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Learning Design and Student Behavior in a Fully Online Course

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Abstract

Student's behavior in an online course is strongly influenced by the learning design of the course, however there are not many discipline-focused studies investigating how students engage with the Learning Management System and course materials. This paper investigates an asynchronous and fully online introductory statistics course with a collaboration component (Collaborative Keys). This study evaluates how students use these and other resources, if they are being used as intended, and how the use is related to performance. We extend the educational analytics literature and introduce a new measure to quantify how students transition between resources, and we evaluate how these transitions differ by student performance over the course of an entire term. The results suggest that the use of course's resources is related to student achievement, with higher performing students focusing on video-related resources and showing more consistency and effectiveness in their use of resources throughout the term.

Keywords: Online learning, learning design, learning analytics, learning management system, behavior patterns, collaborative keys

1. INTRODUCTION

In the statistics education field, most of the studies in online learning focus on comparing students' performance (measured by final course grades, CAOS and SRA assessments, and other course assignment's grades) across different modes of instruction: online, face-to-face, and hybrid. Mixed results have been reported as some studies find evidence of face-to-face students performing better (Scherrer, 2011) while others finding little to no evidence of a difference in statistical literacy (Hahs-Vaughn et al., 2017), statistical reasoning (Gundlach et al., 2015) knowledge, or final course grades (Shotwell & Apigian 2015) across delivery methods. Other studies focus on how student's attitudes and anxieties towards statistics can predict course outcomes and comparison of student's attitudes across different modes of instructions (Zimmerman & Austin, 2018; Gundlach et al., 2015). Some of the findings suggest that students in online and flipped sections perceive statistics as a more difficult subject and online students also have fewer positive feelings towards statistics when compared to students in a traditional section (Gundlach et al., 2015). In addition, test anxiety is a better predictor of course performance for online students than face-to-face students (Zimmerman & Austin 2018) .

While the main focus of online studies in statistics education has been on performance and attitudes, only a few studies provide a more innovative focus of analysis. Shotwell and Apigian (2015) compared student's use of course resources based on a survey administered to students and time spent on the learning tool between online and face-to-face sections of an online introductory business statistics course. Their findings suggest that the primary resource online students use to learn the material was the textbook, followed by homework assignments, and online video tutorials. However, face-to-face students primarily use homework assignments and learning tool quizzes. Regarding an innovative structure of online courses, not much research is found except Rayens and Ellis (2018) who report on the redesign of a course from a traditional setting with lecture and recitation sections to a student-centered online class with more student engagement and more student responsibility over their own learning.

As exemplified by these papers, online research in the field of statistics education is still evolving and no studies have been found that focus on the use of log report data from Learning Management Systems (LMSs) to better understand students' behavior in an online statistics course. LMSs have been widely used in university courses. A great benefit of the LMS is the automatic storage of student data as every action a student takes is recorded (visit to the course website, click in a quiz, submission of a question on an online forum, etc). The fields of Learning Analytics (LA) and Educational Data Mining (EDM) are some of the fields that have been using this data to better understand student behavior and to improve teaching, student learning and learning design. The studies performed in these areas have been focused on predicting performance, understanding and modeling student behavior, predicting and detection of concerning student behavior, among many other topics (Aldowah, Al-Samarraie, & Ghazal, 2019; Papamitsiou & Economides, 2016). Many of the studies in these areas focus on blended, online, and MOOC courses (Vieira, Parsons, & Byrd, 2018) and analyze the data from multiple courses at the same time with fewer studies focusing on specific disciplines and learning designs.

1.1 Interaction and Patterns of Behavior in LMS

Currently, modeling of student behavior in learning systems has been the focus of many EDM and LA studies (Juhanak, Zounek, & Rohlikova 2019). The study by Cantabella et al. (2019) analyzed data from a LMS (Sakai) for all online, face-to-face, and blended courses at the Catholic University of Murcia during 4 academic years. The study investigated relationships between events such as reading instructions for assignments, submitting assignments, posting answers, reading resources, and reading announcements. The results suggest that students (in all learning modalities) read resources available on the LMS before posting an answer to an assignment. Additionally, they found that LMS access and activity was high at the beginning of the week and decreased steadily until Saturday with a slight increase on Sunday. A similar finding was also reported by Hung and Zhang (2008).

Patterns of behavior were also explored by Phillips et al. (2010), who investigated the study process of students in a blended course and how they interact with a web-based lecture-capture technology (Lectopia). Students were classified based on their interactions with Lectopia according to six categories. The results of this study showed that access to Lectopia was higher in the weeks prior to assignments' due dates. Students also seem to be accessing the lectures earlier (closer to the publication day) at the beginning of the course, but later in the course, students were taking longer to access the lecture. These results are also reported by Phillips, Baudains, and Van Keulen (2002) and Hung and Zhang (2008).

Others have investigated student behaviors while completing online assessments. Juhanak, Zounek, and Rohlikova (2017) investigated quiz-taking strategies while students completed an online quiz in a LMS (Moodle). Process mining was used to identify common patterns of interactions between the student, the online quiz, and the materials available. The study reported four types of behaviors. Patterns in student behavior when completing assessments were also observed by Papamitsiou and Economides (2016) that used process mining to examine logs from the LAERS assessment environment with the intent to investigate patterns that could be associated with guessing behaviors during an examination. The results identified patterns for high-, intermediate-, and low-achieving students. Low achieving students had a tendency to not review questions and spend less time answering questions. Whereas high achieving students revisited items and revised incorrect answers.

Many studies focused on the relationship between behavior and student performance. Hung and Zhang (2008) and Cerezo et al. (2016) both used cluster analysis to categorize students according to their interactions with the LMS. Both studies identified an "efficient group" with high performing students. They found that active behaviors in the LMS like posting/responding to messages and no procrastination led to higher academic performance. Agudo-Peregrina et al. (2014) analyzed data from a LMS (Moodle) from six online courses at the Universidad Politécnica de Madrid and two graduate courses at the Universidad de Salamanca. The authors defined three broad categories of student interactions and explored how they relate to academic performance (measured by end of course grades). They found an association between interactions and academic performance only for the online students which include student-teacher, student-student, and student-assessment interactions.

We build on the work of Juhanak, Zounek, and Rohlikova (2017). First, we do not investigate patterns of behavior based on what student access in the LMS as a sequence (i.e. like a position or state). Rather, we quantify how students transition between different resources (i.e. like a first derivative). Like Cantabella et al. (2019), we are primarily interested in how students transition to/from assignments and activities and which resources students use to complete them. We do not cluster students based on how they transition between resources, but study how these transitions differ by student performance and evolve over the course of a term. Additionally, similar to Phillips et al. (2011), we analyze student access to critical course materials including their initial visit and revisit rates. Another substantial point of distinction is the course we study and the intentional learning design.

1.2 Learning Design

A common critique of many LA and EDM studies is the lack of attention towards learning design when data is analyzed and results are interpreted (e.g. Lockyer, Heathcote, & Dawson, 2013; Rienties, Toetenel, & Bryan, 2015). Ignoring instructional conditions can lead to misunderstanding when interpreting results from research studies, more specifically not taking into account learning design can lead to over or under estimation of the effects of LMS features on students' academic success (Gasevic et al., 2016). Recently, new studies have been considering learning design when explaining student behaviors and interactions in the LMS leading to meaningful applications (Viberg et al., 2018).

Lust, Elen, and Clarebout (2013) examined undergraduate student behavior in a LMS for a blended "Learning and Instruction" course but focused on how the use of the LMS tools change for two phases of learning: phase 1 when novice students are being introduced to basic information and phase 2 when students organize, reflect, apply, and transfer knowledge into new situations. Like Clarebout and Elen (2006), Lust, Elen, and Clarebout (2013) also found evidence of students neglecting tools that required higher order thinking (cognitive knowledge modeling tools). Alvarez et al. (2016) used process mining to analyze data from an "Introduction to Programming" course to investigate if students' interaction with the LMS aligned with the intended learning design created by the instructor. Log report data from the LMS (Moodle) was analyzed and the results showed that students were not using the resources as intended by the instructor. This lack of alignment between intended and actual use of resources was also found by Phillips, Baudains, and Keulen (2002) and Nguyen, Huptych, and Rienties (2018).

Instead of focusing on a sole course, Rienties, Toetenel, and Bryan (2015) and Nguyen, Rienties, and Toetenel (2017) investigated student behavior on different types of learning design activities for a large number of courses. Rienties, Toetenel, and Bryan (2015) analyzed data from 40 blended and online courses. In each course, all activities were categorized according to a learning design taxonomy and grouped into four clusters. The authors concluded that the way the course was structured (specific use of learning design activities) influenced students' interactions with the LMS. Rienties and Toetenel (2016) found that the primary predictor of academic retention was the proportion of communication activities in the courses. Nguyen, Rienties, and Toetenel (2017) also investigated a large variety of courses (38) from different areas (Art & Social Sciences; Business & Law; Education, Languages, and Health studies; Science and Technology, and other disciplines) from the Open University UK and found that the learning designs were configured differently depending on the area of study. They also showed that time spent in the LMS was higher when students were engaged with interactive learning activities, and activities requiring communication between students or student and professor.

Many of the studies available using log report data examine a great variety of courses being studied at the same time, sometimes even with a mix of graduate and undergraduate courses (Rienties, Toetenel, & Bryan, 2015; Rienties & Toetenel, 2016; Juhanak, Zounek, & Rohlikova, 2017; Cantabella et al., 2019) with fewer studies focusing solely on a specific course. On one hand, it is important to have studies that look at similarities across courses; however, as stated by Rienties, Toetenel, and Bryan (2015), Rienties and Toetenel (2016), and Nguyen, Rienties, and Toetenel (2017) learning design strongly influences how students engage with the LMS. Therefore, as encouraged by Gasevic et al. (2016) there is need for more discipline-specific studies to more accurately understand student behavior in LMS and its effects.

This line of research and first paper begin with an intentional learning design. This study aims to understand if and how students are using the available resources in the course and if their use of resources is aligned with the intended learning design of the course. Our learning design builds on the work of Lust, Elen, and Clarebout (2013). We break each week of learning into three intentional phases of learning with increasing difficulty. We construct each learning phase so that milestone assignments are intended to be completed using specific resources, and these resources expand as student progress through the learning phases. The LA and EDM used here study how students use these resources, if they are being used as intended, and how the use is related to performance. Additionally, we develop assignments that are designed to motivate student-to-student interaction and student-to-professor interaction. Lastly, we focus on a single introductory statistics course.

2. COURSE INFORMATION

2.1 Participants

This study was conducted at the California Polytechnic State University (Cal Poly). The course is a randomization-based introductory statistics course for undergraduate social science students. This was a 10-week course (quarter system) during Fall 2018 with 29 students (7% freshman, 67% sophomore, 4% junior, and 22% senior), and the course is required for many of the students. This study was reviewed and approved by the University's Institutional Review Board (IRB) and all students completed a consent form asking if they wanted to participate in this study. Two students were not considered in the analysis: one student did not give consent to participate in this study and another did not participate or completed course activities throughout the quarter.

2.2 Learning Design

The course was a fully online and asynchronous course. The only required on-site class meetings were the midterm exams and the final exam. All course materials and instructions were available in the course Moodle page. The course was broken down by weeks where most of the weeks follow the same structure consisting of three phases. Phase 1 and Phase 2 in this design are similar to what Lust, Elen, and Clarebout (2013) characterize as initial and intermediate phases of learning.

- Phase 1 - The beginning of the week (Sunday – Monday): The students were expected to read and/or watch videos from assigned sections of the textbook resources and complete an online reading quiz (Readiness Quiz).

- Phase 2 - The middle of the week (Tuesday – Thursday): The students were expected to complete and upload (individually or as a group) the answers to two activities and create a collaborative answer key (Collaborative Key) for each activity (as a whole-class). Students were also expected to watch videos developed by the instructor (Video Wrap-ups).
- Phase 3 - The end of the week (Thursday – Saturday): The students were expected to complete an online quiz (End of Unit Quiz) covering the critical concepts of the week (and also concepts from earlier weeks as appropriate).

During Phase 1, the students are novice learners being introduced to new information. This phase has a low cognitive demand and emphasizes lower-level comprehension and remembering learning outcomes such as definitions and basic concepts. These concepts are then revisited in Phase 2 when the cognitive demand increases and the students focus on application and analysis often to new real-world situations. The students are also given opportunities to communicate and collaborate with their peers, thus requiring them to critique and assess applications of the materials in context. Additionally, during these initial phases, the students are being informally assessed with formative assessments. After each activity is submitted and initial answers to the Collaborative Key are posted, the students are given feedback to help them identify areas of weakness, understand their mistakes, and correct misunderstandings. Additional feedback is given after students submit their second contribution to the Collaborative Key. Once the students get to Phase 3, they should be ready to demonstrate mastery of the material when they are formally assessed through a summative quiz. A screenshot of typical week of the course is available on the Appendix.

2.3 Textbook Resources

The textbook used in the course was *Introduction to Statistical Investigations* (Tintle et al., 2015). The students were required to have access to WileyPlus which contains an e-book and videos for each section of the textbook. These textbook resources were created by the authors of the textbook and were integrated into the course Moodle page. During Phase 1, the students were expected to read and/or watch videos for assigned sections. The textbook resources are the only resources intended for the students to use before completing the Readiness Quiz, Activity, and their first submission to the Collaborative Key (before the professor's first feedback). The activities students complete every week are modified versions of explorations included in the book. These textbook resources are available to students since the beginning of the week (Sunday).

2.4 Instructor-Developed Resources

We modified textbook materials and developed several resources and assessments to scaffold student learning. These resources include the activities, Collaborative Keys, Video Wrap-ups, Readiness Quizzes, and the End of Unit Quizzes. The innovation in this learning design is the Collaborative Keys. These are designed to have the students work together as a group, similar to how they might work in groups during their face-to-face time in an active learning classroom. Other assessments used in the course were pre- and post-tests, two midterms, and a final exam.

Readiness Quizzes

During Phase 1, the students completed a Readiness Quiz which was composed of multiple-choice questions covering basic concepts from the assigned textbook resources. The goal of the quiz is to ensure that students were completing the readings and being able to remember basic statistical information (i.e lower-level skills). In total, there were seven Readiness Quizzes and they were all graded automatically in

Moodle. The due date for Readiness Quiz was Mondays by 11pm. This assignment was available to students at the beginning of the each week (Sunday).

Activities

During Phase 2, the students completed two activities which covered the concepts from the textbook's readings/videos from Phase 1. These activities were shortened and modified versions of the textbook's explorations which take the students through an investigative process starting with a research question, examining/analyzing the data, and developing/communicating a conclusion using appropriate statistical language. As students complete these activities, they apply the concepts to another real-world situation. The students have the option of completing the activities individually or in groups, but all students chose to work individually. These activities were graded on completion, if students completed the whole assignment, they earned full points, if not they earned no points. There was a total of 17 activities assigned throughout the quarter usually with two activities per week. Midterm weeks (week 4 and 8) and the last week of the quarter had no or a single activity. These activities were graded on completion and they were available to students since the beginning of the week (Sunday).

Collaborative Keys

After working the activities, the students were expected to work as a class to create answer keys for each activity: the Collaborative Keys. The Collaborative Keys have a cooperative learning structure that encourages students to work together to achieve the shared goal of having a rubric for the activities of the course. So, when completing this assignment, students have the opportunity to collaborate with their classmates and with the professor.

Many researchers have used Google Docs to foster collaboration with middle school students (e.g. Woodrich & Fan, 2017; Krishnan et al., 2018), undergraduate students (e.g. Abrams, 2019; Khalil, 2019; Chu & Kennedy, 2011; Zhou, Simpson, & Domizi, 2012), and graduate students (e.g. Ishtaiwa & Aburezeq 2015). We find no peer-reviewed publication on using Google Docs to support a collaborative assignment structure in a statistics course. Only two studies focus on collaborative online assignments in introductory statistics courses, but they did not use Google Docs. The first study, conducted by Mittelmeier et al. (2018), used an online platform called Udio and had students complete an assignment (explore real-world education statistics) in a computer lab during one class period. Zhang and Peck (2003) reported students collaborating on a problem-solving assignment (covering inference and regression) by using an "online forum".

The Collaborative Keys are simply Google Docs that contain all the questions from the activities. Students are required to make two contributions to the Collaborative Key. Each student's first contribution consists of a complete answer to one of the questions (all activities had at least one question per student). Their second contribution is to add an alternative correct answer to an already answered question, correct a wrong answer, or ask a question. There were a total of 14 Collaborative Keys during the quarter, with two assigned each week except during an exam week and weeks with additional project-based assignments. In this paper, Collaborative Keys are named according to the week in which they are assigned and whether they correspond to the first or second activity of the week. For example, Collaborative Key 1.1 was assigned during week 1 and it is composed of all the questions from the first activity of week 1. Collaborative Key 1.2 was also assigned during week 1 and it is composed of all the questions from the second activity of week 1.

After the due dates for the first contribution to each Collaborative Key, we checked their answers, added follow-up questions, and added comments to address mistakes. However, we did not provide or give away the correct answers. The students were expected to reflect on this interaction and correct their initial wrong/incomplete answers in their second contribution to the Collaborative Keys. After the due date for the second contribution, we checked their answers and made additional and final comments.

The Collaborative Keys were visible to students at the beginning of the week (Sunday), but students were required to submit their answers to the activity first and then the link to the corresponding Collaborative Key would become available. This restriction was enforced so that students would attempt the activities and provide their own answers instead of simply copying other students' answers added to the Collaborative Key. The due date for Activity 1 and the first contribution to Collaborative Key for Activity 1 was Tuesday by 11pm. The due date for Activity 2 and the first contribution to Collaborative Key for Activity 2 was Wednesday by 11pm. The due date for the second contribution to the Collaborative Key for both activities was Thursday by 11pm.

The Collaborative Key was designed as an assignment for Phase 2. During Phase 3 (after the instructor's feedback) and for the remainder of the course, the Collaborative Key was intended to be a resource for students to use when they complete the corresponding End of Unit Quiz and, exams later on. So, in Phase 3 the completed Collaborative Key can be considered a resource, rather than an assignment. Throughout the quarter, students had the option to access the Collaborative Key through a URL link in the LMS or download it. This issue will be revisited later in Section 5 (Discussion).

Video Wrap-ups

The instructor-developed and recorded Video Wrap-ups to give students the opportunity to review the most important concepts and information. These videos are concise and focus on the difficulties the students were having. These videos lasted about 10 minutes, and the number of videos per activity varied from one to four. All Video Wrap-ups were hosted on YouTube and students accessed them by clicking on a URL link available in the LMS. These were the only resources that were "hidden" to students in the LMS. The Video Wrap-ups were only available during Phase 2 and 3 after the professor's first feedback on the Collaborative Keys. The reason this resource was only available after the professor's first feedback was because if students got questions wrong on the Collaborative Key, they would be able to watch the video and figure out what the mistake was and how to fix it. Thus, the Video Wrap-ups were intended to be a resource for students after their first contribution to the Collaborative Keys. Because of the detailed content of the Video Wrap-ups and the fact that they were developed by the instructor of the course, it is expected that these videos will be more popular among students than the textbook's videos. It was also intended these videos would be a resource for the End of Unit Quizzes. These quizzes are very similar to the activities so most statistical questions that students might have on the End of Unit Quiz could be answered by watching the Videos Wrap-ups.

End of Unit Quizzes

During Phase 3, the students complete the End of Unit Quiz. The End of Unit Quizzes were composed of two parts. The first part was comprised of a mix of multiple-choice and open-ended questions covering the content of the Video Wrap-ups, to ensure that the students were indeed watching the Video Wrap-ups. It is important to note that Part 1 of the End of Unit Quiz was only introduced in week 3 once the instructor recognized that many students were not watching the Video Wrap-ups. In total, there were five End of Unit Quizzes – Part 1. The multiple-choice questions were graded automatically in Moodle and the open-ended questions were graded by the instructor. The second part of the End of Unit Quiz contained questions covering statistical concepts. There was a total of seven End of Unit Quizzes – Part 2. Two End of Unit Quizzes - Part 2 were composed of multiple-choice and short-answer questions that were graded automatically in Moodle and the remaining five End of Unit Quizzes - Part 2 were composed of mostly open-ended questions and were graded by a student-grader following an instructor-created rubric. The due date for both parts of the End of Unit Quizzes was Saturday by 11pm. The End of Unit Quizzes were designed as an assignment during Phase 3. Once completed and graded, it was intended to be a resource for the students to use when preparing for exams.

2.5 Research Questions

This study aims to understand if and how students are using the available resources in the course and if their use of resources is aligned with the intended learning design of the course. The research questions focus mainly on two important assignments of the course: Collaborative Keys and End of Unit Quizzes. During Phase 2, the resources available for students to complete the Collaborative Keys were the textbook's reading, textbook's videos, and Video Wrap-up. In Phase 3, the resources available for students to complete the End of Unit Quizzes were the resources mentioned already plus the Collaborative Key. So, in Phase 3 the completed Collaborative Key can be considered a resource, rather than an assignment. Research question 1 explores how the available resources are used by the students to complete the Collaborative Key and End of Unit Quizzes. Research question 2 explores how the most important course assignment/resources (Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups) are accessed throughout the quarter.

The research questions explored in this study are below.

1. How are students using the available resources to complete the Collaborative Keys and End of Unit Quizzes assignments?
2. How are the Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups being used by the students throughout the quarter?

3. DATA WRANGLING

3.1 Moodle Log Data Extraction

Our LMS is an implementation of Moodle 2.1 (Moodle, 2011). Moodle logs every click that students make (Romero, Ventura, & Garcia, 2008; Cerezo et al., 2016; Romero et al., 2016; Juhanak, Zounek, & Rohlikova, 2017). The resulting database produces the Moodle event log which many researchers use for their analyses. Romero, Ventura, and Garcia (2008) and Romero et al. (2016) provide an excellent description of the Moodle event log in their case studies which focus on event log processing for clustering applications. Juhanak, Zounek, and Rohlikova (2017) study student access during specific assessments across different courses, we extend this and focus on access to all learning design components and assessment within a single course and, most important, how access to these items changes throughout the term and varies by student performance. Whereas Cerezo et al. (2016) focus on the time spent on many different tasks, we only focus on the time spent completing particular learning design components and assessments.

In addition to the Moodle event log, our analysis also required the Moodle gradebook log and the individual End of Unit Quiz event logs. After being processed, the grade or performance information extracted from the Moodle gradebook log was merged with the Moodle event log. Similarly, Moodle event log summaries were merged with summaries from the Moodle gradebook log. There were a total of nine logs that we obtained directly from our Moodle implementation: one Moodle event log, one Moodle gradebook log, and seven End of Unit Quiz event logs. These logs were available in CSV format and processed using R (R Core Team, 2020).

The Moodle event log is typically what researchers use in their analyses. It logs every click a student makes including the time (Time), user name (User.full.name), and event (Event.context). The time variable was used to create the subsequent time and date variables used in our analysis. The event variable was used to create event super categories. We grouped all of our learning design components and assessments into the following super categories: Collaborative Keys, End of Unit Quizzes - Part 1, End of Unit Quizzes - Part2, Readiness Quizzes, readings (textbook), Video Wrap-ups, and videos (textbook).

Similar to Romero, Ventura, and Garcia (2008) and Romero et al. (2016), we filtered (removed) records that were not material to our analysis of the proposed learning design components and assessments. First, we removed non-student users (i.e. the teacher, graders, administrators) and also students who dropped the course before the drop deadline. Second a la Romero et al. (2016), we subsetted the log to include only the super category log entries to "eliminate those records that contain an action that could be considered irrelevant to the students' performance" which, in our study, pertains to relevant learning design components and assessments. Romero et al. (2016) and Juhanak, Zounek, and Rohlikova (2017) detail the Moodle log actions (event names). Our filtering subsets the event names further to only include course/quiz module viewed, quiz attempt started, quiz attempt submitted, quiz attempt summary viewed, quiz attempt viewed, and quiz attempt reviewed. We did not differentiate between these different events as they belong to the same super category for a given learning design component or assessment.

After filtering the Moodle event log, there were 8,251 records pertaining to the access of relevant learning design component and assessment super category items. With this log, we obtained total clicks (either in total or before/after feedback), the percentage of students that access components/assessments, and the transition probabilities between components/assessments. These data were then merged with grade information.

The Moodle gradebook log contains all of the grades for the course assessments, final course scores and final grades. As with the Moodle event log, non-student users were removed. We also removed +/- tags on letter grades and created super grade categories of A or B (10 students), C (9 students), and D or F (8 students). These final grade categories were used throughout this paper. These were created so grade groups were well populated and they were based on students' final course grade. The grades for End of Unit Quizzes were extracted from this file. Lastly, by student, the super grades were merged with the Moodle event log data.

3.2 Transition Probabilities

Many researchers focus on the amount of time spent doing particular tasks and the order in which course resources are accessed. Some use process mining to identify specific types of interaction with the course resources, primarily based on analyzing sequence of accessed resources. This type of analysis does not quantify or capture changes between course resources, where these changes might represent choices from one course resource to another course resource while learning. For example, a student is working on a Collaborative Key and needs help. What resource does the student view next to get help?

We are able to quantify changes between course resources with transition probabilities, and then use the transition probabilities to determine where students are going for help (resources) when they are stuck on assessments/assignments. We are interested in how students transition from resources to assessments/assignments (vice versa), and how these transitions vary by grade category and change over time. Conditional on a current course resource, there is a probability distribution over the course resources students can transition to.

While there are no peer-reviewed publications in the educational analytics line of research that use transition probabilities, they are a common topic in most probability courses that cover Markov Chain models. In fact, our transition probabilities are inspired by these methods. Our transition probabilities are similarly memoryless in that we only consider the immediate transition from a resource to other resources rather than previous resources, multistep paths or trends. Furthermore, our transition probabilities are computed and stored as transition matrices.

We compute the transition probabilities based on the event logs in the Moodle event log data.

1. We consider only the relevant resources students might be transitioning from and to during a given period of time. Unimportant pages, such as main course landing pages, are filtered out early during the initial management of the log files.
2. We focus only on the resources during a given period of time when the students should be accessing the materials and completing assignments/assessments.
3. We compute the transition probabilities at the student level first. Not all students transition to and from the set of resources. At the student level, it becomes easier to identify the transitions between the various resources.
4. We combine the student-level transition probabilities as a weighted average to determine the transition probabilities for each super grade category.

Transition probabilities were computed for each of the following resources, assignments and assessments, to and from various resources as described below.

- Readiness Quiz
  - From Reading and Videos
  - To Reading and Videos
- Collaborative Key: conditioned on before and after 1st feedback
  - From Reading, Video Wrap-up, Videos
  - To Reading, Video Wrap-up, Videos
- End of Unit Quiz
  - From Collaborative Key, Reading, Video Wrap-up, Videos
  - To Collaborative Key, Reading, Video Wrap-up, Videos

3.3 Other Derived Variables

A "revisit" categorical variable, inspired by Phillips et al. (2011), was created to explore if and when students were revisiting past assignments/resources. Access to assignments/resources before their due dates was categorized as an "initial visit" and access after their due dates was categorized as a "revisit". This variable was calculated for Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups.

To better understand a possible relationship between Collaborative Keys and End of Unit Quizzes, Pearson correlations were computed between the total number of clicks on Collaborative Keys per week and the grade on each End of Unit Quiz.

A list of other derived variables is below:

- For the Collaborative Keys (CK)
  - Percentage of students accessing CK (neither, either, both)
  - Total number of clicks for each CK
  - Initial visits and revisits
- For the Video Wrap-ups (VW)
  - Percentage of students accessing all, non, or at least one not all (ALONA) VWs
  - Initial visits and revisits
- For the End of Unit Quiz (EOUQ)
  - Total number of clicks for each EOUQ by grade
  - Initial visits and revisits

– Score for each EOUQ

The resulting data structures are used within the ggplot2 (Wickham, 2016) framework to make the visualizations presented in the next section.

4. ANALYSIS RESULTS

4.1 Research Question 1

This section reports the results of the analysis to answer the first research question: How are students using the available resources to complete the Collaborative Keys and End of Unit Quizzes assignments?

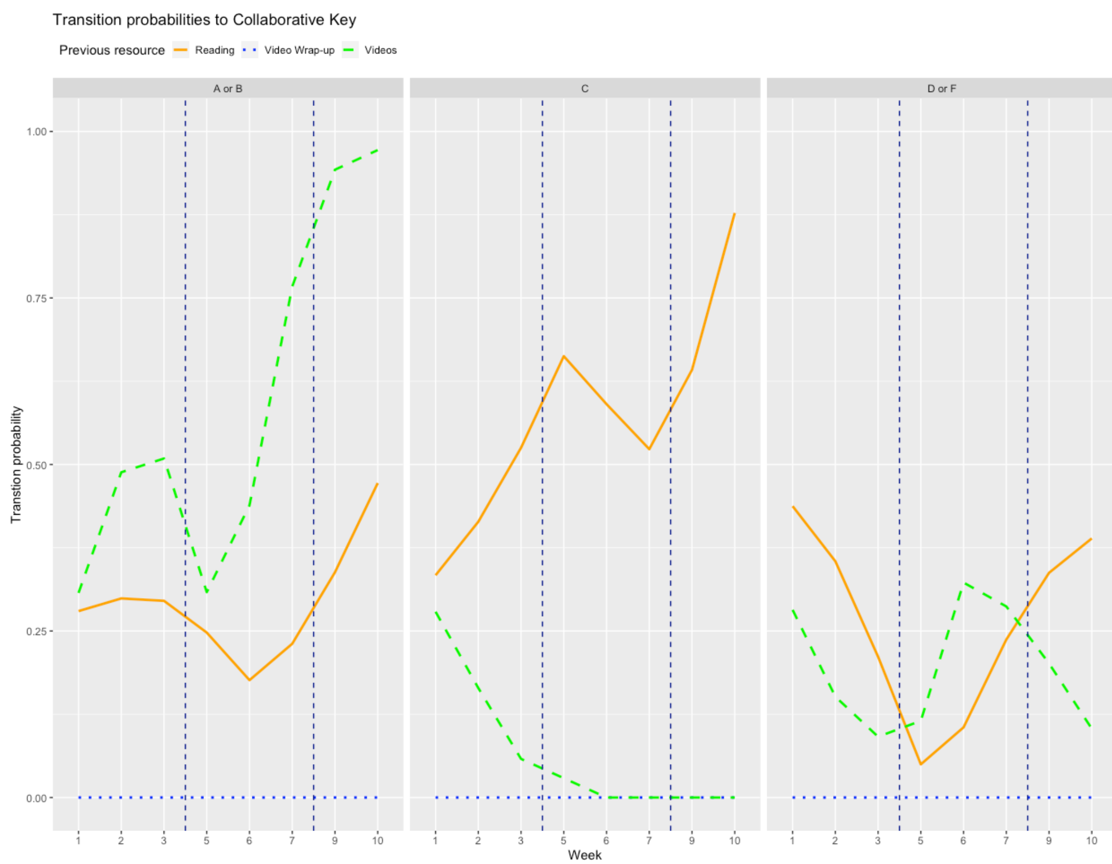

Figure 1: Transition probabilities to the Collaborative Key by grade before the professor's feedback. The dashed vertical lines indicate midterms. Solid orange lines represent reading, dashed green lines represent videos, blue dotted lines represent video wrap-ups.

Figure 1 shows the resources students are using before they access the Collaborative Keys, presumably to work on one or both of the Collaborative Keys in a given week. The available resources for the Collaborative Keys were the textbook's readings and videos (the Video Wrap-ups were not available so their transition probabilities are all zero). We observe that A or B students have a higher probability of transitioning from the textbook's videos to the Collaborative Key than from the textbook's readings, and this transition probability increases throughout the term. The opposite is true of the C students that seem to transition more from the textbook's readings than the videos, and this transition probability increases throughout the term. The results are mixed for D or F students, who do not seem to have a preference of one textbook resource over the other. Throughout the quarter, D or F students seem just as likely to access textbook's readings and textbook's videos prior to accessing the Collaborative Key.

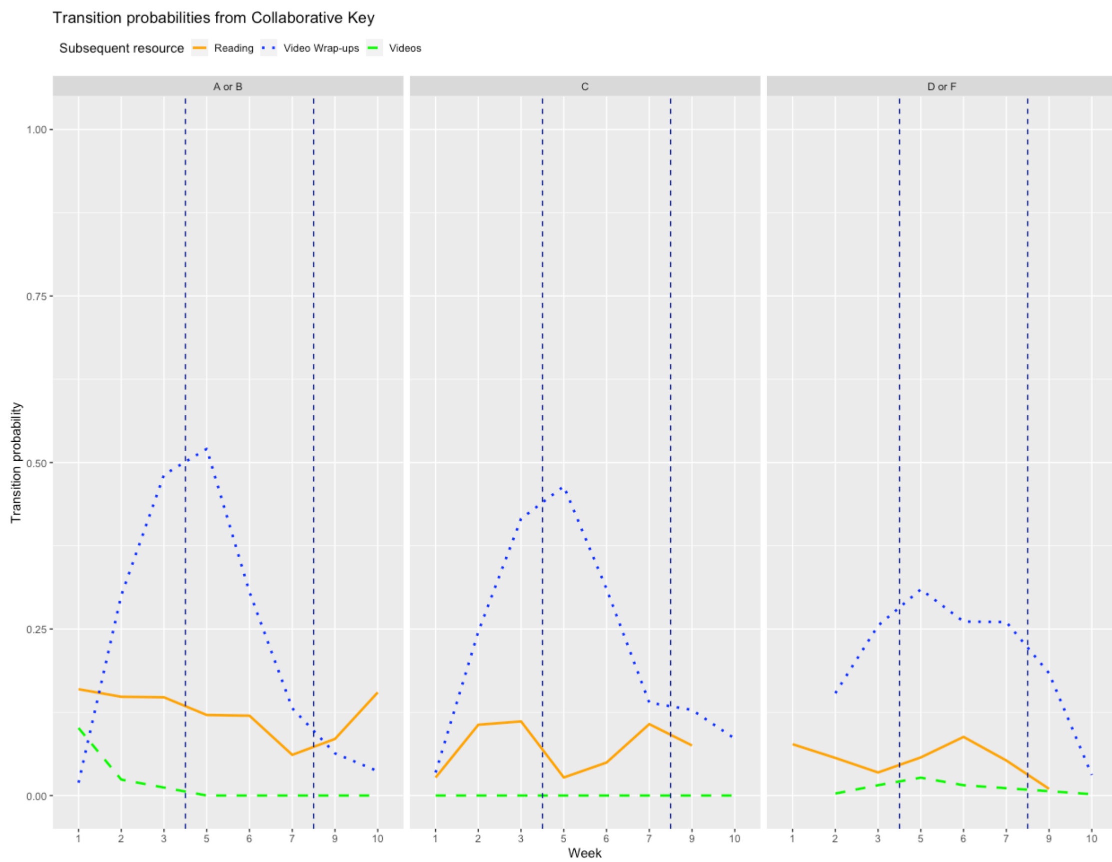

Figure 2: Transition probabilities from the Collaborative Key by grade after the professor's feedback. The dashed vertical lines indicate midterms. Solid orange lines represent reading, dashed green lines represent videos, blue dotted lines represent video wrap-ups.

Figure 2 shows what resources the students use after they access the Collaborative Key when they might be looking for help. After the professor's first feedback, all of the students transition more to the instructor-developed Video Wrap-ups than the textbook's videos, but they do also transition to the textbook's readings with a smaller probability. Although the transition probabilities do evolve differently throughout the term by grade.

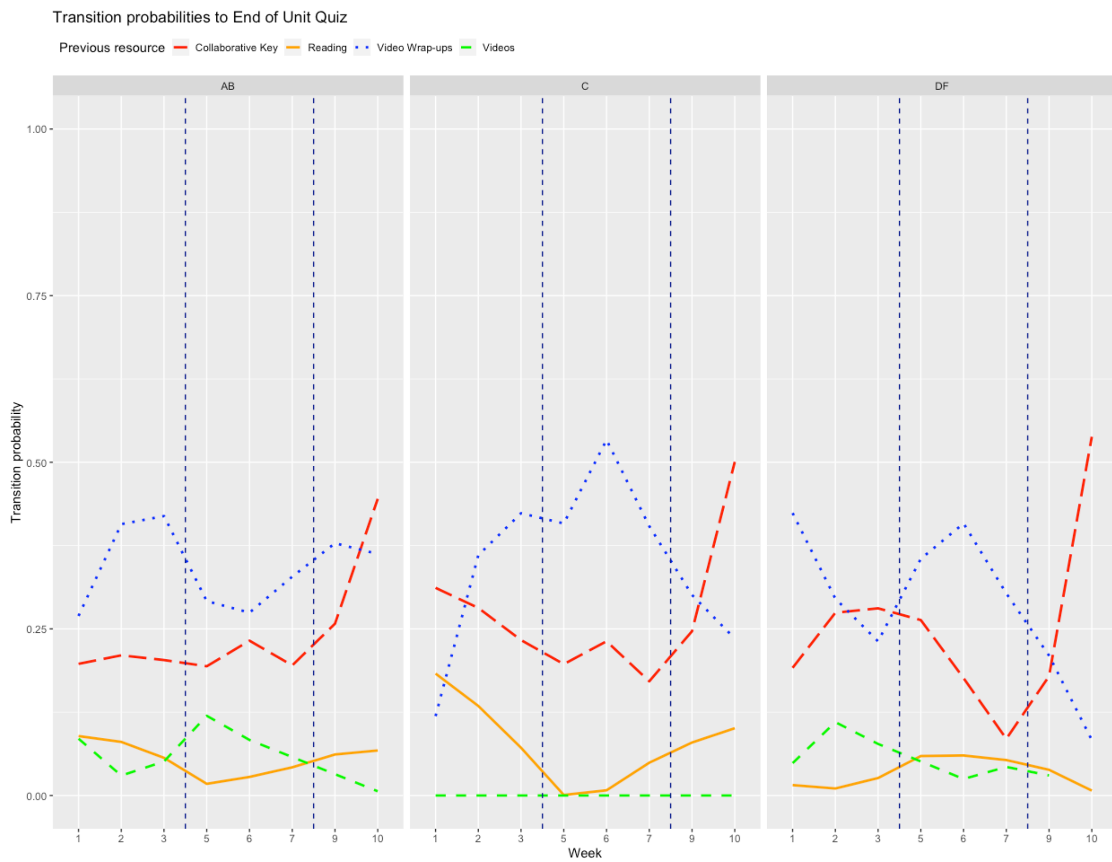

Figure 3: Transition probabilities to the End of Unit Quiz by grade. The dashed vertical lines indicate midterms. Solid orange lines represent reading, dashed green lines represent videos, blue dotted lines represent video wrap-ups, and dashed red lins represent collaborative keys.

Figure 3 shows the resources students are using before they access the End of Unit Quizzes. The transition probabilities from the Video Wrap-ups to the End of Unit Quizzes are typically the highest across all grade levels followed by the transition probabilities from the Collaborative Keys. The transition probabilities for the textbook resources are considerably smaller than the transition probabilities for the Video Wrap-ups and Collaborative Keys. However, it seems that the transition probabilities are more constant throughout the quarter for the A or B students. C students seem to transition less from the Collaborative Keys as the quarter advances. The transition probabilities for D or F students show more variation from week to week when compared to A or B and C students.

For research question 1 (How are students using the available resources to complete the Collaborative Keys and End of Unit Quizzes assignments?), these results show that A or B students prefer to access the textbook's videos before accessing the Collaborative Keys while C students prefer to access the textbook's readings before accessing the Collaborative Keys, before instructor Video Wrap-ups were available. D or F students do not seem to have a clear preference. For both the Collaborative Keys and End of Unit Quizzes, after Video Wrap-ups are available, all students seem to prefer using these resources to the textbook's videos and reading.

4.2 Research Question 2

This section reports the results of the log report data analysis to answer the second research question: How are the Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups being used by the students throughout the quarter?

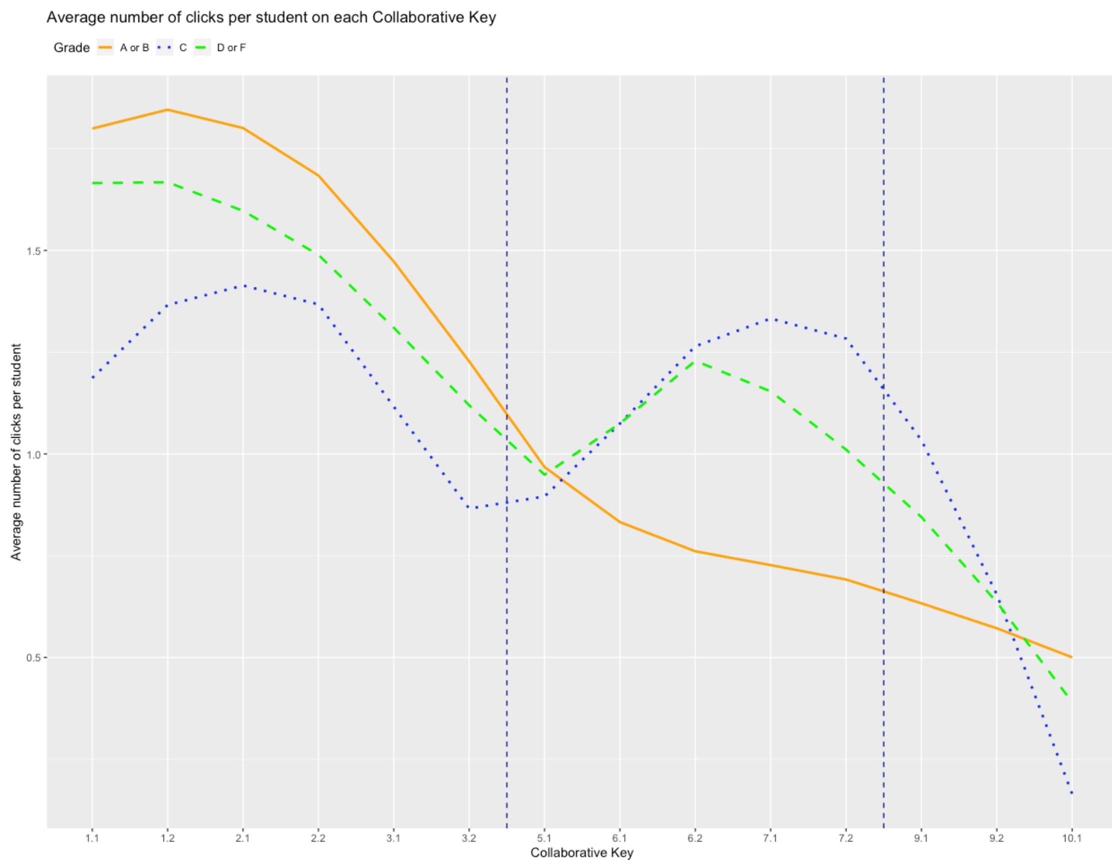

Figure 4: The average number of clicks per student on each Collaborative Key by grade. This is constrained to only the week that the Collaborative Key was assigned to students. The dashed vertical lines indicate midterms. Solid orange lines represent A or B students, dashed green lines represent C students, blue dotted lines represent D or F students.

Figure 4 shows how the access to the Collaborative Keys decreases throughout the term. In the beginning of the quarter, students seem to access the Collaborative Key more frequently up to the first midterm (week 4). After the first midterm, the average number of clicks per student decreases for all grade levels (A or B, C, and D or F). However, this decrease seems to be smaller, on average, for C students. The A or B students seem to display the highest average number of clicks per student before the first midterm, but the average number of clicks per student for these same students became the lowest after the first midterm. Additionally, there is less variation week to week in the average number of clicks per student for A or B students than for C and D or F students before and after the midterm, with C students displaying the most variability. The students' behavior of accessing the Collaborative Keys changes for all students after week 4, but A or B students were still "more constant" in their access when compared to C and D or F students.

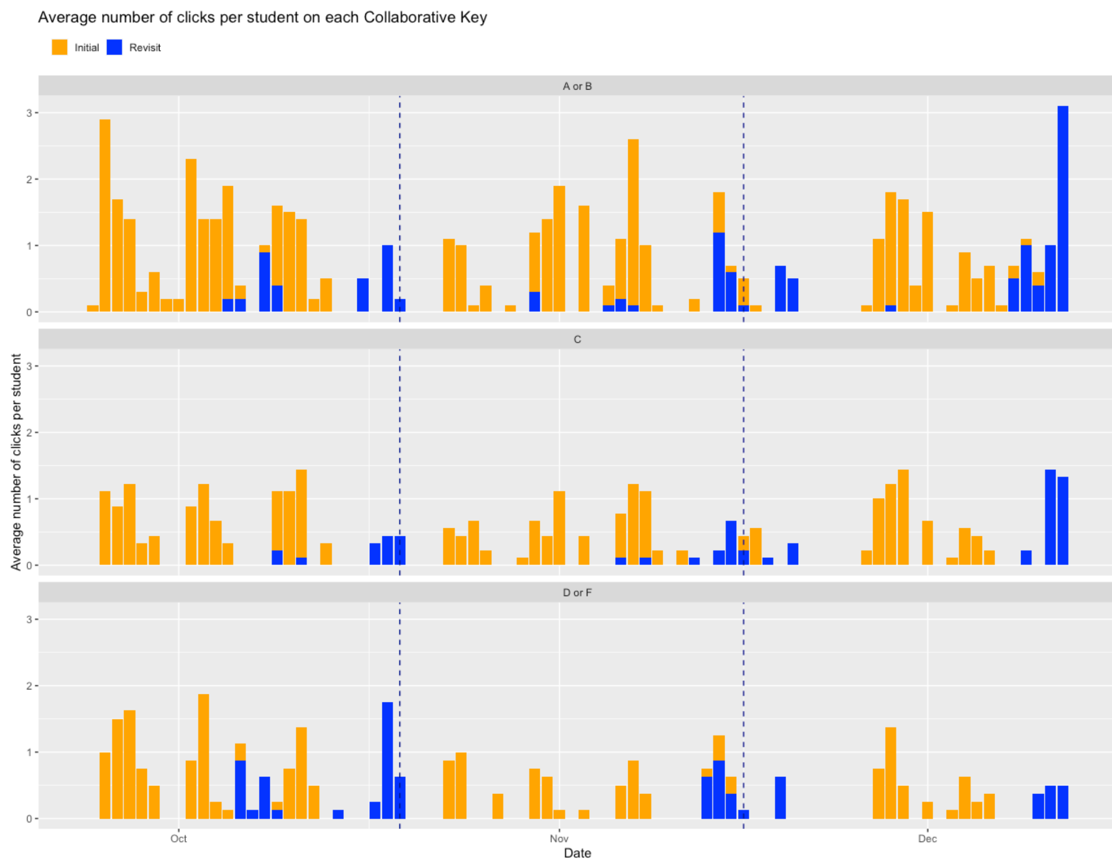

Figure 5: The average number of clicks per student on each Collaborative Key over time by grade for initial visits and revisits. The dashed vertical lines indicate midterms.

Similar to what Figure 4 suggests, Figure 5 shows a decrease in the average number of clicks per student after the first midterm, but also gives insights about revisit rates. Before midterm 2 and the final exam, we find that A or B students revisited the Collaborative Keys earlier and more frequently than other students. Whereas C and D or F students had lower initial visit rates throughout the quarter when compared to A or B students. Even though the average number of clicks per student decreases after the first midterm for A or B students, their pattern of access remains the same (early and frequent visits). This suggests that the decrease in the average number of clicks per student on the Collaborative Keys is not happening because A or B students are giving up on the course, rather these students are optimizing their click frequency and likely being more efficient.

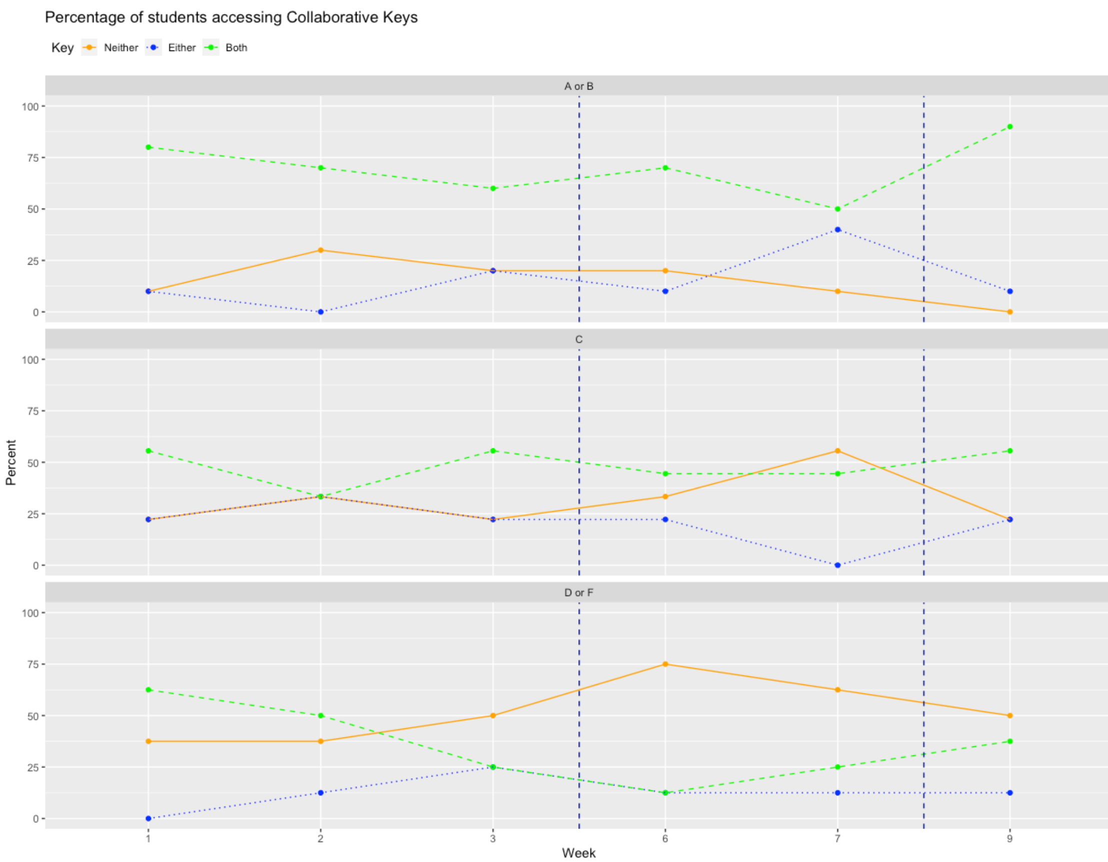

Figure 6: The percentage of students accessing both, either, or neither Collaborative Key each week by grade. Week 10 is not included in this graph because there was only 1 Collaborative Key due that week. The dashed vertical lines indicate midterms. Solid orange lines represent access to neither, dashed green lines represent access to both, blue dotted lines represent access to either.

The percentage of students accessing both Collaborative Keys seems to be related to grade as shown in Figure 6. Most of the A or B students consistently access both Collaborative Keys every week. By the end of the term, nearly all of the student's access both or either Collaborative Keys and very few A or B students access neither.

On the other hand, only about half of the C students access both Collaborative Keys every week, and by the end of the term there is a substantial percentage of C students that access neither Collaborative Keys. This suggests that many C students give up on the resource by the end of term. This evolution is even more pronounced for the D or F students. For the first 2 weeks of the quarter, most of the D or F students access both Collaborative Keys. But, by week 3, about half of the D or F student access neither of the Collaborative Keys each week. Similar to the C students, many D or F students seem to give up on the resource by the end of term.

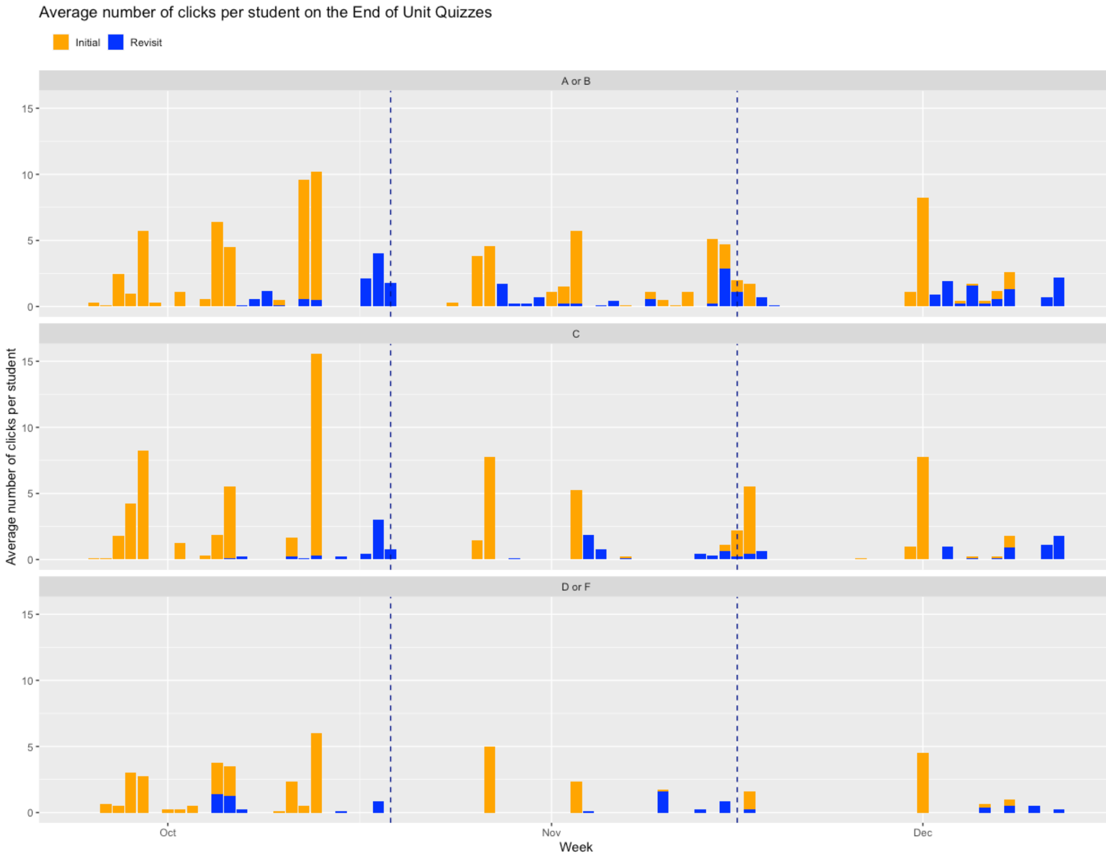

Figure 7: The average number of clicks per student each End of Unit Quiz over time by grade for initial visits and revisits. The dashed vertical lines indicate midterms.

The results of Figure 7 are similar to those from Figure 5, but for the End of Unit Quizzes. The overall initial visits and revisit patterns seems to be similar to the patterns for the Collaborative Keys. A or B students display a higher average number of clicks per student and earlier revisits to the End of Unit Quizzes. The patterns for C and D or F students are somewhat similar, with C students showing a slightly higher average number of clicks per student for initial visits and revisits than D or F students.

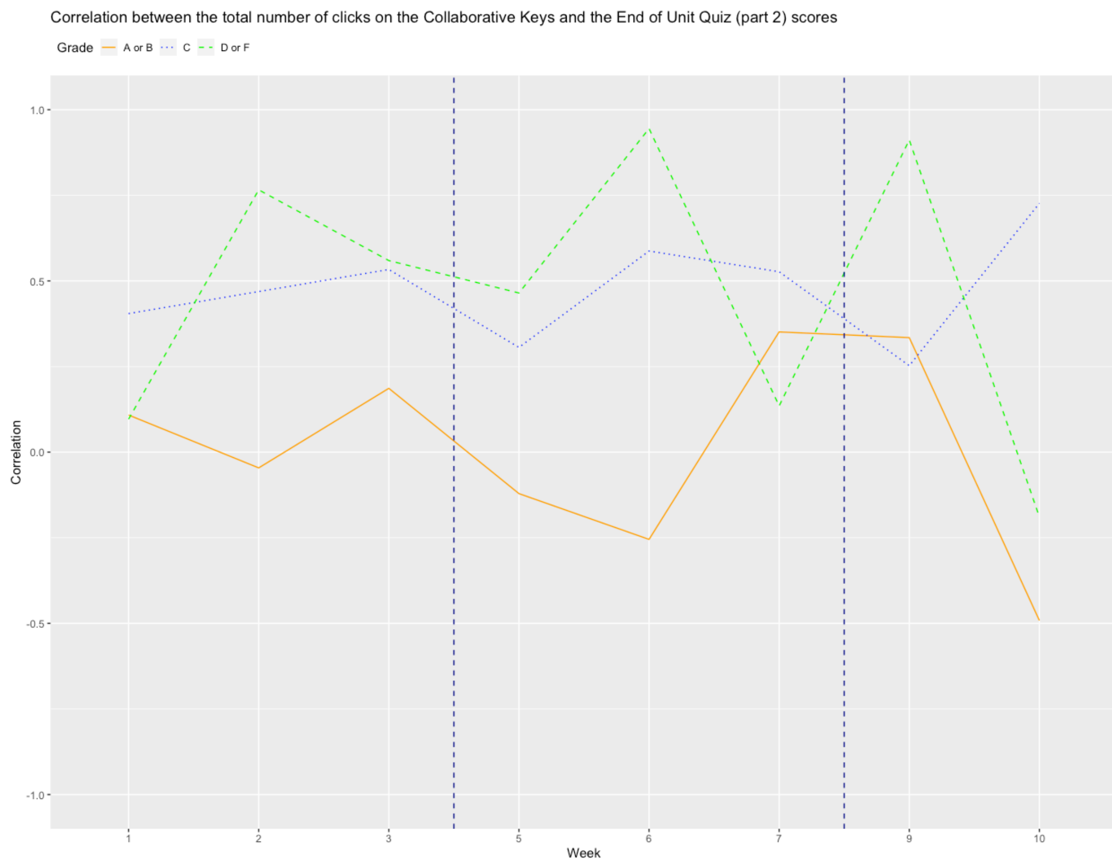

Figure 8: The Spearman rank correlation between the total number of clicks on the Collaborative Key the End of Unit Quiz (part 2) scores by week and grade. The dashed vertical lines indicate midterms. Solid orange lines represent A or B students, dashed green lines represent C students, blue dotted lines represent D or F students.

To measure the association between the total number of clicks on the Collaborative Key and the End of Unit Quiz score, the Spearman rank correlation was used since the association is not linear. As shown in Figure 8, the correlation is fairly consistent over time (with the exception of week 10). In fact, the correlations typically rank order with grade but counter to what might be expected. The correlations are typically stronger for D or F and C students than A or B students.

Figure 9: The percentage of students that access all, at least one but not all (ALONA), or no Video Wrap-ups each week by grade. The dashed vertical lines indicate midterms. Solid orange lines represent access to none, dashed green lines represent access to all, blue dotted lines represent access to at least one but not all.

Figure 9 shows how the percentage of students accessing Video Wrap-ups change throughout the quarter. We find that most of A or B students access all Video Wrap-ups until about week 7. After week 7, about half of A or B students are not accessing any of the Video Wrap-ups and the other half accessing all videos. The access to Video Wrap-ups for C students is somewhat constant throughout the quarter with about half of the students accessing all videos and the other half accessing at least one or none. For D or F students, until week 4 (midterm week), there are about half of the students not accessing any videos and the remaining students accessing all or at least one video. After the midterm, the percentage of D or F students not accessing the videos increases getting to about 75%.

For research question 2 (How are the Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups being used by the students throughout the quarter?), A or B students seem to show more constant behavior throughout the quarter when accessing course resources/assignments. There seems to be a positive association between the frequency of access to the Collaborative Keys and scores on End of Unit Quizzes for lower performing students. Additionally, there is some evidence that A or B students optimize their interactions with the Collaborative Keys with less click frequency. The decrease in their access to the Video Wrap-ups, Collaborative Keys, and End of Unit Quizzes, might indicate less effort from all students by the end of the quarter. However, it is important to note that the differences between grade categories observed in this section could be irrelevant given the small sample size in each category.

5. DISCUSSION

Nearly all of our findings indicate a possible association between how students use the available resources and their achievement (ie. grade) in the course. Additionally, we have found more consistency in A or B students' behavior than in C and D or F students' behavior. A or B students consistently reviewed Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups more and sooner than C and D or F students before each of the exams. Additionally, A or B students showed little variation in their access of these resources throughout the course. This consistency in behavior might be related to overall student organization. As described in the Learning Design section 2.2, the due dates were spread throughout the week with assignments due at 11pm every day, except for Fridays and Saturdays. Therefore, it was expected that students would access Moodle daily to complete and submit the assignments.

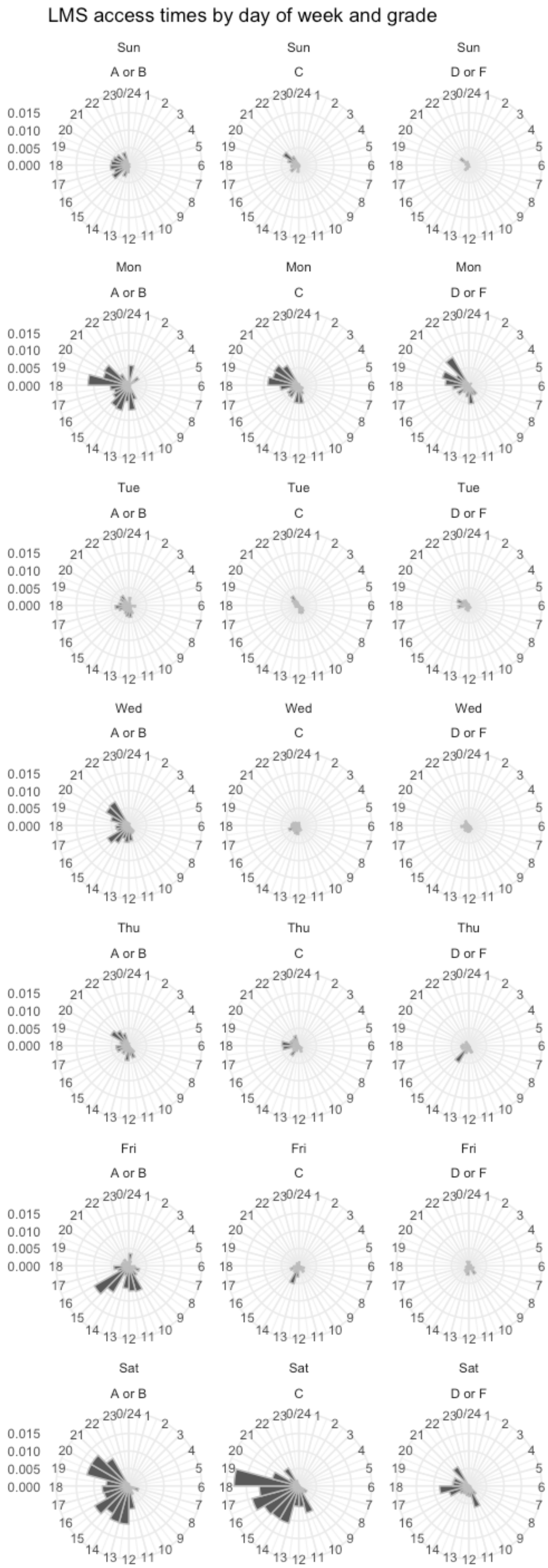
LMS access times by day of week and grade
Sun
Mon
Tue
Wed
Thu
Fri
Sat
A or B
C
D or F
0.015
0.010
0.005
0.000
0/24
1
2
3
4
5
6
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Figure 10: Relative frequencies of student access times to the LMS by week and grade. This is a rose plot similar to a clock. Each row corresponds to day of week and each column corresponds to final grade of A or B, C, and D or F. The due dates were spread throughout the week with assignments due at 11pm every day, except for Fridays and Saturdays.

Figure 10 shows that A or B students consistently access Moodle throughout the week, while C and D or F students focused mainly on Saturday and Monday to complete their work. It seems that C and D or F students did not properly allocate time throughout the week to work on the course and do most of their work on the weekends. This could explain the inconsistency in their week to week behavior. It is important to note that students' access are related to assignment deadlines, and this might explain why the results of this study do not align with results from Cantabella et al. (2019) and Hung and Zhang (2008) who reported high students' access at the beginning of the week.

According to the transition probabilities, it seems that A or B students are more likely to transition from the textbook's videos to the Collaborative Keys, and C students are more likely to transition from textbook's readings to the Collaborative Keys. This same preference for videos by A or B students is also found in their transition probabilities to the Readiness Quizzes which is omitted here for brevity. Under the design of the course, there was no rationale for a possible preference for a certain textbook resource, but we do observe a preference for the textbook's videos by the higher performing students.

The preference for videos by A or B students does not seem to be constrained only to the textbook resources. According to Figure 2, A or B students also preferred the Video Wrap-ups in the first half of the quarter but the use of Video Wrap-ups after accessing the Collaborative Keys decreased after the fifth week. In fact, this same idea was observed in Figure 9. Most A or B students accessed all of the Video Wrap-ups until the seventh week of the quarter. According to the learning design of the course, it was expected that students in general would prefer the Video Wrap-ups instead of textbook's resources, given that the Video Wrap-ups were constructed by the professor and addressed the most important topics of each activity. However, we did not expect the higher performing students to have such a strong preference for this resource.

Even though access to the Video Wrap-ups was not the same across grades, all students seem to transition more from these videos than from textbook's videos and textbook's readings. This behavior is also present for the Collaborative Keys and End of Unit Quizzes. By the learning design of the course, the Collaborative Keys and Video Wrap-ups were intended to be equally likely to be used by the students to complete the End of Unit Quizzes. The transition probabilities in Figure 3 support this aspect of the learning design. There is a higher probability of students transitioning from Video Wrap-ups and Collaborative Keys to the End of Unit Quizzes than transitioning from the textbook resources. However, the transition probabilities across grade levels from the Video Wrap-ups to the End of Unit Quizzes were higher than that of Collaborative Keys. The reason for the preference of the Video Wrap-up could be related to the fact that Video Wrap-ups review the most important points of each activity and the questions in the activities are similar to the one in the End of Unit Quizzes. So it makes sense that students would want to review the material before starting the End of Unit Quizzes.

Recall that Figure 4 and Figure 5 show that the average number of clicks per student on the Collaborative Keys typically decreases throughout the term but specifically after the first midterm. This could be due to students giving up or natural student attention cycles. Another possible explanation, as noted by Hung and Zhang (2008) and Cerezo et al. (2016), is that the clicks become more focused and intentional, in particular for the better students (A or B) who have figured out how to work the course and are more efficient. Between the first and second midterms, the D or F students typically had a higher average number of clicks per students than A or B students. This is not consistent with the assumption that D or F are giving up; rather, they might be attempting to improve in preparation for the next midterm. The average number of clicks per student after the first midterm is slightly smaller for C students, and it seems that C students click on the Collaborative Key more every other week. This is likely consistent with their natural attention and workload cycles. Another explanation for reduced access is that students may have learned to download the

Collaborative Key from Google Docs instead of using the one available online. The reduced access to the Collaborative Keys in the LMS across all students could be mitigated by students accessing the Collaborative Keys offline.

It is important to note that clicks on the Collaborative Keys do not necessarily mean that students are checking feedback or even contributing with answers and comments. Also, higher number of clicks is not necessarily better than lower number of clicks. We do not have the information about what students did after they clicked on the Collaborative Key. Some options could be that they clicked and contributed, clicked and viewed other students' responses, clicked and checked professor's feedback, or clicked and left. On the other hand, there is a small number of students in each category (10 students in A or B, 9 students in C, and 8 students in D or F); therefore, one or two students with different behaviors could greatly impact the number of clicks in their category.

The End of Unit Quizzes also seem to be used as a resource by the students. It was expected to have a larger number of visits to the End of Unit Quizzes because students might be scrolling back and forth between the pages with questions within each End of Unit Quiz. But the number of revisits to the End of Unit Quizzes is still higher throughout the quarter for A or B students. For C and D or F students on the other hand, the access seems to decrease over time, which might suggest that some of these students are giving up on the course. This was also observed in the access to the Collaborative Keys: students stopped accessing it as the quarter advanced.

6. CONCLUSIONS AND COURSE CHANGES

We began this study and course development with an intentional learning design. Our learning design builds on the work of Lust, Elen, and Clarebout (2013), and includes the development and evaluation of our Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups. The LA and EDM used here study how students use these resources, if the resources are being used as intended, and how the use is related to student performance. We extend the work of Juhanak, Zounek, and Rohlikova (2017), by introducing a new LA/EDM measure in our transition probabilities. Another feature of our analysis is that we evaluate how these transitions differ by student performance and over the course of an entire term.

The results of this study demonstrate that, before instructor-developed materials are available, A or B students seem to prefer the textbook's videos and C students prefer the textbook's readings before accessing the Collaborative Keys. The D or F students do not have a clear preference. For both the Collaborative Keys and End of Unit Quizzes, after instructor-developed materials are available (Video Wrap-ups), all students seem to prefer these resources more than the textbook resources (textbook's videos and readings).

In addition, the results also indicate that A or B students behave more consistently in their access to the Collaborative Keys, End of Unit Quizzes, and Video Wrap-ups. The number of clicks on the Collaborative Keys seems to be positively related to performance on the End of Unit Quizzes for C and D or F students, but not for A or B students. As the quarter advances, A or B students seem to optimize their interactions with the Collaborative Keys and seem to be more efficient resulting in lower click frequencies. All students show less effort closer to the end of the quarter which is indicated by decreased access to Video Wrap-ups, Collaborative Keys, and End of Unit Quizzes.

With these results in mind, we considered what worked and what did not work in the course. It was encouraging to see that the videos created by the instructor (Video Wrap-ups) were being accessed by the students and preferred over textbook resources. However, access does not necessarily mean that students were actually watching the videos. Moreover, the access was not constant throughout the course for the majority of students. To keep track if students were actually watching the Video Wrap-ups, we changed from using YouTube to host the videos to EdPuzzle.

In EdPuzzle, it is possible to prevent students from skipping to the end of the video. In addition, if students minimize the browser, the video automatically stops playing. Of course, we acknowledge that there are different ways that students can still "cheat the system". In EdPuzzle, it is also possible to add questions to the videos. All these features were added to the Video Wrap-ups in the next version of the course. Specifically, questions were asked at the end of each video. Most questions were not statistical, but just simple questions to make students accountable for watching the video from beginning to end. Participation points were given to students for watching the videos and statistical questions (graded on correctness) were added to the End of Unit Quiz.

Changes were also made to the Collaborative Keys. As stated already, the Collaborative Keys were also used by the students as a resource to prepare for the End of Unit Quiz and exams. Even though students were accessing the Collaborative Keys, similar to the Video Wrap-ups, it was not clear what students were doing once they accessed or revisited the Collaborative Keys. Additionally, the access was not constant throughout the quarter. After the first midterm, some students engaged with the Collaborative Keys less leading to many questions in the Collaborative Key without answer keys. This was the first indication that the students were not always engaging the Collaborative Keys as intended.

Additionally, the quality of the interactions observed in the Collaborative Keys was not great. Collaborative Keys were created to encourage students to work together as a class (student-to-student interaction) and to provide opportunities for interactions between the professor and students (direct feedback to students and instructor presence). However, there were very few interactions between students. These interactions mostly happened when a student provided a wrong answer and another student corrected their answers providing the correct answer. Instead of helping each other, students were mostly trying to get the correct answers independently. This makes sense as the goal of the Collaborative Keys is to create the answer key to each activity. This is not the same as students collaborating and working with one another to create the answer keys. The interactions between the professor and students were a bit more valuable, but they were also short. This would mostly happen when a student provided a wrong answer, the professor provided direct feedback to the student, and the student responded back to the professor with another answer or a question.

We revamped the Collaborative Keys to provide better (and more) student engagement and interactions between the students. The Collaborative Keys were changed to be group assignments rather than a "class" assignment. The students were assigned to groups (2 or 3 students), and each group collaborated to develop answers to some questions from the activity that each Collaborative Key is based on. With this change, the each Collaborative Key was no longer composed of all the questions from the activities but only the most important questions. This helped to focus the students and have them interact more, and also helped to decrease grading load on the instructor. In addition, the requirements to successfully complete each Collaborative Key were modified to increase the quality of students' answers and increase student-to-student interaction using a more solid cooperative learning structure. All students were required to provide their initial answer to each question. In this way, individual accountability was still present in the assignment. Once all initial answers were provided, the group part of the assignment takes place with students being required to compare and discuss their answers, and create a final group answer that was graded on correctness (shared group goal). With these changes, the Collaborative Keys contained aspects of positive interdependence and individual accountability which motivates collaboration among the students.

Finally, the results of this study also suggested lack of organization from students and inconstant access behavior week to week for lower performing students. To help students get used to the online setting and organize/allocate their time, new assignments were created for students to complete during the first week of class. In addition to the typical "get to know your group member" assignment, we added additional assignments that required students to create a schedule for the course taking into account not only their own availability, but also the available time of their group members. All these changes have already been applied to new versions of the course and the results look promising!

Teaching online asynchronously is a challenge! Although we started with an intentional learning design and what we thought was a well structure course, by the end of the course it became clear that many changes were required to improve student learning. Since March 2020 there was a transition to online teaching all over the world, but educational institutions are still in the early stages of online teaching and learning, and we are all still discovering the best practices. Our collective goal is to develop statistically educated students by providing students with opportunities to think statistically and interact with each other (and the professor) to construct knowledge.

Similarly to Rayens and Ellis (2018), this paper presented a course with a student-centered approach to teaching statistics online. We encourage statistics instructors to reflect on the structure of their course to ensure (1) it supports student engagement and interactions and (2) resources and assignments are intertwined to create a path for students to follow as they advance through materials and assessments. If we are to foster active learning, like it is suggested in the *Guidelines for Assessment and Instruction in Statistics Education* (GAISE; ASA, 2016), our online courses need to have a clear path that supports this goal. One of the ways this can be done is through the use of innovative assignments that encourage students to explore and discover statistical concepts together. We can go beyond lectures and even beyond traditional activities. We can update assignments to encourage discussion among students and inspire student collaboration. The Collaborative Keys in this paper are an example of this type of interaction.

Unlike Shotwell and Apigian (2015), we noticed that some students prefer the instructor created materials over the textbook resources. If at all possible, we encourage teachers to develop their own resources including their own materials to support lectures and software demonstrations, videos, and assessments. It can take a substantial investment of time to develop an entire suite of resources, and so, while instructors develop their own materials, they can fill in the gaps with the available textbook resources.

Many statistics education papers related to online learning focus on predicting student performance (Scherrer, 2011, Hahs-Vaughn et al., 2017, and Gundlach et al., 2015), but do not consider or tie performance to use of course resources. We have found evidence that higher performing students adhered to the intended learning design more consistently and more effectively used course resources throughout the term. Among students that deviated from the intended learning design to create their own learning path, the results are mixed. Checking in with students, keeping grades updated, and providing frequent feedback might be ways to help students recognize whether their current trajectory in the course needs to change. But most importantly, instructors should help students to be organized and regularly schedule time to work on their courses. This can be done the first week of class with a "create your schedule" assignment. We can also ask students to revisit their schedule in the middle of the term and encourage them to adjust their study habbits/strategies. Even in an online class, students should be responsible for their own learning. But as instructors, we can be proactive and design our courses to lead students towards a successful path to learn statistics online.

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Appendix

The figure below shows a typical week of the course.