Using Feature Engineering from Online Learning Environments to Observe Social and Emotional Skills and Academic Performance

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Conclusions

In this study, we coupled social and emotional learning and learning analytics in four undergraduate courses making extensive use of the LMS and examined relationships among social and emotional (SE) skills, behaviors recorded in the LMS, and course grades. Our findings showed that SE skills, LMS data, and grades are largely associated with one another in expected ways, with course grades being robustly correlated with LMS behaviors across all courses, while different sets of LMS behaviors correlated significantly with different SE skills. Implications of results, limitations, and future work are discussed.

So What?

Student interactions with learning management systems (LMS) and other educational technologies provide detailed information about how students interact with learning resources and activities. Learning analytics researchers and educational technologists have demonstrated that these data can be used to predict student course grades. However, much less is known about the psychological constructs that underlie student online behaviors, which are needed to help faculty, advisors, and students themselves interpret predictions and improve learning outcomes.

Now What?

While educational psychologists have found that self-reported social and emotional skills have significant relationships with course grades, little is known about how these skills are enacted in authentic learning contexts. This study and others examining behavioral residue offer promise for unobtrusive SE skill assessment with high validity.

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Introduction

A focus of learning analytics research has been the collection, analysis, and interpretation of data from online academic technologies, particularly in higher education where these technologies are incorporated extensively into the student learning experience. In particular, the learning management system (LMS) has emerged as a technology frequently integrated into all courses, whether online, in person, or hybrid, with three-quarters of students using the LMS in all or nearly all of their courses (Galanek, Gierdowski, & Brooks, 2018). Since the 1990s, learning analytics researchers and educational technologists have been creating predictive models of student academic performance based on "clickstream" data, which are generated by student interactions with LMS resources and activities (Wang & Newlin, 2002). Despite the ultimate goal of improving student learning (vs. simple prediction), there are few empirical studies of intervention efforts. A recent systematic review identified only 11 published studies of interventions, and those studies were of mixed quality and had inconsistent findings (Sønderlund, Hughes, & Smith, 2019).

The scarcity of intervention studies is due to many factors; among them is a lack of attention to the underlying reasons for the captured behaviors in clickstream data. This issue has become known as the "click to constructs" problem (Knight & Buckingham Shum, 2017). Researchers, especially those coming from an educational psychology background, have begun to articulate constructs potentially related to clickstream data. To date, self-regulated learning has been one of the focal constructs of investigation (Roll & Winne, 2015). It is important to focus on such constructs because they are related to the skills and strategies required of students to be effective in their courses. They are linked with study habits and systematic behaviors rather than students' prior knowledge in the particular area of study or mere quantity of activity, which risks reducing analytics to a behaviorist educational theory in which more activity is equated with more learning (but of course, there could be many activities with no actual learning involved). Given that higher education generally requires greater initiative on the part of the student (e.g., students may be required to access course materials and activities on their own volition and, to some degree, on their own schedule), self-regulated learning is a reasonable starting point for this research. In this study, we extend this research to consider constructs from the area of social and emotional learning.

Several social and emotional skills (SE skills) have been identified in the literature as relevant for success in school, work, and life (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007), and it has been noted that these findings generally replicate (Soto, 2019) and generalize across different samples (Soto, 2020). There is ample evidence, for example, that sustaining effort-related skills (i.e., skills related to being organized, persistent, reliable, etc.) are associated with academic success at all levels of education and are even on par with cognitive ability in predicting grades in secondary and tertiary education levels (Poropat, 2009). Given their importance for academic success, assessment of students' SE skills is invaluable, and the LMS and other academic technologies offer the opportunity for unobtrusive assessment at an unprecedented scale. Rather than tasking students with engaging in additional assessment and relying on self-reports which may be limited by issues such as response manipulation or response biases, SE skills may be indirectly observable through LMS clickstream data.

The practice of observing psychological constructs through such digital footprints is becoming more common, allowing researchers to examine so-called “behavioral residue,” which is the physical trace of activity in an environment (Gosling, Ko, Mannarelli, & Morris, 2002), often an environment with high ecological validity (Gladstone, Matz. & Lemaire, 2019), which can give insight into a person’s characteristics such as SE skills. This has been carried out in various settings including Facebook (Kosinski et al., 2015), music collections (Nave et al., 2018), and spending records (Gladstone et al., 2019). We are interested in examining the digital footprint in an academic setting to examine associations among SE skills, LMS behaviors, and course grades. While we know that SE skills are related to course grades, we do not understand the mechanisms by which positive SE skills lead to improved school outcomes. For example, we would expect that having attention to detail, being organized, and goal striving (i.e., having high levels of sustaining effort) would lead to better course grades through better study habits. That is, individuals with higher levels of sustaining effort may be more likely to make use of time-sensitive LMS features, which in turn, results in better course grades. We do not know, however, whether SE skills are expressed through LMS behaviors. In this study, we explore this possibility by examining relationships among SE skills, behaviors recorded in the online learning environment, and course grades. We carry out this study in four separate courses at a single higher education institution.

Method

Participants

Participants were undergraduate students at a mid-sized public research university on the East Coast. Students (*N* = 1,427) from four courses during the spring 2019 semester participated in the study. The sample was diverse with respect to gender, race/ethnicity, first-generation student status, and transfer student status; demographic information, which was extracted from the Peoplesoft student information system, is provided in Table 1 for students in each course. The four courses were web enhanced with varying degrees of technology and LMS integration. Students opted into the study with an incentive of extra course credit.

Data Sources and Measures

Course Syllabi and Instructor Interviews

The course syllabi were reviewed, and relevant dates and learning activities were identified. The faculty members then took part in individual semi-structured interviews. They were questioned about their use of the LMS for the course activities and their experience pertaining to which student behaviors are typically associated with course grades. This information was used to create a preliminary map of features that could be extracted from the LMS data. Once the LMS data were received, the mappings were discussed with the faculty members and an academic technology administrator to ensure that they were accurate. The courses varied in terms of their use of the LMS, both in terms of the features used and the frequency of use (see Tables 2-5).

Blackboard Data (LMS)

The quantitative data analyzed include the activity log data extracted from the Blackboard Learn LMS using data provided by the Blackboard Data product. Activity measures were provided at the individual student-activity level for all interactions with course materials and activities that were recorded in the database, with a total of approximately 1.6 million records across the four courses (approximate values per course were 700,000 for Chemistry, 100,000 for Math, 375,000 for Physics, and 450,000 for Psychology). We only included LMS behavioral data from the activity table; in-course graded items were excluded as these items are not independent from final course grade.

ACT Tessera College

ACT® Tessera® (ACT, 2020) is a SE skills assessment measuring five skills, which are listed and described in Table 6. Students' skills are assessed via three methods – Likert items, forced choice items, and situational judgment tests. This multi-method approach avoids the pitfalls associated with any single item type (Kenny & Kashy, 1992), such as the ease with which test-takers can fake their responses to Likert items (Zickar, Gibby, & Robie, 2004). Responses from these three item types are then aggregated into a multidimensional IRT score for each skill (Anguiano-Carrasco, Walton, Murano, Burrus, & Way, 2017), which roughly fall between ±3. The college version of ACT® Tessera® is not yet operational but has undergone pilot studies to establish its reliability and validity.

Procedure

General Study Procedure

The study was reviewed by the university's Institutional Review Board. All student data were anonymized by using a random identifier generated for this study, and no personally identifiable information was included in the dataset. The school's data privacy policies, which are disclosed to students and posted in the student portal, allow for the analysis of student learning activity data for the purpose of educational improvement without explicit consent. The instructors introduced the complete study to their classes, and interested students opted in to participate in the assessment of SE skills. Participating students were given extra credit points for the course. As a result, all student data were included in analysis that required only LMS use, and for analysis of SE skills, the subset of students that completed the assessment were included (we had ACT Tessera data for 68% of the total sample).

LMS Clickstream Data Processing

The online interaction features were generated from the LMS clickstream data by uniformly formatting log events (Greene et al., 2019) in which clickstream data were manually mapped to learning activities as determined through analysis of the syllabus and instructor semi-structured interviews. After manual inspection, we determined that the action field alone (e.g., "opened") was insufficient and needed to be joined with the label of the item that the action was taken in reference to, which was a complex pairing. For example, course item values in the LMS data include "Week 12: Electrochemistry" or "CHEM 102 Practice Exam 4B," which were easily interpretable from the course syllabus, while others needed confirmation from the instructor (e.g., "2/27 CL" and "18.7 RQ"). Hence, we created broader activity categories (referred to interchangeably as "activity") for these activity measures in the LMS data using the course syllabi with confirmation from the instructors, which resulted in 583 unique activity measures in the LMS data that were recoded to a total of 35 activity categories (Tables 7-10).

Several data transformations were conducted to remove irrelevant data and to control for inaccurate session duration recordings. Activities with a duration of zero seconds were removed as they represented navigation or system activity. The values of activity duration and session (login) ID were also recalculated to control for the known challenge of extracting this type of information from log information. Each activity was truncated to a maximum length of 30 minutes, and a new session was calculated if two hours or more had lapsed between student actions to adjust for students that had ceased using the system but had not logged out. These calculations were made after reviewing the data distributions for empirically justified threshold levels.

We initially developed a design pattern that used evidence-centered design principles (Mislevy, Almond, & Lukas, 2003) to create indicators from the LMS data (Beheshitha, Gašević, & Hatala, 2015) that best described the SE skills. Evidence-centered design is an assessment design process providing the language, concepts, and knowledge representations to build an evidentiary argument for that particular assessment. A key step in this process is domain modeling that builds a design pattern including the student model, task model, and evidence model. The student model may indicate the knowledge, skills, abilities, and behaviors being measures (e.g., sustaining effort). The task model would indicate which activities may elicit the knowledge, skills, abilities, and behaviors (e.g., taking an online practice exam). The evidence model indicates what data provide evidence of those knowledge, skills, abilities, and behaviors (e.g., getting a question correct after multiple incorrect attempts).

Despite undertaking this process for the SE skills, the information captured in the LMS activity measure log proved to be inadequate in generating the needed interaction features based on the design patterns. Therefore, from the reformatted LMS data, we were able to compute student-level interaction features that described access to these activities (LMS activity features). These were then merged to the individual student's SE skill scores, final course grade, and demographic information. This process required extensive manual interpretation and recoding.

From the LMS log data, relevant information about a student accessing a particular activity included the session ID it belonged to, the duration of that activity in a session, and number of instances of that activity in a session. Therefore, for each activity category, we computed its average measures of engagement across all of a student's recorded sessions. These calculations included three average measures: average count or number of attempts at an activity in a session (activity appended with "Attempt"), average time spent or total duration for an activity in a session (activity appended with "TimeSpent"), and average variability of time spent or total duration for an activity in a session (activity appended with "TimeSpentSD"). This approach to summarizing features was used due to its success with similar problems in other learning systems (cf. Baker et al., 2012; Baker, Goldstein, & Heffernan, 2011; Pardos et al., 2014). We accounted for the number of sessions when looking at counts and duration of an activity, instead of count and sum across the entire semester, to have a more nuanced measure of activity engagement. For example, throughout the semester, a student accessed an assignment activity in the LMS across three login sessions, and for each session, the student accessed it twice. Thus, the feature *assignment_Attempt* for this student would be equal to 2. If we included the number of sessions a student had as an interaction feature, there were a total of 106 unique LMS activity features across all students in all four courses.

Results

Associations Among SE Skills, LMS Behaviors, and Course Grades

After generating the features at the student level, we examined the correlations among the LMS behaviors, SE skills, and course grade. Here we present the findings course by course. Any correlations mentioned or presented in the tables are statistically significant ($p < .05$; see Tables 7-10). Descriptive statistics for grades and SE skills across courses are provided in Table 11.

Chemistry

Course grade had the strongest relationship with Sustaining Effort ($r = .34$), as expected, and was also significantly correlated with Maintaining Composure ($r = .16$), Keeping an Open Mind ($r = .14$), and Social Connection ($r = .12$).

Of the four courses, Chemistry made the most use of the LMS. A total of 44 LMS activity measures were found to be significantly correlated with grade or one or more SE skills. Of these 44 features, 32 were associated with grade. Grade was most strongly related to activity measures involving discussion board usage, specifically number of attempts on the board ($r = .36$), time spent on the board ($r = .32$), and variability of time spent on the board ($r = .31$). Of the 32 features, only number of attempts on syllabus was in the negative direction.

With regard to the SE skills' associations with LMS activity measures, as expected, Sustaining Effort had the most statistically significant correlations (with 25 LMS activities), followed by Getting Along with Others (16), Keeping an Open Mind (7), and Maintaining Composure and Social Connection (both with 4). All associations were in the positive direction with just two exceptions—Maintaining Composure-activity correlation and Social Connection-activity correlation. Sustaining Effort was most strongly associated with activity measures related to assignments ($r = .23$), specifically variability of time spent on assignment ($r = .23$), time spent on assignment, and number of attempts on assignment ($r = .21$). The LMS activity measure that was related to the most SE skills (4) was variability of time spent on exam review materials.

Math

The only SE skill that was significantly correlated with course grade was Keeping an Open Mind, and it was not in the expected direction (r = -.22).

Integration of the LMS into the Math course was minimal compared to the other three courses. A total of 27 LMS activity measures were found to be significantly correlated with grade or one or more SE skills. Of these 27 features, 16 were associated with grade. Grade was most strongly related to number of LMS sessions (r = .39). Of the 16 features, only number of attempts on information was in the negative direction.

With regard to the SE skills' associations with LMS activities, Getting Along with Others (8) had the most significant correlations with LMS activities, followed closely by Sustaining Effort (7) and Keeping an Open Mind (6). Social Connection and Maintaining Composure were significantly correlated with only three and two activity measures, respectively. Most associations were in the positive direction with a few exceptions. The LMS activity that was related to the most SE skills (4) was time spent on general content.

Physics

Course grade had the strongest relationship with Sustaining Effort (r = .19), as expected.

A total of 31 LMS activity measures were found to be significantly correlated with grade or one or more SE skills. Of these 31 features, 16 were associated with grade. Grade was most strongly related to number of LMS sessions (r = .36). Fourteen of the features were in the positive direction.

With regard to the SE skills' associations with LMS activities, Sustaining Effort (18) had the most significant correlations with LMS activities, more than double the number for any other SE skill. All associations were in the positive direction. No single LMS activity was associated with more than three SE skills.

Psychology

Counter to expectations, Maintaining Composure and Social Connection were both negatively correlated with course grade (r = -.19), and Sustaining Effort was not significantly related to grade.

A total of 50 LMS activity measures were found to be significantly correlated with grade or one or more SE skills. Forty of the 50 features were associated with grade, and all were positively correlated. Grade was most strongly related to number of LMS sessions (r = .53).

With regard to the SE skills' associations with LMS activity measures, Sustaining Effort (12) and Keeping an Open Mind (10) had the most significant correlations with LMS activities, and no other skill was related to more than three activities. Most associations were in the positive direction, but there were some exceptions. No single LMS activity was associated with more than three SE skills.

Discussion and Conclusion

This study capitalizes on learning analytic techniques to analyze students' clickstream data and link those data to student performance as well as important SE skills, which are of ever-increasing focus in research (e.g., Taylor, Oberle, Durlak, & Weissberg, 2017) and policy (e.g., Dusenbury & Weissberg, 2018). We examined relationships among SE skills, behaviors recorded in the LMS, and course grades in four separate university courses making extensive use of an LMS to supplement in-person instruction. This study allows us to explore SE skills in relation to the "click to constructs" problem (Knight & Buckingham Shum, 2017), which pertains to the lack of attention given to the underlying reasons for observed behaviors in clickstream data. With the current study, we extend early research focusing on self-regulated learning (Roll & Winne, 2015) to consider a broader set of skills. Overall, our findings suggest that SE skills, LMS data, and grades are largely associated with one another in expected ways. We review our findings below and discuss their implications for SE skill assessment and interventions.

Associations Among SE Skills, LMS Behaviors, and Course Grades

As expected, LMS behaviors and course grades were robustly correlated, which is intuitive given the direct relationship between the two; that is, if students are not engaged with class activities and content, their grades should be directly affected in a negative manner. To some degree, the expected associations between SE skills and grades were observed, but not across all SE skills and courses. In Chemistry and Physics, Sustaining Effort had the strongest correlation with grade, which was expected. In Math, Keeping an Open Mind had the strongest correlation with grade, but it was a negative association, which counters what Poropat (2009) reported in his meta-analysis. In Psychology, Social Connection and Maintaining Composure had the strongest correlations with grade, and although the negative direction of those correlations was consistent with Poropat's results, our estimates were considerably greater in magnitude.

Of particular importance for this study, however, we found that SE skills have systematic relationships with LMS behaviors when analyzed in relation to individual activities. Differences across the SE skill-LMS activity correlations provide evidence of the validity of the SE skills; that is, different SE skills are associated with different student actions. As anticipated, Sustaining Effort was associated with the greatest number of LMS activities and to the greatest degree, speaking to the tendency of students with a high level of Sustaining Effort to attend to detail, be organized, and persist at completing their work, all of which are important characteristics for succeeding in an asynchronous online learning environment. As another example, in Chemistry, Keeping an Open Mind was the only SE skill significantly related to activities pertaining to learning objectives, which may reflect the tendency of students with a high level of Keeping an Open Mind to be highly inquisitive and think about high-level ideas, such as how specific learning materials relate to the overarching learning objectives.

Differences Across SE Skills, LMS Behaviors, and Courses

There were some differences observed across variables or courses that warrant consideration. First, some LMS behaviors appeared to be highly related to grade but not SE skills, for example. A concrete illustration of this is in the Chemistry course where activities related to discussion board usage were the behaviors most strongly associated with grade but were only associated with one SE skill (Sustaining Effort), and to a relatively small degree. This is an area in which the faculty interviews had tremendous value. The instructor of this course explained that the discussion forum is infrequently used in the course, but the students who do participate in the forum are the more proactive students who point out errors in the book and ask targeted and insightful questions. Second, some courses had many more significant grade-LMS activity or grade-SE skill correlations than others (e.g., Psychology had nearly twice the number of significant correlations between LMS activities and grade or SE skills as Math) or had different significant associations (e.g., in Physics, one SE skill was significantly correlated with number of sessions in the LMS, whereas three SE skills were significantly correlated with number of session in the LMS in Math). Such inconsistencies can be attributed to the varying designs and requirements of the courses. Not all courses used the LMS with the same frequency or in the same manner. The courses were not designed with a priori mappings of LMS behaviors to SE skills at all, let alone consistently.

Limitations and Future Work

This project was largely exploratory and was conducted at a single university in a limited number of courses, and as such, the findings may not generalize across area of study; for example, we had an oversampling of STEM classes in this study. There are mean-level differences in SE skill-related constructs across majors (Vedel, 2016), and there are possibly differences in the variability of those constructs across majors as well. With differences in variability, it is possible that SE skills may relate differently with grades and LMS behaviors across diverse courses. For example, courses in the arts may have greater effects related to Keeping an Open Mind. Differences in student characteristics across various universities could potentially affect findings as well (although we found no significant subgroup differences in our analyses). As another point of consideration for future study, analyses should include a threshold requirement for inclusion in such studies. For example, courses with low usage of the LMS will naturally have fewer observed LMS-grade and LMS-SE skill associations. Finally, the manual mapping of clickstream log data to course-specific features limits the potential to scale out this work without a significant amount of additional effort. Automated methods to identify features that also have fidelity with the underlying course design would enable broader testing and deployment of models.

Implications

The findings presented above have a number of important implications for practice. This work represents an important example of examining behavioral residue (Gosling et al., 2002) in an environment with high ecological validity (Gladstone et al., 2019). This method of unobtrusively observing students' SE skills in the real world in real time could be invaluable. The LMS and other academic technologies offer the opportunity for SE skill assessment at an unprecedented scale. In addition to allowing for large-scale investigations, this also alleviates a big problem in education, particularly in primary and secondary school, which is too much time spent on testing. An overwhelming majority (81%) of teachers feel as though their students spend too much time taking mandated tests (Rentner, Kober, Frizzell, & Ferguson, 2016), and the sentiment is surely echoed in the student body. Not only can testing be burdensome, but conventional methods of assessing SE skills are subject to various biases and limitations (Wetzel, Böhnke, & Brown, 2016), which may threaten the validity of the assessments. This study and others examining behavioral residue offer promise for unobtrusive SE skill assessment with high validity.

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Table 1. Sample Demographic Data

	Chemistry		Math		Physics		Psychology	
Variable	*n*	%	*n*	%	*n*	%	*n*	%
Female	242	50	74	36	195	61	125	40
Race / Ethnicity								
Asian	141	29	66	32	117	37	86	27
Black / African American	84	17	52	25	61	19	70	22
Hispanic / Latino	43	9	11	5	19	6	25	8
White	189	39	60	29	105	33	106	34
Two or More	29	6	11	5	10	3	19	6
Not specified	3	1	6	3	6	2	7	2
First Generation College Student (yes)	119	24	65	31	86	27	79	25
Transfer Student (yes)	53	11	89	43	101	32	47	15
ACT Tessera Participant (yes)	406	83	104	50	223	70	172	55
Total	489		207		319		314	

Table 2. Distribution of LMS Activities' Total Semester Count: Chemistry

Variable	*M*	*Mdn*	*SD*	*Min*	*Max*
Number of sessions	168.03	162	56.91	18	383
Announcement	267.52	242	131.64	27	1400
Answer key	0.60	0	1.94	0	20
Assignment	256.21	255	113.86	8	893
Discussion board	55.17	24	99.55	0	858
Discussion class	4.53	3	4.88	0	46
Email / Messages	2.37	1	3.24	0	24
Exam review materials	39.24	36	22.86	0	144
General content	187.16	187	39.60	26	366
Gradebook	60.29	44	67.31	3	986
Help resource	3.91	2	5.04	0	45
Information	4.99	0	13.43	0	107
Learning objectives	0.34	0	1.13	0	11
Lecture/Class Activities	13.65	13	7.04	0	61
Orientation	4.47	4	3.39	0	24
Practice assignment	110	97	82.73	0	524
Practice exam	55.64	48	39.40	0	314
Reading quiz	173.04	171	44.42	7	441
Remediation/ Makeup	77.92	77	16.02	17	152
Survey	23.15	24	9.09	0	55
Syllabus	26.69	19	24.67	1	199
Textbook	0.88	0	19.35	0	428

Note. n = 489 students with course grade

Table 3. Distribution of LMS Activities' Total Semester Count: Math

Variable	*M*	*Mdn*	*SD*	*Min*	*Max*
Number of sessions	96.50	87	59.78	2	372
Announcement	61.21	18	93.83	0	585
Answer key	1.77	1	2.81	0	23
Assignment	2.69	0	5.22	0	30
Discussion board	4.82	0	15.31	0	176
Email / Messages	0.43	0	0.90	0	7
Exam	0	0	0.07	0	1
Exam review materials	41.15	33	29.37	0	197
General content	28.59	18	33.28	0	214
Gradebook	37.28	26	36.90	0	321
Groupwork	0.01	0	0.14	0	2
Help resource	0.02	0	0.14	0	1
Information	32.50	19	42.79	0	273
Learning objectives	0.05	0	0.29	0	3
Lecture notes	19.69	11	24.63	0	205
Lecture/Class Activities	0.17	0	0.84	0	7
Orientation	63.95	6	91.73	0	354
Reading quiz	4.36	0	10.26	0	88
Remediation/ Makeup	4.39	3	3.67	0	30
Syllabus	23.10	16	21.24	0	127
Textbook	62.01	18	108.32	0	608
Worksheet	25.82	12	29.86	0	130

Note. n = 207 students with course grade

Table 4. Distribution of LMS Activities' Total Semester Count: Physics

Variable	*M*	*Mdn*	*SD*	*Min*	*Max*
Number of sessions	139.49	129	55.21	36	366
Announcement	131.43	107	129	0	679
Answer key	27.72	21	27.36	0	239
Discussion board	19.31	6	30.72	0	255
Email / Messages	0.44	0	2.09	0	31
Exam	3.30	0	7.28	0	40
Exam questions	5.67	0	13.62	0	114
Exam review materials	17.50	16	11.76	0	84
General content	195.53	182	95.28	42	823
Gradebook	70.33	47	76.13	3	643
Groupwork	0.03	0	0.22	0	3
Help resource	1.80	1	2.87	0	21
Information	1.46	0	3.40	0	42
Lab activities	115.02	114	41.52	27	364
Lab exam	0.09	0	0.41	0	3
Lecture notes	43.11	37	35.39	0	253
Lecture/Class Activities	15	0	38.57	0	265
Orientation	36	31	25.48	2	202
Reading quiz	201.87	207	60.12	26	366
Syllabus	1.91	0	4.85	0	44
Textbook	240.29	164	267.09	0	1527

Note. n = 319 students with course grade

Table 5. Distribution of LMS Activities' Total Semester Count: Psychology

Variable	*M*	*Mdn*	*SD*	*Min*	*Max*
Number of sessions	81.09	68	58.84	1	368
Announcement	52.89	13.50	92.24	0	642
Chapter exam	343.70	371.50	100.85	0	616
Chapter readings	66.76	61	40.16	0	308
Clicker	0.75	0	1.61	0	12
Discussion board	6.75	0	13.86	0	102
Email / Messages	0.36	0	1.12	0	8
Exam	33.02	30.50	16.54	0	90
Extra credit	1.28	0	3.40	0	29
General content	163.83	131	123.35	0	936
Gradebook	30.26	12	49.95	0	385
Groupwork	0	0	0.06	0	1
Help resource	6.09	4	6.37	0	37
Information	23.32	13	30.28	0	209
Lab activities	115.67	109.50	62.30	0	530
Lab assignment	64.52	60.50	42.31	0	307
Learning objectives	0.04	0	0.25	0	3
Lecture/Class Activities	0.03	0	0.22	0	2
Online quiz	16.69	14	11.91	0	74
Orientation	70.80	64	48.03	0	400
Reading quiz	228.05	230	123.25	0	621
Syllabus	13.83	11	10.76	0	84
Textbook	137.84	40.50	293.89	0	3220

Note. n = 314 students with course grade

Table 6. Social and Emotional Skills Assessed with ACT Tessera

Skill	Description Reflects the extent to which a student's actions demonstrate…
Sustaining Effort	… persistence, goal striving, reliability, dependability, and attention to detail at school.
Getting Along with Others	… collaboration, empathy, helpfulness, trust, and trustworthiness.
Maintaining Composure	… stress management, emotional regulation, a positive response to setbacks, and poise.
Keeping an Open Mind	… creativity, inquisitiveness, flexibility, open-mindedness, and embracing diversity.
Social Connection	… assertiveness, influence, optimism, and enthusiasm.

Table 7. Correlations Between LMS Activities and Grade and SE Skills: Chemistry

LMS Activity	Grade	SE	GA	MC	KOM	SC
N attempt: Discussion board	.36	.11				
T spent: Discussion board	.32	.13				
Var of T spent: Discussion board	.31	.12				
Number of Sessions	.31	.18	.14			
T spent: Lecture class activities	.24	.17	.10			
T spent: Announcements	.22	.14	.11			
Var of T spent: Announcements	.21	.15	.13			
T spent: Gradebook	.19	.11				
Var of T spent: Lecture class activities	.19	.12				
Var of T spent: Information	.18					
Var of T spent: General content	.16		.13			
Var of T spent: Exam review materials	.16	.14	.11	.10		.11
N attempt: Announcements	.16	.17	.14		.11	
Var of T spent: Practice exam	.15	.10				
T spent: Practice exam	.15					
N attempt: Information	.15					
T spent: Exam review materials	.14			.13		.11
N attempt: Practice assignment	.14					
Var of T spent: Survey	.13					
Var of T spent: Assignment	.13	.23	.10			
T spent: General content	.13		.10			
T spent: Reading quiz	.13					
T spent: Information	.13	.12				
Var of T spent: Reading quiz	.13		.10		.10	
N attempt: Exam review materials	.12					
T spent: Assignment	.12	.23	.14			
N attempt: Practice exam	.11					
T spent: Orientation	.11	.14	.13			
N attempt: Survey	.11	.10		.12		
T spent: Syllabus	.10	.10				
N attempt: General content	.09	.10				.14
N attempt: Syllabus	-.11					
N attempt: Assignment		.21	.12			
T spent: Email messages		.13	.16		.14	
Var of T spent: Orientation		.13	.11			
T spent: Practice assignment		.12				
N attempt: Orientation		.12				
N attempt: Gradebook		.11			.12	
N attempt: Email messages			.10			
T spent: Discussion class				-.13		
Var of T spent: Learning objectives					.13	
N attempt: Learning objectives					.10	
T spent: Learning objectives					.10	
T spent: Answer key						-.12

Note. SE = Sustaining Effort, GA = Getting Along with Others, MC = Maintaining Composure, KOM = Keeping an Open Mind, SC = Social Connection, N attempt = number of attempts, T spent = time spent, Var of T spent = variability of time spent. All correlations are statistically significant at $p < .05$.

Table 8. Correlations Between LMS Activities and Grade and SE Skills: Math

LMS Activity	Grade	SE	GA	MC	KOM	SC
Number of Sessions	.39	.21	.21	.22		
T spent: Worksheet	.23					
T spent: Remediation makeup	.22					
Var of T spent: Exam review materials	.22					
Var of T spent: Worksheet	.21					
T spent: Exam review materials	.21					
T spent: Discussion board	.20					
N attempt: Information	-.19					
N attempt: Discussion board	.19					
N attempt: Answer key	.17					
T spent: Lecture notes	.16					
Var of T spent: Gradebook	.15					
T spent: Answer key	.15					
N attempt: Reading guide	.15					
N attempt: Learning objectives	.15					
T spent: Learning objectives	.14					
Var of T spent: Information		.31	.28	.31		
T spent: General content		.30	.36		.26	.31
T spent: Information		.27	.28		.22	
N attempt: Assignment		-.26			-.22	
T spent: Assignment		-.24			-.21	
N attempt: Information		.23	.23		.22	
Var of T spent: General content			.29			.20
Var of T spent: Remediation makeup			.22			
T spent: Orientation			.22		-.19	
Var of T spent: Assignment						
Var of T spent: Answer key						-.24

Note. SE = Sustaining Effort, GA = Getting Along with Others, MC = Maintaining Composure, KOM = Keeping an Open Mind, SC = Social Connection, N attempt = number of attempts, T spent = time spent, Var of T spent = variability of time spent. All correlations are statistically significant at $p < .05$.

Table 9. Correlations Between LMS Activities and Grade and SE Skills: Physics

LMS Activity	Grade	SE	GA	MC	KOM	SC
Number of Sessions	.36	.30				
T spent: Answer key	.27	.17				
Var of T spent: Answer key	.27	.18				
N attempts: Answer key	.24	.15				
T spent: Lecture notes	.22	.15				
T spent: Exam review materials	.21	.15				
T spent: Gradebook	.20	.20				
Var of T spent: Exam review materials	.19					
N attempts: Reading quiz	-.18					
Var of T spent: Gradebook	.17					
N attempts: Exam review materials	.15	.14		.13		
N attempts: Lecture notes	.14					
N attempts: Orientation	-.13					
T spent: Help resources	.13					
Var of T spent: Exam questions	.11					
Var of T spent: Lecture notes	.11					
T spent: Reading quiz		.19	.19			
T spent: Discussion board		.18	.14			.15
T spent: Gradebook		.17				.13
Var of T spent: Reading quiz		.17	.22		.14	
T spent: Announcements		.17			.14	
Var of T spent: General content		.16				
Var of T spent: Announcements		.16				
T spent: General content		.14				
T spent: Email messages		.14			.15	.15
Var of T spent: Email messages		.14				.16
Var of T spent: Syllabus			.18			
T spent: Syllabus			.18			
N attempts: Syllabus			.17			
Var of T spent: Exam			.14			
N attempts: Email messages					.14	.15

Note. SE = Sustaining Effort, GA = Getting Along with Others, MC = Maintaining Composure, KOM = Keeping an Open Mind, SC = Social Connection, N attempt = number of attempts, T spent = time spent, Var of T spent = variability of time spent. All correlations are statistically significant at $p < .05$.

Table 10. Correlations Between LMS Activities and Grade and SE Skills: Psychology

LMS Activity	Grade	SE	GA	MC	KOM	SC
Number of sessions	.53	.35	.17			
Var of T spent: General content	.29				-.16	
Var of T spent: Chapter readings	.28					
T spent: Exam	.27					
Var of T spent: Online quiz	.26					
T spent: Chapter readings	.25					
T spent: Information	.25				.20	
N attempts: Help resources	.24	.30				
T spent: Textbook	.24	.18				
Var of T spent: Lab assignment	.24					
T spent: General content	.24				-.22	
Var of T spent: Textbook	.23					-.16
N attempts: Exam	.23					
T spent: Gradebook	.22					
Var of T spent: Gradebook	.22					
Var of T spent: Exam	.21					
Var of T spent: Chapter exam	.20					
T spent: Syllabus	.20			-.19		
Var of T spent: Extra credit	.19					
T spent: Online quiz	.18					
T spent: Extra credit	.17					
Var of T spent: Announcements	.17					
N attempts: Online quiz	.17					
N attempts: Extra credit	.17					
Var of T spent: Information	.16	.15			.16	.23
T spent: Announcements	.16					
Var of T spent: Help resources	.16	.32			.15	
T spent: Help resources	.16	.19				
T spent: Lab assignment	.16					
N attempts: Lecture class activities	.15					
N attempts: Gradebook	.15					
N attempts: Textbook	.15					
Var of T spent: Lab activities	.15					
T spent: Lecture class activities	.14					
N attempts: Announcements	.13					
Var of T spent: Discussion board	.12					
Var of T spent: Orientation	.12					
N attempts: Discussion board	.12					
T spent: Lab activities	.11					
T spent: Discussion board	.11					
N attempts: Email messages		.21			.16	

Table 10. Correlations Between LMS Activities and Grade and SE Skills: Psychology—continued

LMS Activity	Grade	SE	GA	MC	KOM	SC
N attempts: Chapter exam		-.20				
T spent: Email messages		.19			.15	
Var of T spent: Email messages		.18				
N attempts: Lab activities		-.17				
N attempts: Chapter readings		-.17				
N attempts: Orientation			.16		.16	
N attempts: Information			.15		.18	.24
N attempts: Clicker				.21		
N attempts: Reading quiz					-.16	

Note. SE = Sustaining Effort, GA = Getting Along with Others, MC = Maintaining Composure, KOM = Keeping an Open Mind, SC = Social Connection, N attempt = number of attempts, T spent = time spent, Var of T spent = variability of time spent. All correlations are statistically significant at $p < .05$.

Table 11. Descriptive Statistics for Grades and Social and Emotional Skills

	Chemistry		Math		Physics		Psychology	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Grade	2.78	1.07	2.19	1.27	2.70	1.22	2.75	1.30
Sustaining Effort	-.09	.95	-.25	.96	-.19	.90	-.21	.91
Getting Along with Others	-.19	.93	-.02	.99	-.13	.93	-.06	.86
Social Connection	-.18	.89	-.13	.89	-.19	.86	-.18	.94
Maintaining Composure	-.08	.88	.10	.88	-.13	.89	-.04	.90
Keeping an Open Mind	-.22	.92	-.11	.95	-.17	.91	-.15	.92

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