Do Multiple Learner Interactions Improve Learning for Accounting Students Having Differing Academic Achievement and Demographics?

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ABSTRACT

This study examines whether prior academic achievement and certain demographic characteristics affect the types of learner interaction chosen by online introductory accounting students and whether those choices improve learning. The two types of online learner interactions that we study are learner-content (proxied by the viewing of instructor-created videos) and learner-instructor (proxied by the correctness of real-time polling responses). We partition our sample into subsamples based on prior GPA, age, semester hours, major, first time in college, receipt of financial aid, citizenship, gender, and ethnicity. Our results show that younger, male, and Hispanic students tend to select learner interactions that result in suboptimal learning, whereas Asian students and those with higher GPAs or financial aid optimize their learning by selecting multiple interactions. Our findings emphasize the need for educators to include multiple learner interactions in their courses and for students to take advantage of multiple learning aids.

Keywords: accounting, online education, student demographics, student achievement

INTRODUCTION

The COVID-19 pandemic accelerated higher education's digital transformation to online learning. While most observers at the time were impressed at the speed of the transformation, many now question the quality of online learning and wonder whether the one-size-fits-all approach adopted by many educators is appropriate for a diverse generation of students (e.g., Rizvi et al., 2022). Our research is motivated by these concerns. In this paper we examine whether prior academic achievement and differing demographics affect the types of learner interaction chosen by online introductory accounting students and whether the choices made by these students improve learning outcomes.

All learners are unique, and some are more adaptive than others to change (e.g., Seemiller and Thomas, 2018; Gonzalez et al., 2020). The adaptiveness of the learner often relates to (a) baseline tendencies generally measured in terms of prior academic performance, and/or (b) social, economic, and individual-level circumstances. Prior research has identified learner-content and learner-instructor interaction as important components of effective online learning (e.g., Moore, 1989; Arbaugh and Benbunan-Fich, 2007). Learner-content interaction refers to the process by which a learner initiates and interacts in a pedagogically meaningful way with the subject matter or course content but does so on her own. Learner-instructor interaction refers to the process by which the instructor actively guides and facilitates learning. We refer to the combination of learner-content and learner-instructor interactions as multiple learner interactions.

The relationship between the use of multiple learner interactions and academic improvement was investigated in Meade and Parthasarathy (2020). The results showed that students who increased both types of learner interaction after the COVID-19 shift to virtual instruction in Spring 2020 obtained final exam scores that were, on average, over 10 percent higher than students who decreased both types of learner interaction. Compared to students who increased only one type of learner interaction, those who increased both learner interactions attained scores that averaged almost 3 percent higher. This paper extends the earlier work of Meade and Parthasarathy (2020) to investigate whether the choice of learner interactions differs among students with differing prior academic achievement and demographic characteristics and whether the selected interactions improve learning.

PREVIOUS RESEARCH

Effective instruction requires student engagement, and engagement is generally best developed through interaction (e.g., Anderson, 2003; Marks et al., 2005; Malan, 2020). Before the COVID-19 pandemic, most interaction took place in physical classrooms. The pandemic altered the delivery of higher education and, in so doing, impacted the types of interaction available to students (e.g., Sangster et al., 2020). Moore (1989) identified three types of interaction inherent in effective online courses: learner-content, learner-instructor, and learner-learner. In this paper, we focus on the first

two types of interaction. We leave it to future studies to test the efficacy of the third type of interaction (learner-learner) in the context of accounting education.

Learner-content interaction is the process traditionally identified as learning. It occurs when a learner interacts intellectually with the subject matter or course content, resulting in changes to the learner's cognitive structures. Content may take the form of text, audio, video, visuals, or some combination, but it should allow learners to adapt the learning materials to their individual learning style.

Learner-instructor interaction refers to the level of involvement between the instructor and the learner. Although this type of interaction is typically associated with the lecture format, it encompasses all forms of instructor-driven interactions. In synchronous online learning environments, learner-instructor interactions may take the form of virtual lessons, virtual office hours, shared screens, polling, chat, and other tools of engagement. Table 1 provides examples of learning strategies and tools commonly used to promote learner-content and learner-instructor interactions.

Table 1: Examples of Learner Interactions in Online Learning Environments

Interaction	Synchronous	Asynchronous
Learner-content	N/A	Textbooks Adaptive smart books Videos Podcasts Visuals Journals
Learner-instructor	Virtual lessons Virtual office hours Shared screens Virtual whiteboards Polling Chat	Discussion forums Email Voice mail Curated blogs Wikis Announcements Checklists Posted feedback

While learner-content and learner-instructor interactions are present in both face-to-face and online courses, their importance is heightened in online environments due to challenges associated with physical and emotional distance (e.g., Hansen and Reich, 2015; Fogarty, 2020; Lowenthal et al., 2020). Recent studies show that the pandemic and the associated pivot to online education impacted students from different socio-economic backgrounds differently, and that much of the academic and economic impact fell disproportionately on lower-income, women, and minority students (e.g., Dorn et al., 2020; Klebs et al., 2021; National Center for Education Statistics, 2021). Motivated by these studies, this paper seeks to answer the following two research questions.

Research Question 1: Does prior academic achievement and demographic characteristics affect the types of learner interaction selected by students?

Research Question 2: Is improvement in learning from multiple learner interactions descriptive of students having different academic and demographic backgrounds?

RESEARCH DESIGN

Data come from 10 sections of an introductory managerial accounting course that, due to the COVID-19 pandemic, moved from face-to-face instruction to synchronous virtual delivery on Zoom in mid-March 2020. The course was coordinated by a lead instructor and all instructors taught the same content and shared common syllabi, textbooks,

assignments, and exams. Prior to the shift to virtual delivery, students had attended in-person instruction held on the campus of a large, public, doctoral degree-granting university located in the United States and having enrollment of approximately 47,000 students. In 2020, the spring semester commenced in mid-January and concluded in mid-May. The primary topics covered in the course were types of costs, job and process costing, marginal costing, cost-volume-profit analysis, capital budgeting, master budgets, product costing and pricing, business decision evaluations, and performance evaluation.

Required material for the course included a textbook, which came with access to the publisher's website and online learning aids. Students also had access on the course Learning Management System (LMS) to instructor-created videos covering both conceptual knowledge and problem-solving applications. The videos ran between 15 and 20 minutes in length and included narration and handwriting in a style that replicated an instructor giving a lecture while writing on a whiteboard. The videos served as a supplementary learning aid such that students could watch them asynchronously at their own pace either before or after a topic was discussed in the live class. The videos were created by the lead instructor and were available to students enrolled in all 10 sections. Within the LMS, the statistics tracking feature was enabled which allowed the viewing patterns of students to be tracked and analyzed. Course grades were based on student scores on exams, in-class polling questions, and out-of-class assignments.

Before the shift to synchronous virtual delivery, students had completed a midterm exam, several assigned homework problems, and some in-class polling questions. They had also been encouraged to watch the instructor-created videos that corresponded with the covered content. After the COVID-19 pandemic and the move to virtual instruction, students completed the remaining homework assignments, in-class polling questions, and cumulative final exam. In addition, they were again reminded to watch the remaining instructor-created videos. Both before and after the transition to virtual instruction, students were incentivized to attend the face-to-face and virtual classes by including polling scores in the calculation of the final grade. Scores on the in-class polling questions accounted for approximately 7 percent of the course grade. Although the course grade did not explicitly include an incentive for viewing the instructor-created videos, students were awarded with extra credit points worth up to 1.4 percent of the final grade.

Like Meade and Parthasarathy (2020), the design of this research is unique in that the synchronous component of the course incorporated polling in both the face-to-face setting and the virtual classroom. Likewise, the course included short, out-of-class instructor-created videos embedded in the LMS both before and after the transition to online instruction. Absent the pandemic, we would expect that the choice of learner interactions would follow a predictable trajectory, with higher-achieving students maintaining or increasing the two types of learner interaction and lower-achieving students decreasing these interactions. But the pandemic, with its arbitrary disruptions to work schedules, childcare services, schooling, internet connectivity, and study spaces changed this trajectory by forcing students with differing academic and demographic backgrounds to reassess and modify their choice of learner interactions in light of their changed personal circumstances (e.g., Sangster et al., 2020). Our design exploits this setting by using each student as her own control and, in so doing, provides us with a more powerful lens through which to examine the impact of learner interaction choice on exam performance than much of the previous research.

Methodology

The managerial accounting course which we study had 1,019 students enrolled, of which 41 withdrew before receiving a final grade and 24 were new to the university and missing a measure of incoming GPA which we use in our analysis as a measure of prior academic achievement. The final sample, therefore, consists of 954 students. Of these 954 students, the lead instructor taught three sections with a total of 378 students, a second instructor taught five sections with a total of 441 students, and a third instructor taught two sections with a total of 135 students. Untabulated statistical analyses indicate that the instructor did not significantly affect exam performance or the choice of learner interactions.

As in Meade and Parthasarathy (2020), this study uses a 2x2 design to classify each student into one of four learning modes based on her pre- and post-COVID-19 choice of learner interactions. We treat viewing of the instructor-created videos as a proxy for learner-content interaction and measure it as the percentage of available videos watched in the pre- and post-transition periods. We treat the correctness of in-class polling questions as a proxy for learner-instructor interaction and measure it using the ratio of correct polling responses to total possible polling responses in the pre- and post-transition periods.

In support of our choice of proxy measures is a survey by Martin and Bolliger (2018) of 155 online students attending eight universities across the United States. Their study examined student perceptions of various engagement strategies used in online courses, categorized according to the type of learner interaction. Their results showed that students viewed learner-instructor interaction as the most important, followed closely by learner-content interaction.

In our 2x2 design, our four learning modes correspond to changes in a student's learner interactions between the pre- and post-transition periods. Our first learning mode, which we label as "Video Down/Polling Down," is composed of students whose video viewing and polling correctness decreased in the post-transition period. Our second learning mode, which we label as "Video Up/Polling Down," is composed of students whose video viewing increased in the post-transition period, but whose polling correctness decreased. Our third learning mode, which we label as "Video Down/Polling Up," is composed of students whose video viewing decreased in the post-transition period, but whose polling correctness increased. Our fourth learning mode, which we label as "Video Up/Polling Up," is composed of students who increased both their video viewing and polling correctness in the post-transition period. We use a single categorical variable to identify changes in learner interactions rather than two continuous variables because we do not expect a monotonic relation between changes in video viewing/polling correctness and exam performance.

Model and Variables

To test the impact of multiple learner interactions, Meade and Parthasarathy (2020) employed an ANOVA with *ExamDiff* as the response variable and *Learning_Mode* as the predictor variable. We use a model similar to theirs and measure *ExamDiff* as the difference between a student's score on the cumulative final exam, which occurred after the COVID-19 transition to virtual instruction, and the midterm exam, which occurred before the transition. *Learning_Mode* is measured with four levels, which in this paper we label as Video Down/Polling Down, Video Up/Polling Down, Video Down/Polling Up, and Video Up/Polling Up.

To address our two research questions, we partition our sample into several subsamples. We measure prior academic achievement using a student's incoming GPA and classify students into three subsamples representing grades of A, B or C, and D or F. We also categorize students on the basis of age, semester hours, major, first time in college, receiving financial aid, gender, citizenship, ethnicity, and grading option. We test for significant differences in the choice of learner interactions among our continuous variables using an ANOVA; among our categorical variables we use a chi-square test. We include the satisfactory/no credit (S/NCR) grading option in our study because our university, like many others, implemented an interim grade policy shortly after transitioning to online learning. The policy allowed students to elect grades of satisfactory or no credit on a course-by-course basis at the end of the semester after viewing their assigned letter grades. To test for significant differences in the effect of different types of learner interaction across our subsamples, we use pairwise t-tests. These tests use the least square means rather than arithmetic means and adjust for the unbalanced nature of the subsamples.

Descriptive Statistics

Descriptive statistics for our subsamples are presented in table 2, together with the results of our ANOVA and chi-square tests. Although the mean and median scores on the cumulative final exam are generally lower than those on the midterm exam (each exam is worth 100 points), the declines are within the historical range of students enrolled in prior semesters. Not surprisingly, the mean final exam score is lowest for students who decreased both their video viewing and polling correctness (Video Down/Polling Down). Yet, the median change in exam score for these students is the same 2-point decline observed for students in the modes Video Down/Polling Up and Video Up/Polling Up. Students in the learning mode Video Up/Polling Down display a 5-point decline in the median score. ANOVA tests of the means identify statistically significant differences among the exam scores of the four learning modes and indicate that students with higher GPAs increased their reliance on videos as their mode of instruction at the expense of synchronous instruction. An ANOVA test of the means of students' age is also statistically significant, suggesting that different learner interactions appeal to students of differing GPA and age. The means of students' semester hour loads, however, are not significantly different across the four learning modes.

Chi-square tests address whether the proportion of students who selected a particular learner interaction is similar to the expected proportion. Statistically significant differences are observed for all the demographic characteristics except for the indicator variable measuring whether a student is receiving financial aid. Among the more observable differences are the overrepresentation of younger and male students in the Video Down/Polling Down learning mode and the overrepresentation of younger students and those attending college for the first time in the Video Up/Polling Down learning mode. Among the ethnicity categories, Whites are overrepresented in the Video Down/Polling Up learning mode, Asians are overrepresented in the Video Up/Polling Up learning mode, and Hispanic/Latinx are

overrepresented in the Video Down/Polling Down learning mode. Among students electing the S/NCR grade option, the observed clustering in the lower grade categories is not surprising, nor is the concentration in the Video Down/Polling Down learning mode.

Table 2: Descriptive Statistics

	Learning Mode					
Learner Interaction	Video Down/ Polling Down	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up		
Video viewing	Decrease	Increase	Decrease	Increase		
Polling accuracy	Decrease	Decrease	Increase	Increase		
Performance (mean / median)					**F value**	**Pr>F**
Midterm exam score	69.92 / 70.00	74.33 / 77.00	69.31 / 70.00	70.08 / 74.00	6.59	0.0002
Final exam score	63.26 / 68.00	71.22 / 72.00	65.70 / 68.00	70.69 / 72.00	15.52	<.0001
Change in exam score	-6.66 / -2.00	-3.11 / -5.00	-3.61 / -2.00	0.61 / -2.00	6.15	0.0004
Demographics (mean / median)						
Incoming GPA	3.14 / 3.19	3.37 / 3.50	3.11 / 3.18	3.27 / 3.40	10.21	<.0001
Age	20.40 / 20.00	20.43 / 20.00	21.40 / 20.50	21.38 / 20.00	8.15	<.0001
Semester hours load	13.74 / 15.00	14.06 / 15.00	13.59 / 15.00	13.72 / 15.00	1.45	0.2261
Distributions (percent / proportion)					**Chi-square**	**P-value**
Age (20 or less)	71.57 / 34.63	70.18 / 32.36	52.83 / 12.14	56.83 / 20.87	25.51	<.0001
Semester hours (15 or more)	60.87 / 31.22	65.96 / 32.25	55.24 / 13.55	59.03 / 22.98	5.32	0.1500
Business major	54.85 / 33.33	52.98 / 30.69	41.96 / 12.20	51.54 / 23.78	6.81	0.0784
First time in college	72.24 / 31.53	78.25 / 32.55	64.34 / 13.43	67.84 / 22.48	11.57	0.0090
Receiving financial aid	90.30 / 30.72	92.98 / 30.15	90.21 / 14.68	94.71 / 24.46	4.49	0.2135
U.S. citizen	93.31 / 32.56	87.37 / 29.05	91.61 / 15.29	87.22 / 23.10	8.01	0.0452
Gender, male	66.56 / 35.86	60.00 / 30.81	62.24 / 16.04	42.29 / 17.30	33.53	<.0001
Ethnicity					20.08	0.0657
White	17.73 / 29.28	18.25 / 28.73	25.87 / 20.44	17.18 / 21.55		
Asian	21.74 / 24.79	31.93 / 33.96	26.57 / 14.83	32.60 / 27.61		
Black	9.36 / 29.79	10.18 / 30.85	9.79 / 14.89	10.13 / 24.47		
Hispanic/Latinx	40.47 / 36.89	30.53 / 26.52	30.77 / 13.41	33.48 / 23.17		
Other	10.70 / 38.55	9.12 / 31.33	6.99 / 12.05	6.61 / 18.07		
Satisfactory/No credit	51.84 / 40.68	30.18 / 22.57	42.66 / 16.01	34.80 / 20.73	31.95	0.0002
A	0.00 / 0.00	0.00 / 0.00	0.00 / 0.00	0.00 / 0.00		
B	27.74 / 31.85	48.84 / 31.11	21.31 / 9.63	46.84 / 27.41		
C	49.03 / 42.46	40.70 / 19.55	50.82 / 17.32	46.84 / 20.67		
D	17.42 / 50.00	10.46 / 16.67	21.31 / 24.07	6.32 / 9.26		
F	5.81 / 69.23	0.00 / 0.00	6.56 / 30.77	0.00/ 0.00		
Sample sizes	299	285	143	227		
Expected proportion	31.34	29.87	14.99	23.79		

Key Results from Table 2

- Suboptimal learner interactions tend to be selected more often by students with lower GPAs or those who are younger, male, or Hispanic/Latinx.
- Learner-content interactions in the form of recorded videos generally are preferred by younger students and those attending college for the first time.
- White students tend to prefer instructor interactions over content interactions, while Asian students generally seek out both instructor and content interactions.

Pairwise Comparisons

Table 3 reports pairwise comparisons of the effect of learner interactions on the change in exam scores for subsamples of different academic and demographic backgrounds. In an earlier study, Meade and Parthasarathy (2020) showed the students who increased both their video viewing and polling correctness scored significantly better on the final exam than students who had not increased both types of learner interaction. Our pairwise tests seek to determine whether the improvement observed by Meade and Parthasarathy (2020) is descriptive of most students irrespective of their prior academic achievement or demographic characteristics.

Across all the reported subsamples except students electing a letter grade rather than the S/NCR grading option, the greatest improvement in exam scores (as measured by the least square means) occurred for students increasing their use of multiple learner interactions. This finding bolsters the results of Meade and Parthasarathy (2020) and highlights the importance of including multiple learner interactions in online courses. Looking at the pairwise t-tests, the exam score improvement associated with the use of multiple learner interactions (Video Up/Polling Up) is significantly better than the improvement associated with the use of one or no learner interactions for students having an incoming GPA in the A range, those attending college for the first time, those receiving financial aid, and those holding U.S. citizenship.

Subsamples showing that an increase in the use of multiple learner interactions improves exam scores as well or better than a single learner interaction for students aged 20 years or less, those enrolled in 15 semester credit hours or more, those enrolled in less than 15 semester credit hours, those with a major other than business, those of Hispanic/Latinx descent, and those electing either a letter grade or the S/NCR grade option. Subsamples for which increasing the use of multiple learner interactions provides a boost to exam scores only when compared to decreasing the use of learner interactions are students with an incoming GPA in the B or C range, those aged over 20, those majoring in business, and those of White or Asian descent. Both males and females benefited from the use of multiple learner interactions, although as mentioned earlier, males tended to reduce their learner interactions more than females. Subsamples showing no significant difference in exam scores regardless of the types of learner interaction utilized are Black students and those with an incoming GPA in the D or F range. We urge caution in interpreting this latter result, however, because of the small number of students classified as Black or with GPAs in the D or F range. Our insignificant results may simply reflect tests with low statistical power.

Table 3: Pairwise Comparisons of the Effect of Learner Interactions on Exam Scores

	GPA=A		Pairwise Comparisons (Pr > |t| Response variable = Exam_Diff		
Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	190	-4.94	0.2714	0.7821	0.0044
Video Up/ Polling Down	221	-3.05		0.5592	0.0584
Video Down/ Polling Up	89	-4.33			0.0417
Video Up/ Polling Up	165	0.33			

	GPA=B or C		Pairwise Comparisons (Pr > |t| Response variable = Exam_Diff		
	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
	99	-8.43	0.2086	0.1190	0.0090
	60	-3.85		0.7166	0.2069
	47	-2.28			0.4058
	55	1.40			

	GPA=D or F				
Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	10	-21.50	0.1574	0.2518	0.1535
Video Up/ Polling Down	4	5.25		0.6537	0.8286
Video Down/ Polling Up	7	-3.57			0.7849
Video Up/ Polling Up	7	1.00			

	Age 20 or less				
	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
	214	-6.17	0.3201	0.2147	0.0006
	200	-4.31		0.6116	0.0108
	75	-3.04			0.1301
	129	1.02			

Table 3: Pairwise Comparisons of the Effect of Learner Interactions on Exam Scores (continued)

Age over 20

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	85	-8.00	0.0152	0.2653	0.0089
Video Up/ Polling Down	85	-0.27		0.2372	0.9138
Video Down/ Polling Up	68	-4.25			0.1869
Video Up/ Polling Up	98	0.06			

Hours 15 or more

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
182	-5.08	0.03081	0.1182	0.0028
188	-3.21		0.4351	0.0376
79	-1.37			0.3564
134	0.94			

Hours under 15

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	117	-9.04	0.0368	0.4200	0.0022
Video Up/ Polling Down	97	-2.90		0.3145	0.3336
Video Down/ Polling Up	64	-6.39			0.0631
Video Up/ Polling Up	93	0.13			

Business majors

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
164	-3.62	0.5797	0.5766	0.0796
151	-2.48		0.3365	0.2235
60	-5.17			0.0621
117	0.27			

Other majors

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	135	-10.33	0.0080	0.0053	<.0001
Video Up/ Polling Down	134	-3.81		0.6382	0.0651
Video Down/ Polling Up	83	-2.49			0.2369
Video Up/ Polling Up	110	0.96			

First time in college

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
216	-6.64	0.0630	0.6971	<.0001
223	-3.22		0.2972	0.0090
92	-5.71			0.0023
154	2.06			

Financial aid

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	270	-7.01	0.3160	0.0349	<.0001
Video Up/ Polling Down	265	-3.52		0.7097	0.0147
Video Down/ Polling Up	129	-2.77			0.0983
Video Up/ Polling Up	215	0.69			

U.S. citizen

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
279	-6.70	0.0361	0.0836	<.0001
249	-3.40		0.9969	0.0130
131	-3.39			0.0359
198	1.26			

Male

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	199	-7.93	0.0303	0.2217	0.0021
Video Up/ Polling Down	171	-3.56		0.5903	0.2176
Video Down/ Polling Up	89	-4.92			0.1221
Video Up/ Polling Up	96	-0.52			

Female

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
100	-4.10	0.5227	0.4155	0.0302
114	-2.42		0.7622	0.1168
54	-1.46			0.3501
131	1.44			

White

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	53	-12.44	0.0937	0.0232	0.0059
Video Up/ Polling Down	52	-6.02		0.4530	0.2236
Video Down/ Polling Up	37	-2.86			0.6732
Video Up/ Polling Up	39	-0.97			

Asian

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
65	-5.68	0.2278	0.1984	0.0875
91	-1.96		0.7287	0.5431
38	-0.68			0.8876
74	-0.15			

Black

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	28	-7.54	0.7437	0.4160	0.3227
Video Up/ Polling Down	29	-9.24		0.2791	0.1924
Video Down/ Polling Up	14	-2.29			0.9710
Video Up/ Polling Up	23	-2.04			

Hispanic/Latinx

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
121	-5.31	0.0962	0.5230	0.0015
87	-0.78		0.0615	0.1345
44	-7.48			0.0023
76	3.76			

Letter grade

Learning Mode	n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
Video Down/Polling Down	144	-0.89	0.8879	0.0621	0.0736
Video Up/ Polling Down	199	-1.14		0.0372	0.0385
Video Down/ Polling Up	82	3.21			0.7229
Video Up/ Polling Up	148	2.43			

S/NCR grade

n	Exam_Diff Means	Video Up/ Polling Down	Video Down/ Polling Up	Video Up/ Polling Up
155	-12.00	0.1471	0.8152	0.0030
86	-7.65		0.1690	0.1637
61	-12.79			0.0089
79	-2.81			

P-values are based on two-tailed t-tests.

Key Results from Table 3

- Most students, irrespective of prior academic achievement or demographic characteristics, show improvement in exam scores when using multiple learner interactions.
- Students showing the greatest improvement in exam scores when using multiple learner interactions tend to be those with higher GPAs, those attending college for the first time, those receiving financial aid, or those holding U.S. citizenship.

DISCUSSION

Our results show that many introductory accounting students did not select learner interactions that optimized their learning. Instead, many preferred a single type of learner interaction and, as a consequence, these students may have failed to achieve their potential, potentially hindering the advancement of their academic careers. Surveys conducted in similar settings to ours corroborate our observations and show that the pandemic impacted student learning in vulnerable populations (e.g., Aucejo et al., 2020; Dorn et al., 2020). Possibly the interim grade policy, which provided a safety net in the form of satisfactory/no credit grading, functioned as a disincentive to learning and contributed to the choice of suboptimal learner interactions (e.g., Karl et al., 2021). Other possible explanations include elevated demands at work, disruptions in childcare services, home schooling requirements, broadband reliability, and technology limitations. But whatever the reasons, our study finds that the greatest improvement in learning occurred among students who selected multiple types of learner interactions and that this improvement was achievable irrespective of academic or demographic backgrounds.

CONCLUSION

This study provides empirical support of the improvement in learning that occurs when online introductory accounting students are provided with, and take advantage of, multiple learner interactions. We find that final exam scores are better for students using multiple learner interactions and that this result holds across almost all our academic and demographic subsamples. We also find that during the COVID-pandemic lower achieving, younger, male, domestic, and Hispanic/Latinx students tended to reduce their use of learner interactions and that this contributed to suboptimal learning.

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