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Feifei Han* and Robert A. Ellis

Office of Pro-Vice-Chancellor (Arts, Education and Law), Griffith Institute for Educational Research, Griffith University

*corresponding author: feifei.han@griffith.edu.au
ORCiD: https://orcid.org/0000-0001-8464-0854
LinkedIn: https://www.linkedin.com/in/feifei-han-578659a/

Robert A Ellis: ORCiDs: https://orcid.org/0000-0002-8781-3316

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Abstract

Adopting an ecological perspective on student learning in blended course designs, this study investigates the quality of 335 undergraduates' experience in a first-year compulsory engineering course. Interrelations amongst cognitive, social, and material aspects of the student learning experience are examined. The cognitive elements include self-reports of approaches to, and perceptions of, learning; the social elements include self-report collaboration; and the material elements include engagement with online learning tasks. The cognitive elements distinguished students by 'understanding' and 'reproducing' learning orientations. These orientations when combined with students' choice of whether or not and with whom to collaborate, generated five sub-groups of students with different collaborative experience. Students who had an 'understanding' orientation and also collaborated with 'understanding' students tended to have relatively more successful learning experiences than the other sub-groups. Such experiences were characterized by deep approaches to learning in class and online, positive perceptions of the blended learning environment, better positioning in collaboration networks, and relatively higher learning achievement as measured by course marks. This study has potential to guide learning and teaching in blended course designs and offers ecologically informed theoretical insights into university student learning.

Keywords: Ecological perspective, student learning experience, blended course design, student approaches to learning, social network analysis

Introduction

Understanding why the quality of university student learning varies is a key focus of those concerned about the effectiveness of university education. However, understanding differences in student outcomes in blended course designs, a mixture of face-to-face and online activities, is not a straightforward proposition. To investigate variation in blended courses through adopting an ecological perspective, one that triangulates findings by combining self-report and observational evidence and looks at the patterns of interrelations amongst a number of cognitive, social, and material elements, and how these relate to learning outcomes (Han & Ellis, 2020a), a robust understanding of why some students are more successful than others can be achieved.

It is not always clear to researchers how to account for why some students are relatively more successful in experiences of learning, which have an increasing array of choices in where (e.g., going to the library and researching at home), how (e.g., in class and online, going to lectures and interacting with lecture content online, conducting laboratory experiments and simulating experiments online), and with whom to learn (e.g., by themselves and in groups). While prior studies have provided some insights into describing and explaining differences in the quality of university student learning experience, most studies tend to only use one category of data as evidence underpinning their findings. In this study, we seek to add to the research on learning in blended contexts by considering both self-report and observational data across multiple aspects of the student experience as a way of providing robust evidence.

There are a number of research areas which provide a useful background to this study. One substantial body of work, student approaches to learning (SAL), demonstrates that how students' understandings and perceptions of learning and their decisions of the intent and strategies in learning are consistently associated with their academic achievement (Han & Ellis, 2019, 2020a; Biggs & Tang, 2011; Ramsden, 2003). Another body of research focuses on how students learn through working with peers, often referred to as collaborative learning. These studies give us some understanding of different patterns of collaborations and the relative positioning of students in their collaboration networks using social network analysis (SNA) (De Laat, Lally, Lipponen, & Simons, 2007). However, studies in this research area typically do not integrate their findings with other aspects of the learning experience. A third field of research uses educational data mining techniques and learning analytic trace data known as digital footprints by students when they learn in online and other technology-enabled contexts (Siemens, 2013). Learning analytic research provides evidence of what student actually do when they interact with learning technologies, a type of observable evidence. By using observational data and relatively subjective data from self-report instruments, this design of this study is able to offer a type of triangulated evidence across different categories of data and methods (Han & Ellis, 2020a). Drawing on research methodologies from student approaches to learning, social network research, and learning analytics, this study examines the interrelations between cognitive, social, and material elements and student learning achievement in blended course designs. The main research question addressed in the study is: To what extent do cognitive, social, and material elements of the student learning experience reveal variation in the quality of outcomes for student learning? The main research question can be divided into the following supporting research questions:

- What are the relations amongst cognitive elements of learning experience and learning achievement?
- What are the relations amongst cognitive and social elements of learning experience and learning achievement?

- What are the relations amongst cognitive, social, material elements of learning experience and learning achievement?

Ecological perspectives on learning

Ecological perspectives on learning are of significant conceptual and practical values because they offer relatively holistic understandings of learning as experienced by students in authentic settings through looking at the complexity of the phenomenon under investigation and the interaction of multiple parts in context (Han & Ellis, 2020a). In such perspectives, the metaphor of ecology is applied to emphasise a contextualized and complex understanding of the phenomenon built up through complementary analyses. In this study, an ecological perspective is used to frame the research question. This perspective has motivated a combination of using methodologies from the three aforementioned frameworks: SAL research, SNA in educational research, and learning analytics research for their common and complementary features. Common features of the approaches are 1) relationality, that a change in one aspect of the experience may associate with changes in other aspects of the experience; 2) student-centred, that all are used in the literature effectively to uncover variations in student learning; and 3) evidence-based, that each provides a complementary lens on the student learning experience either through measurements of aspects which the others are not designed to do, and/or through using different sources of data. By using a combination of different methods, the research questions driving the design are more robustly answered through a type of triangulation achieved by examination of the consistency of the outcomes of the different stages of analysis.

A number of definitions of learning ecology have been provided by researchers. Being a dynamic ecosystem, a learning ecology constitutes the interdependencies between learners and their intertwining with people and multifarious material resources (Han & Ellis, 2020a). Jackson

(2013) defines a learning ecology as comprising "a unique configuration of purposes, activities, material resources, relationships and the interactions and mediated learning that emerge from them" (p. 2). Similarly, Barron (2006) refers a learning ecology as:

> the set of contexts found in physical or virtual spaces that provide opportunities for learning. Each context is comprised of a unique configuration of activities, material resources, relationships, and the interactions that emerge from them (p. 195).

These definitions share similarities that they all recognise the intricacy of the learning experiences of students and the intertwining nature of the elements involved in the learning experiences. If these definitions are accepted, then adopting an ecological perspective to investigate university student experiences of learning acknowledge that:

- the student learning experience is made up of many elements, which are dynamic, hard to separate, and intricately entwined;
- learning achievement is jointly shaped by multiple elements of the student learning experience and the interplay between them;
- complementary methodologies can be drawn on to reveal different but related aspects of the phenomenon under consideration.

The university student experience of blended course designs

Blended course designs, which are "a systematic combination of co-present (face-to-face) interactions and technologically-mediated interactions between students, teachers and learning resources" (Bliuc, Goodyear, & Ellis, 2007, p. 234), are adopted in higher education sector worldwide. In blended course designs, students are increasingly involved in decision-making in the learning process, such as how they learn in lectures, with whom they work in a laboratory, how many hours they learn online, whether to study in a physical library or log onto an online database. These decisions require students to move between face-to-face and online contexts, across physical and virtual learning environments (Han & Ellis, 2019). Hence, their learning experiences are made up of an interplay of a wide range of factors related to their cognition (e.g., conceptions, approaches, and perceptions) (Prosser & Trigwell, 2017); their social interactions in learning (e.g., their collaborations in learning) (Hadwin, Järvelä, & Miller, 2018); and their engagement with the material elements in the physical and virtual learning spaces (e.g., their participation in the online learning tasks) (Laurillard, 2013), as they move towards achieving their learning outcomes. Each decision made by students in the cognitive, social, and material elements of the course in which they learn can be considered as part of the whole experience and may contribute to relatively more or less successful outcomes. Methodologically, one of the strengths of an ecological perspective on learning is its use of multiple and complementary methodologies. Combining methodologies from research in SAL, social network research, and learning analytics allows the study to investigate the cognitive, social, and material elements of student learning experience respectively. Primarily drawing on the self-report data (e.g., self-report surveys), methodologies in SAL research are suitable to examine learners' cognitions, which concerns learners' internal states. SNA, a set of techniques commonly used in social network research, is robust to detect and interpret roles of individuals in interactive networks in different social context, such as students' collaborations in learning as in this research. The learning analytic functions and methods are particularly powerful to describe and present the large volume of digital trace data, which are able to more objectively reflect students' online engagement, an important material aspect in student learning experience in the blended learning context. While each method has strengths to capture one of the cognitive, social, and material aspects in student learning, complementarily, they allow for an investigation of the interplay amongst these elements.

In this study, it is hypothesized that decisions in successful experiences of learning tend to be aligned and coherent, and are related to relatively higher learning outcomes. This alignment and coherence may include deeper approaches to learning, positive perceptions of learning, proactive choices to collaborate and sufficient interaction in all parts of the experience, including material aspects, such as the online environment. Less successful experiences of learning are hypothesized to have fragmented and unaligned elements, such as being reluctant to collaborate and not being engaged in the online environment. Together these experiences are likely to impede understanding and lead to poorer learning achievement.

While each student will make unique decisions in the course of their studies, their learning experiences may share common features, which allow a broad description into different categories so that shared methods and principled analyses can be derived in order to inform learning and teaching interventions in other contexts. In this study, the investigation of the interrelations amongst different parts of the student learning experience can help clarify the roles of the different aspects in relation to learning achievement, thus, providing an evidence-base for actionable knowledge for interventions. Despite the promise of an ecological perspective to understanding the complexity of student learning experience, there is little systematic research into the area. The following sections review the methodologies and the relevant prior research in the areas of SAL, SNA, and learning analytics.

Student approaches to learning (SAL) research

Methodologies from SAL research identify variations in the student experience of learning, in particular various elements in the cognitive aspects of such experience (Biggs, Kember, & Leung, 2001; Bliuc, Ellis, Goodyear, & Piggot, 2010). Key constructs in this research have shown that the way students conceive of their learning (e.g., cohesive and fragmented conceptions), how they approach their learning (e.g., deep and surface approaches), and the way they perceive their learning context and environment (e.g., positive and negative perceptions) show logical and significant associations amongst these cognitive elements and with the academic achievement (Chan, 2014; Trigwell, Ashwin, & Millan, 2013). Students with fragmented learning concepts see little connection between what they study and the real world, are unable to provide holistic accounts of the phenomena being studied, and do not understand the point of their learning and assessment tasks. These experiences tend to be positively related to surface approaches to learning, which are characterized by mechanistic procedures, seeking to produce formulaic responses, and being not engaged with the ideas and conceptions in learning. Such fragmented conceptions and surface approaches are also typically associated with negative perceptions of the learning context, in which the quality of teaching is often perceived as poor, the goals as unclear, the assessment as irrelevant, and the satisfaction low (Lizzio, Wilson, & Simons, 2002; Prosser & Trigwell, 1999, 2017).

A key insight from SAL research is that students in the same learning context can report contrasting experiences, despite experiencing the same learning tasks and teacher. Other students may report cohesive conceptions with which they are able to see the big picture of how learning tasks fit into the purpose of the course and how the subject matter directly relevant to their degree and their future professional goals. They also tend to adopt deep approaches, which enable them to engage meaningfully with the subject matter, and encourage them to experiment and make decisions about using the most appropriate learning strategies in their studies. These experiences are also likely to be related to positive perceptions of the learning environment, in which satisfaction and the quality of teaching is perceived as high, workload and assessment tasks are considered being appropriate (Ramsden, 2003).

Social network research in education

A limitation of SAL research methodologies is that they do not offer an ability to provide measurements of collaboration in learning. Such a limitation is addressed in our study by complementing SAL methodologies with SNA. SNA identifies, detects, and interprets roles of individuals in a group and patterns of ties amongst them (De Nooy, Mrvar, & Batagelj, 2011). It uses graph theory to visualize various kinds of social networks and to provide mathematical measures to describe features of individuals, their positions relevant to the network graph, and relations amongst individuals (Rulke & Galaskiewicz, 2000). Increasingly adopted in educational research, past research has examined different types of networks amongst students, and how the patterns of the networks are related to student academic performance. These included social and friendship networks (Rienties, Héliot, & Jindal-Snape, 2013); knowledge sharing networks (defined as self-reporting of providing knowledge to other students in the course) (Tomás-Miquel Expósito-Langa, & Nicolau-Julia, 2015); students and teacher interaction networks (Cadima, Ojeda, & Monguet, 2012); online discussion networks (Gašević, Joksimović, Eagan, & Shaffer, 2019), study partner networks (Stadtfeld, Vörös, Elmer, Boda, & Raabe, 2019), and student collaboration networks (Gu, Shao, Guo, & Lim, 2015). However, seldom have past studies looked at how these patterns of networks are related to other aspects of student learning experience. The current study will address this issue by examining how patterns of students' collaborations, an important social element of student learning experience, relate to the cognitive and material aspects of their learning experience.

Learning analytic research

Learning analytic research has emerged in the last couple of decades stimulated by the integration of information communication technologies into learning (Baker & Seimens, 2014). The large amount of digital trace data recorded by technologies when combined with student demographic information can be used profitably to describe student learning behaviors. Learning analytic research has been used to detect at-risk students, identify learning strategies, predict attrition, monitor student affect, provide feedback, advise career plans, and explain learning achievement (Chen, Resendes, Chai, & Hong, 2017; Pardo, Jovanović, Dawson, Gasevic, & Mirriahi, 2019). While claiming objectivity because of the observational type of data it employs, learning analytic research is often limited in its potential to uncover the underlying intentions involved in student learning. To improve the insights from learning analytic methods, complimentary methodologies, such as self-report methods, can be combined to better interpret patterns and trends in the data. The current study uses learning analytic research methodologies to capture measurements of student' online engagement, which shed some light on material aspects in student learning experience; and to complement with self-report data collected through SAL and SNA methodologies, which provide indications to cognitive and social aspects respectively.

Materials and method

Participants and the learning context

A cohort of 335 undergraduate students, who were enrolled in a first-year compulsory engineering course on computer systems, volunteered for the study. The ages of the students were between 17 and 31 years old (*M*=19.66).

The course occurred over a 13-week semester and was designed with both face-to-face and online learning. The face-to-face part of the experience included two-hour lectures, two-hour tutorials, and three-hour laboratory practice each week; and the online part required a minimum of 5 hours a week in a bespoke learning management system (LMS). Apart from disciplinary learning, a key generic graduate outcome for the course was collaboration skill. Strategies for developing student collaboration were through the design of assignments and assessments, which required students to work in collaboration to complete a laboratory project on building an electronic circuit, to co-write an engineering report of the problem-solving processes they were engaged in, and to jointly deliver an oral presentation of the project. Rather than pre-assigned by the teaching staff, students made decisions as to with who to collaborate.

Data sources and instruments

The data sources included self-report closed-ended and open-ended questionnaire data, observational learning analytics data, and academic achievement data. The instruments used to collect the data are described below.

The close-ended questionnaire

The close-ended questionnaire consisted of six 5-point Likert scales with 1 representing "strongly disagree" and 5 indicating "strongly agree". Two scales investigated deep (DAI, 4 items, α=.68) and surface approaches to inquiry (SAI, 7 items, α=.68) respectively. Two scales examined deep (DAT, 6 items, α=.74) and surface (SAT, 5 items, α=.76) approaches to using online learning technologies respectively. Two scales assessed perceptions of blended learning environment. One focused on perceptions of how well the online environment was integrated with the course (INTER, 7 items, α=.86); and the other was on perceptions of appropriateness of the online workload (AWL, 6 items, α=.77). The development of the questionnaire drew on SAL literature and previous questionnaires using the SAL framework (Biggs et al., 2001; Crawford, Gordon, Nicholas, & Prosser, 1998). The reliability and validity of the scales have been reported in previous studies (e.g., Bliuc et al., 2010; Han & Ellis, 2020b).

The open-ended questionnaire

The open-ended questionnaire used the format in the social network research. The questionnaire asked students to reflect upon their experience of collaborations in the course and to write down up to three collaborators in the course according to frequency of collaborations, and to specify whether the collaboration occurred primarily face-to-face or both face-to-face and online (blended).

The 1st most frequent collaborator in the course _______________ face-to-face blended

The 2nd most frequent collaborator in the course _______________ face-to-face blended

The 3rd most frequent collaborator in the course _______________ face-to-face blended

The learning analytic data

The learning analytic data were observed frequencies of access to online learning tasks in the LMS. There were two online learning tasks: sequences of problem-solving and multiple-choice questions. The sequences of problem-solving task, which were constructed using case studies, included two learning events: problem-solving that led to a correct answer (PS_C), and problem-solving that led to an incorrect answer (PS_I). The multiple-choice questions task, which assessed the key concepts in the course, had three learning events: choice of a correct answer (MCQ_C), choice of an inaccurate answer (MCQ_I), and a choice to showing the answer (MCQ_S). Due to large differences of the raw frequencies between the learning events, we derived the percentage of each learning event in relation to its corresponding learning task and used the percentage in the subsequent analyses.

Academic achievement data

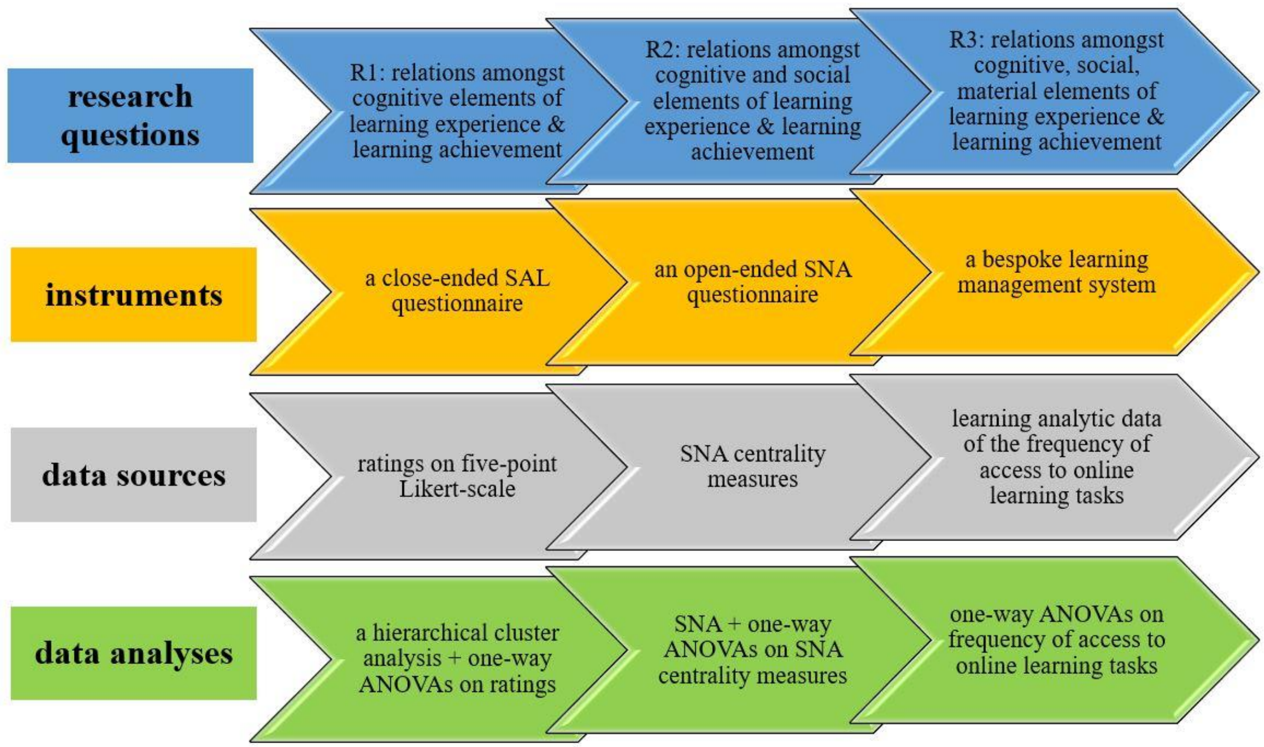
Students’ academic achievement was their final marks of the course, which were assessed by five tasks, including (1) lecture preparation tasks (10%); (2) tutorial preparation tasks (10%); (3) laboratory project (20%), which consisted of the design of an electronic circuit, a report on problem-solving processes, and an oral presentation on the outcome of the project; (4) the mid-term examination (20%), and (5) the final examination (40%).

Data collection and analysis

The study was approved by the ethics committee of the researchers’ university. Following the ethics guidelines, all the students in the course were informed about the voluntary nature of the study and the written consent procedure for participation. They were ensured that the decision as to participation of the research or not would not affect their course marks and all the data would be anonymized and used only for research purposes. Finally, 335 students signed written consent forms.

To answer the first research question, we adopted a hierarchical cluster analysis using the six scales in the close-ended questionnaire and the academic achievement data. To facilitate interpretation, we converted the mean scores into *z*-scores with a *M* of 0 and a *SD* of 1 in the analyses. The cluster analysis aimed to identify sub-groups of students by maximizing similar learning experience within groups and different learning experience between groups. On the basis of the cluster membership, one-way ANOVAs were applied to examine if the sub-groups of students differed in their self-report approaches, perceptions, and the course marks. To answer the second research question, we applied SNA to visualise and describe the features of sub-groups of students with different collaborative experience based on their cluster membership obtained from the cluster analysis and their answers to the open-ended questionnaire. The SNA also generated key SNA centrality measures for each student, including degree, closeness, betweenness, eigenvector, and local clustering coefficients. Using different students' collaborative experience as a grouping variable, we conducted one-way ANOVAs and post-hoc analyses to identify the extent to which the SNA centrality measures differ. For the last research question, we examined how material aspects of learning experience differed by variations of the cognitive and social aspects of learning experience. We compared the percentage of the online learning events in relation to its corresponding task by the grouping variable of different collaborative experience through one-way ANOVAs and post-hoc analyses. The research questions, instruments, data sources, and data analysis methods are visualized in Figure 1.

Figure 1. Visualization of research questions, instruments, data sources, and data analysis methods



Results

Results for research question 1

Table 1 presents the results of the hierarchical cluster analysis and one-way ANOVAs. The cluster analysis produced two clusters: one cluster with 76 students, and the other with 259 students. The one-way ANOVAs showed that all the scales and the academic achievement differed significantly between the two clusters (DAI: $F(1, 334)=59.57$, $p<.01$, $\eta^2=.15$; SAI: $F(1, 334)=53.61$, $p<.01$, $\eta^2=.14$; DAT: $F(1, 334)=84.00$, $p<.01$, $\eta^2=.20$; SAT: $F(1, 334)=126.12$, $p<.01$, $\eta^2=.28$; INTER: $F(1, 334)=84.55$, $p<.01$, $\eta^2=.20$; AWL: $F(1, 334)=97.65$, $p<.01$, $\eta^2=.23$; and marks: $F(1, 334)=26.64$, $p<.01$, $\eta^2=.07$). Students in cluster 1 reported adopting significantly more DAI (M=0.72, SD=0.77), DAT (M=0.82, SD=0.76) than those in cluster 2 (DAI: M=-0.22, SD=0.97; DAT: M=-0.25, SD=0.93); and using significantly less SAI (M=-0.67, SD=0.80) and SAT (SAT: M=-0.96, SD=0.66) than cluster 2 students (SAI: M=0.21, SD=0.96; SAT: M=0.29, SD=0.90). At the same time, cluster 1 students also reported significantly more positive perceptions on INTER (M=0.92, SD=0.72) and AWL (M=0.89, SD=0.94) scales, and obtained significantly higher course marks (M=0.50, SD=0.88) than their peers in cluster 2 (INTER: M=-0.26, SD=0.94; AWL: M=-0.24, SD=0.86; marks: M=-0.15, SD=0.99).

Table 1. Results of the hierarchical cluster analysis and one-way ANOVAs

	1: understanding cluster (N=76)		2: reproducing cluster (N=259)		F	p	η^2
	M	SD	M	SD			
DAI	0.72	0.77	-0.22	0.97	59.57	**.00**	.15
SAI	-0.67	0.80	0.21	0.96	53.61	**.00**	.14
DAT	0.82	0.76	-0.25	0.93	84.00	**.00**	.20
SAT	-0.96	0.66	0.29	0.90	126.12	**.00**	.28
INTER	0.82	0.72	-0.26	0.94	84.55	**.00**	.20
AWL	0.89	0.94	-0.24	0.86	97.65	**.00**	.23
Marks	0.50	0.88	-0.15	0.99	26.64	**.00**	.07

Note: DAI=deep approaches to learning through inquiry, SAI=surface approaches to learning through inquiry, DAT=deep approaches to using online learning technologies, SAT=surface approaches to using online learning technologies, INTER=perceptions of integrated learning environment, and AWL=perceptions of appropriate online workload.

Students' self-report responses on the approaches and perceptions scales reflected that cluster 1 students reported experience characterized as being reflective, proactive, and towards a deep understanding in the learning, hence, referred to as an 'understanding' learning orientation; whereas the cluster 2 students' learning was mostly dependent, mechanistic, and was inclined to reproducing knowledge in the textbooks or lecture notes, referred to as a 'reproducing' learning orientation.

Results for research question 2

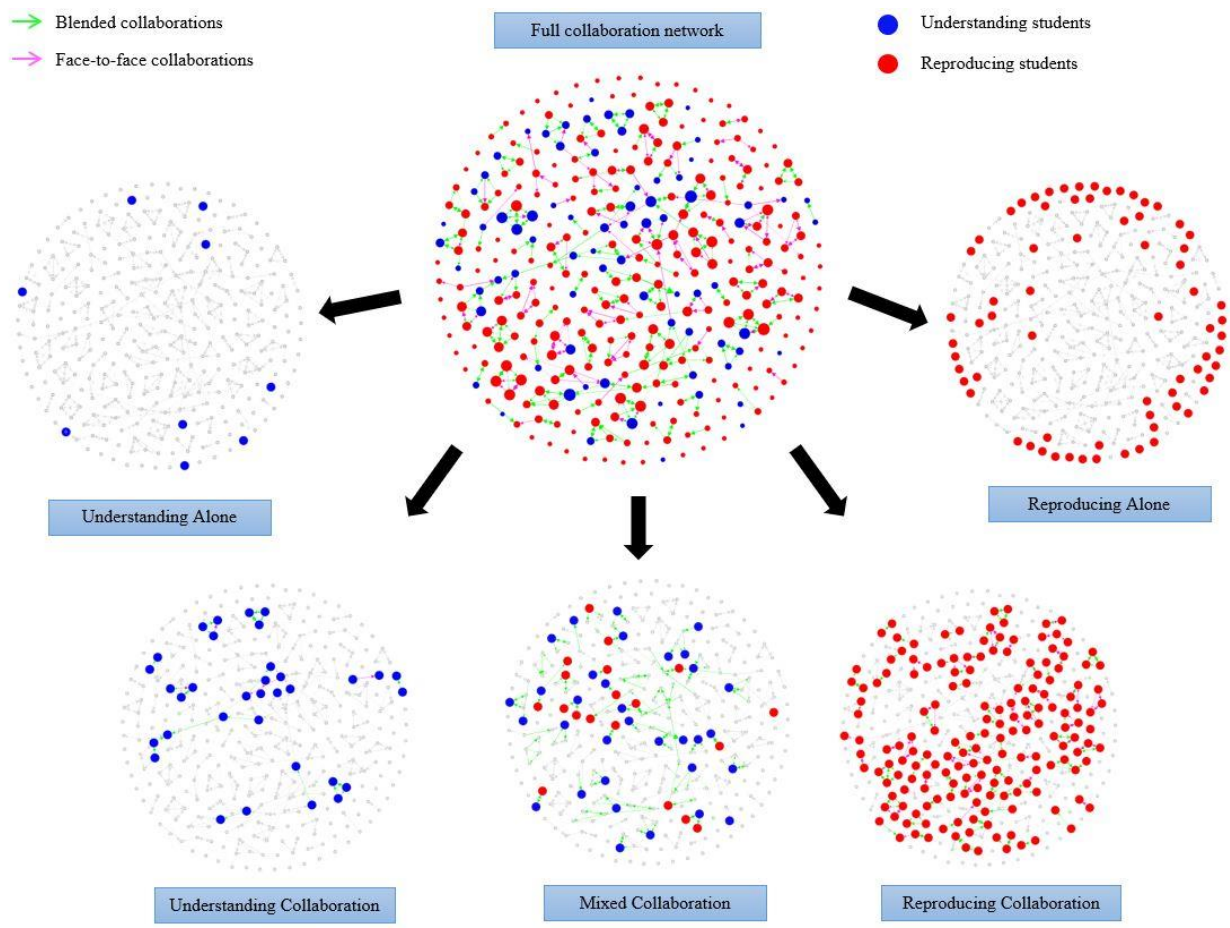
Figure 2 provides visualization of the full collaboration network and the five sub-groups of students with different collaborative experience based on whether they chose to collaborate and with whom they collaborated. Table 2 explains each sub-group and provides the number of students in each sub-group.

Table 2. Descriptions and the number of students in five sub-groups

sub-groups	description	*N*
Understanding Alone (UA)	This sub-group had an 'understanding' learning orientation and did not collaborate.	9
Understanding Collaboration (UC)	This sub-group had an 'understanding' learning orientation and collaborated with students who also reported an 'understanding' learning orientation.	34
Mixed Collaboration	This sub-group had either an 'understanding' or a	52

(MC)	‘reproducing’ learning orientation and collaborated *only* with students who had a different orientation.	
Reproducing Collaboration (RC)	This sub-group had a ‘reproducing’ learning orientation and collaborated with students with students who also reported a ‘reproducing’ learning orientation.	171
Reproducing Alone (RA)	This sub-group had a ‘reproducing’ learning orientation and did not collaborate.	69

Figure 2. Full collaboration network and five sub-groups



Because UA and RA students did not report collaboration, hence SNA centrality measures were not applicable. The one-way ANOVAs and post-hoc analyses of the SNA centrality measures were only conducted amongst UC, MC, and RC, and the results are presented in Table 3. Four of the six centrality measures differed significantly: degree: $F(1, 257)=7.44$, $p<.01$, $\eta^2=.06$; betweenness: $F(1, 257)=19.15$, $p<.01$, $\eta^2=.13$; eigenvector: $F(1, 257)=5.77$, $p<.01$, $\eta^{2=}.04$; and local clustering coefficient: $F(1, 257)=5.63$, $p<.01$, $\eta^2=.04$. We then further conducted post-hoc analyses, which show that the UC (M=3.5882, SD=1.5593) and RC students (M=3.2047, SD=1.4869) had higher degree than the MC students (M=2.4231, SD=1.5383), suggesting that the UC and RC students tended to collaborate more than the MC students. The UC students had relatively higher betweenness (M=.00027, SD=.00049) than both MC (M=.00002, SD=.00011) and RC students (M=.00003, SD=.00013), indicating that they were relatively better positioned to gather information. The UC students (M=.3020, SD=.2329) had a relatively higher eigenvector centrality than both MC (M=.1401, SD=.1928) and RC students (M=.2112, SD=.2202), implying that the UC students tended to collaborate with students who were also relatively better positioned in the network. Both the UC (M=.6078, SD=.4173) and RC students (M=.6172, SD=.4381) had higher local clustering coefficient than the MC students (M=.3846, SD=.4778), suggesting that the UC and RC students tended to form closely knitted groups in collaborations.

Table 3. Results of one-way ANOVAs and post-hoc of the centrality measures amongst UC, MC, and RC

centrality measures	sub-groups	*M*	*SD*	*F*	*p*	η^2	post-hoc
degree	UC	3.5882	1.5593	7.44	**.00**	.06	UC>MC
(the extent of collaboration)	MC	2.4231	1.5383				UC=RC
	RC	3.2047	1.4869				RC>MC

closeness	UC	0.6844	0.2921	1.56	.21	.01	
(the sum of steps to reach their	MC	0.7255	0.2521				
collaborators)	RC	0.7655	0.2605				
betweenness	UC	0.00027	0.00049	19.15	**.00**	.13	UC>MC
(capacity to gather information based	MC	0.00002	0.00011				UC>RC
on the position in the network)	RC	0.00003	0.00013				RC=MC
eigenvector	UC	0.3020	0.2329	5.77	**.00**	.04	UC>MC
(the quality of collaborations of the	MC	0.1401	0.1928				UC>RC
students they directly collaborated	RC	0.2112	0.2202				RC=MC
with)							
local clustering coefficient	UC	0.6078	0.4173	5.63	**.00**	.04	UC>MC
(tendency of students to form closely	MC	0.3846	0.4778				UC=RC
knitted groups in collaborations)	RC	0.6172	0.4381				RC>MC

Note: UC=Understanding Collaboration sub-group, MC=Mixed Collaboration sub-group, and RC=Reproducing Collaboration sub-group.

Results for research question 3

The comparison of the percentage of the learning events amongst the five sub-groups of students using one-way ANOVAs and post-hoc analyses are presented in Table 4. Table 4 demonstrates that the five sub-groups of students differed significantly on the percentage of engagement of the two events of the problem-solving tasks: PS_C: $F(4, 330)=6.12$, $p<.01$, $\eta^2=.07$; and PS_I: $F(4, 330)=6.12$, $p<.01$, $\eta^2=.07$. The post-hoc analyses revealed that while UA (M=0.55, SD=0.11) and UC were equal for engaging with problem-solving tasks with correct answers, UC (M=0.56, SD=0.17) had a higher percentage than MC (M=0.47, SD=0.12), RC (M=0.45, SD=0.12), and

RA (M=0.46, SD=0.12). On the other hand, for the percentage of problem-solving tasks with incorrect answers, UC (M=0.44, SD=0.17) had less engagement than MC (M=0.53, SD=0.12), RC (M=0.55, SD=0.12) and RA (M=0.54, SD=0.12).

Similarly, the percentage of the three learning events in the multiple-choice questions tasks all differed significantly amongst the five sub-groups: MCQ_C: $F(4, 330)=3.93$, $p<.01$, $\eta^2=.05$, MCQ_I: $F(4, 330)=2.47$, $p<.05$, $\eta^2=.03$, and MCQ_S: $F(4, 330)=2.86$, $p<.05$, $\eta^2=.03$. The post-hoc analyses identified that UC (M=0.62, SD=0.11) had higher percentage of answering multiple-choice questions with correct answers than MC (M=0.55, SD=0.11), RC (M=0.54, SD=0.11), and RA (M=0.52, SD=0.12); whereas UC (M=0.29, SD=0.08) had significantly lower percentage of answering multiple-choice questions with incorrect answers than MC (M=0.33, SD=0.07) and RC (M=0.33, SD=0.09). For the multiple-choice questions with showing answers options, RA (M=0.16, SD=0.11) had significantly higher percentage than UC (M=0.10, SD=0.11), MC (M=0.12, SD=0.11), and RC (M=0.13, SD=0.11).

Table 4. Results of one-way ANOVAs and post-hoc analyses of the percentage of the learning events

learning events	sub-group	*M*	*SD*	*F*	*p*	η^2	post-hoc only significant results are displayed
PS_C	UA	0.55	0.11	6.12	.00	.07	MC<UC
	UC	0.56	0.17				RC<UC
	MC	0.47	0.12				RA<UC
	RC	0.45	0.12				
	RA	0.46	0.12				
PS_I	UA	0.45	0.11	6.12	.00	.07	MC>UC

	UC	0.44	0.17				RC>UC
	MC	0.53	0.12				RA>UC
	RC	0.55	0.12				
	RA	0.54	0.12				
MCQ_C	UA	0.56	0.06	3.93	.00	.05	MC<UC
	UC	0.62	0.11				RC<UC
	MC	0.55	0.11				RA<UC
	RC	0.54	0.11				
	RA	0.52	0.12				
MCQ_I	UA	0.30	0.04	2.47	.04	.03	
	UC	0.29	0.08				MC>UC
	MC	0.33	0.07				RC>UC
	RC	0.33	0.09				
	RA	0.31	0.08				
MCQ_S	UA	0.14	0.08	2.86	.02	.03	UC<RA
	UC	0.10	0.08				MC<RA
	MC	0.12	0.11				RC<RA
	RC	0.13	0.11				
	RA	0.16	0.11				

Note: PS_C=problem-solving with a correct answer, PS_I=problem-solving with an incorrect answer, MCQ_C=multiple-choice questions with a correct answer, MCQ_I=multiple-choice questions with an incorrect answer, MCQ_S=multiple-choice questions with showing the answer. UA=Understanding Alone sub-group, UC=Understanding Collaboration sub-group, MC=Mixed Collaboration sub-group, and RC=Reproducing Collaboration sub-group, and RA=Reproducing Alone sub-group.

Discussion

The purpose of this study is to investigate variations in the student experience of learning that how the cognitive, social, and material aspects of the student learning experience are associated with each other; and how they are related to learning achievement. Before discussing the results, it is worthwhile noting its limitations. The study is just one cohort of students in one discipline – engineering. Many more studies involving other disciplines and other cohorts of students are required if generalisation about the associations found here are to be applied with confidence to other contexts. Furthermore, the research design is cross-sectional, which does not reveal the stability and/or fluctuation of the associations in long term. To fully understand the student learning experience in blended course designs, the program of research surrounding this study needs to be designed in longitudinal nature so that the changes of the associations may be captured. Notwithstanding these limitations, the outcomes of this study offer interesting insights into the quality of student learning experience.

One of the merits of our study over previously related ones is its ability to contemporaneously reflect on different aspects of student learning experience rather than focusing on only one or two of the aspects. The ecological perspective adopted in this study has helped conceive of an integrated use of multiple complementary methods from SAL, social network, and learning analytics research. Each method is able to complement the insights discovered in more depth, and to act as a type of triangulation of the findings across all the methods. For example, it would have been contradictory if the majority of students who reported deep approaches to learning did not tend to collaborate, eschewed the online environment, but still achieved relatively high course marks. Another methodological advantage of the study is that the implications drawn from both the self-report and observable data were consistent with each other offering promise to continue such an approach in future studies.

By focusing on different aspects of the learning experience, the analyses were able to tease apart their associations with each other, even though they were integrated into the whole learning experience. In terms of cognitive aspects, students were broadly divided into two sub-groups with contrasting learning orientations: ‘understanding’ and ‘reproducing’. The two sub-groups reported differences not only about their approaches but also in their perceptions. The ‘understanding’ group reported deep approaches to inquiry, deep approaches to using technologies in their learning tasks, positive perceptions of how the online environment was integrated with their course design, and a perception of the appropriateness of workload online. The ‘reproducing’ group, on the other hand, reported surface approaches to inquiry in the course, surface approaches to using technologies in the tasks, a negative perception of integration between the online learning and the course design, and a perception of inappropriate online workload. The differences in cognitive aspects of their learning experience were also logically related to more or less successful learning achievement. These results are consistent with previous SAL research in other academic disciplines, including health sciences (Prosser & Sze, 2014), business (Han & Ellis, 2019), and social sciences (Bliuc et al., 2010) in the blended learning settings. Our results and the similar previous ones together seem to suggest that across disciplines, distinctive learning orientations are associated with variations in learning achievement, highlighting the value of understanding cognitive aspects of learning.

The collaborative experience of the students involved both their cognitive learning orientations and the choices as to whether and with whom they collaborated. Using the two to partition the population sample, five different sub-groups demonstrating varying collaborative experience were identified. The two sub-groups of students who did not collaborate (UA and RA) did not take advantage of the tasks to develop collaborative learning skills, hence failing to meet one of the course objectives – to practise and build capacities and skills of cooperation through learning the contents of the subject matter. Amongst the other three collaborative sub-groups (UC, MC, and RC), UC had relatively more successful collaborative experiences, as they positioned themselves more strategically in their class collaboration networks, which enabled them to have stronger capacity to gather and share course information (betweenness), and tended to study with students who also had more collaborative ties in the network (eigenvector).

The relative higher quality of UC students' self-reported learning experience reflected in cognitive and social aspects was further supported by the observed evidence of their engagement online, the material aspect of their experience. They demonstrated a higher engagement with accuracy in the problem-solving sequences and in the multiple-choice questions. The RA students, who reported a relatively lower quality experience in cognitive and social aspects, revealed by observational evidence that reinforced the findings, generally engaging significantly less online. The results of the material aspects of this study are consistent with findings in a number of previous studies that have identified positive associations among an engagement of using online learning technologies and learning outcomes (Beetham & Sharpe, 2010; Chen, Lambert, & Guidry, 2010) and extend them by integrating the self-report of cognitive and social aspects of learning into the analysis.

Summarising across the three aspects of the student learning experience investigated in this study, the most successful learning experiences were characterized by self-reported deep approaches to learning in class and online, positive perceptions of the integrated learning environment and the online workload, relatively higher quality of collaborations, and relatively more successful engagement observed in the online learning environment, all of which were related to higher learning achievement. The analyses across the three aspects of the learning experience showed consistent evidence that together they formed an integral part of learning experience of students in blended course designs. The results generated by self-report and observational data sources help to triangulate, strengthen the power of the analyses, and reinforce the validity of the results.

Implications and conclusions

The results offer useful suggestions for teaching practice. To holistically improve the quality of learning experience in blended courses, teachers need to address a number of areas in relation to one another. For example, the teaching staff can model desirable approaches to learning by inviting sharing from students categorised in the ‘understanding’ group through peer learning activities or by helping students understand the relationship between the online and face-to-face experience, which may also influence the ways students use online learning technologies in learning and enhance the quality of their interaction with online learning tasks. To encourage collaboration, learning activities and assessment tasks with compulsory collaborative elements should enable UA and RA students to sharpen their collaboration skills. Early assessment of students’ collaborative patterns in courses, like the groupings of students (UA, UC, MC, RC, and RA) can offer teachers a basis for pairing up relatively weaker and stronger students to improve collaboration and to model preferable learning orientations. For instance, teachers may coordinate RA students to join UC sub-groups.

The field of university student learning is becoming increasingly complex through the introduction of new pedagogies, technologies, and learning contexts, each of which may either improve or impede understanding. Only by designing research studies that help to understand the related complexities of these elements can we hope to uncover evidence to assist in the improvement of the university student experience of learning.

Disclosure statement

No potential conflict of interest was reported by the authors.

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