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The role of temporal patterns in students' behavior for predicting course performance: A comparison of two blended learning courses

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Abstract

In higher education, many studies have tried to establish which student activities predict achievement in blended courses, with the aim of optimizing course design. In this paper, we examine whether taking into account temporal patterns of student activity and instructional conditions of a course help to explain course performance. A course with a flipped classroom model (FCM) and a course with an enhanced hybrid model (EHM) were compared. The results show that in both cases, a regular pattern of activity is more effective than low activity. In the FCM, initial low activity is detrimental, whereas in the EHM the strategy of cramming later on in the course can still lead to higher course performance. In the FCM, a combination of face-to-face and online activity led to sufficient course performance, whereas in the EHM, face-to-face or online activity on its own could lead to sufficient course performance. This study offers a methodological and empirical contribution to exploring the role of patterns of activity and instructional conditions for course performance.

Introduction

Courses in higher education increasingly make use of blended learning, ie, the combination of online and face-to-face activities to optimize learning (Staker & Horn, 2012). In higher education, many studies have tried to establish which student activities predict achievement in blended courses, with the aim of optimizing course design and thereby to avoid dropout and to increase retention rates (Tempelaar, Rienties, & Giesbers, 2015). The underlying rationale is that by examining which student activities predict achievement, early intervention on these activities may prevent dropout in subsequent cohorts. As such, this endeavor is an example of learning analytics, which refers to “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Siemens & Gašević, 2012).

Practitioner Notes**What is already known about this topic**

- There is a diversity of blended learning models, with each model having their own specific design principles of the combination of online and face to face activities.
- Student activity in blended courses can be used to predict course performance or enhance course design.
- The explanatory power of these predictions shows a large variability across studies, making it difficult if not impossible to draw general conclusions about the explanatory power of specific learning activities in blended courses.

What this paper adds

- This paper investigated the added value of considering temporal patterns of student activity when explaining course performance.
- Our results show the importance of taking into account instructional conditions related to students' study strategies and course performance.
- In courses with a flipped classroom design, regular study behavior is beneficial, while in a more traditional form of blended learning, procrastination may still lead to sufficient course performance.

Implications for practice and/or policy

- For each blended learning model, students might need different study strategies to perform well in the course.
- When confronted with a new blended learning model, students need time or explicit guidance to adjust to this model, since students tend to use their previous study strategies.
- In courses with a flipped classroom design, it is beneficial to monitor students' activity early on in the course to ensure regular study patterns.

While many studies aim to predict course performance based on students' use of resources or student activity within a blended course (Tempelaar et al., 2015), the complication with these predictions is the large variation in the types of learning activities (eg, posted discussion messages or completed online quizzes) students engage in. This variation results in differences in the strength by which predictions can be made about course performance (Gašević, Dawson, & Siemens, 2015). For example, in their exploratory study, Macfadyen and Dawson (2010) conclude that some, but not all, digital tools used within a course are solid predictors of course performance. They found an explained variance of 33 percent of the usage of tools on course performance, based on three technologies used within the course: number of discussion messages posted, number of assessments finished and number of mail messages sent. In contrast, Zacharis (2015) found a 52% explained variance based on the use of four different learning activities: reading and posting messages, content creation contribution, quiz efforts and number of files viewed.

As overview studies by Tempelaar et al. (2015) and Gašević, Dawson, Rogers, and Gasevic (2016) confirm, there is large variability in the explanatory power of specific learning activities within different studies. It is, therefore, difficult to draw general conclusions about the explanatory power of specific activities in blended courses. The reviews by Tempelaar et al. (2015) and Toetel and Rienties (2016) indeed indicate that when these studies are put together, variables

in terms of separate activities do not substantially predict course performance. Building a generalized theoretical understanding of the success of blended learning, therefore, remains difficult. In this paper, we put forward and investigate two possible explanations for the variation in which specific activities predict course performance.

A first possible explanation is that often, *temporal patterns* of student activity are not taken into account, for example, the sequence and timing of student activity (Barbera, Gros, & Kirschner, 2014). When analyzing information on the level of the whole course, temporal information is lost (Barbera et al., 2014), which leads to a loss of in-depth insights about differences between students or about the role of fluctuations in activity. The predictive value of data about student activity may thus be enhanced when considering either the order in which students engage in activities or the timing of engaging in activities (Greiff, Scherer, & Kirschner, 2017). It is hypothesized that better performing students may be distinguished from lower performing students by examining their patterns of activity (Perera, Kay, Koprinska, Yacef, & Zaïane, 2009). We, therefore, argue that besides examining the relation between types of activity and performance, temporal aspects of student behavior should also be taken into account.

A second explanation for variation in the predictive value of specific learning activities is that often, *instructional conditions* are not taken into account. That is, blended learning models come in many forms, each with distinct goals and theoretical underpinnings of why the choice of activities is suited to achieve a particular goal (Staker & Horn, 2012). Indeed, Gašević et al. (2016) demonstrated that the association between students' activity and course performance is moderated by instructional conditions, showing differences in explained variance of course performance between 21 and 70% for different courses. An activity that is predictive of performance in one course, may not be predictive at all in a course with a different instructional context.

Thus, examining temporal patterns of study behavior as well as the role of instructional conditions could help to explain student achievement. Nguyen, Rienties, Toetenel, Ferguson, and Whitelock (2017) indeed found that engagement in fully online learning environments is influenced by how educational designers balance their learning design activities on a week-by-week basis, confirming the importance of temporal patterns of study behavior and instructional conditions. However, in the context of blended learning, research combining these two factors is scarce. Therefore, the aim of the present study is to investigate to what extent taking into account temporal patterns of student activity as well as instructional conditions can help to explain student achievement. Two blended courses in higher education were chosen that were designed following two different models of blended learning, and which thus differed in their instructional conditions. The first course concerned a flipped classroom model (FCM), in which delivery of content primarily occurs by means of online materials (rather than face-to-face lectures), and the subsequent face-to-face meetings with teachers are used for guided practice and processing of knowledge (Karabulut-İlgu, Jaramillo Cherrez, & Jähren, 2017). In the FCM, online learning activities serve as a preparation for the face-to-face learning activities. In this model, it is therefore hypothesized that student achievement is highest when students regularly engage in (online) preparation and subsequently attend teacher-guided (face-to-face) sessions.

The second course we examine employed an enhanced hybrid model of blended learning (EHM) (Graham, 2006), in which transmission of information primarily occurred in face-to-face lectures and small workgroups, and in which additional and supplementary resources were available online: lecture recordings, PowerPoint presentations and formative assessments. In this model, it is hypothesized that multiple patterns of student activity can lead to successful completion of the course, since none of the activities serve as a precursor for the other activities. It is, therefore, not expected that an emphasis on one particular type of activity is more predictive of student achievement than others.

Table 1: *Weekly structure of the course with FCM*

<i>Preparation (online)</i>		<i>Lecture (face-to-face)</i>		<i>Working group (face-to-face)</i>
Study web lectures and book	→	Guest speaker with practical example	→	Discuss formative questions
Submit formative question		Background information by one of the lecturers		Work and receive feedback on group assignment

Our research question is: *How do a flipped classroom model and enhanced hybrid course model compare concerning the influence of temporal patterns of activity and type of activity on student achievement?*

In the FCM, online learning activities are designed as a prerequisite for the face-to-face activities. A regular study pattern of online activity followed by attending face-to-face activities is therefore expected to be beneficial. On the other hand, in the EHM, online materials are designed to supplement face-to-face instruction. We, therefore, expect no particular study pattern to be most beneficial. Our hypotheses for what predicts student achievement therefore are:

Hypothesis 1: In the FCM a regular, consistent pattern of activity is most beneficial for student achievement, whereas in the EHM different patterns of activity could be beneficial for student achievement.

Hypothesis 2: In the FCM the combination of *both* online and face-to-face activities is most beneficial for student achievement, whereas in the EHM, online *or* face-to-face activity on its own could be beneficial for student achievement.

Method

Description case 1: Flipped classroom model

Course structure

Data were collected in an undergraduate University course in the Netherlands centered around designing educational materials (DEM). The course followed the FCM (Staker & Horn, 2012). Table 1 outlines the weekly structure of the course.

Students studied the course materials (the course book and corresponding web lectures) and engaged in an activity before the face-to-face lectures and working groups. The preparatory activity consisted of creating a formative question about the course materials (with PeerWise software, see Denny, Hamer, Luxton-Reilly, & Purchase, 2008). The preparation was intended to activate students' prior knowledge and for students to become aware of any gaps in their knowledge, so that the face-to-face lectures could be spent on further processing of the material instead of information transmission (Staker & Horn, 2012).

The face-to-face lectures contained practical examples of DEM and further background information. Recordings of the lectures were available afterwards. The formative questions were discussed during the working group and could be practiced again by students as preparation for the exam. During the working groups, time was available to work and receive feedback on the group assignment, which meant students in groups of four or five designed course materials for an actual company (eg, a customer service training for bank employees). The students were divided over seven working groups (each with its own teacher) each of about 20–25 students.

The course lasted 10 weeks. In the first 8 weeks, the course followed the structure outlined in Table 1. In week 9, no more meetings were scheduled. In week 10, the individual exam took

Table 2: Weekly structure of the course with EHM

Preparation (online)	Lecture (face-to-face and/or online)	Preparation (online)	Working group (face-to-face)	Case-based lecture (face-to-face and/or online)
Download PowerPoint	→ Lecture on theoretical concepts	→ Complete formative assessments	Discuss formative questions	→ Lecture on complex, real-life case studies

place. This exam consisted of 30 multiple-choice questions and 4 open questions. It tested students' knowledge about DEM as well as their ability to apply their knowledge to new examples. Final grades were scored on a scale from 1 to 10 with 10 being the highest and 5.5 being the pass mark.

Participants

One hundred and fifty students were enrolled in the course, of which 146 signed informed consent to use their data for research purposes. The mean age of these students was 23.5 years ($SD = 4.6$); 114 students were female.

Measuring student activity

The online activities automatically logged and timestamped: frequency and duration of viewing web lectures, and submitting and practicing formative questions. Attendance at lectures and working groups meetings were recorded on paper at the start of each meeting. The number of hours spent on reading the course book was collected purposefully by means of a weekly, online questionnaire that was filled out by the students at the start of each working group on their smartphone, tablet or laptop. The average number of completed questionnaires over 8 weeks was 130.71 ($SD = 3.5$), indicating a high and steady completion rate (out of the sample of 146). Because measurement of number of reading hours relied on students' presence at the working groups, we did have some missing values (around 15 per week). In the cluster analyses that we used (see below), variables are computed in the form of an aggregated score. When we did not have information about reading hours, those students were not taken into account in the aggregated score. For all other variables, there were no missing values.

Description case 2: Enhanced hybrid model

Course structure

Data were collected in an undergraduate University course in the Netherlands centered around Contract Law (CL). The course followed the EHM (Graham, 2006). The outline for each week can be seen in Table 2.

On the first day of the week, students were offered a face-to-face lecture in which theoretical concepts were addressed, and for which they could download the corresponding Powerpoint presentation beforehand. These lectures were university style lectures, with the instructor lecturing in front of the class. The lectures were recorded and made available directly after the lecture had taken place and were accessible until the exam had finished. If parts of the lectures were unclear, students could use the recorded lectures to study these parts or rewatch the entire lecture if needed. The course consisted of three face-to-face lectures, with a 120-min duration and a 15-min break in halftime. Lecture attendance was not mandatory. In week 4, students took the exam.

Each week, students could attend a working group (sized 20–25 students); attendance was registered by the teacher. Before attending these working groups, students could complete two formative assessments. First, a formative assessment consisting of four short essay questions. These questions were not scored but discussed during the working group. Second, a formative assessment consisting of 10 multiple-choice questions, developed so students could determine their mastery of the course material for that week.

In the final segment of the week, students were offered a case-based lecture in which theoretical concepts were explained with cases and specific situations of CL. These three case-based lectures were also recorded and made available directly after the lecture had taken place and were accessible until the exam had finished. All the recorded lectures were made available through the Learning Management System Blackboard.

The course lasted 4 weeks. In the first 3 weeks, the course followed the structure outlined in Table 2. In week 4, no more meetings were scheduled since the individual exam took place in that week. This exam consisted of 25 multiple-choice questions and four short essay questions. Final grades were scored on a scale from 1 to 10 with 10 being the highest and 5.5 being the pass mark.

Participants

Five hundred sixteen students were enrolled in the course, of which 470 signed informed consent to use their data for research purposes. The mean age of these students was 22.1 years ($SD = 4.9$); 216 students were male.

Measuring student activity

The online activities were automatically logged and timestamped: downloading PowerPoint, frequency and duration of viewing recorded lectures (both the plenary lecture and the case-based lecture) and submitting multiple-choice and uploading formative short essay questions. Lecture and working group attendance was registered on an individual level by scanning student cards upon entry of the lecture hall or by the teacher through an attendance list. There were no missing values: each student was active in the VLE and when students did not attend face-to-face activities, this was registered as absence.

Analyses

For both the FCM and EHM case, two cluster analyses were performed. Two-step cluster analyses were performed in SPSS, which can handle both ordinal and scale data and automatically standardizes scale data. SPSS selects the number of clusters based on the smallest BIC value, which is a fit index that is good at predicting the right number of clusters, even for small sample sizes (Nylund, Asparouhov, & Muthén, 2007). We thus report here the cluster solutions with lowest BIC values and highest interpretational value. We drew on Schwarz (1978) and Rousseeuw (1987) to determine the validity of the clustering; a model fit of at least 0.3 was considered to be fair.

Temporal patterns of student activity

To determine the relation between patterns of activity and course performance, cluster analyses were performed to establish whether students showed different temporal or activity patterns. The clusters were subsequently compared on course performance. For both cases, the cluster analysis was performed on students' activity score for each week, which is the sum score of all activity for that particular student in a particular week (see below).

For the FCM, an activity score was calculated for each of the 10 weeks of the course. A higher score indicates more activities were undertaken in that particular week. Each of the following

activities contributed to the weekly score: (1) watching web lectures or online lectures, (2) being present at the face-to-face meetings (lecture and working group), (3) reading course materials, (4) creating a formative question, (5) practicing with formative questions. Thus, a score was calculated for each of the 10 weeks, with a higher score indicating engaging in more activities (not necessarily the number of hours of activity). For example, a student might attend the lecture and working group, study the book and create a formative question, and watch two web lectures. In this case, the score includes the sub scores for those activities, but the score would have been higher if the student had for example also practiced course material by answering questions in the Peerwise system. The Appendices display how the activity scores are decomposed into scores for the various activities.

Because cluster analysis is most reliable and easier to interpret with fewer variables, the activity scores were calculated in pairs of weeks, so variables for weeks 1 and 2, weeks 3 and 4, weeks 5 and 6, weeks 7 and 8 and weeks 9 and 10 (five variables). In the last two weeks (Weeks 9 and 10), there were no more face-to-face meetings and this variable showed little variance. It was, therefore, excluded from further cluster analyses.

For the EHM, activity scores were calculated for the first three weeks of the course (as in the fourth week, students took the exam). Each of the following activities contributed to the weekly score for the EHM: (1) attending face-to-face lectures, (2) completing formative essay questions, (3) watching the lecture recording, (4) downloading PowerPoint presentation, (5) completing formative multiple-choice questions. Students were able to access the online learning resources on multiple occasions. Each new access contributed to their activity score.

Types of activity

To investigate the relative importance of online and face-to-face activities for course performance, for each week an activity score was calculated for online activities and for face-to-face activities. In the FCM, again weekly pairs were created to lower the number of variables. Thus, variables included “online activity week 1 and 2,” “face-to-face activity week 1 and 2,” “online activity week 3 and 4,” and so on. For the EHM, a similar procedure was followed, although weeks were not paired given the relatively short duration of 4 weeks. Then, a cluster analysis was conducted to examine the activity scores for online and face-to-face activity as the two courses progressed. The clusters were compared for course performance.





































Results

Patterns of weekly activity in relation to student achievement

Flipped classroom model










The cluster analyses with weekly activity showed that students could be placed within four clusters, see Table 3 and Supporting Information Figure S1. The cluster solution, with a fair fit of

Table 3: Cluster solution for activity scores in the Flipped Classroom Model

Cluster	n	Week								Exam score		
		1	2	3	4	5	6	7	8	M	SD	
1	54										6.78	1.02
2	42										6.36	0.98
3	33										7.15	1.01
4	17										6.38	0.74

Note. Dotted grey = average activity; dark grey = low activity; striped = high activity.

Table 4: Cluster solution for activity scores in the enhanced hybrid model

Cluster	n	Week			Exam score	
		1	2	3	M	SD
1	204				7.61	1.58
2	149				7.36	1.66
3	117				6.44	1.86

Note. Dotted grey = average activity, dark grey = low activity, striped = high activity.

around 0.3, showed, in order of size: (1) steady average weekly activity, (2) low first two weeks activity, which continues to drop, (3) steady far above average weekly activity, and (4) very low first two weeks activity, but a rise to average in the following weeks. Cluster 1 seems to vary per week in what type of activity students mostly engage in; the scores for answering formative questions and watching recordings of the lectures show considerable variation, for example. Cluster 2 shows decreasing activity overall, especially concerning lecture attendance and formative questions. Cluster 3 shows overall high activity in both the face-to-face and online activities and seem to engage in every activity that is offered to them. Cluster 4 slowly increases in activity, but the distribution over the several activities varies. Some weeks show higher scores on lecture attendance, for example, and there is also variation in activity around formative questions and amount of reading hours.

The four clusters differed significantly on exam grade ($F(3) = 4.74, p = .004$). The very low activity cluster (cluster 2) had significantly lower exam scores than cluster 1 with steady average activity ($p = .041, d = 0.42$), and cluster 3 with high activity ($p = .001, d = .81$). In addition, the very active cluster (3) scores significantly higher on the exam than cluster 4 ($p = .008, d = .89$).

Enhanced hybrid model

The cluster analysis with weekly activity in the enhancing hybrid course showed a three-cluster solution, see Table 4 and Supporting Information Figure S2. This cluster solution has a fair fit of 0.2. Cluster 1 shows an increase in all the activities as the course progresses. They do not seem to have a clear preference for a specific learning activity. Students in cluster 2 show a similar pattern, but they start attending lectures in the second week, while students in cluster 1 skip lectures during the entire course. Students in cluster 3 show a moderate activity in the first 2 weeks and start preparing themselves in the last week, mainly by watching lectures recordings.

The three clusters differed significantly on exam score ($F(2) = 18.86, p < .001$). Cluster 3 showed a significant lower score on their exam compared to clusters 1 ($p < .001, d = 0.52$) and 2 ($p < .001, d = 0.68$).

Importance of different types of activity for student achievement

Flipped classroom model

A three-cluster solution was selected with a fair fit (0.3), see Table 5 and Supporting Information Figure S3. The first cluster indicated low to average weekly activity in both face-to-face and online activities, with activity decreasing as the weeks progressed. The peaks in weeks 1 and 5 seem to be caused by high scores on lecture attendance and activity with the formative questions. The second cluster showed regular, low to average weekly activity in online activities, but steady weekly activity in face-to-face activities. The variation in online activity seems to concern especially the amount of watching web lectures and practicing with formative questions. The third cluster showed regular, average weekly activity in face-to-face activities, but occasional peaks in

Table 5: Cluster solution for face-to-face and online activity in the Flipped Classroom Model

Cluster	n	Activity	Week								Exam score	
			1	2	3	4	5	6	7	8	M	SD
1	55	Face-to-face Online									6.36	1.04
2	50	Face-to-face Online									6.85	0.95
3	41	Face-to-face Online									6.95	0.93

Note. Dotted grey = average activity, dark grey = low activity, striped = high activity.

online activities. These peaks especially concern watching online web lectures or recorded lectures.

The three clusters differed significantly on the individual exam grade ($F(2) = 4.12, p = .017$). The cluster of students with low weekly activity displayed a significantly lower average exam score than students in the cluster with a focus on face-to-face activity ($p = .006, d = 0.54$) and lower than students in the cluster with a focus on online activity ($p = .043, d = 0.42$). The face-to-face and online clusters did not significantly differ from each other.

Enhanced hybrid model

The cluster showed a four-cluster solution with a fair fit (0.3), see Table 6 and Supporting Information Figure S4. Each cluster shows an increase of the activity throughout the course. Student in clusters 1 and 2 hardly attend any lectures and thereby treated the course as a fully online course. Students in cluster 2 show more online activity compared to students in cluster 1. Students in clusters 3 and 4 used the course materials in a blended fashion; students in cluster 4 do so as intended by the educational design by combining the face-to-face activity with the online

Table 6: Cluster solution for face-to-face and online activity in the Enhanced Hybrid Model

Cluster	n	Activity	Week			Exam score	
			1	2	3	M	SD
1	208	Face-to-face Online				6.88	1.80
2	105	Face-to-face Online				7.81	1.59
3	80	Face-to-face Online				7.32	1.59
4	77	Face-to-face Online				7.35	1.71

Note. Dotted grey = average activity, dark grey = low activity, striped = high activity.

learning resources from the start of the course. Students in cluster 3 start attending more face-to-face lectures as the course proceeds.

There are significant differences in course performance when comparing the differences between online and face-to-face activity ($F(3) = 7.02, p < .001$). Students in cluster 1 scored significantly lower on the exam compared to students in cluster 2 ($p < .001, d = 0.54$).

Discussion

Studying students' study behavior in order to predict course performance is an often-used strategy to optimize course design and prevent dropout. Many studies have tried to determine these behaviors by aggregating frequencies of student activities and correlating them to course performance. In this study, we argued that when examining these behaviors, it is important to take into account temporal patterns of activity as well as instructional conditions in which student activity takes place to determine and interpret the relation between study activities and course performance. Two blended courses in higher education, which differed in instructional conditions, were used as example cases. The results are both of methodological and empirical relevance.

Discussion of findings

Based on the courses' instructional conditions, we generated two specific hypotheses about the relation between temporal patterns of activity and course performance. Our first hypothesis was that in the FCM, a regular pattern of activity would lead to higher course performance, whereas in the EHM several patterns of frequency of activity could be equally effective. The results showed that in both courses, a regular pattern of below average activity led to worse performance than the other patterns of activity. Steady above-average activity was beneficial for course performance. This is in line with general theories about student engagement and empirical studies showing a certain level of effort or engagement is a prerequisite for learning (Chi, 2009).

A difference between the two courses laid in the clusters of students whose study pattern changed during the course. In the FCM, students that started with low activity and then changed to average activity as the weeks progressed, had lower course performance than students with steady above-average activity. In contrast, in the EHM students that managed to change from low to higher activity performed equally well as the students that showed steady activity. One could say that the strategy of "cramming" or procrastination (Schraw, Wadkins, & Olafson, 2007) was thus successful in the EHM, but not in the FCM. This is in line with our hypothesis that stated that a steady level of engagement is successful in the FCM. A possible explanation for students' initial inactivity in this small cluster is that the FCM might take time to get used to. Empirical studies point out the change in attitude and behavior students need to make to let go of strategies that they employ in more "traditional," lecture-based courses when they first encounter the FCM (eg, Orton-Johnson, 2009). As the students in our sample were second-year undergraduate students, this explanation could hold true. In a traditional course, lectures are mostly an explanation of the course material and students can choose to prepare or to study the materials after attending the lecturer. Therefore, we do think students are familiar with the concept of preparing, but also with the option of not doing so. Of course, in the FCM, students still have the choice to not prepare. It might be that as students have more experience with the FCM, they more clearly come to see the advantage of preparing and more often choose to do so. Based on our data, we cannot give a definite answer to that question. A direction for future research is to determine in what way students are best prepared for the FCM. Another recommendation based on this finding of initial low activity is that it might be beneficial to monitor students' activity early on in the course to ensure regular study patterns later on. Automatic monitoring of students' online activity could be a means to do so. The obtained data could be used to provide

support to students directly, or to inform instructors that a student is in danger of low course performance (Macfadyen & Dawson, 2010).

Our second hypothesis concerned the types of activity students engage in, in particular the difference between face-to-face and online activities. As the FCM is based on the idea that online preparation followed by teacher led face-to-face sessions is more beneficial for learning than lectures in which only information transmission takes place (Staker & Horn, 2012), the hypothesis was that students who engage in both type of activities would perform better than those who did not. In contrast, as the EHM provides multiple modalities or media for studying, it was expected that multiple strategies would be effective. The results showed that for the FCM, one cluster was found that showed low numbers for both types of activity. For the remaining students, an almost equal division was found between average online activity and high face-to-face activity, and vice versa. These students thus seem to have adjusted to the FCM in the sense that they at least engaged at an average level in both face-to-face and online activities. Whether they laid the emphasis on the one or the other did not make a difference for course performance. In the EHM, more variation of strategies was found, in which typically either face-to-face or online activity was dominant. Interestingly, the strategies also evolved as the course progressed. Similar to the first analysis, there is one cluster of students that shows low activity overall. This cluster is the only one that scores significantly lower on course performance than the other three. Again, this finding demonstrates the prerequisite of a certain amount of engagement for achievement, but it also shows that, in line with our expectations, the instructional conditions of EHM allowed students to be free in their choice of strategy and to change their strategy during the course. As other studies have shown, providing multiple modalities of course materials in an enhancing hybrid course does not mean students will not go to lectures anymore, but it provides freedom to strategically use the online resources (Larkin, 2010).

Limitations and directions for future research

Some limitations should be taken into account when interpreting the results of the present study. First, some of the cluster analyses we ran did not show the most desirable fit of the data, although we did select the best fitting cluster solutions. A possible explanation is that the variables we clustered the students on are not the characteristics that most clearly distinguish the students. There may be other factors that, if they were inputted into the clustering process, might have resulted in a stronger cluster solution. For example, psychological factors such as motivation and self-efficacy might have helped to distinguish the clusters further, although these constructs are also sometimes difficult to measure as they tend to fluctuate during a course (Winne & Jamieson-Noel, 2002). This relates to a second limitation: While our explicit aim was to select two courses in higher education that differed in their instructional design, some other differences between the two cases may have accounted for differences in study patterns and their relation to students' course performance. In particular, the difference in duration of the courses can be hypothesized to have influenced study patterns, although to the best of our knowledge, a systematic comparison between courses with the same instructional conditions but different duration is not (yet) available. This comparison could thus be a suggestion for future research.

Overall, our study illustrates how patterns of activity and hypotheses about those patterns based on instructional conditions, are a valuable tool in understanding the relation between what student do during a course and how well they subsequently perform. With our analyses, we have moved from aggregate course-level measures to weekly measures of student activity. As Barbera et al. (2014) suggest, temporal analyses could be looked into even more closely with more fine-grained levels of analysis, for example by taking each *event* students engage in as the unit of analysis instead of variables defined at the student level. Another direction for future research is to further delve into theoretical explanations for our findings, in particular to explain what factors

contribute to students changing or adapting their study strategies in blended courses. A mixed method approach where qualitative data is also collected could be a way to move forward.

To conclude, in the present study, an exploration of the role of both temporal patterns of students' behavior *and* the role of instructional conditions were combined, thereby extending existing research that often focuses on one of the two. Understanding of students' course performance in blended learning remains an important topic for future research. The present study contributed to the methodological approach by which we may do so, and yielded new research questions that may guide this investigation.

Statements on open data, ethics and conflict of interest

The data from this research is available upon request from the first and second author.

Informed consent was obtained from all study participants. All collected data was treated confidentially.

The authors confirm that there is no conflict of interest in the research reported here.

References

- Barbera, E., Gros, B., & Kirschner, P. (2014). Paradox of time in research on educational technology. *Time & Society*, 23, 1–13. <https://doi.org/10.1177/0961463X14522178>
- Chi, M. T. H. (2009). Active-constructive-interactive: a conceptual framework for differentiating learning activities. *Topics in Cognitive Science*, 1, 73–105. <https://doi.org/10.1111/j.1756-8765.2008.01005.x>
- Denny, P., Hamer, J., Luxton-Reilly, A., & Purchase, H. (2008). PeerWise: students sharing their multiple choice questions. In *Proceedings of the Fourth International Workshop on Computing Education Research* (pp. 51–58). New York, NY: ACM. <https://doi.org/10.1145/1404520.1404526>
- Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: the effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, 28, 68–84. <https://doi.org/10.1016/j.iheduc.2015.10.002>
- Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: learning analytics are about learning. *TechTrends*, 59, 64–71. <https://doi.org/10.1007/s11528-014-0822-x>
- Graham, C. R. (2006). Blended learning system: definitions, current trends, and future directions. In C. J. Bonk & C. R. Graham (Eds.), *The handbook of blended learning: global perspectives, local designs* (pp. 3–21). Hoboken, NJ: Wiley.
- Greiff, S., Scherer, R., & Kirschner, P. A. (2017). Some critical reflections on the special issue: current innovations in computer-based assessments. *Computers in Human Behavior*, 30, 1–4. <https://doi.org/10.1016/j.chb.2017.08.019>
- Karabulut-Ilgu, A., Jaramillo Cherez, N., & Jahren, C. T. (2017). A systematic review of research on the flipped learning method in engineering education. *British Journal of Educational Technology*, <https://doi.org/10.1111/bjet.12548>
- Larkin, H. E. (2010). 'But they won't come to lectures ...' The impact of audio recorded lectures on student experience and attendance. *Australasian Journal of Educational Technology*, 26, 238–249. <https://doi.org/10.14742/ajet.1093>
- Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an “early warning system” for educators: a proof of concept. *Computers & Education*, 54, 588–599. <https://doi.org/10.1016/j.compedu.2009.09.008>
- Nguyen, Q., Rienties, B., Toetanel, L., Ferguson, R., & Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior*, 76, 703–714. <https://doi.org/10.1016/j.chb.2017.03.028>
- Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modelling: a monte carlo simulation study. *Structural Equation Modeling*, 14, 535–569. <https://doi.org/10.1080/10705510701575396>

- Orton-Johnson, K. (2009). 'I've stuck to the path I'm afraid': exploring student non-use of blended learning. *British Journal of Educational Technology*, 40, 837–847. <https://doi.org/10.1111/j.1467-8535.2008.00860.x>
- Perera, D., Kay, J., Koprinska, I., Yacef, K., & Zaïane, O. R. (2009). Clustering and sequential pattern mining of online collaborative learning data. *IEEE Transactions on Knowledge and Data Engineering*, 21, 759–772. <https://doi.org/10.1109/tkde.2008.138>
- Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, 20, 53–65.
- Schraw, G., Wadkins, T., & Olafson, L. (2007). Doing the things we do: A grounded theory of academic procrastination. *Journal of Educational Psychology*, 99, 12–25. <https://doi.org/10.1037/0022-0663.99.1.12>
- Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 6, 461–464.
- Siemens, G., & Gašević, D. (2012). Guest editorial—learning and knowledge analytics. *Educational Technology & Society*, 15, 1–2.
- Staker, H., & Horn, M. B. (2012). *Classifying K-12 blended learning*. Report by Innosight Institute. <https://doi.org/10.1007/s10639-007-9037-5>
- Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: learning Analytics in a data-rich context. *Computers in Human Behavior*, 47, 157–167. <https://doi.org/10.1016/j.chb.2014.05.038>
- Toeteneel, L., & Rienties, B. (2016). Analysing 157 learning designs using learning analytic approaches as a means to evaluate the impact of pedagogical decision making. *British Journal of Educational Technology*, 47, 981–992. <https://doi.org/10.1111/bjet.12423>
- Winne, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology*, 27, 551–572.
- Zacharis, N. Z. (2015). A multivariate approach to predicting student outcomes in web-enabled blended learning courses. *The Internet and Higher Education*, 27, 44–53. <https://doi.org/10.1016/j.iheduc.2015.05.002>

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