MEASURING SELF-REGULATED LEARNING AND ONLINE LEARNING EVENTS TO PREDICT STUDENT ACADEMIC PERFORMANCE

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Abstract

The aim of this study is to identify whether the combination of self-reported data that measure self-regulated learning (SRL) and computer-assisted data that capture student engagement with an online learning environment could be used to predict student academic achievement. Personally engaged study strategies focused on deep-level learning, the process of taking control, and the evaluation of students' own learning characterize SRL. Diverse theories on how students benefit from SRL underline its positive impact on student academic outcomes. Similarly, there is no doubt that the future trend in education leans towards the integration of technology into teaching in order to exploit its full potential. To benefit from both approaches, a combination of self-reported data and detailed online learning events obtained from an online learning environment were investigated in relation to their ability to predict student academic achievement. A case study of 54 university students enrolled in a blended-learning course showed that of the tested SRL variables and observed learning activities, student interaction with auxiliary materials that were part of the course helped to predict academic outcomes. Despite the relatively low ability of the model to explain why some students were able to become successful learners, the presented results highlight the importance of analysing online learning events in computer-assisted teaching and learning.

Keywords

online learning events, computer-assisted learning, self-regulated learning, academic performance

Introduction

The topic of self-regulated learning (SRL) is not new in recent research (Greene, Moos, & Azevedo, 2011; Winne, 2018). As the term conveys, self-regulated behaviour systematically oriented toward the achievement of learning goals is seen as an increasingly important predictor of academic outcomes (Zimmerman, 2010) and students' conceptual understanding of complex topics, especially in the context of computer-assisted learning (Azevedo, 2005; Greene & Azevedo, 2007). Learning in a blended or online setting requires students to behave as active seekers and processors of information with the ability to initiate cognitive, metacognitive, affective, and motivationally engaged learning processes (Zimmerman, 2002). This means that self-regulated learners are able to plan systematically and control, monitor, and motivate themselves in order to achieve their goals set in various types of learning settings (Purdie & Hattie, 1996). Therefore, self-regulation can play a significant role in understanding why some students can learn faster than and outperform others.

Moreover, learning does not exist in a vacuum but in an environment consisting of a number of interrelated aspects covering teacher and learner characteristics (Kizilcec, Perez-Sanagustín, & Maldonado, 2017), task specification (Schunk & Ertmer, 1999), social support (Perry, Fisher, Caemmerer, Keith, & Poklar, 2015), and feedback (Pérez-Álvarez, Maldonado-Mahauad, Sapunar-Opazo, & Pérez-Sanagustín, 2017; Roberts, Tadlock, & Zumbrunn, 2011), which are integrated into the physical or virtual platform. Winters, Greene, and Costich (2008) emphasized the importance of a comprehensive strategy investigating not only the cognitive and metacognitive aspects of SRL but also the impact of student motivation and self-reactions from a socio-cognitive point of view, where cognitive, affective, and motivational processes are jointly shaped by learners' external and internal environments. To fill this gap, a complex relationship amongst a set of SRL variables covering self-efficacy for learning and performance, goal orientation, test anxiety, academic performance, and engagement with an online learning environment was investigated in this study.

A review of 33 empirical studies (Winters, Greene, & Costich, 2008) of SRL and computer-based learning environments (CBLEs) identified that the traditional SRL strategies adapted by advanced (graduate-level) learners to web-based learning mediated the hypothesized positive relationship between CBLEs and academic performance (Whipp & Chiarelli 2004). Moreover, learner characteristics such as prior domain knowledge (MacGregor, 1999; Moos & Azevedo, 2008) as well as task or instructional hypermedia characteristics (Schunk & Ertmer, 1999) correlated with student SRL when using CBLEs. Improved student learning outcomes and conceptual

understanding have been reported when adaptive scaffolding was implemented in CBLEs (Azevedo, Cromley, & Seibert, 2004). Importantly, Azevedo and Cromley (2004) provided evidence that students can be trained to use particular SRL processes that are considered effective for a given task in CBLEs.

Furthermore, students' ability to self-regulate their learning can be shaped at any educational level (Boekaerts, 1997). However, full responsibility for learning outcomes is most frequently given to students at the university level and covers a wide range of face-to-face and computer-based learning applications (Pintrich & Zusho, 2007). On this basis, researchers who have analysed data about learners and their contexts for the purposes of optimizing learning and the environments in which it occurs have proposed a need to combine learning science and computer science to provide support across physical and digital learning spaces (Dent & Koenka, 2016; Martinez-Maldonado et al., 2016). This was particularly the case regarding the need to increase the range of data capture so that the complexity of the learning process can be better captured in analysis. For instance, Pardo, Han, and Ellis (2017) reported the importance of analysing self-reported learning experiences obtained from online platforms. Moreover, findings derived solely from frequently used self-reports and subjective coding of verbal protocols are not seen as sufficient for investigating how SRL functions over time (Järvelä, Hadwin, Malmberg, & Miller, 2018).

Malmberg, Järvenoja, and Järvelä (2010) responded to this challenge by assessing trace methods that enable recognition of temporal patterns in learner activity which signal SRL in computer-supported collaborative learning. However, earlier research focused on individual learning and not on the captured temporal sequences of regulation in collaborative learning. Such results from sequential analysis have also been presented by Malmberg, Järvelä, and Järvenoja (2017) and Hadwin, Bakhtiar, and Miller (2018). Additional current trends in research on SRL represent a collection of rich multimodal data (tracing a range of cognitive and non-cognitive processes), usage of data-driven analytical techniques (Winne & Baker, 2013; Winne et al., 2006), and an aggregation of these data sources to strategically regulate individual and group cognition, motivation, and emotion (Roll & Winne, 2015).

In line with the mentioned needs within current research, Bannert, Reimann, and Sonnenberg (2014) suggested analysing temporal sequences of SRL with event-based temporal methods. These authors used a process-mining technique (Fuzzy Miner, ProM V 5.0, 2008) to generate students' process models and investigated whether the extreme groups of the most and least successful students differed in their SRL activities during hypermedia learning. They also suggested taking into account not only data that capture

aspects of the process environment (such as what is read in the hypertext), but also quantitative temporal aspects (event duration). In general, these authors' contribution demonstrates that in addition to the occurrence of individual learning and regulation events the temporal structure is also important to learning performance. The presented approach has often been postulated but less often demonstrated empirically. Furthermore, Gunther and van der Aalst (2007) encouraged the use of such techniques and proposed a new process-mining approach to overcome problems when dealing with unstructured processes, as often found in real-life practice. They developed an adaptive simplification and visualization technique based on two novel metrics: significance and correlation. Winne and Baker (2013) presented good examples of exploring the potential of process mining and its application to SRL.

The idea to link pedagogical research with the use of information and communication technology as applied inside and outside of Czech schools to get a comprehensive picture of young people's everyday lives and learning has been emphasized by Arnseth, Erstad, Juhaňák, and Zounek (2016). Even earlier in an analysis of media messages related to such technology in education published in Czech educational journals between 1990 and 2012, Zounek and Tůma (2014) proposed a more comprehensive approach. They invited researchers to conduct comprehensive research shifted beyond the school environment in its scope, extending from undergraduate students to adults and from traditional educational institutions to other various forms of lifelong learning. Although still in the formative stage of development, these calls raise new questions for future study.

Given the scope and page limitations of this study, there is no space to review all of the research on this topic. In fact, such a review would not be very helpful at this point for understanding various tendencies in SRL in the digital age due to the great complexity. Accordingly, the present study was organized around certain general findings that, according to its author, cut across the main research streams that highly motivated the structure and conduct of the presented online learning course and encouraged the author to look for solid evidence to formulate subsequent objectives and research questions. Therefore, based on the theoretical framework and research capturing SRL in technology-enhanced learning, the purpose of the present study is to use detailed statistical analysis to ascertain the effectiveness of using computer-assisted data collection in a blended-learning class. Therefore, the following research questions were addressed: 1. What are the relationships among SRL variables (as manifested in self-efficacy, anxiety, and intrinsic goal orientation), observed student interaction with the online learning environment, and academic performance? 2. To what extent do variables gathered from students' answers to a survey and computer-assisted

data collection contribute to the explanation of the variability in academic performance?

This study is organized as follows: the concept of SRL is defined in the following section. Next, the Methods section presents the context of the research in terms of sample characteristics, data collection measurement, and the data analysis performed, including study limitations. Then follows a section with the main results of the validity and reliability of the scales and data analysis addressing the research questions. The discussion and conclusion naturally complete the study.

Defining SRL

During the 1980s, the concept of SRL became a fascinating topic in the field of pedagogical research (Zimmerman, 1986, 1989). It emphasized the importance of the independence and autonomy of a learner who is responsible for their own learning outcomes (Paris & Byrnes, 1989; Zimmerman, 1989). Zimmerman (1986) introduced a broad definition of SRL, according to which a self-regulated learner is a cognitively, behaviourally, and motivationally active participant in an academic task. Moreover, such students set their own learning goals or achievements, choose learning strategies to reach them, and recognize when different strategies are more effective. Based on this self-directed process, self-regulated learners transform their mental abilities into academic skills (Zimmerman, 2002).

However, there are still some contradictions in perceptions of the static nature of SRL. Some studies perceive SRL as static individual dispositions independent of the context of learning (Boekaerts & Corno, 2005). Nevertheless, many studies have shown that versions of SRL differ in various situations (Hadwin, Winne, Stockley, Nesbit, & Woszczyna, 2001; Wolters, 1999). Therefore, we believe that in combination with students' internal environment (their prior knowledge, ability, or motivational beliefs) an external environment in the form of the type of learning may support students' SRL.

For the purpose of this study, self-regulated learners were approached in accordance with Zimmerman (2008), who perceived them as active participants in their own learning able to control, monitor, and regulate their cognition, motivation, and behaviour. Moreover, the socio-cognitive perspective (Bandura, 1991; Pintrich, 2000) of SRL (wherein individuals acquire knowledge by observing others and interacting socially) was considered while conducting this study. From this point of view, SRL is best understood in terms of a triadic reciprocity involving the interaction among cognitive and personality (self-) processes, the environment, and behaviour (Zimmerman, 1989). Therefore, SRL is perceived as an event-based phenomenon (a temporary status connected to the context) rather than an individual's static personality trait (attribute). On this basis, the contextual features of the

environment can provide both facilitating and inhibiting influences on SRL and in turn may affect overall academic scores (Broadbent & Poon, 2015). According to author of this study, however, self-regulated learners would not intentionally change their approach to SRL (i.e. cognition and metacognition) in different courses. What might change remarkably is their motivation for learning, which can then affect the amount of effort devoted by learners to particular learning activities.

Various models that describe SRL (e.g., Pintrich, 2000; Weinstein, Husman, & Dierking, 2000; Winne & Hadwin, 1998) share a similar structure in terms of the phases occurring during the self-regulation cycle but nonetheless differ in their views on what should be regarded as the main element. Zimmerman and Schunk (2011) and Pintrich (2000) focused their attention primarily on the motivational aspects of SRL, while Winne and Hadwin (1998) focused primarily on cognitive and metacognitive perceptions of SRL. Weinstein, Husman, and Dierking (2000) perceived SRL as an integral part of strategic learning. Boekaerts's perception (2002) was different in that it particularly emphasized that the initial stage of SRL involves students' personal goals. Notwithstanding these differences, all of these perceptions emphasized the autonomous nature of SRL and affirmed that self-regulated learners are internally involved and apply their abilities to modify their cognitive, metacognitive, and motivational learning processes.

Many studies have highlighted the importance of the motivational component in the SRL process (Boekaerts, 2002; Hrbáčková, Hladík, Vávrová, & Švec, 2011; Montalvo & Torres, 2004; Pintrich, 2000; Schunk & Zimmerman, 2008; Wolters & Pintrich, 1998). It turns out that motivation plays an important role in initiating and sustaining SRL (Boekaerts, 1996). Controlling cognitive and metacognitive learning strategies is not enough if students do not have a reason to learn or do not want to learn and therefore cannot motivate themselves sufficiently to learn. Of the motivational components, expectancy, affect, and value were part of the investigations across all kinds of domains, including learning (Pintrich, Smith, Garcia, & McKeachie, 1993). If a student has a positive expectation of being successful at their studies, they develop the tendency to approach difficult tasks as challenges and set appropriate goals which they persist at, believe in, and strive for (Usher & Pajares, 2008). Similarly, students' anxieties experienced during their studies appear to be highly motivational (Jakešová, 2012; Pintrich & De Groot, 1990). At the same time, student anxiety changes in relation with age and grade and negatively correlates with learning success (Peng, 2012). Furthermore, successful students are often described as those who are driven by intrinsic goals, pay attention to analysing their study assignments, and effectively monitor, modify, and adapt existing learning strategies (Winne & Hadwin, 1998).

To answer the aforementioned research questions, this study included self-efficacy, test anxiety, and intrinsic goal orientation alongside student interaction with an online learning system and academic performance. This approach seeks to build upon progressive research of SRL in computer-supported learning (Azevedo, Johnson, Chauncey, & Graesser, 2011; Greene, Muis, & Pieschl, 2010; Nicol, 2009; Winne et al., 2006) and a broader palette of insights that help in understanding why some students perform better than others and how to improve a student's online learning experience.

Method

Participants
This study included 54 full-time university students attending a blended-learning course at a public university in the Czech Republic. Age ranged from 20 to 22 with an average age of 20.94 ($SD = 0.71$). Of these students, 51 (94%) were female students pursuing a Bachelor of Arts in Health and Social Care. The predominance of females is fairly common in the field of helping professions across the country.

Data collection was approved by the University Human Resources Ethics Committee and University Institutional Review Board. Participating students were informed about the nature of the research and told that their participation was on a voluntary basis. Each participant signed a consent form covering online data collection, final marks, and a self-reported questionnaire administered in the traditional paper-and-pencil format.

Measurements
Online learning events
Student interaction with the online learning system was recorded through e-learning software which monitored and recorded the frequency of student online learning events. More specifically, the Moodle learning platform (version 2.9+), designed to provide teachers and learners with a learning management system (Singh, 2017), was used in this study. The selection of Moodle was based on its easy-to-use interface, open-source nature, up-to-date approach, and security and community support features. The platform hosted seven online learning event categories, as described in Table 1.

Table 1
Descriptions of online learning event variables

Title	Code	Description
1. Engagement	Engage	These events were recorded whenever students interacted with any page in the system.
2. Video	Video	These events were recorded when a video-lesson was loaded within a page.
3. Auxiliary materials that were part of the lesson	AML	These events covered student access of additional resources that were part of the curriculum (covering PDF files, books, articles).
4. Auxiliary materials that were part of the course	AMC	These events were recorded whenever students used additional materials with information describing how to learn in Moodle or answering frequently asked questions about course functions.
5. Sample test	STest	These events were recorded when students interacted with a sample version of the final test.
6. Pre-seminar questions	PreSQ	These events were recorded when students answered the 10-item compulsory pre-seminar questions. Each correct answer to a question was awarded 1 point. Students obtaining 10 points could attend the subsequent face-to-face part of the course. Students repeated the set of questions until they reached the full score. Altogether, 5 sets (with 10 items each) were expected to be completed by each student.
7. Seminar task	STask	These events were recorded when students uploaded a seminar task in the form of a compulsory individual research project (including three separate parts). Resubmission was possible and depended on the teacher's review and recommendations for changes.

The blended learning was designed for the course Introduction to Statistics and Quantitative Methodology, which is compulsory for second-year bachelor students. A flipped classroom strategy was used to deliver instructional content outside the classroom and activities such as exercises and homework in the face-to-face classroom setting. On this basis, students' preparation activities included required viewing of several online video lectures, studying additional materials, participating in online pre-seminar questions, and carrying out a research project outside the classroom. Subsequently, class time was used for mastering concept exercises under the teacher's guidance.

The course's face-to-face component involved a two-hour lecture by a teaching assistant and the online component included an approximately two-hour computer-delivered video lecture with auxiliary materials which supplemented the compulsory and optional learning activities. More specifically, completion of the online pre-seminar questions was required prior to attending the face-to-face class scheduled during the following week, and seminar tasks came into play during the second half of the semester.

Academic performance

Academic performance was measured with the final mark in the course. The pass mark on the final exam with multiple-choice and open-ended questions was 50%. The potential range for the final mark was 0 to 46 points, with 23 points representing the pass mark for the course. However, students' final marks ranged from 12 to 45, with a mean of 31 (SD = 8.5). This means that students were generally successful in passing the course. To maintain the heterogeneous nature of the results and to be better able to interpret them, the final mark was further transformed into a Z-score with an M of 0 and SD of 1.

SRL

For SRL, the motivation beliefs subscales of the Motivated Strategies for Learning Questionnaire (Pintrich, Smith, García, & McKeachie, 1991) were used. This self-reported measurement uses a 7-point Likert-scale ranging from 1 (*not at all true of me*) to 7 (*very true of me*), with the higher levels indicating higher self-regulation. A total of 17 items were selected, including learning expectancy, affect, and value, based on a previous adaptation of the instrument for the Czech educational environment (Jakešová & Hrbáčková, 2014). These components seem to be the critical ones for self-regulation strategies in students (Cazan, 2012; Stegers-Jager, Cohen-Schotanus, & Themmen, 2012).

The intrinsic goal orientation subscale (value) consisted of 4 items with a reported *a* of 0.74, self-efficacy for learning and performance (expectancy) consisted of 8 items with an *a* of 0.93, and test anxiety (affect) consisted of 5 items with a reported *a* of 0.80. These particular subscales were selected based on the course outcome and students' need for self-regulatory skills to perform well in the course. Therefore, the referred reasons why students engaged in learning, their concerns, and their self-appraisals of their ability to master learning were further analysed as mean scores on questionnaire subscales.

Data analysis

The study used a multiple methods design to clarify the continuity and integrity of its individual phases. To investigate the relationships among data sources, data collected within the online learning environment, self-reported data, and academic performance as measured by final marks in the course were examined using correlation analysis to identify the strength of associations and cluster analysis to identify the distribution of these associations among the groups. This enabled two investigative approaches: the strength of associations on the variable level in the form of correlation analysis and the

strength of associations on the student level in the case of cluster analysis. Additionally, regression analysis was used to identify which variables best explained the variance in student academic performance. The three steps of data analysis were as follows.

First, descriptive statistics were calculated for online learning events and academic performance. Next, subscales covering SRL were subjected to validity and reliability analysis. Exploratory factor analysis (EFA) with principal component analysis (PCA) procedures using a varimax rotation was applied to self-reported data. Identifying the simple and easy-to-interpret latent structure of the presented factors was desirable. To evaluate the reliability of the subscales, Cronbach's *a* and McDonald's *ω* were compared.

In the second step, the complex relationships among the set of measured SRL variables, online learning events, and academic achievement were investigated through pair-wise comparison. This was followed by hierarchical cluster analysis to detect which factors were better able to differentiate students into sub-groups based on SRL and academic performance. Based on group membership, an independent-samples t-test was performed to see whether students in each cluster significantly differed with respect to academic performance.

In the third step of the analysis, multiple regression analysis was conducted to investigate how the monitored variables contributed to academic performance. The tested model included variables significantly correlated with student academic achievement in the previous analysis.

Limitations

Although the current research had high ambitions to provide desirable findings, two types of limitations need to be pointed out. One limitation comes from before the study was conducted and the other from after its completion. The sample size was quite small compared to the usual ranges for quantitative analysis. However, the research conditions did not enable expansion of the sample because the other subjects taught at the facility did not have such extensive and sophisticated online courses. In other courses, students and teachers used their digital spaces only as a secondary source of information, not as a space where primary learning processes were carried out, as in this study.

The self-reporting survey on SRL included items related to students' overall course experience. The online-learning and face-to-face parts of the course were not distinguished. Therefore, identifying independent variables involving the face-to-face learning experience could reveal detailed relationships. Additionally, student's digital footprints left in the system did not have the potential to fully explain what was occurring during the leaning process. The quality of the evidence could have been significantly modified

by collecting qualitative data about the students' approaches to learning. Pardo, Ellis, and Calvo (2015) and Ellis, Han, and Pardo (2017) argued that both quantitative and qualitative reasoning for why and how students use online tools have great potential to provide an informed basis for explaining variations in student learning outcomes.

Moreover, students with low SRL can change over time in the supportive environment of a culture of learning to gain high SRL (Edwards, Davis, Milford, & Hadwin, 2017; Schapiro & Livingston, 2000). On this basis, collecting self-reported data before and after the course and at different time points during the semester could have improve tracked findings. Lastly, this research concentrated on frequency analysis of online learning events. More sophisticated modules for fine-grain computer-assisted data collection including time stamps for student engagement with information and how they engaged with it would have expanded the research to include au naturel data (Winne, Nesbit, & Popowich, 2017). Log file data could be examined by incorporating the data into mixed-method studies to better understand (a) patterns of studying activities, (b) event timing and sequencing, and (c) the content of student's writing (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). Thus, when modelling academic performance with a combination of self-reported and observed data using both quantitative analysis (Malmberg, Järvenoja, & Järvelä, 2013; Zhou & Winne, 2012) and qualitative analysis (Olakanmi, Blake, & Scanlon, 2010) with process-mining approaches (Bannert, Reimann, & Sonnenberg, 2014) seems to be even more beneficial to gain optimal statistical power.

Results

Student engagement with the online learning environment was captured in the form of digital footprints left in the system. The applied blended-learning course hosted all of the materials needed for the lessons within the Moodle learning platform including videos, auxiliary materials, a sample test, pre-seminar questions, and tasks. Online learning events were recorded during the autumn 2017 semester, which was 14 weeks long. Table 2 presents descriptive statistics for the events

Table 2
Descriptive statistics for online learning events

Variables	Min	Max	M	SD
Engagement (Engage)	285	795	480.44	122.59
Video (Video)	8	67	36.17	15.72
Auxiliary materials of the lesson (AML)	3	38	15.28	9.63
Auxiliary materials of the course (AMC)	0	33	3.67	7.59
Sample test (STest)	0	11	3.56	2.82
Pre-seminar questions (PreSQ)	10	36	24.44	8.66
Seminar task (STask)	4	8	5.94	0.98

Note. M = mean, *SD* = standard deviation.

Means ranged from 3.56 for the sample test to 480.44 for overall student engagement. Moreover, there were high discrepancies not only among the online learning events but also among students, implying a large dispersion of standard deviations for the measured interactions. On this basis, Z-scores with $M = 0$ and $SD = 1$ were calculated for all further analyses. Skewness and kurtosis were considered to be within the acceptable range for a normal distribution (George & Mallery, 2010).

Validity and reliability of SRL variables

Prior to performing a validity analysis, the data were assessed for suitability for EFA was assessed. A check for correlations revealed the presence of a relationship. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.77, which exceeds the cut-off value of 0.60 (Kaiser, 1960), with a statistically significant result for Bartlett's test of sphericity ($x^2(28) = 220.05$, $p < 0.001$). Therefore, the assumptions supporting the factorability of the correlation matrix were fulfilled.

The PCA revealed the presence of six components with eigenvalues exceeding 1 explaining a large proportion of the variance (84%), with explained variance for individual components ranging from 29% to 6%. However, this result was not further supported by Monte Carlo parallel analysis, which supported the presence of only four components with eigenvalues exceeding the corresponding criterion values for a randomly generated data matrix (17 variables/54 respondents). Moreover, graphical visualization of the number of components displayed in the scree plot revealed a clear break after the third component. On this basis, the varimax rotation was calculated and dropped of those items with factor loadings less than 0.50 within a scale and those items with high cross-loadings. The rotated component matrix reached an interpretable three-factor solution (see Table 3).

Table 3

Rotated component matrix with psychometric characteristics for 3-factor solution

Item	F1	F2	F3	h^2	M (SD)	a-i
I'm confident I can do an excellent job on the assignments and tests in this course.	0.87			0.77	5.06 (1.49)	0.74
I'm confident I can understand the basic concepts taught in this course.	0.73			0.55	5.22 (1.45)	0.76
I'm confident I can understand the most complex material presented by the instructor in this course.	0.72			0.58	4.22 (1.49)	0.77
I'm certain I can master the skills being taught in this class.	0.68			0.46	5.22 (1.45)	0.78
I try to understand the content of this course as good as possible.	0.60			0.40	5.94 (1.04)	0.81
I expect to do well in this class.	0.51			0.48	3.89 (1.84)	0.81
When I take a test I think about how poorly I am doing. (r)		0.82		0.84	3.00 (1.65)	0.64
I'm certain I can understand the most difficult material presented for this course.		0.76		0.78	3.72 (1.38)	0.52
When I take a test I think about how poorly I am doing compared with other students. (r)		0.64		0.47	3.50 (1.94)	0.59
In a class like this, I prefer course material that really challenges me so I can learn new things.			0.88	0.80	5.00 (1.35)	0.28
In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.			0.64	0.48	3.44 (1.79)	0.60
When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.			0.51	0.49	4.11 (1.78)	0.56
	SE	AN	IGO	Together		
No. of items	6	3	3	12		
M	4.93	3.41	4.19	4.17		
SD	1.06	1.30	1.21	0.81		
Eigenvalue	5	3	2	10		
Explained variance in %	29	17	13	59		
McDonald's ω	0.82	0.70	.67	0.77		
Cronbach's a	0.81	0.67	0.58	0.74		

Note. Extraction method: principal component analysis. Rotation method: varimax with Kaiser normalization. Values less than 0.50 removed. SE = self-efficacy, AN = anxiety, IGO = intrinsic goal orientation, (r) = reversed items, h^2 = communalities, M = mean, SD = standard deviation, a-i = Cronbach alpha if the item is deleted.

Of the initial 17 items entering the analysis, 12 items remained, creating three scales accounting for 59% of the variance. The three-factor solution with eigenvalues ranging from 2 to 5 comprised factors measuring self-efficacy (6 items), anxiety (3 items), and intrinsic goal orientation (3 items), as expected

by the theory. The component that best explained the variance was student anxiety about learning and performance (*When I take a test I think about how poorly I am doing*). All of the subscales showed good item–total correlations given that the correlation coefficients (*a-i*) did not in any of the cases increase after the item was removed from the particular subscale. Validity analysis covering EFA with PCA extraction method and orthogonal rotation seemed to support the factor structure presented in the data.

Furthermore, the reliability coefficient of Cronbach's *a* ranged from 0.67 to 0.81 and McDonald's *ω* for the new model ranged between 0.67 and 0.82, demonstrating acceptable internal consistency while taking into account the number of items per scale. Taken together, the performed validity and reliability analysis suggested that the general model representing student SRL indicators with three factors covered by 12 items was a reasonable representation of the data.

The descriptive statistics for the SRL activities, including self-efficacy and intrinsic goal orientation, ranged above the central point of the seven-point Likert scale. This means that students on average believed in their own capacity to perform well and their participation was driven by such reasons as challenges, curiosity, and mastery. Furthermore, students' experience with negative thoughts in the form of anxiety lay around the middle point of the 7-point scale. Given the large SDs, however, the observed behaviour varied among individuals meaning that some students had greater concerns than others did. This phenomenon could have been caused by the predominance in the research of female subjects, who generally have higher levels of anxiety than male subjects.

Correlation and cluster analysis

At the variable level, zero-order correlation was used to display linear relationships between pairs of measured variables (see Table 4). These findings show the similarity of pair-wise comparisons. In other words, if a positive or negative correlation between two variables is found, this might predict future trends for the two variables. However, such a prediction might not be correct because correlation does not determine the cause or effect of the relationship.

Table 4

Zero-order correlation coefficients of SRL variables, academic performance, and online learning events

Variable	AN	IGO	AP	Engage	Video	AML	AMC	STest	PreSQ	STask
SE	0.205	0.121	−0.238	0.166	−0.024	0.427**	0.309*	0.194	−0.037	0.151
AN	1	0.214	−0.259	0.259	0.281*	0.236	0.167	0.153	0.111	−0.189
IGO		1	−0.117	0.399**	0.185	0.187	0.162	0.295*	−0.013	−0.483**
AP			1	0.112	−0.155	−0.288*	−0.436**	−0.334*	0.181	0.197
Engage				1	0.246	0.451**	0.257	0.456**	0.714**	0.034
Video					1	0.299*	0.131	0.368**	−0.006	−0.047
AML						1	0.669**	0.430**	0.096	−0.118
AMC							1	0.744**	0.098	−0.102
STest								1	0.238	−0.050
PreSQ									1	0.243

*Note. *p < 0.05, **p < 0.01.*

The findings show small relationships among the first set of variables measuring SRL ranging from −0.121 ($r^2 = 1\%$) to 0.214 ($r^2 = 5\%$). The direction of the relationships was positive, as expected, but did not reach significance ($p > 0.05$). This indicates that the SRL variables seemed to be independent of one another. That is not surprising since these latent variables are the result of the previous orthogonal rotation. Moreover, a similar trend was found between the SRL variables and academic performance. The negative coefficients were not significant, indicating that we should have very little confidence in the obtained results, though the strong influence of the small sample size in the research should be considered.

The relationship between the SRL variables and student engagement with online learning events showed a significant and positive association between self-efficacy and student usage of auxiliary materials that are part of a lesson ($r = 0.427$, $r^2 = 18\%$) and auxiliary materials that are part of the course ($r = 0.309$, $r^2 = 10\%$). Studying course materials in the form of video lessons was also significantly and positively related to student anxiety, which can occur before or during the learning and final testing ($r = 0.281$), but only 8% of the overlap between these two variables was explained. Additionally, there were no other significant associations between anxiety and online learning events, suggesting a lack of connection between students' negative thoughts and worries and their engagement with online learning. Moreover, students driven by an intrinsic goal orientation seemed to interact with online learning more intensively. Intrinsic goal orientation had a significant and positive correlation with student engagement ($r = 0.399$, $r^2 = 16\%$), as did the sample test ($r = 0.295$, $r^2 = 9\%$). Additionally, a medium significant negative

correlation was found with seminar tasks ($r = -0.483$, $r^2 = 23\%$), suggesting that students' intrinsic participation is a means to an end when considering compulsory seminar task processing.

Academic performance significantly and negatively correlated with auxiliary material activities and the sample test. This result seems to suggest that academically successful students engaged more frequently with the auxiliary materials within the lessons ($r = -0.288$, $r^2 = 8\%$), materials explaining the work in the online learning environment ($r = -0.436$, $r^2 = 19\%$), and the sample test ($r = -0.334$, $r^2 = 11\%$).

Furthermore, when checking correlations among online learning variables, overall student engagement with the learning environment was positively associated with auxiliary lesson materials ($r = 0.451$, $r^2 = 20\%$), taking a sample test ($r = 0.456$, $r^2 = 21\%$), and, not surprisingly, completing the pre-seminar questions ($r = 0.714$, $r^2 = 51\%$), i.e. repeating the compulsory set of questions frequently until reaching successful completion. The results also highlight significant correlations between most of online events and student interaction with the sample test ($p < 0.01$). Those students who followed the video lessons and frequently checked the auxiliary materials more often tested their knowledge with the voluntary sample test.

A different pattern emerged when considering the compulsory online activities of the pre-seminar questions and seminar tasks and their connections to the other online events. The results showed they were relatively independent of the other measured events except for a positive correlation between pre-seminar questions and overall student engagement with the system.

Hierarchical cluster analysis was conducted using between-group linkage. The purpose of the analysis was to explore the presence of subgroups of students that could be distinguished according to their self-regulation and academic performance. Based on the increasing distances at which cases were merged, a simple two-cluster solution was obtained. However, it is not sufficient to obtain a clustering solution from the performed analysis. It was necessary to further explore the significant differences among the clusters in self-regulation, academic outcomes, and interactions with online learning events by comparing their means. Based on group membership, an independent-samples t-test was performed (see Table 5).

Table 5
Mean differences in SRL variables, academic performance, and online learning events

Variables	Cluster I: High (n = 42) M (SD)	Cluster II: Low (n = 12) M (SD)	F	t	p	η^2
SRL						
Self-efficacy	0.18 (0.98)	−0.64 (0.83)	2.41	2.65	< 0.01	0.12
Anxiety	0.44 (0.44)	−1.53 (0.22)	12.09	10.55	< 0.01	0.68
Intrinsic goal orientation	0.14 (0.14)	0.50 (0.96)	0.47	2.00	< 0.05	0.07
Academic performance	−0.25 (0.89)	0.87 (0.91)	0.17	−3.85	< 0.01	0.22
Online learning events						
Engage	0.13 (1.07)	−0.45 (0.49)	3.63	1.80	0.08	0.06
Video	0.19 (0.98)	−0.66 (0.79)	0.24	2.76	< 0.01	0.13
AML	0.13 (1.07)	−0.47 (0.49)	4.10	1.89	< 0.01	0.06
AMC	0.13 (1.10)	−0.45 (0.06)	5.40	1.81	< 0.01	0.06
STest	0.18 (1.00)	−0.64 (0.71)	0.68	2.66	< 0.01	0.12
PreSQ	0.07 (1.02)	−0.25 (0.94)	0.71	0.99	0.33	0.02
STask	−0.16 (0.89)	0.57 (1.19)	4.18	−2.32	0.07	0.09

The two clusters differed significantly for all SRL variables and academic performance with the largest effect size, i.e. the largest proportion of variance in the dependent variable explained by the independent variable, for anxiety ($\eta^2 = 0.68$). The first cluster (labelled High) referred to high self-regulation and high academic performance, and the second cluster (labelled Low) referred to low self-regulation and low student achievement.

For the online learning events, the two groups of students differed significantly in video views ($t(52) = 2.76$, $\eta^2 = 0.13$), using auxiliary materials that were part of lessons ($t(52) = 1.89$, $\eta^2 = 0.06$) and the course ($t(52) = 1.81$, $\eta^2 = 0.06$), and taking the sample test ($t(52) = 2.66$, $\eta^2 = 0.12$). On the other hand, no significant variation between clusters was found with respect to overall student engagement or obligatory pre-seminar questions and seminar tasks. Taken together, students with high self-regulation and better achievement interacted significantly more frequently with the learning environment in the cases of videos, auxiliary materials, and the sample test than their classmates from the second cluster did.

Multiple regression analysis

In the final step of the analysis, a descriptive linear multiple regression model was fit. It was investigated whether a set of significantly correlated variables was able to predict student academic outcome. First, the analysis assumptions were checked. Taking into account the recommended 15 participants per

predictor (Pituch & Stevens, 2016), the data set had a satisfactory sample size. Furthermore, the commonly used cut-off points for determining the presence of multi-collinearity (variance inflation factor < 5, and tolerance > 20) unsurprisingly did not violate the regression assumptions because the correlations among all of the tested variables entering the model were not too high.

Simultaneously, the singularity and distribution of scores were checked in terms of their normality and linearity. Furthermore, three outliers were identified which exceeded the critical value for the Mahalanobis distance and so were removed. Cook's distance (max = 0.06) did not reach the recommended value ($D > 1$) for further outlier consideration (Tabachnick & Fidell, 2007). Additionally, homoscedasticity, indicating that the variance in the data of one variable will be more or less the same for all values of another variable, was checked using the Koenker test, which did not indicate any further potential assumption violation. Table 6 presents the results of an ordinary least square multiple regression analysis with unweighted estimates.

Table 6
Regression coefficients for the dependent variable of academic performance

Model	Unstandardized		β	t	p	Correlations			Collinearity statistics	
	B	SE (B)				Zero-order	Partial	Part	Tolerance	VIF
AML	0.13	0.17	0.11	0.73	0.47	−0.14	0.11	0.09	0.75	1.33
AMC	−1.61	0.52	−0.55	−3.11	0.00	−0.44	−0.41	−0.40	0.54	1.85
STest	0.13	0.20	0.11	0.67	0.51	−0.18	0.10	0.09	0.68	1.47

The tested model explained 16% (*Adj. R²* = 0.16) of the variance in academic performance and reached statistical significance ($F(3, 47) = 4.15$, $p < 0.01$, $f^2 = 0.26$). However, to be more specific, only student interaction with auxiliary materials that were part of the course made a statistically significant contribution to the equation ($\beta = -0.55$, $p < 0.01$) and accounted for 16% of variance. If student interaction with auxiliary materials was increased by 1 *SD* (which was 7.59), academic performance would be likely to decrease by −0.55 *SD*. It can therefore be said that the model does not explain 16% of variance by chance. Instead, of the tested independent variables, student interaction with auxiliary materials that were part of the online course best helped to predict academic outcomes.

Discussion

In the present era of rapid information and technology development and the widespread use of online and offline computer-assisted learning environments, the need for skills to self-regulate learning has become increasingly important (Dent & Koenka, 2016; Zusho, 2017). In this context, SRL may function as a positive mediator between computer-based learning environments and student academic achievement (Winters, Greene, & Costich, 2008; Zheng, 2016). In other words, in order to learn successfully through learning technologies, students have to possess a high degree of control and beliefs that they hold the power to affect the situation while taking full responsibility for their own goal-orientated learning outcomes (Mihalca, Schnotz, & Mengelkamp, 2015). Therefore, linking SRL variables, engagement with computer-assisted learning, and academic performance seems to be beneficial.

The aim of this study was to present the main results of how successful a combination of self-reported data and computer-assisted data could be in relation to the ability to predict student academic achievement. On this basis, sets of SRL variables indicating self-efficacy, anxiety, and intrinsic goal orientation were analysed in terms of relationships with observed indicators of student engagement with an online learning environment comprising overall interaction with the system, watching videos, using auxiliary materials, answering pre-seminar questions, and completing seminar tasks and sample tests. As can be seen from the correlation matrix (see Table 4), the SRL variables coming from EFA with orthogonal rotation minimizing the number of variables that have high loadings with each common factor did not share much with one another (ranging between 0.121 and 0.214) or with academic performance (ranging between −0.117 and −0.259). Similarly, Pardo, Han, and Ellis (2017) stated that academic performance was significantly negatively correlated with measured negative aspects of SRL such as test anxiety (−0.28) and negative use of self-regulation strategies (−0.20). Furthermore, in an examination of the relationship between students' test anxiety and academic achievement (Steinmayr, Crede, McElvany, & Wirthwein, 2016), worry negatively predicted changes in student GPA. This is in line with major findings in test anxiety research demonstrating declines in learners' academic performance (Williams, 1991), which might be supported by attentional control theory (Eysenck, Derakshan, Santos, & Calvo, 2007). The theory explains the negative effects of anxiety on student cognitive performance based on reductions in students' attentional focus due to anxiety and increased focus on other stimuli, such as thoughts of worry. The negative correlation between anxiety and student academic achievement indicating improvement in student learning was expected in this study. However, it did not reach significance.

The identified significant relationships between student SRL and online course interactions proved that those two constructs intertwine and interact. However, an even more interesting finding was that a significant correlation emerged between the three online learning events and academic performance, indicating that analysing these processes was valuable. Even more optimistic results were presented in a study by Ellis, Han, and Pardo (2017), where of the eight events recorded in an online environment integrated with a local university learning management system, five had positive correlations with final course marks. Similarly, Dent and Koenka (2015) confirmed that among online learning events, online learning traces that indicated metacognitive strategy use had strong correlations with student performance at an academic task.

Additionally, this study checked correlations among online learning variables. A significant portion of the online events correlated positively with the sample test. A different pattern emerged when considering the compulsory online activities of pre-seminar questions and seminar tasks and their relationships with other online events. One exception was the significant positive correlation (0.714) between the pre-seminar questions and overall student engagement with the system. However, this relationship can be explained by the fact that overall student engagement with the learning system to a certain extent overlaps with all measured online activities including the pre-seminar questions themselves, which could thus cause some type of autocorrelation. The mean for the pre-seminar questions was quite high (24.44) in comparison to the means for the other online variables (other than the mentioned overall student engagement), although with considerable variety among individuals ($SD = 8.66$). This indicates that the 51% of variance in overall engagement explained by the pre-seminar questions could have been influenced by their shared nature or by other unexplained intervening influences.

Clustering results identified two clusters with similar learning patterns (see Table 5). The first cluster of students had high SRL and academic performance and the second cluster had low SRL and academic achievement with lower engagement with the online course environment. Similar results were found with Australian first-year undergraduate students with clustering into two clusters of high and low self-regulation and achievement based on motivational and self-regulation variables, academic performance, and engagement with an online learning environment (Pardo, Han, & Ellis, 2017), with an emphasis on the value of variable combination. Bouchet, Harley, Trevors, and Azevedo (2013) used an experimental approach with MetaTutor, an agent-based intelligent tutoring system designed to foster SRL, and identified 3 different clusters covering 12 variables used for cluster formation (including performance, use of note-taking, and number of sub-goals

attempted). It appeared that learners classified in Cluster 2 (with basically the highest values across nearly all clustering variables) received the most prompts to engage in SRL processes (use of specific planning, metacognitive monitoring, and learning strategies) by pedagogical agents based on higher frequency of page visitation. In contrast, learners in Cluster 1 (with generally the lowest values for clustering variables) received the fewest prompts and learners in Cluster 0 were generally a middle point. Similarly, Barnard-Brak, Lan, and Osland Paton (2010) analysed cluster profiles, providing findings about different "types" of learners. Five profiles of self-regulated students taking online courses were described. According to their profile membership, students significantly differed on academic performance with poor SRL associated with poor academic outcomes (lower GPAs). However, the present study did not address the issue of optimal student interaction patterns. Therefore, a closer inspection of the impact of frequency and tracking of learning sequences of learning events on student success measured online would be valuable. Despite this gap, it can be said that SRL variables have the potential to distinguish learner activities and that self-regulated learners interact in the online learning environment to greater extent and most likely outperform others.

In addition, multiple regression analysis was conducted with the correlated variables, including auxiliary materials and sample tests, to explore the main predictor of academic outcomes. The tested model reached significance with 16% of the variance explained. To put it more precisely, only student interaction with auxiliary materials that were part of the course was a significant predictor of outcome. Thus, it can be said that the model did not explain the dependent variable by chance. Although previous correlation analysis showed significant correlations among the auxiliary materials that were part of the lesson, the sample test, and academic performance, all of these variables showed lower material significance ($r^2 = 0.08$, and 0.11) and no longer held in the regression model. While correlation measures the strength and direction of a relationship between variables, regression analysis measures the ability to predict a dependent variable with multiple independent variables with prediction error. This means that each parameter is estimated along with its standard error indicating the effect of other variables not included in the equation. Therefore, the employed methods involving multiple analysis was favourable because the dependent variable can rarely be explained using only one variable without considering prediction error.

In the line with the present findings from the regression analysis, Kupczynski, Gibson, Ice, Richardson, and Challoo (2011) explained a similar proportion of variance in academic success (14.6%) within a sample of 1,600 learners who had enrolled over one academic year in an online course using the Blackboard learning management system at a university in south Texas.

Frequency of student logins to the online course (sessions), course level, time spent online (in minutes), and freshman status were significant predictors in the regression model. The number of sessions accounted for 10% of the variance, an unexpected outcome which suggests that it may not be the amount of time in spent overall nor the amount of time per session but rather the rate of activity that is a significant predictor of student academic achievement.

Various implementations of training programmes for SRL have been applied over the past three decades. As a result, the scope and interdisciplinary nature of SRL intervention programmes is extensive. However, investigations covering Moodle are less common and, when they appear, most often use self-reported data (Núñez et al., 2011; Ting & Chao, 2013) and less frequently interviews (Maghfiroh, Subchan, & Iqbat, 2017) or computer-based concept mapping (Liu, 2013). Therefore, the usage of the online learning could not be sufficiently examined within the study.

In summary, the present case study of 54 university students enrolled in a blended-learning course brought some evidence about the combination of self-reported data and data recorded by students in a technology-mediated setting. That is why the research questions presented at the beginning of the paper were answered and discussed primarily in relation to the results of the study by the Australian researchers Ellis, Han, and Pardo (2017; Pardo, Han, & Ellis, 2017), which in part motivated the present study. The resultant research differences might be due to the different sample characteristics (such as age, grade, and type of learning environment), online course, measurements, and socio-cultural characteristics, but they nonetheless brought an interesting comparison deserving of further research.

Conclusions

The discussed results from the correlation and cluster analysis reinforce the importance of student experience within online learning. Building on goal-oriented learning actions that are under students' control and also within their capabilities can lead to positive motivation, lower anxiety, and better academic performance. The redesign of a blended-learning context enabling learners to experience various elements of SRL (including feedback and reflection) and customizing compulsory course tasks could bring significantly positive results.

The functional dependence of academic outcomes and interaction with auxiliary materials resulting from the regression analysis highlighted the importance of all materials uploaded within an online course. Although online course conditions can be adapted for work, corresponding to individual needs, the basic course layout and options are unified. This means that if students understand how to behave in a computer-assisted learning system such as

Moodle and do not have to make any extra effort to get orientated in a course, they might benefit from more time spent on learning. It should be mentioned here that the online course required only basic computer skills. No less importantly, account must be taken of compulsory online activities and their attractiveness to students through an explanation of their relevance and applicability to practice in the selected field of study.

The aim of this research was to identify whether the combination of self-reported data and detailed online learning events obtained from observation of student engagement with an online learning environment was able to predict academic performance. The exploratory nature of the study was supported by the use of a relatively uncommon investigation of computer-assisted data collection that can become, in combination with other methods, a stable and reliable part of research data collection. Despite the relatively low ability of the tested model to explain why some students were more academically successful as learners than others, the presented results prove that academic performance is an important but very complex construct influenced by many circumstances that researchers with multiple approaches can further explore.

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