Understanding Student Interactions Through Learning Analytics from an Online Engineering Case Study Course

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Thesis submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

In

Civil Engineering

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28 April 2021

Blacksburg, VA

Keywords: learning analytics, online learning, online engineering course, case study, construction management

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ABSTRACT

Student interactions in learning environments are vital for learning development. The growth of online learning in higher education has led stakeholders to question how to identify student interactions with course material and increase the quality and value of the learning experience. This research focused on leveraging existing learning analytics from the Canvas Learning Management System (LMS) to identify course interactions and make data-informed course design decisions. Learning analytics were collected from 113 students in three course sections of an online construction management course. Three surveys were also distributed to each course section to gather the students' perceptions of the learning methods and their interactions for assistance. An exploratory graphical analysis visually depicted student interactions in the online course through the students' hourly and weekly interaction levels, page visits, and discussion board activity. A paired t-test was used to statistically compare the survey responses on the students' perceptions of the learning methods. The learning analytics results showed the students' interaction levels peaked in the afternoon and evening hours, and their weekly interactions and page visits lessened after the midterm exam. Additionally, based on Pearson's correlation test, the discussion board interactions significantly correlated with student performance. Lastly, the surveys showed that students found watching the lecture videos and reading the lecture slides to be the most helpful methods when learning the course material. These results have important implications for online stakeholders as learning analytics and student perceptions can inform online course design to facilitate student, instructor, and content interactions.

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GENERAL AUDIENCE ABSTRACT

In an online course, students click on lecture pages to watch lecture videos, they use discussion boards to post and reply to their peers, and they visit their courses at whatever time suits them. These interactions are difficult for an instructor to identify. Therefore, making it harder for them to engage with the students, determine which students are at-risk for failing, or develop their courses based on the students' interactions. This research study leverages learning analytics to identify student interactions in an online construction management course to improve academic decision-making and course design. Learning analytics are interaction data collected from a course that includes every student's interaction with the course material (e.g., page clicks, discussion posts & replies). Additionally, surveys were distributed to each of the three online construction management course sections used in this study to gather the students' thoughts about the available learning methods (e.g., video lectures, lecture slides). The learning analytics results showed that student interaction fluctuates by the hour and lessens after the midterm exam. The survey results found watching the lecture videos and reading the lecture slides were the most helpful learning methods. The capabilities of learning analytics must be addressed by online stakeholders when developing future online courses. The growth of online learning is inevitable, and the results of this paper suggest that learning analytics can identify unnoticed student interaction patterns and influence future online course design.

ACKNOWLEDGEMENTS

First of all, I would like to thank all my mentors, counselors, and teachers I had throughout my years of education who inspired me through their work, pushed me to strive for my potential, and be more confident in my abilities. Without them, I would not have made it into engineering nor through my engineering education.

I would also like to thank my graduate advisor, Dr. Frederick E. Paige, for his guidance, commitment, and encouragement to pursue my graduate degree. Freddy taught me how to conduct research, and his guidance proved instrumental over the past two years. He is also extremely invested in the growth and success of everyone on the STILE Research Team within and outside of research.

Assistance provided by Dr. Walter Lee, Dr. Glenda Scales, and Dr. Natasha Watts was invaluable as I embarked on an online engineering education focus for this thesis. I would like to thank all of them for their patience and collaboration as I ventured into unfamiliar technical and theory-based territory. The final product of this thesis would not be of the quality it is today without their feedback.

I would also like to thank my VTEO co-workers for teaching me the inner-workings of Canvas and showing me the hard-work and joy that comes from building and developing online courses. All their guidance and feedback helped me learn new skills and fueled my interest in online learning.

Lastly, I would like to thank my STILE research team for all their support and feedback because, without them, I probably would not have made it this far. Finally, I'd like to thank my family and friends who always supported me in continuing my education and were always there with love, motivation, and advice throughout my education.

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ATTRIBUTION

This foreword describes the contribution of each of the authors for the two manuscripts within this thesis document.

Manuscript 1:

Paige West – Paige reviewed the relevant literature, developed the methods, and analyzed the data. She also wrote the complete first draft of the manuscript and then incorporated feedback from the other authors.

Frederick Paige – Freddy helped build the online course, guided the research concept, helped finalize the research questions and methods, while also providing multiple rounds of feedback and comments on the manuscript.

Natasha Watts – Natasha helped build the online course and assisted with the selection of the case. She also provided insight on data policy and feedback on the manuscript.

Walter Lee – Walt helped with the design of the research and the structure of the theoretical framework. He also provided multiple rounds of feedback and comments on the manuscript.

Glenda Scales – Glenda provided insight on the implications of the study and the value of online data for stakeholders. She also provided feedback and comments on the manuscript.

Manuscript 2:

Paige West – Paige reviewed the relevant literature, conducted the surveys, and analyzed the data. She also wrote the complete first draft of the manuscript and then incorporated feedback from the other authors.

Frederick Paige – Freddy helped build the online course, helped develop the survey questions and finalize the research questions and methods, while also providing multiple rounds of feedback and comments on the manuscript.

Walter Lee – Walt provided multiple rounds of feedback and comments on the introduction, theoretical foundation, and background section of the manuscript.

Natasha Watts - Natasha helped build the online course, provided insight on data policy, and provided feedback and comments on the manuscript.

Glenda Scales – Glenda provided insight on the implications of the study and the value of online data for stakeholders, while also providing feedback and comments on the manuscript.

INTRODUCTION

At the beginning of this research, COVID-19 did not exist. Since the pandemic swept the nation, it is evident higher education must focus on online learning. This research study was fueled by a desire to improve online learning environments for instructors and students. In online courses, the time and location of student interactions with material, such as page visits, go unnoticed. Learning analytics is one of the emerging technology fields that can improve academic decision-making and increase the quality and value of the online learning experience. Multiple studies (Avella et al., 2016; Dietz-Uhler & Hurn, 2013; Viberg et al., 2018) have explored the benefits of incorporating learning analytics into courses. Students can use their data to identify how they are performing and then customize their approaches to learning to be successful in their assessments. Instructors can use their current course data and prior student data to identify how well students meet the learning objectives and make data-informed course design decisions to support student success. To identify student interaction patterns, learning analytics were collected from three course sections of an online construction management course. The manuscripts in this thesis will discuss prior research in learning analytics and how this research seeks to visually describe student interaction patterns that can influence course design.

This document contains two manuscripts that focus on the capabilities of learning analytics to depict student interactions. The research was grounded in social constructivism, which focuses on how interactions with more knowledgeable people help establish understandings that students would not have made independently. Civil engineering is a collaborative and team-based environment; therefore, it is important for course designs to facilitate group work and interactions. Learning analytics provide critical information about student interactions that instructors can leverage to inform course design and subsequent iterative changes. Chapter 1 of this thesis focuses on how learning analytics from 65 students describe student interaction patterns concerning hourly interactions, page visits, and discussion posts & replies. Chapter 1 identifies course improvement areas based on the student interaction levels and provides recommendations for the instructor. Chapter 2 adds 68 more students' learning analytics data (N=113) and focuses on the similarities and differences in each course sections' weekly and hourly interaction levels. Chapter 2 also includes the student perception survey data about the helpfulness of the learning methods and who students sought for assistance. Chapter 2 identifies course design approaches for civil engineering instructors that can be applied to encourage interaction and collaboration in an online course. Through the manuscripts, I hope to spark interest in learning analytics and emphasize how leveraging learning analytics can help all stakeholders have successful online learning experiences.

Chapter 1:

Constructing Insights on Learning Analytic Student Activity Data from an Online Undergraduate Construction Management Course

Conference Paper:

Constructing Insights on Learning Analytic Student Activity Data from an Online Undergraduate Construction Management Course

Intended Outlet for Publication:

ASEE 2021 Conference

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Abstract

The growth of online learning has contributed to researchers exploring innovative ways to develop successful learning environments for students and instructors. Learning analytics is one of the emerging fields that can improve academic decision-making and increase the quality and value of the learning experience when implemented into online courses. This paper discusses how learning analytics describe student activity using a multiple-case study of an online construction management course. The study collected learning analytics through the Canvas Learning Management System (LMS) from forty-five students across two course sections. Results from the learning analytics indicated that student activity is at its peak in the afternoon and evening. The analyses also found discussion participation to be an indicator of course performance. By knowing when and how students are active, instructors can increase instructor-student interactions and improve student outcomes in performance. Establishing learning analytics in online courses can better inform instructors of student interactions and ultimately shed light on the unknown world within online courses.

Introduction

Although distance education has a long history, growth in technology has afforded us the opportunity to improve the user experience in virtual learning design. In addition to a steady increase in distance education enrollment since 2012 (Allen & Seaman, 2017), online engineering education is growing as more people gravitate towards flexible and accessible degree options. In an online asynchronous environment, instructor-student and student-student interactions must be integrated into the course design. Furthermore, instructors must look to other mediums for feedback on the learning experience than the standard look across the room at students' faces (Mattingly et al., 2012). Despite such challenges, many institutions have successfully built and grown online courses and degrees (Bourne et al., 2005). Some institutions (e.g., Purdue University (Arnold & Pistilli, 2012), UMBC (Fritz, 2011), University of Michigan (Mattingly et al., 2012)) have had success leveraging learning management systems (LMS) and analytics to enhance their online learning environments.

As defined by the 2011 Learning Analytics and Knowledge (LAK) conference and re-stated by Long and Siemens (2011), learning analytics "is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long et al., 2011; Long &

Siemens, 2011). Due to the abundance of analytic data available on multiple platforms (e.g., Google analytics, LMSs, MOOCs), there is great potential for universities, instructors, and students to be more successful in online environments. Learning analytics provide real-time insight into student interactions – insights that help plan teaching activities and identify at-risk students (Long & Siemens, 2011). Learning analytics also offer a more personalized learning experience for students than the current online environments where content interactions and student struggles go unnoticed (Dietz-Uhler & Hurn, 2013). As evidenced by the COVID-19 pandemic, online learning is a necessity for higher education. Our study highlights the utility of learning analytics and how instructors can leverage them to develop successful online learning environments.

This paper explains some of the capabilities of learning analytics from an online course in the Canvas LMS. The paper will focus on student activity in an online construction management course and their interactions with the lecture pages and discussion boards. Our study is guided by the research question: In what ways do learning analytics describe student activity in an online engineering course? Altogether, the study aims to identify learning analytics that can assist instructors with data-informed course development decisions.

Previous Works

The emergence of learning analytics has created excitement about better understanding how students interact with online courses. Learning analytics is not a new technology, but its implementation in the past has focused more on face-to-face higher education institutions, leaving a lesser-explored area of implementing learning analytics into online courses (B. T. M. Wong, 2017). Analytics have been frequently used as early warning systems to identify at-risk students. One of the most discussed systems is Purdue Signals. Signals predicts a student's risk of failing by integrating real-time student performance and interaction data with demographic and past academic history (Arnold & Pistilli, 2012). According to Arnold and Pistilli (2012), Signals has seen great success in increasing the number of satisfactory student grades and has had positive responses from the faculty regarding their students being more proactive in their courses.

Because discussion activity is a primary method to encourage student participation in online courses, researchers have studied how learning analytics captured from discussion entries and replies inside the LMS correlate with performance. Macfadyen and Dawson (2010) researched five online undergraduate biology classes that used Blackboard Vista for learning analytic data. After exploring all the LMS tracking data variables, they found the total number of discussion messages posted to correlate significantly ($R = 0.52$, $p < 0.05$) with the students' final grades (Macfadyen & Dawson, 2010). Kim et al. (2016) used in-degree (replies received) and out-degree (replies written) centrality as indicators of the students' prominence and engagement in discussions. The researchers found out-degree centrality to be consistently significant throughout the course (Kim et al., 2016). While both studies looked at discussion activity in different forms, each concluded that discussion activity through entries and replies positively correlates with performance.

Learning analytics have provided instructors with critical information about their students' behaviors in courses. For example, learning analytics supply insight into the number and time of student interactions (Agudo-Peregrina et al., 2014; Castro et al., 2018; Joksimović et al., 2015) and the frequency of viewing content pages (Hui & Farvolden, 2017) and tools (Brozina & Knight, 2015; Macfadyen & Dawson, 2010). Student behavior analytics is often compared to student performance and proven to correlate significantly. Joksimovic et al. (2015) found that the count of student-student interactions in an entirely online course significantly correlated with the students' grades. Also, the time spent interacting with the instructor had positive effects on the final learning outcomes (Joksimović et al., 2015). Agudo-Peregrinal et al. (2014) looked at Moore (1989) and Hillman et al.'s (1994) interaction types and their correlation with the students' final grades for a face-to-face and online course. They found only the online course interactions to have a significant correlation. For an instructor to ensure their students reap the benefits of student-instructor interactions, they must know when students interact and interact with them. Using time and date learning analytics, an instructor could plan course activities (Castro et al., 2018), schedule office hours, and develop student interaction models (Dietz-Uhler & Hurn, 2013).

Based on the number of research studies exploring learning analytics, their potential in online courses is evident. However, there is a plethora of information to cipher through that it can be challenging for an instructor to dedicate time to learn what is useful. The necessary time dedication is why a primary goal of learning analytic systems and research is developing dashboards that provoke self-awareness and decision-making in students and instructors (Duval et al., 2012). Knight et al. (2016) found that students wanted dashboards to help with broader life scenarios, and instructors focused strictly on the class level (Knight et al., 2016). Class level learning analytics can help instructors make data-defined decisions and increase the transparency of activity in online learning environments (Long & Siemens, 2011). Based on the existing literature, this study expands upon the current focus of correlations and student performance to also what learning analytic data from an LMS can detail about online student interaction.

Theoretical Framework

Despite the importance of interactions, a challenge with online learning environments is identifying how students interact with other people in the course and the content. Learning analytics in a learning management system (LMS) overcome the challenge by measuring and collecting all four interaction types defined by Moore (1989) and Hillman et al. (1994): 1) student-content (S-C), 2) student-instructor (S-I), 3) student-student (S-St) (Moore, 1989), and 4) student-system (S-Sy) (Hillman et al., 1994). Researchers (Agudo-Peregrina et al., 2014; Joksimović et al., 2015) have also explored each interaction type defined by the learning analytics and found the interactions to correlate with student performance. The theoretical research for learning analytics is a growing field and can influence learning space design and our ability to use data effectively (J. Wong et al., 2019).

Based on the growing field of learning analytics and learning theory, this study was grounded in Vygotsky's educational theory of social constructivism. Vygotsky's definition of social constructivism focuses on how interactions with adults and more capable peers help establish an understanding that the learners would not have made on their own (Vygotsky, 1978). Vygotsky's social constructivism theory is rooted in the zone of proximal development (ZPD). The ZPD is the distance between what a student is currently capable of doing (independent problem-solving) and the level of potential development through problem-solving with an adult or more capable peer (Vygotsky, 1978). Working in the zone of proximal development and achieving what a student can do with aid emphasizes the importance of social interaction between students and instructors in a classroom environment.

More specifically, this study combines interaction theory and learning analytics with a scaffolding instructional approach in an online social constructivist learning space to determine how learning analytics describe student activity (Figure 1). This paper covers a portion of a larger study, so it will only discuss the dashed boxed section of Figure 1. While all four aforementioned interaction types can be found through learning analytics data (Agudo-Peregrina et al., 2014; Joksimović et al., 2015; Macfadyen & Dawson, 2010), this research paper is focused on two: student-student (S-St) and student-content (S-C). These interaction types interlay directly with social constructivism because social constructivists view learning as a product of conversation, discussion, and negotiation (Woo & Reeves, 2007).

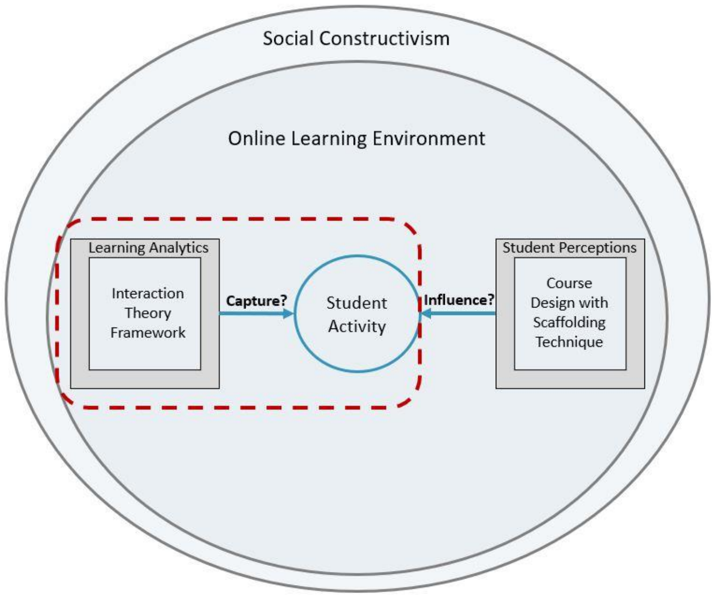

Figure 1: Theoretical Framework

For this study, the student-student interactions are the students' discussion entries and replies on the discussion board. The student-content interactions are the students' page visits, page clicks, and overall course visitation. Even though the study does not explore student-instructor interactions, their effects on learning influenced our exploration of student activity captured by learning analytics.

Research Methods

To explore the utility of learning analytics in an online platform, the researchers conducted a multiple-case study with a convergent mixed-methods approach. Yin defines a case study as "an empirical inquiry that investigates a phenomenon in depth and within its real-life context…that relies on multiple sources of evidence, with data needing to converge" (Yin, 2009). In this study, each section of the Introduction to Construction Management course (Spring 2020 and Summer 2020) is a case. The researchers chose a multiple-case study because it increases the possibility of direct replication and limits the study's vulnerability (Yin, 2009).

We collected multiple sources of evidence for each course section following Creswell and Creswell's convergent mixed-methods approach. Per convergent mixed-methods, the qualitative and quantitative data were collected in parallel, analyzed separately, and then merged (Creswell & Creswell, 2018). Creswell and Creswell (2018) highlight that researchers gain more insight and develop a robust understanding of research problems by mixing data sets that provide different information. Additionally, using multiple sources of evidence allowed for inquiry from different angles to triangulate and answer the research questions (Creswell & Creswell, 2018; Yin, 2009). While the study's research design was convergent mixed-methods, this paper covers only the quantitative portion focusing on learning analytics.

Overview of the Case Study

The case study course was CEE 3999: Construction Management. The researchers collected data from forty-five students from two course sections (Spring 2020 and Summer 2020). CEE 3999 is a required course for CEE majors and is popular with students from other departments as an optional credit-bearing course. The majority of students enrolled in CEE 3999 were junior and senior Civil and Environmental Engineering (CEE) majors. There were also students from other majors, including but not limited to Industrial Systems Engineering and Mechanical Engineering. CEE 3999 was an online asynchronous construction management course designed by a team of instructional designers, multimedia engineers, and the course instructor. The team intentionally designed the course to be modular and to collect learning analytics data. By adapting an existing face-to-face version of the course, which shared a modular format, the online version of CEE 3999 took approximately eight months to create from conceptual design to course start-up.

The course material introduces students to the construction project lifecycle from the conceptual design phase through construction completion and operation and maintenance. All the content delivery was online asynchronous, but there were online synchronous TA and instructor office hours. The course was designed to individualize each interaction the students had with the LMS interface (e.g., lecture page visits, discussion page visits). The design took into account how Canvas measures user interactions inside of modules like the one shown in Figure 2. Each weekly module was unlocked Monday at 12:00 AM. The expectation was to complete the material in the module by the following Sunday at 11:59 PM. Since the course was asynchronous, the instructor pre-recorded the video lectures covering topics in the five course modules: Planning, Economics, Scheduling, Execution, and Leadership. The course also included eight individual homework assignments on a project's lifecycle using an integrated case study, twenty lecture-based discussion boards, and a team-based final project. The students were split into random teams at the beginning of the semester to encourage group work and build a support network in the class.

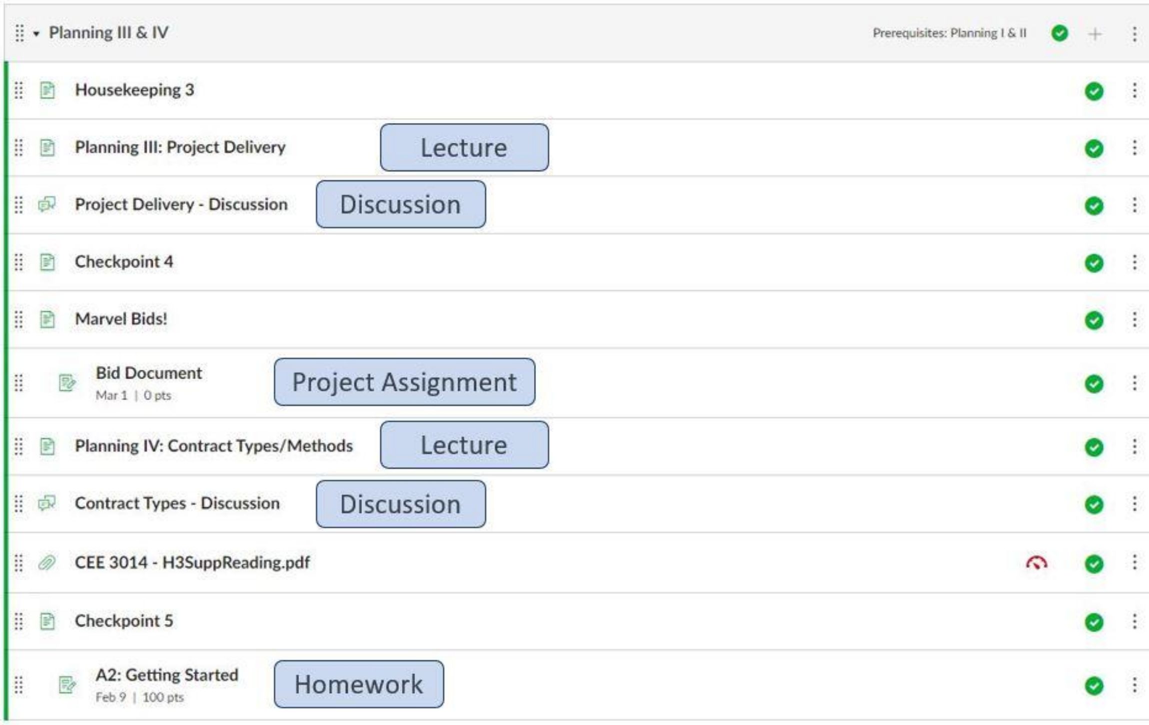

Figure 2: CEE 3999 weekly module layout example

Learning Analytics Data Collection and Data Analysis

Despite their intricacies, a plethora of learning analytic data about student course interactions is within reach of an instructor. The researchers collected data from a course section that lasted sixteen weeks (Spring 2020) and another section that lasted six weeks (Summer 2020). During the traditional length of a semester (spring), there were approximately thirteen weeks of course material, one week of break, and two weeks for final exam preparation. However, in Spring 2020, the COVID-19 pandemic started, so the students had an extra week of spring break while the institution switched to emergency teaching at a distance. In contrast with the traditional semesters, the summer course included six weeks of content without any breaks.

Data Collection

Throughout the study, the researchers collected learning analytic data from CEE 3999 using the Canvas Learning Management System (LMS). The learning analytics came from a Canvas requests table (further noted as analytics). The request table is the foundational source of student activity data on Canvas (Hallmark, 2019) that caters to large data sets and analysis

(*Canvas Data Portal*, n.d.). The requests table collects data any time a user's interaction (e.g., page visits) triggers a callback to the Canvas servers (Hallmark, 2019). Canvas stores the data in a "star schema" convention, where information collects as fact tables referencing multiple dimension tables (*Canvas Data Portal*, n.d.; *DWH Schemas | DwhWorld*, 2009; Harindranathan & Folkestad, 2019). We received the analytics in a csv format that came from downloading the flat files in the Canvas Data Portal. Each interaction a student had with the course was a separate line in the csv, as seen in Figures A1.1 and A1.2 in Appendix A. For example, when a student posted on a discussion board or visited a lecture page, the analytics noted the student's interaction by the student's information system (SIS) ID, the timestamp (date and time) of the interaction, and the URL where the interaction occurred among other notations.

Before the analytic data was accessible for analysis, the researchers had to organize and decipher the interaction data. First, we converted the csv file to an xlsx file. Then we added new columns as well as determined the columns needed for the analysis. The added columns and those required for analysis are shaded in green in Figures A1.1 and A1.2 in Appendix A. Early in the organization process, the researchers discovered that Canvas collects data in Universal Time (UT). Therefore, we created new columns with the eastern time zone (e.g., Canvas Time (ET) and Canvas Date (ET)) to ensure the analytic data matched the course's activity timestamps. Due to Canvas collecting each student interaction using a combination of facts and dimensions, every interaction required various filters in an Excel pivot table to match student actions on Canvas. To determine the proper filters, the researchers compared the analytic data to the Canvas course information. For example, we ensured the time and date of the discussion entries for a student on the analytics matched the course's time and date. Figure A2 in Appendix B goes through the steps of developing the correct pivot table filters when determining the number of discussion entries and replies by the hour. As noted by the data in the red boxes in Figure A2 (Appendix B), the columns can vary depending on the analysis. Altogether, using pivot tables created a quick filtering process that generated the required synthesized data for analysis.

Data Analysis

Using the parsed analytic data, the researchers conducted an exploratory graphical analysis of the combined data from both course sections (N = 45 students) to identify patterns or anomalies in the student activity levels. Since overall student activity in an online course would encompass every interaction with the course material, we broke the activity into two additional components: 1) discussion entries and replies and 2) page visits. Our study defined activity as the sum of student interactions with the course that showed up in the analytics data. For example, each time a student's SIS ID came up in the analytics, that student had one activity value. If a student had an activity value of 14,000, their SIS ID showed up 14,000 times in the analytic data. Since prior analyses of learning analytic data focused on student activity duration, we looked at when interactions occurred. Therefore, we graphed the students' activity by time (e.g., hour, day, week) and examined the peaks to identify popular student interaction times. An important aspect of the hourly analyses and graphs is that each hour is a time range. For example, 4 PM is 4:00:00 PM – 4:59:59 PM. If a student worked from 4:30 PM – 5:30 PM, their activity count spreads across the 4 PM and 5 PM columns.

The second phase of the analysis was determining if student activity correlated with performance in the course. Studies have found that LMS tracking variables such as specific tool use (Brozina & Knight, 2015; Fritz, 2011), content interactions (Joksimović et al., 2015), and quantity of online sessions (Macfadyen & Dawson, 2010) correlate with the students' final grades. Our study used Pearson's correlation test, similar to Brozina and Knight (2015), to assess the correlation of student activity with course performance. We also used Pearson's correlation to determine if discussion posts and replies correlated with course grades, as proven by Macfadyen and Dawson (2010) (Macfadyen & Dawson, 2010) and Kim et al. (2016) (Kim et al., 2016).

Results

Findings from the study aim to make evident how learning analytics describe student activity and identify visuals to depict student interaction in an online engineering course. The results highlight learning analytics capabilities by visually describing patterns in the students' overall hourly activity, page visits, and discussion activity.

Overall Hourly Student Activity

To understand when the students were active, the first part of the analytic analysis focused on overall student activity by the hour. Additionally, we examined the number of students active per hour since instructor-student interactions are less valuable if minimal students are available on the course. As a reminder, activity is the sum of the students' SIS IDs showing up in the analytic data (Appendix A – Figures A1.1 and A1.2), and each column of hourly data in Figure 3 is a time range. Figure 3 displays a combination graph of the average student activity on the course by the hour (line with markers) and the total number of students active each hour (solid line) for the combined course section data. Based on the results illustrated below, both lines follow similar trends until all the students are active and the students' hourly activity levels are the sole cause of fluctuation in the average activity.

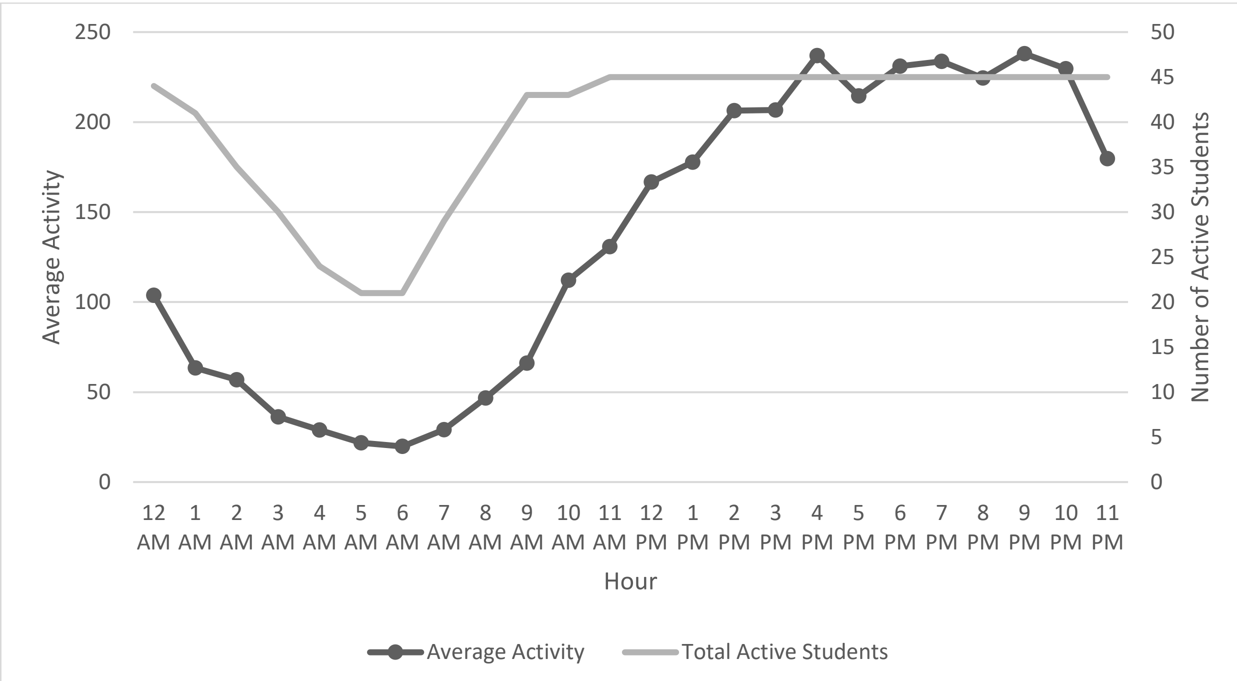

Figure 3: Average activity by the hour and day with the number of active students by hour

Only when all the students are active on the course do the most popular average student activity times occur: 9 PM, followed by 4 PM, and 7 PM. While the graph shows some activity in the early morning hours (1 AM – 6 AM), the researchers attribute most of the activity to students leaving their Canvas course page open during the night. Additionally, as noted by the number of active students line (no markers) in Figure 3, there is a steady increase in students accessing the course starting at 6 AM. By 9 AM, most of the students are active. The students' average activity by hour depicts all interactions in the course, but each course page had different content and purpose that caused the activity levels per page to fluctuate.

Page Visits

The lecture pages were the primary source of content delivery because they included lecture videos. Therefore, to determine what course module and course lecture the students visited the most, the researchers explored individual lecture page visits. Figure 4 displays the total page visits for each lecture page and the average page visits per student (N=45) for the combined course section data.

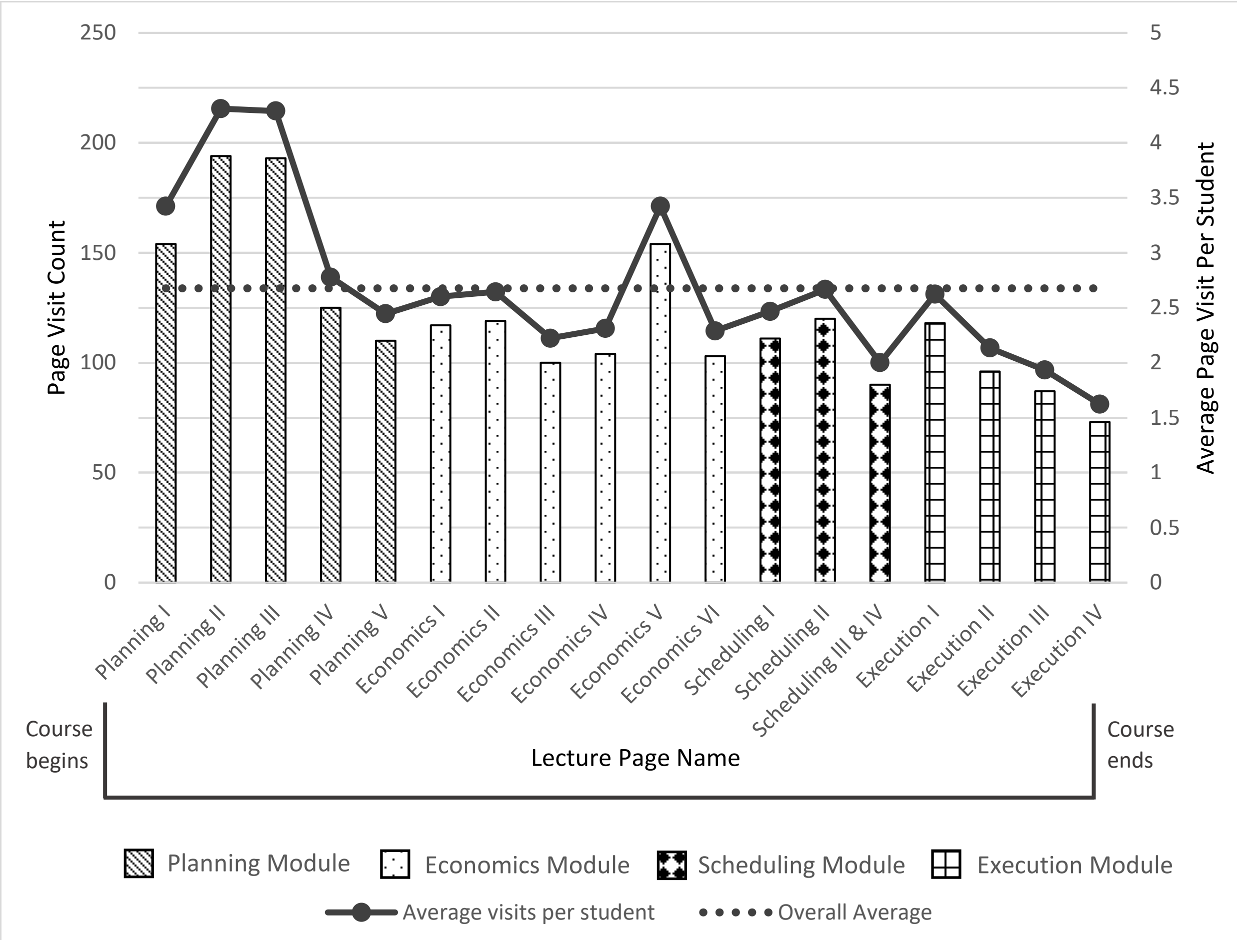

Figure 4: Lecture page visits by page and average page visits per student

Across the courses' eighteen lecture pages, the students had, on average, 2.67 visits to each page. As noted by the average page visits per student line (black with markers), the average fluctuates between 2 - 2.6-page visits for most lecture pages. The students' increased page visits to Planning II and III resulted in the two lecture pages being outliers in the total lecture page visits data. The results also illustrate that the planning and economics module pages were visited more than the scheduling and execution module pages. This result is evident because 5 out of the 11 planning and economics module pages exceeded the average number of page visits (dotted line), whereas the scheduling and execution modules had no page visits above the threshold.

Discussion Board Activity

A significant component of the student's participation grade in the course was completing the weekly discussion boards. Therefore, to pinpoint the least interactive students, the researchers graphed each student's entry and reply activity using the combined course section data set (N=45). Canvas defines entries as when a student answers the discussion board topic, and replies are when a student responds to a peer. As illustrated in Figure 5, the students' total discussion entries positively correlate with their total replies.

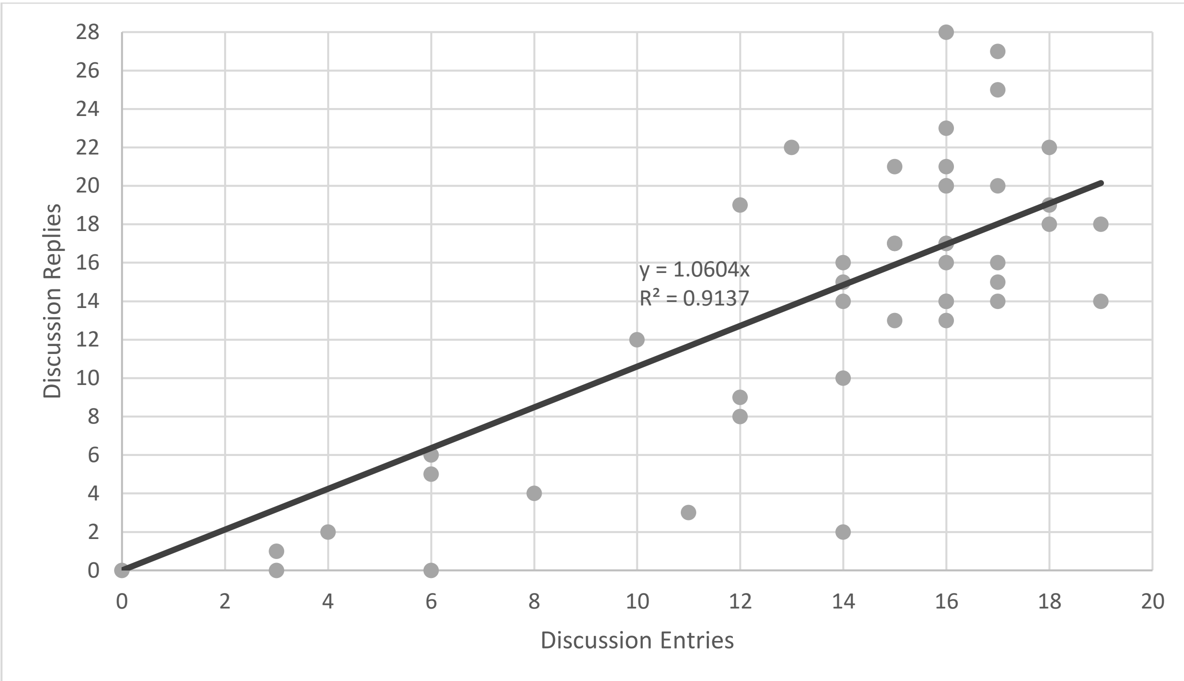

Figure 5: Student discussion entries versus their discussion replies for the combined data set

The linear trendline in Figure 5 emphasizes that whenever a student made one entry to the discussion board, they also made one reply. In addition to the almost one-to-one slope of the entries to replies, the degree of relationship is strongly correlated and statistically significant ($R = 0.797$, $p < 0.001$) as calculated by Pearson's correlation. As a result of the correlation strength and the almost one-to-one relationship, an instructor could predict the number of replies to expect from students based on their entries. The students' discussion activity not only correlated between the number of entries and replies but also with their final grades.

Correlational Analysis

Consistent with Macfadyen and Dawson (2010) (Macfadyen & Dawson, 2010) and Kim et al. (2016) (Kim et al., 2016), the researchers found the students' discussion entries and replies to moderately correlate positively with performance at a level of $p < 0.05$. The researchers conducted Pearson's correlation test with the combined data set from both course sections. We compared the total number of entries, the total number of replies, and the total count of entries and replies to the students' final grades. We also used a two-tailed distribution to determine the statistical significance of the correlation. Table 1 displays the R values, the Rcrit values and the level of statistical significance for each test. Discussion participation was 10% of the final grade, and to make sure participation was not dictating the correlation we also conducted a Pearson's correlation test excluding the discussion participation grade from the final grade. We found a negligible difference between the separate correlation tests, thus indicating the participation grade was not dictating the correlation.

Table 1: Pearson's r correlation of student discussion entries and replies with the final grade

Type	R	Rcrit	p-value
Entries	0.389	0.380	< 0.01
Replies	0.363	0.294	< 0.05
Total	0.394	0.380	< 0.01

To explore how overall student activity correlates to performance, we used Pearson's correlation test on the students' individual total activity and their final grades. Contrary to some literature (Brozina & Knight, 2015; Fritz, 2011; Joksimović et al., 2015; Macfadyen & Dawson, 2010), we did not find a statistically significant correlation at the specified level of $p < 0.05$ between individual students' total activity and their final grade, as noted by the weak positive trend in Figure 6. One hypothesis for the weak correlation is that multiple factors, such as personal situations or exam time limits, affect student grades. Additionally, Canvas only counts activity within the Canvas course, so the students' total activity does not include studying or homework completed outside Canvas.

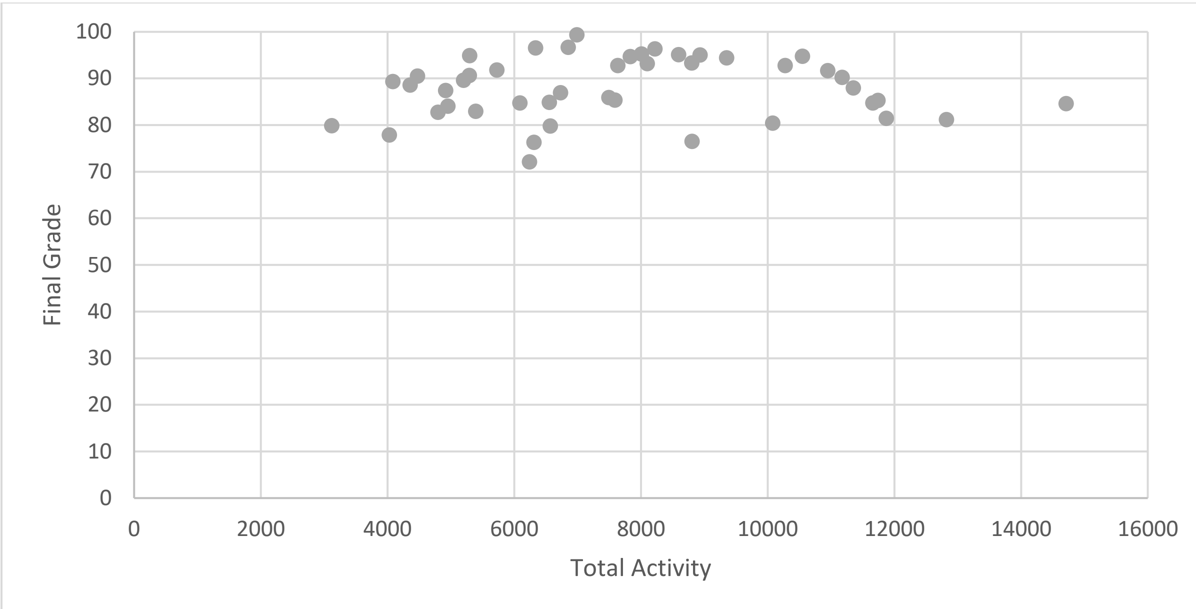

Figure 6: Total student activity versus their final grades for both course sections

Discussion

This case study provides insights into Canvas learning analytics capabilities and how the data can describe student activity. The results from the study are only a fraction of the learning analytics' capabilities. Even so, the data showcased student course activity that would otherwise go unnoticed. In addition to our study highlighting how learning analytics depict student activity, instructors can leverage the data to influence their course and learning design. Some of the analytic findings an instructor can use are: 1) student activity peaks in the afternoon and evening, 2) lecture page visits declined as the semester continued, 3) discussion entries correlate with discussion replies, and 4) discussion activity correlates to course grade more than overall activity.

The student activity trend identifies the highest and lowest levels of activity to expect in the course. Additionally, a graph with the combined total activity and the number of active students can inform the instructor of how many students are on the course and how active they are. Using the peak hours for activity in Figure 3, an instructor could pinpoint when to interact with the largest number of active students on the course. On the flip side, an instructor could know when to update course information based on the least active times with the smallest number of active students. As indicated by social constructivism and interaction theory, instructor-student interactions help students achieve their potential learning development through assistance from a more knowledgeable other (Agudo-Peregrina et al., 2014; Joksimović et al., 2015; Vygotsky, 1978). Therefore, an instructor can leverage student activity learning analytics that convey popular activity hours to incorporate more instructor interactions and help student learning development.

A common use for data visualizations is to aid decision-making (Cota et al., 2017). Figure 4 is an example of the aggregate-level data that instructors want to inform their course-level decisions (Knight et al., 2016). Based on the finding that none of the scheduling and execution module page visits met the average page visits per student threshold (2.67-page visits), and the scheduling and execution modules are at the end of the course, the instructor of CEE 3999 can conclude the students visit lecture pages less as the course ends. As Moore (1989) (Moore, 1989) states, student-content interactions are the backbone of education because they change the learner's understanding or perspective of the material. Using the lecture page visits as student-content interactions, an instructor should be conscious of their learning design and introduce the most important topics earlier in the course when students visit lecture pages more. Alternatively, an instructor could think about methods to increase course participation and bring students back into the LMS to interact with the course material. Another student-focused learning analytic that relied on the course design was interaction with the discussion boards.

The researchers found the students' discussion entry total to correlate with their reply total. When students add an entry to the discussion board, they interact with the topic the instructor posted, but when they add a reply, the students interact with their peers. Similar to student-instructor interaction, student-student interaction also helps students achieve their potential development in learning the course material (Agudo-Peregrina et al., 2014; Joksimović et al., 2015; Vygotsky, 1978). By knowing that more entries on the discussion board lead to more replies, instructors can apply social constructivism and interaction theory to encourage more discussion activity and help their students learn the course concepts from multiple peer perspectives.

The importance of having discussions and knowing which students are engaging with the discussions was supported by the discussion activity correlating with the students' final grades. Knowing discussion activity correlates with student performance establishes the necessity for an instructor to know who is interacting with the discussions. Each point in Figure 5 represents a student's discussion entry and reply total. While each point in Figure 5 does not contain a student's SIS ID, learning analytics can identify each student individually. Therefore with the addition of student labels to Figure 5, an instructor could identify the students who have fewer entries and are not building their social learning network (Kim et al., 2016; Macfadyen & Dawson, 2010). As a result, an instructor could intervene in the low discussion activity by establishing a minimum reply requirement or post a question that motivates more students to reply and engage with the boards (Kim et al., 2016). Since discussion activity correlates with student performance more than overall course activity, an instructor can leverage learning analytics to facilitate a course design that promotes discussion participation and social network building.

Limitations

One limitation of this research was how we defined activity. Activity was defined as a student’s interaction with the course. A student’s total activity was calculated by summing the number of times the student’s SIS ID showed up in the analytics data. As mentioned, prior learning analytic studies focused on student activity duration, but the Canvas requests table used for the analytics does not track duration. By defining activity by the sum of the interactions rather than total duration, comparing quantities of interactions between studies is challenging. On the contrary, there are advantages to counting interactions instead of time on page. For example, if a student leaves their course page open but does not interact with the page, the student will still be considered active. As a result, students who leave their pages open could have higher activity values than those who close the course once they finish working. Learning analytics are still evolving and under development; therefore, further research and development can reprimand notation issues and create consistent terms and measures for other researchers.

Another limitation stems from a miscommunication regarding the weekly module release of the summer course section. Instead of the weekly modules being unlocked consecutively, all the modules were open for the entire course section. While the course was designed to be self-paced, there was still a structure in place that revolved around unlocking weekly modules. Since the weekly summer modules were open for the entire course, some students could have completed their work early instead of following the intended schedule. If students chose to work ahead, their activity would misrepresent the intended weekly course activity timestamps in the learning analytics.

Lastly, the learning analytics came from only one course. We recognize that limiting the study to only one course could reduce the study's findings applying to other courses. Despite the limitation of one course, this study tried not to be course-specific and focused on learning analytics' capabilities as a whole. While we collected data from multiple sections of the same course to capture more comprehensive learning analytics, future researchers should expand on this study and explore various courses.

Conclusion and Implications

Overall, instructors can leverage learning analytics to visualize student interactions and make data-informed course development decisions. Our research demonstrates the possibilities of learning analytics, considering the students' time of interactions, page visits, discussion engagement, and course grades. When developing an online course, it is important to understand how the course facilitates successful interactions between the students, instructors, content, and the interface. If students are under interacting in the course, an instructor can leverage the hourly activity learning analytics to identify when they should host office hours to increase student-instructor interactions. Additionally, lecture page visit learning analytics can help instructors know which lectures need more interaction-based activities to increase student-content interactions. Despite the discussion activity only moderately correlating with the students' final grades, the discussion board learning analytics help instructors pinpoint students falling behind in their participation.

Learning analytics collect an immense amount of data on student interactions. Despite the opportunity to make data-informed course development decisions, the required parsing to organize and analyze the learning analytics is a time-intensive process. Therefore, education is needed on the organization and analysis processes to inform instructors and eventually encourage use of LMS learning analytics. Additionally, the availability of every students' interaction data on every course in an LMS establishes ethical and privacy concerns for students (Avella et al., 2016). In higher education, FERPA protects the privacy of student education records (*Family Educational Rights and Privacy Act (FERPA)*, 2020). But where does learning analytics data fall in the policy? As the research and development of learning analytics continue, policy and ethical implications, specifically student privacy, will be at the heart of the discussion (Avella et al., 2016; Ferguson et al., 2016; Pardo & Siemens, 2014). Based on this study and prior literature (Avella et al., 2016; Dietz-Uhler & Hurn, 2013; Viberg et al., 2018), the contribution learning analytics provides to online learning is evident. Instructors can use their current and prior course data to identify course development decisions that encourage more interaction between the students and content. This study demonstrates the possibilities of LMS learning analytics, so further research into their development and implementation can help establish online courses that leverage interaction data to facilitate student learning development.

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Chapter 2:

Using Learning Analytics and Student Perceptions to Explore Student Activity in and Online Construction Management Course

Journal Paper:

Using Learning Analytics and Student Perceptions to Explore Student Activity in and Online Construction Management Course

Intended Outlet for Publication:

Journal of Civil Engineering Education

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Abstract

The expansion of online learning in higher education has both contributed to researchers exploring innovative ways to develop learning environments and created challenges of identifying student interactions with course material. Learning analytics is an emerging field that can identify student interactions and help make data-informed course design decisions. In this case study, learning analytics were collected from 113 students in three course sections of an online construction management course in the Canvas Learning Management System (LMS). Surveys were used to collect the students' perceptions of the course design and material to correlate with the students' interactions. The survey findings showed that the students found watching the lecture videos and reading the lecture slides to be the most helpful in their learning. Findings from the learning analytics showed students' interactions with the course decreased after the midterm exam. Based on the results, online course instructors can leverage their learning analytics to understand student interactions and make data-informed course design changes to improve their online learning environment.

Introduction

Student enrollment in online courses has increased alongside the growth and expansion of technology that supports innovative teaching methods, making online course development a central concern for higher education. Multiple disciplines and institutions have embraced online learning by developing learning environments that use various media and techniques to teach course material (Bourne et al., 2005). Yet, engineering programs lag in the development of online courses and degree programs (Bourne et al., 2005).

Because teaching methods common in engineering education (e.g., hands-on approaches, problem-solving applications) are challenging to convert to the online environment, engineering educators shift to blended environments (Bourne et al., 2005). Civil engineering is one field where educators have successfully implemented flipped learning strategies, a type of blended learning, to create collaborative and interactive learning environments (Cleary, 2020; Hotle & Garrow, 2015; Li & Daher, 2017; Ling & Gan, 2020; Mojtahedi et al., 2020). A flipped classroom employs in-person group learning incorporating active learning and collaboration strategies with individual instruction outside of the classroom involving watching online video lectures or completing pre-class activities (Bishop & Verleger, 2013; Li & Daher, 2017). Educators in civil engineering have found that students appreciate the flexibility of individual instruction and find individual instruction helpful to learn course material (Hotle & Garrow, 2015; Li & Daher, 2017; Mojtahedi et al., 2020). Success in online instruction in flipped classrooms and the increase in online learning modalities indicate an evident need for further research in online civil engineering courses.

The evolution of online learning produces unprecedented amounts of student data for understanding individual learning dynamics of online learners (Brozina & Knight, 2015). One type of "big data" (massive sets of data computationally analyzed for patterns and trends) central to online learning is learning analytics (LA). Learning analytics "is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long et al., 2011, p. 3; Long & Siemens, 2011, p. 34). LA provides real-time insight into student interactions – insights that help plan teaching activities and identify at-risk students (Mattingly et al., 2012). LA can be collected from multiple platforms (e.g., Google analytics, LMSs, and MOOCS) and is growing in popularity in higher education as researchers and institutions want to know how to improve courses and meet student learning needs (Avella et al., 2016; Viberg et al., 2018). This data informs instructors of pedagogic changes in course design to encourage collaborative student learning behaviors (Harindranathan & Folkestad, 2019; Lockyer et al., 2013).

This study explores learning analytics and student perceptions of an online course to identify methods to improve course design and create a collaborative learning environment. Two research questions guided this study: (1) In what ways do learning analytics describe student interactions in an online engineering course? and (2) To what extent do students' perceptions of the content correlate with their interactions? To answer, LA data was collected from three course sections of an online construction management course in Canvas LMS. Survey data was accrued on the students' perceptions of the course design to understand attitudes towards available learning methods.

Background

Online Engineering Education

Despite the challenges of applying engineering teaching approaches (e.g., hands-on approach) to an online environment, some universities (e.g., Purdue University, University of Michigan) have leveraged LMSs and big data to develop well-established online programs (Bourne et al., 2005; Mattingly et al., 2012). While there are multiple universities with well-established distance programs in various engineering disciplines, this study is one of the few focusing on an online asynchronous course in civil engineering. Prior research on implementing different teaching models in civil engineering courses focused primarily on flipped classrooms (Cleary, 2020; Hotle & Garrow, 2015; Li & Daher, 2017; Ling & Gan, 2020; Mojtahedi et al., 2020). Research indicates that engineering students participate willingly in flipped classrooms, and the flipped model proves effective in helping students meet course learning objectives (Cleary, 2020; Hotle & Garrow, 2015; Li & Daher, 2017; Ling & Gan, 2020). The advantage of mixing components from online and face-to-face modalities affords flipped classroom models the ability to provide insight on innovative learning activities, structured learning environments, and struggling students (Cleary, 2020; Li & Daher, 2017; Ling & Gan, 2020; Mojtahedi et al., 2020). Some of the flipped classroom insights derive from face-to-face components incorporating social constructivism and interaction theory. Students can interact and collaborate with their peers and instructors to achieve potential learning and development goals (Moore, 1989; Vygotsky, 1978) without being hindered by technology. Similar to flipped classrooms, distance engineering studies realize the necessity of interaction in the online learning environment (McMullin & Owen, 2002; Wu et al., 2013, 2015).

Studies exploring distance engineering environments emphasize the importance of communication and interaction (Agdas et al., 2014; McMullin & Owen, 2002; Wu et al., 2013). McMullin and Owen's (2002) study focused on teaching two structural design courses through distance learning with a two-way live video broadcast to two groups of students at different universities. One group of students received the lectures in-person, and another received them remotely. They found that the remote students and instructors struggled with incorporating collaborative interactions into the learning environment.

The development of LMSs for online courses has opened multiple communication and interaction opportunities between instructors and students. Wu et al. (2013) incorporated social constructivist techniques, such as discussion forums and group projects on practical material applications, to encourage collaboration and interaction in a distance construction course design. Of the multiple types of civil engineering, construction education requires significant interaction and social constructivist approaches because the field centers around team-building and practical application problems (Wu et al., 2013, 2015). While there are multiple benefits to online learning and the development of LMSs has made it easier to establish communication networks, online courses must consider their students' perceptions and the facilitation of interaction.

Student Perceptions

Student perceptions of online learning are considered by researchers as one of the leading factors to sustain online enrollment in higher education (Rodriguez et al., 2008; Song et al., 2004). In a survey on student perceptions of online learning, Rodriguez et al. (2008) found that what the students like most about online learning is the flexibility of study time and least is the limited face-to-face interaction. Additionally, most students perceive having assistance by email available 24 hours a day as necessary for online learning (Rodriguez et al., 2008). Song et al. (2004) focused on student perceptions of advantages and challenges in online learning environments. Results indicated the need for effective instructional design for online environments and facilitation of collaboration (Song et al., 2004). Appiah-Kubi and Nichwitz (2020) established a collaborative online international learning environment and found engineering students felt the collaborative environment helped them acquire knowledge on employable skills, such as effective communication, time management, and leadership.

In this study, student perceptions centered around the students' attitudes towards the course learning methods and the content layout. The case study of an online construction management course incorporated scaffolding techniques predicated on social constructivism and the zone of proximal development (ZPD). Originating from Wood, Bruner, and Ross (1976), the scaffolding process is defined as when a more knowledgeable person helps a novice solve a problem they may not have been able to solve alone (Wood et al., 1976). Scaffolding focuses on learners gradually progressing their learning to eventually move from requiring assistance to completing complex tasks independently (Reiser & Tabak, 2014).

As suggested by social constructivism, the importance of interaction in an online course emphasizes knowing when and where interactions occur to encourage more collaborative online environments. Learning analytics (LA) provides data on student interactions in the LMS to elucidate the "when" and "where" of student interactions within an online course. Combining LA with student perceptions of the learning environment offers additional insight into the strengths and weaknesses in instructional material and instructor assistance. LA alone cannot capture the complexity of student needs and interaction online. Of the multiple studies on LA and student perceptions of online material, a single study combined LA and student perceptions. Liu et al.

(2019) investigated learning behavior patterns using LA from interactions with course components (i.e., discussion forums, course readings) and student perceptions in a MOOC for working professionals finding no significant differences between the benefit of the discussion forums and overall usage frequency. However, a researcher examined dimensions of student perceptions on interactions based on Moore's (1989) three interaction types without using LA. Based on their personal learning experiences, the students consistently ranked student-content interactions the highest (Nwankwo, 2015). Evidence demonstrates the combined ability of LA and student perceptions in providing insight into online course interaction in order to inform future course design. This study opportunistically combined these two constructs to explore student interactions in an online learning environment.

Learning Analytics

Learning analytics (LA) provides extensive data on student interactions in an LMS, but it is important to understand that they are not a new technology. Implementation in the past has focused more on face-to-face higher education institutions but leaves a lesser-explored area of LA use and potential in online courses (B. T. M. Wong, 2017). Universities have used LA to make data-defined decisions, identify at-risk students, and incorporate more personalized learning (Arnold & Pistilli, 2012; Dietz-Uhler & Hurn, 2013; Martin et al., 2016). Because one of the challenges in online learning is knowing when students are struggling, researchers have developed early-warning systems that use learning analytics data on student interactions and performance to identify at-risk students (Arnold & Pistilli, 2012; Mattingly et al., 2012). The Purdue Signals system predicts a student's risk of failing by integrating real-time student performance and interaction data with demographic and past academic history. Arnold & Pistilli (2012) state that Signals has received positive faculty responses and has increased student performance.

Learning analytics also provide critical information about student behavior, which influences course design and subsequent iterative changes. Researchers have found that LA provides insight into time-series data about student interactions, specifically the frequency, the time of day, and the duration of interactions in a course (Agudo-Peregrina et al., 2014; Castro et al., 2018; Joksimović et al., 2015; Macfadyen & Dawson, 2010). LA have also been used to determine the frequency of viewing content pages and tools in LMSs (Brozina & Knight, 2015; Hui & Farvolden, 2017; Macfadyen & Dawson, 2010). Time-based analyses with LA often focus on the correlation between interaction duration and student performance (Castro et al., 2018; Joksimović et al., 2015; Macfadyen & Dawson, 2010). Some studies also found statistical significance between the count of interactions with the content, students, instructors, and student performance (Agudo-Peregrina et al., 2014; Joksimović et al., 2015).

Using the data on content page visits and tool visits, LA can influence and inform learning design. Hui and Farvolden (2017) identified frequently accessed material based on student page visits. They suggested instructors adjust course design and move the frequently accessed material to a more prominent location (e.g., course homepage). Similarly, Lockyer et al. (2013) suggested that LA can support an instructor in course redesign instead of relying solely on past experiences in course iterations. Similar data-informed decisions are justified by Long and Siemens (2011) to emphasize how LA provide value in higher education.

Learning analytics is strongly grounded in learning theory and focuses on elements of learning during interactions within an online environment (Ferguson, 2012). Applying learning analytics in an LMS draws on multiple disciplines, from computer science to learning design to educational psychology. Wong et al.'s (2019) systematic literature review on LA and learning theories found multiple learning theories (e.g., self-regulated learning, social constructivism, and motivation) inform the conceptualization of learning analytics. Similarly, Viberg et al. (2018) determined multiple theories, models, and frameworks to explain different aspects of learning analytics (e.g., behavior, learning outcomes, technology use) in higher education. Based on research, different learning theories can be used with learning analytics depending on the goal researchers are seeking from the data.

Theoretical Foundation

This study is grounded in interaction theory (Moore, 1989) - highly informed and embedded in Vygotsky's (1978) social constructivism. Social constructivism focuses on how interactions with adults and more capable peers help establish understandings that learners would not have made on their own (Vygotsky, 1978). The key mechanism of Vygotsky's (1978) theory is the Zone of Proximal Development (ZPD). Vygotsky (1978) defined the ZPD as the distance between what a student is currently capable of through independent problem-solving and the level of potential development with assistance of an adult or more capable peer. Targeting instruction to work within the ZPD to assist students' move from current to potential capabilities is only achieved, according to Vygotsky (1978), through interaction between students and instructors in a classroom environment.

Due to the importance of instilling and identifying interaction in an online environment, LA is suited to investigate the interactions. LMS learning analytics measure and collect all four interaction types as defined by Moore (1989) and Hillman et al. (1994): (1) student-content (S-C), (2) student-instructor (S-I), (3) student-student (S-St), and (4) student-system (S-Sy). This study explored student-content interactions, defined similarly to prior studies, as students' page visits, page clicks, and overall course visitation (Agudo-Peregrina et al., 2014; Joksimović et al., 2015). Altogether, this study combined student learning analytic data from the Canvas LMS and the students' perceptions of the course material to explore student interactions and inform course design improvements in an online civil engineering social constructivist learning environment.

Methods

To explore the utility of learning analytics in an online platform, the researchers conducted a multiple case-study with a convergent mixed-methods approach. Yin (2009) describes the strengths of convergence in case study research with the following words "an empirical inquiry that investigates a phenomenon in depth and within its real-life context…that relies on multiple sources of evidence, with data needing to converge" (p. 18). In this study, each "case" is bound and defined as a section of the Introduction to Construction Management course (Spring 2020, Summer 2020, and Fall 2020). The researchers chose a multiple-case study to increase the possibility of direct replication and limit the study's vulnerability (Yin, 2009).

For each course section, qualitative and quantitative sources of evidence were collected following Creswell and Creswell's (2018) convergent mixed-methods framework. The qualitative and quantitative data were collected with a strategic and integrated approach. Stratified portions of the data were collected in parallel, analyzed separately, and then merged (Creswell & Creswell, 2018). Researchers gain more insight and develop a more robust understanding of research problems by integrating data sets that provide contrasting information (Creswell & Creswell, 2018). Additionally, using multiple sources of evidence allowed for inquiry from different angles to triangulate and answer the research questions (Creswell & Creswell, 2018; Yin, 2009).

Case Study Overview

The case study course was CEE 3999: Construction Management. Data was collected from 113 students from three course sections: Spring 2020 (N=19), Summer 2020 (N=26), and Fall 2020 (N=68). CEE 3999 is a required course for Civil and Environmental Engineering (CEE) majors and is popular with students from other departments as an optional credit-bearing course. Most students enrolled in CEE 3999 were junior and senior CEE majors. There were students from other majors, including but not limited to Industrial Systems Engineering and Mechanical Engineering. CEE 3999 was an online asynchronous construction management course designed by instructional designers, multimedia engineers, and the course instructor. The team intentionally designed the course to be modular and to collect learning analytics data. By adapting an existing face-to-face version of the course, which shared a modular format, the online version of CEE 3999 took approximately eight months to create from conceptual design to course start-up.

CEE 3999 introduces students to the construction project lifecycle from the conceptual design phase to operation & maintenance. The content delivery was online asynchronous, and only the teaching assistant (TA) and instructor office hours were synchronous. The course was designed to stratify student interactions in the LMS interface (e.g., lecture page visits, discussion page visits). The design team took into account how Canvas measures user interactions and strategically separated the course materials to be navigable and interactive. This design helped the students navigate the course in an active manner and resulted in a higher resolution dataset for understanding student interactions. The course assignments and instructional approach contained scaffolding techniques. Since the course was asynchronous, the instructor pre-recorded the video lectures covering topics in the five course modules: Planning, Economics, Scheduling, Execution, and Leadership. Additionally, most lecture videos included the scaffolding technique of instructor-led worked examples explaining the course concepts in organized steps (Reiser & Tabak, 2014). Therefore, students could reference multiple examples for assistance. To further build upon previous knowledge and provide continuous feedback, the course includes team-based activities. At the beginning of the semester, four person student teams are created using the Canvas random group feature (controlling for the isolation of female students). In their groups, the students collaborate on a series of module exercises and a Google Site that describes the project lifecycle of an iconic infrastructure project (e.g., Eiffel Tower, Hoover Dam). Students also interacted with their peers through twenty lecture-based Canvas discussion boards.

Data Collection & Analysis

The researchers collected learning analytic data from the Canvas LMS and conducted three surveys during each course section. The spring and fall course sections lasted 16 weeks, and the summer section lasted 6 weeks. The spring and fall sections were traditional semesters with approximately 13 weeks of content, one week of break, and two weeks for final exam preparation. However, in Spring 2020, the COVID-19 pandemic started, so the students had an extra week of spring break while the institution switched to emergency teaching at a distance. Otherwise, there were no additional impacts due to the COVID-19 online shift. The summer section was delivered in a condensed format over six weeks without any breaks.

Learning Analytics – Data Organization & Analysis

Learning analytics was acquired through a Canvas requests table (further noted as analytics). The request table is the foundational source of student interaction data on Canvas (Hallmark, 2019), catering to large data sets and analysis (*Canvas Data Portal*, n.d.). The requests table collects data every time a user's interaction (e.g., page visits) triggers a callback to the Canvas servers (Hallmark, 2019). Canvas stores the data in a "star schema" convention, where information collects as fact tables referencing multiple dimension tables (*Canvas Data Portal*, n.d.; Harindranathan & Folkestad, 2019). LA data is packaged in a csv format and downloaded from the flat files in Canvas Data Portal. Each student interaction with the course presents as a separate line in the csv. For example, when a student visited a lecture page, the analytics noted the student's information system (SIS) ID, the timestamp (date & time) of the interaction, and the URL where the interaction occurred.

In analysis, researchers imported the csv file into Microsoft Excel, creating an xlsx file to facilitate the organization of interaction data. Early on, a challenge was discovered in the organization process. Canvas collects data in Universal Time (UT) which pushed the researchers to create new time-based columns with the eastern time zone to ensure the analytic data matched course interaction timestamps. Because Canvas collects each student interaction using a combination of facts and dimensions, Excel pivot tables were used to filter student interactions. To determine proper filters, researchers compared the analytic data to the Canvas course information, ensuring instances such as the time and date of a students' discussion posts in the analytics matched the course's time and date.

Using parsed analytic data, the researchers conducted an exploratory graphical analysis to identify patterns or anomalies in the student interaction levels. Total interaction is defined as the sum of the students' interactions with the course that shows up in the analytics data. For example, if a student had an interaction value of 14,000, their SIS ID showed up 14,000 times in the analytic data. Since prior analyses of LA data focused on student interaction duration (i.e., how long students spend on the course), we looked at when interactions occurred. Therefore, we graphed the students' interactions by time (e.g., hour, week) and examined the peaks to identify popular student interaction times. An important aspect of the hourly and graphical analyses is that each hour is a time range. For example, 4 PM is 4:00:00 PM – 4:59:59 PM. If a student worked from 4:30 PM – 5:30 PM, their interaction count spreads across the 4 PM and 5 PM columns. Since the summer course section had a different duration than the spring and fall course section, the summer course section was excluded from some weekly interaction level analyses.

Survey Design, Distribution, and Analysis

Surveys aimed to gather the students' perceptions of the content and assistance available. The Spring 2020 course section was the pilot study, and the students took seven surveys. The response rate to most of the surveys was minimal, so in the summer and fall course sections, the students took only three surveys: a pre-course, a mid-course, and a post-course. For each course section, the researchers emailed the pre-course survey invitation to the students, and the other survey invitations were posted as an announcement on the Canvas course page.

The summer and fall surveys were conducted on the Qualtrics database. Each survey included 5-point Likert-scale (1 = strongly disagree & 5 = strongly agree) and open-ended questions that focused on the students' attitudes towards the course. The mid-course and post-course surveys included module-specific questions that focused on the lecture material delivery. Some questions were similar across all the surveys to identify changes in the students' perceptions of the content delivery. A paired t-test was conducted on Excel and used for the summer and fall course section's survey responses to compare the students' perceptions of the helpfulness of the available learning methods. The paired t-test only included responses from students who responded to all three surveys (Summer N=9; Fall N=19). Since the aim was to identify changes in perceptions, we compared the differences in the pre-course versus post-course survey responses, pre-course versus mid-course survey responses, and mid-course versus post-course survey responses.

Integration of analytics & survey

Pearson's correlation analysis was used to determine the correlation between the students' interaction levels from the analytics and their perceptions of the content material. The analysis covered the students' perceptions of the video lectures explaining course topics from the four overarching course modules (Planning, Economics, Scheduling, and Execution). The students' responses to the content-specific questions were compared to their page visits on the lecture page containing the material. For example, the students' responses about their understanding of the "Contract types" topic from the lecture videos were compared to their respective page visit count to the Planning IV: Contract Types lecture page.

Results

Learning Analytics

Student Interactions by Hour

The exploratory graphical analysis in Figure 7 visually demonstrates students' hourly interactions within the course. The hourly interactions pinpoint opportune times for the instructor to engage with their students. As a reminder, each column in Fig. 7 is a time range. As seen in Fig. 8, the students in the fall and spring course sections had similar hourly interactions per active student levels. The interaction levels per student were calculated by dividing the total interactions each hour by the number of active students in that hour. As seen in Fig. 8, the afternoon and evening were peak interaction times for all three course sections. The fall & spring course sections had 3 PM and 4 PM in their top three peak hours. In contrast, the summer course had peak interaction hours in the evening: 9 PM, 7 PM, and 10 PM.

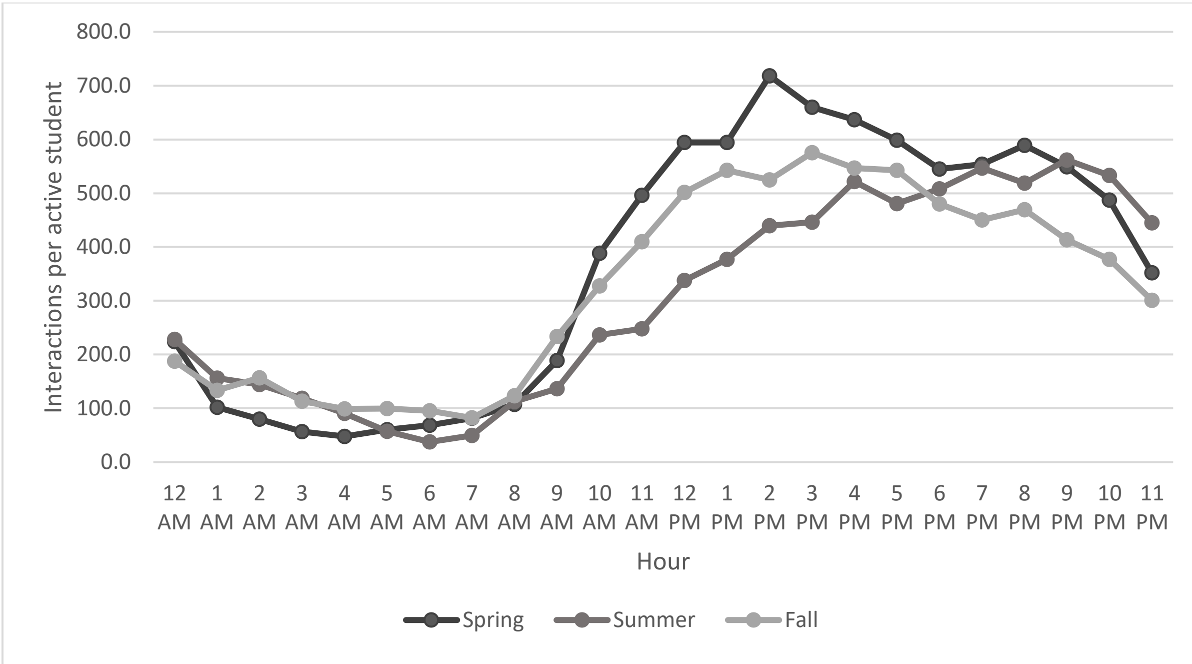

Figure 7: Interactions per active student by the hour for the three course sections

Weekly Interactions

Even though the fall and spring course sections had similar hourly interactions, their weekly levels differed. The fall and spring course sections were the same duration, but they each had different breaks, which caused some weekly fluctuations (Fig. 8). The weekly interactions per active student was calculated by dividing the total interactions per week by the number of active students per week.

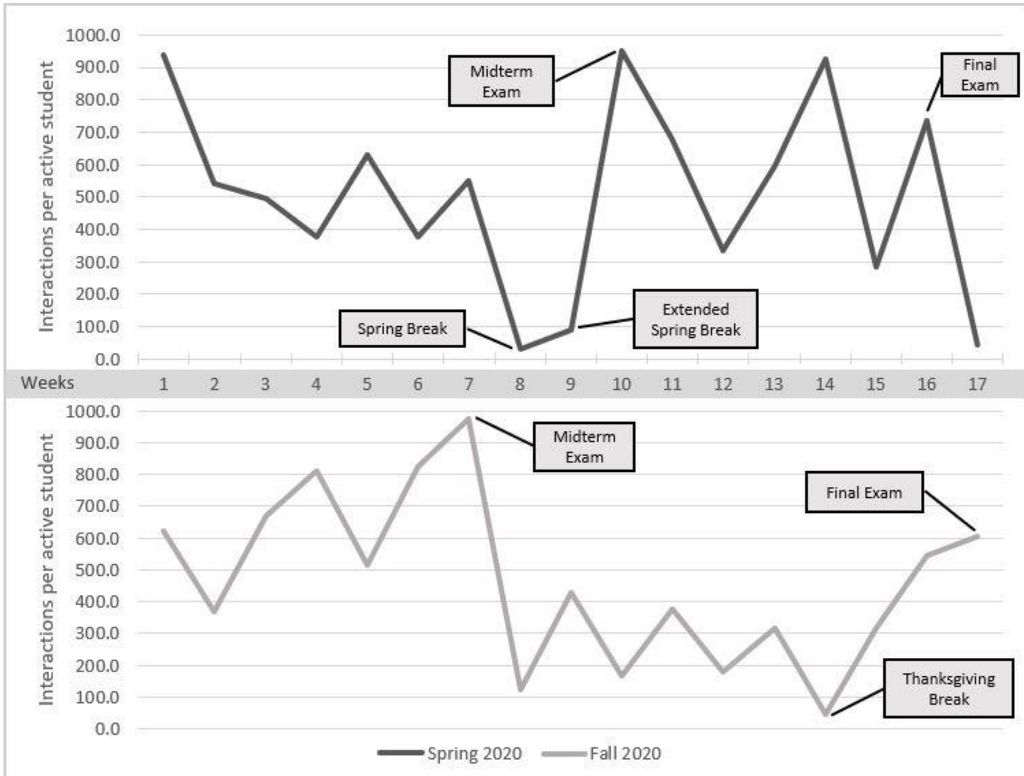

Figure 8: Weekly interactions per active student for the spring and fall course sections

Despite the differences in weekly interaction, the spring and fall had a similar interaction distribution before and after the midterm exam. For both course sections, almost 50% of the students' weekly interactions were before the midterm exam. In comparison, only 33% of the interactions were after the midterm exam. We found a similar split of interaction levels before and after the midterm exam in the summer course section. The same pattern of fewer interactions after the midterm exam was also found in the lecture page visits.

Page Visits

A coveted learning analytics data resource is identifying when and how often students are viewing the course pages. The lecture pages were the most important page group because they included the lecture videos that were the primary source of content. Since the course had a weekly content delivery structure, we graphed the weekly lecture page visits per active student for the spring and fall course sections (Fig. 9). As seen in Fig. 9, the lecture page visits for both course sections decreased after the midterm exam. Most of the weeks, excluding breaks and weeks 1 & 17 in the spring course, with page visits below the average line, were after the midterm exam in each course section, demonstrating a downward trend in page visits (spring = 3/4 weeks & fall = 6/8 weeks).

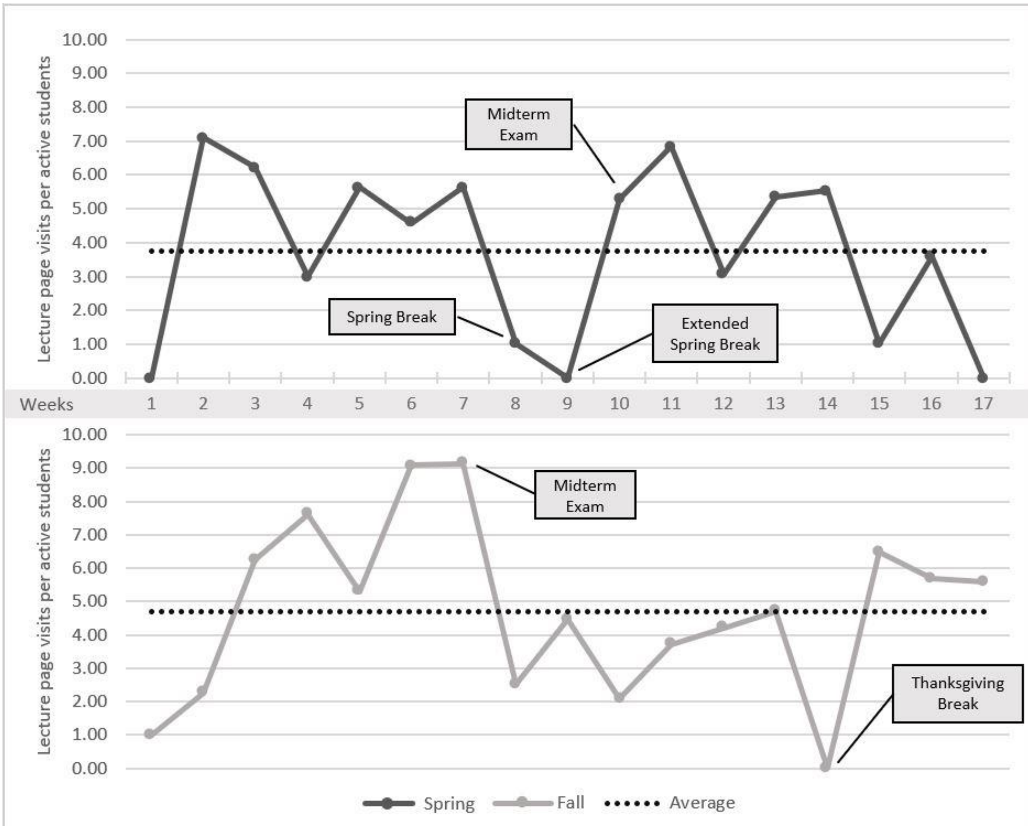

Figure 9: Lecture page visits per active students by week for the spring and fall course sections

Surveys

The three surveys in the summer and fall course section provided insight into the students' perceptions of the course material and course structure. As previously mentioned, the spring course surveys were the pilot surveys and were not included in the analysis. All the surveys in the summer and fall course sections had above a 60% response rate, as seen in Table 2. The following sections discuss the survey findings and the student perceptions of the course learning methods and interactions for assistance.

Table 2: Summer and fall course sections' response rates for the three surveys

	Surveys		
Course Sections	Pre-Course	Mid-Course	Post-Course
Summer (N = 26)	81% (N = 21)	65% (N = 17)	62% (N = 16)
Fall (N = 68)	66% (N = 45)	68% (N = 46)	74% (N = 50)

Perceptions of Learning Methods

Around 55% of the combined summer and fall students (N = 66) responded with "a great deal" when asked in the post-course survey how helpful watching lecture videos were to learn the course material. As seen in Figure 10, reading the lecture slides was a close second, with 51% of the students finding the learning method to help "a great deal."

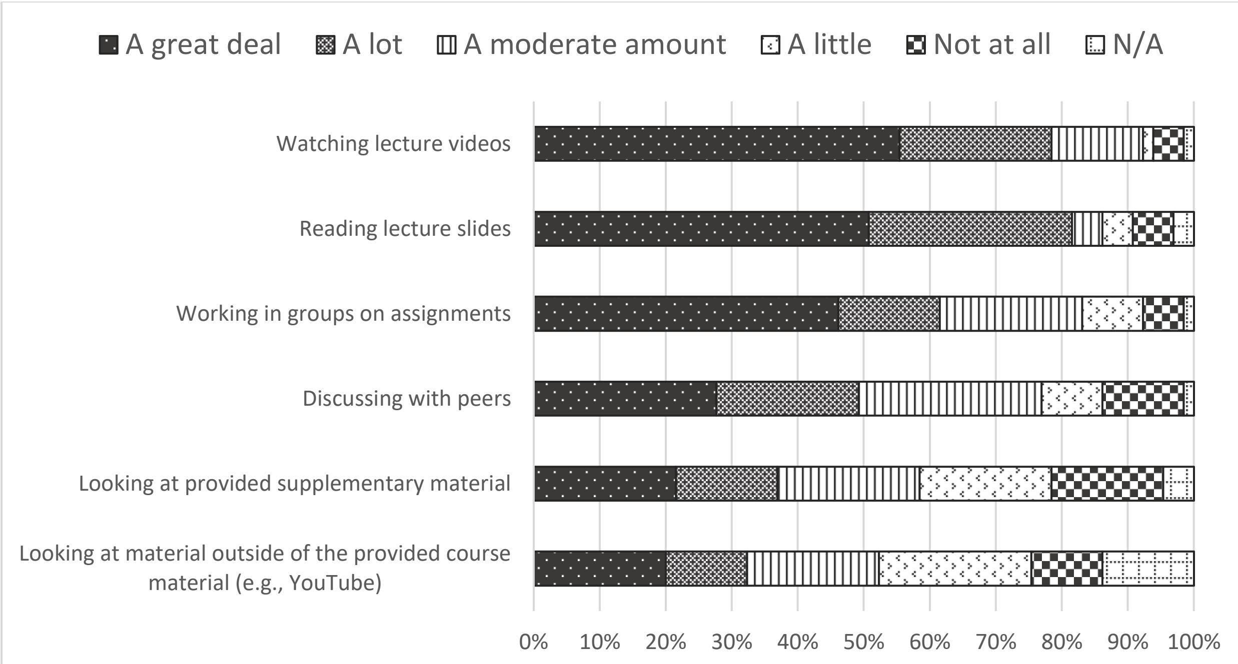

Figure 10: Summer and fall students perceived helpfulness of methods to learn the material

The paired t-test on the helpfulness of the learning methods for the summer and fall course sections found that the students' perceptions stayed the same for most learning methods. As seen in Table 3, most responses' mean values stayed within the moderate amount of helpfulness range. Based on the p-values in Table 3, reading the lecture slides showed statistical significance at the specified $p < 0.05$ level for both course sections. The summer section had statistical significance between the mid- and post-course responses ($t(8) = -2.6$, $p < 0.05$), while the fall section had statistical significance between the pre- and mid-course responses ($t(18) = -3.52$, $p < 0.01$) and the mid- and post-course responses ($t(18) = -5.88$, $p < 0.001$). Working in groups on assignments only showed statistical significance in the summer section between the pre- and mid-course responses ($t(8) = 2.68$, $p < 0.05$) and the mid- and post-course responses ($t(8) = -2.83$, $p < 0.05$).

Table 3: Mean responses and paired t-test survey results for the learning methods' helpfulness

	Summer (N = 9)			Fall (N = 19)			p-values		
Learning methods	Pre	Mid	Post	Pre	Mid	Post	P - M	P- P	M - P
Lecture videos	4.22	4.00	4.67	4.16	4.16	4.32			
Lecture slides	3.89	3.11	4.56	3.05	4.16	4.63	**F	***F	*S
Working in groups on assignments	3.44	2.44	3.11	3.47	4.00	4.11	*S		*S
Peer discussion	3.56	3.11	2.89	3.74	3.47	3.63			
Supplementary material	3.78	3.22	2.89	3.00	3.05	3.16			

Outside material (e.g., YouTube)	3.78	3.44	3.00	2.89	3.21	3.11

Note: * = p<0.05; ** = p<0.01; *** = p<0.001; P – M = Pre-Mid, P – P = Pre-Post, M – P = Mid-Post; F = Fall; S = Summer

Perceptions of Interaction for Assistance

Part of a scaffolded course design and the root of a social constructivist learning environment is collaborating with a more knowledgeable person (e.g., peer, TA, instructor). Despite the importance of instructor-student interactions, when asked how often the fall and summer students sought assistance from their peers, TA, and instructor, the instructor was the least sought after, followed by the TA and peers. A majority of students responded with "never" for the instructor (71%) and TA (58%), whereas when asked about peer assistance, a majority said, "sometimes" (57%). Because students were required to work in groups for their projects, it's surprising that a little more than 20% of the respondents said they "never" went to their peers for assistance.

Discussion

This study examined how learning analytics describe student interactions in an online civil engineering course and how the students' perceptions of the content correlated with their interactions. Student interactions from the learning analytics was illustrated through the hourly and weekly interactions and page visits using different visuals to communicate the findings.

Student interactions by hour

The hourly student interaction levels, as seen in Figure 7, provide coveted information for instructors on student interaction patterns and when logins occurred on the course (Podgorelec & Kuhar, 2011; Verbert et al., 2012). The interactions trends by the hour for the course sections are consistent with Castro et al.'s (2018) study, showing that students are more active between 9 AM and midnight. The similar hourly trends across all the course sections indicate that an instructor can use prior course section data to predict and develop expectations for course interaction trends in their future course iterations. Additionally, awareness of popular student interaction times can encourage more student-instructor interactions by informing the instructor when they should access the course to be available for questions or schedule their office hours (Martin et al., 2016). As mentioned by Moore (1989) and found in multiple distance learning studies, student-instructor interactions are highly desirable and essential to creating a successful learning environment (Agudo-Peregrina et al., 2014; McMullin & Owen, 2002; Nwankwo, 2015; Wu et al., 2013). With an intention to increase student-instructor interactions, an instructor can conclude from the different peak interaction times between the summer and spring & fall sections they may need to adjust their office hours or times to engage with their students between traditional (fall & spring) and non-traditional (summer) semester lengths.

Student interactions by week

Similar to the student interactions by hour, the weekly interactions per active student fosters awareness about the typical levels an instructor could expect for future course iterations, including which weeks students were more or less active. Greller and Draschler (2012) suggest that patterns in the analytics can be used for models to improve curriculum design. Dietz-Uhler & Hurn (2013) mention how learning analytics help make data-informed decisions on improving student success in courses. According to Long & Siemens (2011), they can also help instructors change their pedagogical approaches. Based on the pattern found in all the course sections of less interactions after the midterm exam, the instructor should make a data-informed decision to incorporate more interaction-related activities in the last half of the course to stimulate student interaction with the course material.

Page Visits

Another important finding related to student-content interactions and how learning analytics affect learning design stems from students' lecture page visits. As noted by multiple studies, instructors want to know where and how students spend their time in the LMS (Knight et al., 2016; Podgorelec & Kuhar, 2011; Verbert et al., 2014). Since student-content interactions are the "defining characteristic of education" (Moore, 1989, p. 2), instructors need to identify student interaction with the lecture pages. The lower levels of lecture page visits per student after the midterm exam indicate that the instructor should be conscious of their learning design and introduce the most important topics earlier when students visit lecture pages more. One limitation of the lecture page visits is that we do not know what the students were doing when visiting the lecture pages. Despite the limitations, knowing when lecture pages are visited helps the instructor understand the student-content interactions and develop knowledge of the expected flow in the students' learning patterns to help inform future instructional sequencing.

Surveys

The student perceptions highlight important aspects of the course material and structure. Based on the survey response mean values for both course sections, watching the lecture videos and reading the lecture slides were consistently perceived as very helpful. Working in groups on assignments and peer discussions was perceived much lower in the summer course section than in the fall course section. While we do not know the exact cause of the differences, one hypothesis is that duration played a role. The summer course section was much shorter with the same amount of work, which may have caused the students to rush through group work and discussions that they could have found more helpful with more time, as shown by the higher mean values in the fall section. Additionally, the fall students had to work in groups on 7 out of 8 homework assignments on top of their group projects. In an online environment, it is easy for students to feel isolated (Wu et al., 2013). Group discussions, problem-solving activities, and projects help students establish online learning communities and interact more with their peers (Mojtahedi et al., 2020; Wu et al., 2013; Yehia & Gunn, 2018). Therefore, increased collaboration in the fall course section from the group homework assignments may have increased the students' perceptions of working in groups and peer discussion and decreased reliance on traditional lecture and content delivery.

The finding that more students sought their peers for assistance than the TA or instructor highlights that the course promoted student-student interactions. While instructor-student interactions help student learning development, construction engineering is a collaborative and team-based environment where peers are the support network (Wu et al., 2015). Based on more students responding with "always" or "most of the time" seeking their peers for assistance than the TA or instructor, we can conclude the group work-focused course structure helped facilitate student-student interactions. While building a support network in an asynchronous environment may be challenging, through incorporating social constructivism and scaffolding techniques, such as group work, instructors can help establish a collaborative online learning environment that students perceive helpful.

Conclusion

This study was one of the few to explore an online asynchronous civil engineering course. Our results show that students interact less on the course after the midterm exam, and they found watching the lecture videos and reading the lecture slides to be the most helpful with learning the course material. The student-content interactions are the primary source of education (Moore, 1989); therefore, the finding of fewer page visit interactions as the semester ended indicates improvement areas for the course. The instructor should be conscious of their learning design and incorporate collaborative activities that bring the students back to the LMS to increase interaction after the midterm exam. Additionally, this paper provided insights into how the course design, including content delivery methods and group work, can influence the students' perceptions of the course. While the students' perceptions did not correlate with the learning analytics, their perceptions indicated that watching the lecture videos and reading the lecture slides helped with learning the course material. The students' perspective on interacting with their peers, whether through working on assignments or seeking assistance, highlights the significance of having a course design that facilitates student interactions.

When interpreting the findings, this study had some limitations that should be considered. First, our definition of total interaction as the sum of the students' SIS ID does not fully represent how active a student is on the course. The measurement does not account for the total duration of interactions due to the limitations of the Canvas requests table. Development in learning analytic frameworks could establish processes and definitions to create consistent terms and measures for future researchers. Data itself is another limitation that is bound by the constraints of the human who requisitions it and the humans who use it. Much of the interactions are not visible actions seen by the instructor on the LMS (e.g., clicking on lecture pages), so it was challenging to confirm if the analytic data had incorrect information. Lastly, surveys used to evaluate student perceptions were subject to self-report bias. Self-reporting means students may have over or under exaggerated their perceptions towards the course material and structure. However, the risk of bias is decreased because the perceptions were compared across the course. Future work should focus on increasing sample size and comparing responses across more case studies.

The learning analytics findings have implications for online civil engineering instructors who want to improve the learning environment. Instructors can leverage their LMS learning analytic data to identify student interactions and inform their course design improvements. Civil engineering is a collaborative and team-based environment. By identifying weekly interactions with the course, an instructor can make data-informed decisions to incorporate more interaction-related activities that bring students back to the LMS at times of less interaction. Additionally, civil engineering instructors can incorporate scaffolding techniques such as group work and discussions to establish collaborative online learning environments.

Despite some of the opportunities learning analytics offer, the availability of every students' interaction data on every course in an LMS establishes ethical and privacy concerns for stakeholders. Researchers push for transparency and policy development throughout the collection and implementation of learning analytics (Ferguson et al., 2016; Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Online civil engineering stakeholders can start the conversation on policy development by researching the application of learning analytics and establish online environments where all stakeholders can collaborate and make data-informed decisions using accessible and ethical learning analytic data.

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CONCLUSION

The papers within this thesis suggest that learning analytics from an LMS can help instructors understand student interactions in their online courses. Also, the learning analytics and student perceptions of the learning methods can help make data-informed course design decisions to encourage interaction and collaboration. Chapter 1 shows that student activity is at its peak in the afternoon and evening, and student page visits decrease as the course semester ends. Additionally, the students' total discussion entries and replies correlate with their performance. Chapter 1 provides recommendations for online instructors that could help improve course design by implementing learning analytics. These recommendations could contribute to increased interactions and collaboration between students, instructors, and content within the online LMS.

Chapter 2 echoes the results in Chapter 1 that overall weekly student interaction and their page visits lessen after the midterm exam. The hourly interaction results in Chapter 2 show that the patterns differ between traditional and non-traditional length semesters. Additionally, the students perceived watching the lecture videos and reading the lecture slides to be the most helpful throughout the entire course. Recommendations within Chapter 2 suggest that an instructor be conscious of their learning design and incorporate the most important information earlier in the course or add activities to increase student interaction and collaboration. Adding collaboration and group work can help students build their learning network and seek assistance from their peers more often.

The next steps for this research are two-fold. In order to gather a more comprehensive overview of the student's perceptions on the course design and interaction, future studies could conduct interviews or survey more students. Interviews would provide a more detailed look into the students' opinions of the course design and limit the self-reporting bias that encompasses a survey. The future of learning analytics resides in stakeholders seeing the value of the information. Future researchers could conduct studies with all online stakeholders to identify each stakeholder's needs and challenges with the data. In the studies, the stakeholders should interact with the data to learn what information is gathered and how it could be useful to them. Additionally, further research on learning analytics can help establish methods and frameworks that develop consistent terms and measures for future researchers. Lastly, online stakeholders need to drive the conversations on policy development and guidelines for how to use and collect learning analytics, so every stakeholder knows what information is available to them. Despite the future studies that could be conducted, the results gathered through this thesis highlight the applications of LMS learning analytics and how the data can depict student interactions in the lesser-explored area of an online civil engineering course.

One step forward to assist with the expansion of learning analytics is teaching instructors and online stakeholders about learning analytics from an LMS. To satisfy the need to teach, I created an online self-paced asynchronous Canvas course on learning analytics. The goal of the course is to teach instructors about Canvas LMS learning analytics and how they can leverage their course data to make data-informed course design improvements. The course is structured with three separate modules that cover: (1) Learning analytic types, (2) How to organize, synthesize, and graph the data using pivot tables, and (3) Data-informed course design decisions. While the course centers around Canvas LMS learning analytics, the future goals are to build a community around exploring learning analytics and incorporate other instructors' and stakeholders' experiences and knowledge on learning analytics. Through the learning analytics course, instructors and stakeholders can build their knowledge of learning analytics while contributing to the expansion of using learning analytics to make data-informed course decisions that can create engaging and collaborative online courses.

Please follow this link to visit the course: Utility of Canvas LMS Learning Analytics in an Online Course.

APPENDIX A: Canvas Requests Table Data

For more information about the columns in the Canvas requests table, refer to reference (*Canvas Data Portal*, n.d.)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	unique_name	id	timestamp	Canvas Time (ET)	timesta	timesta	timestamp_day	Canvas date (ET)	user_id	course_id	root_accour	course_acc	quiz_id	discussion_id	discussion number
14		9fe0de97-	2/10/20 4:59 AM	11:59 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17						
15		2dd24b16-	2/10/20 4:59 AM	11:59 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17						
16		fbccb14e-!	2/10/20 4:59 AM	11:59 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17						
17		dc05329b-	2/10/20 4:59 AM	11:59 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17					4.511E+16	677481
18		0d88b442-	2/10/20 4:59 AM	11:59 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17						
19		3bcb3ef9-:	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	-9.37E+16						
20	List of SIS IDs	d5efcc40-(	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17	Keys assigned by Canvas for the user, course, root account, and course account				4.511E+16	677481
21		da714c42-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17					4.511E+16	677481
22		68106432-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	5.668E+17					4.511E+16	677481
23		b9a99f98-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	-2.93E+17						
24		ec39238c-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	-2.93E+17						
25		d2d6d327-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	-2.93E+17						
26		afd0173d-	2/10/20 4:58 AM	11:58 PM	2020	2020-02	2/10/2020	2/9/2020	-2.93E+17						

Figure A1.1: Screenshot of the analytics Excel data columns A-O

P	Q	R	S	T	U	V	W	X	Y	Z
discussion name	conversati	assignment_id	assignment name	url	user_agent	http_method	remote_ip	interaction_	web_application_cor	web_application_action
				/courses/103767/modules/progressions		GET			context_modules	progressions
				/courses/103767/modules/items/assignm		GET			context_modules	content_tag_assignment_dat
				/courses/103767/modules		GET			context_modules	index
Contract Types				/api/v1/courses/103767/discussion_topics /677481/entries/1825416/replies		POST			discussion_topics_api	add_reply
						POST			courses	ping
						GET			wiki_pages_api	show_revision
Contract Types					User brow- ser	POST	IP addresses and interaction micros		discussion_topics_api	mark_entry_read
Contract Types						POST			discussion_topics_api	mark_entry_read
Contract Types						POST			discussion_topics_api	add_entry
		4.511E+16	A2	/courses/103767/assignments/793933/su bmissions/78370?download=12354031		GET			submissions/download	show
						GET			courses	show
						GET			external_tools	jwt_token
			A2			GET			context_module_items_	item_sequence

Figure A1.2: Screenshot of the analytics Excel data columns P-Z

APPENDIX B: Pivot Table Filtering Steps

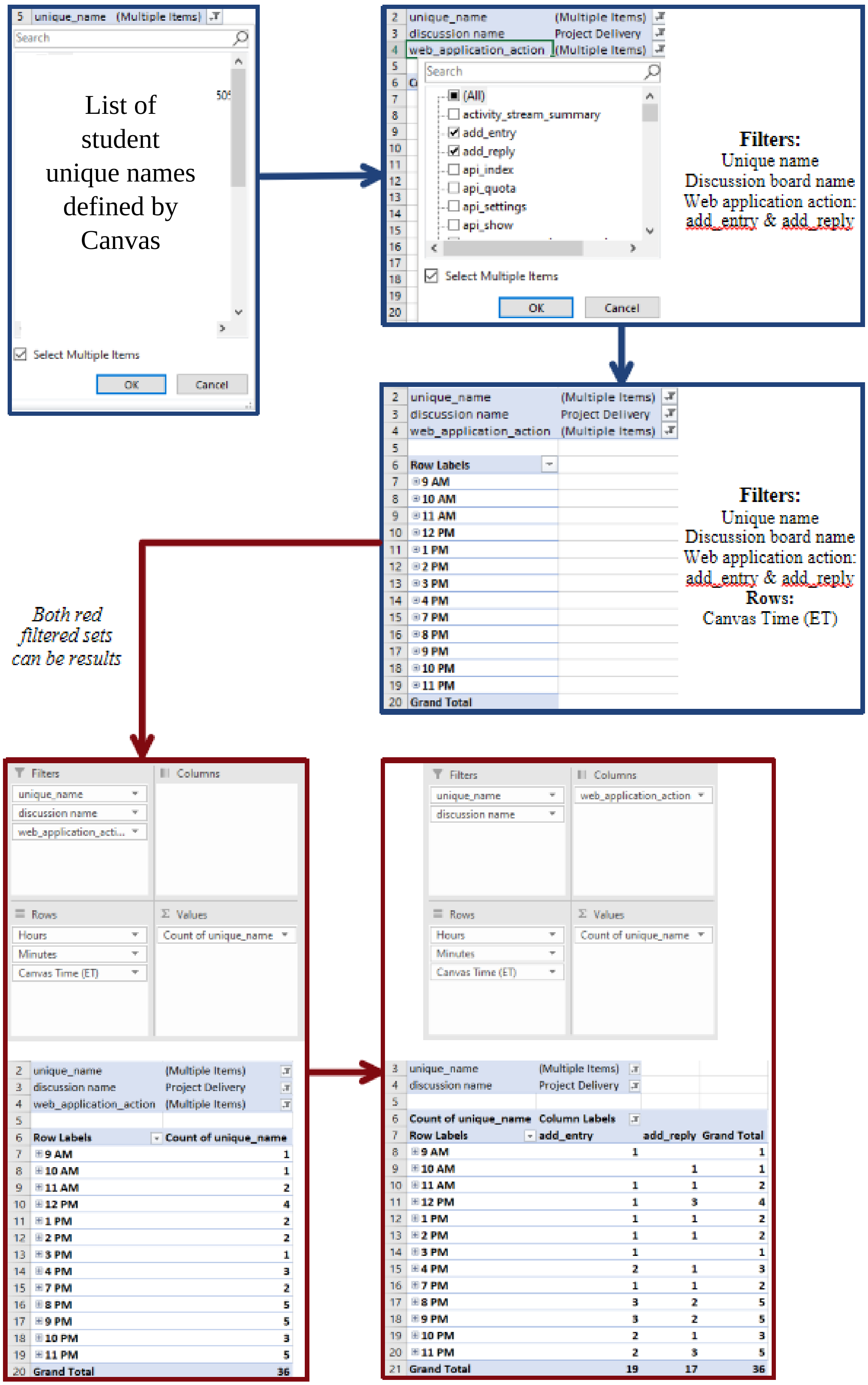

Figure A2: Steps for filtering with pivot tables to create discussion entries and replies by hour

APPENDIX C: Learning Analytics Data Management

This study's learning analytic data came from a Canvas requests table from the Canvas learning management system (LMS). As mentioned in both chapters of this thesis, the requests table collects data any time a user's interaction (e.g., page visits) triggers a callback to the Canvas servers (Hallmark, 2019). Canvas stores the data in a "star schema" convention, where information collects as fact tables referencing multiple dimension tables (*Canvas Data Portal*, n.d.; Harindranathan & Folkestad, 2019). At the university where the study was conducted, there is a division of information technology and a department focused on online learning strategies and development. We received the data from the Director of Software Development within the previously mentioned division. The data was in a csv format that we converted to an xlsx format for the synthesis, organization, and analysis process. Each row in the xlsx file was every interaction every student had with the material during the course's duration. There were also rows of every interaction the instructor, TA, and course designers had with the course. We filtered out all the interactions that were not associated with the students during the analysis process.

The synthesis, organization, and analysis occurred in Microsoft Excel. The first part of the organization required adding new columns to the data set. As mentioned in both chapters, Canvas collects data in Universal Time (UT), so we converted the timestamps to Eastern Time (ET). The conversion process and equations used are discussed in more detail in the videos linked at the end of the section. One important aspect of the time adjustment was considering daylight savings time. At any time of the year, the eastern time zone is either 4 or 5 hours behind UT. Therefore, when daylight savings time occurred, we had to determine where the change took place in the data set so we could adjust the equation for UT to ET.

The next part of the organization required adding columns that identified each quiz, assignment, and discussion by their name. Canvas creates a unique id number for each quiz, assignment, and discussion added to a course. We went to the course and examined the URLs for the unique id numbers associated with each quiz, assignment, and discussion. Once we had the unique id numbers, we developed VBA macros that would examine each cell in the URL column in the data set. The macros looked for the unique id number associated with each quiz, assignment, and discussion and then put the name of the associated quiz, assignment, or discussion in the newly created columns. We used the same code for the quiz, assignment, and discussions. The differences between the codes were the length, the unique id numbers, and the names of the quiz, assignment, or discussions we wanted to identify. The code itself was very repetitive, so it only had to be created once and copied multiple times. The videos linked at the end of this section show an example of the code.

The last part of the data management centered around pivot tables and synthesizing all the data for analysis. We created a pivot table for each course section's data set. The pivot tables allowed us to filter and synthesize the data into smaller chunks we could analyze and use for visualizations. Pivot tables include four boxes: filter, columns, rows, and value. We used the filter box to remove the unnecessary student information system (SIS) IDs associated with the TA, instructor, or course designers, so the pivot table would not count their interactions. The filter box was also used for removing unnecessary interactions that we didn't want for a specific analysis. For example, we filtered the "web_application_action" column to only include "add_entry" and "add_reply" when synthesizing the students' count of posts and replies on the discussion boards. We also filtered by the quiz, assignment, and discussion names depending on the data we wanted for the analyses. We adjusted the information in the column and row boxes depending on how detailed we wanted the synthesized data. For example, we could put the discussion name column in the columns box and see the number of posts & replies on individual discussion boards. Lastly, for most of the analyses, the value box said "Count of unique_name." The value box creates the synthesized data you see once you have added the filters, rows, and columns. Most of the time, we counted the number of times a students' SIS ID showed up in the data. After using the pivot tables to create the synthesized data, we developed the visualizations seen in both chapters of this thesis. While the data management process has a learning curve, once we understood what the requests table detailed and the combination of filters needed for certain analyses, it became a repetitive process that, for the most part, ran smoothly.

Lessons Learned:

- After adding all the columns to the data set and before the pivot table, compare the timestamps in the data set to the ones in Canvas to ensure you adjusted the UT correctly. You can use an assignment submission or a discussion post to compare the timestamps.
- Use the Filter feature on Excel and add it to your dataset so you can filter data in your Excel sheet without needing a pivot table.

- Be prepared for Excel to slow down (depending on your computer) during some of the organization.
- Stay organized and title or label every set of synthesized data so you know later on what the data represents.

Please visit the attached videos with this thesis submission to see the screencasts covering the data management process in more detail with an example data set.

- Screencast 1: Organizing and filtering the data – This video discusses adding the columns to the raw data and developing the macros.
- Screencast 2: Pivot tables with the analytics – This video discusses the pivot table process when synthesizing the data for analysis.