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NUDGING IN BLENDED LEARNING: EVALUATION OF EMAIL-BASED PROGRESS FEEDBACK IN A FLIPPED-CLASSROOM INFORMATION SYSTEMS COURSE

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Research paper

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Abstract

For blended learning (i.e., teaching modes that combine online and traditional classroom-based teaching) to be effective, it is of utmost importance that learners regularly follow asynchronously provided online content so that they appear adequately prepared to the face-to-face classes. This research tests whether certain "nudges", implemented as individualized email-based feedback on the learner's online lecture viewing progress, have a measurable effect on the extent and intensity of online learning behavior. We used a flipped-classroom graduate Information Systems (IS) course as an experimental setting to test whether learners were more likely to view videos (extent) and viewed more video minutes (intensity) subsequent to receiving such a nudging email on week and day levels. We also tested for potential interaction with variables such as gender and time. Our findings not only provide that the email-based nudges are effective, but also that male learners react stronger to these nudges than female learners, while these nudging effects also get weaker over the duration of a course. Our findings hold important implications for the design of learning management systems for online and blended learning.

Keywords: Online learning, Blended learning, Flipped classroom, Education, Nudging, Learning behaviour, Feedback, Field experiment, Panel data analysis, Gender, Learning management systems.

1 Introduction

Blended learning refers to a recent paradigm in higher education that emphasizes the integration of traditional face-to-face and more modern online learning experiences (Garrison and Kanuka, 2004). Higher education institutions are currently looking into blended learning as a way to combine the relative strengths of traditional classroom-based teaching (such as presence and interaction) with the benefits of asynchronous online learning (such as flexibility and individualization) (Porter et al., 2014). For universities in some education systems, the move towards blended learning has in fact become a strategic imperative to defend against the observable threats arising from the proliferation of massive online learning models (Ong and Grigoryan, 2015). One popular form of blended learning is the flipped classroom (Abeysekera and Dawson, 2015). The flipped classroom reverses the traditional learning environment by delivering instructional content (such as lecture videos and quizzes) online, while moving activities commonly considered homework into the classroom (Roehl et al., 2013).

Although research reports various benefits of flipped-classroom blended learning (Bishop and Verleger, 2013), challenges persist. One particular challenge is to ensure that learners are adequately prepared before coming to class (Herreid and Schiller, 2013). Especially in environments where the study of online content prior to class is not mandatory—that is the case, for example, at most universities in Europe—learners do often not adequately follow all the online content required for a class, potentially due to time, motivation, and other issues (Abeysekera and Dawson, 2015). This challenge is in fact consistent with the immense dropout rates reported in massive open online courses (MOOCs) (Perna et al., 2014). However, while MOOCs typically do not rely on learners' preparation and completion, flipped classrooms do. Even in a traditional classroom setting a deficit of learner preparation is typically more condonable. However, since in a flipped classroom knowledge often emerges from applying online content in the class and interacting with others, there is a critical threshold as to which learners *need to* be prepared in order to make the overall learning experience work for all participants.

This research builds on the concept of "nudging" to test whether email-based progress feedback can have a measurable effect on online learning behaviour in a blended learning environment (Damgaard and Nielsen, 2018). As opposed to mandates, nudges are ways of altering people's behaviour in a predictable way but without limiting options or significantly changing the incentives (Thaler and Sunstein, 2008). We used a graduate Information Systems (IS) course as the setting to design a field experiment in which alternating groups of learners received a weekly email describing their lecture video viewing progress in relationships to others. We compared the extent and the intensity of their online viewing behaviour on week and day levels after receipt of this nudge-mail with those that did not receive the email. We employed regression models that control for multiple potentially confounding influences and we also tested for potential interactions with these variables. Building on prior literature on class-based and online education, our principal hypothesis is that: *Progress feedback has a positive effect on the extent and intensity of online study behaviour in a blended learning environment.*

Our results provide evidence that the receipt of nudge-mails has a significant effect on both the likelihood of viewing online videos during a week (the behavioural extent), and on the number of viewed video minutes (the behavioural intensity) on week and/or day levels. Moreover, we found significant interaction effects with gender on the week level and with time on the day level. The first interaction suggests that, while male learners in the course generally viewed less lecture minutes online, nudging emails can bring them on about the same online activity level as their female peers. The second interaction indicates that the nudging effect decreased over the time of this course thus that, by the end of the course, whether a participant received a nudge mail or not did not make a difference anymore to their online learning behaviour.

Our findings have important implications for the design of learning management systems at higher education institutions that wish to effectively embrace the benefits of blended learning. We also discuss the inherent limitations of this study and provide avenues for future behavioural research and design research to extend the study of nudges in blended learning and online learning more generally.

2 Literature Review: Nudging in Education

Thaler and Sunstein (2008) coined the term "nudge" as "*any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives*." The effectiveness of nudges can be explained by theories in cognitive psychology stating that human brain separates between automatic and reflective thinking (Hunnes, 2016). Especially in the absence of sufficient information, experience, or feedback, human decisions tend to be based on automatic thinking and bounded rationality (Thaler and Sunstein, 2008). Nudges are regarded as simple, inexpensive psychological supports that appeal to reflective thinking and thus stimulate more rational decision making.

Nudges have found applications in many different fields including public health, politics, and management. Nudges can help people choose healthier options in the hospital cafeteria (Thorndike et al., 2014). They can also be applied in the work environment to increase productivity, for example when Google designed coffee spots specifically to improve the sharing of information (Ebert and Freibichler, 2017). The Information Systems field has taken great interest in the concept of nudging, given that many nudges relate to the usage of and are provided through information systems. Weinmann et al. (2016) refer to the use of information systems in nudging as *digital nudging* and define this phenomenon as "*the use of user-interface design elements to guide people's behaviour in digital* *choice environments*." Digital nudges can range from push notifications on a smartphone to websites that show options in certain order. For example, in the field of crowdfunding, Tietz et al. (2016) demonstrated that adding less attractive decoy options increased total donations. In the healthcare field, Robotham et al. (2016) showed that patients are more likely to show up when receiving a digital nudge.

Given that the field of application in this study is blended learning, we focused our literature review on nudging in education. Our review strategy was as follows. We chose the comprehensive review by Damgaard and Nielsen (2018) as a starting point and conducted forward searches of one degree and backward searches of up to two degrees (that is, we also reviewed references of their references). We included only empirical studies to discern *what is* from *what could be* (Paré et al., 2015). As can be seen in Table 1, the studies can be divided into two groups: prior research on nudging in education has been either conducted in traditional classroom-based setting, or used data from MOOCs. We did not identify any study that addresses the specific challenges and the potential effects of nudging in *blended* learning.

Reference	**Sample**	**Study Focus**	**Findings**
Classroom-based studies			
(Azmat et al., 2016)	966 students at a university in Madrid	The long term effects of relative feedback on performance and satisfaction	Feedback improved self-assessed performance and satisfaction, but had negative short-term effects
(Azmat and Iriberri, 2009)	3,414 observations at a Spanish high school	The effects of the reporting an average grade on a report card.	Providing average grades had a significant 5% impact over the entire grade distribution
(Bandiera et al., 2015)	7,738 first-year students in the UK	The impact of formative feedback on performance in research essay writing	Knowing the previous test scores motivated students to perform better on the final essay
(Clark et al., 2016)	3,971 students at a US university	The relative effectiveness of performance goals and task based goals	Task based goals were more effective than performance based goals for completion and performance
(Czibor et al., 2014)	529 students in Amsterdam	The difference between relative and absolute grading for performance	Relative grading provides stronger incentives for male students to perform
MOOC-based studies			
(Anderson et al., 2014)	6 MOOCs with 50,000 students each	The impact on forum engagement based on saliency of badges	Making badges more salient gave students more incentives to be active on the forums
(Davis et al., 2017)	33,716 students across 4 MOOCs	The effect of social comparison indicators on MOOC completion	Feedback containing a social comparison had a positive impact on completion rates
(Martinez, 2013)	7,924 students in a Coursera course	The impact of positive and negative framing on effort and performance	Negative framing works better for poor performers, positive framing works better for high performers
(Patterson, 2018)	657 students in a Stanford MOOC	The effect of behavioural tools on time spend, performance, completion	The commitment tool had a significant positive result on all three desired outcomes
(Yeomans and Reich, 2017)	6,0000 students in 3 HarvardX courses	The use of text-based planning tools to improve and predict completion	Students that make a study plan had a higher completion rate

Table 1. Prior literature on nudging in education

2.1 Nudging in classroom-based education

Prior experiments related to nudging in classroom-based education have used feedback both related to performance and progress (e.g., task completion). Bandiera et al. (2015) report on a natural experiment with data from four cohorts of first year master students at a university in the UK. Certain departments provided feedback on essay writing performance before the students started their final essay (formative feedback), while other departments gave feedback only after evaluation of the essay (summative feedback). The authors found that providing early, formative feedback to the students significantly improved their overall test-scores. Clark et al. (2016) reported a classroom experiment involving 3,971 students, in which the instructors first asked two separate groups of students to set themselves performance-based and task-based goals, respectively. Then, after each quiz or test, students received feedback about their personal goal achievement. The authors found that, while performance-based goals had no discernible impact on course performance (i.e., scores and grades achieved), task-based goals had large and robust positive effects on both the level of task completion and course performance. Worth noting is also that task-based goal feedback was reported to be especially effective for males (Clark et al., 2016).

In line with the broader nudging literature, nudges in education have shown to be more effective when enabling some form of a "social comparison" (Azmat and Iriberri, 2009), that is, when including information relative to other learners. One of the first studies focusing on relative performance information is the natural experiment reported by Azmat and Iriberri (2009), who analysed panel data from Spanish high school students. Over a period of nine years (1986-1995; total 3,414 observations) students in one year only (1990; 426 observations) were provided with the class average grade in addition to the usual individual grades on the report card. The authors found that this relative feedback led to a significant increase of 5% in the students' subsequent performance over the entire grade distribution. Azmat et al. (2016) conducted a randomized control experiment with 966 students at a university in Madrid to study the long-term effects of repeated relative feedback. Over the course- of four years (2009-2013), they provided students in the treatment group every half year with relative performance information (their decile position in the grade distribution). The authors found that this relative performance feedback significantly improved the students' self-assessment of performance as well as their self-reported satisfaction. Interestingly, however, the treatment had a negative short-term impact on actual student performance in terms of the number of exams passed and aggregated grade point average. Czibor et al. (2014) tested the impact of relative grading in comparison to absolute grading involving over 500 students enrolled in an economics course at the University of Amsterdam, also taking into account the role of gender. Their findings show that, while female learners performed equally with relative grading, male learners perform significantly better when graded on a curve, thus narrowing the gender gap in student performance (Czibor et al., 2014).

Altogether, the nudging literature on classroom-based education provides some evidence that progress-based feedback can have advantages over performance-based feedback, and that feedback relative to peers can enable a social element that may work better for some learner groups. We considered these prior findings in the design of the experiment reported in this study.

2.2 Nudging in massive online education

The ongoing proliferation of MOOCs spawns new opportunities for the study of nudging in education. The online format and the lack of social presence entails great challenges in ensuring learners' progression towards completion in MOOCs (Perna et al., 2014). At the same time, large-scale data from MOOCs makes learners' activities easily measurable and thus virtually invites to exploit the use of digital nudges (Martinez, 2013). The emerging literature on nudging in massive online education addresses these opportunities (Damgaard and Nielsen, 2018). Authors have primarily focused on progress feedback relative to peers (as opposed to performance feedback) and also explored multiple variants in order to best implement these nudges.

For example, in a large-scale randomized control study researchers at the TU Delft (Davis et al., 2017) provided students in four edX MOOCs with a weekly update about their progress including multiple behavioural indicators such as the hours logged onto the system, quizzes attempted, and others. The researchers found that this weekly progress feedback had a significant positive impact on the course completion rates, albeit only for those learners with high prior education. In addition to the question of whether nudges are effective, the study by Martinez (2013) also focuses on the *framing* of these nudge messages. In a MOOC with 7,924 actively enrolled students, one treatment group received positively framed emails (informing about the proportion of students doing worse) and another group received negatively framed emails (informing about the proportion of students doing better). In simple terms, the results suggest that negatively framed messages work better for the low performing student and positively framed messages for the high performing students (Martinez, 2013).

Beyond simple progress metrics, MOOC-based research has also begun to leverage insights from behavioural economics to explore more creative options of nudging, such as using commitment devices and awarding symbolic incentives. Yeomans and Reich (2017) asked a group of students enrolled in three different HarvardX courses to plan their activities for the duration of the course using text-based input. The students that made such a plan were reported to have a higher completion rate and also more likely to pay for the course certificate. Patterson (2018) designed three different tools to address students' time-management issues: a commitment device, a reminder tool, and a focusing tool. These tools were tested in a MOOC hosted by Stanford University. The author found that the commitment device which made students pre-commit to a time limit for distracting websites, had a positive impact on the time spent on coursework, grade performance, and course completion. In order to make the students more active in the forum of a MOOC on machine learning, Anderson et al. (2014) started awarding badges as symbolic incentives. Students could earn the badges based on milestones for reaching certain activity levels based on contributing to threads, reading content, and voting on content. The authors found compelling evidence that introducing a badge system significantly increased forum participation.

Altogether, massive online learning provides a fruitful testbed for studying and optimizing the use of various digital nudges. It is uncertain, however, if the encouraging findings made in the MOOC domain also hold for a blended learning environment, which is in the focus of this paper. This is because (a) blended learning environments typically operate at a much smaller scale than MOOCs—namely, at the size of a traditional classroom—where (b) learners still have a series of face-to-face touchpoints to synchronize themselves with their teachers and other learners, which can help them reinforce their motivation and learning.

3 Methodology

To test our hypothesis that email-based progress feedback has a positive effect on the extent and the intensity of online study behaviour in a blended learning environment, we designed a field experiment. Field experiments are artificially generated situations taking place in the everyday life of the participants that involve the deliberate manipulation of certain conditions potentially relevant to an outcome of interest (Mingers, 2003). In our case, the participants were students in graduate-level course in an IS program at a large European business university (Copenhagen Business School), the manipulation refers to the receipt of email-based progress feedback, and the outcome of interest is the students' online study behaviour.

3.1 Experimental design and data sources

The course that provided the setting for this experiment was a flipped-classroom course on strategic information systems management. The course was designed that it covered eight topics grouped into four modules (IT strategy, project and portfolio management; enterprise architecture and business process management; IT organization and governance; IT service management and outsourcing). Lecture videos for each of the eight topics were provided for each week. After completion of every module (i.e., every two to three weeks, including a holiday break), there was a four-hour face-to-face classroom session in which students applied the concepts from the video lectures in a case-based exercise. In addition, there were one opening and one closing session, making it total six face-to-face classes with online lectures in-between.

The course consisted of 60 students (42 male, 18 female), which we randomly divided into two groups of 30 students each (group A: 22 male, 8 female; group B: 20 male, 10 female). Each calendar week, one group received as a treatment a semi-automated email about their progress in terms of their completion rates of lecture videos and other activities (e.g., quizzes). Group A received these nudge emails in the odd numbered calendar weeks, group B in the even numbered calendar weeks. We decided for such an alternating treatment design, and against a full exclusion from the treatment for any of the groups, for research ethical reasons to not discriminate any of the groups in their learning experience. Accordingly, we are utilizing the fact that in each week we have a control group (no email) and a treatment group (email) to estimate the effect of receiving a nudge email on viewing behaviour in each subsequent time period. We acknowledge that this design may be subject to potential contamination effects due to information spills-overs between the two groups (Rhoads, 2011).

Nudge emails were sent to either of the groups each Tuesday evening over the whole the duration of the course, face-to-face classes took place on Thursdays in the weeks marked in Figure 2. Figure 2 shows three noticeable spikes in viewing minutes in between the nudge emails and the classes. Our models distinguish the potentially confounding effects from upcoming classes and other influences.

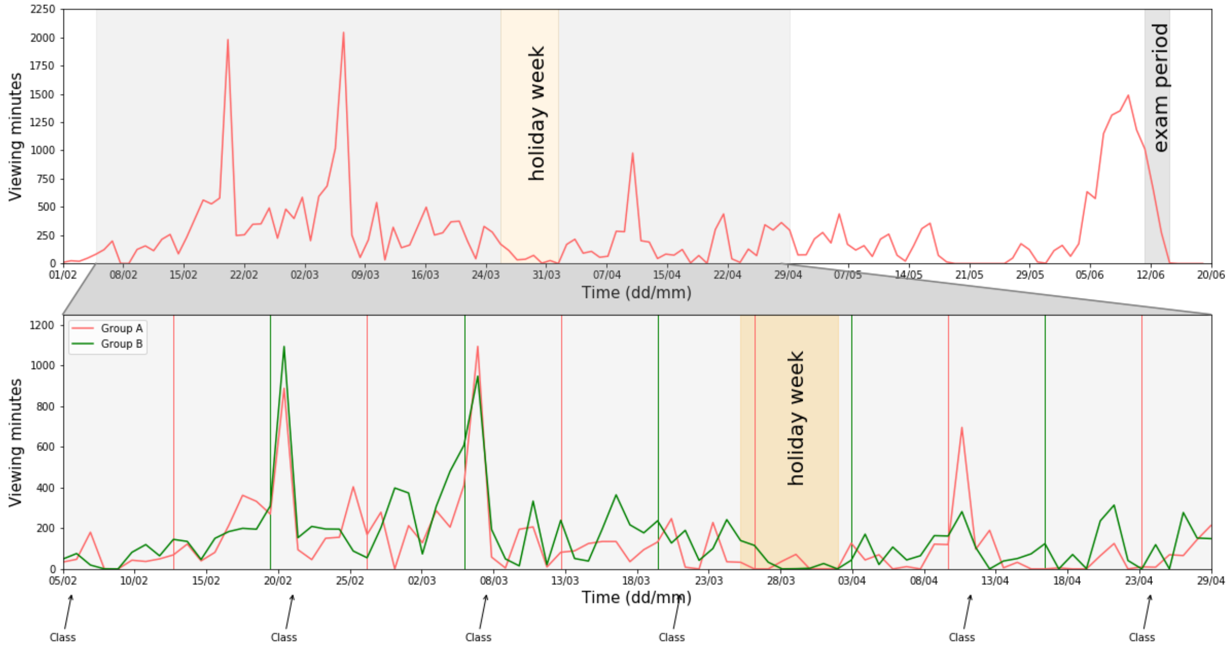

Figure 1. *Course overview: Viewing minutes overall and by student group over the course period (above) and teaching period (below) (vertical lines indicate the nudge emails)*

The nudge email contained the following information. First, a text informed the learners how much progress they had made in the given week. Second, a line chart represented the learner's cumulated total progress in comparison to the average progress of the cohort, as well as the suggested progress according to the course schedule. Third, a second image depicted the progress in each of the topics of the course along the graphical course framework. Lastly, the email carried an attachment with the list of video titles the learner was still missing. The email was framed in a neutral and informative tone.

The data for the emails, as well as for this study, was extracted from log files of the video content platform. The logs contain streaming information per video per user, which we deem a good approximation for video minutes viewed by a learner and more generally for their online study behaviour. From these logs, we created two tables containing one observation for each student per time period. We considered two time periods, a week period (Mon–Sun) and a day period (00:00–23:59). While the week-level data allows us to analyse more broader patterns of behaviour, the day-level data set measures the more immediate effects of our email intervention.

3.2 Variables and measures

This study focuses on two outcome variables. Analogous to common distinctions in economics (Blundell et al., 2011), we define the *behavioural extent* of online activity as the likelihood for a learner to view online lecture videos. We measure the extent as a binary value representing whether the learner has viewed any video in a given time period *t*, and denote this as $Viewing_t$. Analogously, we define *behavioural intensity* of online study activity as the time put into online lecture viewing on condition that the learner is performing online activities at all. We measure intensity in a given time period *t* in minutes as the continuous variable $ViewMins_t$. The manipulated variable *NudgeMail* is operationalized as a binary value representing whether a learner has received progress feedback in the same week for week-level data and on the previous day for the day-level data, respectively.

We control for multiple potentially confounding influences. Firstly, there may be temporal dependencies since the activity of a learner in previous periods may influence the learner's viewing behaviour. Our models consider three periods and include time-lagged $ViewMins_{t-i}$, indicating the video minutes a learner has watched in the periods *t-i*. This makes our model an autoregressive panel data model of the order three.

Since this blended learning course includes multiple face-to-face classes, the prospect of having a class in period $t+i$ may have an influence on the learner's online study behaviour. The binary variable $Class_{t+i}$ represents whether the learner has class in period $t+i$ and thus controls for these influences. In the given course, the teacher also occasionally sent announcement emails to the entire class on a more irregular basis (12 in total), which may have affected the motivation to study online. Therefore, the binary variable $TeacherMail_{t-i}$ controls for whether a learner has received an email from the teacher in period t-i. Since the literature suggest that gender differences may matter for nudging in education, we also include the *Gender* variable coded as 0 for females and 1 for males.

Furthermore, we also control for two student-level characteristics that capture essential aspects of a learner's general level of activity. Specifically, the variable *Coverage* is the ratio between how many video minutes a learner has watched (covered) up to the current period *t* and the total scheduled video minutes up to that period. Thus, this can be interpreted as measure of the studiousness of a learner. We also designed a measure of learner punctuality: *Punctuality* in a period t, is the sum of the difference between the scheduled and the actual week a video was viewed, weighted by the number of minutes of this video. Thus, a learner that procrastinates a lot will have a negative punctuality, a learner that views videos ahead of the schedule will have a positive one. In order to account for changes of the duration of the course, we added the *Week* variable as numbered calendar weeks to have an explicit indication of time. All study variables are summarised in Table 2.

Type	**Variable**	**Scale**	**Description**
Outcome variables	$Viewing_t$	Binary: 0 or 1	Whether a learner watched any videos in *t*, where *t* is days or weeks
	$ViewMins_t$	Cont: [0,∞]	The number of viewing minutes in *t*, where *t* is days or weeks
Manipulated variable	*NudgeMail*	Binary: 0 or 1	Whether the learner received a nudging email in week *t* or at day *t*-1, resp.
Controls	$ViewMins_{t-i}$	Cont: [0, ∞]	The number of viewing minutes in *t*-*i*, where *t* is days or weeks
	$Teacher\text{-}Mail_{t-i}$	Binary: 0 or 1	Whether the learners received an announcement email from the teacher in week *t* or at day *t*-*1*, resp.
	$Class_{t+i}$	Binary: 0 or 1	Whether the learners have class on *t*+*i*, where *t* is days or weeks
	Gender	Binary: 0 or 1	Whether the student is female or male, where 0 is female and 1 is male
	Coverage	Cont: [0,1]	The ratio between the total minutes the learner has viewed (covered) before *t* and the minutes of all lecture videos scheduled before *t*
	Punctuality	Cont: [-∞, ∞]	The sum of the difference between the scheduled week a video and actual week a video was viewed, weighted by number of minutes watched
	Week	Discrete: [5,17]	The calendar week number

Table 2. Variables and descriptions of measures (manipulated variable highlighted)

3.3 Models

Test our research hypothesis, we use a logit model to examine the effects on behavioural extent, and OLS models to examine the effects on behavioural intensity. All regressions use a step-wise approach that first tests a control model and then adds the manipulated variable (*NudgeMail*) and tests for the model improvement. For the OLS models, we further examined potential interaction effects with the control variables. To indicate significance, we use the standard t-test for the coefficients of the model and F-tests for the entire model. To compare the extended model to the smaller model, we make use of an F-test.

Before using linear regressions, we need to verify that there is no strong collinearity and multi-collinearity in the model variables. Table 3 displays the correlation table of the week-level dataset, also including the nudging mail and interaction variables. As can be seen, the raw correlation of 0.11 between $NudgeMail_{t=w}$ and $ViewMins_{t=w}$ is positive and significant. In this table we also present the mean and standard deviation of the data before normalisation. The week squared and the interaction effect were added to the model after normalization of the data. Since the data shows some collinearity, we also measure the multi-collinearity by calculating the variance inflation factor (VIF). We find no VIF scores that are bigger than 5, which indicates that there is no moderate to strong multicollinearity between the manipulated and control variables.

n=840	**Mean**	**STD**	**VIF**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**
A	30.18	55.25														
B	28.32	53.92	1.64	0.24***												
C	25.63	51.14	1.53	0.06*	0.27***											
D	21.79	48.86	1.57	-0.04	0.02	0.13***										
E	0.71	0.45	1.12	-0.2***	-0.12***	-0.02	0.02									
F	0.71	0.45	1.13	-0.02	-0.15***	-0.02	0.02	-0.05								
G	0.43	0.50	1.13	0.18***	-0.08**	-0.08**	-0.12***	-0.09***	0.23***							
H	0.70	0.46	1.13	-0.14***	-0.14***	-0.14***	-0.13***	0	0	0						
I	0.33	0.31	3.12	0.24***	0.51***	0.54***	0.46***	-0.15***	0.04	-0.04	-0.26***	-0.26***				
J	206.63	273.30	1.92	0.02	0.26***	0.3***	0.37***	-0.12***	0.06*	-0.05	-0.21***	-0.21***	0.57***			
K	11.50	4.03	1.91	-0.06*	0.01	0.18***	0.41***	-0.24***	0.16***	-0.04	0	0	0.42***	0.55***		
L	1.00	0.88	1.43	-0.17***	-0.26***	-0.28***	0	0.02	0	-0.1***	0	0	-0.28***	0.01	0	
M	0.43	0.50	1.16	0.11***	0.04	0.04	0.08**	-0.09***	0.07**	-0.02	0	0.15***	0.11***	0.21***	-0.2***	
N	0.21	0.95	1.24	0.04	-0.08**	-0.08**	0.07**	0	-0.02	0.02	0	-0.05	-0.02	0.02	0.01	0
Legend: *p<.05 **p<.01 ***p<.001				A. $ViewMins_{t=w}$ B. $ViewMins_{t=w-1}$ C. $ViewMins_{t=w-2}$ D. $ViewMins_{t=w-3}$			E. $TeacherMail_{t=w}$ F. $TeacherMail_{t=w-1}$ G. $Class_{t=w}$ H. Gender			I. $Coverage_{t<w}$ J. $Punctuality_{t<w}$ K. Week			L. Week squared M. $NudgeMail_{t=w}$ N. Gender*$NudgeMail_{t=w}$			

Table 3. Correlation table including mean and standard deviations for the week-level dataset

For the day-level dataset we provide the same descriptive statistics as in the week-level dataset. Here the VIF scores are also low, indicating that there is no strong multi-collinearity. Furthermore, the table shows that the raw correlation of 0.18 between $NudgeMail_{t=d-1}$ and $ViewMins_{t=d}$ is again positive and significant, see Table 4.

n=1614	**Mean**	**Std**	**VIF**	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**
A	14.92	31.16																
B	14.74	30.95	1.14	-0.01														
C	14.52	30.75	1.06	-0.12***	0													
D	14.33	30.61	1.1	-0.12***	-0.12***	0												
E	0.16	0.37	1.15	-0.08***	-0.01	0.02	-0.07***											
F	0.16	0.37	1.09	-0.04	-0.08***	-0.01	0.02	0.01										
G	0.11	0.31	1.19	-0.09***	0.19***	-0.01	-0.01	0.27***	-0.15***									
H	0.1	0.3	1.63	0.21***	0	-0.01	-0.03	-0.14***	-0.14***	-0.11***								
I	0.08	0.27	1.06	0.03	0.03	0	-0.05*	-0.13***	-0.04	-0.1***	-0.1***							
J	0.63	0.48	1.1	-0.05**	-0.05**	-0.06**	-0.06**	-0.01	0	0.02	0.02	0						
K	0.54	0.26	1.47	0.17***	0.19***	0.2***	0.2***	-0.09***	-0.05**	-0.04	-0.01	-0.01	-0.18***					
L	280.23	305.51	1.7	0.12***	0.11***	0.11***	0.11***	-0.09***	-0.07***	-0.02	0	0.03	-0.11***	0.26***				
M	10.48	3.34	2.12	0.03	0.04	0.04*	0.04*	-0.13***	-0.09***	-0.03	-0.01	0.02	0.08***	0.26***	0.6***			
N	1.00	1.13	1.53	-0.06**	-0.07***	-0.09***	-0.1***	0.04	0.03	0.02	-0.01	0.03	0.03	-0.24***	0.27***	0.43***		
O	0.14	0.35	1.01	0.18***	0	-0.04	0	-0.13***	-0.18***	-0.05**	0.6***	-0.12***	0.03	0.04*	0.04	0.07***	-0.06**	
P	0.07	1.92	1.64	-0.07***	-0.04*	-0.05**	-0.01	0.11***	0.01	0.17***	-0.01	-0.03	-0.01	-0.08***	-.05**	-.08***	0.06**	0.16***
Legend: *p<.05 **p<.01 ***p<.001			A. $ViewMins_{t=d}$ B. $ViewMins_{t=d-1}$ C. $ViewMins_{t=d-2}$ D. $ViewMins_{t=d-3}$				E. $TeacherMail_{t=d-1}$ F. $TeacherMail_{t=d-2}$ G. $Class_{t=d}$ H. $Class_{t=d+1}$ I. $Class_{t=d+2}$				J. Gender K. $Coverage_{t<w}$ L. $Punctuality_{t<w}$ M. Week				N. Week squared O. $NudgeMail_{t=d-1}$ P. Week*$NudgeMail_{t=d-1}$			

Table 4. Correlation table including mean and standard deviations for the day-level dataset

4 Results

This section first tests for the effects of the nudge mail on the behavioural extent using a logit regression on the week-level data. After that, we test for effects on behavioural intensity using ordinary least squares (OLS) regression both on the week-level and the day-level data. The section closes with an analysis of interaction effects.

4.1 Behavioural extent: Logit model on a week level

The results of the logit model are presented in Table 5, where we estimate the behavioural extent: whether or not a learner views videos in a given week. We compare a control model with a main effect model in which we add the *NudgeMail* variable. We find that *NudgeMail* has a significant positive coefficient ($\beta = 0.18$, $p < .05$). This means that if a learners receives a nudge mail in a given week, the learner is more likely to view lecture videos in that week. We calculated the odds ratio: According to our model a learner who received a nudge mail is 1.5 times more likely to view lecture videos in a given week than a learner who did not receive this nudge.

n=840	**Control Model**	**Main Model**
Outcome:	$ViewMins_{w-0}$	$ViewMins_{w-0}$
const	-0.45 (-3.52***)	-0.50 (-3.81***)
$ViewMins_{w-1}$	0.31 (2.84**)	0.32 (2.93**)
$ViewMins_{w-2}$	-0.24 (-2.40**)	-0.22 (-2.21*)
$ViewMins_{w-3}$	-0.31 (-2.97**)	-0.30 (-2.92**)
$TeacherMail_{w-0}$	-0.08 (-0.98)	-0.08 (-0.91)
$TeacherMail_{w-1}$	-0.02 (-0.28)	-0.03 (-0.39)
$Class_{w+0}$	0.45 (5.41***)	0.47 (5.56***)
Gender	-0.12 (-1.47)	-0.12 (-1.46)
Coverage	0.95 (6.60***)	0.94 (6.51***)
Punctuality	-0.18 (-1.65)	-0.18 (-1.62)
Week	-0.50 (-4.51***)	-0.54 (-4.78***)
Week squared	0.12 (1.28)	0.17 (1.72)
NudgeMail		0.18 (2.10*)
Pseudo R-squ.:	0.1489	0.1528
Diff Psuedo R-squ		2.6%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5. Week-level logit regression results (manipulated variable results highlighted)

As to control variables, there are further interesting effects we can observe. First, all three time lagged *ViewMins* variables are significant. While the coefficient of $ViewMins_{w-1}$ is positive, it is negative for $ViewMins_{w-2}$ and $ViewMins_{w-3}$. This suggests a predominance of cyclic patterns in which students are more active over two weeks and then less active for another two weeks. Second, the fact of having a class in a given week ($Class_{w+0}$) has a great influence on the behavioural extent. That is, students are more likely to study online in the weeks they actually have class. Third, *Coverage* is positively related to behavioural extent, suggesting that the level of a student's general studiousness significantly increases the likelihood of viewing videos in a given week. The *week* number, our measure of time, is negatively related to the behavioural extent. In other words, students were more likely to watch videos at the beginning of the course than towards the end, as could also be seen from Figure 1.

4.2 Behavioural intensity: OLS model on a week level

The results of the OLS regression on a week level are provided in Table 6. Here the outcome of interest is behavioural intensity, that is, the viewing minutes in a given week ($ViewMins_{t=w}$). Our step-wise approach considers three model variants: the control model, the main effect model, and the interaction model. Each model is significant and also has a significant improvement on the previous, as expressed by the F-statistics. We find that the *NudgeMail* variable has a positive significant coefficient ($\beta = 5.06$, $p < .01$). Inclusion of the *NudgeMail* variable significantly improves model R-squared by 4%. We calculate that learners who received the nudge mail viewed on average 10 minutes more during that week than learners in the control group, that is 15% of the average total video time per week (65 mins).

As to control variables, we observe similar effect as in the logit model regarding the influences of the time-lagged *ViewMins*, of having a class ($Class_{w-0}$), of *Coverage* and of time (*Week*). In addition, the receipt of announcement emails from the teacher in a given week ($TeacherMail_{t=w-0}$) has a significant influence on the behavioural intensity. This influence is negative, which may have to do with the spe-

n=840	**Control model**	**Main effect model**	**Interaction model**
Outcome:	$ViewMins_{t=w}$	$ViewMins_{t=w}$	$ViewMins_{t=w}$
Const	30.18 (17.43***)	30.18 (17.50***)	30.18 (17.528***)
$ViewMins_{t=w-1}$	4.11 (1.86)	4.35 (1.97*)	4.51 (2.05*)
$ViewMins_{t=w-2}$	-5.37 (-2.52*)	-4.91 (-2.31*)	-4.68 (-2.20*)
$ViewMins_{t=w-3}$	-5.14 (-2.38*)	-4.98 (-2.31*)	-5.34 (-2.47*)
$TeacherMail_{t=w-0}$	-9.141 (-5.00***)	-8.95 (-4.91***)	-8.90 (-4.89***)
$TeacherMail_{t=w-1}$	-2.33 (-1.27)	-2.52 (-1.38)	-2.38 (-1.31)
$Class_{t=w+0}$	8.70 (4.76***)	9.00 (4.93***)	8.90 (4.89***)
Gender	-4.42 (-2.41*)	-4.42 (-2.42*)	-4.36 (-2.39*)
$Coverage_{t<w}$	18.81 (6.16***)	18.33 (6.01***)	18.54 (6.09***)
$Punctuality_{t<w}$	-4.29 (-1.79)	-4.27 (-1.79)	-4.27 (-1.79)
Week	-7.21 (-3.11**)	-8.18 (-3.50***)	-8.24 (-3.53***)
Week squared	-3.35 (-1.75)	-2.25 (-1.16)	-2.12 (-1.09)
$NudgeMail_{t=w}$		5.06 (2.79**)	5.07 (2.80**)
$Gender*NudgeMail_{t=w}$			3.49 (2.01*)
$Week*NudgeMail^{a}$			-2.27 (-1.18)
R-squared (F-stat)	0.185 (17.12***)	0.193 (16.47***)	0.197 (15.57***)
D R-squared (F-stat)		4% (7.77**)	2% (4.03*)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Interaction effects tested in separate models (controls reported for *Gender*NudgeMail* model)

Table 6. Week-level OLS regression results (manipulated variable results highlighted)

cific nature and timing of the teacher emails. Some of these emails communicated the availability of video lectures well ahead in time, others announced activities that were unrelated to, or even substituted the online lectures in some of the weeks (e.g., project work).

Another interesting finding is that in this intensity model *Gender* has a significant negative coefficient (β = -4.42, $p < .05$). We calculate that males view in average 9.6 minutes less lecture videos per week than their female peers, all other variables held constant at mean. Section 4.5 addresses the effects of, and interactions with the gender variable in more detail.

4.3 Behavioural intensity: OLS model on a day level

The results of the OLS regression on a day level are provided in Table 7. The outcome $ViewMins_{d-i}$ measures the behavioural intensity of viewing lectures videos, *once* a student *has* engaged in viewing within a three-day time period. Therefore, we only consider observations where at least one of the $ViewMins_{d-i}$ are non-zero or the response variable is non-zero. This filtering also avoids skewed data. Consistent with the week-level OLS model, we find that the nudge mail manipulation has a significant positive impact on the number of minutes watched (β = 2.44, $p < .01$). We calculate that, according to the main effect model, students who received a nudge mail the previous day in average viewed 7 minutes more than the students who did not receive this nudge.

The control variable effects are consistent with the week-level models in that $Class_{d+1}$ and *Coverage* have a positive influence, and time (*Week*) has a negative influence on behavioural intensity on a day level. The influence of time-lagged *ViewMins* for the previous three days is significantly negative, suggesting that students viewed multiple videos on a single day, rather than distributing their online activities over multiple days. In addition, the *Punctuality* index is positively related to day-level behavioural intensity. This indicates that students who follow the foreseen online video schedule according to plan (or ahead of the plan) also tend to view more lecture minutes on a given day.

4.4 Interaction analysis: Gender and time

We tested for potential interaction effects our manipulation (*NudgeMail*) and all other study variables. Two significant interactions effects were presented that are worth being discussed: gender and time.

n= 1614	**Control Model**	**Main model**	**Interaction Model**
Outcome:	$ViewMins_d$	$ViewMins_d$	$ViewMins_d$
Const	14.92 (20.83***)	14.92 (20.87***)	14.92 (20.92***)
$ViewMins_{d-1}$	-2.84 (-3.72***)	-2.80 (-3.68***)	-2.93 (-3.85***)
$ViewMins_{d-2}$	-5.73 (-7.78***)	-5.62 (-7.62***)	-5.68 (-7.72***)
$ViewMins_{d-3}$	-5.82 (-7.75***)	-5.82 (-7.77***)	-5.82 (-7.79***)
$TeacherMail_{d-1}$	-0.80 (-1.04)	-0.71 (-0.93)	-0.59 (-0.76)
$TeacherMail_{d-2}$	-0.07 (-0.10)	0.12 (0.17)	0.22 (0.29)
$Class_{d+0}$	-1.02 (-1.31)	-1.05 (-1.35)	-0.70 (-0.89)
$Class_{d+1}$	6.14 (8.25***)	4.72 (5.17***)	4.40 (4.80***)
$Class_{d+2}$	1.25 (1.70)	1.41 (1.92)	1.44 (1.97*)
Coverage	7.20 (8.29***)	7.20 (8.31***)	7.18 (8.29***)
Punctuality	5.56 (5.94***)	5.57 (5.97***)	5.58 (5.99***)
Gender	-0.22 (-0.29)	-0.23 (-0.30)	-0.26 (-0.35)
Week	-3.08 (-2.97**)	-3.38 (-3.24**)	-3.65 (-3.49***)
Week squared	-1.45 (-1.65)	-1.18 (-1.34)	-0.95 (-1.07)
$NudgeMail_{d-1}$		2.44 (2.67**)	3.077 (3.27**)
*Gender*NudgeMail*[a]			0.082 (0.11)
*Week*NudgeMail*			-2.14 (-2.84**)
R-squared (F-stat)	0.154 (22.38***)	0.158 (21.37***)	0.162 (20.57***)
D R-squared (F-stat)		2.6% (7.12**)	2.5% (8.07*)

* p < 0.05, ** p < 0.01, *** p < 0.001

[a] Interaction effects tested in separate models (controls reported for to *Week*NudgeMail* model)

Table 7. Day-level OLS regression results (manipulated variable results highlighted)

The interactions between the *Gender* and the *NudgeMail* are reported in Tables 6 and 7. Adding this interaction to the week-level OLS model (Table 6) resulted in a positive significant coefficient ($\beta = 3.49$, $p < .05$). Inclusion of this interaction also significantly improved the model R-squared by 2%. In the day-level dataset (Table 7), we also observe a positive, albeit nonsignificant coefficient ($\beta = 0.082$, $p < .9$).

As can be seen in the left side of Figure 2, the nudge mail has a strong effect for male learners, while it has a negligible effect for female learners. Given that female learners are generally more active in viewing online lectures, the email nudge helps male learners to view approx. 15 min more in a given week, and thus achieve an activity level that is comparable to the level of their female peers.

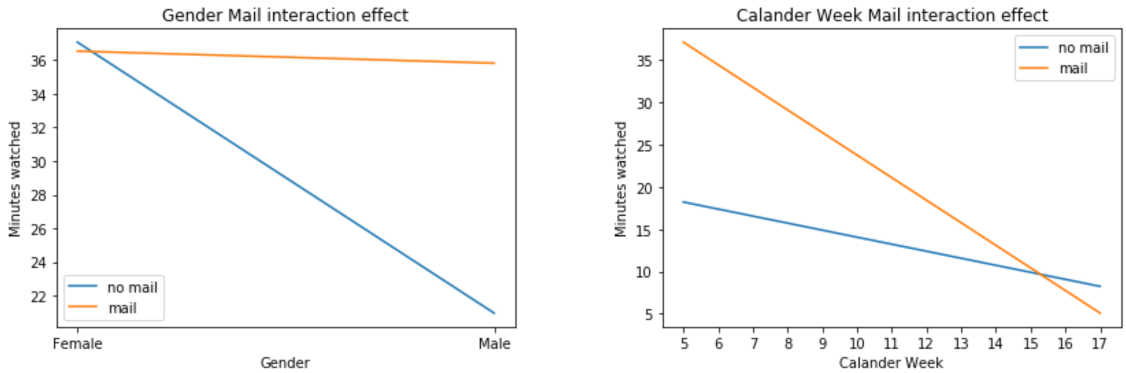

Figure 2. Interaction effects with gender and time (week)

The interactions between the time (*Week*) and *NudgeMail* are reported in Tables 6 and 7. In the week-level dataset we observe a nonsignificant coefficient ($\beta = -2.27$, $p < .25$). For the day-level data, we found a significant coefficient ($\beta = -2.14$, $p < .01$) with the same negative sign.

The right figure of Figure 2 plots the interaction of *Week* and *NudgeMail* based on the day-level model. While at the beginning of the course, learners that received the nudge exhibited a significantly greater behavioural intensity—i.e., they viewed up to 20 minutes more videos than those who did not receive the nudge—this effect becomes negligible, in fact almost reversed, towards the end of the teaching period.

5 Discussion

Our field experiment on nudging in blended learning was motivated by the pressing need to help learners prepare themselves adequately for class in flipped-classroom and similar learning environments, as well as by the dearth of prior empirical research into the value of nudges specifically designed for blended learning environments. Our evaluation of email-based progress feedback using data on online viewing minutes provides robust evidence that this form of nudging has a positive impact both on the extent and the intensity of learners' online lecture viewing behaviour. Specifically, our models suggest that recipients of the nudges are 1.5 times more likely to view lecture videos in a given week and they will spend in average 15% more time on viewing online lectures than their peers. On a day level, nudged learners view in average 7 minutes more, which equated to approximately the length of one video in the studied course.

Our principal finding on the effectiveness of nudges, implemented as relative progress feedback, is consistent with the broader literature on nudging in education, both for classroom-based education and for massive online education. Although studies in classroom-based contexts have primarily focused on performance-based feedback relative to peers (e.g., by providing grade averages), some studies also suggest that progress feedback may in fact be more effective, and potentially less demotivating (Azmat et al., 2016), than performance-based feedback (Clark et al., 2016). The major conceptual difference between progress feedback in classroom-based and blended learning environments is that the progress in blended learning is (at least for some parts) much more measurable (e.g., through the completion of online activities) and can thus be easily be integrated in automated feedback routines.

Emerging MOOC-based studies have provided more ample evidence for the effectiveness of such relative progress based nudges (Martinez, 2013; Davis et al., 2017). MOOCs, however, are by definition detached from the physical encounter and the personal interaction between learners and teachers. Our models control for the relative effects of such interactions through the *Class* and *TeacherMail* variables and thus arbitrate between these confounding effects and the effects of the actual nudge (here: the *NudgeMail* variable). Therefore, the distinctive contribution of this research, against the background of emerging MOOC-based studies, is to demonstrate that progress-based nudges are *still* effective—*irrespective* of the effects arising from the orchestrated classroom interaction and alternative communication channels used by the teacher—in a blended learning environment.

We also explored post-hoc potential interactions between the nudging effect and other variables and made two noteworthy findings regarding gender differences and time. Our findings regarding gender exhibit remarkable parallels with two classroom-based nudging studies that have included gender as an explanatory variable of interest: Czibor et al. (2014) found that introducing relative grading motivated male learners catch up with their female peers in terms of grade performance. Clark et al. (2016) reported progress feedback based on self-defined goals to be especially effective for male learners. Although our study took place in a different domain and used a different experimental design, there appears to be a consistent pattern that male learners react stronger on nudges, especially if these involve some sort of peer comparison. This notion is, in fact, in accordance with literature that has focused more broadly on gender differences in education. For example, both Buechel et al. (2014) and Duckworth et al. (2015) argue that males exhibit less self-control than females in learning situations. Males might therefore might be more responsive to nudges. Relative progress information may influence males more since males are generally more incentivized in competitive environments (Gneezy et al., 2003).

We also found evidence for an interaction effect between the nudge and time. The further along the course the learners were, the less influence the nudge mail had. This might indicate that the feedback information loses its immediate effect. This particular finding is consistent with nudging research in other domains. For example, Damgaard and Gravert (2018) studied reminders for donations. Although there donations increased through nudges, also more people were opting out of the email chain. This suggests a certain *habituation effect*, which may cause nudges to become less effective over time. Following the theory of automated versus reflective thinking in cognitive psychology (Hunnes, 2016), nudges seem to lose their effects when subjects gain experience on which they can back their choices.

5.1 Limitations

Several limitations of this study merit consideration. First, we decided for a non-discriminatory experimental design where treatment and control groups alternated each week. This may have introduced certain contamination effects that tend to make treatment and control subjects look more similar on average (Rhoads, 2011), while the actual nudging effect without contamination may be stronger than measured. Second, this study focuses on the extent and intensity of only study progress. Future studies may need to include performance outcomes such as final grades in order to corroborate the presumed link between online study behaviour and learner performance. Third, like in many other nudging studies, our study design did not check the correct functioning of the manipulation. For example, it was not possible to check whether learners actually opened the nudge email and to check whether they actually followed the lecture content when streaming the videos. Improved research designs may consider the use of unobtrusive manipulation checks (Hauser et al., 2018), such as email open tracking methods known from online marketing. Fourth, generalizability of this study may be limited since our data is based on a series of data from 60 students in a master course on strategic information systems management at one specific school. Students in other programs and at other universities might react differently to the provided nudges due to cultural variations and different learning styles.

5.2 Design implications and future work

Despite these limitations, we argue that our findings hold important implications for the design of learning management systems (LMS) in blended and online learning environments. First, we believe that contemporary LMS should profitably integrate nudging functionality. For example, it would be useful for a teacher to be able to automatically inform learners about their progress. Ideally the email can be adjusted by the teacher by making use of a template and certain triggers. Furthermore, since we saw a decrease of impact of the nudges over time, this design could allow to modify the nudges over time. Since we see an interaction effect of the nudge and gender, the question arises what could be elements of nudges that can make them more effective for female learners.

Taking the effectiveness of nudges in blended learning as a premise, future work may investigate different properties of nudges in blended learning. For example, one can experiment with the layout and the specific information contained in a feedback message. Also in our experiment the nudge mail was always sent on Tuesday evening, and it might be interesting to see whether the sending time has an impact. Emails could be sent during the weekend, morning, or maybe even randomly. As an extension of this experiment, future work might also explore concepts related to gamification, where the nudging receives a more playful element. Similar to the idea of badges (Anderson et al., 2014), points gained from study activities may become a status symbol or be traded against additional learning experiences.

6 Conclusion

In an experiment based in a blended learning course we have found that nudging implemented as individualized progress feedback has a positive effect on the extent and the intensity of the learners' online lecture viewing behaviour. Further, we found significant interaction effects with the gender and time, implying that these nudges can bring males on a similar online activity levels than their female peers, while these nudging effects also seem to lead to some habituation over time. Although prior research has addressed nudging in classroom-based and massive online education, to our knowledge this is the first study to design and evaluate a nudging intervention in a blended learning environment, which faces specific opportunities and constraints. Our findings prompt designers of learning management systems to incorporate elements of automated and semi-automated nudging in their software offerings, and universities to co-develop and adopt these tools. Future research may embark on exploring different properties of nudges that are specifically catered to the growing domain of blended learning in order to provide learning experiences that can outcompete those of the larger MOOC rivals.

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