Can Informational Nudges Improve University Students' Learning Engagement with Online Tools?

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Abstract

The global COVID-19 pandemic has accelerated already existing pressures on education systems to adopt online learning platforms at the primary, secondary, and post-secondary levels. Yet, knowledge of what factors contribute to student uptake of and commitment to online classes is still underdeveloped. In this study, randomized controlled trials were employed to test whether providing university-enrolled students with informational nudges regarding a freely provided online learning platform improves platform engagement as well as co-op placements for students enrolled in a post-secondary management program. We find minimal evidence that low-cost information nudges increase engagement. Only when engagement is required within a course curriculum and tied to a grading incentive do we find meaningful changes in use. Furthermore, we do not find meaningful benefits of supplemental usage for improving co-op placements for management students. We conclude that platform use is not driven by lack of information regarding online tools available, but rather by other motivating forces. We find student GPA is the most significant predictor of use, suggesting that motivation and ability bias override other factors for engagement and any accrued benefits from online learning use are driven by non-random willingness to engage.

Keywords: Distance education and online learning; Post-secondary education

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Section 1. Introduction

The global COVID-19 pandemic has accelerated existing trends in the development of online and remote learning at all levels of education. After the global shutdown in response to the pandemic, primary, secondary, and post-secondary education systems quickly moved to providing much of their services, including teaching, online. In the United States, for example, of the almost 3000 post-secondary education institutions, only four percent relied on reopening models that included no online learning; in contrast, 44 percent moved fully or primarily online (Chronicle of Higher Education, 2020).

Even prior to the pandemic, almost all medium-sized or larger post-secondary education institutions in North America had been offering online classes (Figlio, Rush, & Yin, 2013). And the percentage of total students taking at least one online class has increased from about 10 percent in 2002 to 33 percent in only one decade (Allen and Seaman, 2014). Online learning can take many forms including but not limited to massive open online courses (MOOCs); short self-contained modules; blended online and live face-to-face instruction; "web-based instruction"; and "flipped classrooms" (see McPherson and Bacow, 2015 for a review). There is also a growing interest in "blended" or "hybrid" courses that combine face-to-face interactions in a classroom with online digitized content (see Akçayır and Akçayır, 2020 for a nice review of advantages and disadvantages). Yet, knowledge of what factors contribute to student uptake of and commitment to online classes is still underdeveloped.

A small but growing experimental literature has emerged that examines online learning outcomes – for example, Figlio et al. (2013) conducted a randomized study that compared face-to-face versus purely online teaching and find modest evidence of face-to-face instruction dominates online; Bowen et al., (2014) and Joyce et al. (2015) examined face-to-face versus blended learning; and Alpert et al. (2016) compared face-to-face, online, and blended models) – this study focuses on students' *engagement* with online learning. They find that online only reduced performance on a final exam but no difference between blended relative to face-to-face. These studies all focused on economics or statistics classes.

In this study, we add to the small experimental literature on online learning by conducting three randomized controlled trials (RCTs) to evaluate the role of informational nudging, informational relevancy, and external incentives for increasing engagement with and testing outcomes of supplementary online learning platform use for a university-enrolled population of young adults. In 2017, the Government of Ontario, Canada launched the "Career Kick Start Strategy" with an investment of $190 million. Then-Deputy Premier Deb Matthews, who was also Minister of Advanced Education and Skills Development explained the investment by stating "...a rapidly changing economic environment means students need better supports to enter the workforce" (Ministry of Finance, April 2017). Part of the investment was used to purchase blanket access to Lynda.com (now rebranded as LinkedIn Learning), a provider of online training and development courses, for all faculty, staff, and students in Ontario's postsecondary institutions. This initiative was a blanket purchase for three years, starting in the 2018-2019 academic year and ending in September 2020, by the Ministry of Education to supplement skills training. LinkedIn Learning is a leading online learning platform designed to teach software, creative and business skills and is a subsidiary of LinkedIn. It includes a library of 16,000+ digital courses that focus on business, creative, and technology skills. LinkedIn Learning has more than 27 million users, and 78 Fortune

100 companies utilize the platform (Trent-Gurbuz, 2020). It can be considered one of the largest competitors in the online learning platform market. LinkedIn Learning would not normally be listed as an open educational resource (OER) but in this context (free access to ~100,000 University of Toronto students, staff, and faculty), much of what has been learned about the OER, difficulties with student engagement and high attrition rates would apply in this situation.

Despite free access, user engagement at the university level remained consistently low over the duration of the licencing period. Only 4.7 percent of university students in Ontario engaged with the platform by logging on to it. Only 1 percent of students completed at least one full course (See Pichette, Brumwell, and McKeown, 2019 for a detailed analysis of platform usage in Ontario). Roughly 25 percent of the courses on the platform can be completed in less than an hour and about 80 percent of courses can be completed in less than three hours (Pichette, Brumwell, and McKeown, 2019). Within the University of Toronto, approximately 3,400 individuals accessed the free online learning tool. With 90,077 registered students, 7,068 staff members, and 14,332 faculty, that translates into usage rates of 2 percent, 18 percent, and 1 percent respectively.

Extant literature points to a number of factors as to why use of online technologies might be so low (see, e.g. Reich, 2020). Cost may be a factor; but while the specific online learning platform licence we study has a regular cost of over $1,000, the blanket licencing purchase removes this barrier. Time costs in accessing and engaging with classes and videos remains a barrier, however, especially if courses do not offer temporal flexibility (Veletsianos et al., 2021). The other major barriers to access involve a number of behavioural barriers, examples of which include: lack of engagement and persistence (e.g. Banerjee and Duflo, 2014; Jordan, 2014; Perna et al., 2015; Evans et al., 2016; Bettinger et al., 2017); procrastination (e.g. Elvers, et al., 2003; Michinov et al., 2011); and time management skills (e.g. Roper, 2007; Nawrot and Doucet, 2014). Hew and Cheung (2014), in a review of studies that analyze MOOC uptake and disengagement, found very high drop out rates that relate to lack of incentives, failure to understand content, with no one to assist in problems, and having competing priorities (see also Hew, Qiao, and Tang, 2018). Terras and Ramsay (2015) also examined student engagement with MOOCs and found a number of psychological challenges related to motivation, emotion, and the intellectual commitment of MOOC users, which suggests variation in the kind of learner who benefits from online education technologies (see also Lai et al, 2021 and Xu, 2022 on student motivation and engagement). Bergdahl, Nouri, and Fors (2020) found a significant relationship between student engagement with technology-enhanced learning and their own reported digital skills; but they also found that both students with reported high and low digital skills also disengaged from technology enhanced learning to some extent.

Other aspects of uptake relate to sociodemographic determinants such as gender (De Souza and Perry, 2021; Hoskins and Vn Hooff, 2005) and socioeconomic barriers to online learning access (see e.g. Conole, 2012 and other articles in that issue; Scheerder, van Deursen, and van Dijk, 2017; Tuomi, 2013). And finally, Henderson, Selwyn, and Aston (2017) found in their survey of 1658 Australian undergraduate students that students identified a number of digital learning assisted with the logistics of learning, such as the ability to replay lectures and flexibility in viewing materials, as opposed to the learning of content.

There is a growing literature on overcoming behavioural barriers to using online tools through techniques such as nudges (e.g. Lawrence et al., 2019; Mohammadhassan et al., 2022; and see Damgaard and Nielsen, 2018 for a nice review of nudging in the education context). This study is designed to examine the role that student awareness, interest, and motivation have on students' online engagement and to test the efficacy of some of these nudges.

Section 2 Background and Design

Section 2.1 Study Context

To test factors that affect students' online engagement, we imbedded three RCTs within this project to understand the role of awareness, interest and motivation through a series of interventions including both behavioural nudges and "shoves". In our first study, the University of Toronto Scarborough (UTSC) registrar selected a random sample of UTSC undergraduate students to receive a one-time informational nudge via email on either technical or social and interpersonal skills classes within the online learning platform, LinkedIn Learning. The technical skills courses encompassed videos and courses such as learning to code in HTML and learning Python. Interpersonal skills courses taught topics such as time management and interviewing etiquette.

With the Department of Management at UTSC, we developed two additional RCTs with more program integration. First, a random sample of co-op students who were actively seeking a co-op placement received a series of relevant informational nudges regarding job seeking and interviewing skills over the course of their co-op search. Within this study we further tested whether increased online learning platform use resulting from these nudges improved co-op students' job placements. Finally, a random subset of class sections for a required first year co-op course were required to view online skill-building videos in the syllabus, with viewing worth a small percentage of the students' grade.

If awareness alone explains low user engagement, we expected increased use of the platform through simple low-touch informational nudges. We tested the role of interest or motivation by providing relevant information to co-op students during a crucial job-seeking time. For an additional level of integration, we incorporated required viewing into a class curriculum tied to a small grade percentage. This intervention is considered a "shove" over a nudge by requiring viewing.

Section 2.2 Study Design

Across all three studies, we relied on a randomized controlled trial design, with students randomly assigned to either a treatment or control group. The intervention of each treatment group was study-dependent, ranging from a broad informational nudge to integrated online content into the regular co-op curriculum. We present the main study design for each nudging experiment separately.

Study A: Low-cost informational nudges

In our first study, the registrar of UTSC randomly assigned almost all UTSC undergraduate students into three groups: two treatment arms and one control arm. Two separate treatment groups were given informational nudges on either online learning courses related to technical skills or courses covering interpersonal skills. Conversely, the control group was given no information. On January 27, 2020, the UTSC Registrar emailed the two different treatment groups information on technical or soft skills courses. The students enrolled in programs offered by the Department of Management were not included in this study because we tried to limit possible contamination in the other two studies outlined below. The students in the Department of Management form an insular unit at UTSC with students rarely taking courses outside the department, and Arts & Sciences students rarely taking management courses (UTQAP External Review, 2019).

All students in either the treatment groups or the control group were undergraduates enrolled in Bachelor of Arts or Bachelor of Sciences degrees. Stratified randomization was used to allocate students into treatment or control groups. This stratification ensured balance in the randomization across broad groupings to improve the precision of estimates. Stratification was limited to three characteristics: international student status, year of study and part-time student status. These variables were chosen given that year in study and part-time status may have tangible effects on motivation and time available for a student to interact with online learning material. International student status addressed the concern that online learning engagement might differ due to the limited availability of LinkedIn Learning videos in the student's native language. The majority of course videos available are in English; the platform has at a small number of course videos available in French, German, Japanese, Spanish, Mandarin, and Portuguese.

Study B: Job Search Integrated Informational Nudges

In the second RCT, beginning in January 2020, the UTSC Department of Management co-op program sent recommended online learning content nudges to a randomly assigned group of co-op students who were searching for summer co-op placements. Content was selected to refresh job search knowledge for students during their co-op search term. Treatment group participants received biweekly emails for the duration of their search term on pertinent skills such as emailing etiquette and communication, chosen by the UTSC co-op staff. Treatment group participants received four emails in total. Control group participants received no emails. The students in this study were first to fourth year Bachelor of Business Administration students in the co-op program. We again used stratified randomization to allocate students into treatment or control groups. We stratified by gender, international student status and year of study given that each factor may affect both preferences for online learning use and co-op placements.

Study C: Required Online Learning

The third and final study required online content viewing within a mandatory course curriculum. The UTSC management co-op program requires students to complete a course on Advancing Your Career Exploration classes during their first academic year. This preparatory course helps students navigate the challenges in both co-op placements and in business more generally. This course is highly interactive and is completed before students start searching for their first co-op work term.

This study was randomized at the class section level. There were six sections of 60 students each during Fall 2019 and Winter 2020. Three instructors taught two sections each. The UTSC management co-op program director randomized the classes into four classes that served as a control group and two classes that served as the treatment group. The classes that made up the control group proceeded as business as usual, following the previous 2018/2019 curriculum. The classes that made up the treatment group were required to view a select group of online courses chosen by the UTSC co-op staff. Online content viewing was included as a part of the course content and was worth one percentage point of the course grade.

To study how these various experiments affected online tool usage, in August 2020, the master administrator for online learning at University of Toronto provided de-identified LinkedIn Learning usage data for all the students selected for the study from the period of July 2019 to July 2020. For students seeking co-op placements, the UTSC Department of Management provided researchers with deidentified job placement outcomes for students in Study B in July 2020. Analysis was conducted in Fall 2020.

Section 3: Methods

Section 3.1 Data

The main data in our analysis are comprised of deidentified user data from the online learning platform for LinkedIn Learning on the universe of UTSC undergraduate students. These data include full information starting from activation date, and all engagement points, including specific classes and courses watched, total time spent learning, class completion rates and the specific dates of engagements. Much of the analysis relied on individual aggregation of total time use on the platform, including logins, hours watched, and total classes and courses completed. To understand content interest, top videos were coded to be either technical skills or soft skills-related content based on individual inspection.

Table 1: Balance of Covariates Across Studies A and B

	Study A: General Nudges			Study B: Relevant Nudges	
	Tech Mean (s.d.)	Soft Mean (s.d.)	Control Mean (s.d.)	Treatment Mean (s.d.)	Control Mean (s.d.)
Year of Study	2.53 (1.12)	2.56 (1.14)	2.53 (1.15)	2.60 (0.66)	2.60 (0.65)
International Student (%)	0.23 (0.42)	0.23 (0.42)	0.23 (0.42)	0.51 (0.50)	0.44 (0.50)
Part-time (%)	0.10 (0.30)	0.11 (0.31)	0.10 (0.30)	-	-
GPA (max 4.0)	2.53 (0.85)	2.53 (0.85)	2.53 (0.87)	3.12 (0.42)	3.09 (0.40)
Male (%)	0.44	0.42	0.43	0.44 (0.50)	0.44 (0.50)
N	3,510	3,560	3,527	110	117

Note: Table shows key control variables for our first study using general informational nudges to the entire UTSC student body (Study A). Study B sent relevant informational nudges on the online learning tool to randomly selected co-op students during their co-op search term. Note that there are no part-time co-op students. Study C had no available descriptive statistics on which to balance covariates.

For Study A, we linked the usage data to anonymous UTSC registrar data to control for student characteristics that might drive use. The registrar data included an anonymous student linking identification number and their randomly assigned treatment status. It also included school variables of year of study, international student status, overall GPA, degree, and major. Demographic information included age and self-identified gender. Across the UTSC population, 77 percent of the students were domestic students and 23 percent are international students. Students were spread evenly across year-of-study, at around 25 percent in each of years 1 to 4 or higher. Full-time students constituted the majority of UTSC students in the sample, at 89 percent (10.5 percent part-time). In post-stratification for Study 1, we found that age, gender, GPA and degree type are all balanced across treatment and control groups (Table 1). Gender, degree major and age act as key control variables in our study. Gender variables include four categories: male, female, agender, and undeclared. There are 40 different potential undergraduate degree majors across the arts and sciences. The Bachelor of Science in Life Sciences and Bachelor of Arts in Social Sciences and Humanities were the two most common degree types. The median student age was 21, on a range of 15 to 73. For first-year students, the median age was 19. For fourth-year students or higher, the median age was 23. Part-time students had a median age of 23.

For Study B, we linked LinkedIn Learning usage data to the Department of Management co-op program job placement information. This provided information on similar school and demographic information as the registrar data as well as co-op searching and placement outcomes. The average student seeking a co-op term was in their second or third year of school (Table 1). In the treatment group, 51 percent of individuals were international students, versus 44 percent in the control group. Treatment group participants had a GPA of 3.12 (0.42) versus 3.09 (0.40) in the control group. Co-op placement outcomes of interest included number of applications and interviews and whether the student obtained a first-round placement or a co-op placement overall.

For Study C, we did not have access to covariates on which to balance treatment. Treatment was assigned at the instructor section level, with four sections in the control and two sections in treatment groups. This imbalance was because three instructors taught two sections each. To maintain curriculum consistency across instructors, all sections they taught were either treatment or control (Table 2).

Table 2: Study C Treatment and Control Assignment by Class Section

Section	Control	Treatment
1	34	0
2	0	57
3	56	0
4	0	58
5	54	0
6	49	0
Total	193	115

Section 3.2 Estimation Strategy

As treatment assignment was randomly assigned at either the student or instructor level across all three studies, the empirical analysis to assess the effects of information nudges on online learning engagement is straightforward. To test the effect of treatment interventions on platform use we first estimated simple differences in average engagement by treatment status. Given the randomized design, the parameters estimated provide consistent estimates of the mean impacts of the distinct interventions. However**,** as we had a number of student demographic and schooling covariates available, to improve precision of estimates, we incorporated these variables into a regression analysis. The main estimating equation is:

$$Y_i = \alpha + \beta D_i + \partial X_i + \varepsilon_i \tag{1}$$

Here, Y_i is the outcome variable of interest regarding platform usage for individual i. In each study, the outcomes of interest included activation, unique logins, hours used, and content watched. We estimated treatment effects for each outcome variable in separate models. Treatment group assignment is measured through D_i. Study A contained separate indicators for being in the technical skills treatment group and the soft skills treatment group. The effect of receiving nudges on platform engagement, relative to a control group, is estimated through β. Similarly, for the remaining studies, D_i represents assignment to receive informational nudges during a co-op search term or being in a co-op class that required online learning content viewing. Any available controls were included in X_i. Inclusion of these controls serve to improve the precision of our β estimates and understand demographic factors that increase engagement. Key controls included year of study, international student status, part-time student status, age, gender, grade point average (GPA), and major. Variation in usage that cannot be explained due to observable characteristics in X_i or treatment assignment D_i is captured through ε_i.

To test the effect of the platform usage on co-op placements, the reduced form equation took a similar structure to equation (1). The outcome variable of interest would be whether a student received a job placement in the first round or overall, as well as interviewed obtained. To estimate the marginal effect of online learning use on co-op placements, we took a two-stage least squares approach. We first estimated usage based on treatment status through equation (1), and then estimated a second stage equation as follows:

$$Y_i = \alpha + \theta \widehat{U_\imath} + \partial X_i + \varepsilon_i \qquad (2)$$

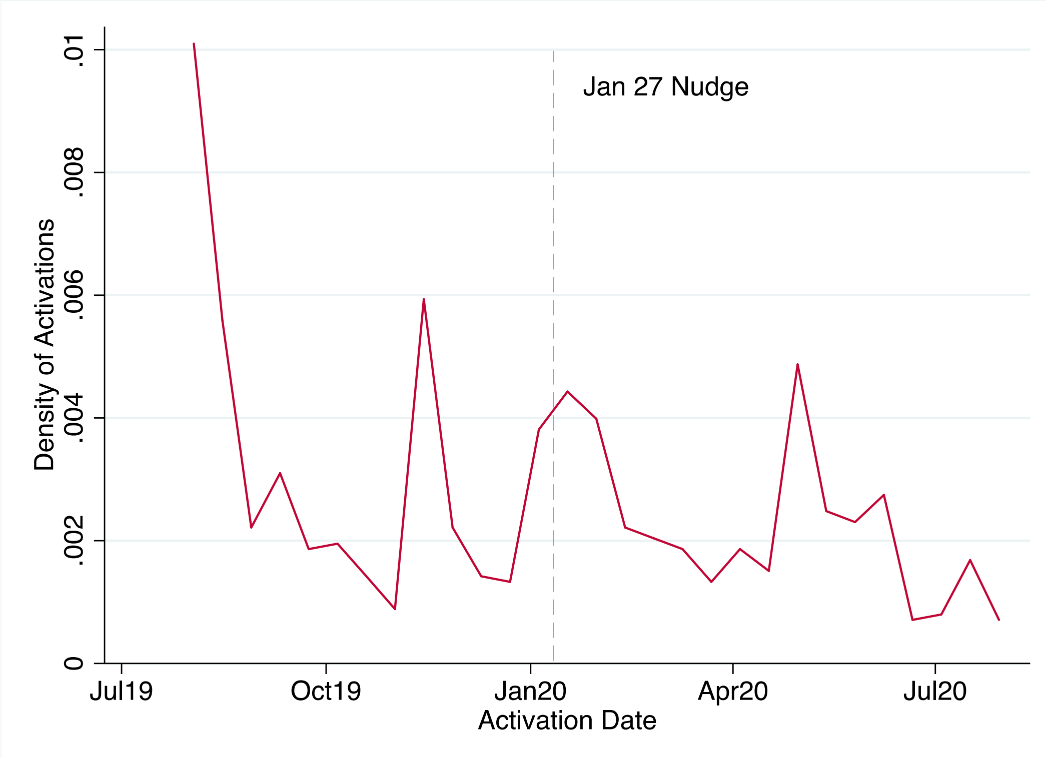
Here, $\widehat{U_\imath}$ is predicted online learning use based on treatment status. The coefficient θ measures the marginal effect of online learning usage on job placements. Control variables included student age, year of study, major, gender, international student status and GPA. Any additional unexplained error is measured through ε_i.

Section 4 Results

Section 4.1 Informational Nudging Alone

We first present results from the large-scale randomized nudging experiment, where randomly selected individuals received a one-time information nudge on either soft or technical skills videos available on the online learning platform. In the week following the January 27 nudge, we observed that 5.4 percent of all activations occurred. Within two weeks, 9.5 percent of all activations occurred.

Figure 1: Activation rates over time



In Table 3, we report whether nudging resulted in a measurable increase in activations within a one- or two-week window. Results show that the nudging experiment increased activations in the week following by 0.5 percentage points, and 0.9 percentage points within two-weeks, specifically for those receiving technical skills nudging. Across all activators, receiving nudging for technical skills increased the likelihood of activation within 2-weeks by 10 percentage points (measured using only the 8 percent of the sample with activation). We observe lower effects in the soft skills nudging treatment group. In the first week after the nudge there was no discernible increase in activations. In the second week, however, there was a cumulative increase by 0.6 percentage points. If one received nudging of soft skills, one was 7.6 percentage points more likely to activate within two weeks amongst those who activated.

Table 3: Effect of Informational Nudging Intervention on Online Learning Activation				
Activation	Full Sample: ATE		Activators Only: ATT	
	1-Week Post Nudge	2-Weeks Post Nudge	1-Week Post Nudge	2-Weeks Post Nudge
	(1)	(2)	(3)	(4)
Treatment: Tech Skills	0.005***	0.009**	0.064**	0.103***
	(0.002)	(0.002)	(0.019)	(0.017)
Treatment: Soft Skills	0.002	0.006**	0.024	0.076**
	(0.001)	(0.002)	(0.012)	(0.024)
N	10,472	10,472	870	870
Adj R-squared	0.002	0.002	0.021	0.027

Note: Standard errors in parentheses are clustered at the stratifying group level. Significance indicated by: * p<0.05; ** p<0.01; ***<0.001. Final two columns include only those who activated.

In Table 4, we expand our outcomes to include engagement with the platform, measured in viewing hours. Panel A presents results from the general information nudges. These are compared to relevant informational nudges in Panel B and required viewing in conjunction with a grading incentive in Panel C. For each outcome we present a baseline model including only the randomly assigned treatment indicator and a second model including available controls. In Panel A this included student age, year in school, GPA, gender, international student status, part-time student status and fixed effects based on their randomization stratification group assignment. Standard errors are clustered at the stratifying level.

We find minimal overall changes in activations in either the tech or the interpersonal skills groups in our baseline or covariate model. Activations do, however, increase with year of study, GPA, male gender (compared to female), and part-time student status. Activations decrease with age and international student status. Despite potentially higher activations with tech skills nudging, we find discernibly less hours viewed for the tech skills group. Regardless, we observe that year of study, GPA, part-time, and identifying as male all have a statistically significant positive impact on engagement. The higher level of male engagement is likely driven by the fact that more computer science students engaged with the platform. However, this finding is non-consistent with the literature on the demographics of online students which shows that online students are more likely to be female than male (e.g. Jaggars & Xu, 2010) even in male-dominated engineering programs (Yukselturk, 2010). Depending on exact degree program, computer science majors are 72 percent to 85 percent male.

Table 4: Effect of Treatment Assignment on Engagement

	(1)	(2)	(3)	(4)	(7)	(8)
	Activation		Hours		Non-Required Videos	
	Panel A: General Information Nudges					
Tech	0.003	0.003	-0.046*	-0.046*	-	-
	(0.007)	(0.007)	(0.019)	(0.019)		
Soft	0.000	0.000	0.010	0.010	-	-
	(0.007)	(0.007)	(0.022)	(0.021)		
Covariates		x		x		
N	10,597	10,472	10,597	10,472		
Adj. R-squared	0.000	0.011	0.000	0.003		
	Panel B: Relevant Informational Nudges					
Treatment	0.124*	0.205**	0.158	0.462	-	-
	(0.051)	(0.076)	(0.223)	(0.404)		
Covariates		x		x		
University Major Fixed Effects		x		x		
N	227	227	227	227		
Adj R-squared	0.025	0.203	0.002	0.075		
	Panel C: Required Viewing					

Treatment	0.653***	0.612***	1.010***	1.107***	11.863***	14.465***
	(0.012)	(0.000)	(0.074)	(0.000)	(1.704)	(0.000)
Covariates		x		x		X
Class Section Fixed Effects		x		x		X
N	308	308	308	308	308	308
Adj. R-sq	0.438	0.432	0.192	0.187	0.110	0.108

Note: Standard errors in parentheses and clustered at the stratifying group level. In Panel C, standard errors are clustered at the class section level.

In Panel B, we compared general nudging to relevant nudging by incorporating specific video links into nudging for students who were searching for co-op placements. We found higher activation rates than the general nudging, with a 12.4 percentage point increase in activation in the treatment arm. Including controls for GPA, year of study, international student status and fixed effects for both major and stratifying group, this effect size increased to a 20.5 percentage point increase in activation. We see no meaningful difference in use, however. Across all students who activated their online learning licence, we found more use for those who received informational nudging but are unable to detect an effect size. Of the activators, use was higher for those in lower study years and in males.

In Panel C, we tested the effect of requiring online viewing along with a grading incentive. We included baseline models that estimated only the treatment effect and models that control for class section fixed effects (no other covariates were available for this experiment). Both sets of models have standard errors clustered at the class section level. When online learning was required, we found that activation increased significantly, with an activation rate 65 percentage points higher in the treatment group than the control. For the treatment group, activation was nearly 80 percent. There were also some spillover effects to other sections in terms of the courses required for viewing; the control group activated at a rate of 18 percent. The difference between the two activation rates by study arm is a statistically significant treatment effect of 0.61 percentage points when accounting for class section fixed effects. Along with robust activation differences, we were able to detect significant differences in usage. Those in the treatment arm logged in 7.4 more times and had an additional 1.11 hours of use. Comparing only those students who activated their licence in both the treatment and control arms, the treatment arm group had almost 4 more sessions and 45 more minutes of use. These results indicate that online engagement can be induced through incentives.

Usage rates for each of the required courses are in Table 5. Of the required courses, a course on confidence was the most-watched. This finding was true for the control group as well. Winter semester courses outside of the confidence course had lower user rates, likely because of school disruptions resulting from COVID-19. Those assigned to the control group had a viewing rate of required videos similar to the University of Toronto-wide activation rate for LinkedIn Learning for the Fall semester courses, but slightly higher for the Winter semester. This result suggests that peers in different sections did learn about required courses and sought them out accordingly, resulting in some spillover effects. Looking at required versus non-required courses, we found that students in the treatment group sought out other videos outside of the required videos at a higher rate than the control group. The average number of non-required videos watched in the treatment group was nearly 16. In the control group, this was 4 other videos, for a treatment effect of almost 12 supplementary videos.

The most popular non-required video continued from the initial email course, around understanding auto-responder emails. Other popular videos included: being punctual, understanding text message etiquette, working on a team, how to be approachable and setting goals. Popular tech skills offerings included working with Excel and Python. For control group users, mindfulness practices and building a growth mindset were the most popular videos.

Table 5: Required Course Viewing by Treatment Arm

	Treatment		Control		
Course	Mean	(s.d.)	Mean	(s.d.)	Difference
Fall Semester					
Emailing	0.67	(0.47)	0.01	(0.10)	0.66***
Communication	0.67	(0.47)	0.01	(0.10)	0.66***
Resiliency	0.55	(0.50)	0.01	(0.07)	0.54***
Winter Semester					
Confidence	0.71	(0.45)	0.06	(0.24)	0.65***
Growth	0.34	(0.48)	0.05	(0.21)	0.29***
Positivity	0.32	(0.47)	0.05	(0.21)	0.28***
Other non-required Courses	15.88	(22.13)	4.02	(11.14)	11.86***
N	115		193		

*Significance levels represented by: * 0.1 ** .05 *** 0.01*

Section 4.2 Benefits of Online Platform Use on Job Placements

Turning to benefits of online learning platform use, we estimated the effect of increased use based on relevant informational nudging on job placement outcomes. At first glance, we see small differences in number of applications sent out and first round co-op placements (Table 6).

Table 6: Co-Op Placement Outcomes by Treatment Status

	Treatment Mean (s.d.)	Control Mean (s.d.)	Diff (s.e)
Applications (N)	12.81 (18.50)	15.06 (21.08)	2.25 (2.64)
Interviews (N)	1.51 (2.20)	1.48 (2.02)	-0.03 (0.28)
First Round Placement (%)	0.62 (0.49)	0.56 (0.50)	0.06 (0.07)
Overall Placement (%)	0.68 (0.48)	0.68 (0.47)	0.01 (0.06)
N	110	117	-

* Note there are no part-time co-op students.

Using regression analysis, we find no evidence of increased applications, interviews or likelihood of receiving a first-round placement or placements overall for those in treatment (Table 7). While there is some evidence of an increase in first round placements, this is not precisely estimated, likely because the nudging experiment did not induce enough difference in use to properly power the sample. It is important to note that the ongoing pandemic did greatly reduce the placement rate for the co-op students. Overall, students had a 68 percent placement rate. Placement rates are usually close to 100 percent. However, first round placements occurred in January and February, prior to the declaration of a pandemic in mid-March. Thus, early outcomes relating to applications, interviews and first round placements should be unaffected by the pandemic. Similarly, using a two-stage least square design to assess the marginal impact of online learning use on first round placement and number of interviews, we found no effects (Panel B).

Table 7: Online Learning Use and Co-op Placements

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N Applications		N Interviews		First Round Placement		Placement Overall	
	Panel A: Reduced Form							
Treatment	-2.251	-2.101	0.030	-0.197	0.063	0.109	0.007	0.014
	(1.843)	(2.154)	(0.236)	(0.345)	(0.116)	(0.147)	(0.058)	(0.065)
GPA		5.440		-0.190		0.097		0.092
		(5.863)		(0.688)		(0.115)		(0.083)
Year of Study		-20.970***		0.744		0.362*		0.364*
		(3.220)		(0.464)		(0.155)		(0.148)
International Student		1.079		0.650		-0.072		0.124
		(4.390)		(0.899)		(0.046)		(0.099)
Male		-28.407		4.426***		0.037		-0.012
		(14.077)		(0.779)		(0.195)		(0.222)
	Panel B: Two Stage Least Squares							
Hours	-14.264	-11.422	0.193	0.129	0.397	0.288	0.042	0.288
	(22.563)	(14.888)	(1.459)	(1.313)	(0.566)	(0.409)	(0.329)	(0.409)
Covariates		x		x		x		x
Observations	227	227	227	227	227	227	227	227

Standard errors in parentheses are clustered at the stratifying group level. Covariate controls and fixed effects included in second regressions.

Section 5 Discussion

Our results show little evidence that awareness is the main driver behind low user engagement. When the intervention involved only informational nudging, there was only limited change in user engagement. In fact, while more students completed an initial registration for use, those nudged to use the platform had less engagement than those who sought the platform on their own. Only when online learning use was imbedded in the course curriculum with an external grading incentive did we see differentiated use. However, even with a required viewing component, full compliance was not reached – only 65 percent of students met the viewing requirement. Finally, we found few effects of online learning platform use on co-op placement outcomes. Students nudged to view pertinent classes and courses related to their job search and new placements did not see an increase in interviews, first round placements or placements overall.

As engagement with supplementary online learning tools use does not appear to be driven by awareness, we explored other motivating factors or barriers to use using linked administrative data. Motivating factors relate to overall ability and interest in the subject matter. Barriers to use may include time, language, and connectivity issues. We found that ability or motivation, as measured through Grade Point Average (GPA) greatly affected use, as well as part-time student status. The students enrolled in programs offered by the Department of Management were not included in this study because we tried to limit possible contamination in the other two studies outlined below. The students in the Department of Management form an insular unit at UTSC with students rarely taking courses outside the department, and Arts & Sciences students rarely taking management courses (UTQAP External Review, 2019).

The highest users in this UTSC population tended to be males watching technical skills videos related to various coding platforms. These factors suggest ability and interest as main motivating factors to use. We also found that international student status predicted lower engagement rates. Given that all required videos were in English, differences in viewing by international student status may point towards language barriers.

In light of the mass move to online learning in March 2020, we also assessed changes in viewing preferences before and after the move online. We tested to see whether there were differences in the use of interpersonal versus technical skills videos and whether the types of videos within these respective categories changed. We found that use of technical skills videos increased following the switch to online learning. This finding suggests that students used the online learning platform as a complementary learning tool to develop new skills while studying from home. While only approximately 20 percent of all videos watched were about interpersonal skills, the courses viewed by students following the move online reflects a shift in concerns. The top videos before the move online focused on success, business and communication. The top videos following the switch to online and the general time of COVID-19 focus heavily on specific tools for time management, overcoming procrastination, avoiding feeling overwhelmed, and maintaining happiness. These videos may be indicative of increased anxieties after the move online and the increased uncertainty that befell to students.

Section 6 Conclusion

In this study, we used an RCT design to evaluate the role of informational nudging, informational relevancy, and external incentives for increasing engagement with online learning. We also used these RCTs to measure the effects of online learning to understand job placement outcomes for university-enrolled co-op students. From the preceding analysis, we find that a minimal number of students at UTSC utilized the free online learning platform overall. Awareness of online learning stood as one potential factor preventing use as activations did increase to some extent with general informational nudges. The increase in this use was, however, minimal. General informational nudges on either interpersonal or technical skills increased activation by less than one percentage point. There is some evidence to suggest information on technical skills programming did increase activations, but this did not lead to increased use.

Students who opted to activate on their own, without an information nudge, or those receiving information on interpersonal skills had higher levels of engagement. This difference may be due to the broader time commitment of learning technical skills like coding over soft skills. We find an increase in activations between first-year students and students in subsequent years. This may reflect the level of engagement in student life and a student's ability to navigate resources available to them. It may also suggest that students are seeking out resources to help them in their future careers, or current careers for part-time students, who are also overrepresented. We do see that providing an informational nudge that included pertinent job skills information for students currently seeking work placements increased activation further. Nevertheless, use was again not meaningfully different for treatment group participants who received this extra information, and we find no evidence of online learning use improving co-op placement outcomes.

Our more prescriptive treatment, where students were required to engage with specific online learning content, lead to significantly higher activation with minimal grade incentives. Those students required to view specific videos had high activation rates and platform use rates beyond the required videos. Knowing whether these observed differences in use due to external grading incentives translates to differing school and employment outcomes remains a topic for future research.

In investigating characteristics of high-use students, we find that they tend to have higher GPAs. The fact that students with higher GPAs activate more aligns with common thinking that those who engage with online learning were more likely to be successful regardless of online learning. We found lower use among international students, which might be indicative of language barriers to activation. Finally, students in computer science are more likely to activate. This finding suggests a difference in willingness to engage based on familiarity with the technology, confirming findings in other studies (e.g. Bergdahl, Nouri, and Fors, 2020). It may also indicate that the online videos for programming and data science are beneficial and interesting to students.

Section 6 References

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