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Improving Learning Analytics – Combining Observational and Self-Report Data on Student Learning

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ABSTRACT

The field of education technology is embracing a use of learning analytics to improve student experiences of learning. Along with exponential growth in this area is an increasing concern of the interpretability of the analytics from the student experience and what they can tell us about learning. This study offers a way to address some of the concerns of collecting and interpreting learning analytics to improve student learning by combining observational and self-report data. The results present two models for predicting student academic performance which suggest that a combination of both observational and self-report data explains a significantly higher variation in student outcomes. The results offer a way into discussing the quality of interpretations of learning analytics and their usefulness for helping to improve the student experience of learning and also suggest a pathway for future research into this area.

Keywords

Learning analytics, Self-report data, Observation, Student approaches to learning

Introduction

Using learning analytics as a tool to improve student learning has caught the imagination and research effort of much of the higher education sector (Siemens, 2013). Amongst a number of applications, it notably has been used to improve student success (Arnold, Hall, Street, Lafayette, & Pistilli, 2012; Martin et al., 2013), to better understand the nature of social learning amongst university students (Buckingham Shum & Ferguson, 2012), to improve approaches to learning design (Mor, Ferguson, & Wasson, 2015), and to guide university education strategy (Rientes et al., 2016).

Accompanying this growing use of learning analytics, there is serious debate about the extent to which they are useful as a tool for improving student learning (Lodge & Lewis, 2012; Lundie, 2014). One debate is about the objectivity of learning analytics; some argue that learning analytics are an objective measure of student activity, but others suggest that without understanding student intent behind the analytics, we have a poor context in which to interpret what the numbers mean (Boyd & Crawford, 2012). Another debate is that learning analytics tell us what students are doing when they learn in an online environment. Doubters argue that they only tell us what buttons they are clicking (Scheffel, Drachsler, Stoyanov, & Specht, 2014). A further debate surrounds the value of very large data sets. Some argue that the more analytics you have about student learning experiences the better, while others argue that a careful selection of analytics must be made in relation to the population sample, otherwise the additional metrics might just create noise in interpreting their meaning. As some studies suggest, indiscriminate approaches to the use of large datasets could lead to unintended consequences in learning interventions (Boyd & Crawford, 2012; Greller & Drachsler, 2012). To remedy some of the perceived shortfalls of learning analytics, some authors argue that the learning analytics should occupy a middle space, somewhere between learning theory and computational measurement, to improve the potential of learning analytics to really address concerns of the quality of student learning (Suthers & Vebert, 2013). To achieve this, they recommend that additional analytic techqniues accompany learning analytic procedures from such fields as epistomology and education studies.

To investigate methodological approaches to address some of the perceived shortfalls of learning analytics, this study investigates the first year experience of undergraduate engineering students in a blended course in two stages. In the first stage, it records their learning events in the online environment and analyses and interprets them in the context of their learning outcomes (Pardo, Han, & Ellis, 2016). While illuminating, this analysis alone could be left open to some of the criticisms described above. In the second stage, methodological approaches from Student Approaches to Learning (Pintrich, 2004) are used and the students' response to closed ended questionnaires (Biggs, Kember, & Leung, 2001) about their experience of learning is investigated. The

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outcomes of this analysis, when complemented by stage 1, both elucidates why some students are relatively more successful than others in the course and provides evidence which suggests why this might be the case.

The purpose of this study is to contribute to the international debate on the value of learning analytics for the quality of the student learning experience and how combined methodological approaches using observational and self-report evidence can improve our understanding of qualitative variation in student learning. By drawing on both types of data from the same experience of learning, this study is designed to see to what extent a combined use of the observational and self-report data improves our ability to use learning analytics to understand why some students are more successful than others.

Prior research

Student approaches to learning in higher education

Student approaches to learning (Pintrich, 2004), henceforth SAL, has systematically investigated university student learning of student learning and quality of learning outcomes. This framework has investigated how qualitative variation in students' approaches to learning are closely related to prior experiences of learning, their perceptions of the learning context, student conceptions of learning and academic performance (e.g., Biggs & Tang, 2011; Marton & Säljö, 1976; Prosser & Trigwell; 1999; Ramsden, 2003). One of the important factors in learning processes is how students go about learning and whether their learning aims at rote memorization (i.e., surface approaches to learning) or their towards a meaningful understanding (i.e., deep approaches to learning) (Biggs & Tang, 2011). In one of the early seminal studies, Säljö (1979) reported an association between the qualitative differences in students approaches to learning and variations in students' learning outcomes. He found that students who adopted a deep approach in a reading task were more likely to perceive it as intended by the author than those who approached it at a more surface level. Since then, a large number of studies have consistently identified variations of deep and surface approaches to learning and confirmed their association with learning outcomes in a wide variety of disciplines (e.g., Hay, 2007; Lindblom-Ylänne & Lonka, 1998; Lizzio, Wilson, & Simons, 2002; Prosser & Millar, 1989; Rossum & Schenk, 1984; Trigwell & Prosser, 1991; Trigwell & Sleet, 1990; Tang, 1998).

In the SAL framework, the approaches to learning adopted by a student are not a personal trait. They are instead related to factors described above (Entwistle, McCune, & Hounsell, 2003). Similar results have been found in blended learning contexts. Students with a fragmented conception of learning are more likely to approach face-to-face and online learning at more of surface level. On the other hand, those students that conceive learning as cohesive and integrated are more likely to adopt deep approaches in face-to-face and online learning (e.g., Bliuc, Ellis, Goodyear, & Piggott, 2010; Ellis, Goodyear, Calvo, & Prosser, 2008).

Learning analytics in higher education

In the last decade, the capacity of educational technology to record student interactions has led to the emergence of research areas such as Learning Analytics and Educational Data Mining (Johnson, Smith, Willis, Levine, & Haywood, 2011). The field is substantial and important to consider as a whole. The following highlights some of the key issues raised by the field relevant to this study.

There is an increasing number of learning analytic software systems that aim to use the records of students' interactions to better understand their learning processes and environment (Baker & Siemens, 2014; Knight, Buckingham Shum, & Littleton, 2014; Lockyer, Heathcote, & Dawson, 2013). Learning analytic techniques use data mining techniques that process the rich data sets captured with technology to produce knowledge and improve the students' learning experience. These systems have focused on aspects such as detecting students at risk to increase retention rates (e.g., Arnold et al., 2012), advising students on their career options (e.g., Bramucci & Gaston, 2012), analyzing curriculum structures (Méndez et al., 2014), and predicting academic performance (e.g., Antunes, 2010; Essa & Ayad, 2012a; Essa & Ayad, 2012b; Romero & Ventura, 2013).

Some studies have observed that the effect of using data mining and learning analytic methods from a purely technological perspective may have severe limitations (Buckingham Shum & Crick, 2012). To address potential and realized limitations, they suggest that techno-centric techniques should be combined with the findings in fields such as epistemology, educational studies, and pedagogy in order to better understand the links between learning and learning analytics (e.g., Buckingham Shum & Crick, 2012; Suthers & Vebert, 2013). Such an approach can be referred to as *the middle space* of learning analytic research (Suthers & Vebert, 2013). Despite the identification of the benefits of this area of research, few studies can be located there.

One study that does begin to flesh out the middle space is a case study into university student learning in engineering (Pardo, Ellis, & Calvo, 2015). This study trialed the combination of instruments derived from SAL research and learning analytic techniques. In the study, several online tools recorded the interactions of students with various digital resources. Additionally, students' conceptions and approaches to learning to three types of online learning activities (problem solving sequence, videos, and feedback), were collected through a qualitative survey. The mid-term examination results were used as students' learning outcomes. The two sources of data were analyzed to examine their relationship academic results. The results showed that the frequency of interactions with three of the online learning tools were able to explain 25.98% of the variance in the mid-term exam results. Furthermore, deep approaches to problem sequences were related to higher marks, and surface approaches related to lower marks. The interpretation of results from both models translated into a set of actions to change the learning design and improve its quality.

This study contributes to the international debate on learning analytics and the benefits of combining methodologies to improve its usefulness. It seeks to confirm if the combination of SAL research and learning analytic techniques helps to identify meaningful qualitative differences in how students learned in an undergraduate engineering course, and to explore of a combination of the techniques improvise the quality of evidence for interpreting and predicting student learning success.

The main research question guiding the study is;
To what extent does the combination of learning analytic techniques and student approaches to learning methodologies improve our understanding of student learning success?

Method

Participants

The data for the study was collected from 291 undergraduate students enrolled in a first year engineering course in a large metropolitan Australian research-intensive university. Approximately 50% of the students agreed to participate in the study voluntarily, resulting in a sample of 145 students.

The learning context

The course is scheduled for the first year students in a Bachelor of Engineering Degree and has the following outcomes: (1) to design, build, configure, program, and test an electronic system for a specific engineering problem observing common professional practice; (2) to understand theoretical knowledge of how computers work, including concepts from the digital logic level to basic programming constructs; (3) to write reports about the design process and the results; and (4) to engage in team-based design work and creative tasks in order to solve an engineering problem. Apart from acquiring specific knowledge and skills in the content area, the course is also organized to build students' generic attributes such as independent inquiry skills, communication skills, information literacy, intellectual autonomy, and the capacity to understand ethical, social, and professional issues.

The course adopts a typical blended learning approach during 13 weeks comprising both face-to-face and online work. The face-to-face component includes one weekly two-hour lecture, one weekly two-hour tutorial, and one weekly three-hour laboratory session. The online component is hosted in a custom-designed online environment integrated with a University Learning Management System (Blackboard.com). The online activities required students to interact weekly with digital material containing subject matter, visualize videos, interact with formative assessment elements, and submit summative assessments. Additionally, the system offered a dashboard with feedback about the individual participation rates in online activities.

Instruments

The data used in the study consisted of the student answers to a self-reported questionnaire about their learning experience, their use of the online learning tools as recorded by their online learning environment, and the academic performance as provided by the final course mark. The choice of these data sets enabled the research design to consider the extent to which using both self-report data from the surveys and observational data from the learning analytics of the online learning environment informed their combined interpretation. A detailed description of each instrument is provided in the following sections.

The Revised Study Process Questionnaire

The Revised Study Process Questionnaire (R-SPQ) was used to collect the students' self-report data (Biggs et al., 2001). The R-SPQ is a 20-item 5-point Likert questionnaire designed to evaluate the learning approaches of students. The theoretical context for its design is the Student Approaches to Learning framework (Biggs, 1987a; Biggs, 1987b; Biggs, 2011). In this study, the factor analysis indicated that the two-factor solution, deep and surface approach, fitted the empirical data, and the values of Cronbach's alpha showed good reliability for both scales. Table 1 presents the outcomes of the analysis.

Table 1. The results of EFA for the R-SPQ

Scales	Description of items	Rotated factor loadings	
Surface approaches to study (.86)	3. My aim is to pass the course while doing as little work as possible.	.73	
	4. I only study seriously what's given out in class or in the course outlines.	.72	
	7. I do not find my course very interesting so I keep my work to the minimum.	.77	
	12. I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.	.69	
	15. I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics.	.82	
	16. I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined.	.60	
	19. I see no point in learning material which is not likely to be in the examination.	.75	
	20. I find the best way to pass examinations is to try to remember answers to likely questions.	.61	
Deep approaches to study (.82)	1. I find that at times studying gives me a feeling of deep personal satisfaction.		.68
	2. I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied.		.68
	6. I find most new topics interesting and often spend extra time trying to obtain more information about them.		.57
	9. I find that studying academic topics can at times be as exciting as a good novel or movie.		.65
	10. I test myself on important topics until I understand them completely.		.75
	13. I work hard at my studies because I find the material interesting.		.75
	14. I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.		.72
	17. I come to most classes with questions in mind that I want answering.		.55

Events recorded in the online environment

As students engaged in this first year engineering course, they were expected to interact with a number of online activities which were made up of individual events (Pardo et al., 2015). The following events were recorded in the online environment:

- Duration: student time spent working on an activity.

- Dashboard: student views of a dashboard with information about the engagement with the weekly activities
- Col-Exp: student views of various sections of the course notes
- Resource: student views of any page of the course notes
- Video: interaction with a video (video is loaded, played, paused or finished)
- MCQ: any interaction with a multiple-choice question embedded in the course notes
- VMCQ: any interaction with multiple-choice questions placed next to a video
- Exercise: student answers to summative assessment exercises.

For each type of event and student, eight variables were calculated with the accumulated number of events over the semester. The descriptive statistics of these variables are shown in **Error! Reference source not found.**.

Table 2. Descriptive statistics of frequencies of online learning events

Variables	Min	Max	Mean	*SD*
Duration	0	93	11.52	17.45
Dashboard	0	233	31.10	41.84
Col-Exp	59	1182	421.97	234.36
Resource	138	2492	818.07	443.00
Video	0	2890	338.59	395.48
MCQ	0	3054	233.01	300.50
VMCQ	0	5598	191.05	471.17
Exercise	353	9957	2723.49	1419.81

Notes. Col-Exp = collapse and expand, MCQ = multiple choice questions, VMCQ = multiple-choice questions embedded in videos.

The frequencies show quite large difference between event types. For example, some variables have a range of values that start at zero (Duration, Dashboard, Video, MCQ, and VMCQ) whereas the minimum value for the Exercise variable is 353. The same effect can be observed with the standard deviations (*SD*s) reflecting the distinct use students make of the online tools. Due to these large differences, all variables were standardized (mean equal to 0 and a *SD* of 1) to facilitate comparisons among them.

Academic performance

The information about academic performance was collected using the final course mark. The final mark was calculated by aggregating six types of assessment tasks: exercises to prepare the lecture (10%), exercises to prepare the tutorial (10%), one written report about a laboratory session (5%), a written report, presentation and demonstration of a collaborative project (15%), a midterm exam (20%) and the final exam (40%). The potential value range for this variable is 0 to 100, but the marks for the participants ranged from 20 to 98.50, with a mean of 65.50, and a *SD* of 16.12. The large *SD* of this variable indicates a wide spread of final marks in the course. As in the case of the previous variables and to facilitate interpretation of the interactions among variables, the final mark was also transformed into a *z*-score with mean 0 and a *SD* of 1.

Data collection procedure

Prior to the data collection, the study was reviewed and approved by the institutional ethics committee. Students were informed that their participation in the study was voluntary, about the use of the online environment to monitor their interaction, that the information collected would be anonymized, and used only for research purpose. Written consent was obtained to use this data together with their course results. The self-report data from the R-SPQ questionnaire was collected in class towards the end of the semester so that students could reflect on the learning processes of the whole course. The data from the online environment was collected throughout the entire course.

Data analysis

The data analysis was performed in three stages; identifying qualitative differences in the student approaches to learning (deep and surface variables), using correlation and cluster analysis to identify the strength of associations amongst the approach variables, the online learning analytics of the events and academic achievement; and finally hierarchical regression analysis to identify which variables most explained variance in the student experience.

In the first stage, a series of Exploratory Factor Analysis (EFA) using Principal Component procedure followed by varimax rotation were used to examine the factor structure of the answers to R-SPQ (self-report data). A number of criteria were used to determine the number of scales and corresponding items. The scree plot was used to determine the possible numbers of solutions for the scales. We deleted those items whose coefficients were < .40 within a factor, and those with high multiple coefficients loaded across factors (Field, 2013). The internal consistency of the retained scales was verified using Cronbach's alpha reliability analyses (alphas above .70).

In the second stage, we investigated the relationship between the three data sources; the self-report data, the data collected from the students' engagement with the eight learning events in the online environment, and their academic performance data as measured by their course mark. Two analyses were used to explore these relations in order to increase the overall integrity of the approach (Prosser, Ramsden, Trigwell, & Martin, 2003). First, we used correlation analysis to show the interrelationship between pairs of variables. Second, we used a hierarchical cluster analysis using the self-report data and academic performance to identify subgroups of students with similar learning experiences within the population sample. The cluster membership information derived from the previous step was used to perform one-way ANOVA to see whether students in different clusters differ from each other with respect to their academic performance.

In the third stage of analysis, we used hierarchical multiple regression analysis to examine the relation between the combined self-report and learning event data and the course marks of the students. The regression model was built with those variables for which a significant correlation with academic outcomes was established by bivariate correlation. The dependent variable of the model was the students' course mark. The independent variables were: the surface approaches to study (from the self-report data), the number of Dashboard learning events, number of Collapse-and-Expand events which indicate student views of different areas of the online environment, number of Resource events which are student views of the course notes, number of Multiple Choice Question events, and number of Exercise events involving summative assessment exercises. All these variables are from the online environment.

Two hierarchical multiple regression models were obtained for comparison purposes, one with self-report data only and a second which included the observational data. The first one was produced considering only the surface approaches to study from the self-report data as there is an established body of research indicating its suitability to predict learning outcomes (e.g., Trigwell, Ashwin, & Millan, 2013; Trigwell, Ellis, & Han, 2012). The second regression model was calculated by adding the five variables obtained from the online environment data. The two models were compared using Cohen's f^2 (Cohen, 1992).

Results

Exploratory factor analysis and reliability of the scale

The results of the first stage of analysis confirm the reliability and validity of the approach scales used in all the analyses. Sixteen out of the twenty items were retained for the two-factor solution with eight items in each factor, shown in Table 1. The two factors are the *deep* and *surface* approaches to study. The Eigen-values of the surface and deep factors were 4.26 and 3.69, explaining 26.59 % and 23.09% of the total variance respectively. The reliability analyses showed that the surface and deep approaches to study scales had Cronbach's alpha of .86 and .82, confirming their reliability.

Correlation and cluster analyses

Stage 2 results include the correlation and cluster analyses. The correlation results identify the strength of associations amongst the variables and the cluster analyses identify the distribution of those associations amongst sub-groups in the population sample who report similar experiences. The correlations between the deep and surface approaches to study (derived from the self-report data), the number of interaction with online tools (observational data), and their academic performance are presented in **Error! Reference source not found.**. The deep approach to study does not show a statistically significant relation to academic performance. However, it has a weak positive correlation with the number of Duration events (r = .17, p < .05), the number of Multiple

Choice Question events (r = .18, p < .05), and the number of Exercise events was (r = .21, p < .05). The associations between the surface approach to study and different types of online events were not significant, but we found that the surface approach to study significantly and negatively correlated with the final course mark (r = -.31, p < .01). The results also show that the final marks have strong and significant correlations with almost all the event counts in the online environment. These positive correlations suggest that the more frequently a student engaged with the online environment the higher final course marks they tended to obtain.

Table 3. Correlation analysis

	Deep	Surface	Course mark
Deep approaches to study	---	---	---
Surface approaches to study	-.08	---	---
Course mark	.05	-.31**	---
Duration	.17*	-.12	.11
Dashboard	.08	-.10	.24**
Col-Exp	.12	.08	.35**
Resource	.14	.04	.43**
Video	.11	.01	.14
MCQ	.18*	.07	.28**
VMCQ	.12	-.14	.14
Exercise	.21*	-.10	.38**

Notes. **p < .01; *p < .05. Col-Exp = collapse and expand, MCQ = multiple choice questions, VMCQ = multiple choice questions embedded in videos.

A hierarchical cluster analysis using Ward's method was conducted using the two factors of the students' learning experience (self-report data) and academic performance to identify and characterize subgroups of students with similar features. Based on the value of the squared Euclidean distance between clusters, a two-cluster solution was obtained. The results are shown in **Error! Reference source not found.**. The second and third columns from the right show mean and SD for the 11 variables. The three columns on the left of the table show the results of ANOVA.

Table 4. Summary statistics of the two-cluster solution

Variables	Deep cluster (43) Mean (*SD*)	Surface cluster (102) Mean (*SD*)	*F*	*p*	η^2
Deep	0.93 (0.73)	-0.39 (0.83)	82.11	.00	.37
Surface	-0.52 (1.18)	0.22 (0.82)	18.74	.00	.12
CM	0.53 (0.99)	-0.23 (0.82)	19.77	.00	.12
Duration	0.20 (1.09)	-0.08 (0.95)	2.42	.12	.02
Dashboard view	0.32 (1.20)	-0.14 (0.87)	6.69	.01	.05
Col-Exp	0.27 (1.02)	-0.11 (0.97)	4.46	.04	.03
Resource	0.33 (1.08)	-0.14 (0.93)	7.10	.01	.05
Video	0.26 (1.39)	-0.11 (0.76)	4.19	.04	.03
MCQ	0.61 (1.54)	-0.15 (0.35)	7.57	.01	.05
VMCQ	0.27 (1.77)	-0.11 (0.28)	4.72	.04	.03
Exercise	0.44 (1.25)	-0.18 (0.81)	12.58	.00	.08

Notes. Deep = deep approaches to study, Surface = surface approaches to study, CM = course mark, Col-Exp = collapse and expand, MCQ = multiple choice questions, VMCQ = multiple-choice questions in videos.

Table 4 shows the students were classified into two clusters: 43 students were assigned to the "Deep" cluster and 102 students were assigned to the "Surface" cluster. The results of one-way ANOVA confirmed our hypothesis that the self-report data and the academic performance had statistically significant contrasts between the two clusters of students with values of $F(1, 144) = 82.11$, $p < .01$, $\eta^2 = .37$, and $F(1, 144) = 18.74$, $p < .01$, $\eta^2 = .12$, for the deep and surface approaches respectively. Statistically significant differences were also found between the two clusters on all variables in our observational data although with small values of Eta squared (effect size).

The mean and *SD* of the self-report variables in the resulting clusters are consistent with their characterization. The deep cluster has a relatively higher rating for the deep approach (mean = 0.93) and relatively lower rating for the surface approach (mean = -0.52), and the situation is reversed for the surface cluster (mean = -0.39 and mean = 0.22 for the deep and surface approach respectively). Furthermore, the variables derived from the observational data have systematically higher means for the deep cluster than the surface cluster. Deep learners engaged more frequently with the various online resources than those in the surface cluster. The final mark variable also shows a pattern consistent with the self-report and observational data. There is a significant difference between the score of the students in the deep cluster (mean = 0.53) and the surface cluster (mean = -0.23). The main conclusion from this result is that both self-report and observational variables are important when identifying the relations with the overall academic performance.

Multiple regression analysis

The results of the third stage of analyses compare two linear models of multiple regression to see the effect of combining the self-report and observational variables that had significant correlation with the final score (see Table 5).

Table 5. Results of multiple regression analysis

Variables	*B*	*SE B*	*β*	*t*	Adjusted R^2	*p*	f^2
Model 1					.09	.00	.10
Surface	-0.31	.08	$-.31^{**}$	-3.84			
Model 2					.34	.00	.52
Surface	-0.29	.07	$-.29^{**}$	-4.16			
Dashboard	0.03	.08	.03	0.31		.75	
Col-Exp	-0.34	.19	-.34	-1.84		.07	
Resource	0.88	.21	$.88^{**}$	4.28		.00	
MCQ	0.29	.12	$.29^{*}$	2.40		.02	
Exercise	-0.26	.18	-.26	-1.40		.16	

Notes. $^{**}p < .01$; $^{*}p < .05$. Surface = surface approaches to study, Col-Exp = collapse and expand, MCQ = multiple choice questions.

Before performing the multiple regression analysis, a series of tests were conducted to examine the assumptions that may affect its reliability. The initial analysis of standard residuals confirmed the absence of outliers (Std. Residual Min = -2.15, Std. Residual Max = 2.54). The tolerance values were above 0.10 for all the variables confirming the absence of multicolinearity. Finally, the Durbin-Watson statistic verified the absence of autocorrelation (Durbin-Watson = 2.08).

Model 1 included only the self-reported surface approach to learning whereas model 2 was obtained with the self-report variable and the five observational variables which have significant correlations with the final score. The results for both models are shown in**Error! Reference source not found.**. Model one reveals that the surface approach to study contributed significantly to the regression model: $F(1, 143) = 14.72$, $p < .01$, $f^2 = .10$. However, the model accounted for only 9% of the variation in the final marks. Model 2 also returned a significant result: $F(5,138) = 10.76$, $p < .01$, $f^2 = .52$, however in this case, the model accounts for 34% of the variation. This means an additional 25% of variation in students' academic performance is explained when the observational variables are included in the model. The increase in R^2 also means that the prediction intervals obtained with the model using all six variables (self-report and observational) will be significantly smaller.

A more detailed analysis of this result shows that three independent variables significantly predicted students' academic performance: the surface approach to study ($\beta = -.29$, $p < .01$), the number of times an online resource was accessed ($\beta = .88$, $p < .01$), and the number of multiple-choice questions answered ($\beta = .29$, $p < .05$). The remaining variables, Dashboard, Col-Exp, and Exercises did not make significant predictions to the final course marks. These results show that the combination of self-report and observational data provides a better predictive model of students' learning outcomes.

Discussion

This study combined research methodologies from SAL research and learning analytics to examine the relationship between students' learning experience, their interactions with online learning tools, and their learning outcomes. To examine the relationship among variables, we conducted correlation analysis, cluster analysis, and multiple regression. The first one looked into the pairwise relationship between variables. The second identified sub-groups of students within the population sample which reported qualitatively different experiences of learning. The third analysis used hierarchical regression analysis and showed that both the learning experience reported by students and the behavior recorded while interacting in an online environment significantly explained the final course marks. Together, the two sources of the data could predict approximately one third of the variance, with the interactions of online learning tools accounting for more than double of the variance (25%) than students' reporting their learning approaches (9%).

Consistent with previous research in SAL, our results confirmed that students who adopted a surface approach to study tended to associate with poorer performance in the same course. Our study showed how students who reported using a deep approach to learning also tended to interact more frequently with the online environment. We also found a positive relation between the frequency of student interactions with the online learning tools and the final course mark. Out of the eight tools deployed for the course, five of them had positive relationship with the final course marks. Our results were consistent with those presented by Romero-Zaldívar, Pardo, Burgos, and Kloos (2012) in which interaction counts of a number of online tools recorded by a virtual appliance were positively related to students' final grades among second year engineering students (correlation ranged between .07 and .16). However, the study described in this paper shows stronger associations (correlation ranged between .24 to .43).

The relationship between students' approach to learning, interaction with online tools, and final course marks were further substantiated using cluster analysis. Students in the deep cluster reported using a deep rather than a surface approach to learning, and obtained relatively better course marks. Significantly, this cluster was observed to have a relatively more intense interaction with the online learning events. These were found to be significantly more frequent among students in the deep cluster than those in the surface cluster. These results support the claim that the observed student behavior is consistent with what they reported in the R-SPQ questionnaire. While the study described by Pardo et al. (2015) found qualitatively differences on how students approached different online learning events, this study suggests that the amount of interaction online can also contribute to students' achievement in a course. We speculate that both the quantity and the quality of using online tools helps to explain variations in the learning outcomes, and the nature of these associations needs to be empirically examined in increasingly fined-grained analysis in future studies.

The results of the hierarchical regression analysis indicated that two of the five learning tools, were significant predictors of academic performance when combined with the surface approach to learning. We find this to be a key outcome of the study and it provides a response to the research question which motivated the study. It highlights the value of combining the different types of data sources (self-report and observational) when assessing the learning experience of university students in order to provide evidence for improving outcomes.

The results offer some key theoretical implications. A key aspect of student learning research theory is the close association between the quality of approaches to learning and relatively higher academic achievement. The results of this study suggest that this is the case, however not just with the approaches and academic achievement, but also with the students' use of the learning technologies themselves. This result highlights the relational contribution of "material" elements of the experience to learning outcomes (Fenwick, 2015) and offers an important area for future investigations and theory building about the contributions of non-human elements in learning. Material elements of the student experience are not typically investigated in student learning research. This outcome calls for further work into the role of material elements in the student experience, particularly the interplay between approaches and learning technologies for example.

Conclusions

The study described in this paper is an initial effort to combine elements of SAL theory and learning analytics in an investigation into a blended university course. The results have revealed how the insight and understanding of the student learning experience can be improved by combining instruments that capture self-reported data, and observational data. While each data source can be used separately, this study has offered a quantified improvement through their combined use and provides one way of fleshing out the middle space between learning and analytics (Suthers & Vebert, 2013).

Various interesting avenues have emerged in this study that warrant further exploration. While our study adopted the theoretical framework derived from SAL, it is possible to explore the integration of other theories in educational psychology and learning analytics. For instance, we can examine the relationship between students' self-efficacy, motivation, and experienced emotions, and their behavior in a learning environment. Second, the variables in the study derived from the observational data were summarized as event counts. A more detailed type of indicator could be derived from this data if combined with descriptions of students' conceptions of using different online tools. Finally, experiences of learning and teaching are highly complex interactions shaped by a large number of interdependent factors. The results of this study offer sufficient promise to continue to investigate the attenuated approaches to the collection and analysis of learning analytics so that researchers and the stakeholders of such research receive a stronger context in which to evaluate the meaning of the results.

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