid=0).

2. Our focus is on higher education. However, the evidence is likewise mixed in earlier education settings (Bulman & Fairlie, 2016).
3. In a study examining honors students in a business school setting, Wurst et al. (2008) did not find that laptops had an effect on GPA. They did find, however, that students with laptops reported significantly lower satisfaction with their classes than those without laptops.
4. Additionally, certain studies argue that laptop or Internet use has a negative effect on student performance even when used outside the classroom (Englander et al., 2010; Jacobsen & Forste, 2011).
5. We note that due to the time that it takes to process the survey data, our understanding is that the survey is not used to conduct interventions prior to receipt of GPA data used for our analysis.
6. U.S. Department of Education, National Center for Education Statistics, Higher Education General Information Survey (HEGIS), "Fall Enrollment in Colleges and Universities" surveys, 1970 through 1985; Integrated Postsecondary Education Data System (IPEDS), "Fall Enrollment Survey" (IPEDS-EF:86-99); IPEDS Spring 2001 through Spring 2016, Fall Enrollment component; and Enrollment in Degree-Granting Institutions Projection Model, 2000 through 2026 (https://nces.ed.gov/programs/digest/d16/tables/dt16_303.70.asp).
7. The National Center for Education Statistics projected that in 2016, individuals who are White, Black, Hispanic, Asian (including Pacific Islander), and Other would make up approximately 57.4%, 14.4%, 17.3%, 6.7%, and 4.3% of Fall 2016 enrollees in degree-granting postsecondary institutions in the United States. See U.S. Department of Education, National Center for Education Statistics, HEGIS, "Fall Enrollment in Colleges and Universities" surveys, 1976 and 1980; IPEDS, "Fall Enrollment Survey" (IPEDS-EF:90-99); IPEDS Spring 2001 through Spring 2016, Fall Enrollment component; and Enrollment in Degree-Granting Institutions by Race/Ethnicity Projection Model, 1980 through 2026 (https://nces.ed.gov/programs/digest/d16/tables/dt16_306.30.asp).
8. U.S. Department of Education, National Center for Education Statistics, IPEDS, Spring 2002 through Spring 2011 and Winter 2011-2012 through Winter 2015-2016, Student Financial Aid component (https://nces.ed.gov/programs/digest/d16/tables/dt16_331.20.asp).
9. R software with the "mice" package was employed for each imputation. Binary variables were imputed using logistic regression (via "logreg") and unordered categorical variables were imputed using polytomous regression (via "polyreg"). We note that there were relatively few missing observations in the sample, with the most missing observations for parental education (154 or 3.7% of the sample) and ability (125 or 3% of the sample), and with all other variables missing less than 2% of sample observations.
10. This is putting aside ethical considerations in demographic-based intervention—for instance, an educational institution choosing to use past data for a specific racial category to design early year intervention efforts seeking to boost performance of all members of that category before it is observed.
11. PSM relies on a number of assumptions. Specifically, it is assumed that laptop ownership by some individuals does not have a spillover effect on performance by nonowners; that conditional on demographics, the laptop nonownership decision indicated in students' survey responses (assignment into the treatment group) is independent of potential future performance (ignorability); and that for each laptop nonowner, there is a laptop owner with similar demographic characteristics (Rosenbaum & Rubin, 1983).
12. This study utilizes R software with the "Matching" package to generate the propensity score and to measure the average effect of laptop non-ownership on students' GPAs.
13. The corresponding results table is available on request from the corresponding author.

14. The ATT following the probit specification was −0.39 ($p = .013$). We note that we used 1:1 matching with replacement to calculate the ATT.
15. The exception consisted of students who stated that they received 75% or more in financial aid, which had an absolute value standardized bias balance of 0.30.
16. Moreover, aside from two financial aid variables with variance ratios equal to 2.13 and 1.85, the next highest variance ratio was 1.39.
17. Genetic matching offers a generalization of propensity score and Mahalanobis distance matching that aims to maximize covariate balance across treated and controlled groups (Diamond & Sekhon, 2013). For a description of the Mahalanobis distance measure, see Stuart (2010).
18. Computing propensity scores based on a probit specification likewise yielded a slightly negative, insignificant coefficient. Weights are stabilized to reduce variability and give individuals with extreme weights less influenced (see Harder et al., 2010). Additional truncation of stabilized weights had a negligible impact on our estimates.

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