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Predictive power of regularity of pre-class activities in a flipped classroom

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ABSTRACT

Flipped classroom (FC) is an active learning design requiring students to complete assigned pre-class learning activities in preparation for face-to-face sessions. Students' timely, regular, and productive engagement with the pre-class activities is considered critical for the success of the overall FC design, as these activities serve to prepare students for effective participation in face-to-face sessions. However, there is limited empirical evidence on the strength of association between students' regularity of engagement with the pre-class activities and their learning performance in a FC course. Hence, the current study uses learning trace data from three consecutive offerings of a FC course to examine students' regularity of pre-class learning activities and its association with the students' course performance. In particular, the study derives several indicators of regularity from the trace data, including indicators related to time management and those reflecting regularity in the pattern of engagement with pre-class learning activities. The association with course performance is examined by building predictive regression models with the defined indicators as features. To examine the relevance of incorporating the specificities of the instructional design in predictive models, we designed and compared two kinds of indicators: generic (i.e. course-design-agnostic) and course-design-specific indicators. The study identified several indicators of regularity of pre-class activities as significant predictors of course performance. It also demonstrated that predictive models with only generic indicators were able to explain only a small portion of the overall variability in the students' course performance, and were significantly outperformed by models that incorporated coursespecific indicators. Finally, the study findings point to the importance of assisting students in regulating their use of learning resources during class preparation activities in a FC.

1. Introduction

Flipped classroom (FC) is a form of active learning that requires students' participation in learning activities both before and during face-to-face sessions (Lage, Platt, & Tregua, 2000). Pre-class learning activities are considered critical for the success of the FC design, as they serve to adequately prepare students for productive participation in face-to-face sessions (Rahman et al., 2015; Yilmaz

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& Baydas, 2017; Yılmaz, Olpak, & Yılmaz, 2017). In essence, it is anticipated that students will complete assigned pre-class tasks on time and with a high degree of regularity. However, meeting this requirement can be challenging for students who have difficulties with regulating their learning (Sletten, 2017). As a consequence, the level and consistency of their involvement in the learning process is often incompatible with the requirements of the FC instructional model (Lai & Hwang, 2016; Mason, Shuman, & Cook, 2013). Nonetheless, students' regulation of learning in a FC in relation to their engagement with pre-class activities has received limited attention. To date, research on FC has been predominantly focused on collecting students' opinions and perceptions of a FC, and/or assessing the extent of improvement in students' performance based on pre- and post-tests and course grades (O'Flaherty & Phillips, 2015; Betihavas, Bridgman, Kornhaber, & Cross, 2016).

Time management is an important component of regulating learning behaviour. It consists of study scheduling and allocating time for different learning activities (Pintrich, 2004). Previous research has shown that students tend to lack time management skills and have difficulties in maintaining a regular study pattern, especially online (Panzarasa, Kujawski, Hammond, & Roberts, 2016; You, 2016). The drawbacks associated with such irregularity of study – including poor academic outcomes, and even withdrawal from a course – have been well demonstrated in research. For example, research in cognitive psychology has shown that intensive learning in a relatively short time period does not lead to a deep understanding and long-term learning, but instead allows for short-term retention only (Kornell, 2009).

Regulation of learning is also evident in the change or adaptation of learning strategies (Winne, 2006). Strategy changes are indicative of higher metacognitive monitoring (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007), and thus suggest higher regulation of learning. Nonetheless, not all strategy changes lead to desired learning outcomes, as learners tend to mismanage their learning (Bjork, Dunlosky, & Kornell, 2013) and choose suboptimal tactics and strategies (Winne & Jamieson-Noel, 2003). As a result, students might not use the available learning resources in a way that can maximize their learning outcomes (Lust, Elen, & Clarebout, 2013). In our earlier work, we found that students had a tendency to change their learning strategy related to pre-class learning activities in a FC course (Jovanovic, Gasevic, Dawson, Pardo, & Mirriahi, 2017). In particular, we detected that 'patterns' of student engagement with pre-class learning activities tended to change over the duration of the course. However, we did not study the association of the observed irregularity of the engagement patterns - considered as manifestations of learning strategies - with the students' course performance.

Considering the above given findings and gaps in the literature, the present study aimed to contribute to the understanding of students' regulation of learning in a FC context. More precisely, the objective was to examine the association between students' regularity and time-management of pre-class activities and their learning performance in a FC. To that end, we relied on the trace data collected from a Learning Management System (LMS) in three consecutive offerings of a course with a FC design. The trace data originated from the pre-class activities that students were requested to complete prior to the scheduled face-to-face sessions in a first-year undergraduate course in computer engineering. From the trace data, we derived several indicators of regularity and examined their association with course performance (operationalized through the final course exam) by building predictive regression models.

2. Background

2.1. Self-regulation of learning in a flipped classroom

Self-regulation of learning is a crucial factor for improving learning outcomes in online education (Broadbent & Poon, 2015; Sun, Tsai, Finger, Chen, & Yeh, 2008; Wang, Shannon, & Ross, 2013). The present research is framed on the constructivist, metacognitive model of self-regulated learning propounded by Winne and Hadwin (Winne, 2006; Winne & Hadwin, 1998). According to this model, learners are active agents employing a set of cognitive, physical, and digital tools to operate on raw information in order to create learning artefacts or products. Learning is regulated by continuously evaluating the quality of the products and effectiveness of the chosen study tools and tactics. This process, known as metacognitive monitoring, is influenced by internal and external conditions. The former includes, for example, a learner's level of motivation, prior knowledge, and affective states. External conditions are determined by elements of the instructional design (e.g., the teacher's role, course requirements, and availability of feedback).

In the present study, we focused on the established instructional tasks (i.e., the pre-class activities), as an important component of the external conditions impacting student self-regulated learning processes. The effect of instructional conditions on self-regulation of learning has been examined and demonstrated in several studies (e.g., Azevedo, Moos, Greene, Winters, & Cromley, 2008; Garrison & Cleveland-Innes, 2005; Trigwell, Prosser, & Waterhouse, 1999). It has also been shown that computational models aimed at predicting student performance need to account for the instructional conditions to aid understanding and improve the learning process (see Section 2.2).

FC is an active instructional design that requires students' timely and regular engagement, and has higher requirements in terms of regulation of learning than more traditional designs (Lai & Hwang, 2016; Mason et al., 2013; Sletten, 2015). In particular, due to its relative novelty in educational practice and its emphasis on learner's agency, FC may require students to develop new or adapt their existing learning strategies to ensure regular engagement with learning activities. To do that successfully, students need a well-developed ability to regulate their learning. Yet, students often have underdeveloped self-regulation skills (Bjork et al., 2013; Winne & Jamieson-Noel, 2003). Hence, the importance of examining self-regulation in the FC instructional context.

Nonetheless, there is a paucity of studies that have examined students' regulation of learning in the instructional context of a FC course. In particular, how students manage and regulate pre-class activities, a distinctive feature of the FC instructional model, and how that affects their course performance has received limited attention. Among the rare contributions to understanding self-regulation of learning in a FC context is a recent study by Sletten (2017). In examining the relationship between students' perceptions of a FC and self-regulated learning (SRL) strategies, Sletten found that students' perceptions of the FC model positively predicted their use of several types of SRL strategies (e.g., study strategies, metacognition, and effort). However, no relationship was detected between student perceptions of FC model and their course achievement (i.e. grades), neither directly nor indirectly, through SRL strategy use. This could be partly explained by the small sample size (N = 76) and the inherent bias of students' self-reports (Winne & Jamieson-Noel, 2003). In a related study, Yilmaz and Baydas (2017) examined undergraduate students' awareness of metacognition, the adopted metacognitive strategies, and learning performance in pre-class activities in a FC. The researchers found a noticeable increase in the students' use of metacognitive strategies as the course progressed, suggesting that students needed time to adapt their strategies to the FC context. Unlike Sletten (2017), Yilmaz and Baydas (2017) reported a highly significant positive association between students' metacognitive strategies and learning performance.

The scarcity of empirical evidence about the relationship between self-regulation of learning and learning performance in FC and the diversity of findings of the existing studies suggest that this line of research requires further exploration.

2.2. Prediction of learning performance

2.2.1. The relevance of instructional design

To date, research on Learning Analytics and Educational Data Mining has largely centred on predicting students at risk of failing a course and/or predicting students' overall academic performance (Bowers, Sprott, & Taff, 2013; Brooks & Thompson, 2017; Dawson, Gašević, Siemens, & Joksimovic, 2014; Siemens, Dawson, & Lynch, 2014). Early research efforts were oriented towards identifying a set of 'generic' predictors of student performance that could be applied across differing courses and institutions (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). However, focusing only on 'generic' predictors such as demographic and behavioural indicators, fails to account for the specificities of course design and disciplinary context (Finnegan, Morris, & Lee, 2008; Macfadyen & Dawson, 2010). The use of such 'generic' indicators tended to produce inconsistent and even conflicting findings from one course to the next. For instance, in their study examining indicators of academic performance in 22 courses, Finnegan et al. (2008) did not find a single predictor that was shared amongst the three investigated disciplines. Likewise, Gašević, Dawson, Rogers, and Gašević (2016) found that the predictive power of the same behavioural indicators varied among courses – even courses from the same disciplinary area. The importance of the pedagogical and disciplinary context for establishing robust predictive models has been confirmed in more recent studies (Gašević et al., 2016; Tempelaar, Rienties, & Giesbers, 2015). These and related studies comparing predictive models across multiple courses (e.g. Agudo-Peregrina, Iglesias-Pradas, Conde-Gonzalez, & Hernandez-Garcia, 2014) have demonstrated that indicators have to include elements of the course context. Gašević et al. (2016) emphasised this point in recommending that any attempts to establish predictive models of academic success must also incorporate the specific instructional conditions.

The aforementioned studies are consistent with contemporary learning theories that state the importance of the elements of a specific learning situation, including student and teacher intentions and mutual interaction (Winne, 2006; Zimmerman, 2008). In other words, contemporary learning theory recognizes that the pedagogical context effectively shapes how students approach and manage their learning tasks, and consequently makes an impact on the academic performance. This further implies that predictive models should account for important differences among the elements that shape learning in different courses.

2.3. Regularity as a predictor of learning performance

There is a limited number of empirical studies employing learning traces (i.e., log data) to examine the predictive power of regularity of learning on student course performance. Most recently, a few studies have attempted to make use of student learning traces, typically collected from a Learning Management System (LMS), to examine whether and to what extent different indicators of regularity and time management can predict student course performance. For example, You (2016) examined the association between students' course achievement and several indicators derived from the data collected from an LMS used in a university-level online course. The study results showed that the indicator of regularity of learning activities (based on the pattern of accessing and watching the course videos) was the strongest predictor of course achievement, followed by the number of late submissions, number of sessions, and proof of reading the course-related information. You (2015) also demonstrated the importance of regularity and timeliness of learning activities in his study on the effect of academic procrastination on course achievement. Procrastination is considered here as a failure in self-regulation of learning (Steel, 2007). Two indicators of procrastination were used: delayed access to and/or incomplete viewing of the lecture videos (primary course material), and late submission of assignments. A regression model with these two indicators explained 59.7% of the variability in the students' course achievement.

Asarta and Schmidt (2013) examined the effects of the timing, volume, intensity, and consistency of learning activities on achievement in a blended introductory statistics course. They defined and used several indicators of regularity: pacing (indicates if a student kept up with the prescribed learning schedule as the course proceeded), anti-cramming (indicates if a student avoided delayed initial access to the course materials until a short period of time before the associated exam), reviewing (indicates if a student accessed lecture materials without much delay and revisited them before an exam), and consistency (indicates if a student accessed lecture materials between adjacent class sessions). The study found pacing, anti-cramming, and consistency as significant predictors of course achievement after controlling for the students' GPA and math skills.

Panzarasa et al. (2016) found that trainees involved in a specialist e-learning medical programme tended to exhibit non-uniform and irregular (bursty) temporal patterns in interaction with online learning activities. They also detected students' tendency to concentrate their involvement in online sessions around specific points in time that coincided with days preceding exams. These findings are in line with earlier related studies (Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011; Steel, 2007).

Saqr, Fors, and Tedre (2017) examined the extent to which students' online activities can predict their performance in a blended course where there was no explicit requirement for students to use the course LMS, but were free to use it based on their self-perceived benefit. In addition to simple counts of various kinds of online activities, the study used five indicators that reflected regularity of different kinds of learning activities and accounted for the fact that students were prone to short periods of high activity followed by prolonged periods of inactivity (Panzarasa et al., 2016). The indicators were derived from the LMS logins, course material views, discussion forum posts, time spent on online course materials, and the use of weekly formative assessment. These indicators showed more consistent and higher correlation coefficients with final grades than simple counts of activities. Among them, the login-based indicator and the formative assessment indicator had the highest correlation with final grades.

Jo, Kim, and Yoon (2015) examined time management strategies of adult learners in an online course. Using the data collected from the course LMS, they defined and used three indicators of the adopted time management strategy: total login time (as a proxy of time allocated to learning (Cotton & Savard, 1981)), login frequency, and regularity of intervals between consecutive logins. Only the indicator of regularity of logins had a significant effect on course achievement.

Most of the aforementioned studies used both generic and course specific indicators, though none of them made an attempt to compare the predictive power of the two kinds of indicators.

2.4. The study objective and research questions

As shown in the previous section, empirical evidence for association of regularity of study and learning performance is still scarce. Nonetheless, the literature does provide some evidence for the relevance of regularity for achieving the desired learning outcomes (e.g., Arnott & Dust, 2012; Kornell, 2009). Regularity of learning is especially relevant in the context of active learning designs (Bell & Kozlowski, 2008; Michael, 2006), such as FC, where students are expected or required to take responsibility for their learning and manage their approach to learning. This suggests that indicators of regularity of learning could be significant predictors of course outcomes in a FC setting. To explore the validity of this assumption, the study reported in this paper examines whether and to what extent indicators of *regularity of engagement with pre-class learning activities* in a FC course can predict student course performance.

We examine regularity from two perspectives, as (i) regular and timely engagement with the pre-class learning activities throughout the course, and as (ii) regular distribution of efforts over the learning resources (e.g., videos, exercises, quizzes, etc.) made available for the class preparation tasks. Whereas the first aspect is about time management, the latter is related to the adopted learning strategies and their consistency or change during the course. Since to our knowledge the relevance of course design specific predictors has not been empirically verified in the FC context, we design and compare generic (i.e., course design agnostic) indicators and course design specific indicators of regularity of pre-class learning activities in a FC. To increase the robustness of the findings, the two kinds of predictors are compared in three consecutive offerings of the same FC course.

Considering the above, the following research questions were defined:

RQ1: *To what extent do generic (i.e. course-design-agnostic) indicators of regularity of engagement with pre-class learning activities in a FC course can predict students' course performance?*
RQ2: *To what extent do context-specific (i.e. course-design-specific) indicators of regularity of engagement with pre-class learning activities in a FC course can improve the prediction of students' course performance (over the prediction enabled by the generic indicators)?*

In the first research question (RQ1), focused on generic indicators, regularity of learning refers only to the timely and consistent engagement with the pre-class learning activities throughout the course (i.e., the time management component of regulation). Being course-design agnostic, generic indicators can only be derived from general forms of engagement with learning resources, such as learning sessions or active days. The second question (RQ2) is focused on the course design specific indicators, and thus allows for examining both: (*i*) timely and consistent engagement with the class preparation activities throughout the course; and (*ii*) regularity in allocating efforts to different kinds of learning resources during class preparation tasks (i.e. consistency of the employed learning strategies).

We restrict our focus on the trace data and indicators of regularity in spite of our awareness that the inclusion of other variables in a predictive model (e.g., socio-demographic and those related to previous performance) might improve the predictive power of the model (Rienties et al., 2016; Tempelaar et al., 2015). While such variables are important in certain contexts, they are also limited in terms of informing the instructional design (Saqr al., 2017), and thus cannot add to the objective of providing teaching staff with actionable analytics (Conde & Hernandez-Garcıa, 2015; Gašević et al., 2016). On the other hand, variables associated with students' regularity of learning can act as indicators of functional risk (i.e., risk associated with low levels of attendance and involvement) thus allowing for the detection of students who would benefit from support interventions (Reschly & Christenson, 2012).

3. Method

3.1. Study context

The data for the study originates from a FC that was deployed in a first-year engineering course at an Australian university. The data were collected from three consecutive offerings of the course, in 2014, 2015, and 2016. In each year, the course lasted 13 weeks. The course recorded a yearly increase in student enrolment numbers ranging from 290 to 486 students (Table 1). In all three years, students had limited previous experience with FC models of teaching.

Table 1
Data used in the analyses: number of students, sessions, and events in each course offer.

Year	N students	N sessions	N events
2014	290	17,237	448,338
2015	371	27,173	726,925
2016	486	33,902	1,218,280

The two key elements of the FC design included a set of pre-class online activities to be completed prior to the face-to-face session with the instructor (i.e., the lecture), as well as a redesigned lecture framed as an active learning session. To actively participate in collaborative problem solving tasks during face-to-face sessions, students had to undertake the preparation tasks (Pardo & Mirriahi, 2017).

The study focused on student interaction with the pre-class learning activities. These activities retained the same structure and flow in all three studied offerings of the course. The activities relied on the following digital learning resources:

- *Videos with multiple-choice questions (MCQs)*: short videos introduced and explained relevant concepts. Each video was accompanied by MCQs covering the concepts discussed in the video and promoting simple factual recall. Students could answer a question, have their answer evaluated, and if it was incorrect, they could either request to see the solution or try again. These MCQs served as formative assessment.
- *Documents with embedded MCQs*: the students were required to read the document and answer the embedded MCQs. These questions were conceptually the same as MCQs that followed course videos, in terms of the students' interaction with them, and also served as formative assessment.
- *Problem (exercise) sequences*: these were framed as summative assessment. If an exercise was correctly solved, the student's score was increased, and the exercise was removed from the sequence. Alternatively, a new exercise was randomly selected and the current problem remained in the sequence. Students received exercises randomly until they solved all of them correctly. To be counted towards their final course mark, the exercises had to be solved before the start of the weekly lecture. This requirement was introduced as an incentive for students to prepare for the lecture.

Students were provided with real-time feedback on their level of engagement with the pre-class activities and the activity scores via an analytics dashboard (Khan & Pardo, 2016). Through the dashboard, students could monitor their engagement with the video resources, their success in answering formative MCQs, as well as their performance on summative assessment exercises. The dashboard also displayed the overall class scores, thus allowing for a level of social comparison. The displayed data was updated every 15 min, and the magnitudes were reset weekly since each week students were provided with new pre-class tasks.

In addition to this real-time feedback available via the dashboard, during the first half of the, 2015 course offering, students were provided with personalized feedback (via email) on a weekly basis. In the third year (2016), the same kind of weekly personalized feedback was provided throughout the course. In both cases, the personalized feedback was generated at the end of each week based on an analysis of student engagement and performance on the pre-class tasks assigned for that week (Pardo, Jovanovic, Dawson, Gasevic, & Mirriahi, 2017). The introduction of personalized feedback represents the only change in the instructional design across the three course offerings.

Detailed description of the FC design, including task examples and feedback offered through the dashboard, is presented in (Pardo & Mirriahi, 2017).

3.2. Indicators of regularity

3.2.1. Data source

The study relied on learning trace data obtained from the students' interaction with and completion of the pre-class learning activities during the active period (weeks 2–13, excluding week 6 which was preparation for the midterm exam) of the three course offerings. In particular, the analyses were based on the events data collected from the course LMS. Each event is represented as a tuple comprising seven elements described in Table 2.

To compute the indicators, we extracted learning sessions from the events data. A session was identified as a continuous sequence of events where any two consecutive events are no more than 15 min apart. The threshold of 15 min was chosen based on the analysis of the distribution of time gaps between consecutive events in all three course offerings. We have removed sessions that were less than 30 s long as these were unlikely to represent genuine engagement in learning activities (Panzarasa et al., 2016). In addition, when computing the indicators, we excluded events and sessions from weeks 1 and 6. Week 1 was the introductory week and as such did not have any pre-class activities. Week 6 was the time period when students prepared for their forthcoming midterm exam. During week 6, learning behaviour was considerably different to other, 'regular' course weeks. Table 1 outlines the resultant counts of sessions and events for the 3 course offerings (2014, 2015, 2016) used in the analyses.

In addition to the trace data, students' scores on the final exam were collected and used as the dependent (response) variable in the analyses. The scores were in the range [0–40] and were computed as the sum of scores on individual multiple-choice and open-ended questions that constituted the final exam.

Table 2
Structure of the original data that were collected from the course LMS.

Item	Description
event id	Unique event identifier
student id	Unique student identifier; fully anonymized
course week	A number in the range [2–13] identifying the week of the event
course topic	Identifier of the course topic the learning event is related to
timestamp	Date and time of the event
type of learning action	The type of learning action that occurred within the event; for the current study, we focused on those types that correspond to *i*) the types of pre-class learning activities listed in Sect. 3.1, *ii*) interaction with the dashboard, *iii*) access to the course syllabus and orientation pages.
learning action details	A string of learning action specific information; e.g., for an MCQ-related event, this string would hold an indicator of the answer's correctness and the unique identifier (URL) of the MCQ

3.2.2. Generic indicators

Based on the findings of previous related studies (see Section 2.2), we defined and examined several generic indicators of timely and regular engagement with the pre-class activities (GRI_1 - GRI_5, Table 3). To control for the effect of the level (i.e. intensity) of engagement with pre-class activities on the course performance, we have also included generic indicators of engagement (GEI_1 - GEI_4, Table 3). These were defined based on the types of engagement indicators that proved relevant in the previous studies (e.g., Davies and Graff (2005); Saqr et al. (2017)).

The first two generic indicators of regularity (GRI_1, GRI_2) measure the regularity of engagement with the pre-class activities throughout the course. They measure the variability in the distribution of study sessions over the course weeks. Before computation of these two indicators, weekly counts were rescaled to neutralise the effect of different numbers of course topics per week. Specifically, weekly counts were scaled to unit length using the Euclidean (L2) norm.

The first indicator of regularity and a few others (i.e., GRI_3 and GRI_5) were based on entropy. Entropy measures the uniformity of a discrete probability function. For example, in the case of the GRI_1 indicator, probabilities were computed by dividing the number of weekly sessions, for each course week, with the total number of sessions (over all the course weeks). Entropy reaches its maximum value when all the probabilities are uniformly distributed, that is, in the context of GRI_1, when weekly counts of sessions are the same. This suggests that the higher the entropy, the higher the regularity of learning activities.

Indicators GRI_3 and GRI_4 served as measures of timely and planned (in the sense of time management) engagement with the pre-class learning activities. The entropy of session counts per weekday (GRI_3) measured the variability in distribution of study sessions over a course week (the higher the entropy, the lower the variability). Indicator GRI_4 measured how frequently a student changed their 'pattern' of engagement with the pre-class activities over the days of a week. It was computed as follows: based on the weekday session counts, proportions of study sessions per weekday were computed for each course week. These proportions can be thought of as the probability distribution of session counts over the days of a week. Then, the change (i.e., difference) from one week to the next was computed as the mean squared difference between every two consecutive weeks (where each week was represented as a vector of proportions). Mean squared difference was used to increase the impact of large differences in proportions. Finally, for each student, we computed the number of times (throughout the course) his/her week-to-week change was above a certain threshold, and thus could be considered as an indicator of a change in time management. As the threshold, we looked for a value that would be well above regular changes that might have been caused by the weekly differences in the course requirements. Accordingly, we selected the 3rd quartile, computed for the given week-to-week difference over the entire class (i.e., all the students).

Indicator GRI_5 was computed as the entropy of weekly counts of active days, where an active day is the day when a student had at least one study session. By focusing on active days, this indicator did not measure the variability in the level (i.e., intensity) of engagement, but the variability in the 'presence' of engagement. Thus, it could be considered a measure of regularity in the 'attention' given to the pre-class activities. As with indicators GRI_1 and GRI_2, before the entropy was computed, weekly session counts were rescaled (to unit length, using L2) to neutralise the effect of different numbers of course topics per week.

The first two generic indicators of the level of engagement (GEI_1, GEI_2) were based on the number of weeks of a student's high activity. That is, weeks when a student's session count was higher than the average study session count for that week. These indicators

Table 3
Overview of generic indicators of regularity and level of engagement that were used in the study.

	Label	Description
Regularity	GRI_1	*Entropy of weekly session counts*
	GRI_2	*Median absolute deviation (MAD) of weekly session proportions*
	GRI_3	*Entropy of weekday session counts*
	GRI_4	*Frequency of change in the 'pattern' of engagement over the week days*
	GRI_5	*Entropy of weekly counts of active days*
Engagement	GEI_1, GEI_2	*Number of weeks with above average session counts before (GEI_1) and after (GEI_2) the midterm.*
	GEI_3, GEI_4	*Number of weeks, before (GEI_3) and after (GEI_4) the midterm, when the number of active days (i.e. days with at least one session) was in the top quartile.*

Table 4
Overview of course specific indicators of regularity and level of engagement used in the study.

	Label	Description
Regularity	CSRI_1 - CSRI_6	Entropy of weekly use (i.e. counts) of different kinds of learning resources available for the pre-class activities: ● multiple-choice questions (MCQs), ● exercises, ● short videos, ● readings from the course e-book, ● readings offering instructions and guidance for pre-class activities, ● resources supporting metacognition (dashboard and pages with course and lesson objectives and the expected outcomes). There is one indicator per each learning resource type (6 in total).
	CSRI_7 - CSRI_11	Entropy of weekly assessment outcomes: ● correctly solved formative assessment item (MCQ) ● incorrectly solved formative MCQ ● request to see a solution for a formative MCQ ● correctly solved summative assessment item (exercise) ● incorrectly solved summative exercise. There was an indicator for each outcome (5 in total).
	CSRI_12	Frequency of change in the 'pattern' of use of learning resources during the class preparation activities.
	CSRI_13	Frequency of change in the 'pattern' of weekly assessment outcomes during the class preparation activities.
Engagement	CSEI_1 - CSEI_6	Number of weeks of high engagement with a particular learning resource type (MCQs, exercises, videos, etc.). These indicators were computed separately for each learning resource type.

captured the intensity of student engagement in the period before the midterm (GEI_1; weeks 2–5) and after the midterm (GEI_2; weeks 7–13). The other two indicators of engagement, GEI_3 and GEI_4, captured the frequency of engagement during a week, by 'awarding' students who had a high number of weekdays with at least one session. More precisely, if a student was in the top quartile based on the number of active days during a particular week, a value of 1 was added to the indicator; GEI_3 was the sum computed over weeks before the midterm, whereas GEI_4 was the sum over the post-midterm weeks.

3.2.3. Course specific indicators

This group of indicators (Table 4) were defined based on the types of learning resources that were made available to the students for pre-class activities and the requirements and expectations regarding the completion of those activities. It was also partially based on our previous insight into the patterns of learning behaviour of students in this course (Jovanovic et al., 2017).

For all the indicators that are based on entropy calculation (CSRI_1 - CSRI_11), weekly counts were scaled before entropy was calculated. This was done by dividing weekly resource use counts by the number of subject matter topics covered in the given week; thus, the scaling was also informed by the course design.

The CSRI_12 indicator of regularity measured how frequently a student was changing his/her 'pattern' of engagement with the pre-class learning activities over the course weeks, and could be considered an indicator of a change in study strategy. It was determined as follows: for each student, we first computed weekly use of different kinds of learning resources (e.g., MCQs, exercises, and videos), and based on that, weekly proportions of different learning resource type use in the pre-class activities. Thus, we obtained weekly proportions formed as a vector of six elements (one for each learning resource type) for the corresponding week. This could be considered as the probability distribution of learning resource type use over a particular week. Next, a change in weekly proportions was computed between each two consecutive weeks. As in the case of generic indicator GRI_4, mean squared difference was used to compute this week-to-week change. Finally, for each student, we have computed the number of times (throughout the course) when his/her week-to-week change in the distribution of learning resource type use was above a certain threshold, and thus could be considered a sign of strategy change. As in the case of the GRI_4 indicator, the threshold was set to the 3rd quartile of the considered week-to-week change for the entire class (i.e. all the students). The CSRI_13 indicator was computed in a similar manner; the only difference being that instead of weekly counts of different learning resource type use, the computations were based on the counts of different assessment outcomes, namely the outcomes used for defining the CSRI_7 - CSRI_11 indicators (Table 4).

Course specific engagement indicators (CSEI_1 - CSEI_6) were computed at the week level, based on the following principle: a score of one was given to a student (for a given week), if he/she had used certain kinds of resources (e.g., video) more than the average (median) use of the same resource type in the given week. The total score for a particular resource type was computed by summing the weekly scores. These course-specific indicators correspond to the generic indicator of engagement GEI_1, GEI_2, and were used only to control for the effect of the engagement level on the course performance.

3.3. Data analysis

To address our research questions, we used multiple linear regression as the primary statistical method. Several regression models were built, each one with students' scores on the final exam as the dependent variable (discrete numerical variable with value range [0,40]). For each course offering (2014, 2015, and 2016), the following models were built:

- Models with generic indicators only (MGI):

- *MGI_Reg* included, as independent variables, all generic indicators of regularity listed in Table 3, namely GRI_1 - GRI_5.
- *MGI_Final* included indicators of regularity that proved significant in the *MGI_Reg* model and the generic indicators of the level (GEI_1, GEI_2) and frequency (GEI_3, GEI_4) of engagement with the pre-class activities.

- Models with generic and course-specific indicators (MGSI):
  - *MGSI_Reg* included, as independent variables, all course-specific indicators of regularity listed in Table 4 (CSRI_1 - CSRI_13), as well as two generic indicators of timely and planned (in the sense of time management) engagement with the pre-class learning activities (GRI_3, GRI_4). The other generic indicators of regularity (listed in Table 3) were highly correlated with the course-specific indicators of regularity, and thus were not included in the model. With GRI_3 and GRI_4 multi-collinearity was not an issue, as among course specific indicators none was related to regularity of engagement at the week level.
  - *MGSI_Final* included indicators of regularity that proved significant in the *MGSI_Reg* model, and the indicators of the level/ intensity of engagement with the different kinds of learning resources available for the pre-class activities (CSEI_1 - CSEI_6).

Models *MGI_Reg* and *MGI_Final* were used to address our first research question (RQ1), whereas models *MGSI_Reg* and *MGSI_Final* served to answer the second question (RQ2). The reason for differentiating between regularity-only models (*MGI_Reg, MGSI_Reg*) and models that include both regularity and engagement level (i.e. intensity) indicators (*MGI_Final, MGSI_Final*) is that we wanted to examine if the regularity indicators remained relevant even after accounting for students' level of engagement.

Creation of each model was preceded by correlation analysis to detect and remove highly correlated independent variables. Subsequently, after the models were built, they were examined for multicollinearity, using variance inflation factor (VIF), and if multicollinearity was detected, predictors with the highest VIF value were removed from the model. In addition, for all the models, all other assumptions for linear models were verified, including linearity, normality and homoscedasticity of residuals, the absence of influential points, and the absence of correlation between residuals and predictors. In case of presence of influential points, robust linear models were built. Robust linear regression (Fox, 1997) is an alternative to traditional linear regression in cases when there are influential points, which are, in robust models, weighted with lower values based on how well such data points behave.

The significance level of 0.05 was used in all statistical tests. All the analyses were done using R statistical language. Robust linear models were built using the *robust* R package (Wang et al., 2017).

4. Results

Due to the space limits, we present in detail only the results of the final regression models (*MGI_Final* and *MGSI_Final*) for the three course offerings (2014, 2015, 2016).

4.1. Predictive power of generic indicators of regularity

Table 5 presents the results of the final set of multiple linear regression models with generic indicators (*MGI_Final*) for the three course offerings. Only indicators that proved significant are reported.

As the table indicates, the predictive power of the model for the 2016 course offering differs substantially from the predictive power of the models for the two earlier course offerings. In particular, the 2016 model explains about 24% of variability in the final course exam ($R^2 = 0.250$, adj. $R^2 = 0.239$); whereas, for the 2015 and 2014 offerings of the course, the examined generic indicators explain only about 12% and 16% of variability in the final exam score, respectively, (2015: $R^2 = 0.121$, adj. $R^2 = 0.111$; 2014: $R^2 = 0.163$, adj. $R^2 = 0.152$).

Even though the models differ with respect to the significant indicators, some common patterns do occur. First, in all three

Table 5
Results for the *MGI_Final* models for the 3 course offerings; only significant indicators are shown.

Course offering	Predictors	Coefficients	St. Error	St. coefficients	p
2016	GRI_1 - entropy of weekly session counts	7.582	1.954	3.88	0.0001
$R^2 = 0.250$	GRI_2 - MAD of weekly session proportions	−20.696	7.652	−2.70	0.0071
Adjusted $R^2 = 0.239$	GRI_3 - entropy of weekday session counts	5.669	1.857	3.05	0.0024
	GRI_4 - change in the 'pattern' of engagement over the weekdays	−0.519	0.245	−2.12	0.0349
	GEI_1 - number of weeks with above average session counts before the midterm	1.202	0.383	3.14	0.0018
	GEI_3 - number of pre-midterm weeks with the number of active days in the top quartile	−1.277	0.594	−2.15	0.0320
2015	GRI_1 - entropy of weekly session counts	9.128	3.071	2.97	0.0031
$R^2 = 0.121$	GRI_4 - change in the 'pattern' of engagement over the weekdays	−0.919	0.245	−3.76	0.0002
Adjusted $R^2 = 0.111$	GEI_3 - number of pre-midterm weeks with the number of active days in the top quartile	−1.363	0.692	−1.97	0.0498
2014	GRI_1 - entropy of weekly session counts	10.975	4.055	2.71	0.0072
$R^2 = 0.163$	GEI_1 - number of weeks with above average session counts before the midterm	1.860	0.470	3.96	< 0.0001
Adjusted $R^2 = 0.152$					

models, at least one indicator of regularity of engagement with the pre-class activities throughout the course proved significant. In particular, entropy of weekly session counts (GRI_1) proved a significant regularity indicator in all three course offerings. Its positive coefficient indicates that the larger the entropy, that is, the more uniformly distributed the students' weekly session counts were, the higher the final exam scores were. In the 2016 model, the association between regularity of engagement with the pre-class activities throughout the course and the final exam performance was also featured in the negative and significant coefficient for the MAD of weekly session proportions (GRI_2). This is another confirmation that higher regularity, i.e. smaller variance in the session counts over course weeks, is associated to higher exam scores.

Second, in the 2015 and 2016 models, the frequency of change in the ‘pattern’ of engagement over the weekdays (GRI_4) proved to have a negative association with the final exam performance. This indicator measures how many times during the course a student changed, from one week to the next, the distribution of his/her effort (i.e., engagement with the pre-class activities) over the days of a week. More changes suggest higher regulation of learning (Hadwin et al., 2007), and thus one might expect better course performance. However, that was not the case in the 2015 and 2016 offerings of the examined course, as shown by the negative value of the coefficients associated with the *GRI_4* indicator in the corresponding models. This might suggest that those students who did not have a regular pattern of engagement over the weekdays were not successful in regulating their learning, a problem that other studies have also reported on (e.g., Lust et al., 2013; Winne & Jamieson-Noel, 2003). However, considering the correlational nature of the study, no causal conclusions can be drawn.

In the 2016 model, entropy of weekday session counts (GRI_3), an indicator of regularity of engagement with the pre-class activities at the week level, proved to have significant positive association with the final exam performance. This suggests that pre-class activities more evenly distributed over the days of a week were associated with higher final exam performance.

As stated in the Methods section, indicators of the level of engagement were introduced to serve as control factors. That is, to allow us to examine whether regularity of engagement with pre-class activities remains a significant predictor of the course performance even after accounting for the intensity of engagement. The final set of models with generic indicators only (*MGI_Final*) confirms that even after introducing engagement intensity in a model (in particular, in *MGI_Reg* models), regularity remains a significant predictor of the course performance. Also, the addition of indicators of engagement level and frequency (to *MGI_Reg* models) led to only a small increase in the level of variance of the outcome variable (i.e. the exam performance) that a model can explain (adjusted R^2 increased by 0.023 in 2016, by 0.005 in 2015, and by 0.071 in 2014 model). Still, it is interesting to note that the indicator of intensity of engagement (GRI_1) proved to be positively associated with the final exam score, whereas the indicator of frequency of engagement (GRI_3) was negatively associated with the exam performance. This suggests that it is not sufficient for students to frequently engage with pre-class activities, but also to devote more time and effort to those activities.

4.2. Improving predictive power with course-specific indicators of regularity

Table 6 presents the results for the final set of multiple linear regression models with generic and course specific indicators (*MGSI_Final*) for the three course offerings. As in Table 5, only significant indicators are shown.

The predictive power of these models is significantly higher than of their counterparts based on the generic indicators only (*MGI_Final*, Table 5). In particular, for the 2016 offering of the course, the predictive power of the *MGSI_Final* model is about 52% higher than that of the model with generic indicators only (specifically, R^2 is 50.80% and adjusted R^2 52.72% higher). For the 2015 course offering, the increase is the highest, as the R^2 and adjusted R^2 are about 3 times higher than that for the best model with generic indicators only. For the year 2014, the predictive power of *MGSI_Final* model is about 84% higher than that of the *MGI_Final* (specifically, R^2 is 82.82% and adjusted R^2 84.87% higher).

Among the examined course specific indicators of regularity, entropy of weekly use of summative exercises (CSRI_2) and the

Table 6
Results for the *MGSI_Final* models for the 3 course offerings. Only significant indicators are shown.

Course offering	Predictors	Coefficients	St. Error	St. coefficients	p-value
2016 course offering	GRI_3 - entropy of weekday session counts	4.892	1.898	2.58	0.0102
$R^2 = 0.377$	CSRI_2 - entropy of weekly use of summative exercises	5.033	1.777	2.83	0.0048
Adjusted $R^2 = 0.365$	CSRI_3 - entropy of weekly use of course videos for the pre-class activities	2.996	0.908	3.30	0.0010
	CSRI_4 - entropy of weekly access to the course e-book	4.083	1.054	3.87	0.0001
	CSRI_9 - entropy of requests to see a solution for a formative MCQ	−2.058	0.864	−2.38	0.0177
	CSRI_12 - change in the ‘pattern’ of learning resource use during pre-class activities	−0.727	0.262	−2.77	0.0058
	CSEI_2 - number of weeks of high engagement with summative exercises	−1.236	0.170	−7.27	< 0.0001
2015 course offering	GRI_4 - change in the ‘pattern’ of engagement over the weekdays	−0.771	0.258	−2.99	0.0030
$R^2 = 0.363$	CSRI_2 - entropy of weekly use of summative exercises	6.061	1.732	3.50	0.0005
Adjusted $R^2 = 0.353$	CSRI_4 - entropy of weekly access to the course e-book	3.088	1.132	2.73	0.0067
	CSEI_2 - number of weeks of high engagement with summative exercises	−1.560	0.158	−9.86	< 0.0001
2014 course offering	GRI_4 - change in the ‘pattern’ of engagement over the weekdays	−0.551	0.277	−1.992	0.0474
$R^2 = 0.298$	CSRI_3 - entropy of weekly use of course videos for the pre-class activities	3.254	0.878	3.704	0.0002
Adjusted $R^2 = 0.281$	CSEI_2 - number of weeks of high engagement with summative exercises	−0.988	0.149	−6.649	< 0.0001

course e-book (CSRI_4) proved to have positive and significant association with the students' final exam scores in the 2015 and 2016 course offerings. Furthermore, significant positive association was detected in 2014 and 2016 for the regular use of course videos (CSRI_3). On the other hand, in 2016, we have detected a significant negative association of regular requests to see the solution of formative MCQs (CSRI_9). This might suggest that some students - those who made regular requests to see MCQ solutions - were not learning from those solutions. That is, it could be the case that they were not making effective use of the available formative assessment. However, it could have also been the case that those students had a lower level of prior knowledge and thus needed to see the solution multiple times to understand it. Since we did not have access to the data about the students' prior knowledge, we identify this as an issue to be examined in a future study. Next, in 2016, a significant negative effect was detected for the frequency of change in a student's "pattern" of engagement with the pre-class activities from one week to the next (CSRI_12). This might suggest that students from the 2016 cohort who did not maintain a regular pattern of engagement with the pre-class activities were not successful in regulating their use of the available learning resources, i.e., they were using the resources in a suboptimal way.

The examined generic indicators of time management of pre-class activities demonstrated a significant association with the final exam score in all three course offerings. In particular, the indicator of regularity of engagement with the pre-class activities at the week level (GRI_3) proved to be a significant positive predictor in 2016. On the other hand, the frequency of change in the 'pattern' of engagement with the pre-class activities during a week (GRI_4) had a negative association with course performance in the 2014 and 2015 course offerings. This indicates that those students who did not exhibit a regular and consistent study pattern across weeks tended to have lower course performance.

Regarding the course specific indicators of the engagement level, common to the *MGSI_Final* models for all three course offerings is a significant negative association between an above average focus on summative assessment (i.e., exercises) (CSEI_2) and the final exam performance. Considering that the engagement indicators were introduced just to control for their effect on the outcome, we observe that even though CSEI_2 significantly contributed to the prediction of the outcome variable ($p < 0.0001$), it did not neutralise the predictive power of regularity. Still, the examined course specific indicators of engagement intensity contributed far more to the models' predictive power than their generic counterparts (see Sect. 4.1). This is particularly the case for the 2014 and 2015 models: by comparing the *MGSI_Final* to *MGSI_Reg* models, we observed that when the course specific engagement indicators (CSRIs) are not considered, the level of explained variance (i.e., adjusted R^2) drops from 0.353 to 0.169 in 2015, and from 0.281 to 0.158 in 2014 (in 2016, the drop is far less, namely from 0.365 to 0.294).

5. Discussion

The results presented in Section 4.1 answer our first research question (RQ1, Section 2.3). In particular, they demonstrate that predictive models of student academic performance established from generic indicators of regularity and level of engagement lack sufficient explanatory power. For the three examined offerings of the studied FC course, predictive models with generic indicators only (Table 5) accounted for between 12% and 24% of the observed variability in the students' final exam score.

In all three course offerings, entropy of weekly session counts (GRI_1) proved a significant regularity indicator, positively associated with final exam performance. This confirms that the more uniformly distributed the students' weekly session counts are, that is, the more they regularly engage with the pre-class activities throughout the course, the higher their final exam performance tends to be. This was further confirmed in the 2016 model with the variance in weekly session proportions (GRI_2) having significant negative association with exam performance.

In the 2015 and 2016 course offerings, we detected a negative association between changes in the 'pattern' of engagement over the weekdays (GRI_4) and the students' final exam performance. This indicates that those students who did not have a stable pattern of engagement with the pre-class activities over the weekdays had lower course performance. Change in the pattern of engagement is considered an indicator of regularity of learning (Hadwin et al., 2007). Hence, the detected negative association might suggest that those students who altered their 'pattern' of engagement over the weekdays were having difficulties in managing their time and consistency of interaction with the weekly assigned pre-class activities. Panzarasa et al. (2016) and Dvorak and Jia (2016) also detected week-level irregularities in students' engagement with online activities. However, they did not examine if the patterns of irregularity changed over the course, nor the effect of the potential change.

The second research question (RQ2) was designed to assess the importance of course specific indicators of regularity for a predictive model of students' exam performance. The results presented in Section 4.2 suggest that indicators of regularity and level of engagement derived from the design of the pre-class activities can improve the prediction of students' final exam score over and above the prediction enabled by generic indicators. In particular, the results (Table 6) demonstrate that the increase in the predictive power is in the range between 52% (in 2016) and over 300% (in 2015).

Among the significant course specific indicators, particularly distinguished are those related to the students' interaction with summative assessment (CSRI_2), course videos (CSRI_3), and the course e-book (CSRI_4). Regular weekly use of course videos (CSRI_3) proved to have a positive association with the students' final exam performance in 2014 and 2016. Similar effect of regular use of the course e-book and regular engagement with summative exercises (CSRI_2) was detected in the 2015 and 2016 course offerings. However, too much focus on summative assessment (CSEI_2) was negatively associated with final exam performance in all three course offerings. This finding is consistent with our earlier analysis of the same course (Jovanovic et al., 2017), as well as studies that examined student's interaction with different kinds of learning resources and identified that selective use of resources was not associated with high study performance (Kovanovic, Gasevic, Joksimović, Hatala, & Adesope, 2015; Li & Tsai, 2017). It is also consistent with the findings of an extensive review of reported empirical studies that examined student interaction with LMS (Lust, Juarez Collazo, Elen, & Clarebout, 2012). Specifically, the review found that students did not use the available tools adequately and often either underused or overused them, trying to game the system. Furthermore, the detected differences in tool use were found to be associated with performance.

Generic indicators of regularity related to time management at the week level proved significant even after introducing course specific indicators (Table 6). In particular, more evenly distributed pre-class activities over the week days (GRI_3) were associated with better exam performance in the 2016 course offering. This is consistent with previous studies that examined the association between time management indicators and student performance (e.g. Asarta & Schmidt, 2013; Jo et al., 2015; Saqr et al., 2017). In the other two years, 2014 and 2015, the frequency of change in the pattern of engagement over the weekdays was negatively associated with exam performance. This suggests that students with an irregular pattern of engagement would benefit from assistance related to time management skills.

It is worth noting a gradual increase in the variety of types of digital learning resources that, if used regularly, proved to be positively associated with exam performance. In 2014, it was just one type of learning resource (course videos, CSRI_3); in 2015, two kinds of resources (summative exercises (CSRI_2) and the course e-book (CSRI_4)), and in 2016, three kinds of digital resources (course videos, exercises, and the course e-book). This widening of the significant learning resource types might be associated with the personalized feedback students received in the first half of the 2015 course and throughout the 2016 course offering (see Section 3.1). The feedback was focused on learning processes and self-regulation, and, as suggested by Hattie and Timperley (2007), aimed at facilitating self-assessment and clarifying expectations (Pardo et al., 2017). This change in instructional conditions may have influenced the students' decision to use the available learning resources (Winne, Jamieson-Noel, & Muis, 2002). However, it seems that not all students were successful in regulating their use of available digital resources as evident in the negative association between the change in the 'pattern' of learning resource use (CSRI_12) and exam performance in 2016, as well as in the negative effect of regular requests to see solutions for the formative MCQs (CSRI_9). This suggests that the provision and framing of the personalized feedback requires some refinement.

Though the present study was not focused on students' level of engagement, but rather used this measure as a control factor, it is worth observing that only when they were defined in terms of course-specific activities, indicators of the students' intensity of engagement significantly contributed to the predictive power of the regression model. In particular, in the models with generic indicators of regularity (*MGI_Final*), the addition of indicators of engagement intensity led to only a small increase in the model's explanatory power (increase in adjusted R^2 ranged from 0.005 in 2015, to 0.071 in 2014). However, in the case of models with course specific indicators (*MGSI_Final*) the increase was several times larger (increase in adjusted R^2 ranged from 0.071 in 2016 to 0.184 in 2015 model). This shows that not only for regularity indicators, but also for engagement indicators, it is important that the measures are derived from the course design.

It is worth noting that the indicators of engagement and regularity examined in this study are based on the class preparation activities only. We did not have access to the data about student engagement and regularity in face-to-face sessions (lectures and labs), and these could also be associated with students' final exam scores. Hence, students' engagement with and regularity of class preparation activities is considered a proxy for their overall engagement and regularity in the course. This limitation of the present study could be, at least partially, overcome with a follow-up multi-modal study where learning traces from online pre-class activities would be combined with data collected from face-to-face sessions through the use of adequate sensor technologies. Latest developments in Multi-Modal Learning Analytics (MMLA) make such studies increasingly possible (Blikstein & Worsley, 2016). For example, Schneider, Di Mitri, Limbu, and Drachsler, (2018) developed Multimodal Learning Hub, a system that allows for collecting and integrating multimodal data from custom configurations of ubiquitous data providers. Rodríguez-Triana, Prieto, Martínez-Monés, Asensio-Pérez, and Dimitriadis (2018) proposed a method for customizing MMLA solutions with active teacher participation in the process, so that a generic MMLA solution is adapted to the needs of a particular blended learning context.

6. Conclusions

The study findings indicate how crucial the role of the course design is in the analytical process. In particular, the results demonstrate that a set of indicators that did not take into account the particularities of course design and its goals explained only a small percentage of the overall variability in the students' academic performance. However, when the indicators were constructed taking into account the learning objectives and activities specific to the course design, their value increased considerably. For example, knowledge about the instructional interventions adopted to promote sustained and deep engagement with the course e-book led to the creation of indicators that reflected the regularity and intensity of student engagement with it. In particular, in the examined FC, students received personalized feedback and suggestions, based on measures of their prior engagement (Pardo et al., 2017), on how to better prepare for the face-to-face class time by reviewing material and activities contained in the e-book. This intervention was deployed in the 2015 and 2016 offerings of the course which is when the e-book related indicators become prominent in the analysis. This example shows how data analysis needs to be situated in the context of the course design. A course design is a reflection of the instructional goals and objectives set for a particular course. These goals and their representation in the design are an essential ingredient to consider in the process of deriving indicators and predictive models.

A comparison of the models with course specific indicators (Table 6) suggests that changes in the course design over the three examined years reflect on the student behaviour. The behavioural differences were evidenced in the differences of significant predictors in the three consecutive course deliveries. The differences were especially prominent between the first (2014) and the two subsequent course offerings (2015 and 2016). This can be, at least partially, explained by the gradual introduction of personalized feedback starting from the, 2015 course offering (see Section 3.1). This further confirms the importance of course specific indicators for designing and validating instructional interventions (personalized feedback, in this case). More generally, it points to a relevant feedback loop between the analytical process and the instructional design: using the enacted design to define the analytical model, and then using the insights derived from the model to inform changes in the design itself (Gašević, Dawson, & Siemens, 2014; Jovanovic, Gasevic, Pardo, Mirriahi, & Dawson, 2018).

The detected negative association between changes in the study strategy and course performance implies the importance of helping students make effective use of learning resources during class preparation activities. In other words, students need to be assisted in regulating their use of learning resources in a manner aligned with the course design (Lust et al., 2013). Recent studies by Yilmaz and Baydas (2017) and Sletten (2017), which examined self-regulated learning in a FC, also stressed the importance of providing students with appropriate assistance and/or guidance to speed up their adaptation to the FC context. This can be achieved through appropriate scaffolds and nudges informed by insights obtained through analytics (Mor, Ferguson, & Wasson, 2015), and iteratively and incrementally improved through a cyclical process at the intersection of learning analytics and design based research (Reimann, 2016).

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