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Competing Interests
Authors FK, AP, and ST have no competing interests to declare. Authors DB and KV work at the University of Michigan Library.

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Abstract

To better understand the longitudinal association between online usage of library-licensed content and short- and long-term student performance, we linked EZproxy logs to institutional university data to study how library usage impacts semester and cumulative GPAs. Panel linear mixed effects regression models indicate online library usage is significantly associated with semester and cumulative GPAs. The library usage effect is larger for semester GPA and varies by on- and off-campus residency. The effect on semester GPA is larger for off-campus students, while for cumulative GPA the effect is larger for on-campus students. Longitudinally linked library-institutional data offers key insights on the library's value.

Introduction

Library usage is correlated with important undergraduate student outcomes including academic performance and retention. However, the relationship between library usage and academic performance is better understood over the short term and for specific subsets of students, such as first-year undergraduate students.[1] We still need to develop a better understanding of this relationship over the long term and for all undergraduate students. One of the reasons for our currently limited understanding of this relationship is that, in most universities, owing to privacy concerns libraries either do not collect or retain user data with identifiers. This makes it impossible to link library usage data with other institutional or administrative data from the university, including that of indicators of academic success and retention. Another reason is that library usage data are often collected as very large logs (millions and billions of records) that may require the application of methodological approaches, such as Big Data techniques, to structure and store in ways that make them more amenable to statistical regression modeling. There is therefore a need for empirical, longitudinal studies that use identifiable library data and employ Big Data and statistical methods to advance our understanding of the library's contribution to student success. In this paper we present the results of a longitudinal study of the association between online library resource usage and student performance for the entire population of undergraduates enrolled at the University of Michigan (U-M) between 2016 and 2019.

The privacy concerns described above are valid. However, advances in the biomedical and social sciences that better serve the privacy requirements of library professional ethics are still not yet widely known in libraries. Other research domains deal with data for which the potential risk of unintended exposure is higher than those of library usage data, such as the type of patient health information covered by the Health Insurance Portability and Accountability Act of 1996 (HIPAA). Fortunately, there are now efforts in libraries to adopt the best privacy practices from the social and biomedical sciences. These initiatives make it possible to employ Big Data methods in longitudinal studies of the links from library usage to academic outcomes for the entire student body. Two such initiatives that are critical to the work described in this paper are described shortly. The first is that, after a multi-year process of engaging with a diverse set of stakeholders including the U-M Learning Analytics Task Force, the U-M Library revised its privacy policy in 2016 to allow the collection and retention of identifiable library usage data.[2]

The second initiative is the Library Learning Analytics Project (LLAP; https://libraryanalytics.org/) which was funded by the Institute of Museum and Library Services (IMLS). LLAP examined how libraries impact learning outcomes including in course instruction. Learning processes require that members of the university community engage in activities such as accessing digital data and publication repositories, conducting literature reviews, managing citations, and creating data management plans. These activities often entail interacting with the library virtually such as when accessing and retrieving library licensed content through the proxy server. This paper reports on analyses performed on the links between off-campus or off-network electronic usage of library resources and undergraduate academic performance over the short- and long-term. The best context for work of this nature is one in which library users have agency with respect to how they engage with the library services in question. For library licensed content, individuals can access these resources via computers that are on-campus (physically located in the library or elsewhere in the university), or virtually via the proxy server should they choose to use these resources when off-campus. For this reason, the authors limited the analysis to the relationship between online library usage and student outcomes to the time before the COVID-19 pandemic. That is, the study focuses on when students had the choice of accessing library licensed content through on- or off-campus means.

Literature Review

This work is informed by models of information behavior.[3] Information behavior describes how individuals seek and utilize information.[4] Information behavior is contingent on factors such as social contexts, socio-demographics, individual expertise, and access to and ease of use of technology(Bates 2017; Haglund and Olsson 2008; Niu and Hemminger 2012).[5] The work also builds on two lines of inquiry. The first is research into the associations between college residence and academic performance. The second is work on digital inequalities or the digital divide. We examine the link from library usage to student outcomes in two ways. 1) defining library usage in terms of online resource use of licensed content provided by the library, and 2) evaluating the impacts of on-campus residency for ease of access to library and other resources and reliable internet.

Research on campus residency has examined the issue of whether there are gains in learning and academic performance from living on- versus off-campus. A study of close to 95,000 first year students in the United States found living on-campus was significantly associated with a range of learning variables even though the residency effect size was small to medium.[6] An earlier study of first-year students found that the benefits of on-campus residency on academic performance were different across and within racial groups. For example, Black students who lived on-campus had significantly higher grade point averages (GPAs) than Black students that lived off-campus.[7] Approaching the issue from a different angle, a study of the causal link between campus residency and academic outcomes found living in university-owned housing had a positive association with student retention.[8] This finding was in line with prior analysis that established an association between on-campus living and academic performance and student retention for first-year students.[9] However, an important caveat is that students who were better prepared academically were more likely to live on-campus as opposed to off-campus.[10] Most studies of the link between on-campus residence and student persistence have been based on four-year institutions. One exception is a quasi-experimental analysis of community college students that found that living on-campus was associated with a significant increase in upward transfer (to a four-year institution) and, subsequently, bachelor’s degree completion rates.[11] It should be noted, however, that the association between on-campus residence and academic outcomes is not always positive. A study that was conducted at a public four-year university in the Southeast United States found that commuter or off-campus students had higher GPAs than residential or on-campus students.[12]

Digital disparities in American K-16 education are shaped by demographic, geographic, and economic factors. These disparities are usually referred to as the "digital divide" or the gap between those privileged to benefit from the internet and other information and communication technologies (ICT), and those who are not. Digital inequalities and disparities impact a broad range of life opportunities and outcomes beyond education, such as economic activity and health care.[13] In education, digital inequalities and disparities are a life-course issue and affect disadvantaged students. Their effects are felt from early[14] to late in the K-16 pipeline.[15] The increasing use of technology inside and outside the classroom has significant implications for the digital divide and its impact on student performance. Importantly, some groups of students are systematically more likely to experience digital disparities than others. For example, in 2015 higher percentages of students who were White (66%) used the internet at home compared to Black (53%), Hispanic (52%), and American Indian/Alaska Native (49%) students.[16] American Indian/Alaska Native students are more likely than other racial groups to have no internet access, or to have only dial-up internet access at home.[17] The interaction of demography and geography serves to disadvantage some students further still. While 18 percent of all students in remote rural areas did not have internet access or had only dial-up access in 2015, a much larger percentage of Black (41%) students in remote rural areas did not have internet access compared to White (13%) and Asian (11%) students. Having no or low-bandwidth internet is detrimental for any form of online learning. For example, students cannot participate in classes offered via video conferencing systems that rely on high-speed internet.[18] The COVID-19 pandemic has deepened or worsened the effects of the digital divide, such as for rural students.[19] A group that has been especially impacted by the pandemic is students of color who, as noted earlier, are more likely to lack access to reliable broadband internet and even computers. For minority students, the pandemic has exacerbated existing educational disparities, and has likely widened the achievement gap for students of low socioeconomic status.[20]

In the United States, the effects of the pandemic on the digital divide are being felt up and down the entire K-16 pipeline. There were varied institutional responses across the American higher education landscape. Perversely, these present opportunities for “quasi-experimental” observations of the impacts of the digital divide on amplifying disparities in student performance. For example, where many colleges and universities stipulated that students residing on-campus leave these residences, some made allowances for students who could not return home and thus enabled them to still have access to reliable broadband internet via the institution.[21] What was fairly universal, however, was the extent and speed with which university libraries adapted to offering primarily online resources,[22] which can only meaningfully be accessed via reliable internet connections. Thus, not only were students no longer able to access the library’s physical collections, but they also no longer had access to the library as a study space including for group or collaborative activities.[23] By examining how “regular” (pre-pandemic) electronic library usage is associated with academic performance, this study may thus help us better understand the likely impacts of the worsening of the digital divide during the pandemic. Based on evidence that the digital divide has worsened during the pandemic,[24] we can safely assume that the importance of the relationship between online library usage and academic performance has only increased.

The literature also indicates that models of student performance need to account for other demographic, socioeconomic, and academic factors including include gender, first generation status, family or household income, high school GPA, and academic class level. Across national contexts in developed countries, female students are more likely to have both higher work ethics and GPAs than males.[25] First-generation students are more likely to contend with barriers to academic success like job and family responsibilities, and inadequate study skills[26] and thus tend to have poorer academic outcomes.[27] Students who enter college with higher family or household incomes tend to have significantly higher GPAs than those from lower socioeconomic backgrounds.[28] High school GPA is a strong predictor of college or university GPA, and especially in the first year.[29] Class level is correlated with GPA as upper class students such as seniors are more likely to have higher grades especially in classes that also have lower class students such as sophomores.[30]

Theoretical Framework

Building on models of information-seeking behavior, we developed a theoretical framework (Figure 1) that correlates student performance with library usage as captured by EZproxy sessions, controlling for factors like socio-demographics and academic background.[31] A key strength of the framework is that it presents testable relationships among demographic and contextual factors, information-seeking behaviors, and academic outcomes.

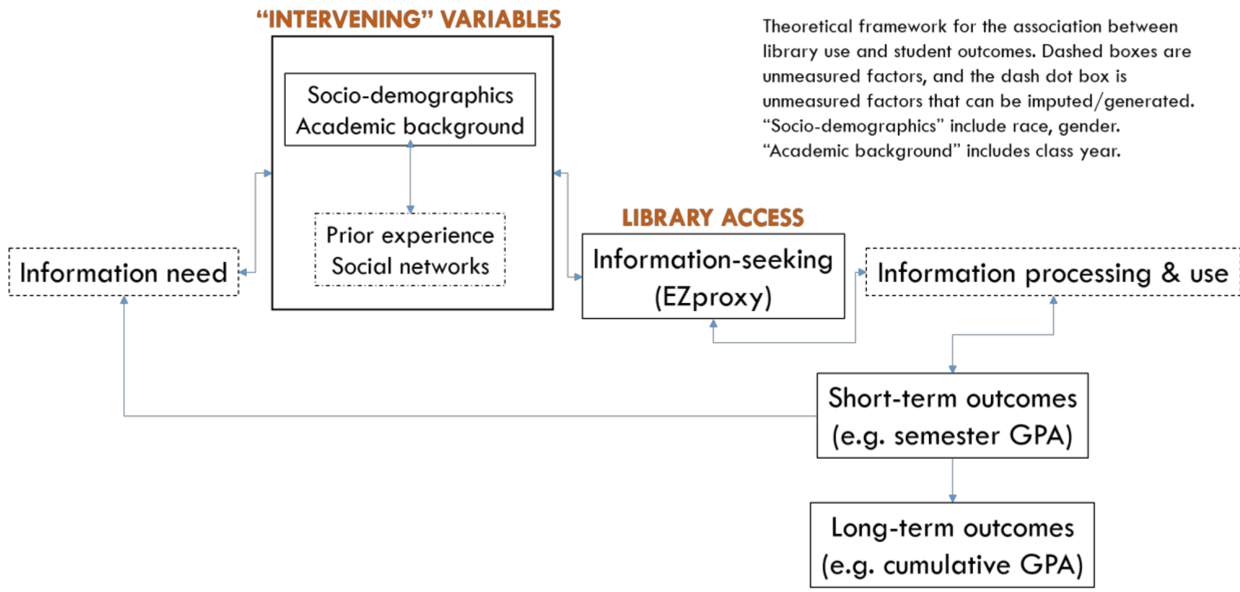

Figure 1. Theoretical framework for associations between library usage and student outcomes adapted from models of information behavior.[32] These models draw on research from multiple fields including information science, psychology, decision-making, innovation, health communication, and consumer research.

This paper focuses on the association between information-seeking behavior (off-campus or off-network electronic library resource use), and semester and cumulative GPA. However, this relationship should be understood in the context of contextual factors ("intervening" variables) that contribute to disparities in access to the digital resources that are needed to make effective use of electronic library licensed content. Research shows that access to and proper use of digital technology generally has a positive correlation with academic performance, and this finding is robust across regional and national settings.[33] Based on these findings we hypothesize that students who are identified as accessing online library licensed content will have better academic outcomes than those students for whom there is no evidence of digital access to these resources. However, there is also evidence that our hypothesized relationship has both short- and long-term implications. While not specific to electronic resources, studies suggest that library usage is positively correlated with student performance both in the short-term,[34] and in the long-term.[35] Therefore:

H1: Students who electronically access library licensed content will have higher semester GPAs.

H2: Students who electronically access library licensed content will have higher cumulative GPAs.

Methodology

The study sample is all undergraduate students (N = 45,254) that were enrolled at the University of Michigan (U-M) from fall 2016 through winter 2019 (or September 2016 through April 2019). We focus on these six semesters before the pandemic because students had more agency with respect to their usage of electronic library licensed content. That is, students could opt to access materials using computers that are physically on-campus, or off-campus access via the proxy server. Library usage data was sourced from EZproxy logs (690,300,076 records) that were stored in a secure repository managed by the U-M Library. Student demographic and outcome data (GPAs) were obtained from the research-focused Learning Analytics Data Architecture (LARC) Data Set maintained by the U-M Office of Enrollment Management. The project team implemented several measures to protect the privacy and confidentiality of the individuals in the library and LARC data. For example, the library data were classified at the "Restricted" level of data security. This is the highest classification or sensitivity level for U-M institutional data and has the most stringent legal or regulatory requirements and most prescriptive security controls. These controls included restricting access to only two members of the project team, storing and curating the data on a secure enclave, setting up access to the enclave via a terminal in a locked and restricted data room, and requiring that all analyses be performed on the enclave.

Our primary interest in this paper is the relationship between information-seeking behavior (EZproxy sessions) and student performance. EZproxy is proxy server software that is widely used by many academic libraries to give authenticated off-campus users access to electronic resources licensed by the library as if they were on campus. Stated simply, after authenticating to a campus system, off-campus users receive an on-campus IP address and are then considered to be a member of the campus community by the information provider. The authors cleaned and normalized raw, unstructured EZproxy logs using Python scripts and regular expressions and then entered the data into a relational database using structured query language (SQL) scripts. Over 80 percent of the EZproxy data have strong university identifiers which facilitate merges with other administrative data, such as LARC. It is critical to note that EZproxy logs available to the study a) did not include any on-campus usage and b) did not include anyone who used the campus VPN. Using SQL and R scripts, we merged the data and exported the resultant data set into Stata 16 for modeling and analysis.[36]

The theoretical framework shown in Figure 1 suggests that student outcomes are a function of factors such as race and gender that apply to all the students in the study (“fixed effects”), and factors such as academic units or schools that cluster student behaviors and outcomes (“random effects”). We also account for student random effects for unobserved, time invariant factors, such as motivation or grit. Thus, we ran panel linear mixed effects regression models of the association between library usage and student GPA, contingent on students being enrolled in at least four semesters over the study period.

Variables

The two continuous dependent variables are semester GPA ("SEM_GPA") and cumulative GPA ("CUM_GPA"), respectively. While SEM_GPA is on a 0 – 4.4 scale and CUM_GPA is on a 0 – 4.314 scale, fewer than 0.5% of students have a semester or cumulative GPA that is higher than 4.0. The dichotomous independent variable "EZproxy Session in Term" is coded one if a student is associated with one or more EZproxy sessions during an academic term and is coded zero otherwise.

We also account or control for potential "intervening" variables as follows. The dichotomous variable "On-campus Residence" is coded one if a student was residing in a university residence, and zero otherwise. The variable "High School GPA" is on a continuous 0 – 4 scale and captures a student's academic performance before matriculation at the university. Gender is captured by the dichotomous variable "GENDER" (1 = Female, 2 = Male). Note that the LARC data set used for the study does not account for non-binary options. The effects of race, first generation status, family income, and class level were controlled for using the categorical variables "RACE" (1 = White, 2 = Asian, 3 = Black, 4 = Hispanic, 5 = Two or More, 6 = Other, 7 = Not Indicated), "FIRST GENERATION" (1 = First Gen, 2 = Not First Gen, 3 = Don't Know), "FAMILY INCOME" (1 = More than $100,000, 2 = Less than $25,000, 3 = $25,000 - $49,999, 4 = $50,000 - $74,999, 5 = $75,000 - $99,999, 6 = Don't Know, 7 = Missing), and "CLASS LEVEL" (1 = Freshman, 2 = Sophomore, 3 = Junior, 4 = Senior), respectively.

Statistical Modeling

We ran panel linear mixed-effects (LME) regression models with random effects for individuals and by school or academic unit (see Table A.7 in the appendix for a list of the 15 schools that undergraduate students were affiliated with). LME models, an extension of simple linear models, are very useful when there is non-independence in the data. This arises from, for example, a hierarchical structure in the data, such as when students are sampled from within academic units. Panel regression approaches are necessary when working with longitudinal study designs, where multiple observations are made on each individual subject. LME models have both fixed effects, which are directly estimated and are analogous to standard regression coefficients, and random effects, which in our case take the form of random intercepts. The fixed effects in our LME models correspond to the "intervening" variables. The random effects account for the fact that student behaviors and outcomes may be, instead of being uniform across all undergraduates, grouped by academic units which map onto disciplinary boundaries that likely shape library usage. The random effects also enable us to account for unobserved, time invariant individual-level factors, such as motivation or grit. Table A.7 in the appendix shows that there are notable differences across schools with respect to the percentage of students that have at least one EZproxy session during an academic term. After each LME model a likelihood-ratio was run comparing this model with a one-level ordinary linear regression. This test was highly significant for each of the LME models in our study, supporting the decision to use the LME model.

Findings and Discussion

Descriptive statistics

Over half of enrolled undergraduates had at least one EZproxy session during an academic term over the study period (Table 1).

Table 1. Percentage of students associated with EZproxy sessions by semester, Fall 2016 – Winter 2019

Academic Term	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	28,682	16,605	58%
WN 2017	27,408	13,434	49%
FA 2017	29,161	16,034	55%
WN 2018	27,852	14,855	53%
FA 2018	29,726	16,191	54%
WN 2019	28,355	16,299	57%
TOTAL*	171,184	94,418	55%

* This is a tally of unique student-term combinations as there were 45,254 enrolled undergraduates over the study period.

There are some notable differences in library usage among the enrolled undergraduates. Table 2 below illustrates differences in library usage by demographic, academic, and residency factors for the winter 2019 term (see the appendix for similar statistics on all semesters). Off-campus students are more likely to have at least one EZproxy session in the academic term than are on-campus students. This makes sense because students who are on-campus are more likely to access electronic library resources on the university's network, in which case authentication is not required. Recall that students are identifiable in the EZproxy logs only when authentication is required. An example of this is when a student accesses electronic library resources outside the university's network such as from an off-campus residence, coffee shop, and so on. There is a significant gender difference with females much more likely than males to have an EZproxy session. This is even though more males (69%) than females (66%) resided off-campus in winter 2019. Note that the likelihood of having at least one EZproxy session increases with each class level.A plausible explanation could that this is because students are more likely to move or reside off-campus as they progress from freshman to seniors. However, a factor that weakens this argument is that at U-M it is not compulsory or mandatory for freshmen and sophomores to live on-campus as is the case in some colleges and universities. An alternative explanation is that lower-level classes are less research-intensive and where there are research and writing projects, they may not need library-provided resources but can rather be accomplished through open-web, non-licensed, materials.

Table 2. Percentage of undergraduate students associated with EZproxy sessions by socio-demographics and academic background, Winter 2019

Variable	**Category**	**Enrolled Students**	**EZproxy Session**	**% ≥ 1 EZproxy Session**
First Gen Status	First Gen	3,890	2,310	59%
	Not First Gen	24,418	13,957	57%
	Don't Know	47	32	68%
Family Income	Less than $25,000	1,507	923	61%
	$25,000 - $49,999	2,212	1,269	57%
	$50,000 - $74,999	2,009	1,217	61%
	$75,000 - $99,999	2,074	1,213	58%
	More than $100,000	13,951	7,892	57%
	Don't Know	515	278	54%
	Missing Income Information	6,087	3,507	58%
Class Level	Freshman	2,557	1,300	51%
	Sophomore	6,397	3,373	53%
	Junior	7,132	4,114	58%

	Senior	12,269	7,512	61%
Race	Asian	5,829	3,137	54%
	Black	1,268	766	60%
	Hispanic	1,899	1,099	58%
	White	16,604	9,738	59%
	2 or More	1,302	745	57%
	Other	46	22	48%
	Not Indic	1,407	792	56%
Gender	Female	14,204	9,219	65%
	Male	14,151	7,080	50%
Residency	On-campus	9,261	4,540	49%
	Off-campus	19,110	11,765	62%
Academic Unit	Architecture	181	124	69%
	Art and Design	524	381	73%
	Business Admin	1,799	740	41%
	Dental Hygiene	101	70	69%
	Education	126	54	43%
	Engineering	6,313	2,847	45%
	Information	260	122	47%
	Joined Deg Prog	10	7	70%
	Kinesiology	954	678	71%
	LS & A	16,409	10,030	61%
	Music, Thtre & Dance	717	515	72%
	Nursing	607	475	78%
	Pharmacy	55	36	65%

Public Health	157	116	74%
Public Policy	142	104	73%

Finally, there are noteworthy differences between academic units. Additional work would be needed to clarify the factors that account for these differences. For example, 45 percent of engineering undergraduates had at least one EZproxy session compared to 73 percent of art and design undergraduates even though both academic units are co-located at the university. A potential explanation could be that these differences reflect disciplinary differences (STEM versus arts and humanities). Another plausible explanation could be that the differences reflect gaps in technological expertise between the two groups of students, with engineering students being more likely to access electronic library resources using the university's virtual private networks (VPNs) which bypasses the authentication process on the library's proxy server. We should also keep in mind factors such as the interplay between residency and socioeconomic statuses. It is more expensive to live on- rather than off-campus, implying that students in the former group may tend to be from better off families. For example, 78 percent of nursing undergraduates had at least one EZproxy session compared to 41 percent of business administration undergraduates. Tabulations of residency for the two academic units showed that 32 percent of business undergraduates resided on-campus in winter 2019, compared to 20 percent of nursing undergraduates. Similarly, tabulations of family income for the two academic units showed that 58 percent of business undergraduates had a family income of more than $100,000, compared to 48 percent of nursing undergraduates. These findings suggest that library usage data have the potential to reveal existing disparities and inequalities and could therefore help libraries make significant analytical contributions of interest to their parent institutions.

Regression models

The results from the regression modeling are summarized in Tables 3 (semester GPA) and 4 (cumulative GPA). The regression models showed positive and statistically significant associations between having at least one EZproxy session in an academic term and both semester and cumulative GPAs, controlling or accounting for residency, race, gender, high school GPA, family income, first generation status, and class level.

Overall, the results from the regression models for semester GPA provide strong support for hypothesis **H1**. That is, students that use electronic library licensed content have higher semester GPAs. Having an EZproxy session *during an academic term* was correlated with a 0.14 increase in semester GPA (model 1). To examine further the impact of campus residency considering the link between authentication requirements and a student's presence in the EZproxy logs, we ran separate models for on-campus (model 2) and off-campus (model 3) students. For off-campus students, having an EZproxy session in an academic term is correlated with a 0.17 increase in semester GPA. In comparison, for on-campus students, having an EZproxy session in an academic term is correlated with a 0.09 increase in semester GPA. For the other "intervening" variables, it is noteworthy that the GPA gender gap in favor of females is smaller for on-campus students compared to their off-campus peers. It is also interesting that, the small sizes of the effects notwithstanding, the first-generation disadvantage of lower GPAs is more pronounced for on-campus students relative to their off-campus peers.

Table 3. Panel LME Regressions for Association between Library Usage and Semester GPA, FA 2016 - WN 2019 (4 or More Semesters)

	(1: All Students)	(2: On-campus)	(3: Off-Campus)
VARIABLES	SEM_GPA	SEM_GPA	SEM_GPA
EZproxy Session in Term	0.138***	0.0837***	0.171***
	(0.00304)	(0.00415)	(0.00419)
On-campus Residence	0.0967***		
	(0.00471)		
High School GPA	0.0273***	0.0435***	0.0211***
	(0.00194)	(0.00345)	(0.00235)
GENDER (Reference = Female)			
Male	-0.0908***	-0.0616***	-0.108***
	(0.00529)	(0.00662)	(0.00685)
RACE (reference = White)			
Asian	0.0499***	0.0534***	0.0404***
	(0.00660)	(0.00838)	(0.00851)
Black	-0.376***	-0.374***	-0.400***
	(0.0128)	(0.0145)	(0.0181)
Hispanic	-0.164***	-0.181***	-0.143***
	(0.0107)	(0.0126)	(0.0145)
2 or More	-0.101***	-0.0812***	-0.121***
	(0.0126)	(0.0150)	(0.0167)
Other	-0.239***	-0.209**	-0.255**
	(0.0631)	(0.0781)	(0.0784)
Not Indic	-0.00568	0.0168	-0.0188

	(0.0121)	(0.0160)	(0.0155)
FIRST GENERATION (reference = First Gen)			
Not First Gen	0.119***	0.138***	0.112***
	(0.00851)	(0.0106)	(0.0112)
Don't Know	-0.166**	-0.0157	-0.202**
	(0.0525)	(0.0845)	(0.0640)
FAMILY INCOME (reference = More than $100,000)			
Less than $25,000	-0.150***	-0.129***	-0.166***
	(0.0127)	(0.0159)	(0.0167)
$25,000 - $49,999	-0.101***	-0.115***	-0.102***
	(0.0106)	(0.0131)	(0.0141)
$50,000 - $74,999	-0.0557***	-0.0719***	-0.0581***
	(0.0104)	(0.0133)	(0.0134)
$75,000 - $99,999	-0.0545***	-0.0528***	-0.0572***
	(0.0100)	(0.0129)	(0.0128)
Don't Know	-0.0505*	-0.0385	-0.0688**
	(0.0196)	(0.0238)	(0.0260)
Missing Income Information	-0.00505	-0.0117	-0.00127
	(0.00652)	(0.00827)	(0.00831)
CLASS LEVEL (reference = Freshman)			
Sophomore	0.0176***	0.0237***	0.0184
	(0.00498)	(0.00455)	(0.0229)
Junior	0.0326***	0.00259	0.0704**
	(0.00605)	(0.00680)	(0.0229)
Senior	0.0815***	0.0403***	0.116***

	(0.00662)	(0.0112)	(0.0230)
Constant	3.207***	3.242***	3.174***
	(0.0357)	(0.0444)	(0.0448)
Observations	151,049	53,896	97,153
Standard errors in parentheses			
*** p<0.001, ** p<0.01, * p<0.05			

Overall, the results from the regression models for cumulative GPA provide strong support for hypothesis **H2**. That is, students that use electronic library licensed content have higher cumulative GPAs. However, the effect of having at least one EZproxy session in an academic term is smaller for cumulative GPA than it is for semester GPA. Model 4 shows that having an EZproxy session in an academic term was correlated with a 0.02 increase in cumulative GPA. To examine the effect of being on- or off-campus, we ran separate models for on- (model 5) and off-campus (model 6) students that show differences between the two groups of students but in ways that are opposite to semester GPA. Having an EZproxy session in an academic term has a larger effect on cumulative GPA for on-campus students compared to their off-campus peers. Note that the magnitude of both effects is very small. Also note that, like semester GPA, the female advantage in cumulative GPA was smaller for on-campus students relative to off-campus students. The first-generation disadvantage with respect to lower cumulative GPAs is more pronounced for on-campus students compared to those that are off-campus.

Table 4. Panel LME Regressions for Association between Library Usage and Cumulative GPA, FA 2016 - WN 2019 (4 or More Semesters)

	(4: All Students)	(5: On-Campus)	(6: Off-Campus)
VARIABLES	CUM_GPA	CUM_GPA	CUM_GPA
EZproxy Session in Term	0.0201***	0.0242***	0.0144***
	(0.000896)	(0.00190)	(0.000871)
On-campus Residence	0.0216***		
	(0.00149)		
High School GPA	0.0222***	0.0364***	0.0141***
	(0.00162)	(0.00313)	(0.00182)
GENDER (Reference = Female)			
Male	-0.0735***	-0.0573***	-0.0841***
	(0.00447)	(0.00603)	(0.00528)
RACE (reference = White)			
Asian	0.0655***	0.0654***	0.0559***
	(0.00558)	(0.00763)	(0.00658)
Black	-0.330***	-0.328***	-0.364***
	(0.0108)	(0.0134)	(0.0139)
Hispanic	-0.157***	-0.168***	-0.150***
	(0.00904)	(0.0116)	(0.0112)
2 or More	-0.0769***	-0.0648***	-0.0885***
	(0.0107)	(0.0137)	(0.0129)
Other	-0.197***	-0.159*	-0.192**
	(0.0549)	(0.0717)	(0.0611)
Not Indic	0.0120	0.0296*	-0.00456

	(0.0102)	(0.0145)	(0.0121)
FIRST GENERATION (reference = First Gen)			
Not First Gen	0.105***	0.118***	0.102***
	(0.00721)	(0.00971)	(0.00867)
Don't Know	-0.209***	-0.0901	-0.233***
	(0.0451)	(0.0786)	(0.0503)
FAMILY INCOME (reference = More than $100,000)			
Less than $25,000	-0.113***	-0.101***	-0.126***
	(0.0107)	(0.0147)	(0.0129)
$25,000 - $49,999	-0.0806***	-0.0963***	-0.0837***
	(0.00901)	(0.0120)	(0.0109)
$50,000 - $74,999	-0.0342***	-0.0543***	-0.0364***
	(0.00883)	(0.0122)	(0.0104)
$75,000 - $99,999	-0.0438***	-0.0416***	-0.0460***
	(0.00850)	(0.0118)	(0.00990)
Don't Know	-0.0326*	-0.0317	-0.0454*
	(0.0165)	(0.0217)	(0.0200)
Missing Income Information	-0.00391	-0.00968	-0.00127
	(0.00553)	(0.00753)	(0.00644)
CLASS LEVEL (reference = Freshman)			
Sophomore	-0.00343*	-0.00615**	0.00310
	(0.00150)	(0.00209)	(0.00513)
Junior	-0.00137	-0.0235***	0.0217***
	(0.00187)	(0.00322)	(0.00517)
Senior	0.0241***	-0.0114*	0.0483***

	(0.00209)	(0.00538)	(0.00520)
Constant	3.430***	3.376***	3.456***
	(0.0275)	(0.0358)	(0.0304)
Observations	151,049	53,896	97,153
Standard errors in parentheses			
*** p<0.001, ** p<0.01, * p<0.05			

The study findings suggest that using library resources has positive impacts on academic performance. These impacts were larger in magnitude for semester GPA relative to cumulative GPA. For example, for semester GPA, first generation students had a lower GPA (-0.119) than non-first-generation students. Further, males had a lower semester GPA (-0.091) than females. Thus, the impacts of gender and first-generation status on semester GPA were smaller in magnitude than the impact of having at least one EZproxy session during an academic term.

Conclusion

Because library data are often not integrated into other university data, there are major obstacles to demonstrating the richness and complexity of the value of academic library usage for the students who use these resources. We show that merging library usage and student outcome data yields valuable insights on the value of the academic library. Understanding patterns of off-campus use of library resources offers an additional point of insight into potential gaps in use by certain groups of students like those living off campus which can be associated with lower academic success and retention. If students in particular programs tend to live off campus, yet their programs are library-research intensive, what could this mean for those students? For example, 4 out of 5 of undergraduate nursing students live off campus, yet we know the nursing program integrates the library heavily in its curriculum. We could explore off campus use by students in this program to potentially identify students at risk of falling through the cracks or to provide indicators to faculty advisors if a student's GPA in research-intensive courses falls below a certain threshold. As additional data from other library services may be added in the future, libraries can develop models to explore other questions around library usage, student success, and curricular integration. The work by LLAP and allied initiatives could be used by libraries to identify opportunities for mitigating educational disparities. Library usage data adds depth of perspective of the student experience, and student engagement broadly, during the undergraduate years. and can be a valuable addition to institutions of higher education as they continue to make data-informed decisions that improve undergraduate education. Further, in the process of doing this work we have created shareable scripts and tools that could be used to replicate our work in other institutional settings. These and other resources can be downloaded for free from the LLAP project's GitHub site (https://github.com/Learning-Library-Analytics-Project) and website (https://libraryanalytics.org/).

Libraries are often new participants within campus learning analytics efforts. The research described here could lead to new partnerships between libraries and other institutional organizations. Much as traditional academic advisors and partners have great insight into the specific needs and capabilities of their students, so could libraries better tailor their service (both group and individual) to those needs. By being better informed about both the kinds of assignments and the needs of the individual students, along with a more granular conceptualization of the technologies they have access to, library staff could be better situated to deliver information services tailored to individual needs. As noted by researcher Megan Oakleaf, designing library services and instruction for average does almost everyone harm (Oakleaf et al. 2020).[37]

Future work could build on our findings by disentangling the effects of students who are off-campus and not using the VPN (and thus need authentication), versus those who are on-campus but choose to access library licensed content via non-university devices, and hence the library proxy server. Undoubtedly there are likely economic, technical, and experiential dimensions to these types of differences in accessing library licensed content. Unfortunately, we were not able to capture them in our study. In addition to multiple socioeconomic factors that could impact student use of library licensed content, there are other factors that could account for these differences, such as the varying nature and demands of curricula across programs and colleges. While there is a healthy demand for library curriculum-integrated instruction (CII) at U-M, programs and instructors may require CII at very different times in the progression of a student's academic career. For example, some programs require library CII in first year experience courses, other programs may only require CII in the third or fourth year. This suggests several lines of future inquiry, such as how course selection impacts the need and motivation to use library-licensed resources, or even how the level of study (such as first year, third year, and so on) correlates to use of licensed resources and, subsequently, to academic outcomes.

APPENDIX

Tables A.1 – A.7 show the percentages of students who had at least one EZproxy session in an academic term by various sociodemographic and academic factors.

Table A.1. Percentage of undergraduate students associated with EZproxy sessions by first gen status, FA16 – WN19

Academic Term	Firstgen Status	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	First Gen	3,520	2,062	59%
	Not First Gen	24,903	14,372	58%
	Don't Know	259	171	66%
WN 2017	First Gen	3,364	1,664	49%
	Not First Gen	23,818	11,631	49%
	Don't Know	226	139	62%
FA 2017	First Gen	3,753	2,054	55%
	Not First Gen	25,316	13,928	55%
	Don't Know	92	52	57%
WN 2018	First Gen	3,605	2,025	56%
	Not First Gen	24,162	12,788	53%
	Don't Know	85	42	49%
FA 2018	First Gen	4,091	2,308	56%
	Not First Gen	25,582	13,855	54%
	Don't Know	53	28	53%
WN 2019	First Gen	3,890	2,310	59%
	Not First Gen	24,418	13,957	57%

Don't Know	47	32	68%

Table A.2. Percentage of undergraduate students associated with EZproxy sessions by on-campus, FA16 – WN19

Academic Term	Residency	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	Off-campus	19,130	11,554	60%
	On-campus	9,552	5,051	53%
WN 2017	Off-campus	17,971	10,353	58%
	On-campus	9,437	3,081	33%
FA 2017	Off-campus	19,993	12,049	60%
	On-campus	9,168	3,985	43%
WN 2018	Off-campus	18,793	11,043	59%
	On-campus	9,059	3,812	42%
FA 2018	Off-campus	20,357	12,014	59%
	On-campus	9,386	4,187	45%
WN 2019	Off-campus	19,110	11,765	62%
	On-campus	9,261	4,540	49%

Table A.3. Percentage of undergraduate students associated with EZproxy sessions by gender, FA16 – WN19

Academic Term	Gender	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	Female	14,296	9,510	67%
	Male	14,386	7,095	49%
WN 2017	Female	13,630	7,817	57%
	Male	13,778	5,617	41%
FA 2017	Female	14,599	9,227	63%
	Male	14,562	6,807	47%
WN 2018	Female	13,910	8,589	62%
	Male	13,942	6,266	45%
FA 2018	Female	14,833	9,304	63%
	Male	14,893	6,887	46%
WN 2019	Female	14,204	9,219	65%
	Male	14,151	7,080	50%

Table A.4. Percentage of undergraduate students associated with EZproxy sessions by class level, FA16 – WN19

Academic Term	Class Level	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	Freshman	5,665	2,982	53%
	Sophomore	6,621	3,724	56%

	Junior	7,035	3,979	57%
	Senior	9,361	5,920	63%
WN 2017	Freshman	2,727	874	32%
	Sophomore	6,296	2,383	38%
	Junior	6,489	3,291	51%
	Senior	11,896	6,886	58%
FA 2017	Freshman	5,387	2,391	44%
	Sophomore	7,043	3,704	53%
	Junior	7,084	3,918	55%
	Senior	9,647	6,021	62%
WN 2018	Freshman	2,511	1,088	43%
	Sophomore	6,407	2,911	45%
	Junior	6,949	3,785	54%
	Senior	11,985	7,071	59%
FA 2018	Freshman	5,440	2,477	46%
	Sophomore	6,957	3,601	52%
	Junior	7,666	4,257	56%
	Senior	9,663	5,856	61%
WN 2019	Freshman	2,557	1,300	51%
	Sophomore	6,397	3,373	53%
	Junior	7,132	4,114	58%
	Senior	12,269	7,512	61%

Table A.5. Percentage of undergraduate students associated with EZproxy sessions by family income, FA16 – WN19

Academic Term	**Family Income**	**Enrolled Students**	**EZproxy Session**	**% ≥ 1 EZproxy Session**
FA 2016	Less than $25,000	1,470	896	61%
	$25,000 - $49,999	2,073	1,206	58%
	$50,000 - $74,999	2,190	1,294	59%
	$75,000 - $99,999	2,356	1,372	58%
	More than $100,000	14,246	8,256	58%
	Don't Know	935	558	60%
	Missing Income Information	5,412	3,023	56%
WN 2017	Less than $25,000	1,417	724	51%
	$25,000 - $49,999	1,973	953	48%
	$50,000 - $74,999	2,114	1,069	51%
	$75,000 - $99,999	2,249	1,145	51%
	More than $100,000	13,636	6,683	49%
	Don't Know	851	435	51%
	Missing Income Information	5,168	2,425	47%
FA 2017	Less than $25,000	1,486	855	58%
	$25,000 - $49,999	2,091	1,139	54%
	$50,000 - $74,999	2,090	1,134	54%
	$75,000 - $99,999	2,210	1,263	57%
	More than $100,000	14,336	7,749	54%

	Don't Know	476	263	55%
	Missing Income Information	6,472	3,631	56%
WN 2018	Less than $25,000	1,441	795	55%
	$25,000 - $49,999	2,026	1,119	55%
	$50,000 - $74,999	2,024	1,123	55%
	$75,000 - $99,999	2,080	1,167	56%
	More than $100,000	13,689	7,095	52%
	Don't Know	430	222	52%
	Missing Income Information	6,162	3,334	54%
FA 2018	Less than $25,000	1,586	911	57%
	$25,000 - $49,999	2,307	1,299	56%
	$50,000 - $74,999	2,066	1,150	56%
	$75,000 - $99,999	2,161	1,204	56%
	More than $100,000	14,632	7,760	53%
	Don't Know	540	285	53%
	Missing Income Information	6,434	3,582	56%
WN 2019	Less than $25,000	1,507	923	61%
	$25,000 - $49,999	2,212	1,269	57%
	$50,000 - $74,999	2,009	1,217	61%
	$75,000 - $99,999	2,074	1,213	58%
	More than $100,000	13,951	7,892	57%
	Don't Know	515	278	54%

Missing Income Information	6,087	3,507	58%

Table A.6. Percentage of undergraduate students associated with EZproxy sessions by race, FA16 – WN19

Academic Term	Race	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	Asian	5,460	3,019	55%
	Black	1,268	730	58%
	Hispanic	1,564	916	59%
	White	17,743	10,439	59%
	2 or More	1,111	642	58%
	Other	53	30	57%
	Not Indic	1,483	829	56%
WN 2017	Asian	5,282	2,425	46%
	Black	1,213	574	47%
	Hispanic	1,500	747	50%
	White	16,876	8,438	50%
	2 or More	1,084	515	48%
	Other	53	23	43%
	Not Indic	1,400	712	51%
FA 2017	Asian	5,685	2,941	52%
	Black	1,291	698	54%

	Hispanic	1,762	955	54%
	White	17,803	10,053	56%
	2 or More	1,206	631	52%
	Other	56	29	52%
	Not Indic	1,358	727	54%
WN 2018	Asian	5,501	2,746	50%
	Black	1,252	683	55%
	Hispanic	1,698	908	53%
	White	16,924	9,220	54%
	2 or More	1,155	599	52%
	Other	54	26	48%
	Not Indic	1,268	673	53%
FA 2018	Asian	6,047	3,063	51%
	Black	1,315	748	57%
	Hispanic	1,972	1,051	53%
	White	17,525	9,794	56%
	2 or More	1,346	702	52%
	Other	49	23	47%
	Not Indic	1,472	810	55%
WN 2019	Asian	5,829	3,137	54%
	Black	1,268	766	60%
	Hispanic	1,899	1,099	58%
	White	16,604	9,738	59%
	2 or More	1,302	745	57%
	Other	46	22	48%

	Not Indic	1,407	792	56%

Table A.7. Percentage of undergraduate students associated with EZproxy sessions by school, FA16 – WN19

Acad. Term	School	Enrolled Students	EZproxy Session	% ≥ 1 EZproxy Session
FA 2016	Architecture	145	65	45%
	Art and Design	495	356	72%
	Business Admin	1,673	890	53%
	Dental Hygiene	111	77	69%
	Education	112	66	59%
	Engineering	6,078	2,736	45%
	Information	208	123	59%
	Joined Deg Prog	10	7	70%
	Kinesiology	946	698	74%
	LS & A	17,306	10,395	60%
	Music, Thtre & Dance	732	447	61%
	Nursing	705	626	89%
	Pharmacy	14	11	79%
	Public Policy	147	108	73%
WN 2017	Architecture	140	71	51%
	Art and Design	462	249	54%
	Business Admin	1,639	746	46%

	Dental Hygiene	107	63	59%
	Education	112	53	47%
	Engineering	5,909	1,958	33%
	Information	186	89	48%
	Joined Deg Prog	8	5	63%
	Kinesiology	918	576	63%
	LS & A	16,400	8,614	53%
	Music, Thtre & Dance	700	402	57%
	Nursing	685	512	75%
	Pharmacy	14	7	50%
	Public Policy	128	89	70%
FA 2017	Architecture	155	82	53%
	Art and Design	497	363	73%
	Business Admin	1,773	869	49%
	Dental Hygiene	112	79	71%
	Education	120	46	38%
	Engineering	6,409	2,666	42%
	Information	253	147	58%
	Joined Deg Prog	12	8	67%
	Kinesiology	976	627	64%
	LS & A	17,160	9,942	58%
	Music, Thtre & Dance	747	495	66%
	Nursing	667	516	77%
	Pharmacy	42	19	45%
	Public Health	85	72	85%

	Public Policy	153	103	67%
WN 2018	Architecture	153	107	70%
	Art and Design	481	356	74%
	Business Admin	1,757	760	43%
	Dental Hygiene	109	82	75%
	Education	118	40	34%
	Engineering	6,150	2,571	42%
	Information	214	122	57%
	Joined Deg Prog	12	7	58%
	Kinesiology	951	594	62%
	LS & A	16,294	9,034	55%
	Music, Thtre & Dance	715	509	71%
	Nursing	636	487	77%
	Pharmacy	42	25	60%
	Public Health	84	72	86%
	Public Policy	136	89	65%
FA 2018	Architecture	181	119	66%
	Art and Design	556	396	71%
	Business Admin	1,826	753	41%
	Dental Hygiene	103	71	69%
	Education	131	60	46%
	Engineering	6,649	2,755	41%
	Information	302	135	45%
	Joined Deg Prog	11	9	82%
	Kinesiology	962	617	64%

	LS & A	17,262	9,918	57%
	Music, Thtre & Dance	743	524	71%
	Nursing	632	543	86%
	Pharmacy	56	33	59%
	Public Health	158	130	82%
	Public Policy	154	128	83%
WN 2019	Architecture	181	124	69%
	Art and Design	524	381	73%
	Business Admin	1,799	740	41%
	Dental Hygiene	101	70	69%
	Education	126	54	43%
	Engineering	6,313	2,847	45%
	Information	260	122	47%
	Joined Deg Prog	10	7	70%
	Kinesiology	954	678	71%
	LS & A	16,409	10,030	61%
	Music, Thtre & Dance	717	515	72%
	Nursing	607	475	78%
	Pharmacy	55	36	65%
	Public Health	157	116	74%
	Public Policy	142	104	73%

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