Winter 12-31-2020

Exploring Student Engagement Factors in a Blended Undergraduate Course

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Abstract

Student engagement is an important factor in academic performance and comprises four dimensions: behavioural, cognitive, emotional (Fredricks et al., 2004), and agentic (Reeve, 2013). Blended courses provide unique opportunities for instructors to use trace data collected during learning to understand and support student engagement. This mixed-methods case study compared the student engagement of two groups of students with a history of low prior academic achievement. The groups were (a) students who ultimately did well in the course and (b) students who did poorly. Data came from two primary sources: (a) log file data from the course LMS, and (b) trace data derived from authentic learning tasks. Data represented five indicators: (a) behavioural engagement, (b) cognitive engagement, (c) emotions experienced during learning, (d) agency or proactive approaches to studying, and (e) overall academic engagement. Findings indicated students who moved achievement groups showed higher levels of behavioural engagement, cognitive engagement, and agentic or proactive approaches to studying and overall engagement. Additionally, students who remained in the low achievement group showed higher levels of positive deactivating emotions (e.g., relief). Implications for future research on student engagement and designing teaching to increase engagement in blended courses are discussed.

L'engagement des étudiants et des étudiantes est un facteur important dans la performance des étudiants et des étudiantes et comprend quatre dimensions : comportementale, cognitive, émotionnelle (Fredricks et al, 2004) et agentique (Reeve, 2013). Les cours hybrides fournissent aux instructeurs et aux instructrices des occasions uniques d'utiliser les données rassemblées au cours de l'apprentissage pour comprendre et soutenir l'engagement des étudiants. Dans cette étude de cas à méthodes mixtes, nous avons comparé l'engagement des étudiants et des étudiantes de deux groupes qui avaient eu antérieurement de faibles résultats académiques. Les groupes consistaient (a) d'étudiants et d'étudiantes qui, en fin de compte, avaient réussi le cours et (b) d'étudiants et d'étudiantes qui avaient obtenu des résultats médiocres. Les données provenaient de deux sources principales : (a) les données du fichier journal du cours LSM et (b) les données de traces dérivées de tâches d'apprentissage authentique. Les données représentaient cinq indicateurs : (a) l'engagement comportemental, (b) l'engagement cognitif, (c) l'expérience émotionnelle durant l'apprentissage, (d) les approches proactives à l'apprentissage et (e) l'engagement académique général. Les résultats ont indiqué que les étudiants et les étudiantes qui avaient fait bouger les groupes de réussite avaient des niveaux supérieurs d'engagement comportemental, d'engagement cognitif et d'approches proactives à l'apprentissage et à un engagement général. De plus, les étudiants qui étaient restés dans le groupe à faibles résultats avaient démontré des niveaux plus élevés d'émotions désactivantes positives (par ex. le soulagement). Les implications pour des recherches futures sur l'engagement des étudiants et la conception de cours pour augmenter l'engagement dans les cours hybrides sont discutées.

Keywords
blended learning, case study, trace data, student engagement, student success, student achievement; apprentissage hybride, étude de cas, données de traces, engagement des étudiants, réussite des étudiants

In the classroom, postsecondary students face diverse challenges across a variety of tasks (Hadwin et al. 2019). Some students successfully navigate these challenges, but some students do not; students who have performed poorly in the past are more likely than their peers to perform poorly in the future (Brown, 2012; DeBerard et al., 2004; McKay et al., 2012). However, at times, students with a history of weak performance are successful. This success is partially due to their engagement in the course.

Students' engagement in both the processes and products of learning are predictors of achievement and performance (e.g., Fredricks et al., 2004). Unlike some student factors (e.g., race, gender, academic history), student engagement is malleable: students can make changes to their engagement (Fredricks et al., 2004). Additionally, instructors have a role to play in encouraging and supporting student engagement (Fredricks et al., 2019; Trowler, 2010). As such, student engagement is a useful area to target both student success inquiry and interventions (Fredricks et al., 2016; Pardo, 2014). The current study investigates the engagement factors contributing to student success in a specific blended learning-to-learn course by comparing students with a history of weak academic performance who were successful and similar students who were unsuccessful.

Student Engagement

The definition of student engagement has varied over time and across disciplines (Azevedo, 2015; Boekaerts, 2016; Eccles, 2016; Fredricks et al., 2016; Sinatra et al., 2015). Broadly defined, student engagement is a "student's active involvement and participation in school-based activities" and encompasses students' "reactions and interactions with the learning material" (Boekaerts, 2016, p. 81). There is general agreement that student engagement is a malleable, multidimensional self-initiated path to important educational outcomes, including academic performance (Fredricks et al., 2004; Reeve, 2013). In their seminal synthesis of the literature, Fredricks et al. (2004) define three dimensions of student engagement: behavioural, emotional, and cognitive. Students who are behaviourally engaged attend and participate in classes. Emotionally engaged students experience interest and enjoyment during learning; Pekrun et al. (2002) labelled these types of positive valence, physiological activating emotions as positive activating emotions. Students who are cognitively engaged are invested in understanding course content and use self-regulated learning strategies, including goal setting, to optimize their learning.

Reeve (2013) posits these three factors should be augmented with the behaviours, thoughts, and actions represented by agentic engagement. Students who are agentically engaged express preferences, ask questions, communicate their thoughts and needs, recommend goals, and seek clarification (Reeve, 2013; Turner et al., 2013). Essentially, agentically engaged students show agency or proactive approaches to studying. Agentic engagement is particularly relevant in the post-secondary setting where participation in learning activities is often at the discretion of the individual student (e.g., attending lectures, reviewing). Reeve (2013) conceived agentic engagement as the student-initiated teacher-student interactions that create a motivationally supportive environment. Blended or fully online learning requires students to use different strategies than traditional face-to-face learning (Ellis et al., 2018). In a blended environment, agentic engagement also encompasses student-initiated student-environment interactions. For example, agentically engaged students would access optional resources, use materials in particular ways, and interact with the environment beyond what is required.

Together the four factors outlined by Fredricks et al. (2004) and Reeve (2013) provide a holistic approach to student engagement and attempt to capture the myriad of dimensions involved

in the complex process of engagement. It is critical to keep in mind that the distinction between the four factors is fuzzy and, at times, the factors overlap or even blend together (Eccles, 2016; Sinatra et al., 2015). For example, Eccles (2016) suggests that agentic engagement is a "type of behavioural engagement" (p. 73), and Pekrun and Linnenbrink-Garcia (2012) view emotional engagement as a precursor to other forms of engagement. Regardless, investigating these factors both separately and in tandem affords instructors and researchers a better understanding of student engagement and, as a by-product, student success.

Student engagement has been associated with a variety of positive educational outcomes (Fredricks et al., 2016; Trowler, 2010; Vytasek et al., 2020); one such positive outcome is academic performance. The evidence linking behavioural engagement and aspects of cognitive engagement with performance is strong (Fredricks et al., 2004). While less research has focused on the link between emotional engagement and performance, some research does support associations between (a) positive activating emotions (e.g., enjoyment) with better performance and (b) other emotions (e.g., positive deactivating, negative activating, and negative deactivating) with worse performance (Fredricks et al., 2004; Pekrun & Linnenbrink-Garcia, 2012). On the other hand, Reeve (2013) measured all four types of engagement using self-report and found only behavioural and agentic engagement were associated with high school student performance.

Measuring Student Engagement

Student engagement has often been measured using self-report measures. For example, the National Survey of Student Engagement (NSSE) collects self-report data on student engagement at the university level (e.g., engagement in class and the university community; NSSE, 2019). Self-report measures have also focused on course level engagement. For example, the Class-Level Survey of Student Engagement (CLASSE) asks students to "reflect on behaviours for a specific class" (Ouimet & Smallwood, 2005, p. 13). Self-report measures provide useful insight into learners' intent and experiences with engagement; however, what learners report may not always line up with their actions (Azevedo, 2015; Winne & Jamieson-Noel, 2002). To move research on student engagement forward, it is critical to draw on additional data sources (Fredricks et al., 2019). For example, the use of educational technology to facilitate learning has created new opportunities to measure student engagement using the trace data collected during the learning process (Azevedo, 2015; Pardo, 2014; Vytasek et al., 2020).

Trace data are the footprints or crumbs that learners leave behind in a digital environment (Winne, 2019). For example, two common types of trace data in a traditional blended environment are log files (i.e., time-stamped records of actions) and learning artifacts (e.g., files, messages, etc.) (Vytasek et al., 2020). Trace data gives researchers and educators access to contextualized in the moment records of student actions in a course (Pardo, 2014). These actions each represent small fragments of student engagement (Winne, 2019), which can be used to assemble a fulsome picture of student engagement. Trace data can be analyzed both quantitatively and qualitatively, and results can be triangulated with other data sources.

As with other complex learning processes, e.g., self-regulated learning, the most effective way to understand student engagement is to draw on multiple data sources. Azevedo (2015) suggests different dimensions of engagement might be best measured using specific types of data and methods of data collection. For example, emotional engagement (i.e., affect) could be garnered from some forms of process data (e.g., facial expressions), self-report data, and discourse analysis. In contrast, cognitive engagement might be garnered from a wider variety of sources, including

product data (e.g., summaries) and different forms of process data (e.g., log files). Thus, it is critical to both draw from multiple data sources and, at the same time, select data sources that are appropriate for the particular dimension of engagement. Matching data streams with engagement dimensions is challenging in part because the dimensions are not mutually exclusive (Eccles, 2016; Sinatra et al., 2015). Nevertheless, by taking the time to understand the course context (O'Brien & Roll, 2019) and creating opportunities to collect specific types of data, it is possible to identify useful proxies for the various aspects of engagement.

Context for Current Study

Course Context

The learning-to-learn course was a semester-long elective undergraduate course and improving academic success was one of the main course objectives. Academic advisors and faculty members often recommend this course to students who are struggling in their other courses. The course introduced students to a variety of regulatory skills, strategies, and beliefs meant to improve their approaches to learning. Students learned about Winne and Hadwin's (1998) self-regulated learning model, procrastination, motivation and emotion, time management, test anxiety, and collaboration. The course had thirteen weeks of instruction, followed by a two-week exam period.

The course was designed with both face-to-face and online components. Each week there was one 90-minute lecture and one 90-minute lab in which students applied their learning. While students met face-to-face for both lecture and lab, coursework and lab activities were completed in an online environment. For example, students completed an applied collaborative test in small groups during which all collaboration occurred in the online environment via a wiki tool and text chat: while students were physically located in the same room, their interactions were primarily online. In addition to coursework, lecture materials (e.g., presentations, readings) were posted online for student review.

The course hub was hosted in the university's learning management system (LMS). Success in this course required students to engage in the online environment actively. For example, students were expected to log in and complete activities at least three times per week (i.e., after the lecture, during the lab, and to complete homework). The online components were designed to take "advantage of the potential of technology" (Bates, 2015, sec. 9.1.1); Bates (2015) refers to this form of blended learning as hybrid learning.

The blended nature of this course allowed us to capitalize on the trace data created during the learning process without needed to interrupt student learning for data collection (Pardo, 2014). Additionally, the design of the course ensured that many of the critical learning activities occurred within an environment where we were able to capture data. Furthermore, understanding our students' online engagement is important for the instructional team because this is a blended course where participation online is a requirement for student success. In a face-to-face course, instructors can monitor student engagement by watching how their students participate in class. The trace data collected online creates a critical window into student actions and affords instructors to monitor online environments as they would a physical environment. Understanding how students interact with the online environment creates opportunities for the instructional team to support student success by both adapting the course and intervening with specific students.

Research Context

Our course actively encourages students to make adaptations to their study life and approach to learning as part of the process of self-regulating their own learning. However, of the students who enter the course with weak academic history (GPAs between 0 and 3 on a 10 point scale), only a minority move out of the cycle of academic risk. In the semester under consideration, only ten students or 22.7% of the high-risk students moved out of this cycle. Our previous findings suggest that students who do poorly in the course are likely to have a history of weak performance and show lower behavioural and agentic engagement throughout the course (Edwards et al. 2017). However, our previous research did not (a) consider how different levels of engagement from students who started with weak performance might connect with performance trajectories or (b) investigate cognitive and emotional engagement. To better support students who enter our course at-risk for weak academic performance, it is critical to understand what differs between students who break out of the academic risk cycle and those who do not.

Purpose and Research Questions

The purpose of this exploratory mixed-methods case study was to explore specific student engagement characteristics distinguishing Stayers and Movers. Stayers were students who entered the course with low cumulative GPAs and remained in the weak performance group. Movers were students who entered with low cumulative GPAs and moved into a higher performance group. Specifically, we had one research question: what factors of student engagement differ between the Movers and the Stayers in our blended course?

Method

Research Design

This research employs a case study design (Yin, 2014), specifically a descriptive mixed methods cross-case comparison study. Case studies are commonly used in self-regulated learning research as they allow for detailed examinations of complex learning processes in authentic settings (Butler, 2011). Researching self-regulated learning requires consideration of how a variety of student factors (e.g., individual, contextual) shapes students' engagement in academic work. Importantly, student engagement is the focus of this study, not self-regulated learning; however, the context of the course included situating self-regulated learning as vital to student success. This study was interested in how and why academic performance differed between students and draws on between-group comparisons using both descriptive and inferential (non-parametric) statistics.

Participants and Sampling Strategy

Participants were sampled from consenting students from a mid-sized, non-urban Canadian university who were enrolled in the course in the January 2016 term. The inclusion criterion was previous semester GPA, measured on a 10-point scale (0 – 9 where 0 = F and 9 = A+). Students were included in the study if their previous semester GPA was 3.0 or lower (≤C+): 44 students were included (of a possible 139 students), see demographics in Table 1.

Table 1
Participant Demographics

| | Overall | Comparison Groups | |
		Movers	Stayers
n	44	10	34
Age	19.27 years (1.69)	19.00 years (1.05)	19.35 years (1.84)
Sex	63.60% male	50.00% male	67.65% male
First Year	45.50%	30.00%	50.00%
Prior Semester GPA	1.64 (0.97)	1.41 (1.13)	1.67 (0.93)

Comparison Groups

Final course grade (measured on the same 10-point scale) was used to identify two comparisons groups: (a) the Stayers, 34 students who completed the course with weak grades (0-3 or F to C+, $M = 2.06$, $SD = 0.15$) and (b) the Movers, 10 students who completed the course with good or excellent grades (4-9 or B- to A+, M = 5.40, SD = 0.34). None of the engagement variables investigated in this study were aggregated to construct the students' final course grade. The Stayers ($M = 1.67$, $SD = 0.93$) and the Movers ($M = 1.41$, $SD = 1.13$), did not differ in incoming prior semester's GPA, (t (42) = 0.73, $p = 0.47$). In charts, Stayers are abbreviated as S and Movers as M.

Context

The course, described in detail in the introduction, was a semester-long elective in which students learned about Winne and Hadwin's (1998) self-regulated learning model and how to apply it to their other courses. The course was taught in a blended format and was comprised of face-to-face (lecture and lab) sessions with online coursework. The course was research-based: unless students opted to withdraw from the research project, students consented to researchers examining regular coursework for research purposes (coursework, LMS data, institutionally collected data, etc.). Data was not accessed for research purposes until the course was completed and final grades were submitted. The Human Research Ethics Board (HREB) at the university approved all study procedures.

Measures

The four dimensions of student engagement (i.e., behavioural, emotional, cognitive, and agentic) and overall engagement were measured using five different measures. The measures captured individual students' engagement at the micro-level (i.e., course-level across the semester; Sinatra et al., 2015). The four dimensions of student engagement were measured using trace data collected during authentic learning tasks. Trace data included logs and information extracted from learning artifacts. Overall engagement was measured using subjective ratings from lab instructors (i.e., observational data). All data was collected and analyzed following completion of the course.

Behavioural Engagement

Behavioural engagement was measured using logs from the LMS. Specifically, we used two frequency counts: the number of completed (a) lecture syntheses activities (out of a possible 9) and (b) MyPlanners (out of a possible 10). The lecture synthesis activities were online review quizzes completed at the end of each lecture. The MyPlanner was an online questionnaire filled out weekly, during and after lab, about goal setting and study challenges. Responses from five random lecture synthesis activities and MyPlanners were marked and received a grade. However, neither the number of completed lecture synthesis activities nor the number of completed MyPlanners contributed to the final course grade. Weekly completion of both activities was an explicit course expectation. Thus, completion numbers for these activities is a gauge of course participation or behavioural engagement. The MyPlanners are abbreviated as MP and lecture synthesis as LS in charts.

Agentic Engagement

Logs from the LMS revealed the number of unique days a student accessed the course. It is challenging to distinguish agentic engagement from behavioural engagement (Eccles, 2016). The agentic actions that students take within a learning situation are behaviours. We selected the number of unique days a student accessed the course as a measure of agentic engagement because, while accessing the course was an implicit expectation, it was not a required course component listed on the syllabus. Counting the days students accessed the course acknowledges that students who accessed the course site chose to proactively engage in a variety of learning activities, both ungraded and graded. This is especially true of students who accessed the course more than the minimum expectation of 36 unique days (three times per week for lab, lecture, and homework over 12-weeks of activities). Furthermore, the simplicity of this measure makes it accessible to practitioners who teach and support the course. The number of unique days a student accessed the course is abbreviated as Days in charts.

Cognitive Engagement

Cognitive engagement was measured by coding the quality of goals set as part of an authentic learning task. Strategic self-regulated learners are cognitively engaged (Fredricks et al., 2004; Trowler, 2010); thus, students who set higher quality goals for learning are more cognitively engaged than students who set lower quality goals. Learning goals guide students' task engagement during learning (McCardle et al., 2017); students who set high-quality goals focused on the cognitive aspects of studying rather than the doing aspects of studying (e.g., to-do-lists) should be more cognitively engaged as they study.

Each week students set a study goal for a specific study session in the MyPlanner activity. The number of MyPlanners completed was used as a measure of behavioural engagement, but the content of the goals revealed cognitive engagement. Specifically, students were given the prompt "My learning goal for this two-hour study session is…" and asked to fill in an open response box with their goal. Students set their goals online during the weekly lab and, later in the week, independently reflected on their progress following their study session.

Emotional Engagement

Emotional engagement was measured using students' self-assessments of academic emotions collected as a component of an authentic learning task. Students reflected on academic emotion in the MyPlanner activity following their planned study session (see Figure 1). Students reported (a) one salient academic emotion they felt while completing their weekly study session, (b) the strength of that emotion, (c) the influence of that emotion on their ability to achieve their study goals, (d) the strategy they used to manage this emotion, and (e) their satisfaction with the strategy. Each of these data points was collected from drop-down lists, see Table 2.

Figure 1
MyPlanner Emotion Reflection

Table 2
Emotion Reflection Drop-Down Options

Item	Drop-Down Options
Emotion	Relieved, hopeful, anxious, happy, proud, bored, frustrated, interested, excited, disappointed, hopeless, afraid/worried, tired, stressed, focused, something else not on this list
Strength	Very weak, weak, moderate, strong, very strong
Difficulty	A lot harder, a little harder, neither harder nor easier, a little easier, a lot easier
Strategy	Took a break, focused on getting the task done, changed my approach to studying, thought about the consequences of finishing or not finishing the task, promised myself a reward for finishing the task, talked to someone, worked with someone, avoided doing the task, changed the way I was thinking about myself or my studying, changed my feeling directly (e.g., took deep breaths), changed my studying location or environment, did nothing, did something else (not on this list).
Satisfaction	Not at all, minimally, moderately, completely

Overall Engagement

Overall engagement, used to triangulate results, was captured using observation data. Lab instructors rated students' overall engagement on a three-point scale: disengaged, engaged at surface level, or engaged at a deep level. Each point on the scale was clearly defined (see Figure 2). The researchers explained the scale to lab instructors and answered any questions during an in-person end of the term lab meeting. Lab instructors were instructed to base their judgments on all aspects of a students' lab engagement evidenced by lab activities, and global engagement based

on the main assignments in the course (lecture synthesis activities, midterm grades, group projects, etc.). Lab instructors rated students following the last week of the course and ratings were unrelated to students' grades. Some lab instructors choose to provide additional qualitative descriptions of student engagement in an open response box. Lab instructor rating is abbreviated as LIRate in charts.

Figure 2
Overall Engagement Rating by Lab Instructors

Level of engagement in the course OVERALL, I would qualitatively describe this student as...	DISENGAGED in the course (not completing work, missing class, not really caring about their learning) 0 points	taking a SURFACE APPROACH to the course (doing the work to get it done, showing up, getting the ticks but not really evidencing any growth, change or learning) 1 points	taking a DEEP APPROACH to the course (trying to learn from the work and from mistakes - demonstrating growth and change) 2 points

Results

In the following sections, we employed a variety of analytical techniques to compare engagement across the two groups (i.e., Stayers and Movers). For measures where between group statistical comparison was warranted, the Stayers and the Movers were compared using nonparametric tests (Mann Whitney U tests) because the assumption of normality, required for parametric tests, was not met. Additionally, our group sizes were both small and uneven. Interpretation of results focused on significance as well as effect size (see Table 3).

Table 3
Results from Mann Whitney U Tests Between-Group Comparisons

Category	Var.	Grp.	Mean	*SD*	Mode	Median	Mean Rank	*U*	Asym. Sig. (2 tailed)	R^2
Overall	LIRate	S	0.78	0.64	1	1	19.44	66.00**	0.001	0.23
		M	1.60	0.52	2	2	32.90			
Behav.	LS	S	6.56	1.24	7	7	18.85	46.00**	0.000	0.32
		M	8.20	0.79	8, 9	8	34.90			
	MP	S	8.09	1.64	8, 10	8	20.72	109.50	0.080	0.07
		M	9.10	1.10	10	9.5	28.55			
Agentic	Days	S	38.15	9.12	41	39	20.21	92.00*	0.029	0.11
		M	45.50	8.64	45	45	30.30			

Stayers n = 34, Movers n = 10
Note. * $p < 0.05$, ** $p < 0.01$

Behavioural Engagement

The number of lecture synthesis activities completed by the Movers was higher (median = 8; mean rank = 34.90) than for the Stayers (median = 7; mean rank = 18.85). The difference

between the two groups was statistically significant ($U = 46.00$, $p <0.05$) and had a large effect size ($r^2 = 0.32$). The number of MyPlanners completed by the Movers was higher (median = 9.5; mean rank = 28.55) than for the Stayers (median = 8; mean rank = 20.72). However, the difference between the two groups was not statistically significant ($U = 109.50$, $p >0.05$). Thus, the two groups had significantly different behavioural engagement as quantified by one measure (lecture engagement) but not the other (MyPlanners) (see Table 3).

Agentic Engagement

The number of unique days the Movers accessed the course was higher (median = 45; mean rank =30.30) than for the Stayers (median = 39; mean rank = 20.21). The difference between the two groups was statistically significant ($U = 92.00$, $p < 0.05$) and had a medium effect size ($r^2 = 0.11$) (see Table 3).

Figure 3.
Mean Course Accesses by Week Between-Groups Comparison
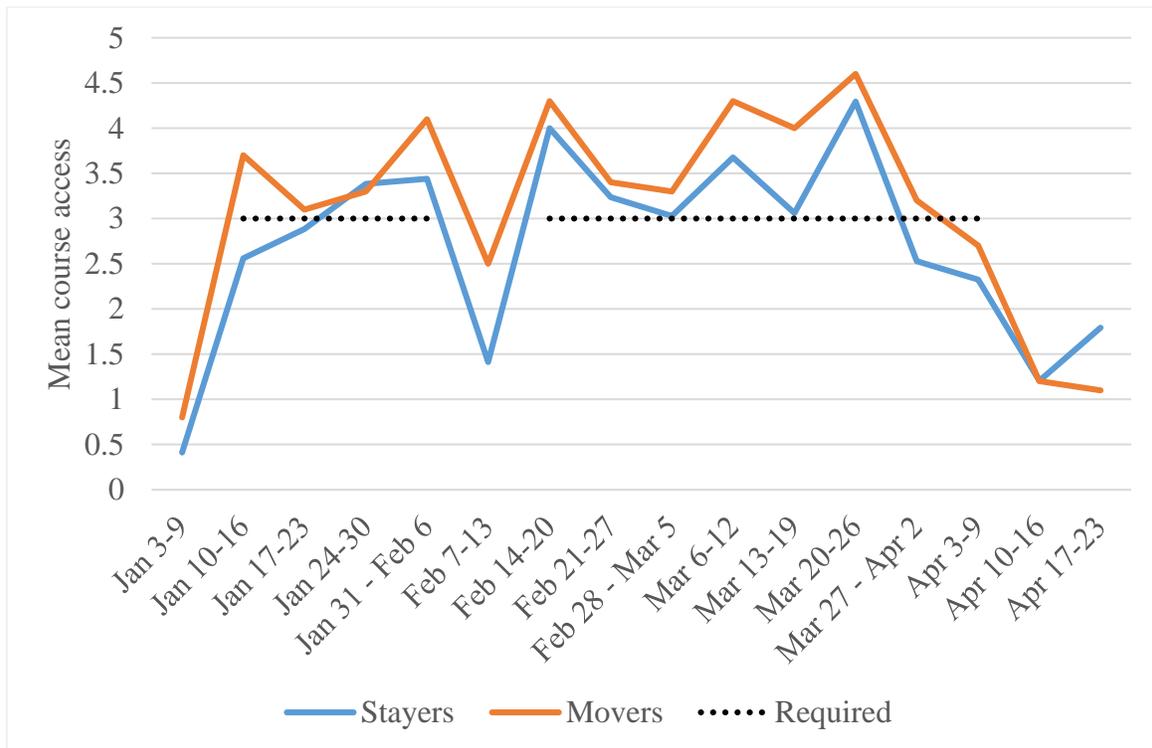
A data visualization of mean course access by week revealed the Stayers consistently accessed the course less than the Movers (see Figure 3). A dotted line demonstrates how often students were expected to access the course. Lower accesses by Stayers was particularly prevalent in weeks two, six, and eleven. Week two (January 10 to 16) was the first week of the lecture and labs. Week six (February 7 to 13) was both reading break and the week before the first midterm (held the week of February 15 during lab). Additionally, February 7 was the last day to withdraw from the course for a 50% reduction of fees. Week eleven (March 13 to 19) was the week before

the second midterm. Lower accesses by Stayers in these particular weeks (weeks two, six, and eleven) suggest that Stayers are less likely to show up at the first lecture or lab (week two), less likely to use the course site to study over reading break for the first mid-term (week six), and less likely to use the course site to study for the second mid-term (week eleven).

However, in week sixteen (April 17 to 23) Stayers accessed the course more than Movers. Week sixteen was the week of the final exam (the final exam was on April 21). More accesses by Stayers the week of the final exam, suggests that these students felt more need to access the course site to prepare for the final exam than did the Movers. It is important to note that students who had an average of greater than 75% across the two midterms earned an exam waiver and were able to use their midterm exam marks in lieu of the final exam. Thus, eight students in the Stayer group and eight students in the Mover group were not required to write the final exam.

Cognitive Engagement

This analysis focuses on goals written in the third and tenth weeks of the course because (a) students learned about goal setting in the third week of the course and (b) the final goal set in the course was in the tenth week. Students learned that high-quality goals include CAST elements: clear content (C), a specific action (A), a measurable standard (S), and a timeframe (T). Thus, following the categorization scheme of McCardle et al. (2017), goals were evaluated for content, action, and standard. Goals were not assessed for timeframe because raters were unable to judge if students had set realistic timeframes. Goals were categorized by two raters, for codes on which raters did not agree, raters reached agreement through discussion. Next, goals were organized into three groups: low, moderate, and high-quality.

Low-quality goals were either vague, to-do lists or plan-to-plan goals. This is an example of a low-quality, vague goal from week three: "I will read the key concept of Java program and understand it. Some action I will take is to remember these concepts and also use these concept in the assignment" (pt. 6). This goal does not contain clear content, a specific action, or a measurable standard.

Moderate-quality goals included one CAS element or included multiple goals where at least one goal included a CAS element. This example of a moderate-quality goal from week three included an action (practice quiz) but did not detail specific content or a standard: "On Friday, I will look up chapter1, 2 and 4 for [course name] from 2pm to 4:30pm. Then I will do the practice quiz online in order to check how well I get these points" (pt. 4).

High-quality goals included several CAS elements. This example of a high-quality goal from week three included all three CAS elements (content, action, and standard):"…my goal is to solidify my knowledge of how to use combinations and permutations, by completing the review questions… if i am unclear on any of them, i will star them and go back to them later" (pt. 2).

In weeks three and ten, higher percentages of Movers than Stayers had moderate or high-quality goals (Movers week three 70% and week ten 60%; Stayers week three 35.50% and week ten 35.94%) (see Table 4). Also, lower percentages of Movers than Stayers did not write a goal (Movers week three 0% and week ten 20%; Stayers week three 14.70% and week ten 26.47%). Findings suggest Movers exhibited higher-quality and higher-quantity cognitive engagement in the course than Stayers.

Table 4
Goal Quality Raw Number and Percentage, Week Three and Week Ten

		Missing		Low Quality		Mod. Quality		High Quality	
		#	**%**	**#**	**%**	**#**	**%**	**#**	**%**
W3	S	5	14.70	17	50.00	7	20.59	5	14.71
	M	0	-	3	30.00	3	30.00	4	40.00
W10	S	9	26.47	13	38.24	8	23.53	4	11.94
	M	2	20.00	2	20.00	3	30.00	3	30.00

Stayers *n* = 34, Movers *n* = 10

Emotional Engagement

Following Pekrun et al. (2002), each reported emotion was categorized by valence (positive or negative) and physiological activation level (activating or deactivating), resulting in four categories: positive activating, positive deactivating, negative activating, or negative deactivating (see Table 5).

Table 5
Pekrun et al. (2002) Emotion Categories and Corresponding Emotions

Category	Emotions
Positive activating	happy, proud, hopeful, interested, excited, focused
Positive deactivating	relieved
Negative activating	anxious, frustrated, afraid/worried, stressed
Negative deactivating	bored, tired, hopeless, disappointed

The proportion of times each student identified each emotion category was calculated over the ten weeks. All students responded to the emotion questions at least four times; thus, all students were included in the analysis. Additionally, if students reported "something else not on this list" the data point was treated as a valid skip. Then, for each category, we calculated the mean proportion of reports by Stayers and Movers (see Table 6).

As shown in Table 6, Movers tended to report more negative activating and negative deactivating emotions than Stayers. Notably, Stayers reported on average three times more positive deactivating emotions (e.g., relief) than Movers: Stayers 0.15 (0.16) and Movers 0.05 (0.09).

Table 6
Mean Proportions of Emotion Categories Reported Over the Semester

	Positive		Negative		Totals (Act/De)	
	Stayers	Movers	Stayers	Movers	Stayers	Movers
Activating	0.39 (0.23)	0.28 (0.27)	0.23 (0.19)	0.33 (0.25)	*0.62*	*0.62*
Deactivating	0.15 (0.16)	0.05 (0.09)	0.23 (0.19)	0.33 (0.21)	*0.38*	*0.38*
Totals (Pos/Neg)	*0.54*	*0.34*	*0.46*	*0.66*	-	-

The Pekrun et al. (2002) method for categorizing emotions is commonly used in research on emotion regulation. However, some scholars (e.g., Webster, 2010) suggest Pekrun's method does not account for individual differences in how emotions are experienced. For example, Pekrun would categorize stress as a negative activating emotion: however, this emotion might be

perceived as either positive or negative. Not all students experience emotions in the same way. As such, self-reports of emotion (a) strength and (b) influence were used to triangulate results.

Emotion strength was categorized as weak, moderate, or strong, and emotion influence was categorized as harder, easier, or neither. Each response was cross categorized by strength and influence; thus, there were nine unique categories: hard-weak, hard-moderate, hard-strong, neither-weak, neither-moderate, neither-strong, easy-weak, easy-moderate, and easy-strong. We then followed the same procedures as above (see Table 7).

Table 7
Mean Proportions of Emotion Strength-Influence Reported Over the Semester

	Weak		Moderate		Strong		Totals (H/N/E)	
	S	M	S	M	S	M	S	M
Hard	0.04 (0.08)	0.05 (0.09)	0.20 (0.20)	0.17 (0.11)	0.12 (0.14)	0.37 (0.35)	*0.36*	*0.59*
Neither	0.03 (0.06)	0.03 (0.07)	0.13 (0.17)	0.04 (0.10)	0.04 (0.07)	0.02 (0.06)	*0.20*	*0.09*
Easy	0.00 (0.02)	-	0.14 (0.16)	0.08 (0.10)	0.30 (0.25)	0.22 (0.19)	*0.44*	*0.30*
Totals (W/M/S)	*0.07*	*0.08*	*0.47*	*0.29*	*0.46*	*0.61*	-	-

Stayers n = 43, Movers = 10

Movers reported high levels of strong emotions (Movers = 0.61, Stayers = 0.46) and emotions which made it hard to complete their goals (Movers = 0.59; Stayers = 0.36). For Movers, the highest percentage of emotions were strong emotions which made it hard to complete their goal (strong-hard, M = 0.37, SD = 0.35). For example, a Mover said: *"During this study session, I mainly felt* **anxious**. *This* **strong** *feeling made it a* **little harder** *to achieve my session goal"* (pt. 3) – emphasis added by authors.

Stayers did not show as strong of tendencies as did Movers. For example, Stayers report relatively high levels of both strong (0.46) and moderate (0.47) emotions, and emotions which made it both hard (0.36) and easy (0.44) to complete their goals. For Stayers, the highest percentage of emotions were strong emotions which made it easy to complete their goals (strong-easy, M = 0.30, SD = 0.25). For example, a Stayer said: *"During this study session, I mainly felt* **hopeful**. *This* **strong** *feeling made it* **a lot easier** *to achieve my session goal"* (pt. 5) – emphasis added by authors.

Overall Engagement

The overall engagement rating for the Movers was higher (median = 2; mean rank =32.90) than for the Stayers (median = 1; mean rank = 19.44). The difference between the two groups was statistically significant ($U = 66.00$, $p < 0.05$) and had a large effect size ($r^2 = 0.23$), see Table 3. Lab instructors provided qualitative descriptions of some students in the Stayer group. For example, some Stayers were described as "doing busy work rather than completely engaging in course material" (description of pt. 7), "complet[ing assignments] to the bare minimum with minimal self-reflection" (description of pt. 8), and "[not being] used to reflective work" (description of pt. 1). Lab instructors did not provide qualitative descriptions of any students in the Mover group.

Discussion

The purpose of this study was to explore how student engagement in a blended learning-to-learn course differed between at-risk students who were successful (the Movers) and those who were not (Stayers). Findings suggested students who were ultimately successful showed higher levels and different patterns of engagement, supporting the claim that engagement is a complex, multidimensional construct (Fredricks et al., 2004). Additionally, using trace data and observational data to investigate engagement and triangulate findings was a useful strategy.

Movers are More Engaged

Movers were generally more behaviourally, cognitively, and agentically engaged than Stayers. Movers completed slightly more of the lecture and lab activities representing behavioural engagement. This indicates that Movers tend to complete a little more work and show up a little more often. Through goal setting, Movers showed both higher quality and a higher quantity of cognitive engagement. This suggests that the Movers may think about studying and learning more and in more complex ways than Stayers. Finally, Movers demonstrated higher agentic engagement by accessing the course more often. This supports the argument that Movers take a more proactive approach to learning.

Our findings regarding these three dimensions of engagement are in line with previous research suggesting that students who demonstrate higher levels of engagement tend to be more successful (e.g., Fredricks et al., 2004; Reeve, 2013). In sum, for behavioural, cognitive, and agentic engagement, quantity of engagement seemed to differentiate between the Stayers and the Movers, with the Movers have more instances of these three types of engagement. These findings lend credence to the idea that student inaction, often represented by missing data, can be a defining student characteristic. At times educational research drops students with missing data from analysis without considering what makes these students unique and the impact of eliminating these students on findings. The current study measured behavioural and agentic engagement quantitatively, future research should further investigate these two dimensions of engagement qualitatively.

Emotional Engagement Differed between Movers and Stayers

Movers demonstrated different patterns of emotional engagement than Stayers, but in an unexpected way. Emotional engagement is defined in the literature as enjoyment or interest (Reeve, 2013). We expected that Movers would demonstrate higher levels of emotional engagement with more positive-activating emotions than Stayers (e.g., Pekrun & Linnenbrink-Garcia, 2012). However, our findings regarding emotional engagement were mixed. First, Movers tended to report more negative activating and negative deactivating emotions than did Stayers. This was unexpected because in previous research both negative activating and negative deactivating emotions have been associated with poor performance (Pekrun & Linnenbrink-Garcia, 2012). However, some scholars have argued that negative emotions can be useful during learning (e.g., Webster, 2019). Second, Stayers reported more positive deactivating emotions than Movers. This finding is aligned with previous research suggesting that positive deactivating emotions (e.g., relief) are connected to poor performance (Pekrun & Linnenbrink-Garcia, 2012). Third, Movers also tended to report both (a) stronger emotions and (b) more emotions that made

goal achievement harder. These findings suggest that, rather than focusing solely on emotion valence and activation, other characteristics might be useful in understanding emotional engagement.

Our findings may differ from previous work in this area because our emotions measure was situated within a specific learning task and asked students to reflect on their emotions directly following the experience. Thus, traditional measures have tapped into emotions about learning and our measure tapped into emotions during learning. Students who are ultimately successful (Movers) may look back on learning experiences fondly (explaining the connection between positive emotions and success in previous work), but these students may experience a different range of emotions during the learning task. Future work could compare retrospective emotions (reported immediately after and/or with a time delay) with emotions reported in the moment. Alternatively, our findings may suggest that Movers are better at monitoring their own emotions than Stayers. For example, Movers and Stayers might experience similar emotions, but Movers might be better at identifying their own emotional state compared with Stayers, who responded with general platitudes about positive emotions (e.g., relief). Future research could compare reported emotions with felt emotions (e.g., measured through biometrics).

Lab Instructor Ratings Mirrored Other Results

Lab instructors rated Movers as significantly more engaged than Stayers. This finding triangulated the results from the other engagement measures. Lab instructors formed impressions regarding student engagement as they interacted with students in the face-to-face classroom and in the online environment. In a course where instructors interact extensively with students either online or face-to-face, instructors' observations might be a useful indicator of student engagement. It is important to note that in this case, lab instructor ratings were collected at the end of the semester: the lab instructors had an entire semester to form their impressions. Lab instructor ratings might be less reliable if collected earlier in the semester. Future research should seek to identify (a) at what point in the semester and (b) at what level of student-instructor interaction instructor observations become a useful measure of student engagement.

Limitations of the Study

The current study aimed to understand a small population in a particular context during a limited timeframe: Sample size was limited to students who entered our course with a low GPA during one semester. Our small sample was both a limitation and an opportunity: The small sample size limits both the power and generalizability of our results but allowed us to do a fine-grained exploration of the engagement factors differing between these two groups of students.

By using student engagement as our theoretical framework, we drew meaningful conclusions from our findings. In our effort to make sense of our data, we categorized engagement measures as either behavioural, cognitive, emotional, or agentic engagement out of necessity. We may have omitted measures in the course that could have offered more to our study, but we did not include them due to our categorization. Also, the categories within student engagement are complex; indicators do not always neatly assess one type of engagement; for example, our measure of agentic engagement (days viewed course) may also capture pieces of behavioural engagement (Eccles, 2016).

Behavioural engagement and agentic engagement were both measured using logs from the LMS. While these measures indicate the amount students engaged with the course (i.e., quantity), they do not indicate the quality of engagement. In this study, our measures of cognitive engagement (goal quality) and emotional engagement provide insight into the quality of engagement for one of our behavioural engagement measures (MyPlanners). Future work will investigate the other behavioural and agentic measures similarly.

Emotional engagement was self-reported immediately following the study session. A self-report measure was selected because in this context it was not possible to measure emotion in other ways (e.g., facial expressions or physiological activation). Furthermore, the data was collected retrospectively because collecting data during the study session would have interrupted the session and may have influenced both emotions and the task at hand (Webster, 2010). Due to the retrospective nature of the measure, students were asked to reflect on a salient emotion that stood out from the study session rather than try to recall the pattern and range of emotions they might have felt over the study session. Results regarding emotional engagement must be interpreted with these limitations in mind.

Finally, cognitive engagement was evaluated using learning goal quality. While a student's intentions for a study should direct their engagement during the study session, goal quality does not paint a full picture of the cognitive engagement during learning. For example, some students may write a poor goal but demonstrate higher quality engagement during the study session. Additional data points representing cognitive engagement (e.g., artifacts from the study session) would strengthen the findings. Additionally, each students' overall engagement was rated by only one lab instructor at one point in time: Future work should evaluate the reliability of this measure.

We conducted this research within a learning-to-learn course. Students chose this course for a variety of reasons, but the course was process-based and focused on improving academic success. Student engagement is particularly relevant within our course context, and the course provides unique opportunities to measure this engagement in situ. In other courses, student performance might not be tied so closely to student engagement or opportunities to measure student engagement might be limited. Thus, the generalizability of our results is limited.

Implications

The findings from this case study suggest low achieving students who improved their performance demonstrated higher levels of engagement across three of the four dimensions of engagement. Furthermore, these students' engagement was recognizable by observers—the lab instructors who rated students' overall engagement. These findings have practical implications for instructors of blended courses. Our sample size was small, and the results may not generalize to all other contexts. However, the following recommendations are grounded in educational theory and research and stand regardless of the generalizability of our results.

Instructors Monitoring Engagement

We recommend that instructors monitor both online and in-class engagement. Instructors might start by mapping out their course to identify student actions and course activities that might serve as useful indicators of engagement. Instructors could ask questions like: Which course activities are required in my course (behavioural engagement)? How might students go beyond what is expected of them (agentic engagement)? Have I created opportunities for students to reflect

on how they feel about their learning in my course (emotional engagement)? How can I see the thought processes that went into student work (cognitive engagement)? In a blended or online course, instructors have unique opportunities to monitor engagement by using the trace data collected by the learning environment. However, most instructors are not educational researchers or data specialists. Thus, the challenges of accessing and using some types of data might be a barrier (Pardo, 2014) to successfully monitoring student engagement. Instructors should select indicators that are both useful and easy to access. In addition to finding opportunities to monitor student engagement, instructors might find it useful to pay special attention to students who are at-risk for failure.

Students Monitoring and Adapting Engagement

Encouraging at-risk students to monitor/evaluate and change their engagement patterns is a practical way for educators to support student performance. Just as it is helpful for instructors to monitor student engagement, it is particularly useful for students to monitor their own engagement. Instructors might consider including student engagement visualizations (e.g., learning analytic dashboards) in their course to facilitate students monitoring of their own engagement (Vytasek et al., 2020). After students (or instructors) have monitored engagement and identified a deficiency, the next step is to adapt or change engagement (Winne & Hadwin, 1998). Instructors can support this process by clearly communicating with students how successful students engage with the course. For example, explicitly telling students how often successful students access the course, what successful students do within the course, etc.

Support Engagement through the Learning Environment

We recommend that instructors create learning environments that encourage engagement. This is critical because low achieving students might require higher levels of support from instructors (Fredricks et al., 2019). In blended or online learning, it is possible to design the learning environment so that the environment itself supports engagement. Behavioural engagement might be supported by using LMS tools like the calendar or an announcement to send automatic reminders. Additionally, the syllabus and activity instructions can make the course requirements and expectations explicit. Cognitive engagement might be supported by designing activities that require students to make their learning processes explicit and by providing learning strategy support (e.g., a learning strategy library within the course or access to learning strategy consultations). Agentic engagement might be supported by providing opportunities for students to explore the material independently (e.g., point to additional resources) and acknowledging when students have gone beyond expectations (e.g., through badging/gamification).

Our findings regarding emotion engagement were mixed, at times successful students do not feel positive emotions. Thus, supporting emotional engagement should not solely focus on sparking positive feelings. Rather, it might be more useful for instructors to develop an emotionally supportive online environment. This might be achieved by increasing instructor presence in the course (Russo & Benson, 2005): Instructors might virtually introduce themselves, make their contact information and office hours clear, and build short check-in surveys into the course. These recommendations for supporting engagement will create a positive learning environment for all students, not just those who are at-risk, and are grounded in general best practices for teaching-and-learning.

Conclusions

Combining trace data, observation data, and self-report data to investigate student engagement provides an interesting and relevant lens in which to examine differences in student performance. By viewing student engagement in our course in a holistic way, we attempted to capture the complexities of how the learning process contributes to performance. We identified useful course-specific proxies for the engagement dimensions by carefully considering the range of data that was already being created by students in our course as part of their coursework. This approach afforded the research team to (a) utilize trace data to move beyond studying engagement purely through self-report measures and (b) select data sources that unique suited the various dimensions of engagement (e.g., Azevedo, 2015). This case study shows the benefits of considering multiple data sources (e.g., learning artifacts, log data, self-reported emotions, lab instructor ratings) in student engagement research.

Our study upholds established knowledge in the field—higher achieving students show up to class more, interact more with the online course components, set higher quality goals, and complete more work. For behavioural, cognitive, and agentic engagement, more seems to be better. However, this distinction of "more" becomes blurred with emotional engagement—higher achieving students reported experiencing more negative emotions when faced with a challenge than lower-achieving students. Going forward, it will be critical to dive deeper into these findings to investigate at a more fine-grained level the strategic actions engaged by students who do more. Studies that continue to combine diverse methods of measurement (e.g., self-report, learning analytics) with robust theoretical frameworks will contribute to both the field's growing recognition of learning as a complex, multidimensional process and to the students and educators who seek to improve their learning and teaching approaches.

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