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Exploring the relation between Self-regulation, Online Activities, and Academic Performance: A case study

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ABSTRACT

The areas of educational data mining and learning analytics focus on the extraction of knowledge and actionable items from data sets containing detailed information about students. However, the potential impact from these techniques is increased when properly contextualized within a learning environment. More studies are needed to explore the connection between student interactions, approaches to learning, and academic performance. Self-regulated learning (SRL) is defined as the extent to which a student is able to motivationally, metacognitively, and cognitively engage in a learning experience. SRL has been the focus of research in traditional classroom learning and is also argued to play a vital role in the online or blended learning contexts. In this paper, we study how SRL affects students' online interactions with various learning activities and its influence in academic performance. The results derived from a naturalistic experiment among a cohort of first year engineering students showed that positive self-regulated strategies (PSRS) and negative self-regulated strategies (NSRS) affected both the interaction with online activities and academic performance. NSRS directly predicted academic outcomes, whereas PSRS only contributed indirectly to academic performance via the interactions with online activities. These results point to concrete avenues to promote self-regulation among students in this type of learning contexts.

Categories and Subject Descriptors
• Applied computing~Computer-assisted instruction • Applied computing~E-learning

General Terms
Measurement, Performance, Human Factors, Theory.

Keywords
Learning analytics, Self-regulation, Higher education, SEM.

1. INTRODUCTION

A significant portion of the Higher education sector has experienced a rapid change through the adoption of Internet and Web-based technologies as an integral part of the student learning experience. This change has resulted in the widespread use of blended (or hybrid) learning contexts. Advances in research have redefined the boundaries of online learning, which is now seen as "learning that is distributed over time and place using various technologies, engaging students in multiple forms of interaction" [14]. Nowadays, students in higher education institutions are participating in learning experiences that go beyond sitting in a traditional classroom context. Blended learning is not only quickly filling the new educational demand, but is also providing new ways for student engagement and to promote their interests and motivation [13, 15, 30]. Research has indicated that students who attend hybrid courses which combine online and face-to-face delivery performed better and perceived learning being more effective than students in traditional face-to-face classroom learning (e.g., [30]). However, researchers argued that effective online learning often requires students to be self-disciplined and self-regulated [11, 21, 24]. These factors may be equally effective when translated to blended learning contexts.

Several research areas related to education have tried to avoid the *one size fits all* problem proposing multiple techniques to adapt a learning experience to the needs of each learner. The areas of learning analytics and educational data mining approach this problem using comprehensive collections of data about students and the use of algorithms to derive the knowledge and insight to help understand and improve their overall experience [5]. But data does not speak by itself, and pedagogical and epistemological assumptions need to be taken into account to fully understand how to improve a learning experience [26]. The research community has identified the need to bring multiple disciplines with different conceptions about learning in what it has been defined as the *middle space,* in order to maximize the potential of learning analytics solutions [43]. However, there is a need for more studies that combine research methodologies from these areas. This paper attempts to explore further this middle space through a study to explore the relationship between self-regulated learning, digital traces of student interaction with online activities, and academic performance.

The rest of the document is organized as follows. Section 2 describes the related work in the areas of self-regulated learning, learning analytics, and the combination of data and educational theories. Section 3 describes the methodology used for the case study. Section 4 presents the results obtained in the study. Section 5 includes a discussion of the main consequences of these results. The paper concludes with a set of conclusions and future avenues to explore described in Section 6.

2. RELATED WORK

The widespread use of Learning Management Systems in higher education institutions has made large quantities of data traces

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available. Data is now being obtained from virtual appliances, social networks, learning management system or enrolment processes. This data was soon identified as a potential source of information to improve the quality of a learning experience [36, 47]. This detailed information has the potential of facilitating the understanding of how students learn [5, 26, 29]. The abundant log data recorded by technologies offers insightful information as to students' interactive patterns with a wide range of online learning activities [29]. There are numerous studies in this area reporting relations between academic performance and information derived from data traces [32].

Data mining techniques have been used to discover relationships among factors in a learning experiences to, for example, create models to predict student academic performance (e.g., [1, 16-17, 41] or detecting students at risk [44].

2.1 Combining educational data mining, analytics and educational theories

However, relying solely on low level data capturing the interaction of students with online activities reveals partial information and does not provide insight about the underlying problems while students learn [42]. To address this limitation, researchers in learning analytics and educational data mining have identified the need for a synergistic approach combining educational data mining techniques and other fields such as educational psychology, curriculum and pedagogy, and sociology in education. The objective is to better identify which factors facilitate or hinder effective behavior in students while they interact in a learning environment (e.g., [42-43]). The study described in this paper explores how data self-reported by students about their self-regulation strategies can be combined with traces of interaction with online activities to predict academic performance.

2.2 Self-regulated learning

Self-regulation is defined as the extent to which students are motivationally, metacognitively, and cognitively engaged in their learning processes [12, 52]. There are various models for self-regulated learning (SRL), each placing emphasis in different aspects (e.g., [3, 8, 12, 37, 48, 53]). For instance, Winne places the focus on the cognitive aspect of SRL, whereas the model proposed by [33] is established based on sociocultural perspectives. Some researchers perceive SRL as an event-based phenomenon (e.g., [2, 4, 22]), whereas others view SRL as a progression through metacognitive monitoring and control (e.g., [48, 51]). Adopting a social-cognitive perspective, Duncan and McKeachie argued that SRL should be treated as "dynamic and contextually bound" [15], wherein SRL behaviors are not a static trait of students per se. This means that students may change their motivation and SRL behavior and strategy depending on the nature of the course, its structure and the proposed learning activities. In this paper we have adopted this conceptualization of SRL. In other words, we assume that the perception that students have of the learning environment and task characteristics (external environment) together with their own state of mind (internal environment) may either facilitate or hamper their use of self-regulating strategies [37-39]. Even though SRL encompasses the areas of motivation, cognition, behavior, and context, this paper explores how students use self-regulated strategies as a whole.

Self-regulation of cognition and behavior forms an essential part of the learning processes. Past research has consistently shown that students' self-regulated learning behaviors affect their level of academic success [6, 31, 55, 57]. Able self-regulated learners are often described as actively setting learning goals, employing effective and efficient learning strategies, making appropriate learning plans, adapting their approach from task to task, monitoring their learning persistently, and making adjustments when needed [10, 35, 40, 54]. While there are numerous publications exploring the design of online learning activities to facilitate self-regulated student behavior (e.g., [14, 19, 27, 46], fewer studies investigate the self-regulation strategies when combined with detailed data about student t interactions with online learning activities, and their academic performance. Winne [51] identified the need to adopt a wider lens to SRL specially when technology is used to support a learning experience where students make choices and decisions about which tools they are going to use and how are they going to use them.

This paper presents the results of a study that explores precisely this type of relation in the context of a first year engineering course. Students are given set online resources that requires them a certain level of interaction. The study explores the relationship between their agency, the type of interactions with the online environment, and their academic performance.

3. METHOD

3.1 Research Context

The study was conducted in a semester-long course on computer system for first year engineering students. By the end of the course, students should be able to design, build and configure an electronic system, demonstrate their understanding of how computers work, and write reports about the design process and its results. In addition to these skills, the course has been designed to promote independent inquiry abilities, effective communication, information literacy, and an understanding of ethical issues in the profession. The course was designed as a blended learning experience consisting of a face-to-face component and online learning component, both of them with their corresponding assessments. The face-to-face learning part involved a weekly two-hour lecture, a weekly two-hour tutorial, and a weekly three-hour laboratory session. The online learning component was required to be completed by students in their own time through a custom-designed learning management system able to trace, monitor, and record all the online learning activities by students' unique login identification number. The online activities were designed with an estimated total dedication of 4 hours per week. An average of seven activities per week were scheduled throughout the semester. This portion of the course was assessed as 15% (1.5% per week) of the overall course mark.

3.2 Participants

The study was conducted with 145 (n = 145) first year students who were studying a four year Bachelor of Engineering Degree in a research-intensive university in Australia.

3.3 Instrument

Three methods were used to collect the data in the study.

3.3.1 Self-regulated strategy use questionnaire

Students were asked to answer the questions included in the Self-Regulation Section of the Motivated Strategies for Learning Questionnaire (MSLQ, [38]). The data was extracted from nine items answered on a 7-point Likert scale, with 1 indicating "never true of me" and 7 representing "always true of me". Three of the nine items were negatively worded. The results were collected during the first week of the course.

3.3.2 *Interactions with online activities*

The course required students to interact with an online environment providing resources such as videos, multiple choice questions, summative and formative assessment, etc. The learning management system hosting these resources recorded the interaction of the students while learning. At the end of the semester the accumulated number of events was obtained for each student in the following categories:

- Access to any HTML page of the course material (Resource).
- Expand/Collapse of a section within a page. Some pages had headings with the content collapsed that was exposed when clicking in the title (Col-Exp).
- Events while using the embedded videos: play, pause, begin, and end a video (Video)
- Events while answering the multiple choice questions next to the videos (VMCQ).
- Events while answering the multiple choice questions in the course notes (MCQ).
- Access to a page containing a dashboard illustrating the level of interaction with the course activities (Dboard).

3.3.3 *Academic performance*

The academic performance was obtained from the final course mark. This mark was calculated by taking into account the following assessments: online lecture preparation activities (10%), online tutorial preparation and participation (10%), written report about laboratory session (5%), collaborative project (15%), mid-term examination (20%), and final examination (40%), on a scale from 1 to 100. The Mean (M) of the final mark was 65.50 with a Standard Deviation (SD) of 16.12.

3.4 Procedure

After ethics approval was obtained for the study, we obtained the written consent for the voluntary participation in the first session of the semester. The collection of the data related to the interaction with the online activities was collected all throughout the semester. Students were required to submit partial work to be assessed every week. The data about academic performance was collected upon course completion.

3.5 Data Analysis

The data analysis has been carried out in five stages. The first stage included Exploratory Factor Analysis (EFA) of the data obtained from the Self-regulation strategy use questionnaire (SRSUQ). Principal Component Analysis was used followed by varimax rotation to examine the factor structure of the results. Following suggestions of [18], we deleted from the result those items whose coefficients were < .40 within a factor and those with high multiple coefficients loaded across factors. In the second stage we examined the reliability of the retained scales. The third stage included the use of correlation analysis to see the relationship between self-regulated strategy use, the interaction with the online activities, and academic performance at the variable level. In the fourth stage we first conducted a hierarchical cluster analysis to identify subgroups of participants where the similarities and the differences in their self-regulated strategy use and academic performance could be maximized. On the basis of the identified clusters, one-way ANOVA was performed to see whether learners in different clusters exhibit different patterns for interactions with online activities. This allowed us to examine the relationship between self-regulated strategy use, online learning activities, and academic performance at the student level. In the final stage of the study we constructed a structural equation model (SEM) to examine the predictions of self-regulated strategy use, tool use, and academic performance.

4. RESULTS

4.1 EFA and reliability of the scales for self-regulated strategy use

The results of the EFA for the SRSUQ are displayed in Table 1. The obtained rotated factor loadings translated in the selection of seven of the nine items from the original questionnaire. The final two factors included 4 items in the Positive Self-regulated Strategy (PSRS) scale, and 3 items in Negative Self-regulated Strategy (NSRS) scale. The eigen-values of the PSRS and the NSRS were 2.07 and 1.96 respectively, explaining 29.51 % and 27.94% of the total variance respectively. The values of Cronbach's alpha were .68 and .72 for the PSRS and the NSRS, implying that the two scales were reliable.

Table 1: Results of EFA for the SRSUQ

Scales (Cronbach)	Item Description	Rotated factor loadings	
PSRS (.68)	I ask myself questions to make sure I know the material I have been studying.	.63	
	I work on practice exercises and answer end of chapter questions even when I don't have to.	.74	
	Even when study materials are dull and uninteresting, I keep working until I finish.	.77	
	I work hard to get a good grade even when I don't like a class.	.69	
NSRS (.72)	When work is hard, I either give up or study only the easy parts.		.73
	I often find that I have been reading for class but don't know what it is all about.		.84
	I find that when the teacher is talking I think of other things and don't really listen to what is being said.		.81

Values less than .40 removed; KMO: .83

4.2 Correlation analysis

The results of correlation analyses are shown in Table 2. While PSRS did not significantly relate to student academic performance (r = -.02, p = .85), the NSRS significantly and negatively associated with academic performance (r = -.20, p < .01). However, the PSRS showed significant and positive association with three of the events registered in the online environment, namely Dboard (r = .18, p < .05), Expand/Collapse-of sections in the course notes (r = .21, p < .05), and Col-exp (r = .23, p < .01). This association means that the more students adopted positive self-regulated strategies in the course, the more likely they used the above three online activities. In contrast, the correlations between NSRS and the access to online activities turned to be non-significant. Additionally, academic performance was found to be positively related to most of the indicators derived from online interactions, including Dboard ($r = .24$, $p < .01$), Col-exp ($r = .35$, $p < .01$), Resource ($r = .44$, $p < .01$), and MCQ ($r = .28$, $p < .01$). This positive correlation suggests that the more frequently an individual engaged with these learning activities, the more likely they were to obtain a higher course score in the course. The significant and positive correlation between PSRS and online activities, and the positive relation between these and academic performance may indicate that the PSRS could contribute to the academic performance via the use of online tools. This means that it is possible that the PSRS contributed to the academic performance indirectly rather than directly. The relation between these factors was used to build a structural equation model as discussed in Section 4.4.

Table 2: Correlation analysis

	PSRS	NSRS	AP
NSRS	.13	---	---
AP	-.02	-.20**	---
D-board	.18*	-.03	.24**
Col-Exp	.21*	.15	.35**
Resource	.23**	.10	.44**
Video	.14	-.03	.14
MCQ	.17	-.01	.28**
VMCQ	.06	-.11	.14

Notes: ** $p < .01$, * $p < .05$,

4.3 Cluster and ANOVA analyses

A hierarchical cluster analysis using Ward's method was conducted using as criteria PSRS, NSRS, and the academic performance. The purpose of this analysis is to see if it is possible to identify subgroups of students with differences in their self-regulated strategy that also have different academic performance. The cluster analysis resulted in three solutions: two, three, and four clusters. Using the increasing value of the squared Euclidean distance between clusters, a two-cluster solution was sought, and the results of ANOVA are presented in Table 3.

As it can be seen, the 145 students were classified into a group of 86 High Self-regulated and High-performing students (cluster 1), and a group of 59 Low Self-regulated and Low-performing students (cluster 2). The students in cluster 1 differed from those in cluster 2 in terms of the PSRS use (F (1, 144) = 90.20, $p < .01$, $\eta^2 = .39$), NSRS use (F (1, 144) = 37.20, $p < .01$, $\eta^2 = .21$), and the academic performance (F (1, 144) = 24.60, $p < .01$, $\eta^2 = .15$). To be more specific, the High Self-regulated and High-performing students reported adopting more of the positive self-regulated strategies ($M = 0.51$), less of the negative self-regulated strategies ($M = -0.38$), and achieved a relatively higher final score ($M = 0.32$) than the Low Self-regulated and Low-performing students. On the other hand, the Low Self-regulated and Low-performing students adopted a less positive self-regulated strategy ($M = -0.75$), more negative self-regulated strategy ($M = 0.55$), and their academic performance was relatively poorer ($M = -0.46$).

Based on the cluster membership, a series of additional ANOVA were performed to examine whether students in the two clusters had differed interaction with the online activities. The results reported from the sixth row in Table 3 reveal that the two groups of students had significant differences in the frequencies of interactions with five of the seven online activities. The factors Dboard (F (1, 144) = 9.82, $p < .01$, $\eta^2 = .06$), Col-Exp (F (1, 144) = 5.76, $p < .05$, $\eta^2 = .04$), Resource (F (1, 144) = 10.47, $p < .01$, $\eta^2 = .07$), MCQ (F (1, 144) = 7.92, $p < .01$, $\eta^2 = .05$), and Exercise (F (1, 144) = 15.17, $p < .01$, $\eta^2 = .10$) had statistically significant differences between the clusters. The two remaining factors Video and VMCQ did not have a statistically significant difference among clusters. The High Self-regulated and High-Performing students interacted significantly more frequently with those five activities than the students with Low Self-regulated and Low performance. These results demonstrate that there is a relationship between the use of a self-regulation strategy, academic performance, and interactions with online activities at the level of individual students.

Table 3: Summary statistics of the two-cluster solution

Variable	High (86)	Low (59)	F	p	η^2
	Mean	*Mean*			
PSRS	0.51	-0.75	90.20	.00	.39
NSRS	-0.38	0.55	37.20	.00	.21
AP	0.32	-0.46	24.60	.00	.15
D-board	0.21	-0.30	9.82	.00	.06
Col-Exp	0.16	-0.24	5.76	.02	.04
Resource	0.22	-0.31	10.47	.00	.07
Video	0.12	-0.17	2.89	.09	.02
MCQ	0.19	-0.28	7.92	.01	.05
VMCQ	0.11	-0.17	2.74	.10	.02

Notes: High = High Self-regulated and High Performing learners, Low = Low Self-regulated and Low Performing learners.

4.4 Structural Equation Model

To examine how PSRS, NSRS, and the interactions with online activities contribute to a student academic performance, we constructed a SEM. The three variables in the model were derived from PSRS, NSRS, and the interaction with online activities. The PSRS and NSRS variables were constructed by computing the mean of each scale. The variable Activity was constructed by aggregating the frequencies of interactions with all the activities. The resulting model is shown in Figure 1.

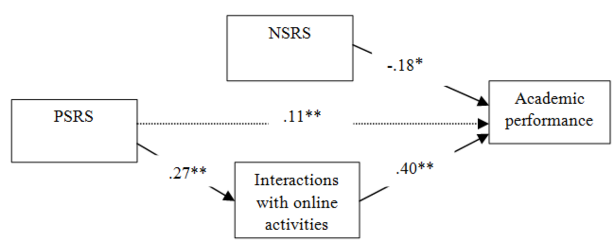

Figure 1: The resulting structural equation model

The following criteria were used to evaluate the fit of the SEM. A non-significant chi-square value led to acceptance of the null hypothesis that the model fits the population [20]. The goodness-of-fit statistics were also consulted for model evaluation. We used the Tucker-Lewis Index (TLI, [45]), the Comparative Fit Index (CFI, [7]), and the root mean square error of approximation (RMSEA, [9]) as our primary goodness-of-fit statistics. The values of TLI and CFI are in the range from 0.00 to 1.00, with values greater than .90 as an acceptable fit to the data [23]. In terms of the RMSEA, according to [9], a value of .06 and below is indicative of a good fit between the hypothesized model and the observed data [9, 23].

The results of the SEM revealed that our data fit the hypothesized model: χ^2 (2) = 0.95, p = .62, CFI = 1.00, TLI = 1.06, RMSEA = .05. The resulting paths are shown in Figure 1. As it can be seen, the NSRS has a significant and negative path to the academic performance (β = -.18, p < .05), whereas the interaction with online activities has a significant and positive path to students' academic performance (β = .40, p < .01). At the same time, PSRS significantly and positively predicted interaction with online activities (β = .27, p < .01). The model also shows that the PSRS has significant and positive indirect effect on the academic performance (β = .11, p < .01). Even though the direct contribution of PSRS to the academic performance is not high, it has a more significant indirect contribution through the interactions with online activities.

5. DISCUSSION

This study has investigated the relationship between students' self-regulated strategy use, interactions with online learning activities, and academic performance in a first year engineering course. The results showed that while PSRS did not show a significant correlation with academic performance, NSRS did have a negative relation with academic performance. Additionally, the academic performance was found to be positively associated with frequencies of interactions with a number of online learning activities. The cluster analysis further identified two groups of students based on their self-reported use of self-regulated strategy and academic performance. The students in the High Self-regulated and High performing group adopted more PSRS, less NSRS, obtained higher final marks in the course, and tended to interact more frequently with online learning activities. The results are the opposite for the Low Self-regulated and Low-performing cluster. The results derived from the structural equation model show indicate that while the NSRS negatively contributed to the academic performance, and the interactions with online activities positively predicted the students' final course mark. Additionally, the PSRS had an indirect but significant path to the academic performance. These results are consistent with previous research in SRL that self-regulated learning behavior is a significant factor affecting students' learning outcomes [6, 31, 55, 57]. We found, however, that PSRS and NSRS contributed to the learning outcomes differently. While NSRS was a significant factor, which directly predicted performance, PSRS only affected students' online learning behaviors directly, and indirectly impacted students' academic performance. These results may mean that interventions that target NSRS could possibly enhance students' learning outcomes, but this postulation needs to be empirically tested via a longitudinal design or intervention studies. The interactions with online learning activities were also found to be a significant contributor to students' final course marks, suggesting that quantity of engagement with online learning is important in this blended learning context.

Although it is difficult to point out directions of causality between PSRS and interactions with online activities with our cross-sectional data, it is plausible that the features of online learning activities are able to foster an increased level of self-regulated learning and enable learners to become more metacognitively aware of learning processes (e.g., [27, 28, 50]). It is also possible that learners who tend to adopt more positive self-regulated strategies in learning also have a tendency to interact with online learning activities more frequently. One way to identify the direction of causality would be through a well-conceptualized intervention study. Researchers may compare the interactions of online activities among four groups of learners: a control group of students interacting with normally designed online activities; a control group of students interacting with online activities whose features are designed to encourage SRSU; an experiment group of students who will receive instructions on how to improve self-regulated strategy use interacting with normally designed online activities; and an experiment group of students interacting with online activities whose features are designed to encourage SRSU. Only through this kind of experiment, may we know the casual relation between SRSU and online learning.

The results of the study offer some practical implications for university lecturers to consider. According to our results, lecturers should consider strategies to reduce students' negative self-regulated strategy use and promote positive self-regulated strategy use. As argued by [29], students "need to be made aware of" self-regulated strategies, and initially use them in "guided and structured manner." (p. 1303). These authors further identified three aspects for self-regulated strategies to be built in the learning environment in order to enhance students' self-regulation, namely: activities for self-regulation, resources for self-regulation, and supports for self-regulation. At the level of activities, those activities, which are able to stimulate learners' reflections on the process of problem-solving are believed to enhance learners' self-regulated learning [8]. Therefore, instructors may use reflective journals or diaries as part of normative assessment for learners to reflect upon their learning processes. At the level of resources, McMahon and Oliver [34] advocate to use multiple sources, which are relevant and challenge, so that these learning sources require learners to process information deeply using self-regulated strategies. At the level of support, instructors should provide learners with constructive and useful feedback to improve their self-regulated learning. There is also a place for instructors to instruct self-regulation directly so that students' awareness of self-regulated learning can be raised.

6. CONCLUSION

Self-regulation has been identified to play a very important role in online and blended learning scenarios contexts. Although there are numerous publications exploring the design of learning activities to foster self-regulation, few studies explore the connection between self-reported self-regulation data with quantitative data about student interaction with activities and their relation with academic performance. This paper presents the results obtained from a case study deployed at a first year engineering course with a blended, active learning strategy.

Three data sources were used for the study. The subset of items inquiring about self-regulation in the Motivational and Self-Regulated Learning Questionnaire were used to encode two factors: Positive and Negative self-regulation strategies (PSRS and NSRS). The number of events accumulated the digital traces produced by the students when interacting with the online activities provided six additional factors. Finally, the academic performance was represented by a single factor with the final score in the course.

An initial correlation analysis showed a lack of significant correlation between PSRS and academic performance. On the other hand, there was a statistically significant negative correlation between NPRS and academic performance. Four of the six factors derived from the digital traces showed also a strong statistically significant correlation with academic performance. A clustering algorithm produced two robust clusters: users with both high self-regulation and performance, and users with both low self-regulation and performance. The factors derived from digital traces had significantly different means in these clusters suggesting that students in these clusters clearly interact differently with the activities.

Finally, a structural equation model was created that provided a more detailed vision of the relation between these factors. NSRS affected negatively academic performance. The interaction with online activities had a very strong positive effect on the academic performance. The model also showed an indirect effect of PSRS on the interaction with online activities.

The main conclusion of these results is that instructors could re-design the course to foster a higher adoption of self-regulation through the online activities. As future work, we envision a more detailed study that allows clarifying the causality relation between self-regulation and how students behave in this blended learning context.

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