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Improving Accessibility of Educational Content - An Exploratory Data Analysis

Short Paper

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Abstract

A recent increase in settlements resulting from violations of the Americans with Disabilities Act (ADA) has resulted in institutions developing processes for improving course material accessibility. We analyze data from about 1670 sections of courses offered at a US school of business, spanning over 9 semesters that include numerical accessibility scores for various components of the course material. We combine this data with student performance and faculty evaluation data from the same period. In our analysis we observed improvement in overall accessibility scores, yet noticed statistically significant reduction in student performance as well as instructor evaluations. We document that one possible explanation for this result can be linked to the drastic reduction of course materials. We conclude that instead of relying only on a measure of accessibility, faculty should be involved in a multi-faceted process that includes communication and training to identify and improve issues with accessibility in course content.

Keywords: Accessibility, ADA, disability, student learning, content analysis

Introduction

Accessibility is a universal right in the modern world, and it is often adopted as law in most countries. In the United States, Section 504 of the Rehabilitation Act of Education (EEOC 1973) specifically provided one of the first civil rights legislation to guarantee equal access for students with disabilities to higher education institutions that receive federal financial assistance. This is widely accepted as a precursor to the American Disabilities Act ADA (ADA 1996) was introduced in the 1990s, and further amended in 2008 to:

> *prohibit discrimination against people with disabilities in everyday activities. The ADA prohibits discrimination on the basis of disability just as other civil rights laws prohibit discrimination on the basis of race, color, sex, national origin, age, and religion. The ADA guarantees that people with disabilities have the same opportunities as everyone else to enjoy employment opportunities, purchase goods and services, and participate in state and local government programs.*

Such legal acts are common in other countries as well, such as the Canadian Human Rights Act (R.S.C. 1985), which establishes access to higher education interactions as a civil right.

One positive societal impact of these legal acts is the ability for persons with disabilities to enroll in higher education to pursue advanced degrees and career aspirations. However, as more persons with disabilities get admitted to universities, some of the older forms of pedagogy are coming to the forefront in their rigidity, because of the difficulty they pose towards students with disabilities. With the accelerated adoption of remote learning since the 2020 COVID-19 pandemic (Lockee 2021), most institutions are adopting information technology in education, and as such, the focus on accessibility in education has become much more technology-driven. Simply ensuring classrooms are accessible is no longer enough to meet the needs of persons with disabilities who are attempting to access the material through technology platforms.

One unfortunate effect of this discrepancy in the increased number of students with disabilities and the lack of accessibility in the educational platforms and their contents is education inequity among the students with the educational institutions and programs. This has led to several legal issues with students filing suits against institutions for violations of their rights. Such lawsuits have become common over the last 10-15 years. Carlson (2023) identifies 175 lawsuits and settlements against 46 institutions (as of April 2023) over the last 15 years with suits naming highly acclaimed institutions such as Harvard and MIT. Most of these lawsuits are filed by students with disabilities who felt discriminated against because of educational methods and technologies used by these institutions which did not incorporate sufficient accessibility characteristics, leading to inequality and inequity in access to educational resources.

One of the methods applied by many of the institutions, often as part of the settlement agreements, is to implement technology that evaluates the level of accessibility in various courses in the curriculum. The typical way of achieving this is by using technology like a web crawler to evaluate course content in courses offered through the institution's Learning Management Systems (LMS). Two of the top tools in this domain are Blackboard Ally (https://ally.cc) and Yuja Panorama (https://yuja.com/panorama). Both tools offer analytics capabilities that can analyze all content in courses, including media content, to evaluate accessibility issues and provide an objective score measuring the level of accessibility of the course. Instructors can view the overall course accessibility score as well as file-by-file accessibility scores and track progress over time. Files with low accessibility scores can be quickly replaced with new versions, or in some cases, can be updated within the LMS to correct the identified accessibility issues.

In this article, we conduct a case study that explores data from the adoption of analytics tools to measure (and potentially mitigate) the level of accessibility in course content, and how such actions affect user performance. In addition, we use litigation and settlement events as a potential source of exogenous shock that may affect the level of accessibility as well as user performance. Readers note that in this article, our users of the data include both the faculty members delivering the content as well as students who are consuming the content.

Literature Review

Although the notion of accessibility in educational content creation and delivery is not new, the processes of implementing accessible content and the effect of these processes on the quality of the content is lacking in Information Systems literature. Much of the accessibility-focused research has been in education, particularly in grade-school/K-12 education. The concept of Universal Design Language (UDL) was first adopted in US K-12 education but has recently gained attention in higher education as well (CAST 2018). UDL allows the creation of learning experiences that incorporates multiple means of engaging with content and participants, representing information, and expressing skills and knowledge. UDL is adopted widely, including in Quality Matters, which is the global organization leading quality assurance in online and innovative digital teaching and learning environments (Chita-Tegmark et al. 2012).

Researchers in education have extensively studied how to respond to students with learning challenges, particularly the interaction between persons with disabilities and other persons (including other students, faculty, and family members (Cook et al. 2009; Murray et al. 2009; Nelson et al. 1990). The concept of accessibility has traditionally been disconnected from disabilities in Information Systems literature, and refers primarily to a design principle of cognition when evaluating research (see e.g., Iivari et al. 2021; Rosemann and Vessey 2008), or as a form of control, availability, authorization and security of information (Kong et al. 2022). The notion of accessibility that we investigate in this article is based on Universal Design, and its applications in the context of developing educational technologies and content accessible to all students, regardless of their physical or cognitive disabilities. Much work has been done to develop systems that focus on accessibility not only during the final deployment, but throughout the development cycle (Paiva et al. 2021). Improving accessibility of systems have also been demonstrated to provide positive outcomes for even persons with impairments that traditionally make such systems unusable to them (Liang et al. 2017). This has also led to bodies of educational institutions and research outlets to commit to the focus on accessibility (Hanson 2017).

Performance of information systems is linked in literature to the quality of the system as well as the quality of the information contained in the system (DeLone and McLean 1992). Much of the recent research on the success of information systems continues to be driven by user satisfaction and organizational impact

(Delone and McLean 2014; Li and Wang 2021). Further research based on this model also shows that in fields such as healthcare, accessibility, navigability and readability of information predict system quality, while physical disability weakens the effect of information quality on perceived risk (Liang et al. 2017). Although accessibility is only one aspect of information quality in educational content, it is one of the most crucial markers of quality in the educational environment today, exemplified by the fact that the entire Section 8 of the Quality Matters (QM) standard (Quality Matters 2018) is dedicated to Accessibility.

The focus on accessibility, and the desire to improve experience and performance for all users have prompted many institutions to adopt technology for evaluating accessibility of course content. This is done with the expectation that improving measures of accessibility through these systems would translate into improved quality of the content. The process, however, is not as simple as improving the accessibility scores as recent research demonstrates the necessity for the involvement of users, developers and management in the creation of accessible IT artifacts (Mäkipää et al. 2022). In this paper, we investigate the effect of objective measures of accessibility on performance and satisfaction using a quasi-experimental setup, and analyze whether reliance on only these objective measures does in fact provide improvement in student performance and satisfaction.

Data Collection

We used a popular accessibility analysis tool to analyze all course shells within the College of Business from Spring 2019 through Spring 2023, for a total of 9 semesters of data. The tool evaluates all pages, files, and media within the course shells to provide a score that approximately determines the level of accessibility of the course on a scale of 0 through 100. The analysis also includes the total number of files analyzed for each course shell, including images and other media. The tool also breaks down the overall score into scores for specific types of documents, such as web pages, images, presentations, etc. In the data set presented in this paper, we only used the overall score normalized into a range of 0-1, as well as the count of the total number of files and the number of image files.

In addition to the analysis of the different course shell content, we also used two other related data sources. We retrieved data from the course scheduling system from the College of Business that provides meta-data of the courses, such as the course numbers, names, modalities, instructor(s), as well as enrollments for the same range of semesters (Spring 2019-Spring 2023). To ensure the confidentiality of the data, we used a de-identification method to remove instructor and course identities. We also retrieved data from the University course evaluation system that provides us with the average class GPA for each section, an average instructor evaluation score, as well as the response rate from the course evaluation survey. We used the same de-identification method to relate the three different data sources for our analysis. After combining the data sets, we removed course sections that did not have any student evaluations or had an enrollment value of 5 or less. This gave us a total of 1670 observations over the 9 semesters. A summary of the variables including basic descriptive statistics is shown in Table 1.

Variable	Description	Obs.	mean	sd	median	min	max
Avg. GPA	Average GPA	1670	3.452	0.361	3.502	1.868	4
Avg. Evaluation	Average evaluation score	1670	4.308	0.511	4.4	1	5
Avg. Accessibility Score	Average accessibility score	1670	0.785	0.133	0.792	0.157	1
Enrollment	The number of students enrolled per section	1670	41.291	20.324	40	5	175.5
Num. Files	The number of files on LMS	1670	142.948	270.646	74	5	3444
Num. Instructors	The number of instructors associated with the course	1670	2.142	2.458	1	1	20
Prop. Online Sections	The proportion of online sections	1670	0.516	0.396	0.5	0	1
Prop. Image Files	The proportion of image files on LMS	1670	0.227	0.192	0.167	0	1
Response Rate	The rate of students who answered the evaluation survey	1670	0.602	0.273	0.576	0.05	1

Table 1. Variables and Summary Statistics

Methods and Analysis

In this section, we present empirical evidence to demonstrate the consequences of accessibility tool adoption. We ensure that our results are robust to alternative specifications and explanations. Further, we employ machine learning techniques to examine heterogeneous treatment effect.

Empirical Framework

Starting in Spring 2021, the university has taken a series of measures to enhance its instructional accessibility scores on the LMS platform following complaints and legal requirements. For example, on May 20th, 2021, Global Accessibility Awareness Day, the university held a "Fix your Content Day" challenge. For 24 hours, the university faculty was on a mission to use the accessibility tool to fix accessibility issues with LMS course shell content. At the end of the day, the campus with the most files fixed was recognized and awarded a prize. This event led to a sharp increase in the accessibility scores along with a drastic decrease in the number of files in course shells, as shown in Figure 1, indicating that, instead of fixing accessibility issues in course materials, which would involve additional effort, faculty turned to simply deleting the files with low accessibility scores. This unintended phenomenon provides us an opportunity to examine the causal effect of the accessibility improvement process on user performance.

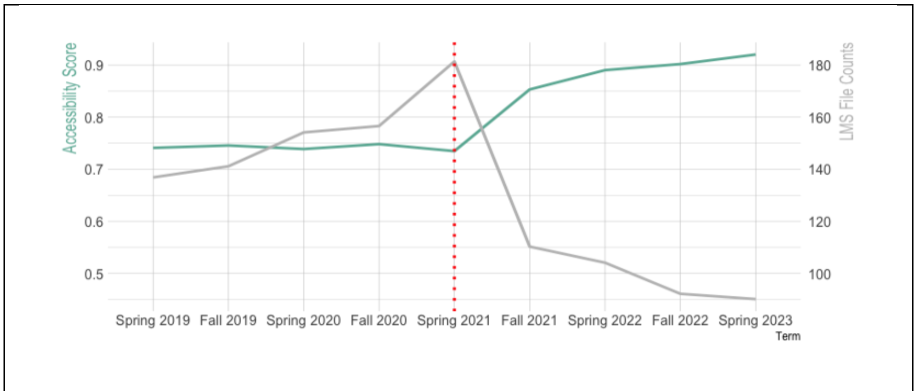


Figure 1. Accessibility Score and LMS File Count by Semester

Treatment and Control Groups

Although this improvement process provides us with an exogenous shock, direct comparisons of course performances between the before and after periods can result in biased estimates because they can be confounded with time trends that are present even in the absence of the shock. For instance, learning modes have changed along with the pandemic evolution, which, in turn, could influence course performance. To isolate such confounding effects, our empirical strategy relies on identifying courses that did not experience the shock as the control group. These control courses experienced the same time trend, although they did not experience an increase in accessibility scores after the institutional adoption of an accessibility improvement plan. We compare the changes before and after for both the treatment and control groups.

We now describe how we define whether a course experienced a discontinuous increase in accessibility score because of the shock. Specifically, we compare the average accessibility scores of the academic years before and after (i.e., 2020-2021 and 2021-2022) the shock. We classify a course as having undergone a sudden surge in accessibility due to the shock if its percentage change exceeds the 75th percentile.[1] The remaining courses are considered as the candidate courses of the control group.

To ensure the comparability of the courses in the treatment and control groups, we use one-to-one nearest-neighbor matching to construct the matched samples that share similar levels, sizes, and online file attributes during the before period. In the matching process, we consider the course-specific characteristics such as the number of sections, the proportion of online sections, the average class size, and the response rate. We also match courses based on LMS-related attributes such as the number of online files, the proportion of images, and the accessibility score in the pre-shock periods. We perform two sets of matching models, in one of which we additionally include the percentage change of online files to account for the effect of this potential confounding factor. We conduct a two-sample t-test on these two sets of matched samples to confirm that the courses in the treatment and control groups are similar along all the specified characteristics. We present the summary statistics of the matched courses and append the p-values from

[1] The results are consistent if we use other cutoffs, such as the 80th or 90th percentile.

the t-tests in Table 2. These descriptive results suggest that, while the accessibility scores are significantly larger in the treatment group, there are no significant differences between the matched treatment and control groups on the other control variables.

		Not Matched with Change of Files		*Matched with Change of Files*	
	Treatment	Control	p-Value	Control	p-Value
Observations	65	65		65	
Num. Instructors (mean (SD))	1.65 (2.14)	1.80 (2.08)	0.678	1.88 (1.62)	0.475
Enrollment (mean (SD))	80.53 (121.72)	90.57 (139.76)	0.663	100.33 (119.28)	0.351
Response Rate (mean (SD))	0.64 (0.25)	0.65 (0.31)	0.888	0.61 (0.23)	0.513
Num. Files (mean (SD))	275.92 (457.99)	231.10 (316.85)	0.518	177.80 (291.28)	0.147
Prop. Image Files (mean (SD))	0.24 (0.18)	0.21 (0.14)	0.339	0.24 (0.16)	0.949
Prop. Online Sections (mean (SD))	0.75 (0.35)	0.74 (0.35)	0.974	0.76 (0.33)	0.835
Evaluation (mean (SD))	4.41 (0.49)	4.43 (0.42)	0.738	4.47 (0.32)	0.379
GPA (mean (SD))	3.42 (0.58)	3.45 (0.67)	0.799	3.45 (0.68)	0.779
Perc. Change of File Counts (mean (SD))	-49.18 (37.43)	-11.03 (43.56)	<0.001	-43.76 (35.39)	0.398
Perc. Change of Accessibility Scores (mean (SD))	45.87 (25.69)	10.89 (9.95)	<0.001	14.89 (7.44)	<0.001

Table 2. Comparison of Matched Samples

Difference-in-Differences Approach

The possibility to construct control and treatment groups before and after the exogenous shock to accessibility scores leads to a quasi-experimental research design. With our matched samples, we estimate the Difference-in-Differences (DID) model of the form:

$$Y_{it}=\beta_0+\beta_d\cdot Treatment_i\times After_t+X_{it}'\cdot\gamma_d+\Theta_i+\lambda_t+\varepsilon_{it}, \qquad (1)$$

where the subscript i denotes course and the subscript t denotes semester. Variable Y_{it} denotes the outcome variable (that is, student performance, measured by the average GPA among students, and student satisfaction, measured by the average score of course evaluation). The binary variable, $After_t$, denotes whether semester t is after the shock (Spring 2021). $Treatment_i$ indicates whether a course i experienced a discontinuous *increase* in accessibility scores because of the fix-content challenge. One can also specify $Treatment_i$ as a continuous variable measured by the percentage of increase instead of a binary variable. Matrix X_{it} denotes course characteristics (e.g., enrollment, response rate, online file counts, etc.). The vector λ_t contains time fixed effects for each semester, and Θ_i contains course fixed effects. We estimate the equation using course fixed effects models to account for potentially unobserved course characteristics and cluster the standard errors at the course level to further control for potential correlations in error terms. We include the semester fixed effects to adjust for the unobserved temporal trends over our study period.

To test the DID model validity and examine the parallel trend assumption, we run the following analogue of our main model using the samples in the before period:

$$Y_{it}=\beta_0+\Sigma_{p\in T}\beta_p\cdot Tratement_i\times Term_t+X_{it}'\cdot\gamma_p+\Theta_i+\lambda_t+\nu_{it}, \qquad (2)$$

where T includes the terms of the before periods and $Term_t$ is the term indicator. The coefficient β_p picks up differences in the trend of the course performance (i.e., student performance and course evaluation) across years before the accessibility improvement. We observe insignificant estimates of β_p, suggesting that the parallel-trend assumption cannot be rejected.

Estimation Results

To investigate the effect of the accessibility implementation on student performance and perceptions, in what follows, we present the empirical results using our quasi-experimental framework. We first present our main results of the effects of the accessibility implementation on student average GPA and the course evaluation score at both the course and the course-instructor level. Then we perform an additional analysis to check the role of the faculty's strategic behavior at play.

Effects of Accessibility Improvement on Course Performance

Table 3 reports the key estimation results of Equation 1 for the effects of the accessibility implementation on course performance. In columns (1) and (2), we present results for our main model specification where the dependent variables are *GPA* and *Evaluation* respectively. With other course characteristics matched, we observe negative coefficients of the interaction term, *Increase×After* for both *GPA* and *Evaluation*; the estimated coefficients are both statistically significant. Students' average GPA and the course evaluation score decreased by 0.056 and 0.162, respectively, for those courses with accessibility issues fixed. The results also hold if we use the continuous variable measured by the percentage of increase instead of a binary variable (as shown in columns (3)-(4)).

	Course Level				*Course-Instructor Level*			
	GPA (1)	Evaluation (2)	GPA (3)	Evaluation (4)	GPA (5)	Evaluation (6)	GPA (7)	Evaluation (8)
Increase × After	-0.056^{**}	-0.162^{***}			-0.043^{***}	-0.085^{**}		
	(0.026)	(0.061)			(0.008)	(0.026)		
% Increase × After			-0.101^{**}	-0.095^{*}			-0.100^{**}	-0.129^{*}
			(0.049)	(0.057)			(0.044)	(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Course (FE)	Yes	Yes	Yes	Yes				
Course-Instructor (FE)					Yes	Yes	Yes	Yes
Semester (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	810	810	810	810	1525	1525	3566	3566
R^2	0.796	0.512	0.795	0.507	0.811	0.650	0.849	0.665
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3. Effect of Accessibility on Course Performance

While, with the matching models, we make sure that our treatment and control groups are comparable in terms of various course and online file characteristics, the lack of instructor-level controls could bring biased estimates because the decision of improving the accessibility score and how to improve the accessibility score was made by instructors. We minimize this potential bias by checking the consistency of our results at the course-instructor level. We repeat the matching process and rerun the DID models with the course-instructor pair as our analysis unit. We present the estimation results in columns (5)-(8) of Table 3, in which we include the course-instructor fixed effect across all specifications to account for the heterogeneity among instructors. We find consistent results from this course-instructor level analysis, suggesting that our finding still holds after controlling for instructors. To verify our results are not driven by our matching method, at both the course and the course-instructor levels, we rerun our analysis using the full sample and find consistent results across all specifications. In summary, our results indicate that the accessibility implementation leads to a significant reduction in student performance as well as the perception of instructors.

	Course Level				*Course-Instructor Level*			
	GPA (1)	Evaluation (2)	GPA (3)	Evaluation (4)	GPA (5)	Evaluation (6)	GPA (7)	Evaluation (8)
Increase × After	−0.028	−0.060			−0.035	−0.011		
	(0.026)	(0.056)			(0.028)	(0.050)		
% Increase × After			−0.065	0.087			−0.117	−0.026
			(0.052)	(0.113)			(0.070)	(0.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Course (FE)	Yes	Yes	Yes	Yes				
Course-Instructor (FE)					Yes	Yes	Yes	Yes
Semester (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	832	832	832	832	1624	1624	1624	1624
R^2	0.808	0.525	0.808	0.524	0.835	0.668	0.835	0.668
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

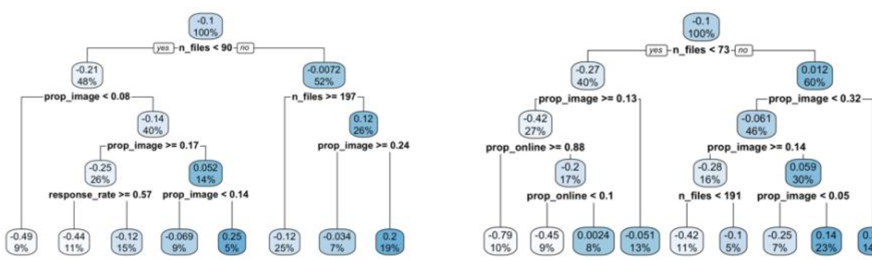
Table 4. Insignificant Effect after Controlling for File Deletion

Mechanism Examination: Controlling for File Reduction Percentage

As noted, our analysis indicates faculty responded to the content-fix challenge primarily by deleting files with lower accessibility scores instead of fixing these files. This strategic behavior of faculty, confounding with accessibility score improvement, could shape an underlying mechanism that explains the inferior consequences observed in student performance and course evaluation. To examine this potential mechanism, we re-construct the control group by including percentage changes of file counts in LMS as an additional matching variable (as shown in Table 3). With the re-matched samples, we rerun the DID analysis at both the course and the course-instructor levels and present the estimation results in Table 4. As shown in the table, after controlling for the file deletion percentage, the coefficients of the interaction terms, *Increase×After* and *% Increase×After*, are *not* significant. This result indicates that the decrease in course performance associated with the accessibility improvement can be explained by the drastic reduction of files in LMS.

Heterogeneous Treatment Effects: Causal Tree Learning

Because of the heterogeneity across courses in terms of their objects, sizes, materials, etc., users' responses to sudden curriculum changes can be different. Thus, it is important to understand heterogeneous responses to institutional measures and how to further optimize them. Considering this, we examine heterogeneous treatment effect (HTE) across courses. Specifically, we follow advances in state-of-the-art machine learning by using a causal tree (CT) algorithm (Wager and Athey 2018). This algorithm can decompose overall average treatment effects within a population into various subpopulation local treatment effects by learning and splitting the data without making any assumptions about the possible linear, nonlinear, or interactive model specifications of course and section characteristics (e.g., enrollment, file volume, response rate, etc.). We focus on simulating the HTE of accessibility implementation over these characteristics at the course level, as illustrated in Figure 2. Our results remain consistent from using the course-instructor level dataset. The results of Figure 2 suggest that the institutional adoption of the accessibility plan has an overall negative treatment effect on student GPA (-0.1, 100% of the observations) and course evaluation (-0.1, 100% of the observations). However, substantial heterogeneity exists across courses with different number of online files. Specifically, if the quantity of online files is small (e.g., fewer than 90 in Subfigure i and fewer than 74 in Subfigure ii), the negative effects of accessibility adoption on user performance, reflected by student GPA and course evaluation, are even more salient. These results suggest that courses with fewer materials to begin with are disproportionately impacted by the unfavorable consequences following the accessibility improvement process.



i. GPA, Course level

ii. Evaluation, Course level

Figure 2. Testing Heterogeneous Treatment Effects with Causal Tree

Additional Robustness Checks

We perform a set of additional analyses to ensure that our results are robust to alternative variable and model specifications. First, we examine the differential effects of accessibility improvement in short (here, in Fall 2021) and long terms (after Fall 2021). In doing so, we use two dummy variables to capture the short and long period windows. We repeat our DID analysis by using these two dummies in the place of the dummy indicator, *After*; we observe consistent results, that is, there is an immediate decrease in both course evaluation and student average GPA in Fall 2021 and the decrease continues even after Fall 2021.

Our main analysis takes advantage of the phenomenon that the rate of increase in accessibility scores after the Spring 2021 differs across courses and sections. In fact, every course has been affected by universitywide accessibility initiatives. In addition, our results can be confounded by seasonality factors, that is, there might exist systematic differences in student performance and perceptions between Spring and Fall, even in the absence of the initiatives. Thus, to improve upon the causal identification of the study, we resemble a DID model with the previous year as the control (see e.g., Bandiera et al. 2005; Daron Acemoglu et al. 2004). Specifically, we focus on four sequential semesters, namely, Spring 2010, Fall 2020, Spring 2021, and Fall 2020; observations in Spring 2010 and Fall 2020 are regarded as the control group while observations in Spring 2011 and Fall 2021 are regarded as the treatment group. We presume the treatment group experiences a shock such that Fall semester is the after-shock period. With this model framework, we find our results still hold – the accessibility implementation has a significantly negative effect on course evaluation and student GPA.

Discussion and Conclusion

Accessibility initiatives and the laws and acts surrounding them have a profound societal impact, by ensuring that all human beings, regardless of their physical and mental abilities, are allowed to achieve their educational goals. While many institutions have implemented tools to analyze and guide faculty to "correct" accessibility problems in course materials, time required to make these changes and the perceived low return on the time investment both make faculty members strategically choose to remove content with low accessibility scores. This strategic choice often leads to unfavorable outcomes in terms of student performance and instructor perceptions. In this study, we conducted a quasi-experimental analysis of over 4 years of accessibility information for the entire curriculum of a US College of Business, two years before and after an institutionally adopted curriculum improvement plan aimed at enhancing the accessibility of educational content. Our analysis indicates that while the overall accessibility measures did improve, student performance and course evaluation seemed to suffer. One possible underlying reason we identified is the reduction in the amount of course content. Our refined causal tree (CT) analysis further suggests that the volume and variety of online files play a significant role in shaping the heterogeneous treatment effects of accessibility implementation.

While these findings may seem to indicate that implementing an objective scoring tool for accessibility measures may have negative consequences, we posit that institutions should not rely solely on objective accessibility measures to determine the quality of accessible content in the course. Instead, improving accessibility can be a multi-pronged approach, as identified by Mäkipää et al. (2022). Using this model, we suggest that faculty should communicate transparently about accessibility initiatives and involve students in the process by utilizing the LMS's accessibility evaluation tools, following guidelines, and ensuring course content compatibility with Accessibility Technologies (AT). Schools should prioritize both improving the accessibility and quality of content within their LMS, while also ensuring a sufficient volume and variety of content through, for example, training on creating accessible course materials to all LMS users, and incentivizing faculty members for taking on this potentially time-consuming task. Administrators and policy makers should encourage institutions to form accessibility committees comprising faculty, staff, and students. Our findings suggest an unintended effect of implementing IT in social goods, which stems from behavioral elements. This unintended effect highlights the importance of alighting interests between the principal (e.g., administrators or regulators) and agents (e.g., schools and technology users).

We acknowledge certain limitations in our analyses. First, our analysis focuses on a case study with data derived solely from one prominent college of business in the U.S., while data from other colleges, universities, or elementary and secondary schools are not included in this study. This limitation restricts the scope of our study and prevents us from conducting a comprehensive evaluation of accessibility implementation across various types and levels of educational institutions. Another limitation is surrounding potential confounders that happened around the same time as the improvement process, such as the global pandemic, LMS feature updates, proportion of students with disabilities, and other local-, state- or federal-level policy changes. Furthermore, to verify the potential justification for the observed impacts resulting from the reduction in course content, qualitative research methods such as surveys and interviews, as well as experimental studies, may be carried out. Lastly, it is necessary to conduct more research to determine the strategies that institutions can adopt to enhance the quality and accessibility of course content, with the aim of enhancing student learning outcomes and course performance.

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