ONLINE STUDENT RESOURCE USE AND THE EFFECT ON STUDENT COURSE PERFORMANCE

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ABSTRACT

The purpose of this study was to identify potential factors of student resource use that could indicate student success in an online course. This would allow instructors to look for in patterns of use to identify students that may not be successful. Statistical components of the course management system, Blackboard, and online lecture resource, Tegrity, were used to collect student resource use (clicks). Duration of access was also available exclusive to the Tegrity resource. The findings of the study indicate students that used online resources more often were more successful. Successful students used online resources nearly twice as often as their counterparts. Additionally, they spent nearly twice the amount of time engaged in lecture resources watching, on average, 59% of the lecture resources available. Furthermore, there appeared to be a critical window where those who accessed the resources in the first five weeks had a greater likelihood of course success.

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Above average user (AA): Use of the Tegrity resource that was calculated as above the mean for that week.

Achievement: General term used to describe either success or failure in a course; i.e. successful and non-successful.

Below Average user (BA): Use of the Tegrity resource that was calculated as below the mean for that week.

Blackboard: This is the course management system used at NDSU used a platform from which to deliver the course information. Blackboard was also the primary tool in this class used as a way to communicate, post course information, grades, etc.

Connect: Textbook online resource that contains flashcards, multiple-choice questions, true-false questions, multiple-answer questions, fill-in-the-blank questions, cards with multiple questions and ranking questions.

Duration: Amount of time spent in a resource.

Non-Successful: Completing the course but earning a grade of a D or lower.

Non-user (NU): No use of Tegrity resource for that week.

Participation: Use of a resource.

Retention: Successful completion of an online course.

Successful: Completing and passing the course with an A, B or C.

Tegrity: An online resource supported by the publisher of the textbook for this course that allows the instructor to record lectures and to post them online for students to view at their convenience.

INTRODUCTION

Teaching online courses can be a daunting task. Faculty members are very often apprehensive and in need of convincing to agree to teach online courses (Gerlich, 2005). One of the main concerns expressed, is the steep learning curve that is associated with learning to teach online. Another concern is the time associated with course development as well as quality of online courses. Online teaching is, according to Gerlich, often perceived to be more difficult than traditional teaching as it is considered to be more labor intensive because instructors are monitoring online student grades, grading online work and maintaining online relationships/contact with students. A common mistake frequently made by new online instructors is that they often believe that the quality of an online course can be measured by the amount of time students spend on the course rather than the level of engagement (Shieh, Gummer, and Niess, 2008). Often, time spent on the course is measured collectively from all resources or just by counting discussion posts or responses. Neither of these describes student engagement nor do they monitor retention in the course.

An essential part of any successful course is student retention. Studies have suggested that retention in online courses is of great concern (Liu, Gomez and Yen, 2009; McLaren, 2004; Morris, Finnegan, and Wu, 2005). There is an established increasing demand for online courses from students as well as universities (Allen & Seamen, 2010), but why offer more courses if students are not completing them? Ultimately, there are questions that emerge regarding how online student retention can be increased. These questions include: what factors determine whether or not students complete their courses? or what factors play a role in the online student success? Rovai and Barnum (2003) have found that students related their learning in online courses positively to the number of course interactions they had. Interactions included not only their own posts or assignments but also feedback by, and interaction with, instructors was also considered important. Supporting online faculty by providing tools, current technology, and helpful strategies that provide students with the tools to succeed will not only help students, it will support and retain online faculty as well (Keengwe, Kidd, & Kyei-Blankson, 2009).

This information may in fact lead to one of the more important success factors in online courses; the role of the online instructor. Generally speaking most instructors will communicate to you the importance of student-instructor contact. Communication with, and identification of, those students that are not engaging in the course is critical for student success. Student-teacher interaction and time-on-task are common concepts in education and have been identified by Chickering and Gamson's (1987) as two of the seven principles for quality practice in undergraduate education. Graham and colleagues (2001) emphasized the need for communication as a quality practice in undergraduate education stating, "good practice encourages student/ faculty contact", and "good practice emphasizes time on task." One question that arises is, how this can be done other than by simply measuring time on task? How can instructors use students' participation and react accordingly?

My own interest in online courses began seven years ago when I began my high school teaching career as an online instructor for The North Dakota Center for Distance Education (NDCDE). A portion of my job description included designing courses that were to be offered online. While designing my first course I questioned the value of many of the resources that I was making available to students, as this type of design was very different than a traditional classroom. I wondered if students valued the resources that I thought they would, and did those resources help them to learn this material at a distance? Were they engaging in their courses? If students were in fact using the materials provided, did they successfully complete their courses? In other words, did their resource use increase their success? Did simply accessing online resources in online courses result in a higher probability of a successful completion? Is it the accessing that makes the difference or is the duration of the visit (time on task) more telling? Finally, is it possible to predict student success in online courses using this data and use it to help students to be more successful? These experiences and reflections led to this study. The research questions posed are:

1. How does online participation (measured in clicks) predict online student achievement?
2. How can duration of time spent on participation in an online course predict online student achievement?
3. How can online student achievement be predicted from student online resource use?

In an online course that is designed as content review with virtually no discussion-based participation available, resource access and viewing time can then be used to indicate student participation. While it is difficult to determine if viewing time and engagement in material are synonymous, in this study, viewing time of lecture resources was the only measure available as a proxy for engagement as the student is in control of the start and end times for their viewing.

The growth in online courses at North Dakota State University (NDSU) provided an opportunity to explore these research questions. NDSU began offering online courses in the 1997-1998 academic years with only three courses. As of last academic year there were 536 sections of online courses to choose from, with continuous additions planned. In the sciences at NDSU, the number of sections has increased from 45 to 56 in the last three academic years see (Table 1).

Table 1. Online course offering at NDSU in the College of Science & Mathematics from 2009-2012

Academic Year	Number of course sections	% growth from previous year	% growth from 2009-2010 AY	Number of students	% growth from previous year	% growth from 2009-2010 AY
2009-2010	45	-	-	1759	-	-
2010-2011	50	11.11%	11.11%	1839	4.55%	4.55%
2011-2012	56	12.00%	19.64%	1847	0.44%	5.00%

The current study was an effort to develop a strategy to help instructors identify “at-risk” students and to intervene with them before the critical point of inevitable course failure occurred. If we were able to identify how often students were accessing resources and the duration of their use, this information could then be used to measure participation and ultimately success in the course. It was the hypothesis of the researcher that those students who spend more time accessing and viewing online course resources in their online courses will perform better in their course. The design framework is illustrated in Figure 1.

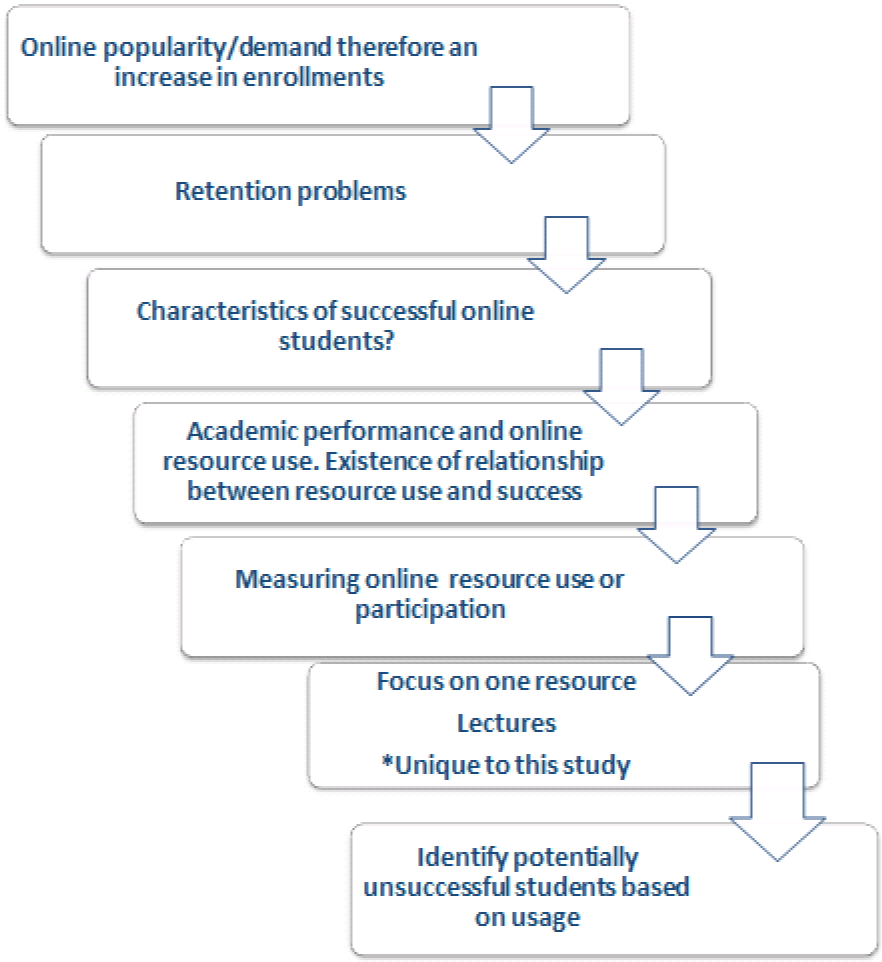


Figure 1. Framework for current study

LITERATURE REVIEW

The popularity of online learning has increased tremendously. Much of this increase is due to the "flexible access to content and instruction at any time, from any place" (Means, Toyama, Murphy, Bakia & Jones, 2010; p.1). Even with the increase in demand and the increase in online course offerings nationwide, retention in online courses has remained problematic. Several studies have identified several factors that influence withdrawals (i.e. auditory learning style, computer skills, computer accessibility etc.) as well as pre-entry variables (i.e. gpa, computer experience, class rank, etc.) that may influence retention in online courses (Dupin-Bryant, 2004; Morris & Finnegan, 2005; Packham, Jones, Miller & Thomas, 2004).

Hart's (2012) review of the retention literature identified specific facilitators of and barriers to persistence in online courses. Harrell and Bower (2011) have also identified characteristics of successful online students that include: learning style, locus of control, computer experience and access, previous online experience, and demographics. Learner online participation has also been linked to retention rates (Rovai, 2002). Online participation as an indicator for student learning has been studied by Hrastinski (2008); he theorized "participation and learning are argued to be inseparable" (p.81). There are models of participation that have predicted performance; however, most seemed to have been based on discussion-based participation (Ivankova & Stick, 2007; Macfayden & Dawson, 2010; Morris, Finnegan & Wu, 2005;). Current methods to measure the use of online resources tend to focus on tracking student use in terms of course navigation. Some use specially-designed software (Hardy, Bates, Hill & Antonioletti, 2008; Mazza & Dimitrova, 2004), and some log resource access (defined as "number of hits") (Bates, Hardy, Hill & McKain, 2007), frequency and duration of participation (Morris, Finnegan &

Wu, 2005), and the measurement of the relationship between academic performance and online resource access (Crampton, Ragusa & Cavanagh, 2012).

When considering the relationship between persistence and achievement we can look at Morris, Finnegan and Wu (2005), who have identified online resources, that when used, improve student persistence and achievement. These resources included the number of content pages that were viewed, the seconds spent viewing, and discussion board posts. One of the most common resources used in online courses are online lectures. Because online lectures are often a focus of study in regards to online courses (Green,Weaver, Voegeli, Fitzsimmons, Knowles, Harrisson, & Shephard , 2006; Lewis & Harrison, 2012; Myers & Schlitz, 2012) as well as hybrid courses (Grabe & Christopherson, 2008; Lancaster, McQueeny & Van Amburgh, 2011; Scheines, Leinhardt, Smith & Cho, 2005; Traphagan, Kucsera & Kishi, 2009;) and in some cases supplementary resources in traditional face-to-face courses (Lewis & Harrison, 2012), it would be prudent to focus on one type of resource.

Online enrollment increase

Enrollment in online courses in degree-granting post-secondary institutions grew from 1.6 million to 6.6 million enrollments nationally between 2002 and 2010. Online enrollments as a percentage of total enrollments increased from 9.6% to 29.3% (Table 2) over the same time (Allen & Seamen, 2010).

Table 2. Total and online enrollment in degree granting post-secondary institutions fall 2002- fall 2009. Developed from “Learning on demand: Online education in the United States, 2009,” by I. E. Allen and J. Seaman, 2010, The Sloan Consortium

	Total enrollment	Annual growth rate total enrollment	Students taking at least on online course	Annual growth rate online enrollment	Online enrollment as a percent of total enrollment
Fall 2002	16,611,710	NA	1,602,970	NA	9.6%
Fall 2003	16,911,481	1.8%	1,971,397	23.0%	11.7%
Fall 2004	17,272,043	2.1%	2,329,783	18.2%	13.5%
Fall 2005	17,487,481	1.2%	3,180,050	36.5%	18.2%
Fall 2006	17,758,872	1.6%	3,488,381	9.7%	19.6%
Fall 2007	18,248,133	2.8%	3,938,111	12.9%	21.6%
Fall 2008	18,698,630	2.5%	4,606,353	16.9%	24.6%
Fall 2009	19,036,860	1.2%	5,579,022	21.1%	29.3%

Institutions are also reporting the percentage of undergraduates enrolled in distance education courses or degree programs has steadily increased from 8% to 20 % between 2000 and 2008 (Radford, 2011). Allen and Seamen (2010) further report “virtually all recent growth in online enrollments has come from the growth of existing offerings, not from institutions new to online starting new programs” (p. 4). This phenomenon seems to indicate that since these online courses are most often derived from existing courses and taught by existing teachers; a need to continue to support, revamp and improve the current online courses that are offered and help instructors to make them the best that they can be to compete is required.

Student retention

Prediction of student retention or achievement in online courses is valuable to instructors and universities. An understanding of retention or achievement would provide an opportunity to intervene before students drop, or continue unsuccessfully, through their online courses. Pre-entry variables such as grade point average, class rank, internet search training, and enrollment/completion of previous online courses have been identified as significant factors in retention in online courses (Dupin-Bryant, 2004). Furthermore, Morris, Finnegan and Wu, (2005) determined that GPA is an important indicator of retention and in pre-determining student online success. More studies have identified additional significant variables in predicting online student success such as auditory learning style and basic computer skills (Harrell & Bower, 2011; Hart, 2012). Hart (2012) had identified studies that provide evidence for facilitators of and barriers to retention in online environments. These factors are summarized in Table 3.

Success factors

Student satisfaction, social presence, and ease in navigation are reoccurring themes that emerge and may be additional factors to consider in online student success. Levy (2007) determined academic locus of control and student satisfaction were key indicators in student decisions to persist in an online course. Liu, Gomez, and Yen (2009) studied the relationship between student retention and social presence in online courses and the predictability of final grades. They defined social presence as “the degree of one’s feeling, perception and the reaction to another intellectual entity in the online environment.” Social presence was identified as an important indicator of both retention and success.

Table 3. Facilitators and barriers to online student retention identified by Hart (2012)

Facilitators	**Authors**
College status and graduating term	Levy, 2009
Flexibility in online courses	Müller, 2008
Goal commitment	Ivankova & Stick, 2007
GPA	Harrell & Bower, 2011, Morris, Finnegan & Wu, 2005
Satisfaction and relevance	Ivankova & Stick, 2007; Levy, 2009; Müller, 2008
Self-efficacy and personal growth	Holder, 2007; Kemp, 2002; Ivankova & Stick, 2007
Social connectedness or presence	Ivankova & Stick, 2007; Liu, Gomez & Yen, 2009; Müller, 2008
Support that includes emotional	Holder, 2007; Ivankova & Stick, 2007; Müller,2008
Technical	Bunn, 2004; Ivankova & Stick, 2007
Barriers	**Authors**
Auditory learning style	Harrell & Bower, 2011
Basic computer skills	Harrell & Bower, 2011; Soong et al.,2001
College status and graduating term	Dupin-Bryant, 2004; Levy, 2009
Difficulty in accessing resources	Bunn, 2004
Isolation and decreased engagement	Bunn, 2004; Ivankova & Stick, 2007; Morris et al., 2005
Lack of computer accessibility	Stanford-Bowers, 2008
Non-academic issues	Aragon & Johnson, 2008; Bunn, 2004; Ivankova & Stick, 2007
Poor communication	Aragon & Johnson, 2008; Bunn, 2004

Packham and colleagues (2004) identified both extrinsic (student profile and circumstances) and intrinsic factors (course elements and student perceptions) that resulted in student withdrawal. Both types of factors are subjective and can be influenced by many things. The authors provided suggestions for approaches to “overcome the intrinsic and extrinsic factors” that included: recruitment policies, academic and technical support, effective communication mechanisms, flexible course structure, and robust virtual learning environments that allow for easy navigation. Soong and colleagues (2001) concluded that one of the critical success factors for online courses are that the intended users perceive the resources provided in the courses as user friendly. Hence, students that are able to more easily navigate their online courses are more likely to be successful and students that are more satisfied in their online courses report higher levels of activity and higher levels of learning (Swan, 2001).

There are many things that can contribute to the success of students in both traditional classrooms as well as online courses. Specific to online courses, Soong and colleagues (2001) identified critical success factors for online course resources. They determined factors success factors such as adequate time spent on the course by both students and instructor, student technical competency, a constructivist mindset in the learner, a course design that encourages high levels of collaboration, and a user friendly IT infrastructure. Müller (2008) found that appreciation for convenience of the course, engagement in the learning community, and motivation to complete degrees were factors that were supportive in persistence. Packham and colleagues (2004) found that successful "e-learners" were typically self-employed, most often females, with ages ranging from 31-50.

Measuring participation

Researchers have identified several factors that contribute to persistence and indicate that online participation and achievement are related. Morris and colleagues (2005) measured student persistence and achievement in online courses using tracking logs that included amount of time on task. Data collected in these tracking logs included pages visited, tools used, and discussions read, created, and replied to. They concluded that the number of discussion posts viewed, number of content pages viewed, and seconds of viewed time on discussion pages were all significant in measuring achievement and were good predictors of final grades. This may lead one to conclude that student performance can be predicted by measuring student participation (i.e. resource access) and online engagement (duration).

Multiple studies show student online course participation has been measured a number of ways. These methods include tracking software (Hardy et al., 2008; Mazza & Dimitrova, 2004), quantity of discussions (Hrastinski, 2008), and relationships with access and grades (Crampton et al., 2012). Mazza and Dimitrova (2004) used tracking software to help instructors gauge what was happening in their courses by determining the behaviors of students. They mapped student access to content pages, global accesses to course, progress with course schedule, messages, quizzes and assignment submissions and developed “representations” of student learning to show student usage patterns. The purpose was to give instructors an idea of what students were doing in their classes by using developed software to track behavior. What they found was that the software that they were using, “CourseVis”, helped the instructors quickly identify “cognitive, social, and behavioral” aspects of their students. However, the study was mainly used to help to develop this specific software in an effort to use these representations as indicators for interventions, so without the software, instructors may not be able to identify those desired aspects.

By comparison, Hardy et al. (2008) utilized special software to track student usage in online courses. Hardy and colleagues’ method visualized the way that students actually navigate through courses. Their study focused on the actual routes, defined in the paper as the “spatial and temporal routes” that students took through the courses. The spatial routes referred to the routes taken and pages accessed in order, and temporal referring to the consideration of time spent in resources. The routes were grouped by extent of use and then compared to final grades. By comparing end-of-course examinations, they did not find any correlation between the range of usage metrics including number page hits, number of sessions, average length of session, number of hits in a particular section and the final exam grades. Macfadyen and Dawson’s (2009) “early-warning-system” consisted of using the online learning management system (LMS) to identify “at-risk” students using specific variables. They originally tested 15 variables but ultimately only three were found to be statistically significant: total number of discussion posts, total number of mail messages sent and total number of assessments completed. They determined that they could not define causation, they could show only indication that there were relationships and that increased usage resulted in higher achievement, however found no relationship with time spent and student success.

Most traditional didactic classrooms contain a lecture component in which students are passive listeners and instructors stand-and-deliver. In online courses, the nature of this phenomenon is very different. Lecture can still exist but its delivery method can vary. Lectures can take the form of podcasts (Grabe & Christopherson, 2008; Lancaster et al., 2011), can be given electronically in PowerPoint Presentation formats, online recitation (Schenies et al., 2005), can use interactive web conferencing programs such as *Elluminate* (Myers & Schlitz, 2012), or a combination can be used such as Tegrity that consists of PowerPoint presentations with voiceover from the instructor. Online resource access and time spent viewing may be a helpful way to measure student participation and success from a specific type of resource. This data then compared to course achievement may indicate that student learning can be predicted from student online resource use.

Participation and achievement

Hrastinski (2008) identified six levels of conceptions of online learner participation, five of which consisted of discussion types of participation and one that focused on resource use. Hrastinski identified that the most commonly used measures of online learner participation are quantity of messages or units, message quality, learner perceptions, message length, system accesses or logins, read messages, and time spent. Hrastinski (2009) developed a theory of online learning as online participation ultimately stating that "if we want to enhance student learning, we need to enhance online learner participation" (p.1760).

What is online participation? Generally speaking, in much of the literature, it is assumed that online participation involves participation in written form (i.e. discussion boards) (Hrastinski, 2007; Vonderwall & Zachariah, 2005). There are those that have identified that there are limitations to this measure and recognized the need for a better measurement of participation. Hrastinski's (2008) definition of online learner participation is "a process of learning by taking part and maintaining relations with others… it is a complex process comprising doing, communicating, thinking, feeling, and belonging which occurs both online and offline" (p.1761). This definition indicates a need for a better way to measure student online participation than simply written participation, especially when written opportunities are scarce in the courses taken.

Summary

It has been shown that there is a tremendous increase in online enrollments and that this growth is a phenomenon that does not seem to be slowing down. Many studies have attempted to pinpoint those student characteristics that contribute to student success, but have found that with the myriad of variables that can be of influence it often comes down to student motivation and commitment. Uniting all of these results would lead one to believe that the easier the course is to navigate, the more satisfied students are with their courses, they may be more likely to establish a social presence, the more they will use their courses, and ultimately the better they will do in their courses. So stating what seems to be the obvious, if students use the resources in their courses, they do better in them.

The present study has proposed to connect the use of online course resources (lectures) using duration and other course resource access with the success or potential success of the student. The study included two of these most commonly used measures of online learner participation: system access and time spent. In addition, the study differs from previously reported studies in the use of final course grades as opposed to final exam grades and the focus on the duration of *only* lecture instead of *all* online activities. In essence, the aim was to develop a "warning system" that can identify "at risk students" early in a semester so as to intervene in time for a student to complete successfully.

METHODS

Course selection

Human Anatomy and Physiology II (HAP2) was selected as it met the conditions of being offered during the summer and/or fall of 2011 and the instructor was willing to allow access to all data collected from their course. HAP was the second in a two-semester series that explores the structural makeup of the human body and how it functions to maintain homeostasis, respond to disease and injury, and carry out special activities. The course examined a number of organ systems and related physiological processes, such as hormonal regulation, respiration, digestion, circulation, body defenses, elimination of wastes, water regulation, and reproduction.

Course materials

There were a number of course materials that were available in this course. The course textbook Saladin (2010) was required in print or in an electronic version. Students also had access to Blackboard (BB), an online course management system, and were expected to routinely use it as it was the primary tool in this class to communicate, post course information, check grades, etc. Weekly quizzes and exams were also given on BB.

An additional online resource, Connect, complemented the textbook, was also available for students. Connect included activities and quizzes that helped students to better understand the concepts they learned and tested their knowledge and comprehension. These activities were flashcards, multiple-choice questions, true-false questions, multiple-answer questions, fill-in-the-blank questions, cards with multiple questions and ranking questions.

Tegrity was the final resource made available to the students. Tegrity was an online resource supported by the publisher of the textbook for this course that allowed the instructor to record lectures and to post them online for students to view at their convenience.

Course organization

Students were provided with written guidance for each chapter, including recommended reading assignments, suggested activities found on Connect, and worksheets posted on Blackboard (BB). Students also had access to instructor developed PowerPoints and recorded lectures. Students were required to purchase access to Connect and Tegrity in order to view the recorded lectures. Although there were numerous recommended activities, none of them were collected for credit. Both audio and visual materials were recorded for students with voice over from the instructor. The course material was divided into four units, each covering several chapters of assigned material. An exam was administered at the end of each unit. Quizzes were assigned throughout the unit, approximately one per week. Students were expected to check BB daily to ensure that they would not miss important course announcements as events they came near.

Course instructor

The course instructor of HAP2 was a senior lecturer in the Department of Biological Sciences at NDSU. The instructor has been a lecturer at NDSU for 14 years and has taught "many sections" of approximately 10 different traditional face-to-face courses. In addition the instructor has also been an instructor at other universities in the region. In regards to online courses, this instructor has taught four sections of two online courses in total and has never taken an online course as a student. This was the second time this course was offered online. The instructor had never received any professional development training for teaching online courses and developed all of the resources and designed the course alone.

Data sources and analysis

The statistical software in BB allowed for the tracking of student access (clicks) of resources when the statistic tracking enabling option is selected. Reports were generated for each resource available (See Appendix B) indicating number of times each student accessed each resource, the day of the week it was accessed and the time of day. It was not possible to log the duration of student access of all resources in BB, only the number of accesses. Data collected and its relationship to the research question also method of analysis is summarized in Table 4.

Data analysis

Correlation and regression analyses were performed to determine relationships among data. If correlations existed with resource use and course achievement, it may be possible to predict which students will be successful and provide instructors with indicators to identify possible intervention points in which to contact the student. Although not fundamentally related to this study, data for time of day and day of week access logs were also tabulated and interpretations have been included. The researcher compiled this data for all resources into day of week and time of day. This information was useful as a potential source for instructors to guide or provide them with a general idea of when students may be working in their courses and may offer insight into beneficial course design (due dates, office hours, etc.).

Table 4. Research questions included with the data points that will be collected and the method that will be used to analyze data

Research Question	Data Points	Method of analysis
How does online participation predict online student achievement?	• Blackboard (BB) access (clicks) • Tegrity lecture resource access (clicks). • Final course grades	• Compare online access from BB in testing periods to final exam grades • Compare Tegrity online access to final exam grades • Compare achievement groups from Tegrity and BB and access
How can duration of time spent on participation in an online course predict online student achievement?	• Duration of all access in lecture resource. • Final course grades	• Compare duration and final grades and access and final grades. (correlations) • Compare achievement groups in terms of access and duration • Scatterplots to show correlations • Correlations regarding weekly viewing and final grades • Decision trees to compare categories of weekly usage • Chi-Square analysis
How can online student achievement be predicted from student online resource use?	• Access and duration of Tegrity and final grades • BB access (clicks) in achievement groups	• Correlations and regression analysis • Categorical weekly use of the resource Tegrity.

Weekly reports from the Tegrity course lecture resource data were collected by the course instructor and provided via email to the researcher. These reports provided the number of times each lecture resource was accessed as well as the duration of time that was spent by each student in each lecture resource. During analysis of Tegrity data, achievement groups (successful and non-successful) were identified in an effort to search for possible relationships between resource use, average duration and achievement. Scatterplots were also created using Tegrity data to further visualize the relationships regarding access and final grades and duration and final grades. Because of the strong correlation $r\ (22) = 0.986$ between duration and access in Tegrity lecture resources, duration was chosen as a proxy to represent the lecture resource use.

Descriptive statistics were collected for all data and tabulated. Correlation and regression analysis were performed to determine relationships among data. If correlations existed with resource use and course achievement, it may be possible to predict which students will be successful and provide instructors with indicators to identify possible intervention points in which to contact the student. Because the statistical data proved to be significant however it was not possible to develop a predictive model due to the sample size, further analysis was conducted using decision trees. Data was divided in to successful and non-successful students for weekly use for five weeks in which groups consisted of non-users, below-average users, and above-average users for each week (averages recalculated each week and non-use was not included in average calculation). Each instance of usage was based on the average of usage of that week. These data were then used to identify patterns of use for each group. The researcher then summarized data from each group into table form and a chi-square analysis was conducted to determine if there was a significant difference between the successful and non-successful students.

FINDINGS AND DISCUSSION

HAP2 began with an enrollment of 37 students in the summer of 2011. After withdrawals were taken into account, 24 students (21 female, 3 male) completed the course. The average score of all completing students was 65%, a D (Table 5), with13 of the 24 completing with a passing grade. The demographic of such a highly female population in the course corroborate Packham and colleagues (2008) findings of females often being those who complete online courses.

Table 5. HAP2 final grading scale out of 500 and students earning each letter grade (*n*= 24)

Successful	**Students Achieving**
89.5% and above (447 or more) A	A= 1
79.5% - 89% (397-446 points) B	B= 7
69.5% - 79% (347-396 points) C	C= 5
Non-Successful	
59.5% - 69% (297-346 points) D	D= 5
< 59% (296 or less) F	F= 6

The student population consisted of 6 seniors, 11 juniors, 6 sophomores and 1 freshman. Seniors were the only population in which all students were successful in the course (Table 6). This is not unexpected given all seniors needed to pass for their near term graduation as either a general education or degree requirements. Müller (2008) had previously identified motivation to complete as a critical factor of success in online learning environments. College graduation is indeed a strong motivator. Juniors, who made up nearly half of the student population, had a mean score that was failing with just over one-third being successful in the course. The four who were successful were all majoring in a science-related field. These data support findings by Dupin-Bryant (2004) in which class rank could be used as an indicator of retention in online courses.

Table 6. Class rank and achievement groups including actual number of participants (*n*=24)

Class Rank	Senior	Junior	Sophomore	Freshman	Total
Successful	6	4	3	0	13
Non-Successful	0	7	3	1	11
Successful when HAP2 required for major	1	3	3	0	7
Mean grade	399.8 B	283.8 F	335 D	302.5 D	326.38 D

Twenty-one of the 24 students enrolled were majoring in some science related area with 16 of them in programs where this course was a specific requirement of their major. Further, 12 of the 13 successful students were majoring in the sciences. This could lead one to conclude that not only did upperclassman tend to be more successful in this course, but those students that were enrolled in “science programs” were also more successful (Table 7).

Table 7. Describes the number of majors, average grades per major and whether or not the course was required for the specific major

Majors	Required for major	Number of students	Average final grade
*Human Development	No	1	396.5 B
Art	No	1	110 F
Non-Degree	No	1	302.5 D
*Microbiology	No	2	408.5 B
*Zoology	No	3	407.2 B
*Dietetics	Yes	1	347 C
Respiratory Care	Yes	2	222.3 F
Exercise Science	Yes	3	340.7 D
Health Education	Yes	1	175 F
*Pharmacy	Yes	2	434.5 B
Radiologic Sciences	Yes	7	304 D

- Indicates that those students in those majors had passing averages. Majors that are shaded are considered to be "science programs"

Different majors often have different motivations, expert levels, study habits, etc. (Knight & Smith, 2009). The finding of a higher than expected non-successful performance by all students, but especially those where the course is not required for the major, corroborated ongoing discussions in the department of removing Human Anatomy and Physiology from the General Education offerings at North Dakota State University. An unexpected finding was the high rate of non-successful completers at the junior level. Anecdotally, instructors in the department had considered only allowing upper-level students into the online course as they were considered more likely to be successful than under-classmen. Although a limited sample, these data refute that supposition by the instructors, at least with respect to the juniors enrolled in the course during this offering. Further, these data indicate that all students and especially non-science majors need to be provided with pre-enrollment warnings that their class and major may have an impact on their success in this course. Additionally, the instructor can provide early warnings during the course to the students.

Descriptive details regarding student completion and success are described in Table 8. Data reveal most students enrolled in this course fell into the "non-successful" category of achievement (see Table 6). An average of 108 access clicks in BB (all resources besides lecture) and a total viewing time of lecture resources of 16 hours 39 minutes and 55 seconds would likely result in a passing but "below average grade" ultimately landing the student into the non-successful achievement group. Presumably, any access or duration of time spent in excess would be of benefit and may provide students with a better chance at successfully completing their online courses.

Table 8. Sample descriptive indicators for HAP2

Descriptor Variable	Count	St Dev
n (completers)	24	NA
Male/Females	3 Males/ 21 Females	NA
Average final grade (points)	326.38 points or 65%	+/- 100.75 points
Average duration in Tegrity	16 hours 39minutes 55 seconds	14 hours 21 minutes 52seconds
Average number of access in Tegrity	28.58 clicks	25.24 clicks
Average number of access in BB	108.05 clicks	124.49 clicks

Tegrity analysis

When considering Tegrity resource access and duration, data indicated students that earned a successful grade in HAP2 spent nearly twice as much time, on average, compared to their peers and accessed the resources nearly twice as many times also (Table 9). Those students that accessed their lecture resources on average 37 times and spent at least 21:25:02 or 59% of total duration offered of the time available were successful in this course. Those students that fell into the non-successful category had an average access time of 11 hours, 02 minutes and 58 seconds, less than half of the average of the successful completers. These data affirm the obvious and are supported by the literature. Those students that spent more time on their courses (time on task) and accessed the resources more were more often successful (Hrastinski, 2008; Rovai, 2002).

Table 9. Tegrity HAP2 resource access and duration averages for students divided into achievement groups; successful and non-successful

Tegrity	Average total time spent using resource Hours: Minutes: Seconds (% of time used of available)	Average number of access times to resource (clicks)	Average final grade (points)
Total Successful (A, B and C)	21:25:02 (59% of time duration)	36.54	396.69 B
Non-Successful (D and F)	11:02:58 (31% of time duration)	19.18	243.27 F

Correlations were performed using both Tegrity and BB resources. Combinations included comparisons with the final grades and weekly viewing for five weeks. Weeks one, two, four, and five viewing correlations were found to be statistically significant. However, when developing a predictive model the low sample size led the results to be non-significant. Final grades and Tegrity viewing, and final grades and Tegrity access were also compared and both found to have moderate correlations and found to be statistically significant (Table 10). Because the correlations of both Tegrity duration and accesses measured with final exam grades were similar, and the two indicators were closely correlated to one another (0.986) it was prudent to focus on one as an indicator and to use the one that was most highly correlated (duration) as the proxy for student use.

Table 10. Simple correlations of tracking variables with student final grades. Variables include Tegrity weekly views, Tegrity access and duration

Variable	r_s	r^2	p
Final Grade/ Week 1 viewing time	0.36	0.13	0.04*
Final Grade/ Week 2 viewing time	0.35	0.12	0.04*
Final Grade/ Week 3 viewing time	0.25	0.06	0.12
Final Grade/ Week 4 viewing time	0.41	0.17	0.02*
Final Grade/ Week 5 viewing time	0.42	0.18	0.02*
Final Grades and Tegrity Duration	0.52	0.27	0.00*
Final Grades and Tegrity Access	0.49	0.24	0.01*

* Correlations that were statistically significant $p<.05$

Regression analysis was performed on final grades and predicted grades based on Tegrity total access, Tegrity total duration, and both access and duration. All three analyses show significance in that both access and duration were significant and therefore were found to be good indicators of online course success. As previously discussed, due to a low sample size, reliance on statistical analysis was useful, but proved to be non-statistically and for this reason a decision tree was created in an effort to further describe the data (See Appendix B).

The decision tree was originally used to demonstrate/model student behavior through the first five weeks of the course examining Tegrity duration usage. The model was discontinued after five weeks as previous data had shown that those first weeks were most critical in signifying success or non-success (Table 10). Student activity was grouped weekly into three groups according to usage: non-usage (NU), below average usage (BA), and above average (AA) usage and means were recalculated for each week. There were ultimately 11 non-successful and 13 successful students. Each student's pattern of usage in the first five weeks was different as shown in (Table 11). When considering the first week use, 73% of those who were ultimately non-successful started the first week of their course as a non-user. As a comparison, only 38% of successful students began their course with a non-use week. In most cases, if students failed to use their resources or used them in a below average capacity after week one they were far more likely to be non-successful in their course. In addition, if they failed to use in an above average manner at any time in the measured data, they were far more likely to be non-successful in their course.

A summarization of the data shows that non-successful students did not use the Tegrity resource 67% of the time and used it above average only 7% of the time. When comparing the two achievement groups it is evident that successful students used the resource far more often (Table 12) using the resources above average 32% of the time in comparison to the non-successful students that used the resource above average only 7% of the time.

Table 11. Students pattern of categories of usage for successful and non-successful students for weeks 1-5 of HAP2

Non-successful	Week 1	Week 2	Week 3	Week 4	Week 5
1	BA	BA	NU	BA	AA
2	BA	BA	AA	BA	BA
3	NU	NU	NU	NU	NU
4	NU	NU	NU	NU	NU
5	NU	NU	NU	NU	NU
6	NU	NU	NU	NU	NU
7	NU	NU	NU	NU	NU
8	NU	NU	NU	NU	NU
9	NU	NU	AA	BA	BA
10	NU	BA	NU	NU	NU
11	AA	BA	BA	BA	BA
Successful					
1	NU	NU	NU	NU	NU
2	NU	NU	NU	NU	NU
3	NU	NU	AA	NU	NU
4	NU	BA	AA	BA	AA
5	NU	AA	NU	BA	AA
6	BA	NU	NU	NU	NU
7	BA	NU	NU	BA	BA
8	BA	BA	BA	AA	BA
9	BA	BA	BA	NU	AA
10	BA	AA	NU	AA	AA
11	AA	AA	BA	AA	AA
12	AA	AA	NU	AA	AA
13	AA	BA	BA	AA	AA

Table 12. Percent of categories of usage of grouped usage summarized from table 10 for both successful and non-successful students for the first five weeks of HAP2

	NU	BA	AA
Non-Successful	67%	26%	7%
Successful	40%	28%	32%

Non-successful and successful students appeared to have different patterns of usage. The levels of activity in BA and AA were far greater in successful students than in non-successful. Successful students' categories of use of each level show that successful students have a far greater instance of AA use (Table 13) and the usage of each level is fairly consistent week by week. Progressively over the five week period usage seems to migrate towards over half of successful students using this resource in an AA manner.

Table 13. Successful students' percent of categories of activity for first five weeks, for each level of use (NU, BA, and AA) of all successful students and in parenthesis of all students

% of successful of all successful (% of total)	Week 1	Week 2	Week 3	Week 4	Week 5
NU	38% (21%)	38% (21%)	54% (29%)	38% (21%)	31% (17%)
BA	38% (21%)	31% (21%)	31% (17%)	23% (13%)	15% (8%)
AA	23% (13%)	31% (17%)	15% (8%)	38% (21%)	54% (29%)

Table 14 provided evidence that the primary category of usage for non-successful students is NU with the high level of non-use maintained as the weeks progress. In addition, nearly all of the categories of usage for non-successful students were located in the below average or non-use categories. Above average use was miniscule with a slight peak at the 3rd week of the course. This may be due to those at risk students attempting more use to recover from possible low grades, ultimately however those students with the pattern of NU and BA use are shown to typically be on the road to nonsuccess.

Table 14. Non-successful students' percent of categories of activity for first five weeks, for each level of use (NU, BA, and AA) of non-successful students and total students in parenthesis

% non-successful of non-successful (% of total)	Week 1	Week 2	Week 3	Week 4	Week 5
NU	73% (33%)	64% (29%)	73% (33%)	64% (29%)	64% (29%)
BA	18% (8%)	36% (17%)	9% (4%)	36% (17%)	27% (13%)
AA	9% (4%)	0% (0%)	18% (8%)	0% (0%)	9% (4%)

A chi-square analysis was used to determine if the frequency counts (number of categories for NU, BA use and AA use) were distributed differently for the 2 groups (successful and non-successful students). The chi-square test performed yielded a significant value χ^2 (2, N=120) =13.2, p= 0.001. Results indicated that there was a significant difference and therefore demonstrating that there is a difference between the usage behaviors of successful and non-successful students. The identification of indicators can be predictive and valuable to recognize those students that are at risk of becoming non-successful. If these indicators were made available to the instructors ideally toward the beginning of the course by and they simply sorted these data, instructors will be able to use them to flag those students that are in jeopardy of failure and intervene.

The creation of scatterplots was also very valuable to demonstrate the relationships between the variables of interest. Scatterplots provided support for Macfadyen and Dawson's (2010) findings of a positive correlation between use and success. They also supported evidence of what Morris and colleagues (2005) called "documenting the obvious" (p. 229) again referring to the phenomenon of the time spent to the relationship of a successful outcome. Scatterplots were developed for Tegrity access use and duration and both showing a positive linear relationship to final grades (Figure 2). This demonstrated the significance of using duration and access as indicators of course success. Analysis of the plots identified two outliers that do not seem to follow the same trend. Further analysis revealed both students were majoring in the sciences one was a senior and the other a sophomore. There are a number of factors that could explain the lack of use, and subsequent success in the course. Since this was not a common occurrence in the course, one conjecture could be that the students had at some time already taken the course (presumed due to class rank or summer enrollment), or because they were both majoring in the sciences, they may have had previous experience in the topics that were covered in the courses. As previously discussed, this inference is supported by data (Table 6) that showed that upperclassman and science majors were more successful in this online course.

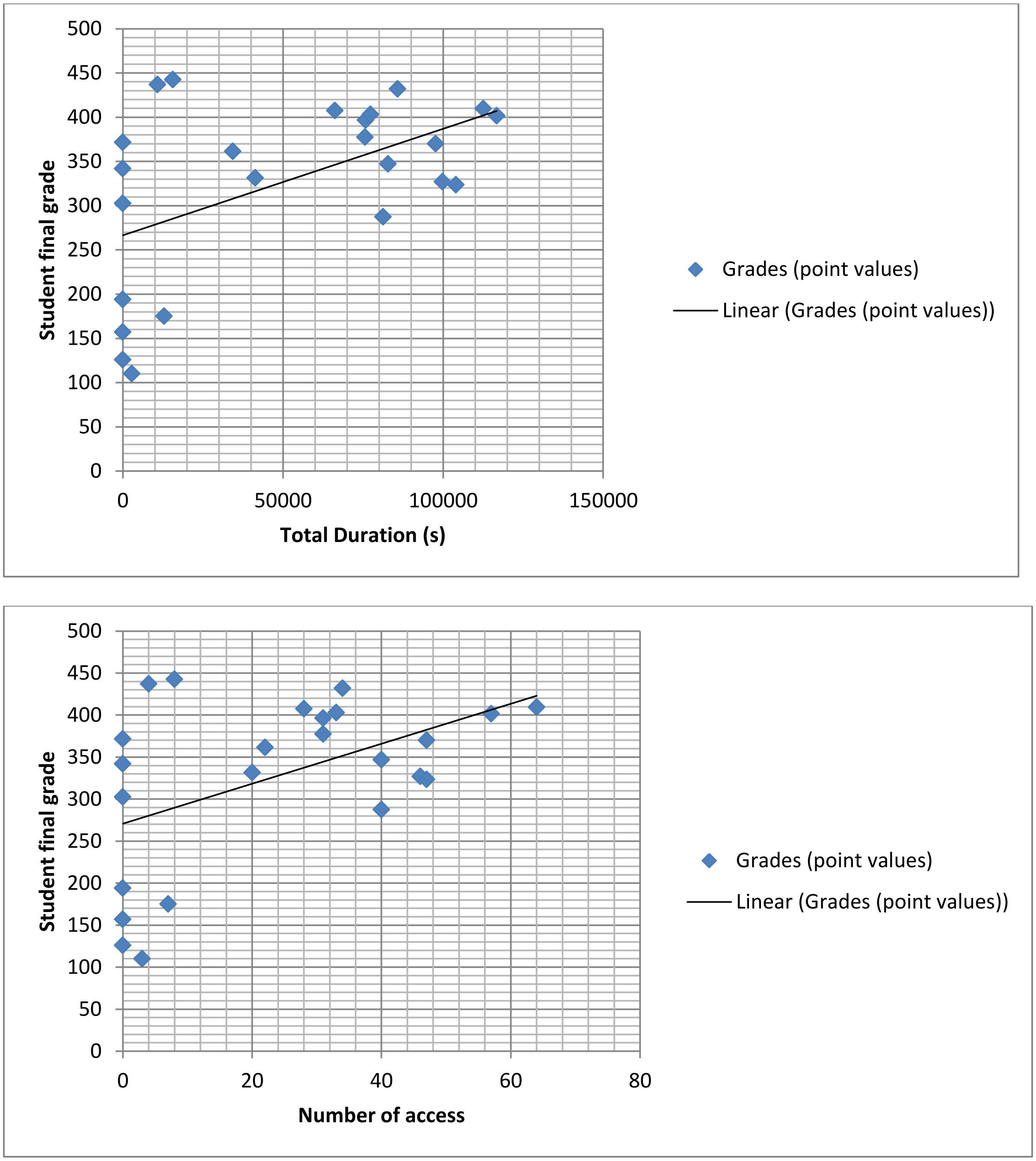


Figure 2. Scatterplots of Tegrity access and duration with final grade

Blackboard analysis

While each of the resources in BB was not individually predictive, collectively BB access data does have value. An interesting observation is that an impact of success in an online course is not so much the type of resource provided, or the number of resources, but the interaction time that students spent with those resources and how often they were accessing those resources. Students earning grades that were considered non-successful (D or F) spent less than half the amount of time online interacting with the material as those who earned average or above grades. Thus, it may be more beneficial for instructors to worry less about how information is provided but that what is provided is engaging for students so as to encourage engaged learning (increased duration). BB data was a compilation of the resources available, again the data seem to indicate that those students that are successful in this course were using this resource twice as much (Table 15).

Table 15. Descriptive statistics for Blackboard access (n=24)

	Mean	Median	Max	Min	SD
Successful BB Access (clicks)	447	468	787	0	209.89
Non-Successful BB Access (clicks)	296.82	277	815	0	265.25

Usage of resources in BB indicated patterns and peaks of usage in relation to course events (Figure 3). Prediction of events (tests and quizzes) was possible based on peaks of usage, demonstrating that resource use increased before all graded events.

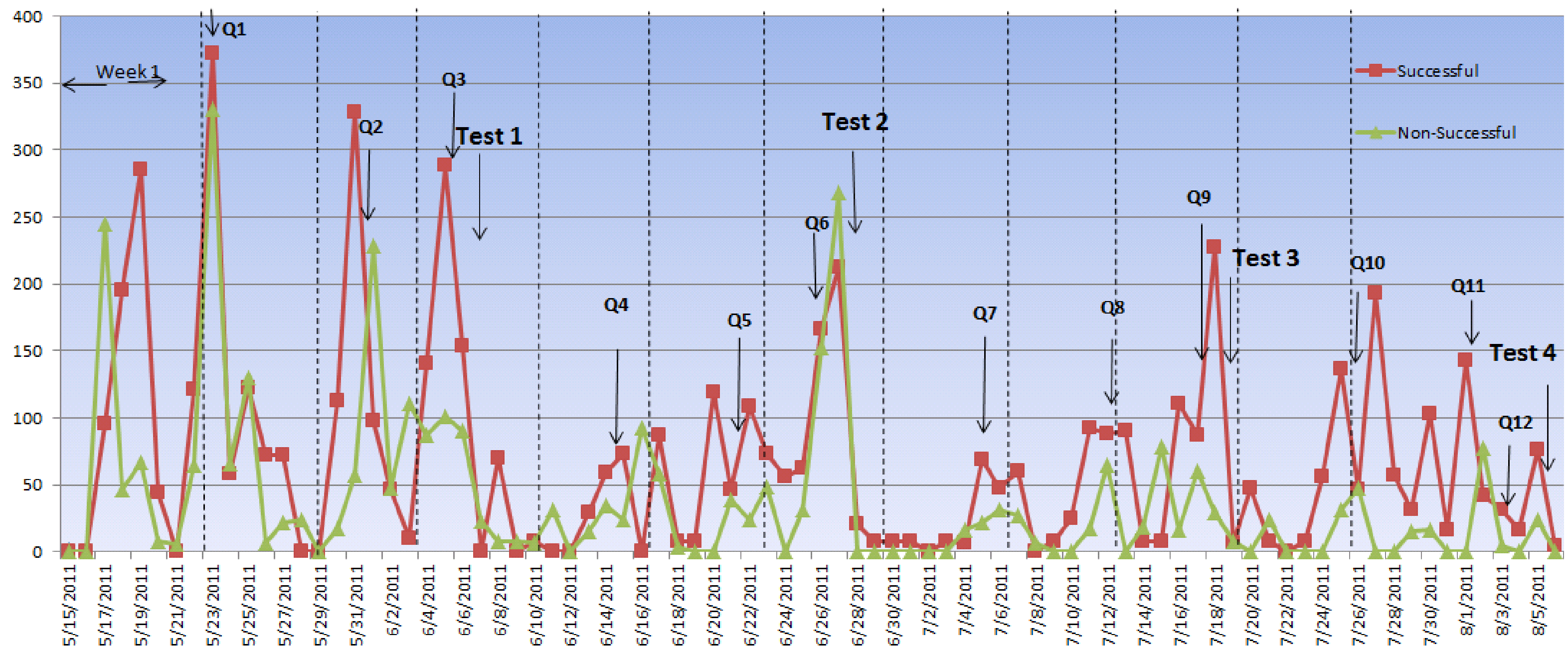


Figure 3. Comparison of successful and non-successful students' resource access with indications of events such as exams and quizzes; includes total number of access times for all Blackboard resources from 5/15/11 to 8/06/11

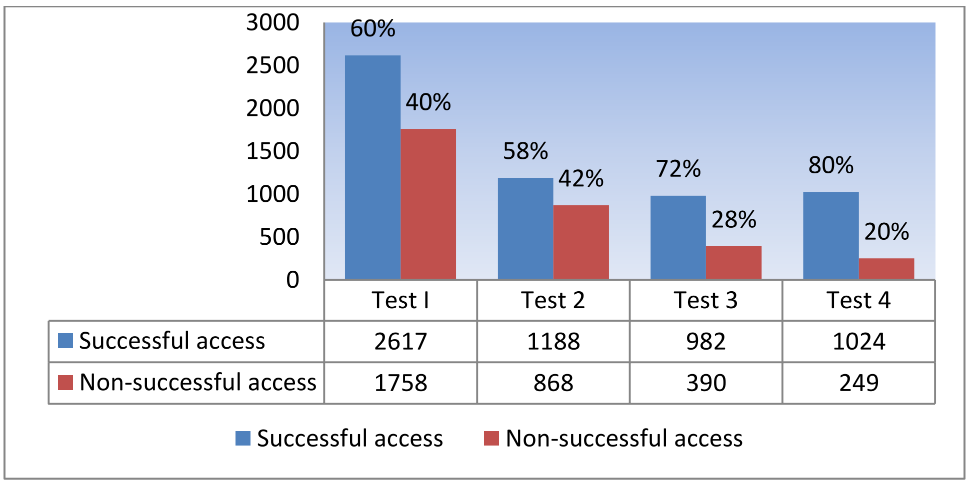
It was also possible to show that course resource use progressively diminished as the semester continued, and towards the end of the course, was very minimal. Using events such as exams to divide the figure into time periods, it is easy to visualize the students' usage. Both successful and non-successful students tend to have similar activity towards the beginning of the course. However, successful students access the course more than below average students up until right before the first exam. Quiz one would be too early to identify troubled students because student use is nearly identical and follows similar trends all the way through test one. After the first exam, activity drops dramatically for all students and then rises to peaks for the quiz events until the exam two at which time again activity drops significantly. A separation appeared beginning at approximately week five of the semester. When the activity began to pick back up, it was apparent that those non-successful students were not accessing the course resources at any significant level.

After test two, (including the six remaining quizzes), and two remaining exams there again appeared to be a differing pattern between successful and non-successful students. This again lead the researcher to believe that there was a critical window that occurred before the second exam (approximately in the 5 week interval) about midterm, in which it may be beneficial to intercede with those students that were not accessing the course resources. Students that were going to ultimately be successful stayed active in the course, and it appeared that at approximately the five week mark, those students that were ultimately non-successful in the course reduced activity dramatically. A sharp decline in BB access occurs as after exam two for both groups (Table 16), but more drastically for the non-successful students. These data for each testing period for each achievement group further supported the theory that those students that accessed resources most often did better in their courses. Similar to the Tegrity findings earlier discussed, again successful students in each testing period accessed the BB resources nearly twice as many times as non-successful students and again after test two, access was dropped to below half.

Table 16. Average number of BB access times per testing period for both achievement groups

	Successful (clicks)	Non-Successful (clicks)
Test 1	113.78	76.43
Test 2	56.57	41.33
Test 3	46.76	18.57
Test 4	53.89	13.11

To further emphasize the significance of the usage difference among successful and non-successful students, Figure 4 shows the actual number of access clicks comparing both achievement groups in testing periods. Again, after the second exam there is evidence of a tremendous decrease in activity between groups. These data further emphasize the need for intervention prior to test 3.



	Test I	Test 2	Test 3	Test 4
Successful access	2617	1188	982	1024
Non-successful access	1758	868	390	249

Figure 4. BB data showing number of access times (clicks) in testing periods comparing achievement groups

Day of week/hour of day

Day of week and hour of day data that was collected revealed that students in HAP2 on average accessed their courses during the hours of 9am and 11pm with spikes of activity at 9am, 11am, and 9pm (Figure 5).

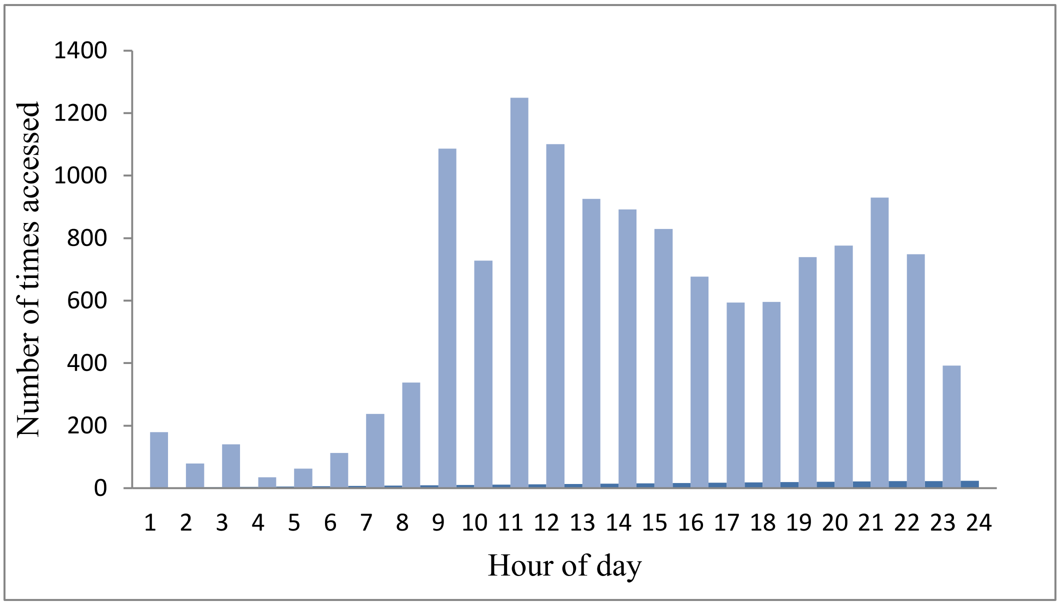


Figure 5. The number of BB access times (clicks) during all hours of the day for entire semester

These levels of activity have the potential to inform instructors of the best possible times to make assignments available. If students are primarily working at certain times in their courses instead of making assignments due at midnight, perhaps it would be more prudent (in this course) to make assignments available at noon while most students are potentially working. Of course the data could be influenced depending on the course, as it could in fact be course specific, however, identifying when students work could help an instructor ascertain when students are most likely to be online. Not only are these data invaluable as to indicate when students are working, it also serves as an indicator as to when students would be available to contact. If instructors know that students are primarily working at these specific hours, they can send their interventions at those times, or make themselves available via physical or virtual office hours. Although the data in this case was course specific, the data was indicative of patterns that could emerge in other online courses. When considering this course specifically, day of the week access revealed that the most access was shown to be between Mondays and Wednesdays (Figure 6).

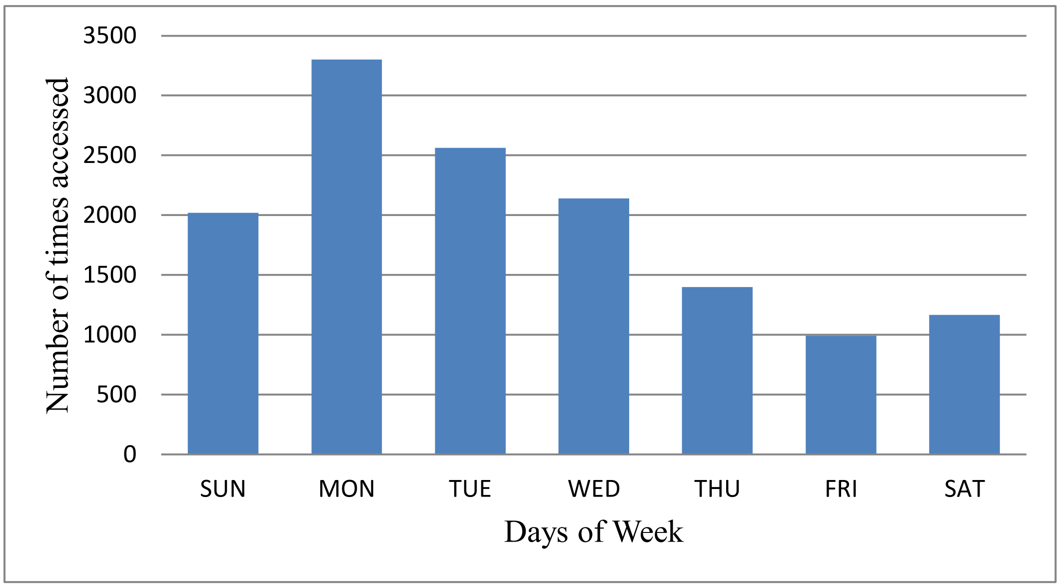


Figure 6. The number of BB access times during specific days of week for entire semester

This pattern would be expected as 75% of course exams were on Mondays and 67% of all quizzes were on Mondays and Tuesdays. All exam and quiz times for this course fall between the same time periods as indicated by the graph and all but one major assessment fell between Sunday and Tuesday. What does this tell us? This data shows that when students' use their online courses, this information can be exploited as potential intervention points or course design factors with the ultimate goal of helping students. One of Soong et al., (2001) critical success factors for online course resources requires that among others, resources have a good infrastructure and that collaboration is important. If instructors know when students are accessing their courses collaboration would be facilitated and they would have a greater chance of accessing and subsequently helping their students.

LIMITATIONS

There are a number of limitations that have been identified in the current study. All data are derived from only one course at one institution during a summer semester. Additional courses were originally included in the study design; due to circumstances outside of the author's control, complete data sets were not provided for analyses. An *n* of 24 is relatively low. Original course enrollment was 37 with one-third of the students dropping throughout the term. Any conclusions drawn here would apply to a skewed female population. While the literature supports higher retention and completion of female students, 88% is high even for those studies. The instructor's course design, grading scale and methods may also have had influence on student resource access. Isolating all of the information for quizzes and other mandatory assignments would tease out the mandatory use from non-mandatory use all of which could have provided a better picture in to student resource use and its relationship to academic performance.

IMPLICATIONS

These data show a link between student resource use and achievement thus supporting the findings of many other studies (Crampton et al., 2012; Hrastinski, 2008; Morris et al., 2005). This research will help instructors to identify students that are at risk of receiving a non-successful grade early on in the semester. When indicators show students are not accessing resources or are not spending time engaged in the material, the instructor has the ability to provide an intervention warning before the end of the course.

These results may also play a role for the need of the provision of preparatory information for potential or beginning online students as indicated from data from this study. The results of this study could also be used to inform instructors of the research supported data regarding need of student resource access and engagement in their online courses for successful completion. The five week point/mid-semester seems to be where the critical window lies between failure and success for online students. For example, if students are not accessing online resources within the first week this should immediately indicate that this could be a good intervention point. Intervention could be something as simple as an email recognizing and explaining to the student that they are on a path of non-success by not using their course materials. Although it is not possible to give instructors an exact number of clicks necessary for success as the identification of this number would be course specific, it is possible to provide instructors with a research supported critical window in which non-use or below average resources use could result in non-success in the course. In addition, these data provide a range or percentage of lecture viewing time that denotes success of students, in the context of this course it is a total of no less than 59% of lecture resources available.

This study has provided evidence that online course participation does predict online student achievement and that those students that participate more often (i.e. access their online resources) were more successful than their counterparts. This supports Crampton's (2012) findings that "students who accessed the online resources achieved greater academic success." (p.11). This study has also provided evidence that duration of time spent viewing online lectures can be indicative of potentially successful students, differing from the findings of Macfadyen and Dawson (2010). This difference in results could stem from the resources from which the duration was measured. The current study measured duration of only online lectures whereas the duration in the Macfadyen study was that of hours spent in total online. These can be very different depending upon the design of the course and the number of resources available. The measurement of the duration of lectures only, which is a tool that is used in most if not all classrooms, and one in which the viewing is controlled by the student, is potentially a more accurate measure of engagement. If that is true, it is more precise and therefore more convincing in measurable potential achievement. This study has also provided evidence that student achievement can be predicted using factors such as access and duration to anticipate student successful completions. The five-week window of successful and below-average students based on resource use was supported and it would be beneficial to perform the same measurements on a larger scale to solidify and narrow down the critical window needed for intervention resulting in a higher success rate. In addition, correlations between resource use and final grade, and duration and final grade were convincing, again further study on a larger scale needs to be conducted to supply more statistically sound evidence. Regardless of the statistical significance, this study does show that correlations do exist and decision tree data further supports the patterns of use.

Even further, the chi-square analysis provided more evidence that successful students and non-successful students do in fact have different patterns of resource use. If they do not use their resources with in the first week, or most certainly the second week, their probability of successfully completing their courses is reduced significantly. With this knowledge, instructors can identify those students that are not accessing their courses or course resources in the first week, second week, or third week time period and intervene before it is too late. They can also provide students at risk with the information that indicates their probability of success with their class, major and method of course use.

Finally, it may be possible to show that those students that have succeeded in this course are shown to have accessed the course resources X number of times and spent X number of minutes engaged in viewing resources (in this case, lecture resources) and to provide them with a guideline to follow to help them succeed.

Guidelines for instructors to identify potentially at-risk students

- Student major or class rank (may be course specific)
- Patterns to look for::
    - Non-Use of all resources in first week but most certainly by the third week of course
    - Non-Use or below average use of lecture resources in first week, second or third week of course.

Further studies

Using the identified indicators as flags, this study on a larger scale (multiple courses and a larger number of students) could provide even more convincing evidence of the value/necessity of resource use and duration as well as showing more support that the first five weeks indicate evidence of being the critical window of time for student use to deliver student success. The possibility of providing interventions for those students enrolling from non-science majors, or those that are underclassman, or providing interventions to those students that are accessing their course work at a below average rate or below in the first few weeks may too be interesting further studies to conduct. Along the same line, testing differing intervention methods at different critical points would also be very interesting.

The architecture of an online course supports the entire learning design and online resources support the learning outcomes associated with the course was concluded by Bates et al., (2007). It may in fact be that those resources that students tend to use most often will be those that can be identified as successful online resources that support successful students. This study may have implications to further support the idea of "critical success factors" (Soong et al., 2001) and that included in those factors may be time spent (duration) and access in the first five weeks of an online class. Determining whether or not there are peaks of usage that tend to coincide with events or assignments could prove to be interesting. This information may show not only what types of resources students use, but when in terms of course events they use them which may ultimately aid instructors in the design of courses. The designation of due dates and times may need further consideration as they will differ depending on the course. Due dates of materials can influence dates of access but time can be indicative of the generalizability for instructors and use of this data may be a critical component in the design (Bates et al., 2007) and thus the success of the course.

This was a highly descriptive study and although the *n* was relatively low the findings indicated that further study on a larger scale in multiple courses may advance understanding of when the critical point is reached in a student's activity or lack thereof in their online courses and the effect of their activity on their success in the course.

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APPENDIX A. IRB APPROVAL

NDSU NORTH DAKOTA STATE UNIVERSITY

Institutional Review Board

Office of the Vice President for Research, Creative Activities and Technology Transfer
NDSU Dept. 4000
1735 NDSU Research Park Drive
Research 1, P.O. Box 6050
Fargo, ND 58108-6050

701.231.8995
Fax 701.231.8098

Federalwide Assurance #FWA00002439

Friday, May 13, 2011

Dr. Lisa Montplaisir
Biological Sciences
Stevens Hall 322

Re: IRB Certification of Human Research Project:

"Resource-Rich online courses: A look at what resources students use and value"
Protocol **#SM11279**

Co-investigator(s) and research team: **Tonya Greywind**

Study site(s): **NDSU** Funding: **n/a**

It has been determined that this human subjects research project qualifies for exempt status (category # 1, 2) in accordance with federal regulations (Code of Federal Regulations, Title 45, Part 46, *Protection of Human Subjects*). This determination is based on the protocol form received 5/11/11 and consent/information sheet received 5/13/11.

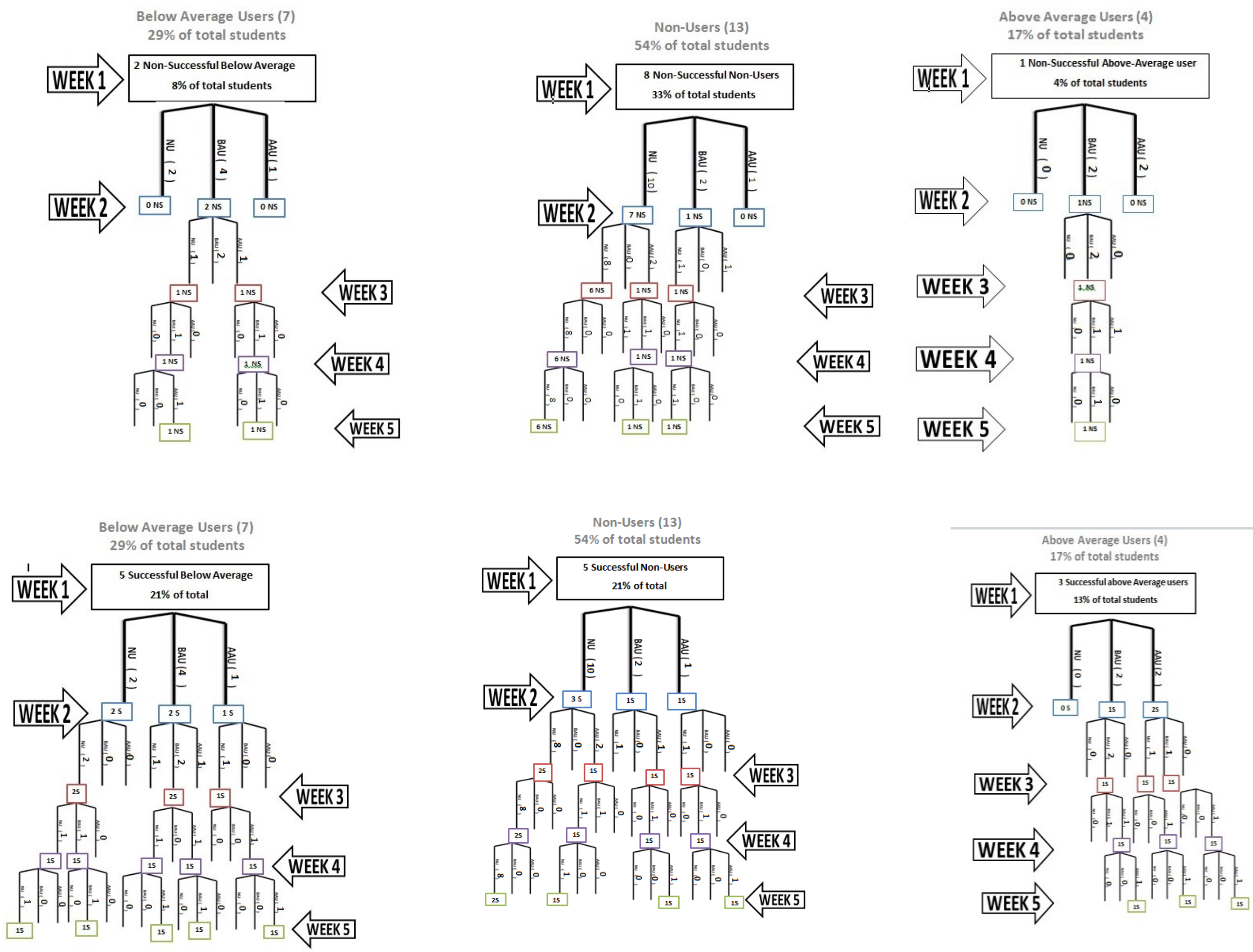
Please also note the following:

- This determination of exemption expires 3 years from this date. If you wish to continue the research after 5/12/2014, the IRB must re-certify the protocol prior to this date.
- The project must be conducted as described in the approved protocol. If you wish to make changes, pre-approval is to be obtained from the IRB, unless the changes are necessary to eliminate an apparent immediate hazard to subjects. A *Protocol Amendment Request Form* is available on the IRB website.
- Prompt, written notification must be made to the IRB of any adverse events, complaints, or unanticipated problems involving risks to subjects or others related to this project.
- Any significant new findings that may affect the risks and benefits to participation will be reported in writing to the participants and the IRB.
- Research records may be subject to a random or directed audit at any time to verify compliance with IRB policies.

Thank you for complying with NDSU IRB procedures; best wishes for success with your project.

Sincerely,
Kristy Shirley
Kristy Shirley, CIP, Research Compliance Administrator

APPENDIX B. DECISION TREES FOR SUCCESFUL AND NON-SUCCESFUL STUDENTS FOR THE FIRST 5 WEEKS OF THE COURSE



APPENDIX C. RESEARCH QUESTIONS INCLUDED WITH THE DATA POINTS THAT WERE COLLECTED, THE METHOD THAT WAS USED TO ANALYZE DATA AND THE OUTCOME OF THE ANALYSIS

Research Question	Data Points	Method of analysis	Outcome of analysis
How does online participation predict online student achievement?	• Blackboard (BB) access (clicks) • Tegrity lecture resource access (clicks). • Final course grades	• Compare online access from BB in testing periods to final exam grades • Compare Tegrity online access to final exam grades • Compare achievement groups from Tegrity and BB and access	• The more that students access their courses the more successful they are in their courses. • Student activity in resources in first few weeks of course shows activity is related to success.
How can duration of time spent on participation in an online course predict online student achievement?	• Duration of all access in lecture resource. • Final course grades	• Compare duration and final grades and access and final grades. (correlations) • Compare achievement groups in terms of access and duration • Scatterplots to show correlations • Correlations regarding weekly viewing and final grades • Decision trees to compare categories of weekly usage • Chi-square analysis	• There is a relationship between time spent in lecture resources and success • The more time students spent on their lecture resources the more likely to be successful in their course.
How can online student achievement be predicted from student online resource use?	• Access and duration of Tegrity and final grades • BB access (clicks) in achievement groups	• Correlations and regression analysis • Decision trees	• Student achievement can be predicted based on resource use. • First 3-5 weeks are critical in success

APPENDIX D. BLACKBOARD RESOURCES

Blackboard Resources

Common to all chapters

Building Vocabulary

Chapter Intro

Connect Saladin Main Folder (recommended activities; folders within)

PPP

Primary Objectives

Review questions

Textbook Reading assignment

Chapter 17:

- Pretest
- Posttest
- Endocrine System IA Quiz
- Hormonal Communication Animation
- Blood Sugar Regulation animation

Chapter 18:

- Pretest
- Posttest
- Ch18 Hemoglobin Breakdown animation

Chapter 19:

- Pretest
- Posttest
- Ch19 system of heart animation
- Ch19 ExIN anatomy of heart
- Ch19 Cardiac Cycle Animation

Chapter 20:

- Pretest
- Posttest
- Ch 20 Fluid exchange across cap
- Ch 20 Baroreceptor reflex of BP animation

Chapter 21:

- Pretest
- Posttest
- Ch 21 Activation of Complement
- Ch 21 Antiviral activity quiz
- Ch 21 cytotoxic hypersensitivity animation
- Ch 21 Cytotoxic T-cell activity
- Ch 21 IgE Med animation
- Ch 21 Tcell antigen animation
- Ch 21 the immune response

Chapter 23:

- Pretest:
- Posttest:

Chapter 25:

- Pretest:
- Posttest:

Chapter 27:

- Pretest
- Posttest
- Ch27 spermatozoa animation
- Ch27 meiosis animation

Chapter 28:

- Pretest
- Posttest
- Ch 28 oocyte animation
- Ch 28 Positive/negative feedback animation