Variations in the coherence and engagement in students' experience of blended learning

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We report a study which examines coherence of engagement of 344 first year engineering students' blended learning experience. Using self-report and observational data sources, we demonstrate that student perceptions of the blended learning environment, academic learning outcomes, and engagement with the online learning activities are logically related at the variable level as shown by correlation analyses; and at the level of student groupings of similar learning experience and behaviors, as revealed by cluster, ANOVA, and 2 x 2 contingency analyses. Using self-report data, we found that when students perceived the learning activities in the f2f and online environments were integrated, they were more likely to be engaged with the online learning and to perform relatively higher on the assessment tasks than students who perceived disintegration between f2f and online learning. Using the observational data, students who were more engaged with the online learning tended to perceive that the online learning was well integrated with the f2f learning, that the online contributions were valuable for the whole learning experience, and achieved relatively higher than less engaged students. A 2 x 2 contingency table revealed a logical relationship between the groupings of students based on the self-report and observational data: moderate and positive association was found between students with coherent perceptions and more engagement; and between students with fragmented perceptions and less engagement. The use of multiple data sources and methods enabled triangulation, strengthened analysis power, and offered a more comprehensive picture of students' blended learning experience.

Introduction

The last decade has witnessed the rapid development of learning analytic methods and tools in order to monitor, trace, and record students' learning behaviors (Baker & Seimens, 2014; Knight, Buckingham Shum, & Littleton, 2014; Lockyer, Heathcote, & Dawson, 2013). With the assistance of different data mining techniques, which use algorithms to derive knowledge and insight from log and trace data held in online learning systems, educational researchers and teachers use the results to uncover students' learning patterns in order to improve students' learning experience and to facilitate teaching (Antunes, 2010; Essa & Ayad, 2012 a, b; Romero, López, Luna, & Ventura, 2013). One risk of fully rely on learning analytics and educational data mining is that the analyses and identification of learning patterns is primarily based on empiricism without being theoretically informed (Long & Siemens, 2011). This can result in reduced insight into the patterns of learning; and limits their use to locate problems in learning, to offer ideas for pedagogy reform, and to provide guidance for better design of learning environments (Shum & Crick, 2012).

Not everyone agrees with the risks of atheoretical approaches to educational data mining. Some researchers suggest that the analyses and advancements of learning analytics as a matter of empiricism should be used to shed light on learning theories. Using observational data of actual use by students of online learning systems, such methods are sometimes referred to as the bottom-up approaches (Berland, Martin, Benton, Patrick Smiths, & Davis, 2013, Chen, 2015). In contrast, other researchers argue that theories from educational psychology, curriculum and pedagogy studies, educational assessment, or sociology in education should be explicitly adopted in the research design to guide the approach to educational data mining in order for learning analytics to be useful for decision-making about learning and teaching issues (Knight et al., 2014). Using self-report data from questionnaire completed by students, these methods are sometimes referred to as top-down approaches (Suthers & Verbert, 2013). In this paper, we present a study which discusses how top-down and bottom-up approaches are combined to reveal variations in the coherence and engagement in an experience of blended learning in a first year university engineering course.

Background

Relational student learning research

Relational student learning research seeks to demonstrate qualitative variations in students' learning outcomes and identify variables which explain differences in their academic achievement. Studies have shown that a number of interrelated factors, including the departmental factors, students' prior learning experience, their conceptions of learning the subject, their approaches to study, and their perceptions of teaching and learning, are closely related to the quality of student learning (Asikainen, Parpala, Lindblom-Ylänne, Vanthournout, & Coertjens, 2014; Edmunds & Richardson, 2009; Lonka, Olkinuora, & Mäkinen, 2004; Prosser & Trigwell, 1999). Past research has found that students' qualitative differences in learning outcomes relate to these variables across many different disciplines and cultures (Dolmans, Loyens, Marcq, & Gijbels, 2016; Ellis & Goodyear, 2013; Entwistle, 2009)

Relational student learning research has identified that student perception variables, such as clear goals and standards in teaching, appropriate assessment, and appropriate workload play important roles in students' learning experience (Ramsden, 1991, Richardson, 1994; Wilson, Lizzio, & Ramsden, 1997). Studies report that positive perceptions (that teaching is of a high quality, that assessment is suitable for the course, and that the course workload is appropriate), are related to cohesive conceptions of and deep approaches to learning, and relatively higher levels of academic achievement. In contrast, negative perceptions (unclear goals and low teaching quality, and inappropriate assessment and workload) are associated with fragmented conceptions of learning, surface approaches to study, and poorer academic performance (Ginns, Prosser, & Barrie, 2007; Lizzio, Wilson, & Simons, 2002; Wilson & Fowler, 2005).

Learning analytics research

In the last couple of decades, the advancement in learning analytic software systems and data mining techniques have been captured observational data of student use of the online environments with a view to understanding their learning processes and facilitate design of learning environment (Baker & Siemens, 2014; Martin et al., 2013). The rich and 'big data' sets captured with learning analytic technology have been used for many purposes. They have been used to track students' retention rate (Arnold, Hall, Street, Lafayette, & Pistilli, 2012), in providing professional advice on students' future career plans (Bramucci & Caston, 2012), in supporting students' collaborative learning (Kaendler, Wiedmann, Rummel, & Spada, 2015), in identifying learning patterns and strategies (Chen, Resendes, Chai, & Hong, 2017), in detecting students' affect (Ocumpaugh, Baker, Gowda, Heffernan, & Heffernan, 2014), and in predicting academic success (Antunes, 2010; Romero et al., 2013). Despite the usefulness of big data, researchers point out the danger of relying fully on learning analytics and advise combining educational theories and data mining techniques to inform research design, methodologies and interpretation (Buckingham Shum & Crick, 2012; Suthers & Vebert, 2013).

In this study, we use self-report data which assess students' perceptions of the blended learning environment as part of students' learning experience on the one hand, and the extent of students' engagement with online learning activities as revealed by learning analytics on the other. Using a top-down approach, we examined to what extent variations in students' learning experience are related to levels of engagement with online learning sessions. Using a bottom-up approach, we investigated how levels of engagement are related to students' qualitatively different learning experience. We then consider what the combined perspectives offer in terms of insights into learning experience.

Method

Participants and the research context

The research was conducted with 334 first year engineering undergraduates in one core semester-long course. According to the procedures stipulated by the university ethics committee, all the students were invited to participate in the research on a voluntary basis and we explained ways to ensure the anonymity of their identity. The course had four major teaching aims: (1) to provide students with a solid foundation on the concepts of computer architecture and digital logic design; (2) to equip students with engineering communicative abilities to accurately and concisely present specific information on issues related to design; (3) to familiarize students with professional and ethical conducts and practice to meet standards when working with hardware and software; and (4) to enable students to experience team-based design and cooperation in solving engineering problems.

The course is designed as a blended learning experience with a two-hour lecture, a two-hour tutorials, and a three-hour laboratory sessions each week; and a range of online learning activities and resources, including compulsory and supplementary readings in pdf format, URL links, and videos related to the course contents; course notes; problem solving sequences; multiple choice questions; and multiple choice questions embedded with videos. The students were expected to use the online activities and resources as preparation and follow up for each of their face-to-face (f2f) sessions. The online learning activities were hosted in a bespoke learning management system (LMS), which were able to capture the kinds of activities a student is engaged with, the starting and ending time for each type of activities, and the break time between the activities when a student logged into the LMS. The learning analytics are able to arrange student engagement with the activities in a sequence of events in a format which could be directly exported and downloaded for analyses.

Instruments

We collected information on students' perceptions of blended learning environment (i.e., self-report data), students' learning outcomes for the course, and the online learning sessions they were engaged in throughout the semester (i.e., observational data). Each of these is explained in turn.

Perceptions of blended learning environment.
A questionnaire was used to evaluate students' perceptions of blended learning environment in this course. The questionnaire was constructed using the literature of the relational research on student learning (Ramsden, 1991; Ellis, Ginns, & Piggott, 2007). The questionnaire had three scales: (1) perceptions of integration between f2f and online learning (7 items, α = .86; A sample item is: "I found it helpful to follow up ideas from class in the online environment in this course"); (2) perceptions of appropriateness of the online workload (6 items, α = .77; "A better balance between the online activities and the other tasks would help my workload" is an example item); and (3) perceptions of usefulness of the online contributions (6 items, α = .87; A sample item is: "Online contributions from others in this course prompted me to reflect more on the ideas in this course"). All the items in the questionnaire were on a 5-point Likert scale, with 1 representing strongly disagree, and 5 indicating strongly agree.

Learning outcomes. The learning outcomes were measured using the total mark for the course, which was made up of six different assessment tasks: (1) preparatory exercises for lectures (10%), (2) preparatory exercises for tutorials (10%), (3) laboratory performance (5%), (4) a report of a research project (15%), (5) the midterm examination (20%), and the final examination (40%). The total course mark was the aggregated score of the six tasks out of 100 points.

Engagement with online learning sessions. Students' engagement with online learning sessions was extracted using the criterion that a sequence of events comprised one or more online learning activities which had lags less than 30 minutes between activities. Using this criterion, the number of online learning sessions per week for each individual student was derived for 12 consecutive weeks. The 12-week online learning sessions were then averaged and used as indicators of students' engagement with online learning sessions.

Procedure

We distributed the questionnaire towards the end of the semester so that the students could reflect on their whole learning experience of the course. The questionnaire took approximately 10 minutes to complete. With the consent from the students, we retrieved the data representing their online learning sessions from the LMS and obtained the total marks upon completion of the course.

Data analysis

To investigate how students' learning experience and engagement with online learning sessions are related at the level of variables, we conducted correlation analyses. Then in order to investigate the distribution of the associations amongst the variables across the population sample, we used cluster analysis and Analysis of Variance (ANOVA) in two stages. In the first stage, we classified students based on their perceptions of learning environment and the learning outcomes of the course, and compared students' engagement of online learning sessions by their cluster membership using ANOVA. In this stage, the groupings of the students were derived from the relational perspectives (i.e., top-down approach), and the analyses were able to show how students' learning experience was closely related to their engagement with online learning sessions.

Subsequently, in the second stage, we grouped students using the *Mean (M)* scores of the engagement with numbers of online learning sessions, and conducted ANOVA to examine if students differed on the perceptions of blended learning environment and the learning outcomes by levels of engagement with online learning sessions. In the second stage, the groupings of the students came from the learning analytics data (i.e., bottom-up approach), and the analyses reflected how students' engagement with online learning sessions affected their perceptions and learning outcomes. Lastly, to examine how the grouping variable from the top-down approach is associated with the grouping variable from the bottom-up approach, we conducted a 2 x 2 contingency table. This analysis allowed us to see whether the top-down and the bottom-up approaches of groupings converges, that is the strength of association between variations in students' learning experience (i.e., coherent or fragmented learning experience) is associated with qualitatively different levels of online engagement (i.e., more or less engaged as reflected by *M* numbers of online learning sessions).

Results and discussion

Descriptive statistics

The descriptive statistics of the three perception scales, the learning outcomes, and engagement with online learning sessions, including means (*M*s), standard deviations (*SDs*), minimum (Min.) and maximum (Max.) values the variables are displayed in Table 1.

Table 1: Descriptive statistics

Variables	*M*	*SD*	Min.	Max.
Perceptions				
Integration of f2f and online learning activities	2.87	0.76	1.00	5.00
Appropriateness of online workload	3.74	0.72	1.00	5.00
Usefulness of online contributions	3.18	0.88	1.00	5.00
Academic achievement				
Course marks	67.28	14.43	25.00	98.00
Observational data				
Online learning sessions	3.25	0.71	1.58	5.00

Results at the variable level

The results of correlation analyses regarding the relationship between the learning experience and engagement with online learning sessions are presented in Table 2.

The correlation results in Table 2 shows that the students' perceptions of the integration of f2f and online learning was positively and weakly related to perceptions of the appropriateness of online workload (r = .15, p < .01) and the course marks (r = .14, p < .01). It had positive and moderate association with the perceptions of usefulness of online contributions (r = .43, p < .01). Students' perceptions of online workload was negatively and weakly related to the perceptions of online contributions (r = -.11, p < .05), but it had positive and weak relation with the course marks (r = .20, p < .01). Engagement with online learning sessions was positively and weakly related to the perceptions of usefulness of online contributions (r = .18, p < .01) and it was also positively and moderately correlated with the course marks (r = .51, p < .01). These correlation results show logic pairwise relations amongst variables of students' perceptions, course marks, and the engagement with online learning sessions: the positive appraisal of values of online contributions in the course is related to higher achievement in the course, and more engaged with online learning on average throughout the course.

Table 2: Results of correlation analyses

Variables	Appropriateness of online workload	Usefulness of online contributions	Course marks	Online learning sessions
Integration of f2f and online learning	$.15^{**}$	$.43^{**}$	$.14^{**}$	.10
Appropriateness of online workload	---	$-.11^{*}$	$.20^{**}$	-.01
Usefulness of online contributions	---	---	-.01	$.18^{**}$
Course marks	---	---	---	$.51^{**}$
Online learning sessions	---	---	---	---

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

Results of the top-down approach

Table 3 presents the cluster analysis using the students' learning experience variables (i.e., the three perceptions scales and the learning outcomes) and the ANOVA, which examined the contrast of these learning experience variables as well as the learning analytic data (i.e., engagement with online learning sessions) using the cluster membership derived from the learning experience variables. To facilitate interpretation, we converted all the raw scores into z-scores with a M of 0 and a SD of 1 in the analyses.

Table 3: ANOVA results of based on the learning experience variables

Variables	Coherent experience (N = 226)		Fragmented experience (N = 108)		F	p	η^2
	M	SD	M	SD			
			Perceptions				
Integration of f2f and online learning	0.44	0.70	-0.95	0.89	240.96	**.00**	.42
Appropriateness of online workload	0.13	0.96	-0.23	1.05	9.63	**.00**	.03
Usefulness of online contributions	0.29	0.92	-0.61	0.88	72.86	**.00**	.18
			Academic achievement				
Course marks	0.31	0.93	-0.64	0.83	83.29	**.00**	.20
			Observational data				
Online learning sessions	0.16	0.95	-0.34	1.03	20.01	**.00**	.06

Using the increasing value of the squared Euclidean distance between clusters, we retained a two-cluster solution. Table 3 shows that of 334 students, 226 students were classified as students who reported a coherent learning experience, consisting of positive perceptions of the blended learning environment and relatively higher academic achievement in the course;

whereas the rest of 108 students were those who had a fragmented learning experience with negative perceptions of the blended learning environment and relatively lower academic achievement. As shown by the ANOVA results, all the differences on the perceptions scales (integration between f2f and online learning: F (1, 333) = 240.96, p < .01, η^2 = .42; appropriateness of online workload: F (1, 333) = 9.63, p < .01, η^2 = .03, and usefulness of online contributions: F (1, 333) = 72.86, p < .01, η^2 = .18) and the course marks (F (1, 333) = 83.29, p < .01, η^2 = .20) between the two clusters of students were statistically significant. The students with coherent learning experience had higher ratings on the perceptions of integration between f2f and online learning (M = 0.44, SD = 0.70); felt the online workload was more appropriate (M = 0.13, SD = 0.96); considered the online contributions being more useful (M = 0.29, SD = 0.92), and performed relatively academically higher in the course (M = 0.31, SD = 0.93); than those with fragmented learning experience, who had lower ratings on all the perceptions scales (integration between f2f and online learning: M = -0.95, SD = 0.89; appropriateness of online workload: M = -0.23, SD = 1.95; and usefulness of online contributions: M = -0.61, SD = 0.88), and achieved relatively poorly (M = -0.64, SD = 0.83). On the basis of this cluster membership, the ANOVA also identified statistically difference of numbers of online learning sessions between the two clusters (F (1, 333) = 20.01, p < .01, η^2 = .06). It revealed that the students who reported a coherent learning experience were more engaged with online learning activities (M = 0.16, SD = 0.95) than their counterparts who reported a fragmented learning experience in the course (M = -0.34, SD = 1.03).

From the top-down approach, we found that at the levels of groups of students identified by maximising their similar learning experience, their learning experience were related to the level of engagement they displayed with the online learning sessions. Students who perceived that the f2f and online learning environments were integrated and valued the online learning in the courses, were more engaged with the online activities. Those students also tended to achieve relatively higher in academic assessment tasks. In contrast, students in the cluster of the fragmented blended learning experience did not perceive a connection between the f2f and online activities, did not appraise the online postings contributed by their peer classmates, considered the online learning workload was heavy, and obtained relatively lower course marks. Those students with the fragmented learning experience also tended to be relatively less engaged with using online learning activities.

Results of the bottom-up approach

To compare with the findings of the top-down method which clustered the population sample using the self-report data, in this stage we commenced with the learning analytic data in order to find grouping of students in the population sample. Table 4 presents the ANOVA results with the grouping variable 'online learning sessions'. Students are grouped based on their relative levels of engagement with online learning sessions in relation to the M of the online learning sessions for all the 334 students. Those above the M were classified as 'more engaged' and those below the M were classified as 'less engaged'.

Table 4: ANOVA results based on the online learning session

Variables	More engagement (N = 144)		Less engagement (N = 190)		F	p	η^2
	M	SD	M	SD			
Observational data							
Online learning sessions	0.92	0.59	-0.70	0.61	592.75	**.00**	.64
Perceptions							
Integration of f2f and online learning	0.14	1.01	-0.13	1.00	5.72	**.02**	.02
Appropriate-ness of online workload	0.09	1.00	-0.03	0.99	1.17	.28	.01
Usefulness of online contributions	0.27	0.87	-0.19	1.03	18.35	**.00**	.05
Academic achievement							
Course marks	0.46	0.87	-0.34	0.95	61.13	**.00**	.16

From Table 4, we can see that among 344 students, 144 students were relatively more engaged (M = 0.92, SD = 0.59) with the online learning activities and 190 students were relatively less engaged (M = -0.70, SD = 0.61), as reflected statistically by the ANOVA, F (1, 333) = 592.75, p < .01, η^2 = .64. Using this as a grouping variable, the ANOVA also showed that between the more and less engaged students, there were statistical differences on perceptions of integration between f2f and online learning, F (1, 333) = 5.72, p < .05, η^2 = .02, usefulness of online contributions, F (1, 333) = 18.35, p < .01, η^2 = .05, and course marks, F (1, 333) = 61.13, p < .01, η^2 = .16. We found that students who were more engaged with online learning tended to have positive perceptions about the integration between f2f and online learning (M = 0.14, SD = 1.01), had a positive perception of the value of online contributions (M = 0.27, SD = 0.87), , and achieved relatively higher learning outcomes (M = 0.46, SD = 0.87) than less engaged students, who felt that f2f and online learning was not well connected (M = -0.13, SD = 1.00), did not consider online postings were useful (M = -0.19, SD = 1.03), and obtained lower scores in the course (M = -0.34, SD = 0.95).

From a bottom-up approach using the observational data, it shows that when students were more engaged with the online learning activities, they felt online learning was well integrated with f2f learning, online contributions were valuable for the whole learning experience in the course. The more engaged students also tended to perform at a higher academic level than the less engaged students, who perceived the f2f and online learning as separate aspects and did not think they could learn from other students' online postings.

Results of association between top-down and bottom-up groupings

To look at the association amongst the top-down and bottom-up groupings of students, specifically, the extent of logical congruence amongst the groupings, we conducted a 2 x 2 contingency table to examine how students' membership based on types of learning experience and levels of engagement with online learning sessions was associated. We used the chi squared statistics to determine if the observed and expected frequencies of the groupings are significantly different, and used phi statistics to determine the strength of the association. Table 5 presents the 2 x 2 contingency table results.

Table 5: Frequency distributions and proportions by levels of learning experience and engagement with online learning

Groupings	More engagement		Less engagement		Total	
Coherent experience	116	34.7%	110	32.9%	226	67.7%
Fragmented experience	28	8.4%	80	24.0%	108	32.3%
Total	144	43.1%	190	56.9%	334	100.0%

$\chi^2 = 19.23^{**}$, $\phi = .24^{**}$, ** $p < .01$

The chi-squared statistics (χ^2 (1) = 19.23, $p < .01$) and phi ($\phi = .24$, $p < .01$) show that a 'coherent experience' is significantly and moderately associated with 'more engagement' with online learning sessions; and a 'fragmented experience' is related to 'less engagement' with the online learning activities.

Conclusion

The research is replete with studies which argue the merits of different categories of data as evidence of learning (Chan, 2009; Smith, 1993). Here we combined two sources of data as evidence of learning and investigated the congruency in outcomes when contrasting different sequence of methodologies. While we used the same methods (cluster and ANOVA with both data sets) in the two sequences of analyses, we partitioned the population sample in two ways using top-down (based on self-report quality of learning experience) and bottom-up approaches and (based on level of observed engagement with online activities). Using a 2 x 2 contingency table, we found the groupings in the two methodologies were logically and structurally coherent and consistent; that is reported coherent experiences of learning were found to be positively related to observed higher levels of online engagement; and reported fragmented experiences of learning were found to be negatively related to observed less levels of online engagement in both methods.

By using both categories of data and discovering similar findings, we not only confirmed the usefulness of using both types of data, but also revealed a more holistic understanding of the student experience of blended learning and the reasons why some learning experiences are more successful than others. Students who reported relatively more coherent experiences of learning as indicated by positive perceptions of the integration of the learning activities in class and online, who valued the postings of other students, and who perceived that the workload was appropriate, were observed to engage more often and for longer periods of time in the online environment and achieved relatively higher academically. In contrast, students who reported relatively more fragmented experiences of learning as indicated by negative perceptions of the integration of the learning activities in class and online, who did not value the postings of other students, and who considered the workload being heavy, were observed to engage less often and for shorter periods of time in the online environment and achieved relatively lower academically. In this study, we employed multiple analyses, including correlation, cluster and ANOVA, and a 2 x 2 contingency table, these methods triangulated with each other and strengthened the power of the analyses, presenting a more comprehensive picture of students' blended learning than a single method and approach can offer. The findings offer a number of implications for teaching.

For teaching and activity design, the results suggest that helping students to develop positive perceptions of the relatedness of the in-class and online activities is important for perceptions of workload, the online contributions of other students and overall achievement. This observation could be worked into the design of the activities, pointing backwards and forwards between the online and classroom contexts in the activity design to remind the students of the links between the ideas raised in both contexts and how they related to tasks and course outcomes. Equally important could be discussions in class that show how and why some students are relatively more engaged online with the activities. This could be achieved through peer learning activities in small groups or through plenary demonstrations in which active students demonstrate 'what they do' and 'why they do it' in the online environment to the whole class. In both examples, the results suggest that such strategies are likely to help students experience more coherent and engaged experiences of learning in blended contexts.

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