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Using academic and learning analytics to explore student success in an online graduate program in communication

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USING ACADEMIC AND LEARNING ANALYTICS TO EXPLORE STUDENT SUCCESS IN AN ONLINE GRADUATE PROGRAM IN COMMUNICATION

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of

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Megan N. Bergman

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For my father, Paul J. Bergman, Jr. who left this world too soon in 2007.

Thank you for making my education a priority from the start.

Thank you for showing me that my brain is my most valuable asset.

I cannot help but know I have made you proud beyond your wildest expectations.

Love, “Babe”

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ABSTRACT

Bergman, Megan N. M.A., Purdue University, December 2016. Using Academic and Learning Analytics for an Online Graduate Program in Communication. Major Professor: Bart Collins.

Fueled by the increase in data associated with the use of learning management systems, scholars and practitioners alike have been trying to explain and predict student success; yet the use of data analytic methods (academic and learning analytics) in higher education has created challenges and shortcomings for those who wish to adopt learning and academic analytics practices for their institution or program. Very little is known about either online education, particularly in the field of communication, as well as in online graduate and professional degree programs in any field from a learning and academic analytics perspective. This work reviews the literature on academic and learning analytics and related approaches, outlines the challenges regarding these approaches, articulates a working model of factors contributing to student success, outlines a methodology for analysis of data from a learning management system, application data, and final course grades. Last, this work reports and discusses the results of the analysis.

CHAPTER 1. INTRODUCTION

There is a growing desire in higher education to predict and explain student success, however, student success can be defined in a myriad of ways, which can make accurate prediction and explanation difficult for administrators and instructors. For example, Kuh and colleagues (2006) define student success as "academic achievement, engagement in educationally purposeful activities, satisfaction, acquisition of desired knowledge, skills and competencies, persistence, attainment of educational objectives, and post college performance" (p. 7). Even with multifaceted definitions of the term such as this one, scholars and practitioners are attempting to demystify what truly constitutes student success, yet their attempts have only been conducted in certain contexts and have been constrained and limited by a number of factors. Typically, these attempts are used as a way to tackle many student success issues, such as student attrition and persistence, the justification of creating new educational ventures to help students be more successful, and to help students who are particularly at risk for being placed on academic probation.

Historically, attempts at predicting and explaining student success have occurred in admissions contexts. Hartnett and Willingham (1980), note that many attempts in admissions contexts are done to solve the "criterion problem," which describes the shortcomings of differing admissions criteria (e.g., student grade point average, volunteer activities, involvement in clubs and organizations) and admissions practices when selecting students for admission into a higher education institution with the hope that past successful performance will generate future success on campus. However, they make it quite clear "that for the foreseeable future measurement specialists will have to be content with less-than-satisfactory criterion measures when embarking on research on… student performance" (Hartnett & Willingham, 1980, p. 289).

Although Hartnett and Willingham predicted the future of defining and measuring student performance, and by extension success, as bleak in admissions contexts, other scholars since then have been attempting to ensure that the future they have depicted will no longer exist. One of the populations in higher education that has yet to receive much attention in solving student success issues is the graduate student population, however, some scholars have attempted to do so by modeling student success.

Mitchelson and Hoy (1984) ultimately find from their study that a compensatory model of admissions better determines which students will be less likely to succeed than a non-compensatory model. A compensatory model is a model in which admissions staff will overlook unmet criteria if other, more desirable criteria are better met instead, whereas admissions staff who use a non-compensatory model will give equal weight to meeting or not meeting all criteria. As another example, Sime, Corcoran, and Libera (1983) conclude from their study of nursing graduate student success that more sensitive measures of student behavior should be used to determine a graduate student's success.

Moreover, scholars have also attempted to create particular models specifically for masters and doctoral students. Girves and Wemmerus (1980) see graduate student success as a student's progress within their degree program. They conclude that there are particular models for masters and doctoral students. The data used in creating these models included both departmental and student characteristics, the amount of financial support students receive, and students' perceptions about the faculty in their department. For masters students, they found that departmental and student characteristics have an immediate link to degree progress, while doctoral students' involvement, consisting of financial support and perceptions of the faculty, were a salient predictor of their degree progress. From these models, Girves and Wemmerus argue that interventions can be well-timed and beneficial for students who are struggling to complete their requirements to earn their degrees. Additonally, they argue that knowledge gained from developing these models can assist in creating spaces where graduate students can successfully progress towards degree completion.

While scholars have endeavored to make strides in this area of work, these studies are "exacerbating the diverse conclusions in the fact that researchers have not achieved concurrence on a definition of what graduate school 'success' is" (Nelson & Nelson, 1995, p. 1). What is even more problematic is that not enough attention is given to consider student success after students have been admitted, where student success tends to vary greatly from student to student. Furthermore, these attempts to address these issues are usually done out of the best of intentions for students, but they are often done *post hoc*, meaning it is often "too little, too late" for students to increase, regain or maintain a certain level of success. Hence, appropriate interventions for students are often done after the proper time to do so or it could be that students are informed about how successful they are or how well they are doing in school at a later time than what would be beneficial to their success.

While these problems exist, areas of study like academic and learning analytics attempt to solve these issues more rapidly. Now more than ever, organizations are beginning to harness the power of big data. Many organizations and institutions are starting to create processes for analyzing the large amounts of data they have to create intelligence upon which they can act. While this type of work has mainly been in the business arena, educational organizations and institutions are beginning to follow this trend of analyzing big data as well.

Higher education institutions are increasingly using these processes to disentangle and demystify student success in order to not only define it, but also to create intelligence that can pave the way for positive and appropriately timed interventions. This process usually occurs by visualizing data and creating seemingly immediate feedback loops to students, instructors, and administrators by displaying these visualizations to them quickly. However, simply showing individuals what the data looks like does not create actionable intelligence to promote student success because the data is likely not linked to meaningful outcomes. The end goal of generating actionable intelligence in this case would be that models of student success should not just be a mirror held up to students, faculty, and administrators; it should be used to positively intervene so that students can be even more successful in their studies and coursework.

Although the future looks bright for the adoption and use of academic and learning analytics (defined at the beginning of Chapter 2), there are barriers to conducting this type of work that leaves attempts and efforts to suffer and succumb to shortcomings. There is a shift toward online degree programs, particularly in graduate and professional education (See Allen & Seaman, 2013 regarding US trends in shifting to fully online education). When courses are delivered online, there is an influx of data because of the popular use of learning management systems (LMSs). However, even when armed with more data available to scholars and practitioners than in the past, using data and using it advantageously has become a challenge for a number of institutions of higher education, and even more so, individual programs within colleges and universities. To possess the knowledge of analyzing educational data is an even greater challenge. Higher education institutions are finding that it is difficult to employ specialists in this area who have the knowledge and capability to perform LA and AA work (Goldstein & Katz, 2005).

Overall, the primary problem is that program administrators do not have enough data to accurately predict online graduate student performance based only on the use of popular forms of education data. Mitchelson & Hoy (1984) conclude from their study on graduate admissions and graduate student success that (1) using only undergraduate grade point average and letters of recommendation do not provide the most holistic view of a prospective student academically and is not appropriate to use only these markers for admitting graduate students, (2) it is not advisable for admissions staff to assume that once graduate students are on campus they will do work that will make up for past poor performance during their undergraduate career, and (3) graduate student success is difficult to predict because graduate students' lives outside of school and coursework provide far too many reasons for failure.

While this comes from an admissions context, one can see how the combination of these three conclusions would be even more difficult to deal with in predicting student success in online graduate degree programs. Graduate students in online degree programs face many more challenges in becoming academically successful because they are not embedded in an on-campus support environment, are usually working full-time while going to school, and may have additional family obligations that older students typically face. Given this, there is an increasing need to focus on determining and modeling student success of graduate students in online degree programs.

This exploratory project's goal is to address the limitations of academic and learning analytics, as well as student success prediction and modeling by examining the use of learning and academic analytic approaches to study student success in an online graduate degree program in communication. In the rest of this work, I will first describe what is typically meant by the terms academic and learning analytics and why overcoming these aforementioned challenges is key for creating actionable intelligence. Then I will describe how examples of academic and learning analytics have been used in attempting to solve the mystery of student success and discuss the shortcomings of these techniques. I will then explain a working model of student success for online graduate degree programs and the methodology for this project. Finally, I will provide the results of the analysis and discuss them more in-depth.

CHAPTER 2. ACADEMIC AND LEARNING ANALYTICS

In scholastic literature, academic and learning analytics (noted as AA and LA respectively in the rest of this work) have been used numerous times to examine issues with measuring and modeling student success. AA and LA, as much as one could consider that these terms overlap a great deal, are two different concepts in actuality. AA primarily sits at the program or institution level, whereas LA finds its place at the course level (van Barneveld, Arnold, & Campbell, 2012). AA is “a process for providing higher education institutions with the data necessary to support operational and financial decision making,” while LA is “the use of analytic techniques to help target instructional, curricular, and support resources to support the achievement of specific learning goals (van Barneveld, Arnold, & Campbell, 2012, p. 5).

A large portion of the research exists for LA’s role in the literature, however, what has been done to date in this area also presents some challenges for why even the best intentioned efforts to tackle student success in online graduate degree programs have suffered to date. These shortcomings include difficulties in adopting best practices, technical challenges, a decided focus on undergraduates, extensive use of only LMS data and sole examinations of variations in student data.

2.1 Past Studies and Research

The uses of AA and LA in higher education institutions are attempts to solve a large number of issues, particularly because of an increasing amount of data being generated by LMSs, admissions data, and course data. However, there has been a large focus on student success in courses within higher education institutions in past studies and research that attempt to solve the issue of explaining the predicting student success. First, Campbell, DeBlois, and Oblinger (2007) review efforts at several universities including Baylor, Alabama, and Purdue. Baylor University used student background data to determine enrollment decisions. The University of Alabama conducted an experiment that used background data to identify students who might be at risk for academic probation or being dropped from the university due to failing.

As another example, Purdue University has also developed a program called *Course Signals* (Arnold & Pistilli, 2012; Pistilli & Arnold, 2010; Arnold, 2010), which takes student data from undergraduate applications such as high school GPA and SAT/ACT scores as well as their LMS usage to show students a visual representation of how they are doing in any given course. The visualization is portrayed as a stoplight, where the colors, red, yellow, and green represent a student's success. This system lets students know if they are likely to be successful in the course by the end of the semester based on the culmination of their performance up to certain points in the semester. As an additional example, Ball State University has made student success more accessible by developing a smartphone application that rewards students who partake in behaviors that best correlate with student success (Ransford, 2015).

More examples of LA projects that have a focus on student success are also present in academic literature. bin Mat and colleagues (2013) highlight multiple projects including E^2 Coach from the University of Michigan, an individual learning plan and early alert system at Sinclair University, STARS at Albany Technical College, PACE at Rio Solado Community College and eLAT from RWTH Aachen University. Although these projects are conducted with the motivation to do what is best for students, these projects do not bring together data and analysis in meaningful ways because they have not captured the true essence of AA and LA themselves.

Campbell, DeBlois, and Oblinger (2007) find that the current use of AA and LA does not create what they conceptualize as “actionable intelligence.” Actionable intelligence is the ability to use data and analytics to make decisions and perform tasks. When data and analytics techniques are being used to their fullest potential, then more actionable intelligence is being created. For higher education institutions, actionable intelligence could have the goals of increasing student retention, assisting failing students, recruiting the best students out of application pools, and redeveloping courses to best meet the needs of the students that enroll in them.

2.2 Shortcomings in LA and AA Use for Explaining and Predicting Student Success

Many scholars agree that AA and LA can assist higher education institutions in identification of student learning issues and how to create positive interventions when students are not as successful as intended (Prinsloo, Slade, & Galpin, 2012). While most scholars generally agree with Campbell, DeBlois, and Oblinger (2007) that the use of these analytic techniques should be adopted to create positive change for the institution as well as to benefit stakeholders (i.e., instructors, students, and administrators), much of the research in this area only outlines calls to action for future research to overcome challenges in their use. This lack of actionable intelligence as a result of LA and AA projects creates a challenge in and of itself for scholars and practitioners to answer the numerous calls. Challenges exist in AA and LA, namely that "learning analytics [is] an academic challenge, and academic analytics [is] a political and economic challenge" (Mattingly, Rice, & Berge, 2012, p. 246).

2.2.1 Issues with Best Practices

Many scholars have attempted to grapple with defining best practices for LA even with a large number of challenges (Chatti, Dyckhoff, Schroeder, & Thüs, 2012; Clow, 2012; Beer, Jones, & Clark, 2012). Chatti et al. (2012) propose a reference model of LA that shows the most popular methods and practices. Clow (2012) argues that there is a cycle of learning analytics (which includes four parts: learners, data, metrics, and interventions) and this cycle, when used as intended, can make LA projects more successful. Overall, most scholars agree that LA should enact practices which improve or maintain effective pedagogical strategies and that all potential stakeholders should be participatory at appropriate points within the LA project process (Gašević, Dawson, & Siemens, 2015; Chatti, Dyckhoff, Schroeder, & Thüs, 2012).

As one can conclude, even the outcomes for stakeholders of LA projects are problematic. Because LA is used more often than AA, certain stakeholders are left to participate in projects that might not necessarily concern them. As a large focus has been on the use of LA at the course level, it is not ideal for administrators of the institution or in programs within institutions who want to get the macro view of what is going on regarding their students and instructors.

Administrators would also benefit from the use of analytics, but would not likely find actionable intelligence at the granularity of the course level. For example, an instructor would find it useful to know that Chelsey is not engaging in the course enough to be successful, but to an administrator who oversees a large number of students, getting a bigger picture of all the students in the program Chelsey in in would be more useful in order to have knowledge to make decisions at the program level. Therefore, proper analytic approaches should be used to match the goals of the stakeholder groups such that multiple stakeholder groups are benefitting from the use of both LA and AA.

Furthermore, different scholars and institutions propose and use their own best practices. These are likely to differ greatly because their needs are different. Beer, Jones, and Clark (2012) note that because higher education institutions and their academic needs and goals are different, LA and AA projects are often specific, which increases the difficulty of adoption and use while reducing generalizability to other institutions and programs. Institutions and their instructors have different goals amongst themselves for what student success looks like and how it can be attained. In the case of best practices, then, what works for one, for another, unless they are highly similar to the institution or scholar using that best practice, is likely difficult to adopt that same best practice. The varying degrees of difference between institutions, scholar perceptions, and course structures (including pedagogical differences) are likely to increase the difficulty of adoption of best practices regarding LA and AA. Hence, for those who want to adopt best practices for these types of work, it becomes problematic to determine which practices are best to adopt for their needs and goals, leaving them to resort to making their own analytics plan to tackle their problems.

Last, from an organizational perspective, LA and AA are difficult to implement because of the ways in which higher education institutions are managed and organized. These organizational factors create road blocks for scholars and practitioners to perform LA and AA projects (Goldstein & Katz, 2005). Because organizational constraints exist, champions of AA and LA are likely to encounter issues in conducting LA and AA projects because these limitations curtail the spread of knowledge and decrease information seeking, which is likely to put a damper on student success (Beer, Jones, & Clark, 2012).

For example, an institution's stance on teaching and instruction management could limit the usefulness of AA and LA. If teaching, instruction, and pedagogy within the institution or a program are not open to being data-driven, LA and AA projects can be swept under the rug never to resurface again. Another example might regard who owns the data in LA and AA projects, especially because this is unknown, which makes ethics an issue. If students are the owners of their own educational data, then they must give permission for scholars and practitioners to use it in projects, but if the institutions own educational data, then the question arises as to whether or not it is okay for institutions to own student data. While the jury is still out on the ethics of LA and AA approaches, another limitation might be that an institution feels that its faculty should be taking on these projects, yet faculty might not have time because of other duties and responsibilities. Therefore, for some institutions, it is likely unfeasible to adopt best practices because of their organizational composition and management practices.

2.2.2 Technical Challenges

As noted, the right human capital to conduct AA and LA work is a challenge for higher education institutions. A particular technical challenge in regard to human capital is that there must be individuals who are knowledgeable about AA and LA present with the technical knowledge necessary to conduct educational data mining, use LMSs, and known which analyses are best to use (Goldstein & Katz, 2005). Even though, institutionally and programmatically, having the necessary human capital is a challenge, there are other technical challenges that exist in working on LA and AA projects, including uses of technology and issues with LMSs.

A vast amount of LA projects also presents a number of technical challenges. Many projects are typically examining the data by visualizing “frequencies of clicks,” which is a descriptive means of gauging student behavior, especially with LMS data and supplemented with other forms of data. However, even with an influx of projects, a growing concern is that more must be done in the areas of AA and LA besides ‘making the data look pretty.’ Scholars and practitioners must get past visualizing frequency data (more descripting and less prescriptive reporting and usage) to instead using data to create actionable intelligence.

For example, a result of LA or AA might be to show students and their instructor the number of times they are accessing required readings within the course’s LMS page. This might be represented as a graph or chart in the LMS page. However, what is unclear is whether or not the visualization is producing actionable intelligence. It is unknown whether or not students and/or instructors change their behaviors because they see the visualization. It could also be that students and instructors might not ever look at the visualization, leaving the overall effort of the scholar or practitioner to be all for naught. Therefore, simply visualizing the data as past projects have done are a humble start to addressing issues regarding student success, however more must be done to make the data used in LA and AA projects more worthwhile and beneficial to the stakeholders involved.

Furthermore, the current analytics technology nested within LMSs is not usually capable of explaining and predicting student success. MacNeill and colleagues (2014) argue that even though LMSs have their own built-in analytics tools, suites, and plugins, these tools are not enough to create actionable intelligence because there is a very small amount of salient student behavior captured in the LMS that can be linked to student success or learning outcomes. Often times, the data that LMSs provide or collect from users do not give the clearest picture or the most desirable metrics when looking at explaining or predicting student success. Usually it is likely to be more about quantity than quality of work and behaviors.

It is additionally arguable to consider that data collected from LMSs also presents a technical challenge. LMS data in its purest form incites a need for further technologies or individuals that can get the data into a useful format for analysis (Dyckhoff et al., 2012; Goldstein & Katz, 2005). This need for the incorporation of further technology use creates difficulty in understanding the usefulness of LMS data in LA and AA projects, as well as carrying them out correctly and effectively. Some scholars and practitioners are either not capable of doing the extra work themselves or because the picture it paints might not be clear enough to help understand the behaviors of students and instructors. Therefore, these scholars and practitioners are likely unwilling to take to the task of utilizing it in their projects due to the increased potential of running into technical difficulties with LMS data (Phillips et al., 2012).

2.2.3 Focus on Undergraduates

Another shortcoming of AA and LA projects is a focus on certain populations of students rather than others. A large focus of the applications of AA and LA is primarily for undergraduate students. These projects, in particular regard to student success, focus on undergraduate data from undergraduate courses and degree applications. It is understandable to desire to tackle the issues of the largest population of students within higher education institutions, yet it is additionally worthwhile to start using AA and LA to benefit graduate student populations, particularly those who complete degrees in online programs, which is justified by the growing number of these programs in higher education institutions across the US.

Attention to graduate students should also be made because of the nature of graduate courses and the expertise of graduate students who apply. Graduate-level courses are often seminar courses, meaning that classes are not lectures, but are instead intense discussions about key readings. In this course format, a great deal of work is done outside of class by either reading required pieces or working on projects and papers. Translating this into an online course, then, also makes the course a seminar as well, but usually the discussion takes place in an online forum or discussion board.

The nature of the course based on its subject can also differ. Gašević and colleagues (2015) show that the nature of the course can greatly differ by subject area, simply based upon what is incorporated into the LMS for the course. For example, a class in economics is different in nature than that of a communication course because while both host assignments in an LMS, the economics course in Gašević et al. used a "manual" hosted in the LMS that helped students to be successful in the course, yet the communication course used the discussion forums as a method for peer feedback and questions on assignments beyond general question and answer spaces.

As another example, a mathematics course looks different in the LMS than would a course in biology, according to the same study. The math class hosts assignments online, whereas the biology course does not. Furthermore, the biology course has a guide for student success and questionnaires available in the LMS unlike the math class; yet both classes use the discussion forum for general question and answer spaces.

Hence, based on how courses in different areas of study appear differently in LMSs, it is increasingly possible to address the student success issues of the online graduate student population using LA and AA. This phenomenon is due in part because more online graduate degree programs exist for which a large amount of data is available. Moreover, it is a unique opportunity to examine graduate courses in communication, and even more so, those that are offered in online graduate degree programs, as this is a growing trend in higher education.

The expertise of a student can also vastly differ when they apply to a college or university's undergraduate or graduate degree program. Undergraduate and graduate students have very different academic and professional backgrounds before entering the next phase of their education, of which graduate and professional students are likely to have stronger academic and professional backgrounds than undergraduate students. For graduate students in online graduate degree programs, it can be purported that they are typically working and cannot make it to a physical classroom to take courses. They already have a great deal of experience and education far beyond the typical undergraduate student, which makes their background metrics different in value and type (e.g., professional or academic) to that of an undergraduate student and should be treated as such when using AA and LA to attempt to model or explain student success in online graduate degree programs.

All in all, it is worth noting the difference between graduate students and undergraduate students because a large portion of the literature regarding student success, AA and LA are focused primarily on the undergraduate population and not on the graduate population. One cannot universally propose in this instance that what is “good for the goose” is also going to be “good for the gander” because of these differences. Therefore, further research is clearly warranted on how AA and LA would be capable of providing beneficence (i.e., actionable intelligence) in graduate or professional degree programs, specifically in the area of student success in online graduate-level seminar courses.

2.2.4 Participation in the LMS is Only a Part of the Learning Experience

The popular use of LMS usage data in LA and AA projects regarding student success is caused by a growing adoption of LMSs in higher education institutions. However, when using only LMS data in LA or AA, scholars and practitioners are only seeing a part of the learning experiences of students. It is arguable to consider that “usage logs simply record users’ [behavior] in an e-learning environment, but they do not explain why that [behavior] occurs” (Phillips et al., 2011, p. 998).

To combat this issue, scholars and practitioners who engage in LA and AA projects typically use multiple forms of data including standardized test scores (e.g, GRE, MCAT), final course grades, background data (e.g., demographics), and survey data over a wide variety of topics to supplement LMS usage data (Bach, 2010). However, while these supplementary sources of data are often used, the utility of using certain forms of data over others is unclear. It is additionally unclear if certain forms of data are worthwhile to use in creating models of students' success because of their capability to predict student success on their own (e.g., the predictive abilities of SAT scores are still highly debated; see Marsh, Vandehey, & Dickhoff, 2008).

Therefore, it is problematic to use only certain forms of data to explain or model student success because some forts of data are widely debated and contested among scholars and even more so that using only certain sources of data over others is an unclear use of data in LA and AA projects. If scholars want to use data in LA and AA projects, it is clear that they will have to incorporate data from more than one piece of students' learning experiences (i.e., LMS usage data).

2.2.5 Only Variations in Student Data Are Utilized

Another shortcoming of LA and AA projects is a focus on students and how they impact their own success. However, there are others within higher education institutions that play a role in student success, yet are left out of models and projects. Numerous projects that use data for the purpose of examining student success in AA and LA projects often forget the role of the instructor or faculty member who teaches any given course. Empirical studies in prior literature have examined the effects of the instructor upon student success in face-to-face courses, but in online courses as well. In specific regard to analytics, adding the instructor of a course into the mix has also presented its own challenges. However, because of the importance of an instructor to a face-to-face course in graduate school to a students' success, it is key to incorporate the instructor into a model of student success in online graduate degree programs.

For example, Wegner, Holloway, and Garton (1999) found in their study regarding online courses and student learning that instructor-based factors play a role in how much students reach learning outcomes from an online course. These factors include immediacy behaviors, engagement behaviors, guidance ability, and subject-area credibility. Overall, they conclude that the role of the instructor in an online course is such that they "respond to and accommodate learners in assisting [students] to develop their own meaning for the material rather than interpreting the material for them" (Wegner, Holloway, & Garton, 1999, p. 104). Overall, most scholars agree with the same results that Menchaca and Bekele (2008) have found regarding instructors in general; the more involved and credible instructors are to teach a course, the more likely students are ensured to be successful.

Going more in-depth, some of the factors that Wegner, Holloway, and Garton discovered in their study have also been previously examined. Instructor immediacy behaviors have been studied and have been found to predict student success in addition to an instructor's clarity in communication with their students (e.g., Arbaugh, 2001; Sidelinger, 2010). In specific regard to online courses, Mandernach, Donnelli, and Dailey-Hebert (2006) have found that the motivation of the instructor to participate in the course is critical for students to successfully complete courses delivered online.

Additionally, Mazzolini and Maddison (2003) in their study regarding instructors' online discussion board posting frequencies found that the more an instructor posts on discussion boards, the more students in the course perceived the instructor to have more expertise and enthusiasm regarding the course.

Last, teaching presence online is equally important to student success in online courses. Since the growing rise of Computer Mediated Communication (CMC) in prior research, social presence of teachers and students in online courses has been studied. Many of these studies have been linked to student satisfaction in online courses. However, research has started to take a look at how social presence plays a role in student success, in particular with online courses and the accomplishment of learning outcomes by students (see Picciano, 2002; and Rourke et al., 2001).

Multiple definitions of online social presence exist, including the degree of interaction and relationship (Short, Williams, & Christie, 1976) and level of involvement in the online space (Whiteman, 2002), among others. However, the most boiled-down and widely used definition across the literature is Gunawardena & Zittle's (1997) definition, which states that social presence is "the degree to which a person is perceived as a 'real person' in mediated communication" (p. 9).

There are two versions of social presence in the online environment, (1) the presence of students, and (2) the presence of the instructor. Students have quite a profound impact on each other in the LMS, with the particular focus of the research in this area surrounding what occurs in discussion boards within online courses. As an example, through their mixed methods study, Swan and Shih (2005) find that the more students perceive that others are communicating online and are part of the conversation, the more inclined they are to participate in the discussion, and conclude that the way discussions are presented online matters to social presence. The authors also contend that this perception of greater social presence (and not their perception of their degree of how often and how much they interact) is correlated to their degree of satisfaction with their instructor, their perceived amount of learning, and their perceived amount of interaction with others in the environment.

Swan and Shih (2005) also make a note about the presence of the instructor, also known as teaching presence. They argue in the same article that teaching presence is not just their participation in the discussion boards, rather that instructors are using other engaging behaviors such as grading assignments and providing feedback, as well as posting resources and writing e-mails to students to be a part of the online learning environment. Extending that argument to this project, then, opens up a gateway for other instructor-based LMS behaviors to be explored for their potential impact or effect on student success.

Therefore, it is worthwhile to consider how the instructor might impact student success in AA and LA projects. Although the general expectations for students in online courses is that they make a great deal of their success happen on their own, prior research can clearly evidence how important the instructor can be in facilitating courses such that students have the greatest opportunity to be successful, especially in particular regard to an instructors' online social presence. To leave them out of models of student success is leaving out a potential major factor influencing student behavior and performance.

2.3 Lack of Analytics in Communication and Online Graduate Degree Programs

Furthermore, it should be mentioned that there exists a dearth of research regarding the use of learning and academic analytics for online graduate degree programs as well as communication courses and programs in general. Next to no research has been conducted in the literature to suggest that LA and AA have been utilized in online graduate degree programs. As the number of these programs grows within the realm of higher education, it becomes even more increasingly important to determine whether or not LA and AA would be a worthwhile contribution to their maintenance and improvement.

In the communication discipline specifically, there is, again, next to no use of LA and AA to examine communication degree programs and courses. A look at the prior literature only surfaces the National Communication Association's 2004 doctoral reputation study as well as Stephen's 2008 article in *Communication Education* presenting the results of a programmatic evaluation regarding communication program reputation and productivity (Hollihan, 2004; Stephen, 2008). While communication scholars are publishing other assessment studies in prior communication literature, there is a dearth in the use of analytics, not only for undergraduate but also graduate education, and likewise, online graduate education in the communication discipline. Therefore, it becomes increasingly important to examine the usefulness and pragmatics of LA and AA in online graduate degree programs, particularly in the communication discipline. Clearly the lack of specific research focused on this area warrants research regarding the use of AA and LA in online graduate degree programs, especially those in communication disciplines.

CHAPTER 3. A WORKING MODEL OF STUDENT SUCCESS FOR AN ONLINE GRADUATE DEGREE PROGRAM

To guide this project, a working model based on the literature is used in order to inform the analysis of data to potentially explain and predict student success for online graduate degree programs.

3.1 A Mediation Model of Student Success

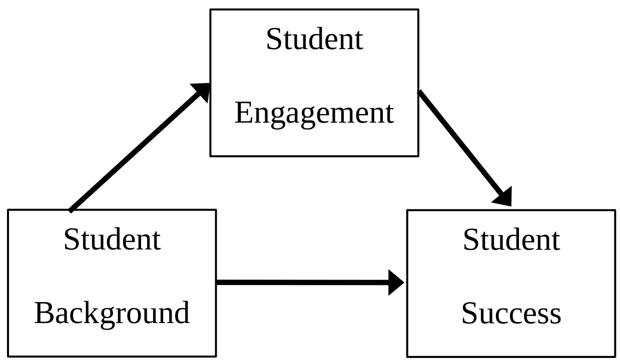


Figure 1. The working mediation model of student success.

A working mediation model of student success for online graduate degree programs is presented above in *Figure 1*. Each piece of this model can be considered as a “cluster” or “grouping” of multiple metrics that have the potential to apply to a model of student success for an online graduate degree program (see *Tables* in Appendix A for a list of variables for each grouping or cluster and their description).

In essence, this model argues that student success and student background are mediated by student engagement. Student background is defined as who students are prior to beginning the degree program and is made up of both their professional and academic backgrounds. Student engagement is defined by Marks (2000) as "a psychological process, specifically, the attention, interest, investment, and effort students expend in the work of learning" (p. 154-155). Student success is defined as the degree to which students accomplish the learning objectives in the course through the completion of assignments and is noted as a student's final grade in the course.

3.2 Recognizing the Role of Faculty and Course Characteristics

As evidenced in past research, faculty members play a role in a student's success and the degree to which students engage in the LMS. Therefore, recognition should be taken to incorporate the role of faculty engagement in the LMS with student success in online graduate degree programs. A grouping of variables regarding faculty has been developed for this project. Since faculty engagement has the opportunity to play a role in student success, examining their effects on student success and student engagement was conducted as part of this project.

As previously mentioned in Chapter 2, the difference in course characteristics might mean something for student success. For this project, the sole course characteristic being explored is the designation of a course as required or elective. The difference between these two distinctions could have the potential to explain students' motivations and could additionally provide insight into whether or not time spent in the program up to a certain point matters (required courses are taken before elective courses in the program being studied). However, for course characteristics, it is difficult to determine or propose where it also belongs in the model.

3.3 Research Questions

All in all, there is a need to develop a model of student success by addressing the issues of AA and LA projects for graduate degree programs that are presented in an online-only format. It is clear that models of student success for the undergraduate population are not suitable for online graduate degree programs because of both the nature of applications and experiences of students as well as how graduate-level courses operate. Furthermore, AA and LA projects should move toward prescriptive projects that create actionable intelligence for a multitude of stakeholders in higher education institutions. By creating a model of student success and using analytics and educational data, it has become possible to accomplish the needs for research that are clearly warranted in this particular area of focus. Therefore, the following research questions are presented:

RQ1: What student background characteristics are associated with student engagement?

RQ2: What student engagement factors are associated with student success?

RQ3: What student background characteristics are associated with student success?

RQ4: Does student engagement mediate the relationship between student background and student success?

RQ5a: Does faculty involvement in the LMS have an impact on student success?

RQ5b: Does faculty involvement in the LMS have an impact on student engagement?

RQ6: Does participating in a required or elective course have an impact on student engagement or student success?

CHAPTER 4. METHODS

In this section, the proposed methodology for this project will be presented based on prior research revolving around past methods, analytics, and student success. First, this section will discuss the subjects, site, and data. Then statistical methods will be introduced.

4.1 Subjects, Site, and Data

The subjects for this project are graduate students taking seminar courses in an online masters in communication program. This program is offered by a school of communication housed at a large Midwestern research university. The online graduate degree program (the site), which recently launched in the Summer of 2014, also offers a certificate in strategic communication and at the time of this study had an approximate enrollment of 375 students. This program uses a custom-built version of the Moodle LMS open-source software.

The average age of a student in the program is 35 years old (*SD*=9.454), while the average undergraduate grade point average is 3.27 out of 4.00 (*SD*=0.413). There are marginally more females than males in the program (29.6% male, 70.4% female), and the number of students who have a prior degree in communication versus those who do not is split fairly evenly (49.4% have no prior degree in communication, 50.6% do have a prior degree in communication). For grades, most of them are in the A and B range, while there are some students who are in the C range with very few students in the D and F ranges. The average final course grade for the eight-week semester was 94.938 out of a possible 100 percent (*SD*=5.4864).

Data for this project were collected by program management staff and de-identified to provide anonymity to subjects before being permitted for use in this project by an institutional review board. For this specific project data were collected from courses that were in session during an eight-week term within the Summer 2016 semester. The data are a collection of the variables and metrics in Appendix A for approximately 330 students who were enrolled in 21 courses taught by 16 unique instructors. All students were enrolled in only one class during the eight week semester, however, three instructors taught two classes each.

Data were also collected from user logs within the Moodle environment as well as from the director of the program and de-identified before being used in this project. Student background data were collected from student applications; faculty and student engagement data were collected from the custom-built Moodle environment. The data are categorized into the different clusters/groupings as they pertain to the working model: (1) student background data, (2) student engagement data, (3) faculty engagement data, (4) student success data, and (5) course characteristic data.

4.2 Statistical Methods

In past literature, many methodologies have been used in studies to attempt to explain and/or predict student success. Some form of multiple regression is commonly used to model student success in order to reach this popular research goal. For this project, multiple regression and a mediation analysis will be utilized to analyze the data, because the working model incorporates a great deal of various metrics and variables. Research questions 1, 2, and 3 were explored using multiple regression, research question 4 was explored using a mediation analysis, research question 5 was answered using a bivariate correlation analysis, and research question 6 was answered using ANOVA and MANOVA.

In this study, multiple regression is useful because it will allow for examination and exploration of multiple potential predictor variables of student success and student engagement, the dependent variables. For research questions 1, 2, and 3, standard and/or hierarchical multiple regression is used. Multiple linear regression (and sometimes hierarchical) is frequently used in past studies regarding the explanation or prediction of student success. While there are numerous examples that demonstrate how frequently multiple linear regression is used to create student success models, especially as predictive mechanisms, for this project and its working model, it is not the only statistical method that is utilized.

Since this project is based upon a working model of students' success as a mediation model, mediation analysis was used in this study to understand whether or not student engagement mediates student background and student success. Mediation analyses were used to explore research question 4 in this project. Furthermore, ANOVA and MANOVA are not used as frequently in studies regarding student success as multiple regression, but are still present in studies in prior research literature. ANOVA and MANOVA were used for research question 6 in this project. Additionally, simple slopes analyses are used when interaction terms are found to be significant predictors in the hierarchical regression analyses to determine how the interaction is impacting the dependent variable.

Finally, it is important to discuss particular treatments of the data that were done prior to conducting certain analyses. Most importantly, the student engagement metrics were split up by time because it is plausible to suspect that student engagement changes over the course of the semester. Therefore, student engagement data was split into early semester (first three weeks), mid-semester (middle two weeks), and end-of-semester (last three weeks). Then, instructor engagement metrics over the full semester were done as median splits to dichotomize them into high and low engaging instructors. Additionally,, continuous data used in the ANOVA and MANOVA analyses were mean centered. Last, interaction effects of the student background metrics were created to use in the hierarchical regression models. Possible interaction effects were explored to see if background metrics were helpful in understanding whether or not pieces of a student's background were working in tandem to impact student engagement or student success.

CHAPTER 5. RESULTS

This project explored potential explanations or prediction of student success for graduate students in an online communication masters program. These research questions were explored by conducting multiple regression analyses, bivariate correlation analyses, a mediation analysis, an ANOVA, and MANOVAs. For research questions 5a and 5b, the instructor engagement metrics were treated as median splits. For the hierarchical regressions conducted for research questions 1 and 3, the continuous variables (age, undergraduate GPA) were mean centered before being multiplied to create interaction terms. *Table 25* in Appendix B displays the results of the bivariate correlation analysis for many of the variables used in this study.

5.1 Research Question 1

First, research question 1 was posed in order to explore student background metrics as possible predictors of student engagement metrics. To start, bivariate correlations were computed to investigate the relationships among student background characteristics and engagement metrics. The results of the correlation analysis show in *Table 25* (Appendix B) that there are positive, yet weak relationships between age and the three full semester engagement metrics. Out of these three significant relationships, age was the most correlated with module viewing. The results also show that undergraduate GPA has a positive, weak relationship with full semester forum posting.

For the full semester, even with these weak, positive relationships, age was still found to be a significant predictor of forum viewing (R^2=0.066, $F(4, 319)$=5.612, p<0.001), forum posting (R^2=0.075, $F(4, 319)$=6.484, p<0.001), and course module viewing (R^2=0.081, $F(4, 319)$=7.072, p<0.001). Furthermore, undergraduate grade point average was found to be a significant predictor of full semester student forum posting behavior (R^2=0.075, $F(4, 319)$=6.484, p<0.001). More in-depth results from this regression analysis are in *Table 1* below.

Table 1. Regression analysis results for overall student engagement.

	Forum Posting[A]			Forum Viewing[B]			Module Viewing[C]		
	B	*SE B*	ß	B	*SE B*	ß	B	*SE B*	ß
Age	0.298	0.066	0.244***	3.564	0.809	0.240***	2.805	0.538	0.282***
Gender	0.281	1.367	0.011	16.819	16.692	0.055	2.377	11.101	0.012
COMDeg.	-0.405	1.249	-0.018	17.933	15.259	0.064	3.855	10.147	0.021
UGPA	3.727	1.524	0.133*	25.551	18.614	0.075	16.004	12.379	0.070
Constant	9.198	5.695		-76.719	69.569		20.139	46.265	

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.075***, B=0.066***, C=0.081***

The same procedure was conducted to explore the possible impact of student background metrics on early semester student engagement behaviors for the first three weeks of the eight-week semester. These analyses were done because it is plausible to suspect that student engagement changes over the course of the eight-week semester. The results of the correlation analysis (in *Table 25* in Appendix B) show that age has a positive, weak relationships with all three early semester student engagement metrics.

Age was found to have the strongest correlational relationship with early semester module viewing. There was also a very weak and positive relationship between UGPA and early semester forum posting.

From the regression results, as displayed in *Table 2* below, in the first three weeks of the eight-week semester, age was found to be a significant predictor of student forum viewing (R^2=0.054, F(4, 319)=4.539, p=0.001), forum posting (R^2=0.059, F(4, 319)=5.019, p=0.001), and module viewing (R^2=0.055, F(4, 319)=4.675, p=0.001). Additionally in this regression model, undergraduate GPA was a significant predictor of student forum posting behaviors (R^2=0.059, F(4, 319)=5.019, p=0.001).

Table 2. Regression analysis results for early semester student engagement.

	Forum Posting[A]			Forum Viewing[B]			Module Viewing[C]		
	B	*SE B*	ß	B	*SE B*	ß	B	*SE B*	ß
Age	0.121	0.032	0.208***	1.471	0.367	0.220***	1.091	0.265	0.226***
Gender	-0.212	0.655	-0.018	5.444	7.571	0.040	-1.234	5.460	-0.012
COMDeg.	-0.380	0.599	-0.035	6.874	6.921	0.054	1.320	4.991	0.014
UGPA	1.723	0.730	0.130*	10.692	8.442	0.070	9.437	6.089	0.085
Constant	3.683	2.730		-27.726	31.553		9.627	22.758	

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.059***, B=0.054***, C=0.055***.

Table 3. Regression analysis results for mid-semester student engagement.

	Forum Posting[A]			Forum Viewing[B]			Module Viewing[C]		
	B	*SEB*	ß	B	*SE B*	ß	B	*SE B*	ß
Age	0.084	0.019	0.236***	0.844	0.201	0.230***	0.506	0.140	0.200***
Gender	0.142	0.397	0.019	4.658	4.139	0.062	0.634	2.887	0.012
COMDeg.	-0.103	0.363	-0.015	2.593	3.784	0.037	-1.467	2.639	-0.031
UGPA	1.316	0.443	0.162**	6.932	4.615	0.083	1.640	3.220	0.028
Constant	0.572	1.656		-21.571	17.250		15.678	12.034	

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.079***, B=0.062***, C=0.043***.

Correlation and regression analyses were also conducted to explore mid-semester student engagement behaviors. The bivariate correlation analysis results in *Table 25* in

Appendix B found that age has weak, positive relationships with the three mid-semester student engagement metrics. Out of these three significant relationships, age has the strongest correlations with both mid-semester forum viewing and forum posting. Undergraduate GPA was also found to have a weak, yet positive relationship with mid-semester forum posting.

The regression results in *Table 3* on the previous page show that age is a significant predictor for mid-semester forum viewing (R^2=0.062, $F(4, 319)=5.263$, $p<0.001$), forum posting (R^2=0.079, $F(4, 319)=6.862$, $p<0.001$), and course module viewing (R^2=0.043, F(4, 319)=3.549, p<0.01). Undergraduate grade point average was also found to be a significant predictor of mid-semester student forum posting behaviors (R^2=0.079, $F(4, 319)=6.862$, $p<0.001$).

Table 4. Regression analysis results for end-of-semester student engagement.

	Forum Posting^A			Forum Viewing^B			Module Viewing^C		
	B	*SE B*	ß	B	*SE B*	ß	B	*SE B*	ß
Age	0.113	0.024	0.251***	1.243	0.271	0.249***	1.129	0.195	0.311***
Gender	0.480	0.504	0.052	5.740	5.602	0.056	2.949	4.021	0.039
COMDeg.	0.239	0.461	0.028	8.376	5.121	0.089	3.791	3.676	0.055
UGPA	0.945	0.562	0.092	6.939	6.246	0.061	3.247	4.484	0.039
Constant	3.365	2.102		-23.519	23.346		2.828	16.759	

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.072***, B=0.070***, C=0.098***.

Last, the same procedure was conducted for end-of-semester student engagement behaviors. The results of the bivariate correlation analysis, as displayed in *Table 25* in Appendix B, show that age has a positive, weak relationship with all three end-of-semester student engagement metrics, with the strongest relationship being with module viewing. The results of the regression (as seen in *Table 4* above) show that age is a significant predictor of end-of-semester forum viewing (R^2=0.070, $F(4, 319)=6.047$,

$p<0.001$), forum posting ($R^2=0.072$, $F(4, 319)=6.154$, $p<0.001$), and module viewing ($R^2=0.098$, $F(4, 319)=8.630$, $p<0.001$).

To explore this question even further, follow-up sets of hierarchical regressions were conducted to understand whether or not interactions were occurring between background metrics and whether or not they had an effect on student engagement. Continuous predictor variables (age, undergraduate GPA) were mean centered before conducting these analyses. More detailed results of these hierarchical regression analyses are located in *Tables 13* through *25* in Appendix B.

First, the results of the regression analyses for full semester student engagement behaviors found that for forum viewing ($R^2=0.089$, $F(10, 313)=3.064$, $p=0.001$) and positive behaviors ($R^2=0.058$, $F(10, 313)=3.001$, $p=0.001$), undergraduate GPA is the sole significant predictor when two-way interactions are included in the model. The results also show that age, undergraduate GPA, and the interaction of age and undergraduate GPA are all significant predictors of module viewing behaviors ($R^2=0.113$, $F(10, 313)=3.987$, $p<0.001$).

To explore the interaction effect of age and undergraduate grade point average on full semester module viewing behaviors, a simple slopes analysis was conducted (chart in *Figure 2* on page 36). These results show that younger students with lower GPAs view modules less than students who are older than them. However, students who have high undergraduate GPAs, no matter if they are younger or older, tend to view approximately the same amount of modules over the course of the eight-week semester.

The results of the regression analyses for early student engagement metrics show that a significant predictor of forum posting behaviors ($R^2=0.077$, $F(10, 313)=2.593$, *p*=0.005) and module viewing behaviors (R^2=0.075, *F*(10, 313)=2.521, *p*=0.006) is undergraduate GPA when potential two-way interactions are added to the regression model. There were no significant predictors of forum viewing when two way interactions were added into the regression model (R^2=0.072, *F*(10, 313)=2.441, *p*=0.008).

The results of the regression analyses for mid semester student engagement show that for forum posting, there are no significant predictors when two-way interaction terms are incorporated into the regression model (R^2=0.084, *F*(10, 313)=2.852, *p*=0.002). However, for forum posting behaviors, undergraduate grade point average is a significant predictor (R^2=0.095, *F*(10, 313)=3.286, $p<0.001$), while both age and undergraduate grade point average significantly predict module viewing behaviors (R^2=0.077, *F*(10, 313)=2.603, *p*=0.005). There were no significant interaction effects in these particular regression models.

Here, to further examine the interaction effect of age and undergraduate GPA on mid-semester module viewing, another simple slopes analysis was conducted. (*Figure 3* on the next page). The results of the analysis show that younger students with lower undergraduate GPAs view modules less than older students with lower GPAs. Students with higher, above average undergraduate grade point averages tend to view modules during the middle two weeks of the semester in approximately the same frequency, regardless of age.

The results of the regression show there are no significant predictors for end-of-semester forum viewing behaviors when two-way interaction terms are added to the regression model, R^2=0.097, *F*(10, 313)=3.349, $p<0.001$. However, for forum posting behaviors, undergraduate GPA is the sole significant predictor, R^2=0.080, *F*(10, 313)=2.714, *p*=0.003, when interaction terms are added into the model. For module viewing behaviors, age, undergraduate grade point average, and the interaction of age and undergraduate GPA are significant predictors when interaction terms are added, R^2=0.147, *F*(10, 313)=5.411, *p*<0.001.

To explore the interaction of age and undergraduate GPA on end-of-semester module viewing, a simple slopes analysis was once again conducted. (*Figure 4*). The results of the analysis indicate that younger students with lower undergraduate grade point averages tend to view modules considerably less than their older colleagues. Students with higher undergraduate GPAs tend to view modules at the end of the semester with approximately the same frequency.

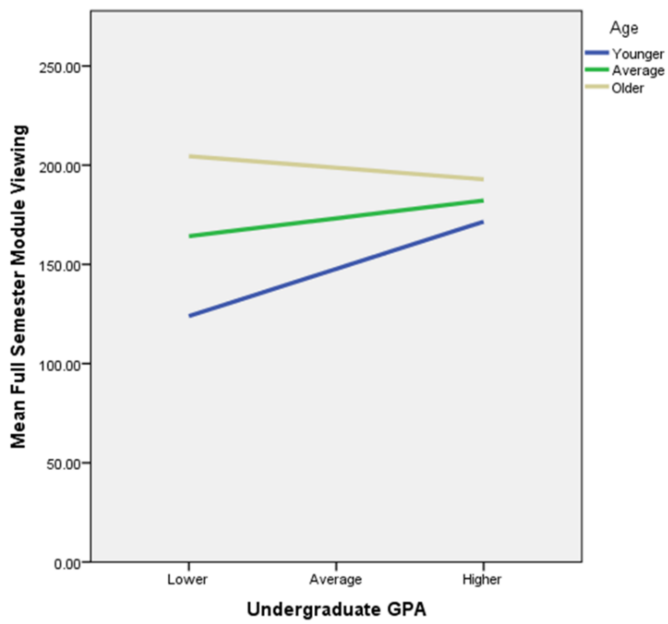


Figure 2. Simple slope analysis results for the interaction of age and UGPA on full semester module viewing.

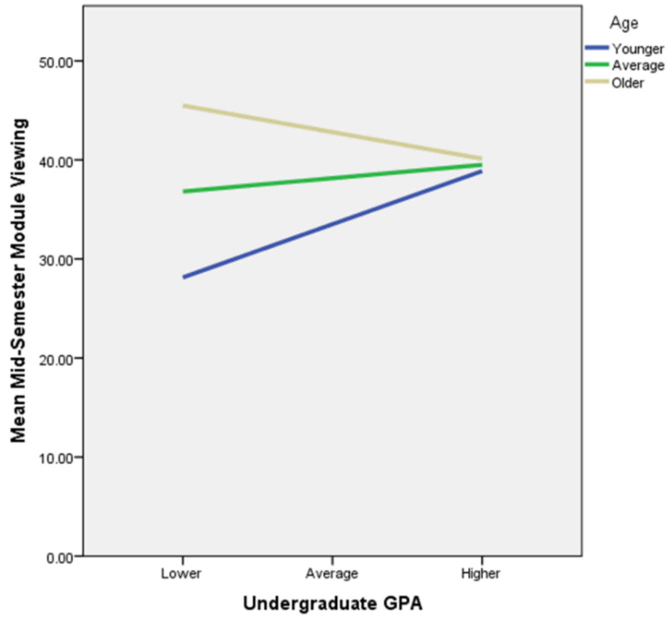


Figure 4. Simple slope analysis for the interaction of age and UGPA for mid-semester module viewing.

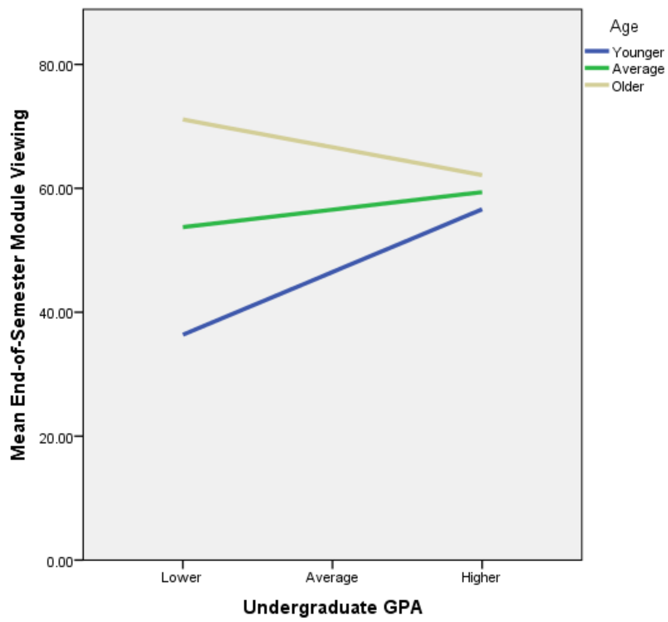


Figure 3. Simple slope analysis for the interaction of age and UGPA on end-of-semester module viewing.

5.2 Research Question 2

Next, research question 2 asked whether or not student engagement metrics are associated with student success. Like the analyses conducted in research question 1, a correlational analysis and a regression analysis were conducted. The correlation analysis (*Table 25* in Appendix B) results show that all three full semester engagement metrics have a positive, yet weak relationship with student success (i.e., final course grades). Out of these three significant relationships, forum posting was found to be most correlated with final course grades. The results of the separate regression analyses conducted for each different dependent variable (*Table 5* on page 40) additionally show, however, that student forum posting over the entirety of the eight-week semester is the only sole predictor of a students' success (final course grades). The regression model was found to be significant, R^2=0.086, F(3, 331)=10.334, p<0.001.

Similar analyses were conducted for the early semester student engagement metrics. The results from the correlation analysis show (in *Table 25* in Appendix B) that all three early semester student engagement metrics have a weak, positive relationship to student success. Like the full semester results, the strongest correlational relationship was with forum posting over the middle two weeks of the eight-week semester The results of the regression (*Table 5*) show that student forum posting behavior at the beginning of the semester is a significant predictor of a student's final course grade, R^2=0.054, F(3, 331)=6.314, p<0.001.

For mid-semester student engagement metrics, the same analyses were conducted. From the correlation analysis, the results show that all three student engagement behaviors in the middle two weeks of the semester are significantly related to student success; they have a positive, weak relationship. Again like the results that have previously been discussed in this section, final course grades are most strongly correlate with early semester forum posting behaviors. The regression analysis for the mid-semester student engagement metrics (*Table* 5) showed once more that student forum posting behaviors were significantly predictive of students' final course grade (i.e., their success). The overall regression model was found to be significant, R^2=0.069, F(3, 331)=8.147, p<0.001.

Last, the same analyses were conducted for student engagement behaviors of the last three weeks of the semester and their possible relationships to and predictability of student success. The correlation results show that all three engagement behaviors in the last three weeks have a weak, positive relationship with student success. Again, the strongest correlation between the end-of-semester student engagement metrics and final course grades is forum posting. The regression analysis results (*Table 5*) additionally show, however, that end-of-semester forum posting is the sole significant predictor of final course grades out of the three end-of-semester engagement behaviors. The regression model itself is significant, R^2=0.082, F(3, 331)=9.904, p<0.001.

Table 5. Regression analysis results for student success prediction.

	Student Success (Final Course Grade)		
	B	*SE B*	ß
Student Background[A]			
Age	0.031	0.033	0.054
Gender	0.445	0.677	0.037
COMDeg.	-0.438	0.619	-0.40
UGPA	1.560	0.755	0.116*
Constant	88.645	2.822	
Full Semester Engagement[B]			
Forum Posting	0.144	0.032	0.300*
Forum Viewing	-0.002	0.003	-0.059
Module Viewing	0.003	0.005	0.047
Constant	90.242	0.932	
Early Semester Engagement[C]			
Forum Posting	0.228	0.069	0.226***
Forum Viewing	-0.002	0.007	-0.023
Module Viewing	0.004	0.010	0.032
Constant	91.750	0.820	
Mid-Semester Engagement[D]			
Forum Posting	0.421	0.102	0.258***
Forum Viewing	0.003	0.013	0.016
Module Viewing	-0.002	0.018	-0.010
Constant	91.603	0.798	
End-of-Semester Engagement[E]			
Forum Posting	0.344	0.079	0.265
Forum Viewing	0.001	0.010	0.009
Module Viewing	0.006	0.012	0.036
Constant	90.809	0.858	

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.020, B=0.086***, C=0.054***, D=0.069***, E=0.082***.

5.3 Research Question 3

Table 6. Hierarchical regression results for the prediction of student success.

	Student Success (Final Course Grade)			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.031	0.033	0.054	
Gender	0.445	0.677	0.037	
COMDeg.	-0.438	0.619	-0.40	
UGPA	1.560	0.755	0.116*	
Constant	88.645	2.822		0.020
Model 2[B]				
Age	0.068	0.071	0.116	
Gender	0.705	0.991	0.058	
COMDeg	-0.144	1.133	-0.013	
UGPA	2.072	1.483	0.154	
Age*Gender	-0.073	0.075	-0.106	
Age*UGPA	-0.169	0.086	-0.113*	
Age*COMDeg	0.025	0.066	0.029	
Gender*UGPA	-0.163	1.568	-0.009	
Gender*COMDeg	-0.513	1.361	-0.044	
UGPA*COMDeg	-0.215	1.519	-0.011	
Constant	85.506	5.518		0.019

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values: A=0.020, B=0.039.

Research question 3 explores whether or not student background metrics are associated with student success. A correlation analysis and regression analysis were conducted. The results of the correlation analysis in *Table 25* in Appendix B show that undergraduate GPA is significantly correlated with student success (a weak, positive relationship). Regression analysis results (*Table 5*) show that student background characteristics overall were not found to be a significant predictor of students' success in the online graduate degree program, however, undergraduate grade point average was found to be a significant predictor of student success. The overall model was not found to be significant, R^2=0.020, F(4, 319)=1.662, p=0.158.

Additionally, a follow up hierarchical regression analysis was conducted to explore potential interaction effects between student background characteristics that may have an effect on student success. The results of the regression analysis (*Table 6* on the previous page) found that the interaction of age and undergraduate grade point average is a significant predictor of student success, yet the model, when interaction terms are added was not significant, R^2=0.039, F(10, 313)=1.274, p=0.244.

A simple slopes analysis was conducted to further explore the interaction of age and undergraduate grade point average on student success (i.e., final course grades). The results of this analysis are displayed in *Figure 5* below. The results suggest that older students, regardless of their undergraduate GPA are going to get about the same final course grade. Younger and average-age students with lower than average undergraduate GPAs are likely to earn a lower grade than those with above average undergraduate

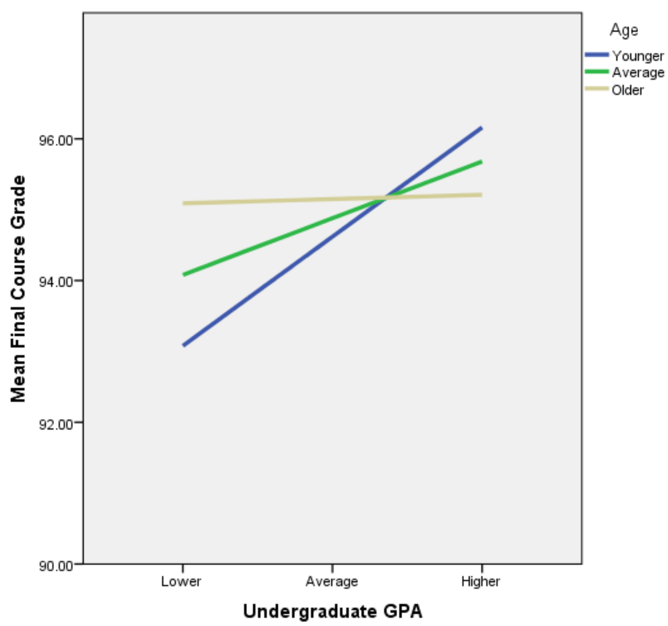
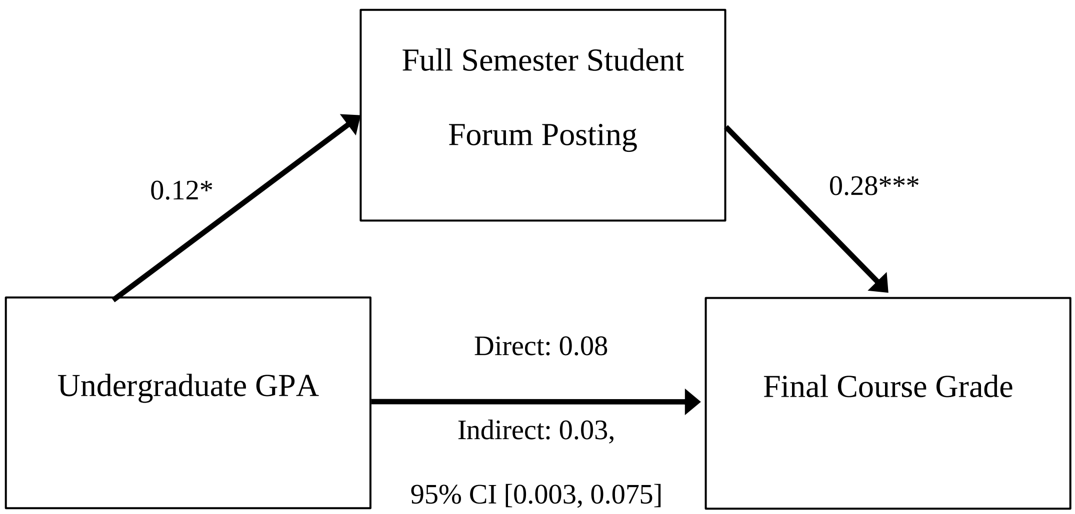


Figure 5. Simple slopes analysis for the interaction of age and UGPA on final course grades.

GPAs. An interaction point occurs for all age groups between the average UGPA point and the above average UGPA point, which suggests that a slightly above average UGPA, regardless of age, will yield the same grade. Therefore, UGPA tends to be more predictive of younger students' success but predicts much less about older students who are likely 10-20 years out from college.

5.4 Research Question 4

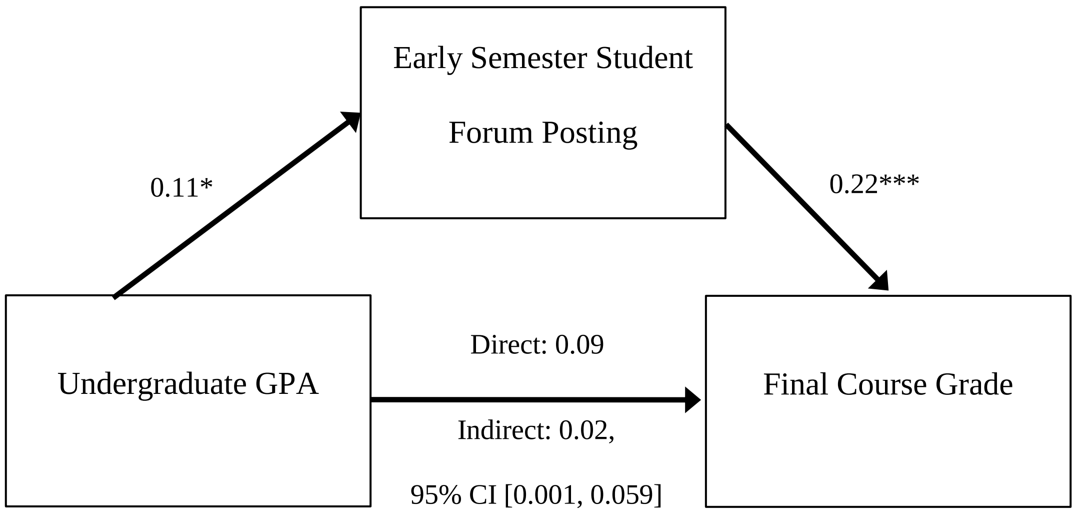


Note. ****p*<0.001. ***p*<0.01. **p*<0.05.

Figure 6. Mediation analysis results for full semester student forum posting as a potential mediator.

Research question 4 explores whether or not the proposed working model is a mediation model. A mediation analysis is permitted for exploration because of the links between predictors in the regression models. Undergraduate grade point average, full, early, and mid-semester forum posting behaviors were significant predictors of final course grades. Undergraduate grade point average was additionally found to be a significant predictor of full, early, and mid-semester forum posting behaviors.

Using Hayes' PROCESS module for SPSS, a mediation analysis (Model 4) was conducted to see if these forum posting (student engagement) metrics mediate undergraduate grade point average (student background) and final course grades (student success). The variables were all standardized before the analysis was conducted (done in the PROCESS module).



Note. ***$p<0.001$. **$p<0.01$. *$p<0.05$.

Figure 7. Mediation analysis results for early semester student forum posting as a potential mediator.

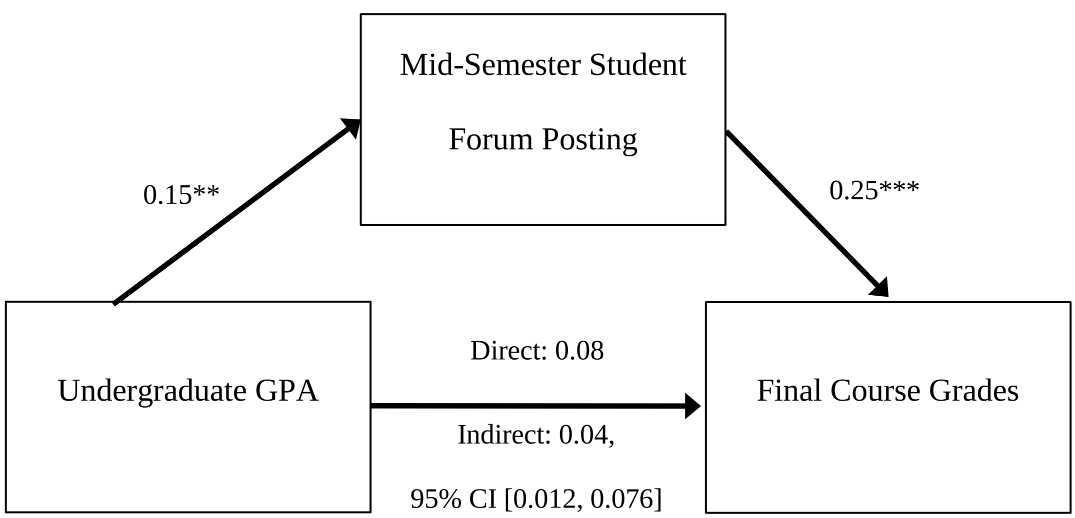
For the full semester mediation (*Figure 6* on the previous page), there was a significant indirect effect of undergraduate grade point average on student success (final course grades) through full semester student forum posting behaviors, mediation occurred, $ab=0.03$, BCa CI [0.003, 0.075]. The mediator could only account for four-tenths of the total effect, $P_M=0.40$.

The results of the early semester mediation (*Figure 7* on this page) showed that there was a significant indirect effect of undergraduate grade point average on student success (final course grades) through early semester student forum posting behaviors.

Mediation did occur *ab*=0.02, BCa CI [0.001, 0.059]; the mediator could only explain about a quarter of the total effect, P_M=0.27.

Mid-semester mediation analysis results (*Figure 8* on the next page) found there was again a significant indirect effect of undergraduate grade point average on student success (final course grades) through student forum posting behaviors, *ab*=0.038, BCa CI [0.012, 0.076]. Mediation did occur, the mediator did account for almost a half of the total effect, P_M = 0.47.

Overall, the mediation analysis results suggest that as undergraduate GPA increases, student forum posting behavior increases, which in turn increases students' final course grades. The results additionally suggest that more of students' final course grades can be explained through the path of mediation more so than the direct effect of undergraduate GPA's impact on final course grades in the program.



Note. ****p*<0.001. ***p*<0.01. **p*<0.05.

Figure 8. Mediation analysis results for mid-semester student forum posting as a potential mediator.

5.5 Research Question 5a

Research question 5a is one of the two questions in the project that involves the participation of faculty in the course. This question in particular looks at any potential impact that faculty involvement in the LMS might have on student success. To explore this question further, a correlation analysis was conducted. The results of the correlation analysis (in *Table 25* in Appendix B) show there are no correlations between faculty engagement metrics and student success.

5.6 Research Question 5b

Research question 5b sought to understand if faculty engagement behaviors in the LMS have any impact on student engagement behaviors. Faculty engagement had some impact on the degree to which students engage in the LMS. Overall faculty engagement is weakly and negatively correlated with early semester module views and mid-semester forum posting. Faculty forum posting is also negatively and weakly correlated with end-of-semester forum posts and module views.

5.7 Research Question 6

Research question 6 was designed to explore whether or not a potential course characteristic could be at work and impacting student success or student engagement. The singular course characteristic studied was whether a course was a required course or an elective course. A one-way ANOVA was conducted in order to explore this research question for the impact on student success. The results of the one-way ANOVA found that the difference between a course designated as required or elective does not significantly play a role in a student's success, $F(1, 332)=2.631$, $p=0.106$, partial $\eta^2=0.008$.

MANOVAs were conducted for student engagement for the full, early, mid-, and end-of-semester student engagement metrics. The detailed results of these analyses can be found in *Table 7* on the next page. The results for the full semester MANOVA displayed a statistically significant difference in full semester student engagement behaviors based upon whether or not the course is required or an elective, $F(3, 330)=7.018$, $p<.001$; Wilk's $\Lambda=0.940$, partial $\eta^2=0.060$. Additionally, the results show that the difference between required and elective play a significant role in the frequency of student forum and module viewing behaviors. Students in required courses are likely to post more and view more modules than those in elective courses.

Table 7. MANOVA results for impact of course characteristic on student engagement.

Outcome Variable	Sum of Squares	*df*	*F*(1,332)	Partial η^2
		Full Semester Student Engagement		
Forum Viewing	163439.465	1	8.735**	0.026
Forum Posting	406.161	1	3.115	0.009
Module Viewing	168503.035	1	20.309***	0.058
		Early Semester Student Engagement		
Forum Viewing	41928.415	1	11.097***	0.032
Forum Posting	236.843	1	8.146**	0.024
Module Viewing	534468.070	1	27.648***	0.077
		Mid-Semester Student Engagement		
Forum Viewing	11685.658	1	10.224**	0.030
Forum Posting	56.032	1	4.986*	0.015
Module Viewing	5271.085	1	9.622**	0.028
		End-of-Semester Student Engagement		
Forum Viewing	8003.376	1	3.715	0.011
Forum Posting	0.001	1	0.000	0.000
Module Viewing	10807.462	1	9.375**	0.027

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. MANOVA, Multivariate Analysis of Variance.

Early semester MANOVA results showed once more that the difference between a course being required or an elective incites a statistically significant difference in early semester student engagement behaviors, $F(3, 330)=9.426$, $p<0.001$; Wilk's $\Lambda=0.921$, partial $\eta^2=0.079$. Between-subjects results show that the difference between required and elective courses creates statistically significant differences for all three early semester student engagement behaviors (forum viewing, forum posting, and module viewing). Again, the results suggest that students in required courses are likely to be viewing forums more, posting more, and viewing course modules more than students in elective courses.

Mid-semester MANOVA results found once again that there is a statistically significant difference in mid-semester student engagement behaviors which are contingent upon whether or not the course is an elective or required, $F(3, 330)=3.931$, $p=.009$; Wilk's $\Lambda=0.965$, partial $\eta^2=0.035$. Furthermore, between-subjects results show that there are statistically significant differences in all three of the student engagement behaviors in the middle two weeks of the semester (forum posting, forum viewing, and module viewing). Once more, students in required courses are more likely to have higher frequencies of engagement than those in elective courses.

Last, end-of-semester MANOVA results found that yet another statistically significant difference in end-of semester student engagement behaviors based on whether or not the course is classified as an elective or as required, $F(3, 330)=3.771$, $p=.011$; Wilk's $\Lambda=0.967$, partial $\eta^2=0.033$. Between-subjects results show that the difference between required and elective only creates significant difference for end-of-semester student module viewing. Like previous results from the exploration of this research question have evidenced, students in required courses are likely to engage more by viewing modules more frequently in the last three weeks of the semester than students in elective courses.

CHAPTER 6. DISCUSSION AND CONCLUSION

6.1 Discussion of Results

This chapter discusses the results from Chapter 5 more in-depth. Then, the limitations of the project are discussed. After, the summary of the project and future directions are noted.

6.1.1 Research Question 1

A result of the exploration of research question 1 was that age was such a frequent and pervasive predictor of many, if not all, forms of student engagement, even if the semester was split up into weeks at a time. Age was additionally found to have positive, yet weak relationships with all student engagement metrics. In this instance, it is possible that age could be thought of as a "proxy" for other units of time for students such as how long their career history is and when they graduated with their undergraduate degree (unless they were a non-traditional undergraduate student, of course).

Age was also found to be most strongly correlated with module viewing behaviors across the board (with the exception of the middle two weeks of the semester, where age was also correlated similarly with forum posting frequency). It could be that age creates a disparity between how much students engage, especially since the correlations suggest that older students engage more than younger students. Some of the reasons for this might be that older than average students seek more assistance in their studies than others, they may have recently found that communicating online is key to their daily life and exploit it, or they may find that the comradery of their classmates in the LMS is worth adding to, participating in, and experiencing. It is also possible that students who are of average age and younger rely on technology to communicate often already, since it has become ubiquitous and pervasive in their lives. This explosion of communication technologies (of which discussion forums and education technologies can call home), allows the younger and average age students to get and share their information more quickly, therefore possibly reducing the frequency by which they need to engage in the course in the LMS.

An example of why this phenomenon could occur might stem from heavy social media use by younger and average age students. For example, Ryan (age 25) might be likely more akin to using popular social media sites, some of which act as pure online forums (e.g., Reddit), than that of Robert (age 50) who is newer to the world of online communication. If the younger and average age students are used to participating in online discussions before coming into the program, the more likely they are to know how to use them advantageously to send and receive information for which they are learning about. This experience could potentially lead to less engagement by students because their habits might simply lessen the need to engage in the course in the LMS.

Undergraduate grade point average was also found to have positive, weak relationships with early and mid-semester forum posting behaviors. These correlational relationships are slightly weaker than that of age. UGPA was also found to be a significant predictor of forum posting over the full, early, and mid-semester, but not the end of the semester. It might be that the last three weeks of the semester, where students are working on projects and papers, is the “great equalizer” of engagement in regard to undergraduate grade point average. To this end, it is important to think about whether or not students who perform better at the undergraduate level (evidenced by their GPA) indeed suggests that “smarter,” or more motivated and organized students engage more.

Furthermore, the results from research question 1 note that UGPA tends to matter the most for forum posting behaviors. Forum posting is incorporated into students’ final course grades. Students who have found out what works best in order to get a higher course grade, evidenced by their undergraduate GPA, are likely to know that engaging in behaviors that increase their chances of earning a higher grade are important to do and in turn, do them. In this case then, students who engage more know that it is better to engage more in the forums in the LMS than in other ways, however, more attention should be given to why students who are more successful at the undergraduate level tend to not look at forums and modules as much as students who were less successful.

Results from research question 1 yielded results which suggest that demographic characteristics may interact to influence student engagement levels. The interaction between age and undergraduate UGPA has the greatest impact on the degree to which students view modules in the course in the LMS. The results show that students with above average (higher) undergraduate grade point averages engage about the same than students who have average or below average undergraduate GPAs. Major disparities occur according to age for students who have average or below average undergraduate grade point averages.

Older students with lower GPAs tend to engage much more frequently than younger and average age students, with the younger students engaging by looking at course modules the least. A potential guess as to why this might be could be that younger students are likely to have recently graduated with an undergraduate degree and because of their poor performance in undergraduate studies, it impacts how they believe they should perform in graduate studies. Average age and older students might increase their frequency more because they have likely had more experiences in which responsibility and keeping in touch with deadlines and duties matters (e.g., jobs they have held), which could translate into their desire to be more ahead of the game by viewing course modules more frequently.

6.1.2 Research Question 2

The correlations between the student engagement metrics and student success metric (final course grades) were all weakly and positively correlated. Forum posting behaviors across all time points were more correlated than forum and module viewing behaviors. Like the aforementioned discussion regarding UGPA and forum posting behaviors, forum posting is a part of a student's final course grade.

The results of the regression analyses for research question 2 also show that forum posting is an important predictor of student success, even across the time points in the semester. However, what is interesting here is, again, at the end of the semester, forum posting does not significantly predict student success. Therefore, more attention should be paid to what students do at the end of the semester and whether or not these engagement behaviors truly matter in the last three weeks of the semester. However, the lack of significant predictors of student success at the end of the semester in this case could mean that students are spending more time outside of the LMS, yet still engaging in the course by working on projects and assignments typical of graduate-level seminars.

6.1.3 Research Question 3

It also appears through the results of the analyses conducted for research question 3 that the "criterion problem" Hartnett and Willingham (1980) describe and the notion that past performance predicts future performance is still not as advisable to use when admitting students into degree programs, and furthermore in this case, online graduate degree programs. Age, gender, and whether or not students had prior studies in communication were found to not be significant predictors of nor significantly correlated with student success.

However, even though undergraduate GPA was found to be a significant predictor, (1) holistically, who a student is on their application does not predict their success in this instance, because the overall regression model was not significant and (2) even though undergraduate GPA was a significant predictor and correlate, it is only predictive of their forum posting behaviors in the LMS, which is often a part of an online student's final course grade. It would be interesting to explore this potential link better by attempting to understand what students know about being successful in collegiate coursework before coming into the program then comparing this information with their background and final course grades.

The hierarchical regression results regarding the potential impact on and prediction of student success by interaction effects were also compelling to think about further. The interaction of undergraduate grade point average and age and its impact on student success (i.e., final course grades) was interesting. For older students, it does not matter what their undergraduate grade point average is, they are likely to receive the same grade across the board. However, major differences emerged for younger and average age students.

Younger students who have higher, above average UGPAs were found to be the most successful students in the eight-week semester, yet their lower, below average UGPA counterparts had the lowest final course grades. Average age students with low, below average UGPAs had higher final course grades than their younger peers, however average students with high, above average undergraduate grade point averages have higher final course grades than older students, but not younger students.

A reason as to why this might be could stem from the fact that younger students who have low undergraduate GPAs might not have been prepared adequately in their undergraduate studies for graduate-level course work as much as their older classmates. More research should be conducted regarding the intricacies of why older students receive the similar grades across the board regardless of their undergraduate grade point average, especially when their engagement differs from their classmates because of their age (and certain forms of engagement are a part of their final course grade).

The interaction point for all three age groups between average and higher undergraduate GPAs is additionally interesting. A potential “sweet spot” for final course grades might exist at this particular point where the differences in age no longer matter. A smart conclusion from this point is to conduct studies to understand more about the intersection of age, undergraduate grade point average, and how final course grades are given in online (and even face-to-face graduate courses).

6.1.4 Research Question 4

The results of the mediation analyses from research question 4 all showed that undergraduate grade point average and final course grades are mediated by forum posting behaviors. As previously mentioned in the discussions for research questions 1 and 2, students who performed better in their undergraduate careers (which it can be assumed is evidenced by their undergraduate GPAs) are more likely to know what behaviors to enact in to get a higher final course grade. The results of the mediation analyses from research question 4 confirm that this is likely true.

Furthermore, the results from the exploration of this research question indicate that using past performance to predict future performance is somewhat the case, with a twist, of course. Using past performance in this case (undergraduate GPA) positively predicts engagement behavior (forum posting), which positively predicts student success (final course grades). One cannot say as a result of this project that only undergraduate GPA is a direct link to final course grades for online graduate students, rather higher undergraduate GPAs lead to more forum posting engagement, which leads to higher final course grades. However, more research should be conducted to show whether or not these results are also consistent with online graduate degree programs where forum posting is not incorporated into a students’ final course grade.

6.1.5 Research Questions 5a and 5b

The analyses of research questions 5a and 5b yielded results that were inconsistent with prior studies regarding teaching presence in online courses. Multiple past studies in the literature have shown that the impact of the instructor in the LMS is large for getting students to engage. In this project, the results of the correlation analysis showed a negative, weak relationship between overall instructor engagement and end-of-semester forum posting and viewing. There were also negative, weak relationships between faculty forum posting and early semester module viewing and mid-semester forum posting.

One possible explanation for why this might be the case could be that instructors are not engaging as much when students have a good grasp and strong comprehension of course content and material. Hence, a faculty member might have a “chilling” or “warming” effect on the students in the course. A chilling effect might occur when an instructor engages and incites less engagement from students (e.g. unexpected engagement, poorly-timed engagement). An instructor might have a “warming effect” when an instructor engages and incites more engagement from students (e.g. well-timed engagement, expected engagement). Future research should definitely take into account whether instructor engagement causes students to engage and vice-versa. Future studies might also look at the experience of the instructor to see if the more seasoned, veteran instructors have different engagement patterns than newer instructors.

6.1.6 Research Question 6

Last, for research question 6, the difference between a required or elective course matters for student engagement, but not for student success. In this specific program, required courses are taken early in the degree completion process before elective courses can and are taken. One take-away from the results regarding student success would be that it does not matter how long a student has been in the program for a student to be successful. There does not seem to be any knowledge about how to be successful in the courses in the program that are gained over time along the way in the degree completion process that will make students more successful at the end of the program or the beginning.

Another key take-away regards student motivation. It can be assumed that students who take elective courses are more likely to be intrinsically motivated to study and master the material because these courses match their interests. This mastery of material could then be measured by their final course grade. However, with the results of the ANOVA suggesting that the difference between required and elective does not apply to differences in student success, therefore suggesting that students' motivation about learning the material or taking the course is also not likely mean much for their level of success.

For student engagement behaviors, however, the difference between required and elective makes some statistically significant difference. The difference in course designation makes a significant difference in module viewing behaviors across the time points in the semester, as well as during the entire eight-week semester. Additionally, the difference between required and elective seems to only matter for differences in early and mid-semester forum posting behaviors, while it additionally seems to impact differences in full, early, and mid-semester forum viewing behaviors.

It is tenable to suggest that these results are as such because students are engaging less in the LMS at the end of the semester because they are likely working on projects and papers which involve engagement outside of the LMS (a typical feature of graduate-level courses). Unlike the impact of the course characteristic on differences in student success, these results show that there are differences.

The specific differences show that students in required courses are engaging more than students in elective courses, with the biggest impact being on module viewing. A reason why this might be could stem from the fact that students who are newer to the program are likely more motivated to do well in their courses (yet are new to the program and likely find the experience new and novel to them), therefore maximizing their engagement from the start of their degree completion journey. Students in elective courses might know exactly how much engagement it takes to do well, but no longer strive to go above and beyond in their coursework, even if the course is one that they elected to take. Additionally, since required courses are taken first, students might be more inept to engage more in order to keep from failing out of the program early. Students who are in the elective portion of their studies might have a well-established GPA and are likely to not worry in so much about failing out of the program instead of earning their diploma.

6.2 Limitations of This Project

As this project has evidenced, there are some strides being made in using academic and learning analytics to potentially predict or explain student success for students in online graduate degree programs, particularly in the communication discipline. However, even with these first steps, this exploratory project still has its limitations. These limitations include the time frame the data encompasses, and even more so, the incorporation of survey data to potentially understand what students are facing outside of the LMS and if this is impacting their success.

First, a large limitation is based upon data collected for this project. The data is only from a single eight-week semester of courses that is not a purely comprehensive data set of any given students' success in an online graduate degree program. To this end, to track a student from the start of their degree program to the end would be beneficial to understanding student success over the course of their post-baccalaureate education. However, a large caveat here for scholars and practitioners alike will be how to handle such a large amount of data and likewise, determining what student success would be when tracking students from the beginning to the end. In this project, student success was a students' final grade in the course from the eight-week semester, however it will be a challenge to determine if student success for online graduate students is degree completion, course grades (or grade point averages), or the degree to which students meet the learning objectives for each course.

Furthermore, this project was not able to use data about what students and instructors do outside of the LMS to either further engage or increase their success (i.e., grades). While the addition of survey data would be useful, the inclusion of data such as discussion board post word counts to understand their quality and the effort of the student, understanding whether or not students and instructors are constrained by personal factors such as work commitments or family issues would prove to be useful in projects of this nature. Information regarding students' time management skills as well as their study skills and habits would additionally be useful because it has a possibility of explaining or predicting student success as well.

The other reason why survey data would be critical would be because there are other non-academic factors that can inhibit or possibly propel a student's success. Even for undergraduate students, there are forces outside of the university that can impact their work and the completion of assignments and learning in a course. For a graduate student in an online program who is likely working or has a family, these can be an impact on their success. In this regard, the lack of data, particularly regarding what students and instructors do and are faced with outside of the LMS during their studies or employment is missing in this project and is a limitation that should be heavily addressed in the future regarding research in this area to give an even more holistic picture of students and instructors in and out of the LMS with the goal of an even further understanding and prediction of student success.

An additional limitation is that the LMS logs used for this analysis do not adequately represent all potentially meaningful possible data that could be collected for a student. As an example, LMS course logs do not detect and capture other behaviors in the LMS such as when students e-mail their instructor. Moreover, though the number of posts a student or instructor makes were counted in the LMS course logs, logs in this particular LMS do not include information such as the length of a forum post or the time spent looking at resources outside of the LMS, just that they posted to the forum and accessed the resource. As LMS log systems become more advanced and have the capability to capture more data from students and instructors, more salient metrics of student and instructor engagement might yield new insights into their behaviors in (and out) of the LMS.

Another limitation of this study is that discussion posts are factored into grades in this program. Because there are no changes in the expectations surrounding discussion posts in the program, engagement should look quite similar over the course of the eight-week semester. With this particular metric, though, engagement is improving performance above and beyond what I would expect if this metric only captured that posts are graded assignments.

Additionally, another possible limitation with engagement metrics is that they are all very strongly correlated with each other. However, while these engagement metrics are highly correlated with each other, forum posting has a stronger relationship than other metrics with grades. These other ungraded, and perhaps unseen forms of engagement could be part of why students perform better, but in the regression models, more of the variability in grades was captured by forum posting behaviors.

Another limitation was that the subject population in this study were graduate students. Typically, graduate students are usually “better” students. Because of this typicality, having graduate students as the subject population in this study may not accurately reflect the variation of student quality that is more clearly evident among undergraduate students. Therefore, in special regard to thinking about performance as grades, and grades as success, then, might additionally be a limitation for this project. In general, grades are likely not a good measure of student success and because graduate students are usually admitted because they are strong-performing students, usually their grades do not vary much, compounding the potential problem. Translating this to results then likely means that a lack of variation in grades might have the tendency to weaken the impact of student background and student engagement on student success or performance. Therefore, grades as the metric of student success in this project might not have been the best or very particularly sensitive one to use.

6.3 Summary of Project

To summarize this project, first there was a strong need to conduct this research based on past literature regarding student success, graduate admissions research, and research regarding learning and academic analytics. Then, a working model was developed in order to explore the intersections of these areas for an online graduate degree program in communication. Six research questions were developed and analysis was conducted using bivariate correlations, multiple regression, and when appropriate, MANOVA.

Overall, and even with this project's limitations, this study did find some important results regarding online graduate student success. Age is a pertinent factor in whether or not a student is successful as well as whether or not they engage in the LMS, however, it should be noted that age in this instance may be acting as a proxy for more pragmatic background metrics. Student forum posting behaviors were consistently found to impact student's success in their course (i.e., had an impact on their final grade). A surprising result from the data showed that instructors in online graduate seminar courses do not seem to have a great deal of impact on how much students engage or on their success in their courses. Another interesting result from the data emerged as the difference between whether or not a course is required or not makes an impact on how students engage, but not on their final course grade (i.e., success).

6.4 Implications

The implications of this project can be divided into scholastic implications as well as implications for practitioners of LA and AA. Scholars now have a more complete understanding of how students' backgrounds and engagement behaviors have on their success. Scholars now also have an additional piece of understanding how instructors in online graduate courses impact their students, if at all. They are now also further encouraged to find out what student success means, especially for students in online graduate degree programs. Last, scholars are also given a unique opportunity to focus their attention to the graduate student population and their academic issues.

From an LA and AA perspective, this is one of the few studies in which the graduate student population has been examined and likely to be one of the first few in which online graduate students have been considered. To have a project conducted using AA and LA approaches is key to inciting more research about the applicability of AA and LA for graduate programs not only online, but also in face-to-face format. While this project is not the silver bullet for understanding and predicting student success for online graduate students, it is a start for considering if and how AA and LA approaches could be appropriate for assisting the graduate student population without a great deal of technical challenges.

For practitioners, especially for those who have long been addressing the needs of undergraduate students, this project is hopefully the first of many to come to help graduate students become successful or improve upon their level of success. This project is also imperative to help practitioners use appropriate metrics and think about the relationships between metrics regarding student background, student engagement, and student success when they embark upon projects to explain or predict student success in not only graduate degree programs, but especially those that are offered online.

The idea of a mediated model as a start to understand online graduate student success was explored in this project, but it should not be the end-all, be-all model for student success. Practitioners should be thinking about how to best incorporate educational data into models to see if a particular combination works best, but to also begin to ponder about generalizability to most online graduate degree programs. All in all, this project opens the gateway for more creative and forward-thinking practices for using LA and AA to further assist the graduate student population, online or face-to-face.

This study also serves as a unique intersection for the communication discipline and academic and learning analytical approaches. In this area, more research should be conducted to understand whether or not the communication discipline is an appropriate juncture for the application of AA and LA research. As more communication programs start their transition to offering graduate studies online, this area of research will need to increase to ensure that students are learning and at the same time are successful students. Communication pedagogy and assessment scholars in particular could make a strong impact in this area in the future.

Last is the impact on the Online Masters Program in Communication. A large focus of why many LA and AA projects are ineffective are because they do not produce actionable intelligence. However, in the case of this project a large implication is that the results of these analyses provide some actionable intelligence that the program could use to appropriately intervene to improve the rate of student success. An example of how actionable intelligence is present and possibly used would be that the knowledge gained from this project could be used to create a early warning system for students and instructors, located in the LMS. Because the results show that early and mid-semester engagement is important to student success, students who are not engaging enough can be alerted and at the same time given tips and tricks on how to engage more.

An additional example is for the program's admissions purposes. Because the project's results showed significant interaction effects between undergraduate GPA and age on student engagement, the program might further consider whether or not younger students with lower grade point are adequately prepared for graduate studies in an online, off-campus environment and are, consequently ready for admission. A last example would be improvements to the LMS such that courses are designed to increase student engagement and that coding algorithms that capture data for LMS logs could advance as technology advances in order to capture and promote more student behaviors that are potentially salient predictors of or relators to student success.

6.5 Future Directions

Obtaining self-report survey or qualitative data especially in regard to time management, study skills, and life for students outside of their studies. Because not much is known about what students do outside of the LMS in online courses, these types of information would provide additional insight into other student behaviors that might have a link to student success. However, the caveat to using this type of data is to be cognizant of self-reporting biases to ensure the accuracy of students' behaviors like the behaviors that are logged in the LMS.

At the end of this project, it is crucial to consider the argument that Nelson and Nelson (1995) put forth; there is still very little understanding to what success in graduate school looks like. As the results of this project demonstrate, it appears that there are still more mysteries to be solved in order to finally put all the pieces of this puzzle together. Future research that is conducted in this area should continue to attempt to understand what graduate student success actually looks like, not only for the traditional, in-class graduate student, but also those in the ever-growing number of online graduate degree programs.

Another consideration to make regarding the future of research and work done in this area would be to consider whether or not certain LA and AA approaches are useful for studying graduate students, and furthermore, those graduate students that are taking classes online. In this study in particular, some ideas about what the use of LA and AA are possibly for predicting and explaining student success for online graduate students, however, it is imperative for further research to determine if there are improvements to be made to the approaches done here or to take these approaches and develop them even further.

Because the research is so vast, it is greatly worthwhile to understand how the instructor plays a role in how graduate students communicate on and utilize the LMS.

The results from this project are confounding with results from previous studies, not insomuch that the impact of instructors in the LMS does not predict grades, but that the impact of the instructor did not predict or show a strong link to student engagement behaviors. Further research should take into careful consideration whether or not undergraduate students and graduate students behave the same way when instructors get involved in the LMS, and even more so, how it could differ for on-campus and online graduate degree programs.

In the communication discipline, this project hopefully becomes one of the many studies that incorporate data-driven analytics into assessment and evaluation work. The use of big data is becoming increasingly important in a number of fields, and communication studies should no longer be strangers to this type of work. It is absolutely critical for the communication discipline to get out in front of this area of research earlier in the future than not in order to be contributors to a much larger issue of how successful their students are academically and when preparing them for future careers in communication.

From this previous idea comes the idea of determining whether or not success for students comes after they have completed a degree program. Not only is this for the communication discipline, but also for all disciplines. The potential consideration of what students do after they finish their work for their degree might be a good marker of success as well. If future studies and projects thought about the ends, there may just be a good chance that the means to those ends can also be justified. For student success in regard to both undergraduate and graduate education, beginning with the end in mind would be a good place to start.

With the highest of hopes for the future of projects and studies in this particular area of research regarding graduate student success in online degree programs, these future directions should be given serious consideration for the sake of understanding or predicting student success for online graduate degree programs. The pondering that should take place regarding the definition of student success, the appropriateness of certain AA and LA practices, as well as the use of key metrics and variables in these analytics projects will positively propel this area of research towards the goal of helping all graduate students, online or not, to be successful. All in all, more research is clearly needed in this area to understand more about face-to-face and online graduate degree programs and their students to ensure that academic success is not out of any student's reach.

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APPENDICES

Appendix A Metrics

Table 8. Student Background Metrics

Variable	Description	Examples & Non-Examples
Age	The age of the student. Calculated by subtracting the student's year of birth on their application from the current year.	*Ex:* 2016 – 1946 = 70, 2016 – 1986 = 30
Gender	The gender of the student as reported on their application.	*Ex:* Female = 1, Male = 0
ComDeg	Indicates whether or not the student has a prior degree at any level in communication or allied field.	*Ex:* Public Relations, Journalism, Advertising *Non-Ex:* Accounting and Finance, Geology, Secondary Education
UGPA	The student's highest undergraduate grade point average reported for their baccalaureate degree on their application.	*Ex:* 3.64, 2.27 *Non-Ex:* Degrees from International Schools, GPAs Not Reported

Table 9. Course Characteristic Metric

Required_Elective	Indicates whether or not the course the student was enrolled in was a required or elective course during the second session of the Summer 2016 semester.	*Ex:* Required = 0, Elective = 1

Table 10. Faculty Engagement Metrics

Variable	Description	Examples & Non-Examples
Faculty Forum Engagement	The amount of engagement of the instructor in discussion board posts during the semester.	*Ex:* Posting in discussion boards in the LMS.
Faculty Overall Engagement	The overall amount of relevant faculty engagement behaviors in the LMS including forum posting.	*Ex:* Posting resources, posting extra readings, grading assignments, posting in forums and discussion boards.

Table 11. Student Engagement Metrics

Variable	Description	Notes
Student Forum Posting	The amount of engagement of the student in discussion board posts during the semester.	*Note:* These were also split into early (first three weeks), mid- (middle two weeks), and late (last three weeks) semester totals as separate variables.
Student Forum Viewing	The amount of times a student viewed a forum during the semester.	*Note:* These were also split into early (first three weeks), mid- (middle two weeks, and late (last three weeks) semester totals as separate variables.
Student Module Viewing	The frequency of views of a course module during the semester	*Note:* These were also split into early (first three weeks), mid- middle two weeks, and late (last three weeks) semester totals as separate variables.

Table 12. Student Success Metric

Variable	Description	Examples & Non-Examples
Final Course Grade	The final grade of the course for the student out of 100 percentage points.	*Ex*: 95.23, 84.30, 72.99

Appendix B Results

Table 13. Hierarchical regression results for full semester student forum viewing.

	Full Semester Student Forum Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	3.564	0.809	0.240***	
Gender	16.819	16.692	0.055	
COMDeg.	17.933	15.259	0.064	
UGPA	25.551	18.614	0.075	
Constant	-76.719	69.569		0.066
Model 2[B]				
Age	0.878	1.749	0.059	
Gender	31.339	24.341	0.103	
COMDeg	37.311	27.831	0.133	
UGPA	70.757	36.455	0.208	
Age*Gender	2.432	1.833	0.139	
Age*UGPA	-2.854	2.114	-0.076	
Age*COMDeg	1.743	1.622	0.080	
Gender*UGPA	-23.030	38.537	-0.053	
Gender*COMDeg	-27.596	33.454	-0.094	
UGPA*COMDeg	-55.043	37.327	-0.113	
Constant	-140.051	135.603		0.023

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.066***, B=0.089***.

Table 14. Hierarchical regression analysis results for full semester student forum posting.

	Full Semester Student Forum Posting			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.298	0.066	0.244***	
Gender	0.281	1.367	0.011	
COMDeg.	-0.405	1.249	-0.018	
UGPA	3.727	1.524	0.133*	
Constant	9.198	5.695		0.075
Model 2[B]				
Age	0.184	0.144	0.151	
Gender	0.925	2.005	0.037	
COMDeg	0.629	2.292	0.027	
UGPA	7.839	3.002	0.281**	
Age*Gender	0.083	0.151	0.058	
Age*UGPA	-0.053	0.174	-0.017	
Age*COMDeg	0.110	0.134	0.061	
Gender*UGPA	-4.264	3.174	-0.119	
Gender*COMDeg	-1.487	2.755	-0.061	
UGPA*COMDeg	-2.849	3.074	-0.071	
Constant	-0.568	11.168		0.012

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.075***, B=0.088***.

Table 15. Hierarchical regression analysis results for full semester student module viewing.

	Full Semester Student Module Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	2.805	0.538	0.282***	
Gender	2.377	11.101	0.012	
COMDeg.	3.855	10.147	0.021	
UGPA	16.004	12.379	0.070	
Constant	20.139	46.265		0.081
Model 2[B]				
Age	2.950	1.157	0.297*	
Gender	5.343	16.110	0.026	
COMDeg	9.251	18.420	0.049	
UGPA	57.126	24.128	0.251*	
Age*Gender	-0.176	1.213	-0.015	
Age*UGPA	-3.729	1.399	-0.148**	
Age*COMDeg	-0.259	1.074	-0.018	
Gender*UGPA	-40.134	25.506	-0.138	
Gender*COMDeg	-9.614	22.142	-0.049	
UGPA*COMDeg	-20.778	24.705	-0.064	
Constant	-121.065	89.750		0.032

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.070***, B=0.085***.

Table 16. Hierarchical regression analysis results for early semester forum viewing.

	Early Semester Forum Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	1.471	0.367	0.220***	
Gender	5.444	7.571	0.040	
COMDeg.	6.874	6.921	0.054	
UGPA	10.692	8.442	0.070	
Constant	-27.726	31.533		0.042
Model 2[B]				
Age	0.485	0.795	0.073	
Gender	10.063	11.071	0.073	
COMDeg	13.380	12.658	0.106	
UGPA	32.200	16.581	0.210	
Age*Gender	0.887	0.834	0.113	
Age*UGPA	-1.236	0.962	-0.073	
Age*COMDeg	0.644	0.738	0.065	
Gender*UGPA	-15.253	17.528	-0.078	
Gender*COMDeg	-9.384	15.216	-0.071	
UGPA*COMDeg	-20.951	16.978	-0.096	
Constant	-66.361	61.677		0.043

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.054***, B=0.072**.

Table 17. Hierarchical regression analysis results for early semester forum posting.

	Early Semester Student Forum Posting			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.121	0.032	0.208***	
Gender	-0.212	0.655	-0.018	
COMDeg.	-0.380	0.599	-0.035	
UGPA	1.723	0.730	0.130*	
Constant	3.683	2.730		0.059
Model 2[B]				
Age	0.062	0.069	0.107	
Gender	0.441	0.958	0.037	
COMDeg	0.623	1.096	0.057	
UGPA	3.465	1.435	0.261*	
Age*Gender	0.073	0.072	0.107	
Age*UGPA	-0.043	0.083	-0.029	
Age*COMDeg	0.009	0.064	0.010	
Gender*UGPA	-2.558	1.517	-0.150	
Gender*COMDeg	-1.436	1.317	-0.125	
UGPA*COMDeg	-0.241	1.470	-0.013	
Constant	-0.357	5.339		0.017

Note. ****p* < 0.001 or *p* = 0.001. ***p* < 0.01. **p* < 0.05. R^2 Values, A=,0.059*** B=0.077**.

Table 18. Hierarchical regression analysis results for early semester module viewing.

	Early Semester Student Module Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	1.091	0.265	0.226***	
Gender	-1.234	5.460	-0.012	
COMDeg.	1.320	4.991	0.014	
UGPA	9.437	6.089	0.085	
Constant	9.627	22.758		0.055
Model 2[B]				
Age	0.750	0.573	0.155	
Gender	2.423	7.982	0.024	
COMDeg	7.112	9.126	0.078	
UGPA	25.148	11.954	0.228*	
Age*Gender	0.345	0.601	0.061	
Age*UGPA	-1.032	0.693	-0.084	
Age*COMDeg	0.137	0.532	0.019	
Gender*UGPA	-21.413	12.637	-0.151	
Gender*COMDeg	-8.628	10.970	-0.090	
UGPA*COMDeg	-1.751	12.240	-0.011	
Constant	-31.911	22.758		0.019

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.055***, B=0.075**.

Table 19. Hierarchical regression analysis results for mid-semester forum viewing.

	Mid-Semester Student Forum Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.844	0.201	0.230***	
Gender	4.658	4.139	0.062	
COMDeg.	2.593	3.784	0.037	
UGPA	6.932	4.615	0.083	
Constant	-21.571	17.250		0.062
Model 2[B]				
Age	0.250	0.434	0.068	
Gender	8.536	6.042	0.113	
COMDeg	7.532	6.908	0.109	
UGPA	15.927	9.049	0.190	
Age*Gender	0.529	0.455	0.122	
Age*UGPA	-0.633	0.525	-0.068	
Age*COMDeg	0.390	0.403	0.072	
Gender*UGPA	-1.158	9.565	-0.011	
Gender*COMDeg	-7.034	8.304	-0.096	
UGPA*COMDeg	-15.151	9.265	-0.126	
Constant	-32.891	-33.659		0.022

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.062***, B=0.084**.

Table 20. Hierarchical regression analysis results for mid-semester forum posting.

	Mid-Semester Student Forum Posting			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.084	0.019	0.236***	
Gender	0.142	0.397	0.019	
COMDeg.	-0.103	0.363	-0.015	
UGPA	1.316	0.443	0.162**	
Constant	0.572	1.656		0.079
Model 2[B]				
Age	0.023	0.042	0.066	
Gender	0.202	0.582	0.028	
COMDeg	-0.049	0.665	-0.007	
UGPA	1.784	0.871	0.219*	
Age*Gender	0.037	0.044	0.089	
Age*UGPA	0.001	0.051	0.001	
Age*COMDeg	0.071	0.039	0.136	
Gender*UGPA	-0.013	0.921	-0.001	
Gender*COMDeg	-0.045	0.799	-0.006	
UGPA*COMDeg	-0.934	0.892	-0.080	
Constant	1.143	3.240		0.016

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.079***, B=0.095***.

Table 21. Hierarchical regression analysis results for mid-semester module viewing.

	Mid-Semester Student Module Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.506	0.140	0.200***	
Gender	0.634	2.887	0.012	
COMDeg.	-1.467	2.639	-0.031	
UGPA	1.640	3.220	0.028	
Constant	15.678	12.034		0.043
Model 2[B]				
Age	0.853	0.301	0.337**	
Gender	0.052	4.187	0.001	
COMDeg	-2.155	4.788	-0.045	
UGPA	8.810	6.271	0.152	
Age*Gender	-0.431	0.315	-0.144	
Age*UGPA	-0.959	0.364	-0.149**	
Age*COMDeg	-0.129	0.279	-0.035	
Gender*UGPA	-5.511	6.629	-0.074	
Gender*COMDeg	0.336	5.755	0.007	
UGPA*COMDeg	-4.204	6.421	-0.051	
Constant	-19.498	23.327		0.034

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.043**, B=0.077**

Table 22. Hierarchical regression analysis results for end-of-semester forum viewing.

	End-of-Semester Student Forum Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	1.243	0.271	0.249***	
Gender	5.740	5.602	0.056	
COMDeg.	8.376	5.121	0.089	
UGPA	6.939	6.246	0.061	
Constant	-23.519	23.346		0.070
Model 2[B]				
Age	0.395	0.586	0.079	
Gender	10.827	8.155	0.106	
COMDeg	10.035	9.325	0.160	
UGPA	22.348	12.214	0.196	
Age*Gender	0.695	0.614	0.119	
Age*UGPA	-1.252	0.708	-0.099	
Age*COMDeg	0.641	0.544	0.087	
Gender*UGPA	-7.343	12.912	-0.050	
Gender*COMDeg	-9.627	11.209	-0.097	
UGPA*COMDeg	-18.343	12.506	-0.112	
Constant	-47.600	45.434		0.026

Note. ****p* < 0.001 or *p* = 0.001. ***p* < 0.01. **p* < 0.05. R^2 Values, A=0.070***, B=0.097***.

Table 23. Hierarchical regression analysis results for end of semester forum posting.

	End-of-Semester Student Forum Posting			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	0.113	0.024	0.251***	
Gender	0.480	0.504	0.052	
COMDeg.	0.239	0.461	0.028	
UGPA	0.945	0.562	0.092	
Constant	3.365	2.102		0.072
Model 2[B]				
Age	0.104	0.053	0.232	
Gender	0.431	0.742	0.047	
COMDeg	0.216	0.848	0.025	
UGPA	2.209	1.111	0.215	
Age*Gender	-0.018	0.056	-0.034	
Age*UGPA	-0.003	0.064	-0.002	
Age*COMDeg	0.046	0.049	0.069	
Gender*UGPA	-1.210	1.174	-0.092	
Gender*COMDeg	0.017	1.019	0.002	
UGPA*COMDeg	-1.005	1.137	-0.068	
Constant	-0.387	4.131		0.008

Note. ***p < 0.001 or p = 0.001. **p < 0.01. *p < 0.05. R^2 Values, A=0.072***, B=0.080**.

Table 24. Hierarchical regression analysis results for end-of-semester module viewing.

	End-of-Semester Student Module Viewing			
	B	*SE B*	ß	ΔR^2
Model 1[A]				
Age	1.129	0.195	0.311***	
Gender	2.949	4.021	0.039	
COMDeg.	3.791	3.676	0.055	
UGPA	3.247	4.484	0.039	
Constant	2.828	16.579		0.098
Model 2[B]				
Age	1.196	0.415	0.329***	
Gender	1.947	5.773	0.026	
COMDeg	2.726	6.600	0.040	
UGPA	20.336	6.645	0.244*	
Age*Gender	-0.058	0.435	-0.014	
Age*UGPA	-1.852	0.501	-0.201***	
Age*COMDeg	-0.160	0.385	-0.030	
Gender*UGPA	-11.172	9.139	-0.105	
Gender*COMDeg	0.654	7.934	0.009	
UGPA*COMDeg	-14.583	8.852	-0.122	
Constant	-0.387	4.131		0.050

Note. ***$p < 0.001$ or $p = 0.001$. **$p < 0.01$. *$p < 0.05$. R^2 Values, A=0.098***, B=0.147***.

Table 25. Bivariate correlation analysis results.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1 Grade																				
2 Age	0.05																			
3 Gender	0.05	0.00																		
4 COM Deg	-0.04	-0.10	-0.04																	
5 UGPA	0.12*	-0.06	0.15**	-0.01																
6 Req/Elec	0.09	-0.03	-0.04	0.06	-0.02															
7 Faculty Forum Posting	0.01	-0.04	-0.04	-0.06	-0.02	-0.26***														
8 Faculty Overall Engagement	-0.02	-0.08	-0.13**	-0.03	0.00	0.40***	0.41***													
9 Full Forum Views	0.15**	0.22**	0.06	0.03	0.06	-0.16**	0.01	-0.06												
10 Full Forum Posts	0.29***	0.22***	0.03	-0.04	0.12*	-0.10	-0.03	-0.08	0.59***											
11 Full Module Views	0.17**	0.29***	0.02	-0.02	0.05	-0.24***	-0.05	-0.09	0.77***	0.55***										
12 Early Forum Views	0.14**	0.20***	0.05	0.02	0.06	-0.18***	0.03	-0.05	0.97***	0.58***	0.74***									
13 Early Forum Posts	0.23***	0.19***	0.03	-0.05	0.11*	-0.16**	0.01	-0.07	0.55***	0.92***	0.52***	0.59***								
14 Early Module Views	0.15**	0.23**	0.00	-0.02	0.06	-0.28***	-0.02	-0.14**	0.73***	0.56***	0.93***	0.76***	0.59***							
15 Mid Forum Views	0.14**	0.22***	0.07	0.01	0.07	-0.17**	0.03	-0.07	0.96***	0.60***	0.76***	0.92***	0.56***	0.72***						
16 Mid Forum Posts	0.26***	0.22***	0.05	-0.05	0.15**	-0.12*	-0.09	-0.13*	0.47***	0.83***	0.48***	0.45***	0.70***	0.48***	0.52***					
17 Mid Module Views	0.12*	0.21***	-0.02	-0.06	0.01	-0.17**	-0.01	-0.02	0.66***	0.50***	0.89***	0.63***	0.47***	0.78***	0.73***	0.46***				
18 End Forum Views	0.17**	0.24***	0.06	0.06	0.05	-0.11	-0.50	-0.07	0.95***	0.52***	0.72***	0.88***	0.44***	0.63***	0.88***	0.41***	0.59***			
19 End Forum Posts	0.29***	0.24***	0.07	-0.01	0.09	0.00	-0.11*	-0.08	0.48***	0.85***	0.44***	0.44***	0.66***	0.40***	0.45***	0.65***	0.36***	0.50***		
20 End Module Views	0.15**	0.31***	0.04	0.01	0.02	-0.17**	-0.12*	-0.07	0.66***	0.40***	0.87***	0.58***	0.32***	0.66***	0.61***	0.35***	0.71***	0.73***	0.42***	

Note. ***p<0.001 or p=0.001. **p<0.01. *p<0.05.