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Relationship Between Active Learning Methodologies and Community College Students' STEM Course Grades

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This is to certify that the doctoral study by

Cherish Lesko

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Walden University
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MMSE, University of Delaware, 1999

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Active learning methodologies (ALM) are associated with student success, but little research on this topic has been pursued at the community college level. At a local community college, students in science, technology, engineering, and math (STEM) courses exhibited lower than average grades. The purpose of this study was to examine whether the use of ALM predicted STEM course grades while controlling for academic discipline, course level, and class size. The theoretical framework was Vygotsky's social constructivism. Descriptive statistics and multinomial logistic regression were performed on data collected through an anonymous survey of 74 instructors of 272 courses during the 2016 fall semester. Results indicated that students were more likely to achieve passing grades when instructors employed in-class, highly structured activities, and writing-based ALM, and were less likely to achieve passing grades when instructors employed project-based or online ALM. The odds ratios indicated strong positive effects (greater likelihoods of receiving As, Bs, or Cs in comparison to the grade of F) for writing-based ALM (39.1-43.3%, 95% CI [10.7-80.3%]), highly structured activities (16.4-22.2%, 95% CI [1.8-33.7%]), and in-class ALM (5.0-9.0%, 95% CI [0.6-13.8%]). Project-based and online ALM showed negative effects (lower likelihoods of receiving As, Bs, or Cs in comparison to the grade of F) with odds ratios of 15.7-20.9%, 95% CI [9.7-30.6%] and 16.1-20.4%, 95% CI [5.9-25.2%] respectively. A white paper was developed with recommendations for faculty development, computer skills assessment and training, and active research on writing-based ALM. Improving student grades and STEM course completion rates could lead to higher graduation rates and lower college costs for at-risk students by reducing course repetition and time to degree completion.

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Dedication

For Lisa, for igniting the spark of curiosity that grew into this doctoral research, and for my students past, present, and future, for teaching me more than I teach you and for giving my work meaning.

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Section 1: The Problem

Active learning methods (ALM) have been studied for their effectiveness when compared to passive lecture methods and have been found to have a positive effect on student achievement in science, technology, engineering, and math (STEM) disciplines (Freeman et al., 2014; Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2012; Kim, Sharma, Land, & Furlong, 2013). The issue of student achievement, specifically the issue of course completion, is a critical problem in the local context. Within the STEM undergraduate education context, understanding how the use of ALM relates to student grades as course completion indicators may provide important guidance in preparing faculty to provide the best opportunity for success for all students. In the current study, I investigated the predictive power of the use of ALM on STEM course student grades controlling for class size, course level (introductory or nonintroductory), and academic discipline (i.e., mathematics, applied sciences, natural sciences, engineering, and technology, and health sciences).

The Local Problem

The STEM disciplines at the postsecondary level, particularly engineering and nursing, suffer unusually high attrition rates approaching 50% in the first year (Abele, Penprase, & Ternes, 2013; Kerby, 2015; Perez, Cromley, & Kaplan, 2014; Salinas & Llanes, 2003; Wladis, Hachey, & Conway, 2015). High attrition rates are costly for both the students and the school (Abele et al., 2013; Schneider & Yin, 2012). Attrition rates vary by the type of institution with open admission community colleges experiencing the highest dropout rates (Nakajima, Dembo, & Mossler, 2012). Attrition rates and extended time to graduation can be linked to low course completion rates specifically in STEM disciplines (Flanders, 2015; Prystowsky, Koch, & Baldwin, 2015). Therefore, the problem investigated in this study was the low completion rates in STEM courses at the local community college.

Rationale

The problem of low course completion rates, specifically in STEM courses, was evident at Midwest Community College (MCC) [pseudonym] (MCC Provost, personal communication, August 15, 2016). MCC is located in a mid-size urban area and serves a large percentage of minority and nontraditional students (National Center for Educational Statistics, 2015). For the academic year 2015-2016, MCC had an overall course completion rate of 72.3% compared to a statewide average of 76.3%. Affecting the overall completion percentage, introductory STEM courses represented a large portion of the courses offered at MCC (21%) and had a completion rate of 67.2% (MCC internal document, 2016).

Definition of Terms

Active learning methods (ALM): Pedagogical methods that encourage students to actively construct their own knowledge rather than passively listening to a lecture (Chickering & Gamson, 1987).

Course completion: Achieving a grade of A, B, C, or D as a final grade as opposed to a failing grade (F) or an unofficial withdraw (UW) as designated by the Ohio Department of Education for the evaluation of state-funded institutions of higher education (Ohio Board of Regents, 2015).

Minority students: Students from population minority groups as defined by demographic data for race, ethnicity, and gender (National Center for Educational Statistics, 2015).

Nontraditional students: Students from age groups that differ from the majority college student population (National Center for Educational Statistics, 2015).

Underrepresented minorities: Students from demographic groups that do not have high participation rates in STEM fields (Hernandez, Schultz, Estrada, Woodcock, & Chance, 2013).

Significance of the Study

The improvement of STEM course completion rates among the students served by MCC may enable positive social change. Improving STEM course completion by improving student grades could potentially lead to higher graduation rates and lower cost especially for at-risk students by reducing the number of courses repeated and the time to degree completion (Schneider & Yin, 2012). In 2015, the faculty senate of MCC approved new strategic plan initiatives to increase overall course and program completion rates including a college-wide commitment to use ALM (MCC Assistant Dean of Arts and Sciences, personal communication, October 29, 2015). This study may be able to provide impetus for campus-wide change in teaching methodologies (see Borrego & Henderson, 2014).

Assisting at-risk students to degree completion by improving individual course grades may provide opportunities to access higher paying jobs and more economic security while increasing opportunities for minority participation in fields where they are traditionally underrepresented (Wladis, Hachey, et al., 2015). Increasing minority participation may also yield greater economic security and mobility as STEM fields have lower unemployment rates, better salaries, and smaller pay gaps by race and gender than non-STEM fields (Byars-Winston, 2013).

In addition to improving the economic prospects for students who complete STEM programs, increasing completion of minorities and women in fields where they are traditionally underrepresented may create social change within the professional fields. Science, engineering, and math fields are facing critical shortages of qualified candidates required to keep the United States technologically and economically competitive (Olson & Riodan, 2012). Improving completion in STEM programs could potentially help address this critical socioeconomic issue. Increasing the completion percentages of women and underrepresented minorities also may have the lasting social and professional benefit of improving collaborative creativity and innovation (American Society for Engineering Education, 2013; Chesler et al., 2015).

Deep conceptual learning about the basic and unifying principles of science and mathematics could produce a transformative educational experience that allows students to see not only how science applies to their career fields, but also to the functioning and sustainability of the natural world (Talanquer, 2014). Effecting meaningful change in the understanding of scientific principles helps to create knowledgeable consumers who will become more capable students, better trained professionals, and more discerning citizens. When citizens have the scientific understanding to interpret and make sense of the world, they become capable of taking informed action (Weasel & Finkel, 2016). Understanding

ALM and how these methods could benefit the diverse population at MCC may permit the construction of the best possible educational and social experience in which instruction is built for positioning every student for success personally, professionally, and globally as citizens of a sustainable world (Reimer et al., 2016).

Research Questions and Hypotheses

Midwest Community College had increased its focus on course completion in all academic disciplines (MCC Provost, personal communication, August 15, 2016). This was a result of the performance-based state funding formulas in which 50% of the institutional funding was dependent on course completion rates (Ohio Board of Regents, 2015). With institutional course completion rates (72.6%) below the state average (76.3%), it was imperative for MCC to address discipline areas and courses with low completion rates or risk reductions in state funding (Ohio Board of Regents, 2015). The STEM courses, especially introductory-level STEM courses that had completion rates of 67.2% and accounted for 21% of the courses offered, were areas where improvements in course completion rates could significantly impact the overall institutional completion rate.

There was, however, a lack of data on the current instructional methods used in the courses at MCC as well as how the instructional methods related to student grades and overall course completion rates (MCC Provost, personal communication, August 15, 2016). Active learning methods have shown effectiveness in improving academic achievement (Freeman et al., 2014; Kim et al., 2013). Class size (Freeman et al., 2014), whether the course is an introductory or later level course (Gasiewski et al., 2012), and academic discipline (Coppola & Krajcik, 2014; Pike, Smart, & Ethington, 2012) are factors that have also been shown to affect instructors' choice to use ALM and to predict student achievement.

In light of the need to increase STEM course completion and the research showing the influences of ALM on student achievement, MCC needed to develop a better understanding of how the instructional practices in the courses were related to STEM course student grades. Controlling for the influence of class size, course level, and academic discipline in a regression analysis allowed me to determine the relationship between ALM factor scores and STEM course student grades independent of these control variables. The National Survey of Instructional Strategies Used in IS (Information Systems) Courses (NSIS) developed by Djajalaksana (2011) was the instrument used in the study. The ALM factor scores provided by this instrument were measurements of the ALM factors of in-class ALM, highly structured activities ALM, online ALM, project-based ALM, writing-based ALM, and portfolio-based ALM (Djajalaksana, 2011).

The following research question (RQ) guided the study: After controlling for class size, course level (introductory or non-introductory), and academic discipline, do the ALM factor scores as measured by the NSIS predict STEM course student grades during Fall semester 2016 at MCC?

Null hypothesis (H_0): After controlling for class size, course level (introductory or nonintroductory), and academic discipline, there is no predictive relationship between the ALM factor scores and STEM course student grades during fall semester 2016 at MCC.

Alternate hypothesis (H_A): After controlling for class size, course level (introductory or nonintroductory), and academic discipline, there is a predictive relationship between the ALM factor scores and STEM course student grades during fall semester 2016 at MCC.

Review of the Literature

Theoretical Framework

The theoretical framework for this study was Vygotsky’s social constructivism. Similar to other forms of constructivism, social constructivism is based on the theory that learners go through a process of building their own meaning and understanding to make sense of their personal experience (Merriam, 2007; Strobel, Wang, Weber, & Dyehouse, 2013; Vygotsky, 1978). In contrast to Piagetian cognitive constructivism in which the locus of learning is the individual, social constructivism incorporates the influence of the learning environment and social contexts on the learner’s development (Kivunja, 2014). Liu and Matthews (2005) explained how Vygotsky’s historical-dialectical-monist philosophical beliefs underpin social constructivism through the definition of the role of social collectivity in learning where individual mastery is dependent on both history and culture. The participatory collaboration in shaping perceptions of the world and of history create a collective subjectivity, and Vygotsky interpreted the individual and the society as behaving in functional unity (Liu & Matthews, 2005). Because of this philosophical foundation, social constructivists see language, learning, and meaning as a dynamic, continually evolving environment in which the learner constructs meaning (Liu & Matthews, 2005). Because social constructivism rejects positivistic, behavioristic, and mechanistic models, educational structures focus on cognitive development, critical thinking, and deep learning rather than learned behaviors or objective goals (Fosnot & Perry, 1996). The focus on cognitive development and critical thinking creates a dynamic, process-oriented approach that enables learners to actively participate in the building of their own understanding and has been shown to improve student outcomes (Fosnot & Perry, 1996). Most notably, a large meta-analysis of research on ALM in STEM courses showed a mean reduction in failure rates of 12% (Freeman et al., 2014, p. 8411).

Vygotsky's social constructivism dictates that the learning environment plays a crucial role in the construction of knowledge, implying that the social context in which the ALMs are used influences their effectiveness (Merriam, 2007). Therefore, the research question in the current study addressed the social context of learning through the use of ALM factor scores. The ALM factors were used to divide the list of 52 ALM into six groups that demonstrate different levels of social interaction. For example, in-class and project-based ALM factors have high levels of social interaction while online and highly structured activities ALM have moderate levels of social interaction, and portfolio-based ALM and writing-based ALM have little or no social interaction (Prince, 2004). The list of the 52 ALM by factors with definitions is included in Appendix C.

Social constructivism specifies that through the use of language and symbols, learning is not just an active construction of an individual understanding but an indoctrination into the speech and manner of the group (Cobb, 1994). Vygotsky (as cited in Merriam, 2007) theorized that "learning is socially mediated through a culture's symbols and language" (p. 292). Including the academic disciplines as a control variable of the study was also grounded in the desire to explore the social context of the ALM factors as well as the fact that the cultures of different academic disciplines influence the use of language and symbols in the classroom.

Vygotsky's theory on social constructivism is also noted for the concept of the zone of proximal development, which is foundational to the understanding of scaffolding (Karagiorgi & Symeou, 2005). Vygotsky (1978) defined the zone of proximal development as the gap between what the student can learn on his or her own and what the student can learn with the help of a more knowledgeable guide or tutor. The three components necessary for the development of the student's understanding within the zone of proximal development are authentic activities, social mediation, and individual growth (Doolittle, 1997). Social mediation provides the student with an enculturation to the skills, language, and psychology of the academic discipline (Doolittle, 1997).

Scaffolding, an important aspect of ALM, is a method of instruction that addresses the zone of proximal development for each student to provide the optimal level of intellectual challenge (Doolittle, 1997). Scaffolding assists the instructor in guiding learners from the known to the unknown by assisting the students to build on previous frameworks (Karagiorgi & Symeou, 2005). A meta-analysis of empirical research on the use of computer-based scaffolding by Belland, Walker, Kim and Lefler (2016) showed consistently positive effects for critical thinking, deep content knowledge, and student outcomes in promoting transition from application-level thinking to concept-level thinking necessary to apply scientific knowledge to new or ill-defined problems.

Vygotsky’s social constructivism was also the philosophical foundation for Leontiev’s cultural-historical activity theory (Meittinen, Paavola, & Pohjola, 2012; Merriam, 2007; Nardi, 1996). Activity theory, like social constructivism, emphasizes the dynamic nature of the activities that provide the context in which learning occurs (Nardi, 1996). Activity theory additionally borrows the concepts of reality, meaning, and knowledge from social constructivism (Marra, Jonassen, Palmer, & Luft, 2014). Vieira and Kelly (2014) posited that the external activities of learning derive from the internal activities rooted in a need or desire. Activity theory is the theoretical foundation of problem-based learning and other similar methods (Marra et al., 2014).

Vygotsky’s social constructivism provided a strong foundation for addressing the predictive relationship between ALM factor scores and STEM course student grades. Social constructivism proposes that the process of learning is active rather than passive through interaction in the social context (Merriam, 2007). Social constructivist learning environments promote the creation of artifacts (projects, designs, reflective essays) that demonstrate personal and group acquisition of knowledge and understanding (Jonassen & Land, 2012). Based on the theory and research on student outcomes, I posited a predictive relationship between ALM factor scores and STEM course student grades.

Review of the Broader Problem

The remaining literature review addresses the role the community college plays in developing the STEM workforce and the research on ALM. In the section on the community college’s role in STEM, differences in demographics and outcomes are addressed. The review of the research on ALM in STEM with respect to student outcomes focuses on STEM in general as well as in disciplines of physics, chemistry, biology, engineering, applied sciences and technology, and health sciences. Synthesizing the current research and concluding with the outlining of the alignment of the research question and hypotheses with the results of the literature review produced a strong case for the need of the project study.

The hidden STEM. Van Noy and Zeidenberg (2014) examined the contribution that community colleges make in the development and education of the STEM workforce and called community college programs the "Hidden STEM." The community college system plays a significant role in the education of STEM professionals from workforce retraining to certificate completion to associate's degrees and university transfers (Hagedorn & Purnamasari, 2012; Packard, Tuladhar, & Lee, 2013). Due to open enrollment, reduced costs, flexible scheduling, and other community college characteristics, community colleges are the primary educational pathway for many diverse students (Barrow, Richburg-Hayes, Rouse, & Brock, 2014; Jackson, Starobin, & Laanan, 2013; Johnson, Starobin, & Santos Laanan, 2016; Strawn & Livelybrooks, 2012; Wang, 2013). In comparison to students at four-year universities, community college students are more likely to be older, first-generation college students, single parents, and underprepared (Van Noy & Zeidenberg, 2014; Wickersham & Wang, 2016). Community college students are also more likely than students at four-year institutions to participate in a practice labeled "swirling" (Van Noy & Zeidenberg, 2014), which describes the practice of taking classes at multiple institutions that have been associated with lower degree completion rates.

According to researchers, 50% of STEM graduates of four-year institutions at one point attended a community college (Jackson et al., 2013; Leggett-Robinson, Reid Mooring, & Villa, 2015; Wladis, Conway, & Hachey, 2015). Additionally, community colleges fulfill the important function of certification and workforce training in many STEM fields not offered at traditional four-year institutions, with subbaccalaureate positions accounting for one fourth of the STEM workforce (Hagedorn & Purnamasari, 2012; Van Noy & Zeidenberg, 2014). The various STEM pathways within the community college setting such as certification, Associate's in Arts or Sciences, and transfer present a heterogenous STEM student population that makes assessing STEM outcomes at the community college level more complex (Van Noy & Zeidenberg, 2014).

Active learning to increase STEM success. Constructivist theory began in the 1920s with Dewey elucidating the need for active learning (Ilica, 2016; Kivinen & Ristela, 2003; Kruckeberg, 2006; Ültanir, 2012). Chickering and Gamson (1987) stated that "learning is not a spectator sport" (p. 4), and since then empirical research into the effect of active learning methods on educational performance has increased significantly. By 2013, 225 studies were identified that specifically linked ALM in STEM undergraduate education with either exam scores or course failure rates (Freeman et al., 2014, p. 8410). Freeman et al. at the Proceedings of the National Academy of Science posited that research comparing ALM to traditional lecture methods was so extensive and decisive that the comparison should no longer be a topic of debate, but instead put forth that new research should focus on which ALM are most effective in improving student outcomes in the local context. Research articles spanning 2005 to 2016 that provide results in support of the argument that ALM produce better student outcomes with respect to traditional lecture within the broader context of STEM fields are reviewed below.

STEM as a whole. Empirical evidence from the current literature that shows positive effects of ALM on student achievement, student motivation, and other outcome variables typically fall into one of three categories: STEM as a whole, specific methodologies, and particular disciplines or classes. Gasiewski et al. (2012) produced one of the key studies on the relationship between ALM and student engagement in STEM, which continues to be widely cited. Gasiewski et al. conducted a sequential, explanatory mixed-methods study that included quantitative data from surveys of 2,873 students in 73 STEM classes across 15 diverse colleges and universities and qualitative data culled from 41 focus groups at eight of the institutions. Key findings for active learning included positive predictive power for collaboration, group work, class discussion, innovative teaching, and supportive class climate, and negative predictive power for lecture methodology (Gasiewski et al., 2012).

Carlson, Celotta, Curran, Marcus, and Loe (2016) conducted a mixed-methods matched-pair study to evaluate the effect that involvement in peer-led team-learning programs had on students in gateway calculus, biology, statistics, and chemistry classes with qualitative results indicating that most students felt that the program was instrumental in helping them succeed and that they developed an appreciation for conceptual understanding in place of memorization. Gao and Schwartz (2015), in reaction to the intense focus on introductory STEM courses, investigated whether there would be a difference in outcomes between introductory-level and advanced-level STEM courses when using ALM. Gao and Schwartz found that the increases in student learning and engagement were present and significant at both levels of course work.

Gehrke and Kezar (2016) hypothesized that reforms in STEM education are supported by faculty participation in communities of practice. The authors used a sequential, exploratory mixed-methods study to evaluate the change perceived by STEM faculty who participated in four communities of practice that encouraged change in STEM education. The results indicated that personal and institutional changes were recognized by large percentages of faculty involved with these organizations with greater gains reported by women and persons of color. Weasel and Finkel (2016) focused on the need for STEM classes to provide education for good citizenship, particularly in introductory-level classes attended predominantly by non-STEM majors. Weasel and Finkel discussed an ALM called deliberate democracy aimed to increase student engagement through discourse and encourage participatory citizenship through decision-making in the public sphere. The authors used a pretest/posttest to quantify increases in conceptual understanding and critical analysis skills but did not use a control group for comparative effects.

In contrast to the large majority of studies linking active learning to successful student outcomes, Reimer et al. (2016) spent 1 year making observations in 40 sections of eight large, introductory-level courses at a selective four-year research institution to study the connection between instructional methods and student success. The method involved a student-level, cross-course, fixed-effect design in which Reimer et al. analyzed the relationships between instructional methods and student grades, subsequent enrollment in the next course in the sequence, and student grades in the next level course. Using logistic and ordinary least squares regression, Reimer et al. found little evidence that different instructional strategies affected improvement in student outcomes except in the case of first-generation students. Although this seems contradictory, Reimer et al. acknowledged that the results may support other research findings that ALM are most effective for the most at-risk students. Students successful in gaining admission to highly selective universities are typically at low risk for nonpersistence because they already exhibit the motivation, study skills, and self-efficacy needed to overcome poor learning environments. Rissanen (2014) also performed research on ALM versus traditional lectures and found that there was no difference in student performance as a result of active pedagogies. The study, however, was conducted at a military academy that involved a specific population of high-performing and conforming students (Rissanen, 2014), which was significantly different from student populations at community colleges.

Focus on methods. Wash (2014) discussed the results of a student survey about the use of the Socrative™ polling application from MasteryConnect™ for interaction and formative assessment. Using descriptive statistics, Wash showed that students had positive attitudes towards the use of the technology which increased engagement and satisfaction. Stover, Noel, McNutt, and Heilmann (2015) conducted a survey of students in five classes using the similar polling app, Poll Everywhere™. They performed an exploratory factor analysis to identify the significant responses (Stover et al., 2015). The software program, NVio10™, was used to analyze the open-ended questions for themes.

Stover et al. also used bivariate analysis to look for a correlation between the perceived student learning and classroom engagement which produced a significant correlation (r = .55, $p < .01$, n = 91). Most students reported the opinion that using the polling application increased their participation and helped them understand the material. A limitation to this study was the reliance on student perceptions instead of using performance metrics such as grades or concept inventories (Stover et al., 2015). Lawrie et al. (2014) also found that formative feedback similar to that from polling methods was essential to the development of self-regulated learning, but summative assessment still needed to be included in order to encourage students to engage with the technologies.

Along another avenue of methods application, Koenig, Schen, Edwards and Bao (2012) examined the effectiveness of creating a scientific thought and methods course as a prerequisite to higher-level science coursework. The class was designed to assist students who were not able to begin their major coursework because of placement into remedial classes. The students who participated in the scientific thoughts and methods class showed significantly higher retention in STEM majors than nonparticipants who were also placed in remedial math (Koenig et al., 2012). In the same theme as course design, Moore and Smith (2014) proposed integrating the STEM disciplines to teach all components in a project-based setting. The integrated STEM project classes would be developed to use engineering design to create a technology using principles learned from science and math foundations (Moore & Smith, 2014).

Reynolds, Thaiss, Katkin, and Thompson (2012) proposed a community-based approach to increasing higher-order thinking by incorporating writing skills into STEM programs. The supposition they made was that the writing process involves restructuring of the information which leads to active constructivism (Reynolds et al., 2012). The article, however, did not provide empirical results to confirm the authors' supposition as it was primarily a literature review and program white paper.

Active learning in physics. In the application of active learning methods to specific disciplines, Wieman and Perkins (2005) presented one of the seminal position papers on the change necessary in physics education through the use of active learning and educational technologies such as clickers and simulations to reduce students' cognitive loads. Their work led to the establishment of pHET® interactive simulations that incorporated their propositions on ALM in physics and have expanded to include simulations in math, chemistry, Earth science, and biology. Clark, Nelson, Chang, Martinez-Garza, Slack, and D'Angelo (2011) reported the results of a quasi-experimental, pretest/posttest measure of physics conceptual understanding for middle school science students using the SURGE© physics game environment. Matched pair t-tests indicated significant gains on the posttests and item analysis showed that gains were made in similar items across samples in two countries indicating the benefits of gamification may translate well cross-culturally (Clark et al., 2011). Mendez-Coca and Slisko (2013) produced an initial feasibility study on the use of real-time polling technology to help instructors assess student learning in real time and re-explain problem areas using just-in-time methods in a physics education class. Students were surveyed for opinions on using the polling app and the majority expressed that the use was fun, encouraged discussion and argument, and improved their understanding of the physics concepts (Mendez-Coca & Slisko, 2013). In a study of retention in physics programs, Watkins and Mazur (2013) investigated peer instruction in combination with clicker questions showing that the immediate feedback resulted in higher scores on assessments.

More recently, Pedersen et al.(2016) described the results of quasi-experimental research on the use of a virtual learning environment (VLE) in a graduate-level quantum mechanics class. The VLE included simulations, quizzes, video lectures and gamification features. Pedersen et al. used two cohorts (2013 and 2014) as the control and experimental group. Mann-Whitney U test results showed a strong correlation between the use of the VLE and grades on the exams. These results were not correlated with prior GPA indicating that the use of the VLE had equal benefits for both stronger and weaker students (Pederson et al., 2016). Türkay (2016) used a between-subjects experimental design to examine the effect of lesson formats on subjective experiences, immediate knowledge retention, and behavioral measures of engagement in physics. The remote lesson formats that Türkay tested were audio only, text only, narrated slides, and whiteboard animations. Türkay used multiple statistical methods to analyze the results which showed consistent support of the hypothesis that students receiving the lesson in the group with whiteboard animations have significantly higher positive results and attributed the difference to the students' perception of a first-person experience when using the whiteboard animations.

Active learning in chemistry. In chemistry, Eichler and Peeples (2016) presented the results of an ex post facto quasi-experimental study on the effect of flipped classroom methods (pedagogies that present the lecture portion via electronic media while normal class times are used for problem-solving) on course completion and student performance in a large, freshman chemistry class. Eichler and Peeples used descriptive, ANOVA, and linear regression statistical models to process data from two sections of the same chemistry class where one used flipped classroom methods and the other did not. Results indicated that there was no significant difference in final exam scores between the two sections, but the flipped classroom had higher levels of student satisfaction, three times lower withdrawal rates, and final grades rose 18% higher (Eichler & Peeples, 2016). Yestrebsky (2015) also investigated the use of flipped classrooms in general chemistry through a mixed-method study. The quantitative portion of the study used the final exam as a posttest only experimental design and the qualitative measures were the student perceptions of instruction obtained by survey (Yestrebsky, 2015). In the analysis of the data, Yestrebsky divided students by previous academic performance and showed that the flipped classroom methods were helpful to improving the outcomes for average performing students, but had negligible benefit to the highest or lowest performing students.

Like the field of physics, much research has been done on the use of simulations in chemistry. In a summary of the state of the art for the American Chemical Society, Jones and Kelly (2015) described how the difficulty students face in understanding chemistry can be attributed to the fact that the study of chemistry involves the intersection of the visible, the symbolic, and the submicroscopic worlds. Animations and simulations construct the bridges to connect the different worlds and allow students to observe unobservable phenomenon (Jones & Kelly, 2015). Pyatt and Sims (2011) measured the performance and attitudes of students using simulations to perform virtual laboratories versus a control group performing physical experimentation and found that the use of virtual labs produced greater conceptual change and students expressed overwhelming favorable attitudes toward the use of computer simulations.

Active learning in biology. Describing a novel active learning method, Weasel and Finkel (2016) used a deliberate democracy approach that required non-major biology students to engage in discourse on critical and current topics. Requiring that students perform critical analysis of scientific journal articles and popular media, Weasel and Finkel showed increases in scientific and information literacy by encouraging students to seek out evidence. Batz, Olsen, Dumont, Dastoor, and Smith (2015) examined the use of voluntary peer tutoring in an introductory biology class. Struggling students, those defined as having failed the first exam, were offered participation in the peer-tutoring program and those that selected to participate scored on average one full letter grade higher than those that did not participate (Batz et al., 2015).

Connell, Donovan and Chambers (2016) took a different approach to researching the effect of active learning on student performance. Instead of comparing the ALM to lecture methods, Connell et al. compared two sections of biology, both using active methods, but one section used ALM moderately with interspersed lectures and the other section used highly-structured and extensive ALM. Connell et al. showed that the class section that utilized ALM extensively achieved higher exam scores and more expert attitudes than the class that only used active methods moderately even with the same instructor, content, and lab teaching assistants indicating that there are implications concerning the amount of instructional time dedicated to active learning methods.

Active learning in engineering. In the engineering disciplines, Davis and Wilcock (2005) addressed the use of case studies in the teaching of material science. The evaluation of three pilot cases was accomplished using content learning criteria and student evaluations. The majority of the students surveyed believed that the case studies helped them in understanding the content (Davis & Wilcock, 2005). Lehmann, Christensen, Du, and Thrane (2008) presented three case studies of process-oriented, problem-based learning (POPBL) to demonstrate the use of POPBL in sustainability engineering programs and to show how this method of teaching sustainability development increased community outreach, interdisciplinary learning and development of diverse skills. Chesler, et al. (2015) presented research on the application of simulations for virtual internships for freshman biomedical engineering students. Chesler et al. used Epistemological Network Analysis (ENA) to code the pretests and posttests in the form of interviews to quantify and to visualize the students' cognitive networks which enables the instructor to characterize student thinking in the process of complex problem solving. Using the results of the ENA, Chesler et al. showed that students developed high levels of engineering thinking and identity through the use of the virtual internships. Halupa & Caldwell (2015) reported on a quasi-experimental study that compared the student test scores for a control group that used traditional lectures with an experimental group that used online videos and demonstrations as supplements to traditional lectures in an engineering statics class. The results indicated a slight increase in test scores for the experimental group, but the increase was not statistically significant (Halupa & Caldwell, 2015). A Likert-style survey was also administered and the results indicated that the students believed the supplementary material to be helpful (Halupa & Caldwell, 2015). Halupa and Caldwell pointed out that the results were limited by the potential of nonequivalent groups as students self-selected the section to attend.

Active learning in health science. ALM has a strong presence in the health sciences. Problem-based learning (Woltering, Herrler, Spitzer, & Spreckelsen, 2009) and guided-inquiry (Conway, 2014; Goeden, Kurtz, Quitadamo, & Thomas, 2015) are two of the methods of particular attention in this field. Woltering et al. showed increases in motivation, subjective learning, and satisfaction when using blended learning along with problem-based learning. Conway examined the effects of using a wide-ranging guided-inquiry methodology in a pre-nursing organic chemistry class. The posttest, control group experiment showed that not only did the guided-inquiry students have higher final exam scores but also a significant increase in the number of students achieving the grade of A for the class (Conway, 2014). Goeden et al. expanded on the idea of guided-inquiry methods through the development of community-based inquiry methods for their allied health biochemistry students. Using case studies, cooperative small group learning, and student-designed lab experiences, Goeden et al. showed significant improvements in students' critical thinking skills.

In a break from the majority of the research focusing on introductory undergraduate courses, Miller and Metz (2014) examined the use of interactive lectures in a physiology course at the professional doctorate level in a school of dentistry. The engaging lectures were credited with creating an 8.6% increase in the grades on the unit exams and an increase of 22.9% on the final exam (Miller & Metz, 2014). Miller and Metz noted that while the increases in student achievement were significant, the amount of prep time for the instructors using active methods was significant enough to be burdensome.

Active learning in applied sciences and technologies. In the applied sciences and technologies, Warren, Dondlinger, McLeod, and Bigenho (2012) reported on a pilot phase of implementing a combination of problem-based learning with virtual reality game elements in an introductory computer class. In the sequential, explanatory mixed-method study, Warren et al. collected quantitative data on completion and failure rates, final exam grades, and student satisfaction. This data was combined with qualitative data retrieved from students' weekly blogs and interviews with students and faculty using a constant-comparative approach and while results were mixed, improvements were seen in completion rates (Warren et al., 2012). Crandall et al.(2015) discussed a quasi-experimental examination of the use of simulations in the form of virtual labs for a food science class. The virtual lab was structured around a simulation but also had elements of gamification and was used for a between-subjects research design using two sections of the class (Crandall et al., 2015). The test results indicated that there was no statistically significant difference in the acquisition of knowledge between students who learned in a traditional lab as compared to students who used the virtual lab. Additionally, survey results indicated that students had a generally positive opinion of virtual labs (Crandall et al., 2015). Researchers de Jong, Linn, & Zacharia (2013) presented a review of the most recent research on the use of virtual laboratories in science education. Using the collected research, de Jong et al. summarized the advantages and disadvantages of physical labs and virtual labs as well as discussed educational opportunities to combine both types of labs to increase conceptual understanding.

Application of STEM instructional models research. In the research on ALM and the impact on student performance, there were limitations in generalizing the research to the local community college context. Specifically, the majority of the research on ALM in STEM fields has been completed at large, research-intensive, four-year universities (Mesa, Celis, & Lande, 2014; Van Noy & Zeidenberg, 2014; Wang, 2013; Wladis, Hachey, et al., 2015). For example, there was very little research on the effectiveness of math education in community colleges even though 83% of all remedial mathematics instruction occurs at a community college level (Mesa et al., 2014). Community colleges are uniquely responsive to the workforce training and employment needs of the communities they serve (Mesa et al., 2014). The differences due to community needs and differences in student demographics made the application of the main body of research on active learning to the local community college context not readily generalizable (Mesa et al., 2014, Wladis et al., 2015). Research on STEM programs and student achievement that has been published focuses on the successful transfer and completion of four-year degrees (Van Noy & Zeidenberg, 2014) which ignored the multiple successful STEM pathways present at local community colleges such as job retraining, certifications, transfers and associates degrees.

Previous research as foundation for study. As Freeman et al. (2014) suggested, the new direction of research should examine how ALM work in the local context. Looking at the context was particularly important when the local context of the study, a community college, had student demographics substantially different from the populations represented in most of the research. Although the vast majority of research on active learning methodologies showed positive benefits to student outcomes (Freeman et al., 2014; Gasiewski et al., 2012), it remained to be seen whether the benefits extend to the local context.

With the theoretical foundations of the study being that of social constructivism, the review of literature demonstrated how the use of ALM improved student outcomes. Using the background research, therefore, as a logical starting point, the current study asked whether there was a predictive relationship between the use of ALM and student grades for STEM courses at the local community college (Freeman et al., 2014). Based on the research presented in the review of literature, particularly in the benefits of ALM for minority, nontraditional and female students, the alternate hypothesis also aligned by positing that increases in positive student outcomes were correlated with increased use of these methodologies (Connell et al., 2016). As seen in the context of the completed review of literature, the study was a logical extension of the past and current research.

Implications

With local evidence of the predictive relationship between ALM and STEM course student grades, an evaluation of potential directions for pedagogical change was made possible. Additionally, the research indicated that different academic disciplines had different correlational results. As a result of the collection and analysis of the data, the project deliverable was a white paper summarizing the results of the research and making evidence-based recommendations to the administration of MCC for the implementation of targeted activities to improve student success.

Summary

Midwest Community College desired to improve the completion rates in all courses. In STEM courses, introductory STEM courses particularly, failing to complete the course prevented degree completion or successful transfer to a four-year institution. The problem of low completion rates in STEM courses erected barriers to success for the large numbers of underrepresented minorities and nontraditional students served by the school. Because each local community college is responsive to the local environment to provide workforce training, STEM technician degrees, and transfer programs salient to the local needs, it was important to situate any pedagogical change in the local context (see Finelli, Daly, & Richardson, 2014). Demographic differences between two-year, open access institutions and four-year, research intensive institutions necessitated the validation of the effectiveness of ALM published in the literature to the local context (Wladis, Hachey, et al., 2015).

Section 2: The Methodology

This study was a nonexperimental correlational study with regression analysis to examine the relationship between the use of ALM and STEM course student grades. I studied the relationship between a criterion variable (STEM course student grades) and predictor variables (ALM factors scores) while controlling for class size, course level, and academic discipline. The research design and approach, sampling method, instrumentation, and data collection plans and their alignment with the research question are discussed in the following sections.

Research Design and Approach

The research design was a nonexperimental correlational design with multinomial regression analysis. The research was ex post facto because the teaching with ALM had already occurred and the student grades had already been assigned (see Creswell, 2012; Lodico, Spaulding, & Voegtle, 2010). This approach and design aligned with the problem and research question because the results of the multinomial regression analysis would indicate whether a predictive relationship exists between use of ALM and STEM course student grades when controlling for class size, course level, and academic discipline. Correlational design with multinomial regression is used to determine the presence and strength of relationships between criterion and predictor variables without implying causality. A correlational study with multinomial regression analysis provided a powerful method to study all of the independent variables as they interact with the criterion variable (see Lodico et al., 2010).

Several statistical methods including hierarchical linear modeling (HLM), ordinary least squares (OLS) regression, and logistic regression are common in educational research. Hierarchical linear modeling is a complex, leveled method in which effects of variables in nested layers can be evaluated (Gelman, 2006). The multilayer approach of HLM provides more flexibility in the modeling process, but the method's complexity makes it susceptible to confusion and misuse (Ferron et al., 2004). Conversely, the simplicity of OLS generates continued use in the social sciences, but OLS is limited by the inability to reliably handle dependencies among variables or noise in the data. The results of HLM and OLS may have similar correlation coefficients but different estimates of standard error (Rocconi, 2013). Logistic regression is an accepted method for making predictions of dichotomous variables (Schumacher, Olinsky, Quinn, & Smith, 2010). For this study, the data were not multilevel, and therefore the complexity of HLM was not warranted. With the expected multicollinearities in the study's independent variables, OLS also would not have sufficed. Logistic regression would have been appropriate if the completion indicators had been binary; however, the completion indicators (student grades) were based on a nominal scale. Multinomial regression techniques were appropriate for relating multiple independent variables with a degree of collinearity to a single dependent variable on a nominal scale. It was reasonable to assume that with multiple independent variables of this type and number that some level of interrelation would exist leading to multicollinearity (see Nathans, Oswald, & Nimon, 2012).

Setting and Sample

Midwest Community College enrolls a large percentage of nontraditional and minority students. In fall 2014, 46% of students who enrolled were first-generation college students, and 62% of the students were from lower socioeconomic status as defined by being Pell-grant eligible (MCC Provost, internal communication, January 21, 2016). Additionally, 58% of the fall 2014 cohort was older than 25 years, and 71% were required to take at least one remedial course (MCC Provost, internal communication, January 21, 2016).

Census sampling was used to produce data sets for all students and instructors of STEM courses offered in the fall of 2016 semester. Census sampling was chosen because it does not lead to sampling error and is likely to provide more detailed and more accurate information on the identified subgroups of academic disciplines than random sampling methods (Levine & Stephan, 2015; Triola, 2012). For this study, the courses identified as belonging to the sample included a required lecture component, which eliminated all online courses and hybrid courses in which the lecture portion of the class was online. Hybrid courses that had a traditional lecture portion combined with an online laboratory were included in the sample.

Courses that are added after term registration has begun to accommodate additional and late registration students have shown preliminary, local, empirical evidence of significant differences in completion rates (MCC Faculty Senate President, personal communication, October 17, 2016). Observations over the last several years indicated that the differences in course completion rates between regularly scheduled classes and late-added sections exceeded 50% (MCC Faculty Senate President, personal communication, October 17, 2016). With only a small number of sections (approximately 10-12) of courses added late during the fall 2016 semester, these late-added sections were excluded from the sample with the potential for further study. Using the information on MCC's registration portal, I identified 358 STEM courses to fit the sample criteria from the fall 2016 semester. These 358 STEM courses were taught by 131 instructors and had 3,766 students. Faculty members instructing more than one STEM course were asked to complete surveys for each course.

Recruitment of Participants

All instructors of fall 2016 STEM courses were asked to complete a survey indicating the grades students achieved and how often ALM were used in the course, as well as course information including academic discipline, course level, and class size. The inclusion criteria for the sample was all instructors who completed the fall 2016 semester teaching at least one STEM class that was neither online nor added late. There were no additional exclusion criteria for the faculty or students besides participation in online STEM courses or late-added sections. Protected groups such as pregnant women and students with disabilities were not automatically excluded due to the nature of the research being similar in task and risk to other activities performed regularly as part of their roles as faculty and students.

The faculty members identified as part of the study population were recruited via electronic invitation to participate in the survey. A sample of the letter is provided in Appendix B. E-mail addresses for the faculty members were collected from the public syllabus database, and e-mails were sent individually to the selected faculty through the campus e-mail system with the statement that the research was being conducted for the purpose of completing an academic degree. The study was designed to follow closely after the end of the semester when the grades for the fall 2016 semester had been finalized and the semester was fresh in participants' minds, which increased the likelihood of accuracy in self-reporting. Because a major limitation to the validity of survey research methods is a low response rate (Edwards et al., 2009; Fincham, 2008), several steps were taken to increase response rates. First, Fincham (2008) proposed steps that have shown the possibility to increase the response rates on electronic surveys, including making multiple contacts with the participants, improving the appearance of the survey, providing incentives, personalizing the survey invitation, and indicating sponsorship. Edwards et al. (2009) in a large meta-analysis of survey research did not find any influence for indicating sponsorship, but did find that improving the survey appearance by using a white background and simplifying the header improved response rate. Additionally, Edwards et al. identified shorter questionnaires, more interesting topics, personalization, textual representations of response categories, nonmonetary incentives, and a deadline increased response rates, while mentioning "survey" in the e-mail subject line and having a male signature decreased response rates.

With the increased use of computerized surveys, response rates have been declining (M. J. D. Adams & Umbach, 2012; Schoenherr, Ellram, & Tate, 2015). Researchers face increased risk of nonresponse, which has been attributed to "survey fatigue" (M. J. D. Adams & Umbach, 2012). Currently, a response rate of 10-15% is generally expected, and when results are analyzed for data irregularities, the accurate response rates could reach single digits (Schoenherr et al., 2015). Table 1 shows methods used to improve response rates in the current study.

Table 1

Methods to Increase Response Rate

Suggested methods for increasing response rates	How the methods will be implemented
Multiple contacts (Fincham, 2008)	1. Presentation of the research topic in a faculty assembly assuring members that the survey is completely voluntary and anonymous 2. E-mail invitation to participate 3. Paper reminder to participate in faculty mailboxes 4. E-mail follow-up requesting participation from those that have not yet been surveyed
Improved appearance (Edwards et al., 2009; Fincham, 2008)	5. White background for questions 6. Simple survey description header 7. Short survey (ten questions) 8. Choose header colors to match school colors
Personalizing (Edwards et al., 2009; Fincham, 2008)	9. Personalize e-mail invitations with faculty names and titles 10. Include STEM course registration number instead of "survey" in e-mail subject line 11. Include handwritten note of thanks at the bottom of the hardcopy reminder
Providing a deadline (Edwards et al., 2009)	12. Deadline to complete the survey will be included in all correspondence

Power Analysis

The statistical power is calculated as $1-\beta$, where β represents type II errors (false negatives) and can be interpreted as the probability of incorrectly accepting the null hypothesis when the alternative hypothesis is true (Kalla, 2009). A statistical power level of $1-\beta \geq 0.80$ is considered acceptable by the U.S. Department of Education in educational research (Hedges & Rhoads, 2009). The significance level (α) is related to the type I error (false positives) in which the null hypothesis is rejected when it is true (Kalla, 2009). Significance levels in educational research are normally set at $\alpha \leq 0.05$ (Triola, 2012). There is no standard way to calculate a priori power for multinomial regression. Using a standard rule of thumb, an appropriate sample size calculated for multinomial regression was the number of independent predictors times 10, which required 90 individual observations or cases for this study (Statistic Solutions, 2017). A more conservative estimation involved a factor of 30 times the number of independent predictors for a sample size of 270 cases (see Kalla, 2009; Statistic Solutions, 2017).

Instrumentation and Materials

The instrument for collecting data from the faculty was A National Survey of Instructional Strategies Used to Teach Information Systems Courses (NSIS) (Djajalaksana, 2011). The main constructs measured by the survey were the frequency of use of ALM in instructional activities. The instrument was originally designed to survey faculty at multiple universities within the single discipline of information systems. However, the construction of the survey was completed and the validity was tested with the intention to make it available for use with other disciplines (Djajalaksana, 2011). Adaption of the survey for the project study occurred in the course information section only; there were no changes to the content on which the constructs were tested. This survey was successfully piloted, validated, and published as part of Djajalaksana's (2011) dissertation and was used with her permission (Yenni Djajalaksana, personal communication, September 6, 2016).

In the construction of the survey instrument, Djajalaksana (2011) used both faculty demographics and course information to perform regression on the results from a national survey of information systems instructors. The predictor variables and significant correlations with the six formed factors of ALM from Djajalaksana's regression analysis are summarized in Table 2.

Table 2

Variables Used in the Original Survey Instrument and Significance Results (Djajalaksana, 2011, pp. 82–87)

Predictor variables	Significant correlations
Faculty characteristics	
Gender	Significant for in-class active learning methods only with female instructors more likely to use
Rank	Slightly significant for writing-based and in-class only. The higher the professional rank, the less likely the instructor used these methods
Age	Significant only for writing-based and portfolio methods. The younger the instructor, the more likely they would use these methods.
Years of experience	None
Course characteristics	
Course level	Significant for all factors except portfolio and online methods. The instructor was more likely to use these active learning methods in higher level courses.
Delivery format	Significant only for online only delivery correlations with online methods
Class size	Significant for all factors. The larger the class size, the less likely active learning methods were used
TA availability	None

The results of the analysis by Djajalaksana (2011) indicated that the use of class size and course level as predictor variables in this study was justified as they showed significant correlations with all or most of the ALM factors. Other predictor variables as indicated in Table 2 were eliminated from the current study because they showed little or no correlation with all or most of the ALM factors.

The survey was reviewed by a panel of experts in teaching excellence; higher education; adult, career, and higher education; management information systems; geography; English; anthropology; and psychology supporting the claim of generalizability to other disciplines (Djajalaksana, 2011). The list of ALM included in the survey was not specific to the information systems discipline, but included a list of 52 active learning methods (listed and defined in Appendix C) used in all disciplines (Djajalaksana, 2011; Freeman et al., 2014). Djajalaksana (2011) reported the calculated measures of validity and reliability as part of the publication of the instrument. Internal consistency reliability was tested with Cronbach's alpha for the constructs with results ranging from 0.67 to 0.87 (Djajalaksana, 2011). An instrument is normally considered reliable if the Cronbach's alpha for the constructs is 0.70 or greater (Gliem & Gliem, 2003). However, the calculation of this reliability test is dependent on the number of items in each of the subscales. Only two of the constructs had Cronbach's alpha values slightly below 0.70 (highly-structured activities at 0.67 and project-based strategies at 0.67) and this was attributed to having only four items in each of subscales (Djajalaksana, 2011). Factor analysis was used to successfully test for construct validity (Djajalaksana, 2011). The factor analysis of the survey instrument used parallel analysis which compares Eigenvalues from the actual data to Eigenvalues of random data (Djajalaksana, 2011). The initial factor analysis returned seven extracted factors, and using an oblique rotation method, Djajalaksana checked the model fit for four, five, six, and seven factors. She found that with seven factors, the number of items per factor was too small, and the divisions of items into factors was too ambiguous for the results of four and five factors. As a result, Djajalaksana chose to use a six-formed factor solution and fit statistics were calculated using Chi-square, CFI (comparative fit index), RMSEA (root mean square error of approximation), and SRMR (standardized root mean square). The RMSEA and SRMR values were within the acceptable range while the CFI value was slightly lower (0.88) than the acceptable value of 0.95 (Djajalaksana, 2011). Additionally, the chi-square statistic was larger than typical for a good fit, but that effect was attributed to the large sample size.

The adaptation of the course information section of the survey allowed for the collection of the student grade data with the same anonymous instrument utilized to collect information on the ALM used. The survey instrument had questions for identifying course data including academic discipline of the course, the class size, the course level, and the grade frequency distribution. Whether the class was an introductory STEM course was determined by asking whether the course had prerequisites other than remedial courses or ENG-1111 (a first-year requirement in all disciplines). The response scale for the ALM variables was a Likert-style scale with definitions of the scale as “0” for “*never use*”, “1” for “*rarely use*”, “2” for “*occasionally use*”, “3” for “*frequently use*” and “4” for “*almost always/always use*”. The survey tool instructions specified that "*rarely*" represented 1-3 times per semester, "*occasionally*" represented use in less than half of the classes, "*frequently*" represented use in more than half of the classes, and "*almost always/always*" represented use in most or all the classes. Using the survey to collect the study information introduced the limitation common in survey research of self-reporting error (Strickland & Mercier, 2014; Strickland & Suben, 2012; Wilholt, 2009).

The faculty who were invited to participate in the survey completed the task using an online, anonymous survey available on SurveyMonkey®. Completing the survey required approximately 10 to 20 minutes of the instructors' time. The raw data from the survey was compiled in spreadsheet form for integration with IBM SPSS Statistics 23®. The data set and code book for the SPSS analysis was kept on a password-protected, personal device to ensure the confidentiality of study participants.

Data Collection

Course Grades

The survey asked instructors to report their grade frequency distribution as the number of students achieving each possible grade. Student grades, as an indicator of course completion, were a nominal variable (Triola, 2012). Because the grade categories include F and UW, the dependent variable was not able to be classified as ordinal or interval values (Dr. Matt Jones, Walden University Office of Quantitative Research, personal communication, February 6, 2017). Using the student grades as a nominal variable supported the use of multinomial regression and as such allowed the use of the student grades in determining correlational and regression effects (see Lovelace & Brickman, 2013).

Active Learning Methods

The ALM factor scores were measured with the same survey and functioned as continuous, interval variables. The measurement of the use of ALM depicted frequency of use in a Likert-style scale with definitions of the scale as “0” for “*never use*”, “1” for “*rarely use*”, “2” for “*occasionally use*”, “3” for “*frequently use*” and “4” for “*almost always/always use*”. The survey tool instructions specified that “*rarely*” represented 1-3 times per semester, “*occasionally*” represented use in less than half of the classes, “*frequently*” represented use in more than half of the classes, and “*almost always/always*” represented use in most or all of the classes. Likert scale-based response data can often be viewed as either ordinal or interval scale variables (Creswell, 2012). It is common in social science research to assign interval scale values and to use parametric tests for data derived from Likert-style measures (Creswell, 2012). Additionally, the survey instrument developed by Djajalaksana (2011) was originally implemented using parametric methods including exploratory factor analysis and multiple regression indicating the design of the survey instrument assumed interval scale variables. However, the scale for the student grades in this study was nominal due to the inclusion of both the F and UW grades. The self-reporting of the use of various ALM in the classroom presented validity risks common to survey methodology such as the social desirability effect and self-reporting bias (see Frey et al., 2016). Additionally, the ALM factor scores reported by the instructor were applied to the grade data of each student in the course.

The use of control variables was needed to minimize omitted variable bias (Levine & Stephan, 2015). Omitted variable bias can occur when testing for the direct effect of the independent predictor on the dependent variable where there are other independent variables that exhibit some degree of correlation with the variable of interest and therefore create an indirect effect on the dependent variable. Evidence from the literature indicated that correlations may have existed between the independent variables used in this study. For example, class size has been associated with both completion rates (Kokkelenberg, Dillon, & Christy, 2008) and the use of active learning methods (Gasiewski et al., 2012) suggesting that correlations existed.

The ALM factor scores may have been related to STEM course student grades directly or indirectly though correlations with class size, academic discipline, or introductory course level. Using class size, academic discipline, and course level as control variables in the regression analysis provided odds ratios for the ALM factors that represented effects independent of the control variables (*Control variables in regression*, 2015; Stockburger, 2016). Table 3 classifies the variables that were used in this study by type and measurement scales.

Table 3

Variable Types and Measurement Scales

Variable type	Variable	Measurement scale
Criterion	STEM course student grades	Categorical/nominal
Predictor	ALM factor group scores (6)	Continuous/interval
Control	Introductory course level	Categorical/nominal
Control	Class size	Continuous/ratio
Control	Academic discipline	Categorical/nominal

Data Analysis Procedure

To present the means and standard deviations, I calculated descriptive statistics for the study variables. I rank ordered the frequency of use for the ALM to describe the most commonly and least commonly used methods within each academic discipline and overall in the institution. The descriptive statistics also included the number of responses for ALM items individually and in factor groups. The ALM identified in the survey instrument are categorized in Table 4 by their validated factor groups (Djajalaksana, 2011).

Table 4

List of ALM Used in Survey Instrument Grouped Into Six Factors (Djajalaksana, 2011)

Subcategory	Specific Methods	
In-class ALM	Interactive lecture Question/answer with personal response device Think/pair/share Whole group discussion Small-group student discussions Minute paper/sentence summary Brainstorming Student/peer teaching Informal writing Video critique Concept maps/mind maps	Role play Simulations/games Debates Background knowledge probe/just-in-time teaching Case studies Lecture note sharing/comparing Student-generated quizzes/exams
Highly-structured activities	Demonstrations Computer-based learning	Applications tutorial Labs
Project-based ALM	Analysis and design project Problem-based learning (PBL)	Cooperative/team-based learning Student/peer assessment
Online ALM	Flipped classroom/online lecture Online discussions Online collaborative projects Reflective blogs Wikis	Self-directed learning Participation in social networking Formative quizzes
Writing-based ALM	Annotated bibliography/webliography Literature review Original research portfolio	Short paper Major term paper Student presentations
Portfolio-based ALM	Learning portfolio Online/e-portfolio Service learning	Personal reflection journals

To determine whether the use of ALM had a predictive relationship on STEM course student grades, I employed multinomial regression techniques. For regression using categorical variables, I assigned numeric codes through a process called dummy coding (see Stockburger, 2016). This created a coded system of yes/no variables using zeros and ones that allowed meaningful interpretation of the regression results (Stockburger, 2016). In explanation of the code, zero means “not”, so that a code of zero for introductory-level course is interpreted to mean the course is not an introductory-level course. For categorical variables that have multiple, unranked levels, the number of digits in the code was equal to the number of options minus one so that each digit represents one of the options. Dummy values for categorical variables are summarized in Table 5.

Table 5

Categorical Variable Assigned Values

Categorical variable	Dummy variables	
Course level	0 = Not introductory	1 = Introductory
Discipline area	1 = Mathematics	1000
	2 = Natural sciences	0100
	3 = Applied sciences	0010
	4 = Engineering technology	0001
	5 = Health services	0000

Multinomial regression techniques were appropriate tests for relating multiple, independent variables with a degree of collinearity and a single dependent categorical variable (see Laerd Statistics, 2013; Starkweather & Moske, 2011). The independent variables were the ALM factor scores, class size, course level (introductory or non-introductory), and academic discipline while the dependent variable was STEM course student grades. The use of a grade scheme including F and UW requires that the grades be treated as nominal and not ordinal variables (Dr. Matt Jones, Walden University Office of Quantitative Research, personal communication, February 6, 2017). Correlations between STEM course student grades and each independent variable individually were determined before the completion of the regression analysis.

Assumptions, Limitations, Scope, and Delimitations

Various assumptions had to be made in order to complete the study. Primarily, I assumed that the instructor-reported grade results and the frequency of use of ALM were accurate to the best of the instructors' knowledge. Additionally, I assumed that the ALM factor scores were properly developed and that they reasonably represented varying levels of social interaction. I also assumed that the ALM factor scores as calculated from the Likert-style survey were interval scale variables.

A potential limitation of the study was the self-reporting bias of anonymous surveys. However, the most ethical and prudent way to conduct the study was using an anonymous survey. An additional limitation was the potential for nonresponse bias should the survey have experienced low response rates. The use of an individual professor's ALM factor scores for multiple students to create the data sets also artificially inflated the results (see Bell, Olivier, & King, 2013).

The scope of the study was the STEM courses at MCC during the fall semester of 2016. This sample definition provided the boundaries that restricted the study from examining non-STEM programming or courses outside of the prescribed semester.

A delimitation of the proposed study was the exclusion of student demographic data. I made the choice to exclude student demographic data from the study to keep the survey anonymous and not link specific students with courses, instructors, or outcomes. Additionally, I chose to investigate the use of the ALM factor scores instead of other possible measures of active learning for the regression analysis to highlight the differences in the social aspects of the different ALM factor categories.

Protection of Participants' Rights

This study involved an anonymous survey of faculty members concerning classroom practices and student achievement. Neither the students nor the faculty were identified nor identifiable. Courses were categorized by academic discipline instead of by course number which prevents identification of the instructor. Completion of the electronic survey was implied consent. Electronic data was password protected and archived on a device not belonging to MCC.

The study was subject to two separate Institutional Review Board (IRB) procedures. First, Walden University IRB approved the study on March 13, 2017 (Approval #03-13-17-0557479). Second, MCC, through a contract with a larger research institution for IRB services, approved the study on April 4, 2017.

Data Analysis Results

As the purpose of the study was to examine whether the use of active learning methods (ALM) influenced STEM course student grades at the local community college, the results represented in the following sections evaluate these potential influences as garnered from the survey of instructional faculty teaching STEM courses during the fall semester of 2016 at MCC. Specifically, the research question and hypotheses pertaining to this purpose are repeated below.

The following research question (RQ) guided the study: After controlling for class size, course level (introductory or non-introductory), and academic discipline, do the ALM factor scores as measured by the NSIS predict STEM course student grades during Fall semester 2016 at MCC?

Null hypothesis (H_0): After controlling for class size, course level (introductory or nonintroductory), and academic discipline, there is no predictive relationship between the ALM factor scores and STEM course student grades during fall semester 2016 at MCC.

Alternate hypothesis (H_A): After controlling for class size, course level (introductory or nonintroductory), and academic discipline, there is a predictive relationship between the ALM factor scores and STEM course student grades during fall semester 2016 at MCC.

In the following data analysis sections, I discuss statistics pertaining to data collection including sample characteristics, response rates and representation of the sample population. I have provided descriptive statistics to characterize the sample, and I performed a univariate analysis to justify inclusion of the covariates. I addressed each of the assumptions of multinomial logistic regression to determine the appropriateness of the model. Finally, I evaluated the results of the multinomial logistic regression analysis with respect to the research question and the hypotheses.

Data Collection

I collected the data for this study using the *National Survey of Instructional Strategies Used in IS Courses* (NSIS) developed by Yenni Djajalaksana (2011) for two weeks between Wednesday, April 5, 2017 and Thursday, April 20, 2017. I followed the recruitment procedures in the outlined plan approved by the Walden University IRB with no significant discrepancies. I sent initial recruitment emails during the first three days of the two-week data collection time window. Additionally, I sent hardcopy reminder letters requesting participation in the survey through campus mail on days six and seven of the process. I had the opportunity to present a description of the project with a verbal request to participate at the faculty assembly on Monday, April 17, 2017 which I followed the next day with the final reminder email.

Of the initial 360 classes identified as STEM classes during the fall semester of 2016, there were 88 classes that were excluded from the sample due to class cancellation, instructors unavailable to be surveyed due to leaving the college, or misclassification as a traditional lecture class. I surveyed the remaining 272 classes, and instructors from 74 classes participated in the anonymous online survey for an overall response rate of 27.2%. The 272 STEM classes surveyed had 3,055 students registered, and the surveys returned included grades for 1,140 students which represents 37.4% of the students enrolled in STEM courses during the fall semester of 2016 at MCC. Table 6 shows the breakdown of the response rates by discipline.

Table 6

Response Rates for Classes/Students by Discipline

Discipline	Number in sample	Number of responses/students	Percentage
Mathematics			
Classes	54	23	42.6%
Students	806	378	46.9%
Natural science			
Classes	54	12	22.2%
Students	668	140	21.0%
Applied sciences			
Classes	48	10	20.8%
Students	439	116	26.4%
Engineering tech			
Classes	26	9	34.6%
Students	250	104	41.6%
Health sciences			
Classes	90	20	22.2%
Students	892	404	45.3%

The sample of data that I obtained from the survey provided a good representation of the population of STEM students at MCC. All disciplines had over 20% response rates for the classes and all disciplines had at least 21% of the students represented in these responses. I chose census sampling for the invitation to participate in the survey, and the resulting similar response rates across the disciplines indicated adequate representation of the population which is critical for external validity (Nussbaum, 2015).

Descriptive Statistics

The dependent variable for the study was student grades. The dependent variable had six categories as MCC did not use plus or minus distinctions on the grades. Of the 1,140 grades earned in STEM courses in fall semester of 2016, the most frequent grade received was a B. The distribution of grades for all students in STEM courses during fall semester of 2016 is shown in Figure 1. While the graph appears to demonstrate a distribution of grades without normality, normality is not a requirement of multinomial logistic regression (see Pentzke, 2016; Statistic Solutions, 2017). The grade distributions did vary by discipline and the variance was posited to be a result of unequal distribution of introductory-level courses. Mathematics, which as a discipline had the highest percentage of introductory courses, was the only academic discipline to have a strong binomial grade distribution affecting the overall grade distribution with the contribution of the binomial peak in F grades. The histograms of grade frequencies by academic discipline are available in Appendix E.

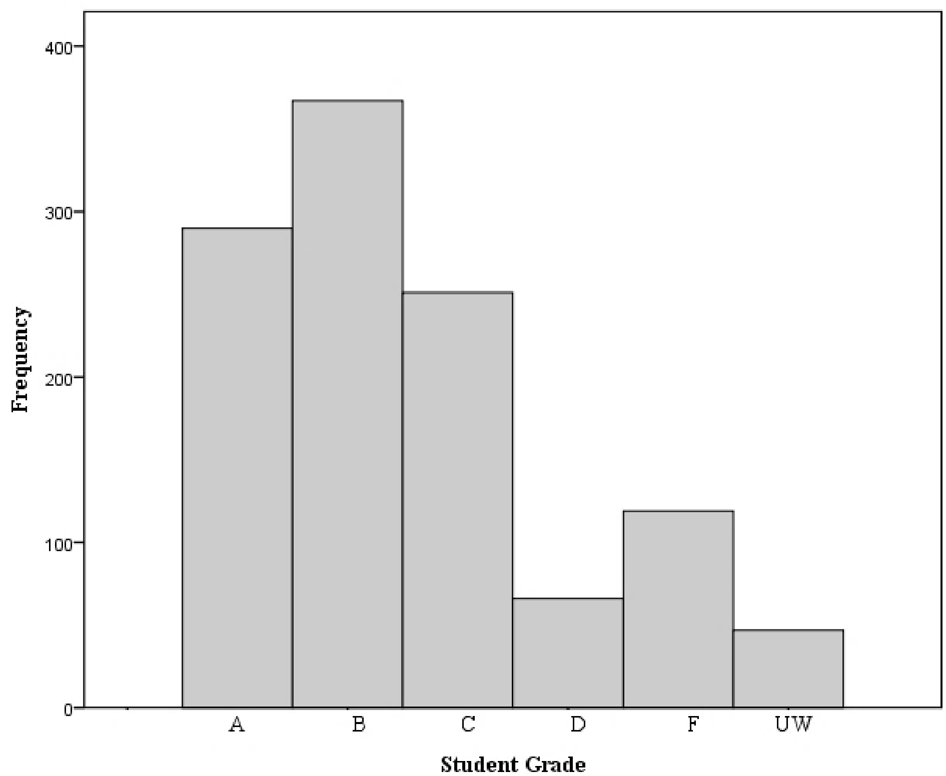

Figure 1. Grade frequency distribution for STEM courses for fall semester 2016 at MCC.

The control variables in this study included discipline, class size, and course level (introductory or non-introductory). Overall, 28 of the 74 respondent courses (37.8%) were introductory-level courses. Class sizes for the 74 respondent courses varied from 3 to 38 (μ = 15.4; σ = 8.98). In Table 7, the means and standard deviations of the class sizes and percentages of introductory-level courses were tabulated by academic discipline.

Table 7

Descriptive Statistics of Class Size and Course Level by Discipline

	Class size				Introductory
Discipline	Min.	Max.	Mean	St. Dev.	
Mathematics	6	27	16.43	6.30	69.6%
Natural science	5	19	11.67	4.89	41.7%
Applied science	3	23	11.60	5.97	40.0%
Engineering technology	6	19	11.44	4.42	33.3%
Health sciences	3	38	20.20	13.24	15.0%

For the predictor variables, the ALM factor scores, I summed and tabulated the survey responses made from using a Likert-style scale using the value of zero for “never use”, one for “rarely use (1-3 times per semester)”, two for “occasionally use (less than half the classes)”, three for “frequently use (more than half the classes)”, and four for “always use/almost always use”. Because each of the formed factors had a different number of items, I included the maximum possible score for each factor in Table 8 along with the means and standard deviations of the ALM factor scores for the sample. The ALM factors computed by Djajalaksana (2011) using factor analysis did not contain equivalent numbers of individual items. In-class ALM (Factor 1) was comprised of 18 individual instructional methods while online ALM (Factor 4) was comprised of eight individual instructional methods and writing-based ALM (Factor 5) was comprised of six individual instructional methods. Highly-structured activities ALM (Factor 2), project-based ALM (Factor 3) and portfolio-based ALM (Factor 6) each had four individual instructional methods included. I included a breakdown of the ALM factor scores for each discipline in Table 8 to demonstrate the differences in disciplinary preferences for the use of ALM in the classroom. I have provided the individual instructional method scores for all STEM students at MCC as well as broken down by discipline in Appendix E. The top five most used individual instructional methods in all STEM courses at MCC were lecture (3.11), interactive lecture (2.35), problem-based learning (1.85), lab activities (1.68) and whole group discussion (1.66) where the number in parentheses is the mean of the Likert-style survey responses for that method with a maximum possible value for each method of 4.00.

In Table 9, I have displayed the top five most used individual instructional methods by discipline, and in Table 10, I have presented the individual methods with zero usage by discipline. In the data for the most used methods, while strong preferences remain for the use of lecture and interactive lecture as instructional methodologies, the data in Table 9 indicated that instructors in different academic disciplines exhibited differences in preferences for using varied types of ALM. The data in Table 10 indicated that there were many individual instructional methods that are not used at all by instructors in mathematics, natural science, applied science, and engineering technology.

In contrast, health sciences had only one individual instructional method (video creation) that exhibited no usage with an item score of .00.

Table 8

Means and Standard Deviations for ALM Factor Scores

	In-class ALM Factor 1 (72.00)*		Highly-structured ALM Factor 2 (16.00)*		Project-based ALM Factor 3 (16.00)*		Online ALM Factor 4 (32.00)*		Writing-based ALM Factor 5 (24.00)*		Portfolio-based ALM Factor 6 (16.00)*	
	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
All STEM	15.4	8.16	4.49	3.41	3.5	2.48	3.43	4.15	1.42	2.44	.43	1.06
Mathematics	7.09	5.6	1.3	2.14	2.83	1.9	0.74	1.14	.17	.83	.04	.21
Natural science	12.6	5.79	6.17	1.4	4.75	1.14	4	3.25	.92	1.08	0	0
Applied science	9.1	6.3	7.9	2.71	3	2.71	8.3	4.11	2.7	3.62	0	0
Engineering tech	6.67	6.06	5.89	3.1	5	2.78	2.22	4.02	1.89	2.89	.33	.71
Health sciences	17.5	9.56	4.8	3.21	3.1	3.01	4.3	4.55	2.3	2.79	1.4	1.64

* Values in parentheses are the maximum scores possible for each of the ALM factors.

Table 9

Top Five Individual Instructional Methods and Item Means Reported by Discipline

	Mathematics	Natural science	Applied science	Engineering tech	Health science
1	Lecture (3.81)	Problem-based learning (2.77)	Self-directed learning (3.3)	Labs (3.03)	Lecture (3.36)
2	Interactive lecture (2.37)	Interactive lecture (2.75)	Lecture (3.1)	Interactive lecture (1.9)	Interactive lecture (2.62)
3	Problem-based learning (1.96)	Labs (2.51)	Labs (3.0)	Quizzes (1.72)	Whole group discussion (2.22)
4	Whole group discussion (1.58)	Demonstrations (2.36)	Computer-based learning (2.3)	Analysis and design project (1.71)	Case study (2.15)
5	Review sessions (1.23)	Lecture (2.27)	Online lecture (2.2)	Problem-based learning (1.63)	Small group discussion (1.77)

Table 10

Individual Instructional Methods With Zero Use by Discipline

Mathematics	Natural science	Applied science	Engineering tech	Health science
Q&A with clickers, minute paper, student presentations, debates, case study, original research proposal, short paper, major writing/term paper, annotated bibliography, learning portfolio, field trips, service learning, video creation, reflective blogs, participation in social networking, e-portfolio, wikis	Minute paper, role play, original research proposal, major writing project/term paper, application development/ programming project, application tutorial, video critique, annotated bibliography, personal reflection journal, learning portfolio, field trips, service learning, reflective blogs, participation in social networking, e-portfolio, wikis	Q&A with clickers, role play, student-generated quizzes/ exams, concept maps/mind maps, student attitude survey, campus events, personal reflection journal, learning portfolio, field trips, service learning, reflective blogs, e-portfolio, wikis	Q&A with clickers, minute paper, role play, debates, original research proposal, video critique, annotated bibliography, personal reflection journal, video creation, reflective blogs, participation in social networking, background knowledge probe/just-in-time teaching, wikis	Video creation

To test whether the predictor variables, the six ALM factor scores, as covariates should have been included in the regression model, I applied a univariate analysis technique. Using the univariate analysis of the predictive relationships of the independent predictor variables on student grades, I provided justification for the inclusion of each of the predictor variables in the final model (see Hosmer & Lemeshow, 1989; Laerd Statistics, 2013). Using multinomial logistic regression, I regressed each predictor variable on the dependent variable of student grades individually. The resultant Chi-square statistic of the -2 log likelihood test indicated the difference between the regression model with the intercept (β_0) only and the regression model including the predictor variable. As shown in Table 11, the large Chi-square values, which were all significant ($p < 0.05$) except for ALM factor 3 and ALM factor 4, indicated which of the predictor variables should have been included in the final model. While the Chi-square values presented in Table 11 indicate that the two variables, ALM factor 3 and ALM factor 4, should not be included in the model, I used the goodness-of-fit statistics in the final regression analysis to compare the fit of the final model with nine variables versus the final model with seven variables.

Table 11

Chi-Square Statistics of Individual Predictor Variables on Student Grades

Predictor	Chi-square	Sig.
Discipline	136.379	.000
Course level	119.516	.000
Class size	42.934	.000
ALM factor 1	86.208	.000
ALM factor 2	47.658	.000
ALM factor 3	8.096	.151
ALM factor 4	6.326	.276
ALM factor 5	82.057	.000
ALM factor 6	76.303	.000

Assumptions of Multinomial Logistic Regression

To develop an accurate and stable predictive model for student grades using the specified control and predictor variables, I evaluated whether the study data met the assumptions of the multinomial logistic regression model. The assumptions of multinomial logistic regression include the use of an appropriate sample size, independence of irrelevant alternatives, multinomial linearity, no significant outliers, and no multicollinearity (Aragon, 2017; Laerd Statistics, 2013; Pentzke, 2016). I have provided the statistical results for tests of each of the assumptions in the following sections.

Appropriate sample size. The a priori sample size calculations for an appropriate sample size to achieve significance ($p < .05$) at a power of .80 indicated that a minimum sample size of 90 cases was needed based on the estimate of 10 cases per independent variable included in the model (see Statistic Solutions, 2017). A more conservative model estimated that 30 cases per independent variable provided a more accurate model which indicated the need for 270 cases (see Kalla, 2009; Statistic Solutions, 2017). The survey data included 1,140 cases. Therefore, this study met the sample size requirements and was sufficiently powered.

Independence of irrelevant alternatives. The assumption of the independence of irrelevant alternatives (IIA) describes the relationship of the nature of the dependent variable and the study design. The outcome observations must have clearly defined, mutually exclusive, and exhaustive categories to be independent (Aragon, 2017; Pentzke, 2016). Specifically, the selection of one choice in the dependent categorical variable must not be influenced by the availability or attributes of one of the other choices (Hausman & McFadden, 1987). If such dependency occurs, nested logistic regression models are required to derive an accurate prediction model (Vijverberg, 2011).

The assumption of IIA is most often tested using the Hausman-McFadden test (Cheng & Long, 2007; Starkweather & Moske, 2011). The Hausman-McFadden test uses the parameter estimates of the final predictive model, the parameter estimates of a restricted model in which one of the outcome choices is removed, and the differences in the estimated variance matrices to determine whether the final distribution of outcomes matches the Chi-square distribution (Hausman & McFadden, 1987). Simplified, the Hausman-McFadden test examines the estimated logit model for the full model and the estimated logit model for the restricted model for significant difference (UC Berkeley, 2000; Vijverberg, 2011). Since SPSS v.23 does not perform the Hausman-McFadden test directly, I used tests of the correlations of the estimated parameters to evaluate whether the full model and the restricted model were significantly different (see Vijverberg, 2011). I performed Pearson's r correlation on the estimated parameters of both models as shown in Table 12. The correlation statistic (*r* = 1.000, *p* < .01) indicated that the two models were perfectly correlated, that there was no significant difference between the estimated outcomes with the restricted model, and that the IIA assumption was met. The tables of the parameter estimates for the full model and the restricted model are included in Appendix E.

Table 12

Correlations of the Parameter Estimates for Models in the Hausman-McFadden Test of IIA

		Full	Restricted
Full	Pearson correlation	1	1.000**
	Sig. (2-tailed)		.000
	Sum of squares and cross-products	11.206	11.240
	Covariance	.287	.288
Restricted	Pearson correlation	1.000**	1
	Sig. (2-tailed)	.000	
	Sum of squares and cross-products	11.240	11.275
	Covariance	.288	.289

**. Correlation is significant at the 0.01 level (2-tailed).

Cheng and Long (2007), however, using Monte Carlo simulations and multiple sample structures determined that tests of IIA were subject to substantial size distortions and were unsuitable for applied work. Vijverberg (2011) also noted that the Hausman-McFadden tests were unsuitable due to the tendency for the estimated variance matrix to become indefinite. The dependent variable in the study, student grades, however, met the criterion of IIA notwithstanding these objections since a student could not have been assigned a final grade in more than one category and the assignment of the final grade for the student was not dependent on the other choices for the final grade.

Multicollinearity. Multicollinearity is the result of two or more of the independent variables being highly correlated (Harrell, 2015; Hosmer & Lemeshow, 1989; Jeeshim & KUCC625, 2002). To determine whether there were significant correlations in the independent variables, I performed several different tests since the independent variables included continuous (interval and ratio) and categorical (nominal) types. For the assessment of the correlations between the interval and ratio variables (Table 13), I used Pearson's r correlation while I employed Kendall's tau correlation for the assessment of the correlation between the two nominal variables (see Levine & Stephan, 2015; Nussbaum, 2015). The Kendall's tau test of the association between academic discipline and course level resulted in τ = -0.493 (p < 0.01). For the association of interval to nominal level variables, I based the computation of the correlation statistics on the use of Intraclass (Type C) correlation coefficients (Table 14) (see Atenafu et al., 2012; Mak, 1988).

Table 13

Pearson Correlations of Interval and Ratio Variables

	Class size	ALM 1	ALM 2	ALM 3	ALM 4	ALM 5	ALM 6
Class size	1						
ALM 1	0.211*	1					
ALM 2	-0.161*	0.497*	1				
ALM 3	-0.076*	0.530*	0.450*	1			
ALM 4	-0.102*	0.427*	0.624*	0.242*	1		
ALM 5	0.126*	0.337*	0.233*	0.164*	0.091*	1	
ALM 6	0.305*	0.580*	0.290*	0.364*	0.220*	0.328*	1

* $p < 0.01$

Table 14

Intraclass Correlations of Categorical and Interval Variables

	Class size	ALM 1	ALM 2	ALM 3	ALM 4	ALM 5	ALM 6
Discipline	0.238*	0.319*	0.474*	0.172*	0.389*	0.548*	0.639*
Course level	-0.066	-0.077	-0.203	-0.156	-0.081	-0.337	-0.668

* $p < 0.01$

The results for the Kendall's tau, Pearson's r, and the intraclass correlations indicated that there was possible multicollinearity between some of the independent variables. These methods, however, examined the pairwise correlations which may not necessarily represent any group or full model effect. The variance inflation factor (VIF) provides another method to evaluate the data for the presence of multicollinearity and considers the regression of a single independent variable onto the other independent variables as a group. A large change in the variance resulting from that regression as seen in a large VIF signals the presence of multicollinearity (de Jongh et al., 2015; Jeeshim & KUCC625, 2002; Salmerón Gómez, García Pérez, López Martín, & García, 2016). As a rule of thumb, VIF values greater than 3.0 indicate potential multicollinearity while VIF values greater than 10.0 indicate strong multicollinearity (Jeeshim & KUCC625, 2002;

Salmerón Gómez et al., 2016). In addition to VIF, multicollinearity can be evaluated based on tolerance values, Eigenvalues, and condition indices. Tolerance values less than 0.1 and Eigenvalues less than 0.01 indicate the presence of multicollinearity while values of the condition index greater than 30 also show the data has multicollinearity (Jeeshim & KUCC625, 2002). Eigenvalues that have relatively similar values also provide evidence that any multicollinearity present is not significant (Jeeshim & KUCC625, 2002). I performed analysis of these multicollinearity measures using IBM SPSS v. 23 and reported the results in Table 15. Using the evaluation of the pairwise correlations and the multicollinearity tests, I demonstrated that the study data appeared to have small to medium correlations, but the effects were below the threshold to reject the multinomial logistic model based on the presence of multicollinearity.

Table 15

Multicollinearity Test Statistics for Each Independent Variable Regressed Onto the Others

Variable regressed	VIF*	Tolerance value**	Eigenvalues#	Condition index&
Academic discipline	2.306	.434	.043	11.451
Course level	2.399	.417	.061	10.171
Class size	2.352	.425	.053	10.427
ALM factor 1	2.378	.420	.042	11.655
ALM factor 2	2.380	.420	.043	11.616
ALM factor 3	2.224	.450	.046	11.221
ALM factor 4	2.308	.433	.040	12.140
ALM factor 5	2.402	.416	.041	12.269
ALM factor 6	2.400	.417	.043	11.964

* Largest VIF from the regression set (threshold for multicollinearity > 3.0)
** Smallest tolerance value from the regression set (threshold for multicollinearity < 0.1)
# Smallest Eigenvalue from the regression set (threshold for multicollinearity < 0.01)
& Largest condition index from the regression set (threshold for multicollinearity > 30)

Multinomial linearity. The linearity assumption for multinomial logistic regression requires that the transformed values of any continuous independent variable have a linear relationship with the logit of the dependent variable, the odds ratio, as noted in the multinomial logistic regression as *Exp*(*B*) (Nussbaum, 2015; Statistic Solutions, 2017). I tested this assumption using the Box-Tidwell procedure in which a transform term, in the form of $X*ln(X)$ where X was the variable of interest, was added to the multinomial regression analysis so that the Box-Tidwell model included both the continuous and the transformed variables. If any of the transformed terms were significant, the significance indicated nonlinearity. When continuous predictor variables violate this assumption, any model returned is subject to increased inaccuracy (Pentzke, 2016). In Table 16, I defined the Box-Tidwell transform variables for the continuous variables in this study.

Table 16

Definition of the Box-Tidwell Transform Variables From Continuous Variables

Predictor variable	Box-Tidwell transform variable
Class size	ClassSizeBT
ALM factor 1	ALM1BT
ALM factor 2	ALM2BT
ALM factor 3	ALM3BT
ALM factor 4	ALM4BT
ALM factor 5	ALM5BT
ALM factor 6	ALM6BT

Since the calculation of the linearity assumption employed multiple independent tests concurrently, I applied the Bonferroni Correction to adjust the threshold of significance. According to the Bonferroni Correction, the significance level, $p < 0.05$, as applied to the model as a whole, may not be the appropriate comparison for the individual significance tests that apply to parts of the model (Weisstein, 2017). Using the most conservative approach, the individual *p*-values were set to $\frac{p}{n}$ where n is the number of comparisons (Weisstein, 2017). As applied to this study data where n = 5 for the nominal dependent variable student grade which has six categories, the Bonferroni Corrected significance for individual test was set to $p \leq 0.01$. In Table 17, I have provided the *p*-values of the regressed model for the Box-Tidwell transformed predictors. After the Bonferroni Correction, only one instance of nonlinearity was evidenced for ALM factor 2 when comparing the odds ratio of the student receiving an F versus a UW. The non-linearity in ALM factor 2 could have potentially lead to misinterpretation of the likelihood ratios for this comparison; however, unlike other course grades, the interpretation of F and UW was very similar and the nonlinearity was unlikely to cause large effects on the prediction model (see Janes H et al., 2010). The full record of the Box-Tidwell transforms and the Bonferroni Correction statistics are included in Appendix E.

Table 17

The p-Values for Box-Tidwell Transformed Continuous Predictor Variables

Student grade[a]	Sig. vs. A	Sig. vs. B	Sig. vs. C	Sig. vs. D	Sig. vs. UW
ALM1BT	.628	.551	.192	.400	.294
ALM2BT	.326	.821	.941	.175	$\boxed{.004}$
ALM3BT	.055	.401	.518	.291	.503
ALM4BT	.901	.795	.588	.055	.434
ALM5BT	.449	.034	.013	.405	.663
ALM6BT	.697	.491	.982	.470	.495
ClasssizeBT	.021	.058	.982	.272	.218

[a] Reference category: F

Significant outliers. The presence of outliers in research data can cause the resultant model to imply irrelevant inferences (Pentzke, 2016). To check for outliers, I employed two methods. I used box-whisker plots to present a graphical interpretation of outliers while using the outlier labeling rule to quantify the outlier limits (see Hoaglin & Iglewicz, 1987; Pentzke, 2016). In the box-whisker plot in Figure 2, the boxes represent the interquartile range of values that are the middle 50% of cases. The line through the box represents the median and the lines extending from the box represent the range of values which are no greater than 1.5 times the interquartile range. The circles on the box-whisker plot for ALM indicate the presence of outliers which were cases with values between 1.5 and 3.0 times the interquartile range. The asterisks represent extreme values exceeding 3.0 times the interquartile range. Using the box-whisker plot shown in Figure 2, I interpreted that outliers existed for ALM factor 4 and ALM factor 5 while extreme values were present in both ALM factor 5 and ALM factor 6. The very small interquartile ranges represented in ALM factor 5 and ALM factor 6 were due to the large number of responses of zero for “never use” for the ALM grouped in these factors. While ALM factors 4, 5, and 6 had nonzero means, the medians of ALM factors 5 and 6 were zero, and the modes of ALM factors 4, 5, and 6 were zero as well. These measures of central tendency implied very low usage of any of the instructional methodologies grouped into these factors. In fact, 44.2% of all cases recorded a zero for ALM factor 4, 56.6% of all cases recorded a zero for ALM factor 5, and 79.0% of all cases recorded a zero for ALM factor 6.

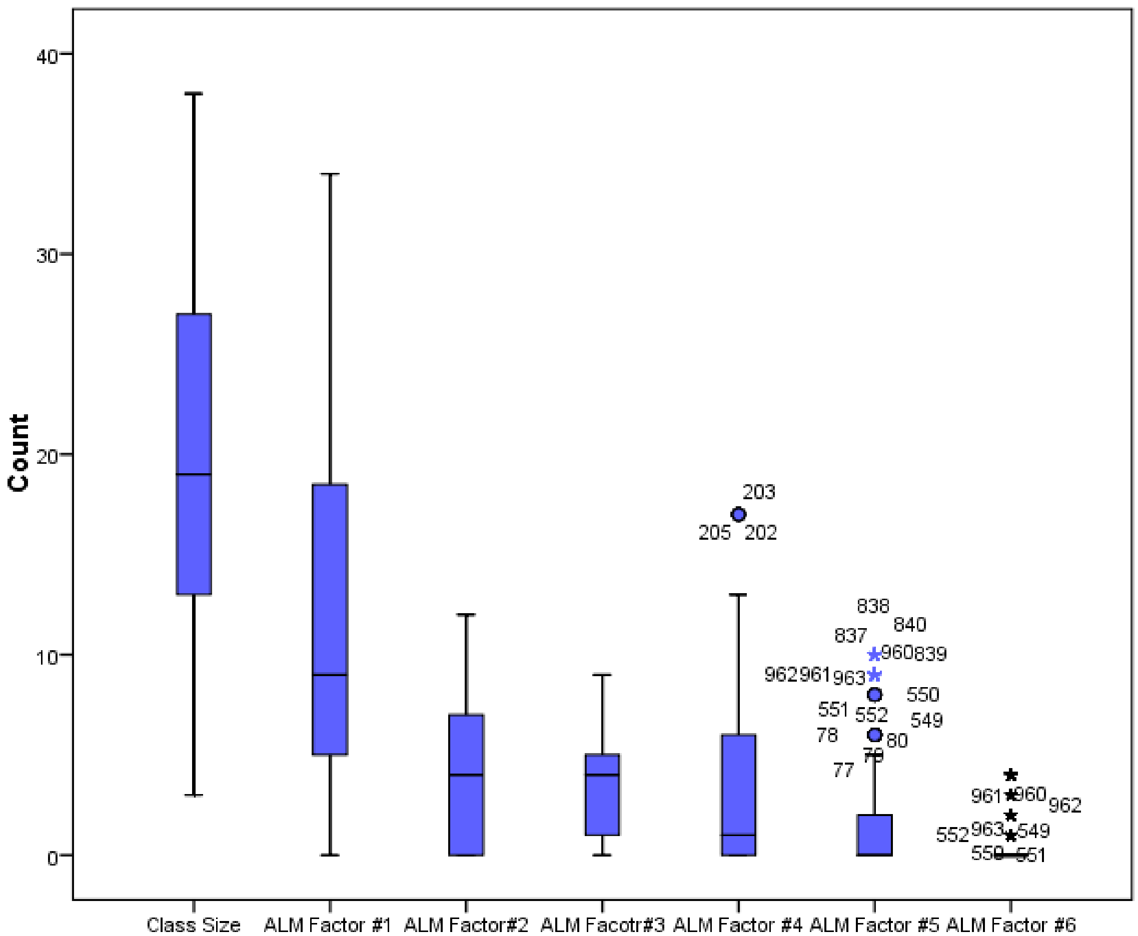

Figure 2. Box-whisker plots of continuous predictor variables

Using the outlier labeling rule, I further investigated the student-level data for these three ALM factor scores that exhibited outliers. The outlier labeling rule uses the difference of the values of the first and the third quartiles multiplied by a factor of 1.5 for sample sizes greater than 1,000 cases (Aragon, 2017; Hoaglin & Iglewicz, 1987). Table 18 includes the calculations of the upper and lower limits for determining outliers.

Table 18

Outlier Labeling Rule Calculations

Variable	Q1	Q3	Lower limit	Upper limit	Number of outliers
Class size	13	27	-8	48	0
ALM factor1	5	18.75	-15.625	39.375	0
ALM factor 2	0	7	-10.5	17.5	0
ALM factor 3	1	5	-5	11	0
ALM factor 4	0	6	-9	15	12
ALM factor 5	0	2	-3	5	104
ALM factor 6	0	0	0	0	249

The results of the outlier labeling rule calculations indicated a larger number of outliers than from the box-whisker plot. For ALM factor 6, for example, due to the large number of cases in which no elements of this factor were present, the values of both the first quartile and the third quartile were zero making all non-zero values outliers. For ALM factor 4 and ALM factor 5, the large numbers of zeros impacted the variable by giving very low medians and narrow interquartile ranges, forcing many of the cases in which the instructors facilitated any of the methods in these factors to become outliers. As a result, these outlier values had a high impact on the regression model and it was reasonable to speculate that odds ratios for ALM factor 5 and ALM factor 6 could have exhibited inflation and required qualification during interpretation (see Lamothe, 2014; Zijlstra, van der Ark, & Sijtsma, 2011).

Analyses of Research Questions

The research question asked if there was a predictive relationship between the use of the active learning methods and the student grades. In alignment with the theoretical framework of social constructivism, the ALM factor scores represented differing levels of social interaction in the learning process and needed to be evaluated for their individual predictive relationships. The factor analysis of the 52 ALM performed by Djajalaksana (2011), formed six factor groupings, in-class ALM, highly-structured activities ALM, project-based ALM, online ALM, writing-based ALM, and portfolio-based ALM. The in-class ALM factor by including methods such as group discussions, debates, and review sessions represented instruction that incorporates significant social interaction with both the instructor and peers (Brand & Kasarda, 2014; Mondisa & McComb, 2015). Highly-structured activities ALM with methods such as laboratory exercises and demonstrations limited peer interaction, but increased student-instructor interaction (Jensen & Jetten, 2015). Project-based ALM focused on methods that emphasized peer-to-peer interaction (Ertmer, Schlosser, Clase, & Adedokun, 2014) while online ALM focused on methods that increased social distance in both peer and instructor communication (Gaytan, 2013; Wladis, Hachey, & Conway, 2014). Both writing-based and portfolio-based ALM included instructional methods that provided minimal social interaction (Leggette & Homeyer, 2015). The complete list of the 52 ALM grouped by factors is included in Table 4 with definitions in Appendix C. Thus, the multinomial logistic regression model was employed correctly to explore the predictive effects of each ALM factor as independent variables.

Using SPSS v.23, I performed the multinomial logistic regression on the study data. The model fitting criteria, shown below in Table 19, shows the calculated -2 log likelihoods and the likelihood ratio (LR) test for the null versus the final model. The Chi-square statistic demonstrates the difference between the null model (no predictors) and the final model (fully fitted for all predictor and control variables).

Table 19

Model Fitting Statistics for Null Versus Final Regression Models

	Model fitting criteria	Likelihood ratio tests		
Model	-2 Log likelihood	Chi-square	df	Sig.
Intercept only	1410.351			
Final	1097.060	313.291	45	.000

In Table 20, I present the -2 log likelihood of the reduced model for evaluation of the importance of each of the independent predictor variable to the full fitted model. The Chi-square LR test subtracted the value of the reduced model from the full fitted model and the difference represents the change in the model fit when that predictor was removed. Each of the Chi-square tests had significant results ($p < .05$) except for the variable class size ($p = .068$) indicating that each predictor variable except class size added to the accuracy of the fitted model. Contrary to the univariate analysis which indicated that ALM Factors 3 and 4 should be removed from the model, the Chi-square LR test indicated that the inclusion of these predictors improved the model fit. Since all the ALM factor scores were significant to the fitted prediction model ($p < .05$), the null hypothesis that when controlling for academic discipline, class size, and course level, there is no predictive relationship between ALM factor scores and student grades was rejected.

Table 20

Likelihood Ratio Tests

	Model fitting criteria	Likelihood ratio tests		
Effect	-2 Log likelihood of reduced model	Chi-square*	df	Sig.
Intercept	1115.976	18.916	5	.002
Discipline	1122.048	24.988	5	.000
Course level	1126.859	29.799	5	.000
Class size	1107.339	10.279	5	.068
ALM factor1	1133.128	36.068	5	.000
ALM factor2	1114.386	17.326	5	.004
ALM factor3	1112.274	15.214	5	.009
ALM factor4	1130.508	33.447	5	.000
ALM factor5	1113.587	16.527	5	.005
ALM factor6	1113.885	16.825	5	.005

*The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

In demonstrating that the ALM factor scores were significant to the predictive model of student grades, the magnitude of the effect the use of these methods had on the change in the student grades was of interest (see Hosmer & Lemeshow, 1989). The R^2 statistic is derived from the ordinary least squares regression as a goodness-of-fit measure that uses the total variability of the dependent variable in a full model in relation to the null (intercept only). The R^2 is the square of the correlation between the model's predicted values and the actual values (Koenker & Machado, 1999). Logistic regression, since it calculates the maximum likelihood, does not have a true R^2 value (Walker & Smith, 2016). Several pseudo R^2 have been developed in the attempt to approximate the idea of calculating a goodness-of-fit model for logistic regressions (Allison, 2014). The Cox-Snell pseudo R^2 is the ratio of the likelihoods subtracted from one. The higher the value of the Cox-Snell pseudo R^2, the greater the improvement of the fitted model over the null model (Allison, 2014). McFadden pseudo R^2 uses a ratio of the natural logs of the likelihoods subtracted from one, and as such, the McFadden pseudo R^2 is higher for fitted models with greater likelihoods and is used as a comparison between successive model iterations (Walker & Smith, 2016). The Nagelkerke pseudo R^2 is an expansion of the Cox-Snell to adjust the range of results to the familiar usage of $0 < R^2 < 1$ for clearer interpretation of results (Walker & Smith, 2016). Because the different pseudo R^2s use different scales, it is invalid to compare results from different methods; the pseudo R^2 values should only be compared with those calculated by the same method to compare different models as a judgement of better fit. For the study data, the pseudo R^2 statistics were low (Cox-Snell = .240; McFadden = .087; Nagelkerke = .251. While pseudo R^2 is the logistic analog of R^2 in ordinary least squares regression, and it is considered a goodness-of-fit statistic, many writers have shied away from using the direct statement that pseudo R^2 is a direct measure of the proportion of variance accounted for in the dependent variable. These low pseudo R^2 results allow room to consider other factors that may influence student grades including faculty demographics such as teaching experience and instructor level (see Figlio, Schapiro, & Soter, 2015) as well as student demographics such as placement scores, high school GPA, socioeconomic status, race/ethnicity, gender, motivation measures, and self-efficacy (see Boekeloo, Jones, Bhagat, Siddiqui, & Wang, 2015; Loughlin, Watters, Brown, & Johnston, 2015; Rabitoy, Hoffman, & Person, 2015; Wladis, Conway, et al., 2015) that have been excluded from the study to protect the anonymity of the faculty and students that are the subjects of the study.

Additionally, in the interpretation of the parameter estimates of the final model, while each of the ALM factor scores were significant to the improvement of the fitted model, each ALM factor score was not significant in the estimation of the odds ratios for every comparison. The odds ratio, *Exp(B*), is the exponentiation of the fitted model coefficient *B*. Since logistic regression models use a log likelihood statistic, the exponentiation of this value gives an odds ratio (Hosmer & Lemeshow, 1989). This statistic is calculated because it allows more intuitive interpretation. The interpreted statistic implies that for every one unit increase in the predictor variable such as going from a Likert score of one for “rarely use” to a score of two for “occasionally use”, the odds ratio is the percentage of likelihood that the outcome changes (see Hosmer & Lemeshow, 1989; Levine & Stephan, 2015; Starkweather & Moske, 2011). Odds ratios equal to 1 indicated that the outcome event (student grade) was equally likely to occur as the reference outcome (grade of F). Odds ratios greater than 1 indicated that the outcome event was more likely than the reference event and odds ratios less than 1 indicated that the outcome event was less likely than the reference event. The 95% confidence interval for the odds ratio is interpreted as the range where there is 95% confidence ($p < .05$), that the odds ratio of the true population lies between the bounds. Since the null hypothesis was that the coefficient of the predictor variable, B_i, was zero, if the range of the 95%

confidence interval of Exp(B_i) includes the value of 1, the analysis fails to reject the null hypothesis (Laerd Statistics, 2013). I have summarized the significant results using the odds ratios from the multinomial logistic regression for the use of ALM below. The complete table of parameter estimates for the final model appears in Appendix E.

- Use of in-class ALM (factor 1) makes it 5.0% ***more likely*** that students will achieve a grade of B and 9.0% ***more likely*** that students will achieve a grade of C instead of a grade of F.
- Use of highly-structured ALM (factor 2) makes it 16.4% ***more likely*** that students will achieve a grade of A, 22.2% ***more likely*** that students will achieve a grade of B, and 16.7% ***more likely*** that students will achieve a grade of C instead of a grade of F.
- Use of project-based ALM (factor 3) makes it 20.9% ***less likely*** to achieve a grade of B and 15.7% ***less likely*** to achieve a grade of C instead of a grade of F.
- Use of online ALM (factor 4) makes it 16.1% ***less likely*** to achieve a grade of A, 20.4% ***less likely*** to achieve a grade of B, and 19.3% ***less likely*** to achieve a grade of C instead of a grade of F.
- Use of writing-based ALM (factor 5) makes it 43.3% ***more likely*** to achieve a grade of A, 43.1% ***more likely*** to achieve a grade of B, and 39.1% ***more likely*** to achieve a grade of C instead of a grade of F.
- Use of portfolio-based ALM (factor 6), while significant to the final prediction model, did not have any individually significant odds ratios.

- There were no significant odds ratios for predicting the grades of D or UW instead of a grade of F.
- The two ALM with the highest social interaction, in-class ALM (factor 1) and project-based ALM (factor 3), showed mixed results. Use of in-class ALM (factor 1) improved the likelihood of higher grades while the use of project-based ALM (factor 3) decreased the likelihood of higher grades.
    - Project-based ALM (factor 3), which had the largest responses for the methods of problem-based learning and cooperative/team-based learning included social interaction primarily with peers through teamwork and cooperative activities.
    - In-class ALM (factor 1), which had the largest responses for interactive lecture and whole group discussion included social interaction with peers and instructors.
- The two ALM with moderate social interaction, highly-structured activities ALM (factor 2) and online ALM (factor 4) also had mixed results. Use of highly-structured activities ALM (factor 2) increased the likelihood of achieving a higher grade while the use of online ALM (factor 4) decreased the likelihood of achieving a higher grade.
    - Highly-structured activities ALM (factor 2) which had the largest responses for lab activities and quizzes exhibited activities predominately comprised of student-instructor social interaction.

  - Online ALM (factor 4) which had the largest responses for online lecture and online discussions exhibited predominately student-peer interaction and increased social distance for student-instructor interaction.

- Use of writing-based ALM (factor 5) increased the likelihood of attaining a higher grade, but has little or no social interaction involved. However, the results of this ALM factor may be compromised by the presence of large numbers of outliers and must be interpreted with qualifications.

Summary

The methodology that I used in testing the hypotheses for this research study included an anonymous online survey of faculty, descriptive statistics, and multinomial logistic regression. The survey resulted in a higher than average response rate that provided a reasonable representation of the population of students in STEM courses during the fall semester of 2016 at MCC. I used descriptive statistics to show grade distributions, class sizes, course levels, and use of ALM as a college and grouped by academic discipline. To test the hypotheses, I employed multinomial logistic regression and showed that the use of ALM did have predictive relationships with the student grades at a level that permitted the rejection of the null hypothesis. Interpreting the odds ratios from the multinomial logistic regression, I provided the likelihoods of completion grades (A, B, C, and D) when compared to a failing grade (F). Using the likelihoods of the grades when regressed using the ALM factor scores, I provided a discussion of which instructional methodologies were most beneficial for the academic achievement of the local students. In the following section, I describe the final project which evolved from the results of the research.

Section 3: The Project

A white paper including an analysis of the research data and the recommendations for new faculty development, computer skills assessment and training, and active research on writing-based ALM course modules functioned as the project deliverable. In this section, the rationale for using the format of a white paper is presented followed by a scholarly review of literature in support of the recommendations for practices. A practical description of the final project, the project evaluation plan, and the project implications are included as well.

Rationale

The results of the research study presented in Section 2 provided insights into potential policy, instructional, and institutional changes that could benefit the academic success of the diverse students at MCC. The acceptance of any proposed change is dependent on the shared knowledge and values of the organization (Irvine & Price, 2014). The successful transfer of knowledge from the realm of research to the arena of practice can be subject to cognitive, social, and institutional barriers (Curran, Grimshaw, Hayden, & Campbell, 2011). To facilitate successful knowledge transfer, researchers should present evidence in a user-friendly method (Curran et al., 2011). Consensus that practice should be evidence-based is wide-ranging, but there remains an evidence-to-practice gap (Curran et al., 2011; Hines & Bogenschneider, 2013; Kahn et al., 2009).

The white paper format selected for the final project is a widely accepted method for communicating research results and recommendations for change when the audiences of interest are policymakers, as in the case of the administration of MCC (Hines &

Bogenschneider, 2013). Policymakers in all contexts, including academia, rely on brief, concise research reports due to time constraints and to counter biased info from special interest groups (Hines & Bogenschneider, 2013; Willerton, 2013). Providing solid, unbiased research to academic policymakers is critical to initiation of administratively supported long-term change in educational practice (Kahn et al., 2009).

Additionally, the STEM faculty participants in the survey research are familiar with the white paper format. As a marketing product, the white paper is used in many of the business and industry fields in which the faculty have experience (Willerton, 2013). The scientific and technical communities accept the white paper format as a flexible, time-appropriate means of disseminating authoritative, research-based information (Gelfand & Lin, 2013).

The research results from Section 2 indicated several independent areas in which the problem of student success in STEM courses could be addressed. These issues may be addressed at various levels of the college's organization including administrative policy, professional development, and classroom methodologies. Due to the varied nature of the results, a white paper was the most inclusive method for communicating recommendations in a timely, effective, and efficient way (Curran et al., 2011; Gelfand & Lin, 2013).

Review of Literature

In the following review of literature, I present a thorough, critical analysis of how current peer-reviewed research supports the development of the recommendations advanced as a result of the study. The study findings indicated that use of in-class ALM

(Factor 1) and highly structured activities ALM (Factor 2) demonstrated a higher likelihood of students earning completion grades (A, B, and C compared to F). A nontraditional faculty development methodology called professional conversation (Irvine & Price, 2014) was recommended for the purpose of allowing instructors at MCC to explore avenues and methods of incorporating more of these active learning techniques into their classroom practice. Conversely, the use of online ALM (Factor 4) demonstrated a lower likelihood of students achieving a completion grade, which was contrary to expectations (see Greyling, Kara, Makka, & van Niekerk, 2008; Halupa & Caldwell, 2015; Poon, 2013). The negative impact of the use of online ALM (Factor 4) may have been associated with a lack of the prerequisite digital literacy skills necessary for MCC students to effectively engage in online ALM, which may be due in part to socioeconomic factors or self-efficacy issues (see Jesnek, 2012; Pagani, Argentin, Gui, & Stanca, 2016; Ritzhaupt, Feng Liu, Dawson, & Barron, 2013; Zhang, 2015). The recommendation to improve preparedness for technical-enhanced education and online course work was to institute computer-literacy placement testing and remediation for all incoming students. The large positive odds ratios for the use of writing-based ALM indicating large increases in the likelihoods of students earning As, Bs, and Cs in comparison with Fs indicated the need for further inquiry. The number of nonzero cases indicating use of writing-based ALM in the classrooms (495 out of 1140, approximately 43%) indicated there may have been validity issues requiring caution in the interpretation and applicability of the results, but the strong positive results should not be summarily ignored. As discussed in the data analysis section, the large number of zero cases for writing-based ALM (645 out of 1140) caused the cases that use these methods to be classified statistically as outliers requiring that interpretation with the qualification that the magnitude of the results was not certain, but the directionality of the strong positive results could be assumed to be correct. This qualification translated into the recommendation that the effect of using writing-based ALM should be subject to further study through the incorporation of the methods in the classroom as part of the action research project. The recommendation was to develop pilot programs and instructional modules for integrating more writing into STEM courses for initiating a localized and focused action research project at MCC. The final two factors, project-based ALM (Factor 3) and portfolio-based ALM (Factor 6) were both recommended for future research. The use of project-based ALM (Factor 3) resulted in lower likelihoods of students achieving As and Bs than Fs, which was opposite of the expected outcome (Ertmer et al., 2014; Overton & Randles, 2015). Further research into the dynamics of this unexpected result would be necessary before recommendations of policy changes could be made, which exceeded the scope of this study. Additionally, the very small number of instructors using any of the portfolio-based ALM (Factor 6) may have contributed to the factor’s lack of significance in predicting the parameter estimates. The recommendation was to focus on the other ALM factors that did show significant prediction powers on student grades for the highest effectiveness. The multiple directions these recommendations took indicated that the white paper was the best option as the project deliverable.

In keeping with the theoretical foundations of the research study, the recommendations as summarized previously were researched and developed in the framework of social constructivism. Additionally, the recommendations were developed in alignment with the unifying policy of the MCC Strategic Plan (MCC internal document, 2015) that has policy goals to increase student success by developing a comprehensive first-year experience, admission, and advising model that increases preparedness and to develop an innovative learning environment through providing resources and professional development that facilitates teaching and learning and improves services. Proposals for the faculty development initiative focused on collaborative methods of professional development to encourage the use of ALM in the classroom. The recommendation for assessment and remediation in digital literacy was based on the socioeconomic discussion of the digital participation divide and how MCC could improve the first-year experience of underprepared students. The recommendation to prioritize research in the use of writing-based ALM diverged from the theoretical foundation as the methodologies in the factor had little or no social interaction; however, constructivism was the predominant learning theory behind many initiatives to increase writing in college curriculum (Khan, 2015; Leggette & Homeyer, 2015).

For the literature review, I searched ProQuest, Academic Search Complete, Education Source, and ERIC databases as well as the Google Scholar search engine. The key words for the searches included *non-traditional professional development*, *collaborative faculty development*, *inquiry-based faculty development*, *professional learning community*, *digital divide*, *digital participation divide*, *online orientation*, *mandatory online orientation*, *digital learning*, *online learning*, *technology-enhanced learning, writing in STEM*, and *writing-intensive courses.* Hundreds of articles were returned and were filtered by references to community colleges or higher education.

Professional Conversation

The professional learning community (PLC) has become a staple in educational institutions with a shift in philosophy from professional development to professional learning (Stewart, 2014; Watson, 2014). A PLC is governed by the principles of shared vision and values, collective responsibility, collaborative focus on learning, and professional reflection (Watson, 2014). Grounded in the situated learning model, PLCs and other communities of practice provide an open venue in which participants can work together to build collective wisdom and solve problems (Dichter & Zydney, 2015; Owen, 2014).

However, shared vision can evolve into conformity (Watson, 2014) and groups can suffer from the desire to keep familiar and comfortable practices from changing (Tagg, 2012). Divergent or innovative ideas have the potential to be rejected because of a hegemony disguised as inclusion while openness and continual review may become interpreted as intrusive oversight (Watson, 2014). Faculty may become resistant to change they see as counter to their academic freedom and autonomy (Tagg, 2012).

In contrast, a professional conversation is a constructivist and conversational model of collaborative learning (Irvine & Price, 2014). The development of this method of professional learning is an outgrowth of a shift toward informal and self-directed learning (Owen, 2014; Stewart, 2014). Professional conversations are inquiry-driven, action research-infused methods that emphasize collaborative reflective practice while embracing the dissonance of divergent views (Irvine & Price, 2014). Additionally, agency, autonomy, and flexibility make the structure of the professional conversation attractive to instructors in higher education (Penick Brock et al., 2014; Voogt et al., 2015).

Developed as a safe environment for exploring, questioning, and experimenting, the members of the professional conversation accept that innovation and change exist in conflict and that dissonance can be productive as a change agent (Watson, 2014). The cognitive dissonance required for deep learning does not perpetuate from repetition of existing practices (Tagg, 2012), but authentic, productive discussion encourages disagreement (Falbe, 2015). Growth in practice is facilitated by deep and challenging self-reflection (Voogt et al., 2015). Participants must suspend judgment and exhibit discipline to allow authentic curiosity and an attitude of change (P. Adams, 2009). The group learning environment of the professional conversation provides a venue for creative strengths to merge with nonlinear problem solving to manifest in a dynamic, cyclical process of change (Donnelly, 2009; Penick Brock et al., 2014; Voogt et al., 2015).

Action research is widely regarded as an important facet of the role of the faculty (Owen, 2014). As a vehicle for action research, the professional conversation is dependent on an attitude of genuine curiosity and supportive integration into practice (P. Adams, 2009). Allowing faculty members to respond quickly to evidence from their classrooms and their students embodies the principle of continuous improvement

(Donnelly, 2009; Nicholson, Capitelli, Richert, Bauer, & Bonetti, 2016). Design and redesign in the context of mutual support and reflection helps faculty develop a sense of ownership, not only over their own learning and the action research in their own classrooms, but in the progress toward institutional change (Samarawickrema, Benson, & Brack, 2010; Voogt et al., 2015). The feeling of ownership of faculty learning and the change process is essential in overcoming resistance to institutional change (Tagg, 2012).

Advancements in network and educational technologies facilitate the construction of an asynchronous platform for the professional conversation. Online, asynchronous methods of faculty development are becoming popular for their flexibility to accommodate busy schedules and travel distances as well as for their ability to provide continuous, situational support of educational practice (Surrette & Johnson, 2015). In addition to the normative aspects of faculty development, online methods allow designers to increase communication, increase long-term collaboration, and customize the learning activities to the needs of the participants (Falbe, 2015). Extending the learning activities beyond the typical multiday workshop structure to an on-demand format provides more benefit to the participants (Bauer, 2010). Facilitating group interaction and reflection of shared experiences develops artifacts of conversational threads that not only build the sense of community but situate the learning within current practice (Bettoni, Bernhard, Eggs, & Schiller, 2011). Online, asynchronous professional conversations maximize productivity and facilitate goal-focused processes by establishing written communication norms to prevent misuse and misunderstanding (Dichter & Zydney, 2015).

New Digital Divide

Advancements in educational technologies benefit students as well. Online modalities offer flexibility and access to students, especially nontraditional and minority students who would otherwise not be able to attend college (Doherty, 2006). A large meta-analysis of instructional modalities showed that online learning improved student achievement regardless of content or student learning types (Means, Toyama, Murphy, Bakia, & Jones, 2009). Additionally, interactive, online learning has been characterized as mandatory for engaging college students deemed digital natives (students born after 1980) (Lewis, Fretwell, Ryan, & Parham, 2013). The benefits of using online and interactive educational technologies has led to substantially increased use in traditional, face-to-face classrooms as well (Jesnek, 2012).

Despite the well-researched and widely reported benefits of online modalities and technology-enhanced courses, retention in online classes is consistently 10-20% lower than in traditional face-to-face classes (Doherty, 2006; Gaytan, 2013; Wladis et al., 2014). This retention gap can be correlated with lack of success and degree completion (Wladis et al., 2014). The differences in retention between traditional and online courses has been attributed to several factors including lack of faculty interaction (Lewis et al., 2013), amount of learner control (Means et al., 2009), and poor course design (Tirrell & Quick, 2012). Wladis et al. (2014), however, in a study with community college students found no course-level variables that influenced a student’s retention in the course and determined that the differences in retention between traditional and online courses were likely the result of student characteristics.

Community college students are ethnically, generationally, and economically diverse. Nontraditional community college students, experiencing educational technology as digital immigrants, have a diverse background of digital experience (Naidoo & Raju, 2012). Socioeconomic status, ethnicity, and racial differences have also been associated with discrepancies in access to digital technology and has been referred to as the "digital divide" (Harris, Straker, & Pollock, 2017; Ritzhaupt et al., 2013; Robles Morales, Antino, De Marco, & Lobera, 2016; White & Selwyn, 2012; Zhang, 2015). Governments, schools and nonprofit organizations have worked to address the digital divide by ensuring that all students have access to digital technology and the internet (Harris et al., 2017); eliminating the digital divide, however, has not eliminated the digital inequities (Harris et al., 2017; Pagani et al., 2016; Robles Morales et al., 2016; Zhang, 2015).

The new digital divide is not one of access, but one of participation (Harris et al., 2017; Naidoo & Raju, 2012; Robles Morales et al., 2016; White & Selwyn, 2012). White and Selwyn (2012) noted that increased availability and access of the internet and educational technologies has not led to reciprocal increases in adult learning. White and Selwyn also described how age, occupational class status, and amount of education were strongly related to participation in educationally-oriented digital usage whereas gender and ethnicity were not. Zhang (2015) posited, based on Bordieu's capital theory, that individuals pattern their internet usage to accommodate their existing social positions and showed that 39% of the variability in internet searches in the sample was attributable to socioeconomic status. Harris et al. (2017) also discussed how socioeconomic factors were related to how students chose to use computers. The distinction between the advantaged and the disadvantaged in the new digital participation divide is one of skills and social capital (Jesnek, 2012; Pagani et al., 2016; Zhang, 2015).

Now that basic computer skills and information literacy are critical to every student's success in the college curriculum, faculty in community colleges need to accept the fact that they are becoming responsible for remediating computer skills deficits along with deficiencies in mathematics, reading, and writing (Dixon et al., 2012; Jesnek, 2012). Since the new digital participatory divide has been related to socioeconomic groups that represent the student body of many community colleges, it cannot be assumed that students are entering post-secondary education with the skills necessary for success nor that all students traditionally considered "digital natives" are equally proficient in technology use (Kelso, 2011; Thompson, 2013). The lack of proficiency in basic computer skills exacerbates issues related to online learning because students need to be able to work comfortably within the LMS software, do basic troubleshooting, and communicate effectively online to succeed in online and technology-enhanced courses (Doherty, 2006; Jesnek, 2012). Pagani et al. (2016) presented strong evidence for the positive relationship between academic achievement and basic digital skills. Colleges and universities, in fact, may be perpetuating digital inequities through the use of online and technology-enhanced courses when student experience isolation and frustration due to their inability to deal with the technology component of the course (Cho, 2012; Kinghorn, 2014; Stephens, Hamedani, & Destin, 2014).

Solutions proposed to community colleges to help bridge the new digital participation divide include tutoring/peer mentoring (Dixon et al., 2012; Kinghorn, 2014;

Lee, Choi, & Kim, 2013), computer skills proficiency testing (Beck & Milligan, 2014; Gaytan, 2013; McClenney, 2013; Pagani et al., 2016; Thompson, 2013), and online orientation (Cho, 2012; Derby & Smith, 2004; Jesnek, 2012; Kelso, 2011). Kinghorn (2014) suggested that peer-to-peer interactions online assist in developing virtual collaboration skills as well as providing support and guidance for self-regulation. Lee, Choi, and Kim (2013) associated self-regulation skills with persistence and success in the online course environment. Improving student success and completion requires assessment and remediation to ensure readiness with computer skills as much as with math or reading (McClenney, 2013) and 85% of faculty surveyed expressed that computer skills were necessary for success in college-level coursework (Jesnek, 2012). Appropriate assessment is needed to provide adequate intervention in digital skills deficits (Beck & Milligan, 2014). Pagani et al. (2016) encouraged testing in lieu of self-reporting as students underestimate the digital skills necessary for academic performance.

Participation in online student orientations also correlates with student achievement (Cho, 2012) and with a lower likelihood of dropping out (Derby & Smith, 2004). A universal online orientation or training also alleviates the issue of inaccurately assuming a base level of computer knowledge in students (Jesnek, 2012). When surveyed, 80% of students thought it was a good idea for colleges to offer a technology training course before taking online courses, and 55% of the students surveyed thought it should be mandatory (Kelso, 2011). In addition to the research in literature, the lack of basic computer skills is a recognized issue at MCC and basic computer skills training has been previously added to an extended First-Year Experience (FYE) class; however, students are placed in the FYE plus computer skills class based on placement scores in math, reading, and writing, not a computer proficiency test (Director of Success Center, MCC, personal communication, June 12, 2017).

A Focus on Writing

Incorporating writing-intensive courses into all curriculum areas has been identified as a high impact practice (Kilgo, Ezell Sheets, & Pascarella, 2015; Sweat, Jones, Han, & Wolfgram, 2013). High impact practices are identified for their effect on cognitive and behavioral student engagement (Sweat et al., 2013). Writing-intensive courses improve student learning due to the need to apply and organize information in an orderly and logical manner (Kilgo et al., 2015; Mills, 2015). Writing tasks additionally help students to develop critical thinking skills, communication skills, and intellectual competence (Leggette & Homeyer, 2015). Writing also encourages metacognition and reflection (Dively & Nelms, 2007).

Academic writing has context-specific and discipline-oriented requirements and goals (Leggette & Homeyer, 2015). Evaluation of a writing-intensive biology course showed that students not only increased their biology competencies, but also expressed increased confidence in their scientific thinking and in their abilities to comprehend and communicate research findings (Brownell, Price, & Steinman, 2013). In a comparison of microbiology course modalities, the writing-intensive modality had the highest percentage of Fs as the final grade, but also had the highest percentage of correct answers on the concept inventory item analysis (Khan, 2015). Writing-intensive courses additionally enable students to discover, process, develop, organize, and disseminate scientific ideas (Leggette & Homeyer, 2015).

The benefits to writing-intensive courses notwithstanding, science faculty tend to be hesitant to teach writing (Mills, 2015), and the attitude of the faculty in developing and implementing any writing program is paramount (Salem & Jones, 2010). A survey study by Salem and Jones (2010) showed that non-writing faculty lacked confidence in their ability to teach and review grammar and composition. Additionally, in discussing the addition of writing-intensive courses across the curriculum, faculty were concerned about the fairness of the workload, the need to remediate underprepared students, and a loss of academic freedom and autonomy (Salem & Jones, 2010). Many of the concerns raised by faculty during the implementation of writing programs were tied to deeply held beliefs about education and identity (Salem & Jones, 2010). The attitudes of the faculty toward including writing-intensive courses, like other institutional changes, is dependent on the way the change is presented (Tagg, 2012) and whether the changes are presented without consideration for individual choice (Penick Brock et al., 2014).

Project Description

I chose a white paper as the final project to communicate the research findings to the administration and faculty of MCC. The white paper presented a condensed literature review, the methodology of the research, significant findings, and recommendations for practice. The white paper also included graphics and images that enhance the readability and appearance of the document. The following discussion presents the practical project planning details including needed resources, existing support, potential barriers and solutions. Additionally, the timeline and activities required to implement the recommendations is included along with roles and responsibilities of faculty and administration personnel involved in the implementation process.

Resources and Support

The process of preparing the white paper as the final project required relatively few resources other than time. The cost of preparing the document was negligible. Graphic design help and image copyrights were the only concern. The marketing and public relations personnel at MCC assisted through the provision of in-house media and usable images. The cost of using in-house media and MCC copyrighted images with permission was also negligible.

Potential Barriers

There were no barriers encountered in the preparation of the white paper. Barriers which may be encountered during the implementation of the recommendations include the lack of institutional support, faculty resistance, and lack of resources. The professional conversation can be enabled using the current learning management system while the recommendation for an action research project for the inclusion of writing-intensive courses would not likely require large capital investment. The recommendation for the use of a basic computer skills proficiency test may involve substantial resources depending on whether the student services staff choose to use a validated, published measure for the proficiency testing or choose to develop the test locally. Several Ohio community colleges offer basic computer skills assessments and can serve as a resource in the implementation of this recommendation.

Recruitment of faculty to participate in each of the recommended initiatives is a primary concern. The professional conversation mode of ongoing, informal faculty development requires faculty members to become invested and take ownership of the collaborative project. Without the faculty taking charge of the project, the implementation of the recommendation for faculty development may become an administrative-led initiative which risks increasing faculty resistance. Faculty buy-in is not required for development of a basic computer skills proficiency test and remedial computer course because the proficiency testing is run through the student services department. Recruiting faculty to participate in developing and testing writing-intensive modules for STEM courses will likely face the greatest challenge of faculty resistance. Faculty loads in the STEM fields are already burdensome and fears that introducing writing-based curriculum will increase workloads on already overtaxed instructors is legitimate.

Exploring opportunities to overcome these barriers before they are encountered could enable smoother implementation. It is possible that as a result of reviewing the white paper, the administration of MCC decides that one or all of the recommendations are not worth implementing. Simplifying the recommendations and stressing the low-cost aspects of the potential implementation may garner increased institutional support. Additionally, the current budgetary crisis resulting from falling enrollment may lead to a lack of resources for implementing any new initiatives. This also could be overcome by focusing on the low-cost pieces of the projects with a phased implementation which saves the more expensive pieces of the recommendations until a later date. Overcoming faculty resistance may be challenging, but there are options. One example of a potential solution is to recommend reclassifying the workloads of writing-intensive courses to compensate faculty for the extra time it is expected to require. Another potential avenue to explore is to frame the incorporation of the writing-intensive courses into the curriculum as the foundation of an action research project in which instructors who volunteer to participate may be able to derive publications and advancement opportunities within the college. Finally, persuading the faculty to become involved in the professional conversation faculty development exercise may involve time, energy, patience and leadership (P. Adams, 2009; Nicholson et al., 2016; Penick Brock et al., 2014). The professional conversation works best when it is organic and curiosity-driven. Having the faculty development committee integrate some of the professional conversation tasks into the pre-semester work days in exchange for meeting release could encourage faculty to get started with the activity. Including participation in the professional conversation as part of the new faculty orientation plan could be used to acquaint new instructors with the resource.

Proposal for Implementation of Recommendations

Implementing the recommendations included in the project white paper can run concurrently as different groups will hold responsibility for different tasks. The responsibilities of managing and implementing the recommendations will be delegated to multiple faculty and campus-wide committees in deference to the self-governance structure of the institution. Likewise, the tasks as conceived include group work in development of policy, negotiation of standards, design of assistive templates, and recruitment of faculty participation for increased diversity of input and democratic self-governance. The concurrent implementation of the recommendations is possible due to the use of separate committee groups; however, the tasks in the timelines are dependent on the schedule of committee meetings. The specific responsibilities, tasks, and timelines for the three recommendations are presented below.

Recommendation 1: Professional conversation. The faculty development committee will hold the responsibility for implementing this initiative. Specific tasks that will need to be accomplished for this recommendation to be implemented are the design of the conversation structure, the building of the Blackboard course shell, the negotiation of communication standards, the selection of facilitators, the recruitment of contributors and researchers, recruitment of team leaders, and priority ranking of ALM to be included. The role of the faculty development committee after this initial phase will be the upholding of communication standards and development/scheduling of the new ALM to be added to the conversation. Facilitators will be faculty members that work to encourage continued conversation through posting questions and redirecting conversational threads back to the content focus area. Contributing researchers will have the responsibilities to create brief mini-modules to provide instructional background material about specific ALM from peer-reviewed journals and other credible sources as well as listing links to video, blogs, and other online content which they found helpful in understanding the ALM. The team leaders will be instructional faculty who will recruit two to three other faculty in other academic disciplines to run action research projects in their courses through testing of specific ALM. The teams will independently design their respective action research projects.

Table 21

Implementation Plan for Professional Conversation Faculty Development

Task	Responsible	Expected duration
1. Oversight/monitoring	FDC*	Ongoing
2. Determine conversation structure	FDC	1 month
3. Build Blackboard course shell	FDC	2 months
4. Negotiate communication standards	FDC	2 months (concurrent with 1 and 2)
5. Select facilitators	FDC	1 month
6. Recruit research contributors	FDC	2 months (concurrent)
7. Recruit team leaders	FDC	2 months (concurrent)
8. Prioritize ALM selection	FDC	2 months (concurrent)
9. Background research uploaded	Contributors	2 months
10. Initial discussion questions posted	Facilitators	1 month
Time to readiness		9 months

* Faculty development committee

Recommendation 2: Basic computer skills proficiency testing and online student orientation. The college-wide completion committee will hold the responsibility for the recommendation to implement a basic computer skills proficiency test and online student orientation specific to MCC's student portal and learning management system. The development of these processes will be open to the interpretation of the committee. As the completion committee is a college-wide committee, members of the administration, faculty, and staff participate in the committee actions and, therefore, would provide endorsement, contribution, and support of any agreed upon initiatives. However, the likely tasks involved in implementing this recommendation are surveying of all faculty for online applications and skills used in online, hybrid, and traditional classes, deciding to use a published or self-developed assessment, determining passing levels on basic computer skills proficiency test, developing remediation plans, building online student orientation course, and hiring and training computer skills peer tutors. There will be no additional hardware requirements as computer testing access is available to all students through the Success Center.

Table 22

Implementation Plan for Computer Skills Proficiency Testing and Online Student Orientation development

Task	Responsible committee member	Expected duration
1. Survey faculty for computer skills needed	Institutional research	2 months
2. Selecting/building proficiency test	Success center	2 months
3. Negotiate passing levels	Faculty	1 months
4. Develop remediation plans	Tutoring services	1 month
5. Build online student orientation course	Technology team and faculty	3 months
6. Hire/train computer skills tutors	Success center	2 months
Time to readiness		12 months

Recommendation 3: Action research on writing-intensive courses. An ad hoc faculty committee will need to be assembled to implement this recommendation. There is not currently a committee or program at MCC that would have purview over this type of activity. After the ad hoc committee is formed, the research plan will be developed which will examine the effects of implementation of writing-based activities on student success. The output of the action research project will be assignment modules and implementation guidelines for using writing-based ALM in STEM courses. The assignments and guidelines would not encompass an entire class, but act as supplemental material for instructors to use in current class structures. The ad hoc committee will begin construction on the writing modules through the development of implementation guidelines, Blackboard content, and assignment and rubric templates. Table 23 displays the anticipated timeline for the implementation of this recommendation.

Table 23

Implementation Plan for Local Research on Writing-Intensive Courses

Task	Responsible party	Duration
1. Develop research plan	Ad hoc committee	3 months
2. Develop assignment templates	Individual instructors	2 months
3. Design rubric templates	Individual instructors	2 months
4. Negotiate implementation guidelines	Ad hoc committee	2 months
5. Build Blackboard course content	Individual instructors	3 months
6. Oversight and reporting	Ad hoc committee	Ongoing
Time to readiness		15 months

Project Evaluation Plan

The project evaluation plan is goal-based (Bailey, Freeman, & Curtis, 2001; Van Osselaer & Janiszewski, 2012). The goals of the project were to communicate the results of the research and make a persuasive argument for changes to faculty development, proficiency testing, and emphasis on writing in all curricular areas. This is the appropriate type of evaluation for a white paper project as measuring the outcomes of the implementation of recommendations are time-prohibitive. The evaluation plan will include an electronic survey of key stakeholders who have been provided with a copy of the white paper. The survey will be provided within one week after the delivery of the position paper to determine if the goals of communication and persuasion were met. The key stakeholders who would be included in the distribution of the white paper are the deans of each division, the academic vice president/provost, the college president, the director of student services, the faculty development committee, the curriculum committee, and faculty senate officers. Distribution to the entire faculty will be at the discretion of the administration.

Project Implications

The project endeavored to communicate the results of the research on how the use of ALM predicts STEM course student grades at MCC and to present recommendations for changes in practice. Changes in instructional practice which enable more students to complete more classes has the potential to create social change for the students and the institution as local stakeholders. In the broader context, very little research has been done on the use of ALM at the community college level and this project will lead to the dissemination of the research with the potential for application and social change at other institutions as well.

Local Context

For the students as stakeholders, improving the likelihood of achieving higher grades may enable more students to complete their programs faster and with less debt. Reducing the likelihood of failure in STEM courses, especially those courses which act as barriers to persistence or major program entry, increases the potential for completion of a degree program that may improve the students' job prospects, social capital, and socioeconomic status.

For the institution, making improvements in student success can have significant benefits financially and academically. As a state supported community college, MCC competes yearly for its share of state money. Improving course and program completion rates improves the chances of increasing the state share of funding. Increased state funding provides resources for providing better student services, increasing campus security, maintaining functional facilities, and retaining quality faculty. Additionally, MCC can gain increases in reputation as being an institution that is responsive and sensitive to students' academic needs drawing more students to the college in a time when statewide community college enrollment is decreasing.

Broader Context

Improving the likelihood of STEM course completion by improving the likelihood of higher student grades could potentially lead to higher graduation rates and lower cost for at-risk students by reducing the number of courses repeated and the time to degree completion (Schneider & Yin, 2012). Assisting at-risk students to degree completion by improving the likelihood of higher individual course grades can provide opportunities to access higher paying jobs and more economic security while potentially increasing opportunities for minority participation in fields where they are traditionally underrepresented (Wladis, Hachey, et al., 2015). Increasing minority participation can also potentially yield greater economic security and mobility as STEM fields have lower unemployment rates, better salaries, and smaller pay gaps by race and gender than non-STEM fields (Byars-Winston, 2013).

In addition to improving the economic prospects for students who complete STEM programs, increasing completion of minorities and women in fields where they are traditionally underrepresented can create social change within the professional fields. Science, engineering and math fields are facing critical shortages of qualified candidates required to keep the United States technologically and economically competitive (Olson & Riodan, 2012). Improving completion in STEM programs will potentially help address this critical socio-economic issue. Increasing the completion percentages of women and underrepresented minorities also has the lasting social and professional benefit of improving collaborative creativity and innovation (American Society for Engineering Education, 2013; Chesler et al., 2015).

Deep conceptual learning about the basic and unifying principles of science and mathematics may produce transformative educational experiences that allow students to see not only how science applies to their career fields, but also to the functioning and sustainability of the natural world (Talanquer, 2014). Affecting meaningful change in the understanding of scientific principles will help to create knowledge consumers that will become more capable students, better trained professionals, and more discerning citizens. When citizens have the scientific understanding to interpret and make sense of the world, they become capable of taking informed action (Weasel & Finkel, 2016). Understanding ALM and how these methods benefit the diverse population at MCC will potentially permit the construction of the best possible educational and social experience where instruction is built for positioning every student for success personally, professionally, and globally as citizens of a sustainable world (Reimer et al., 2016).

Conclusion

In this section, I discussed the development of the final project as a white paper and the recommendations for the improvement of practice based on the results of the research study. I conducted a review of literature to build support for the recommendations for changes in faculty development, computer skills proficiency testing and remediation, and action research on the potential incorporation of writing-intensive courses into the curriculum. Additionally, I presented the outlines of tasks and responsibilities for each recommendation in a proposal for implementation. Finally, I described the role that the final project may play in the facilitation of social change in both the local and the broader contexts. In the next section, I have presented a professional reflection, and I have evaluated the project for strengths and limitations as well as the implications and directions of future research.

Section 4: Reflections and Conclusions

In the final section of the study, I present reflections on the strengths and limitations of the project and on the impact the research and project development had on me as scholar, practitioner, and project developer. The implications and importance of the work involved in this final study are discussed. Potential directions for future research are proposed.

Project Strengths and Limitations

The white paper included in Appendix A and constructed as the project deliverable provided a strong foundation for situating the study within the genre of educational research. The primary strength of the white paper project was consolidating the literature review, research methodology, statistical results, and recommendations into a user-friendly format. In the genre of white papers, the purposes can vary from communicating technical ideas to generating product interest to creating a persuasive argument (Gelfand & Lin, 2013; Willerton, 2013). To promote change in the educational practices at the local institution, it was beneficial to present the results in a persuasive format rather than as a standard research report or journal article. The persuasive stance of the white paper was designed to build support for the recommendations for change using research-based evidence (see Powell, 2012).

The white paper also allowed the use of creativity and personal expression because of the lack of formatting conventions (Gelfand & Lin, 2013). In addition to strong evidentiary support, a white paper should be visually appealing (Powell, 2012). The project deliverable had the strength of being visually appealing and of being presented in a professional manner. The more professional and visually appealing, the more likely the intended audience will invest the time in exploring the content (Powell, 2012). Finally, the white paper enabled a connection between the concerns of the key stakeholders, the administration and faculty of MCC, and the study research and recommendations. Key stakeholders are more apt to consider and follow through on white paper recommendations if the connection to the local problem is clearly evident (Powell, 2012).

Using a white paper as the project deliverable does have limitations. The recommended changes in practice involved additions and changes to the faculty development program and the new student proficiency testing. With a white paper, the control over how the recommendations are implemented is given to the institution, which may result in misapplication or divergence from the original intent. Conversely, control over the implementation of the recommendations may be retained but may result in additional unexpected workload. Although the white paper provided a good summary of the quantitative research in this study, it did not allow me to include all of the details of the analysis and results, which may lead to a misinterpretation of the findings.

Recommendations for Alternative Approaches

I investigated the relationship between student grades and the instructional methodologies used in the classroom to improve course completion rates within the framework of social constructivism. The local problem was low completion rates in STEM courses. The statistical analysis included multinomial logistic regression, which was an advanced technique not commonly used in educational research literature, making interpretation by readers difficult (El-Habil, 2012; Hossain, Ahmed, & Howlader, 2014). Additionally, using student grades as the criterion variable had the advantage of creating a large data set for the statistical analysis, but due to the need to protect the privacy of both the instructors and the students, the student level data could not be connected with other student-level variables such as GPA, placement test scores, socioeconomic status, major, number of completed credits, and demographic data that have all been previously associated with student grades (see Djajalaksana, 2011; Freeman et al., 2014; Junco, Heiberger, & Loken, 2011; Loughlin et al., 2015; Watkins & Mazur, 2013). Several alternative methods of studying the problem of low completion rates in STEM course at the local community college could be explored.

The first alternative method that bears consideration would be to study the completion issue at the course level rather than the student level. The completion percentage (the number of students earning a grade of A, B, C, or D divided by the number of students in the class) could be correlated with the ALM factor scores. This was the original idea for the study. However, with the small number of classes to survey at the local site and the typical response rates in the 10-15% range, it was not possible to achieve the number of responses necessary to satisfy the a priori power analysis. If the study was designed to survey faculty of STEM courses at multiple community colleges within the state system, the population would be greatly increased making it more likely to achieve the number of responses necessary to reach the appropriate statistical power. This would reflect a change in the definition of the local problem from the locale of the single community college to the statewide community college system. The alternative solutions that may arise from this alternative approach would probably be similar to the recommendations formed from the current study due to possible population similarities. The solutions at the course-level are dependent on student-level grades but are viewed from a holistic perspective which views the grade of A the same as a grade of D, which does not reflect the more complex nature of student success.

The problem could be alternately defined as low completion rates across all disciplines instead of just STEM disciplines. With this alternate definition, the problem of the low sample size could also be eliminated. The number of categories in the academic disciplines variable would be increased, which would counter any advantage gained by a larger sample size unless the academic discipline categories were defined as the binary STEM versus non-STEM. This alternate approach to the categorization would enable clarification of any STEM-related effects. A unique approach for solutions derived from this research option could be the development of interdisciplinary collaboration activities for faculty development.

The previously discussed alternative research methods would require quantitative designs. A qualitative approach could also be used to address the issue of low completion rates in STEM courses. A subtle difference would emerge in the definition of the local problem from what the instructors are doing in the classroom to the attitudes and responses of students to the different instructional methodologies. Interviews with students, both completers and noncompleters, would be designed to investigate how the students felt about different ALM. The interviews would address topics such as motivation, self-efficacy, and student attitudes. Because the students who would be interviewed would have to sign an informed consent form, this alternative approach could easily metamorphize into a mixed-methods approach that addresses the relationship between student attitudes and demographics such as gender, socioeconomic status, race, and prior academic performance. Solutions developed as a result of these alternate options would probably include faculty development on the effect of student characteristics on classroom approach as well as information produced for the student services personnel to use for advising, counseling, and tutoring services.

Scholarship, Project Development, and Leadership and Change

Through the process of the research and development of the final project, I learned a great deal about the process of the scholarship of teaching and learning. Beginning the process with years of experience in scientific and engineering research and development, I was pleased with the academic rigor of the research involved. Developing and using survey-based data rather than experimental data was a new experience, and the level of statistics required to analyze the results was surprising. The statistical analysis of multinomial logistic regression is graduate-level statistics. Because I did not have a comprehensive statistics class, I was required to teach myself what was needed to use the method.

In the development of the project deliverable, I was able to draw on years of experience in technical and engineering writing to build the persuasive argument for change in the educational practices at MCC. The processes used in constructing the white paper were not unexpected. As a result of completing this research and project development, I was able to explore new avenues of interest, build self-confidence, and construct a new dimension of professional identity. Personal reflections in the areas of scholarship, practice, and project development follow.

Self as Scholar

The transition of perspective from engineering research to education research has not been easy. Social science research, which includes educational research, is less objective than the experimental methods with which I am familiar. However, having a background in higher level mathematics certainly was helpful while I was teaching myself how to perform multinomial logistic regression. Being able to complete the final study with the expectation of earning a doctorate in education gives me increased self-confidence and credibility as I communicate my knowledge and beliefs about education and the importance of reflecting on instructional methodology and committing to continuous improvement.

Self as Practitioner

Early in my course work at Walden University, I was tasked with constructing a philosophy of education. A small excerpt from that document is included here as part of my reflection as a practitioner:

> In reflecting on why I chose to pursue a career in education, I am reminded of one of my students who had a transformational impact on my views of education as a career and my philosophical orientation. Lisa entered my chemistry class as a middle-aged African American woman who was returning to school out of the necessity to take care of her family after a divorce. She had not been in school in 30 years and struggled

> tremendously with chemistry. As I got to know Lisa better, I felt that she was the ideal candidate for the nursing program because of her compassion, wit, and sincerity; it saddened me when she failed the class. She reenrolled in the same class the next semester. Because I was experimenting in my class with various active learning techniques, the class was transformed into a collaborative study session. Lisa blossomed with the change in methods. When she completed her final for the second time and learned that she had earned a B in the class, she burst into tears and hugged me saying that she could not have done it without my help. This is the best way I can describe why I chose to teach because if I can make a difference for just one woman who never thought she could make it, I have spent my time and effort in a worthwhile endeavor.

Lisa's experience in my chemistry classes has been one of the most influential experiences in my teaching career. In fact, Lisa's transformation with the changes I made in instructional methodologies was one of the motivating factors in choosing the direction of this final project.

As I reflect on how I have changed as a practitioner as a result of the research and development involved in this final project, I have become aware of how little I know about the options for incorporating active learning in my courses. The research for this project opened new avenues of interest by exposing me to active learning methods with which I was not familiar and which I believe will make good additions to my practice. Additionally, I have learned that experimentation in practice is beneficial. Previously, I would have been concerned about the implications for fairness if I changed methods across sections or semesters. Committing to a culture of continuous improvement, however, gave me impetus to overcome that objection.

Self as Project Developer

Developing the white paper for this project study permitted me to reflect on how my previous experience in engineering writing and my current position as a college educator have become integrated. Prior to the research and development of this final project study, I believe I held a dichotomous view of my identity. I held onto my perceptions of myself as a scientist/engineer with a disconnect between my previous job in composites research and development and my current path as an educator. The research on the topics of active learning methods and the construction of the project has helped me to construct a cohesive identity by constructing a bridge between my two career paths.

I have also built a lot of self-confidence in my abilities to be a project developer through the course of this project. As a result, I am taking on new projects and expanding my role as a practitioner. Some of the new projects in which I am involved include redesigning the chemistry curriculum to convert from a textbook-based model to an OER (online educational resources) model. Additionally, I have been tasked with constructing the LMS interface for an introductory engineering class to use more ALM with the intent to increase student grades and completion.

Reflection of the Importance of the Work

The importance of the work involved in this project can be seen in the change of practice in the local context as well as adding to the body of research. I believe that it is critical for any educator to want to do the best possible job for all students in his or her courses. The recommendations for institutional change included in the project white paper were made to assist not only instructors but also student services and administrative personnel in better serving the students at MCC.

This study also adds to the body of research on ALM. The addition to the body of research is important because very little of the research on ALM has been conducted at the community college level. The results of the study confirmed that although ALM generally improve student outcomes, online ALM and project-based ALM had negative effects on student success. This result was contrary to most of the published research in these methods and may be attributable to the differences in student demographics at community colleges. Understanding that research performed at large four-year research institutions is not universally generalizable to the community college setting is of critical importance for educators searching for new methods to improve practice.

Implications and Applications

The implications of this study present the opportunity for significant change at the individual and institutional levels. For the individual instructors, understanding that small changes can create large impacts in student outcomes represented by student grades could empower experimentation and build a sense of career worth. The white paper potentially could instigate individual instructors to begin research of their own on what works to improve student success in their classrooms. For individual students, especially students like Lisa, small changes in instructional methodologies could lead to significant changes in their educational trajectories leading to better jobs and increased financial prospects. Application of the study recommendations at the individual level for instructors includes participation in the professional conversation informal development activities. Enforcing the ideas of collaboration and collective knowledge, the more instructors who participate in the conversation, the more diverse and deep the information developed on the application of ALM in the local context will become.

At the institutional level, the implications of increasing the completion rates in STEM courses by improving student grades could lead to more funding and increased educational reputation. State share of funding formulas work in the favor of institutions that are actively involved in attempts to improve completion rates. Additionally, increasing student success may lead to increases in student satisfaction improving long-term retention and new student recruitment. Applying the recommendations at the institutional level will involve establishing a new process for testing the computer proficiency and providing digital skills training for incoming students. This new process will ensure that the students who sign up for classes with high levels of technology integration are competent in the computer skills necessary to succeed.

Directions for Future Research

The recommendations developed as a result of the study research include several avenues for future research. The professional conversation style of faculty development incorporates an ethos of action research into the practice of all instructors involved in the conversation. The development of computer skills proficiency test and remediation offers several aspects to investigate as well. Additionally, the incorporation of writing-intensive programs into STEM courses requires positioning the change as research.

The action research involved in the professional conversation is driven by each instructor's own curiosity and interests. I am intending that my first contribution to the conversation will be an investigation into the effect of using computer simulations in the introductory chemistry courses on conceptual understanding. The study will involve an item analysis of final exam questions related to concepts covered in simulation assignments with a comparison of student responses before and after the simulation assignments were added to the course.

In addition to the immediate plan of evaluating the benefits of simulations in chemistry, a long-term project could involve research into the effectiveness of the professional conversation itself. This research could involve quantitative analysis in the form of surveys of faculty members who had participated in the conversation to assess how they have integrated new instructional methodologies into their courses, how they perceived the benefits of the conversation, and extent of collaboration. Additional quantitative methods could use data analytics to measure changes in patterns of access in conversational topics and content areas.

Research based on the second recommendation would take the form of program evaluation and look specifically at the computer skills proficiency testing and online orientation efforts with respect to retention and completion statistics before and after the implementation of the new program. Surveys of students could also gather information on reactions to the testing or the online student orientation. A pretest/posttest experimental project could look at student computer confidence changes as a result of the online orientation program.

Finally, the incorporation of writing-intensive courses into the STEM disciplines will not be accomplished without definitive evidence that there is substantial benefit. An action research project including faculty and administration to evaluate the benefits of writing activities on student outcomes would require a major commitment, but a phased implementation method could provide evidence of any early successes. Unlike the flexibility afforded by the professional conversation method for small, course level, semester-long projects, the evaluation of writing-intensive courses will be a major, long term project encompassing multiple departments, multiple personnel, and several years.

Conclusion

The problem of low completion rates in STEM courses at the local community college and elsewhere is a complex and multifaceted issue. Research into how to improve completion rates, therefore, must take a multipronged approach. The research from this study sheds some light onto a few changes that the local institution can make to improve the chances of success for their students, but the work is far from complete. Just as educational practice is committed to cycles of continuous improvement, research into how to improve the student outcomes must be continually pursued.

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Appendix A

The white paper produced as the project deliverable is presented here beginning on the next page.

Relationship between Active Learning Methods and STEM Course Student Grades

Project Results and Recommendations

Cherish Lesko

This white paper summarizes the results of a recent research study on the relationship between the use of active learning methods (ALM) and the student final grades in STEM classes during Fall semester 2016 at [redacted] Community College. The research was conducted using an anonymous survey of the faculty. Quantitative analysis included descriptive statistics and multinomial logistic regression. Use of In-class ALM, Highly-structured activities ALM, and Writing-based ALM were shown to improve the likelihood of students receiving grades of A, B, or C instead of F. Project-based ALM and Online ALM were shown to decrease the likelihood of students receiving grades of A, B, or C instead of F. Analyses based on these results lead to several recommendations for evidence-based educational practice for the improvement of student course completion and success including faculty development activities, student support activities, and new course structures.

Executive Summary

A research project was completed to examine the predictive relationship between the use of active learning methodologies (ALM) student grades when controlling for class size, course level (introductory or non-introductory), and academic discipline. The data was collected with a survey of faculty members who taught traditional, face-to-face STEM courses at [redacted] Community College during the Fall semester of 2016. The survey had a 27.2% response rate reasonably divided between mathematics, natural sciences, applied sciences, engineering technology, and health sciences. The collected data was analyzed using descriptive statistics and multinomial logistic regression. Multinomial logistic regression results provide the likelihood of a student achieving a grade of A, B, C, or D in comparison to a reference grade of F when different ALM were used in the classroom.

The results of the regression indicate that students at [redacted] have a higher likelihood of earning an A, B, or C than an F if the instructor uses In-Class ALM, Highly-structured Activities ALM, and Writing-based ALM. Additionally, students at [redacted] have a lower likelihood of earning a grade of A, B, or C than an F if the instructor employs Project-based ALM or Online ALM. The results for the Project-based ALM and the Online ALM are counter to published research on the use of ALM. It is posited that the reason for this difference is the differences in preparedness, digital equity, and socioeconomic demographics that differentiate community college students from students at research-intensive four-year universities.

Three recommendations are made that draw from the results of the research and align with the stated goals of the college's strategic plan. The recommendations include an informal, ongoing faculty development project called a professional conversation, the implementation of a basic computer skills proficiency test and remediation plan, and an action research project for developing and implementing writing-intensive modular assignments for STEM classes. Each of these recommendations can be implemented at the committee level and have timelines ranging from two to four semesters. The implications of the implementation of the recommendations include the possibility of higher success rates for the students and higher state share of funding for the college.

Table of Contents

Opportunity Knocks

Completion.

What comes to mind when you hear that word? Success? Frustration? Stress? Avoidance?

Working in a community college, we strive together to provide the best chances for our students to complete their courses and their programs while still holding to the standards of higher education. We do our jobs every day in the hopes that we truly are making a difference.

Whether you have been in education for twenty months or twenty years, whether you are faculty, staff or administration, small changes can add up to big differences for our students.

This white paper includes a summary of research on instructional methodologies and recommendations for changes in practice. The recommendations included are aligned with the college's strategic plan and the stated policies of implementing advising, programming and faculty development opportunities that support teaching and learning and improve student success.

It's someone else's job.

I know what I am doing works. It's not my fault if students fail.

There's too much pressure on completion. It's just easier to let everyone pass.

Some students won't succeed no matter how much help I give them.

I'm too busy with teaching and grading to worry about anything else.

What else can be done?

Review of Current Literature

The Local Problem

The STEM disciplines at the postsecondary level, particularly engineering and nursing, suffer unusually high attrition rates approaching 50% in the first year (Abele, Penprase, & Ternes, 2013; Kerby, 2015; Perez, Cromley, & Kaplan, 2014; Salinas & Llanes, 2003; Wladis, Hachey, & Conway, 2015). High attrition rates are costly for both the students and the school (Abele et al., 2013; Schneider & Yin, 2012). Attrition rates vary by the type of institution with open admission community colleges experiencing the highest dropout rates (Nakajima, Dembo, & Mossler, 2012). Attrition rates and extended time to graduation can be linked to low course completion rates specifically in STEM (Flanders, 2015; Prystowsky, Koch, & Baldwin, 2015). For academic year 2015-2016, [redacted] had an overall course completion rate of 72.3% compared to a state-wide average of 76.3%. Affecting the overall completion percentage, introductory STEM courses represent a large portion of the courses offered at [redacted] (21%) and had a completion rate of 67.2%.

The Theoretical Framework

The theoretical framework for this study is Vygotsky's social constructivism. Similar to other forms of constructivism, social constructivism is based on the theory that learners go through a process of building their own meaning and understanding in order to make sense of their personal experience (Merriam, 2007; Strobel, Wang, Weber, & Dyehouse, 2013; Vygotsky, 1978). In contrast to Piagetian cognitive constructivism where the locus of learning is the individual, social constructivism incorporates the influence of the learning environment and social contexts on the learner's development (Kivunja, 2014). Since social constructivism rejects positivistic, behavioristic and mechanistic models, educational structures focus on cognitive development, critical thinking, and deep learning rather than learned behaviors or objective goals (Fosnot & Perry, 1996).

The Proposed Solution

The community college system plays a significant role in the education of STEM professionals from workforce retraining to certificate completion to Associates degrees and university transfers (Hagedorn & Purnamasari, 2012; Packard, Tuladhar, & Lee, 2013). Due to open enrollment, reduced costs, flexible scheduling and other key community college characteristics, community colleges are the primary educational pathway for many diverse students (Barrow, Richburg-Hayes, Rouse, & Brock, 2014; Jackson, Starobin, & Laanan, 2013; Johnson, Starobin, & Santos Laanan, 2016; Strawn & Livelybrooks, 2012; Wang, 2013). In comparison to students at four-year universities, community college students are more likely to be older, first-generation college students, single parents, and underprepared (Van Noy & Zeidenberg, 2014; Wickersham & Wang, 2016).

Active learning methods (ALM) have been studied for their effectiveness when compared to passive lecture methods and have been found to have a positive effect on student achievement in science, technology, engineering and math (STEM) studies (Freeman et al., 2014; Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2012; Kim, Sharma, Land, & Furlong, 2013). In fact, by 2013, 225 studies were identified that specifically linked ALM in STEM undergraduate education with either exam scores or course failure rates (Freeman et al., 2014, p. 8410). Freeman et al. at the Proceedings of the National Academy of Science posited that research comparing ALM to traditional lecture methods was so extensive and decisive that the comparison should no longer be a topic of research, but instead put forth that new research should focus on which ALM are most effective for improving student outcomes in the local context.

There are limitations in generalizing the research to the local community college context. Specifically, the majority of the research on ALM in STEM fields has been completed at large, research-intensive, four-year universities (Mesa, Celis, & Lande, 2014; Van Noy & Zeidenberg, 2014; Wang, 2013; Wladis, Hachey, et al., 2015). For example, there is very little research on the effectiveness of math education in community colleges even though 83% of all remedial mathematics instruction occurs at a community college level (Mesa et al., 2014). Community colleges are uniquely responsive to the workforce training and employment needs of the communities they serve (Mesa et al., 2014). The differences due to community needs and differences in student demographics make the application of the main body of research on active learning to the local community college context not readily generalizable (Mesa et al., 2014, Wladis et al., 2015).

Research Methodology

This study was a nonexperimental correlational study with regression analysis to explore the relationship between the use of ALM and STEM course student grades. In this study, the relationship between a criterion variable, STEM course student grades and the predictor variables, ALM factors scores, was studied while controlling for class size, whether the course is introductory-level, and academic discipline as specified in the research question shown below Correlational design with multinomial logistic regression determined the presence and strength of relationships between criterion and predictor variables without implying causality.

Census sampling was used to produce data sets for all students and instructors of STEM courses offered in the Fall of 2016 semester.The instrument for collecting data from the faculty will be "A National Survey of Instructional Strategies Used to Teach Information Systems Courses" (NSIS) (Djajalaksana, 2011). The main constructs measured by the survey are frequency of use of the six types of ALM in instructional activities. Fifty-two instructional items were grouped into six formed factors – In-Class ALM, Highly-Structured Activities ALM, Project-based ALM, Online ALM, Writing-based ALM, and Portfolio-based ALM - shown in the table on the following page (Djajalaksana, 2011).

The study was subject to two separate Institutional Review Board (IRB) procedures. First, Walden University IRB approved on March 13, 2017. Second, [redacted], through a contract with a four-year university for IRB services, approved the study on April 4, 2017.

Research Question:

After controlling for class size, course level (introductory or non-introductory), and academic discipline, do the ALM factor scores as measured by the NSIS predict STEM course student grades during Fall semester 2016 at [redacted] Community College?

List of ALM used in survey instrument grouped into six factors from survey validation study by Djajalaksana (2011)

Factor	Specific Methods	
In-class ALM	Interactive lecture Question/answer with personal response device Think/pair/share Whole group discussion Small-group student discussions Minute paper/Sentence Summary Brainstorming Student/peer teaching Informal writing Concept maps/mind maps	Role Play Simulations/Games Debates Background knowledge probe/just-in-time teaching Case studies Lecture note sharing/comparing Student-generated quizzes/exams Video critique
Highly-structured Activities ALM	Demonstrations Computer-based learning	Applications Tutorial Labs
Project-based ALM	Analysis and design project Problem-based learning (PBL)	Cooperative/Team-based learning Student/peer assessment
Online ALM	Flipped classroom/online lecture Online discussions Online collaborative projects Wikis	Self-directed learning Participation in social networking Formative quizzes Reflective blogs
Writing-based ALM	Annotated bibliography/webliography Literature review Original research portfolio	Short paper Major term paper Student presentations
Portfolio-based ALM	Learning portfolio Online/E-portfolio	Personal reflection journals Service learning

MOST USED INSTRUCTIONAL METHODOLOGIES:

1. Lecture
2. Interactive lecture
3. Problem- solving
4. Lab activities
5. Whole group discussion

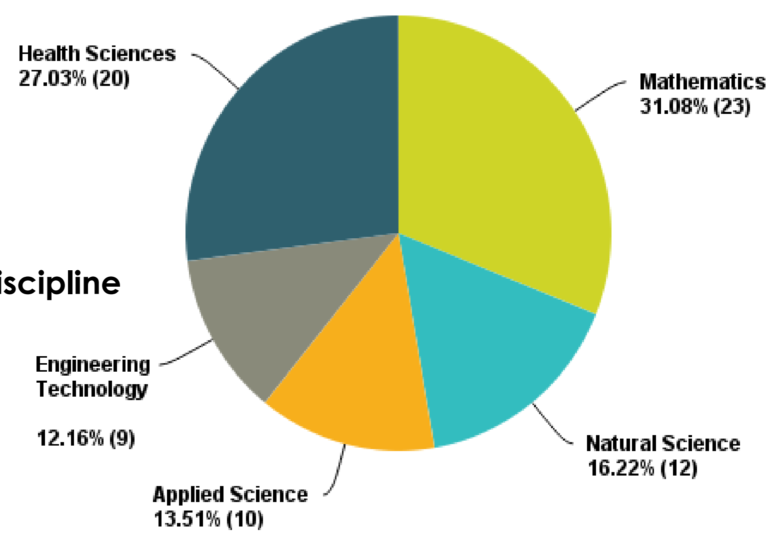
LEAST USED INSTRUCTIONAL METHODOLOGIES:

1. Wikis
2. Reflective blogs
3. Portfolios
4. Video creation
5. Annotated Bibliography

Descriptive Statistics

Of the initial 360 classes identified as STEM classes during the Fall semester of 2016, there were 88 classes that were excluded from the sample due to class cancellation, instructors unavailable to be surveyed due to leaving the college, or misclassification as a traditional lecture class. The remaining 272 classes were surveyed and instructors from 74 classes participated in the anonymous online survey for an overall response rate of 27.2%. The 272 STEM classes surveyed had 3,055 students registered, and the surveys returned included grades for 1,140 students which represents 37.4% of the students enrolled in STEM courses during Fall semester of 2016 at [redacted]. Class sizes for the 74 respondent courses varied from 3 to 38 (μ = 15.4; σ = 8.98).

Response rate by academic discipline



The survey response included five discipline areas in the percentages shown in the pie chart above. The results of the survey included 37.8% introductory and 62.2% non-introductory classes. The most and least used instructional methods tabulated from the survey are listed in the callout box above.

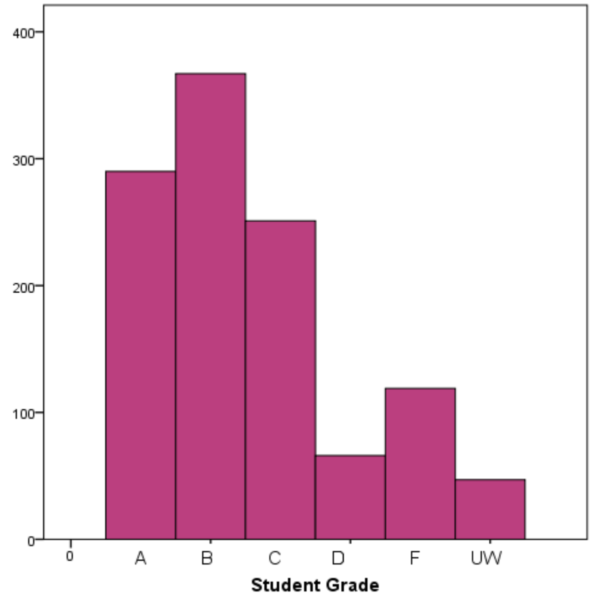
Means and standard deviations for ALM factor scores

	In-Class ALM Factor 1 (72.00)*		Highly-Structured Factor 2 (16.00)*		Project-based ALM Factor 3 (16.00)*		Online ALM Factor 4 (32.00)*		Writing-based ALM Factor 5 (24.00)*		Portfolio-based ALM Factor 6 (16.00)*	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
All STEM	15.4	8.16	4.49	3.41	3.5	2.48	3.43	4.15	1.42	2.44	.43	1.06
Mathematics	7.09	5.6	1.3	2.14	2.83	1.9	0.74	1.14	.17	.83	.04	.21
Natural Science	12.6	5.79	6.17	1.4	4.75	1.14	4	3.25	.92	1.08	0	0
Applied Science	9.1	6.3	7.9	2.71	3	2.71	8.3	4.11	2.7	3.62	0	0
Engineering	6.67	6.06	5.89	3.1	5	2.78	2.22	4.02	1.89	2.89	.33	.71
Health Sciences	17.5	9.56	4.8	3.21	3.1	3.01	4.3	4.55	2.3	2.79	1.4	1.64

* Values in parentheses are the maximum scores possible for each of the ALM factors.

The non-normal student grade distribution for the respondent courses is shown below. The predictor variables, the ALM factor scores, were summed from the responses made using a Likert-style scale and were tabulated using the value of zero for "never use", one for "rarely use (1-3 times per semester)", two for "occasionally use (less than half the classes)", three for "frequently use (more than half the classes)", and four for "always use/almost always use". The resulting means and standard deviations are shown in the table above.

The univariate analysis of the predictive relationships of the independent predictor variables on student grades provides justification for the inclusion of each of the predictor variables in the final model (Hosmer & Lemeshow, 1989; Laerd Statistics, 2013). Using multinomial logistic regression, each predictor variable is regressed on the dependent variable of student grades individually. The Chi-square statistic of the log likelihood test indicates the difference between the regression model with the intercept (β_0) only and the regression model including the predictor variable. Large Chi-square values, which are all significant ($p < 0.05$) except ALM factors 3 and 4, indicated which of the predictor variables should be included in the final model.



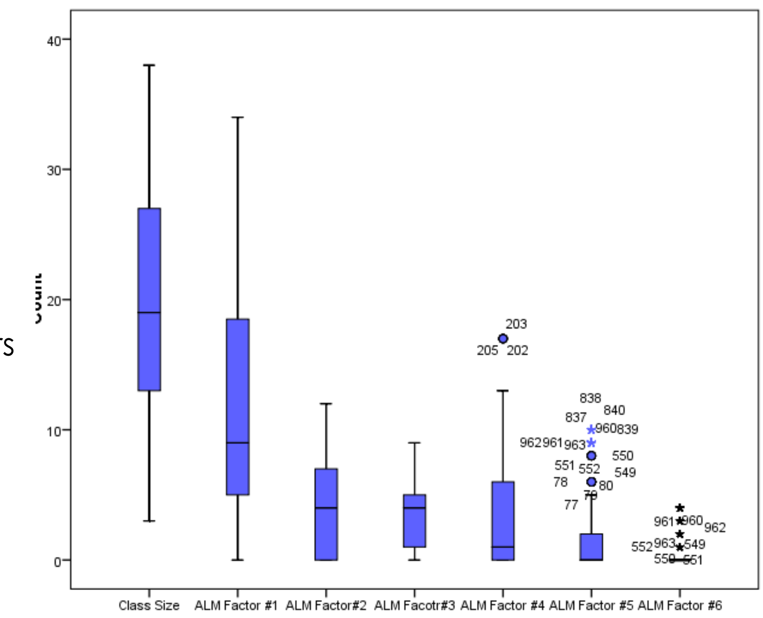
Student Grade Distribution

Multinomial Logistic Regression

To develop an accurate and stable predictive model for student grades using the specified control and predictor variables, the study data needed to meet the assumptions of the multinomial logistic regression model. The assumptions of multinomial logistic regression include the use of an appropriate sample size, independence of irrelevant alternatives, multinomial linearity, no significant outliers, and no multicollinearity (Aragon, 2017; Laerd Statistics, 2013; Pentzke, 2016). Appropriate sample size was determined using the rule of thumb of 30 cases per independent variable. Independence of irrelevant alternatives was tested using the Hausman-McFadden test. Multinomial linearity was tested using the Box-Tidwell transform with the Bonferroni correction. Presence of significant outliers was determined using a box-whisker plot as well as the outlier labeling rule. Multicollinearity was evaluated pairwise using Pearson's r correlation for tests between interval variables, Kendall's tau correlation for tests between categorical variables and Intraclass correlations for tests between interval and categorical variables. Group effects of multicollinearity were tested using variance inflation factors, Eigenvalues, and condition indices.

The sample data exhibited small to medium pairwise correlation; variance inflation factor values indicated correlations were below the threshold to fail the assumption.

For ALM Factor 4 and ALM Factor 5, the large numbers of zeros impact the variable by giving very low medians and narrow interquartile ranges forcing many of the cases in which the instructors facilitated any of the methods in these factors to become outliers. These outlier values have high impact on the regression model and it is reasonable to speculate that odds ratios for ALM Factor 5 and ALM Factor 6 could exhibit inflation and require qualification during interpretation.



Box-whisker plot to identify outliers

Multinomial logistic regression calculates a regression coefficient (β) that represents the log likelihood of one event compared with another event (Starkweather & Moske, 2011). For this study, the reference event was earning a grade of F and the comparison events were earning any other grade. To make the interpretation of the results of logistic regression more intuitive, the odds ratio is calculated as the exponentiation of β. The odds ratio can then be used to interpret which event is more or less likely (Starkweather & Moske, 2011). The multinomial logistic regression was performed in IBM SPSS v. 23 and the significant results are presented below.

- Use of In-Class ALM (Factor 1) makes it 5.0% ***more likely*** that students will achieve a grade of B and 9.0% ***more likely*** that students will achieve a grade of C instead of a grade of F.

- Use of Highly-structured ALM (Factor 2) makes it 16.4% ***more likely*** that students will achieve a grade of A, 22.2% ***more likely*** that students will achieve a grade of B, and 16.7% ***more likely*** that students will achieve a grade of C instead of a grade of F.

- Use of Project-based ALM (Factor 3) makes it 20.9% ***less likely*** to achieve a grade of B and 15.7% ***less likely*** to achieve a grade of C instead of a grade of F.

- Use of Online ALM (Factor 4) makes it 16.1% ***less likely*** to achieve a grade of A, 20.4% ***less likely*** to achieve a grade of B, and 19.3% ***less likely*** to achieve a grade of C instead of a grade of F.

- Use of Writing-based ALM (Factor 5) makes it 43.3% ***more likely*** to achieve a grade of A, 43.1% ***more likely*** to achieve a grade of B, and 39.1% ***more likely*** to achieve a grade of C instead of a grade of F. Care must be taken in the interpretation of these odds ratios, however, due to the presence of outliers in this factor. The direction of influence agrees with other research, but the magnitude of the effect is suspect.

- Use of Portfolio-based ALM (Factor 6) while significant to the final prediction model did not have any individually significant odds ratios.

Recommendation 1: A Professional Conversation

A professional conversation is a constructivist and conversational model of collaborative learning (Irvine & Price, 2014). The development of this method of professional learning is an outgrowth of a shift toward informal and self-directed learning (Owen, 2014; Stewart, 2014). Professional conversations are inquiry-driven, action research-infused methods that emphasize collaborative reflective practice while embracing the dissonance of divergent views (Irvine & Price, 2014). Additionally, agency, autonomy, and flexibility make the structure of the professional conversation attractive to instructors in higher education (Penick Brock et al., 2014; Voogt et al., 2015).

Developed as a safe environment for exploration, questioning, and experimentation, the members of the professional conversation accept that innovation and change exist in conflict and that dissonance can be productive as a change agent (Watson, 2014). The cognitive dissonance required for deep learning does not perpetuate from the repetition of existing practices (Tagg, 2012), but authentic, productive discussion encourages disagreement (Falbe, 2015). Growth in practice is facilitated by deep and challenging instructor reflection (Voogt et al., 2015). Participants must suspend judgment and exhibit discipline to allow authentic curiosity and an attitude of change (P. Adams, 2009). The group learning environment of the professional conversation provides a venue for creative strengths to merge with nonlinear problem solving to manifest in a dynamic, cyclical process of change (Donnelly, 2009; Penick Brock et al., 2014; Voogt et al., 2015).

Recommendation 2: Computer skills proficiency testing and online orientation

The new digital divide is not one of access, but one of participation (Harris et al., 2017; Naidoo & Raju, 2012; Robles Morales et al., 2016; White & Selwyn, 2012). White and Selwyn (2012) described how age, occupational class status, and amount of education were strongly related to participation in educationally-oriented digital use whereas gender and ethnicity were not. Zhang (2015) posited that individuals pattern their internet usage to accommodate their existing social positions and showed that 39% of the variability in internet searches in his sample was attributable to socioeconomic status. Harris et al. (2017) also discussed how socioeconomic factors were related to how students chose to use computers. The distinction between the advantaged and the disadvantaged in the new digital participation divide is one of skills and social capital, not access (Jesnek, 2012; Pagani et al., 2016; Zhang, 2015).

Basic computer skills are critical to every students' success in the college curriculum, and faculty in community colleges need to accept the fact that they are becoming responsible for remediating computer skills deficits along with deficiencies in mathematics, reading, and writing (Dixon et al., 2012; Jesnek, 2012). Since the new participatory divide is related to socioeconomic groups that represent the student body of many community colleges, it cannot be assumed that students are entering post-secondary education with the skills necessary for success nor that all students normally considered "digital natives" are equally proficient in technology use (Kelso, 2011; Thompson, 2013). The lack of proficiency in basic computer skills exacerbates issues related to online learning because students need to be able to work comfortably within the LMS software, do basic troubleshooting, and communicate effectively online to achieve success in online and technology-enhanced courses (Doherty, 2006; Jesnek, 2012). Colleges and universities, in fact, may be perpetuating digital inequities through the use of online courses when students experience isolation and frustration due to their inability to deal with the technology component of the course (Cho, 2012; Kinghorn, 2014; Stephens, Hamedani, & Destin, 2014).

For the computer-illiterate, integrated educational technology becomes a detriment to persistence and a hindrance to academic goals. (Jesnek, 2012)

Solutions proposed to community colleges to help bridge the new digital participation divide include tutoring/peer mentoring (Dixon et al., 2012; Kinghorn, 2014; Lee, Choi, & Kim, 2013), computer skills proficiency testing (Beck & Milligan, 2014; Gaytan, 2013; McClenney, 2013; Pagani et al., 2016; Thompson, 2013), and online student orientation (Cho, 2012; Derby & Smith, 2004; Jesnek, 2012; Kelso, 2011). Kinghorn (2014) suggested that peer-to-peer interactions online assist in developing virtual collaboration skills and well as providing support and guidance for self-regulation. Lee, Choi and Kim (2013) associated self-regulation skills with persistence and success in the online course environment. Improving student success and completion requires assessment and remediation to ensure readiness with computer skills as much as with math or reading (McClenney, 2013) and 85% of faculty surveyed expressed that computer skills were necessary for success in college-level coursework (Jesnek, 2012). Appropriate assessment is needed to provide adequate intervention in digital skills deficits (Beck & Milligan, 2014). Pagani et al. (2016) encouraged testing in lieu of self-reporting as students underestimate digital skill necessary for academic performance.

80% of students surveyed think institutions should offer online orientation courses. 55% think is should be mandatory. (Kelso, 2011)

[redacted] currently uses the math, reading, and writing placement scores to determine whether new students should be placed in the First-Year Experience (FYE) class with additional computer skills training. A specific computer skills proficiency test would be a more accurate assessment of which students require additional computer skills to be successful. Additionally, it is recommended that all students take a mandatory online student orientation course.

Recommendation 3: Action research on writing-based ALM in STEM classes

Incorporating writing-intensive courses into all curriculum areas has been identified as a high impact practice (Kilgo, Ezell Sheets, & Pascarella, 2015; Sweat, Jones, Han, & Wolfgram, 2013). Writing-intensive courses improve student learning due to the need to apply and organize information in an orderly and logical manner (Kilgo et al., 2015; Mills, 2015). Writing tasks additionally help students to develop critical thinking skills, communication skills, and intellectual competence (Leggette & Homeyer, 2015). Writing also encourages metacognition and reflection (Dively & Nelms, 2007).

Academic writing has context-specific and discipline-oriented requirements and goals (Leggette & Homeyer, 2015). Evaluation of a writing-intensive biology course showed that students increased their biology competencies and increased confidence in their scientific thinking and in their abilities to communicate research findings (Brownell, Price, & Steinman, 2013). In a comparison of microbiology course modalities, the writing-intensive modality had the highest percentage of Fs as the final grade, but also had the highest percentage of correct answers on the concept inventory item analysis (Khan, 2015). Writing-intensive courses additionally enable students to discover, process, develop, organize, and disseminate scientific ideas (Leggette & Homeyer, 2015).

The benefits to writing-intensive courses notwithstanding, STEM faculty are hesitant to teach writing (Mills, 2015) and the attitude for the faculty in developing and implementing any writing program is paramount (Salem & Jones, 2010). A survey study by Salem and Jones (2010) showed that non-writing faculty lacked confidence in their ability to teach and review grammar and composition.

Additionally, faculty expressed concern about the fairness of the workload, the need to remediate underprepared students, and a loss of academic freedom and autonomy (Salem & Jones, 2010). The attitudes of the faculty toward including writing-intensive courses, like other institutional changes, is dependent on the way the change is presented(Tagg, 2012) and whether the changes are presented without consideration for individual choice (Penick Brock et al., 2014).

Development and Implementation of Recommendations

Implementing the recommendations included in the project white paper can run concurrently as different groups will hold responsibility for different tasks. The responsibilities, tasks, and timelines are presented below.

Recommendation 1: Professional Conversation

The faculty development committee will hold responsibility for implementing this initiative. Specific tasks that need to be accomplished for this recommendation to be implemented are the design of the conversation structure, the building of the Blackboard course shell, the negotiation of communication standards, the selection of facilitators, the recruitment of contributors and researchers, recruitment of team leaders and priority ranking of ALM to be included. The role of the faculty development committee after this initial phase will be the upholding of communication standards and development/scheduling of new ALM to be added to the conversation. Facilitators will be faculty members that encourage continued conversation through posting questions and redirecting conversational threads back to the content focus area. Contributing researchers will have the responsibilities to create brief mini-modules to provide instructional background material about specific ALM from peer-reviewed journals and other credible sources as well as listing links to video, blogs and other online content which they found helpful in understanding the ALM. The team leaders will be instructional faculty who will recruit two to three other faculty in other academic disciplines to run action research projects in their courses through testing on one specific ALM. The teams will independently design their action research project however they prefer. The implementation of this recommendation may take two semesters.

Recommendation 2: Basic computer skills proficiency testing and online student orientation

The college-wide completion committee will hold responsibility for the recommendation to implement a basic computer skills proficiency test and online student orientation specific to [redacted] student portal and learning management system. The development of these processes will be open to the interpretation of the committee. As the completion committee is a college-wide committee, members of the administration participate in the committee actions and would provide endorsement and support of any agreed upon initiatives. However, the likely tasks involved in implementing this recommendation are surveying of all faculty for online applications and skills used in online, hybrid and traditional classes, deciding to use a published or self-developed proficiency assessment, determining passing levels on basic computer skills proficiency test, developing remediation plans, building online student orientation course, and hiring and training computer skills peer tutors. There will be no additional hardware requirements as computer testing access is available to all students through the Success Center.

Recommendation 3: Action research on writing-intensive courses

An ad-hoc faculty committee will need to be assembled in order to implement this recommendation. There is not currently a committee or program at [redacted] that would have purview over this type of active. After the ad hoc committee is formed, the research plan will be developed which will examine the effects of implementation of writing-based activities on student success. The output of the action research project will be assignment modules and implementation guidelines for using writing-based ALM in STEM courses. The assignments and guidelines would not encompass an entire class, but act as supplemental material for instructors use in current class structures. The ad hoc committee will begin construction on the course modules including the development of implementation guidelines, Blackboard content, and assignment and rubric templates. The anticipated timeline for the implementation of this recommendation is four semesters.

Conclusion

This white paper endeavors to communicate the results of the research on how the use of ALM predict STEM course student grades at [redacted] and present recommendations for changes in practice. Changes in instructional practice which enable more students to complete more classes has the potential to create social change for the students and the institution as local stakeholders.

For the students as stakeholders, improving the likelihood of achieving higher grades enables more students to complete their programs faster and with less debt. Reducing the likelihood of failure in STEM courses, especially those courses which act as barriers to persistence or major program entry increases the potential for completion of a degree program or certification that will improve the students job prospects, social capital, and socioeconomic status.

For the institution, making improvements in student success can have significant benefits financially and academically. As a state supported community college, [redacted] competes yearly for its share of state money. Improving course and program completion rates improves the chances of increasing the state share of funding. Increased state funding provides resources for providing better student services, increasing campus security, maintaining functional facilities and retaining quality faculty. Additionally, [redacted] can gain increase in its reputation as being an institution that is responsive and sensitive to students' academic needs drawing more students to the college in a time when statewide community college enrollment is decreasing.

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[redacted]

COMMUNITY COLLEGE

Cherish Lesko
cherish.lesko@waldenu.edu

Research was performed as part of the requirements for the Ed.D in College Teaching and Learning at Walden University.

Appendix B

Initial E-Mail Invitation – Local Study

Dear Prof. ________,

Along with my duties as a visiting professor at Clark State, I am currently working on a doctorate in College Teaching and Learning at Walden University. I am researching potential relationships between active learning methods and student outcomes, and if those relationships vary by academic discipline. This research is being conducted in my role as student at Walden University and is completely separate from any of my duties or roles at Clark State.

To date, very little of the research on active learning and course completion has been accomplished at the community college level and since we understand that our students are demographically different than students at four-year research intensive universities, it is vital to investigate whether the published research on active learning is applicable to our local enterprise. You are invited to participate in this research survey because the class you instructed during Fall semester 2016 (identified in the above subject line) falls into one of the following categories: natural science, applied science, engineering technology, mathematics, or health sciences.

Your responses will help provide detailed information on the use of active learning methods on our campuses. It may be beneficial to you to see the many options of active learning methods available for use in college classrooms from the list included in the survey.

If you are willing to participate in this **voluntary study**, you will be asked to complete a brief, online survey (approximately 10-20 minutes) about the course and section indicated in the e-mail subject line. It is possible that you may receive more than one invitation depending on your Fall 2016 schedule and the classes sampled. This unfunded research is considered to be a minimal risk investigation and there will not be any compensation for participation or penalty for non-participation. The research is **confidential** in nature, the survey de-identifies your participation, and the research results will be reported in an aggregate manner. You have the right to decline to participate, and declining or discontinuing participation at any time during the survey will have no negative impacts either professionally or personally.

If you have any question, concerns or complaints about this study, please contact Cherish Lesko either by e-mail at cherish.lesko@waldenu.edu or by phone at (937) 266-4993. Additionally, if you have questions about your rights as a participant in this study or any complaints, concerns or issues you want to discuss with someone outside of the research, email the Office of Sponsored Programs and Research at Central State University at irb@centralstate.edu (IRB# CSCC04032017-01) or Walden University at irb@waldenu.edu Walden University's approval number for this study is 03-13-17-0557479 and it expires March 12, 2018. This e-mail represents the consent documentation and participation in the survey is voluntary and implies informed consent. You should print out and retain a copy of this document as reference.

I appreciate your time and would like to thank you in advance for considering participating in this study.

By clicking on the link for the survey below, you are granting your informed consent to take part in this research.

https://www.surveymonkey.com/r/LESKO2016

Cherish Lesko

EdD Candidate, Walden University

Appendix C

Descriptions of the surveyed ALM grouped by factors as presented by Djajalaksana (2011)

In-Class ALM	
Interactive lecture	Instructor presented material with breaks for group discussions, problem solving, and other student-teacher interaction on the material
Guest lecture	Material presented by instructor other than the primary instructor
Question/answer with personal response device/clicker	Student engagement method that utilizes handheld/wireless technology to solicit responses to group posed questions (Clicker, Socrative, PollEverywhere, etc.)
Think/pair/share	Students answer questions or prepare responses and share it with a partner before participating in a large group discussion
Whole group discussion	Sustained, facilitator-led question/answer time or conversation involving the whole class
Role play	Students act out situations or contexts identified by the instructor
Simulations/Games	Computer-generated, interactive games such as Jeopardy or interactive models for real-life situations or experiments
Debates	Students and/or teams argue a position on class issues or topics
Review sessions	Review activity or question/answer times in class
Background knowledge probe/ just-in-time teaching	Brief pre-test or pre-class assignment that allows the instructor to design the content for the needs of the students
Small group student discussions	Students form small groups to discuss class topics
Minute paper/sentence summary	Short, informal writing summary to provide feedback to the instructor on students’ grasp of main idea or other topic

Brainstorming	Free flow writing assignment where students note preexisting knowledge or creative ideas about a topic or issue
Student/peer teaching	Either individually or as a group, students are responsible to prepare and present material to the rest of the class
Informal writing	Short writing assignment that is not graded but presented as enhancement of class material
Video Critique	Students watch and respond to a media element
Case studies	Using real-life or fictional scenarios, students develop responses and solutions using concepts and principles discussed in class
Lecture note sharing/comparing	Students share and compare lecture notes to improve note taking and to ensure all key concepts from the class are recorded
Student-generated quizzes & exams	Students identify main concepts and submit potential questions for future quizzes and exams
Concept map/mind map	Construction of a drawing or diagram connecting the main ideas in a graphical/visual manner
Highly-Structured Activities	
Demonstrations	Instructor demonstrates content, skill, or extension of class material in practical application
Computer-based learning	Interactive, highly-structured computer activities or assignments
Labs	Structured practice and/or problem solving in a laboratory setting
Lecture	Material presented by primary instructor for the majority of the class period
Quizzes	Graded or ungraded assessment of subject mastery
Application tutorial	Step-by-step instructions in the use of computer applications/programs that will be used as part of the class
Project-based ALM	

Analysis and design project	Students analyze, design, and/or prototype system or process individually or as a team
Application development/programming project	Construction of computer programs or apps individually or as a group
Problem-based learning (PBL)	Realistic, multi-step problems are posed to students who must seek out class material and content in order to address a problem which may not have a defined solution
Cooperative/Team-based learning	Students work together to socially construct knowledge or skills
Student/Peer assessments	Students evaluate peer work against criteria or rubric to suggest improvements
Online ALM	
Online lecture/flipped classroom	Instructor delivers class material/lectures through online media (synchronous or asynchronous)
Online discussions	Online discussion or forum designed to engage with class material
Online collaborative projects	Students construct group work through online interface
Reflective blogs	Reflective, online personal journal
Wikis	Students contribute to class website or wiki
Self-directed learning	Students engage at their own pace and on their own schedule with course material provided online through learning management system (i.e. Blackboard)
Participation in social networking	Students and instructor use social networking tools to improve class communication
Formative quizzes	Ungraded online quizzes on class content to improve mastery and to review content
Writing-based ALM	
Annotated bibliography/webliography	Students write summaries of journal articles/websites
Literature review	Student exploration of course topic through investigation of published, peer-reviewed literature

Original research proposal	Students prepare proposal for an original idea for a project or scientific investigation
Short paper	Papers on course content less than ten pages
Major/term paper	Major writing assignment of significant work that explores or expands on course content
Student presentations	Students present individually in class
Portfolio-based ALM	
Learning portfolio	Documentation of student learning in class or program portfolio
Online/e-portfolio	Documentation of student learning stored online
Service learning	Involvement in community-based service activities relevant to the class content or learning objectives
Personal reflection journals	Students document personal learning, experiences, ideas, and understandings in
Other Learning Methods (included in survey, but removed during factor analysis for showing zero effect)	
Field Trips	Visiting locations that improve, extend, or deepen understanding of class content or met course objectives
Campus Events	Participation and response to campus-sponsored out-of-class events (guest lectures, concerts, etc.)
Student Attitude Surveys	Survey of student attitudes or beliefs about the course material or their personal ability to perform well in the class
Video Creation	Short video presentations (YouTube, etc.) created to be shown in class

Appendix D

Permission to Use Published Survey from Copyright Owner

RE: Survey

Yenni Merlin Djajalaksana <yenni.md@maranatha.edu>
Tue 9/6/2016 6:42 AM

To:Cherish Lesko <leskoc@clarkstate.edu>;

Dear Cherish,

I hereby give my permission to you to use my dissertation survey for your research. Please kindly cite my work in your dissertation as well as future publications related to this instrument. Thanks very much and I wish you the best for your doctoral journey.

Sincerely,

Yenni M. Djajalaksana, Ph.D.
Secretary General of the University
Maranatha Christian University
Phone: +62-22-2012186 ext. 7005
Email: su@maranatha.edu
Site: www.maranatha.edu

- - - - - Original Message- - - - -
From: Cherish Lesko [mailto:leskoc@clarkstate.edu]
Sent: Monday, September 5, 2016 10:46 PM
To: Yenni Merlin Djajalaksana <yenni.md@maranatha.edu>
Subject: Survey

Yenni-

Thank you so much for communicating by Facebook about your dissertation survey. For my official records, could you please respond to this email with permission to use the survey.

The survey will be adapted in the demographics section only as I will be using it only in one location (2-yr community college) and with faculty in multiple STEM disciplines - so I do not need some of the questions.

I will cite your survey in both the actual survey and in all supporting research documentation and any publications.

Thanks so much,
Cherish Lesko
Interim Professor of Chemistry
Clark State Community College

Appendix E

Additional statistical data, tables and charts are included in this section.

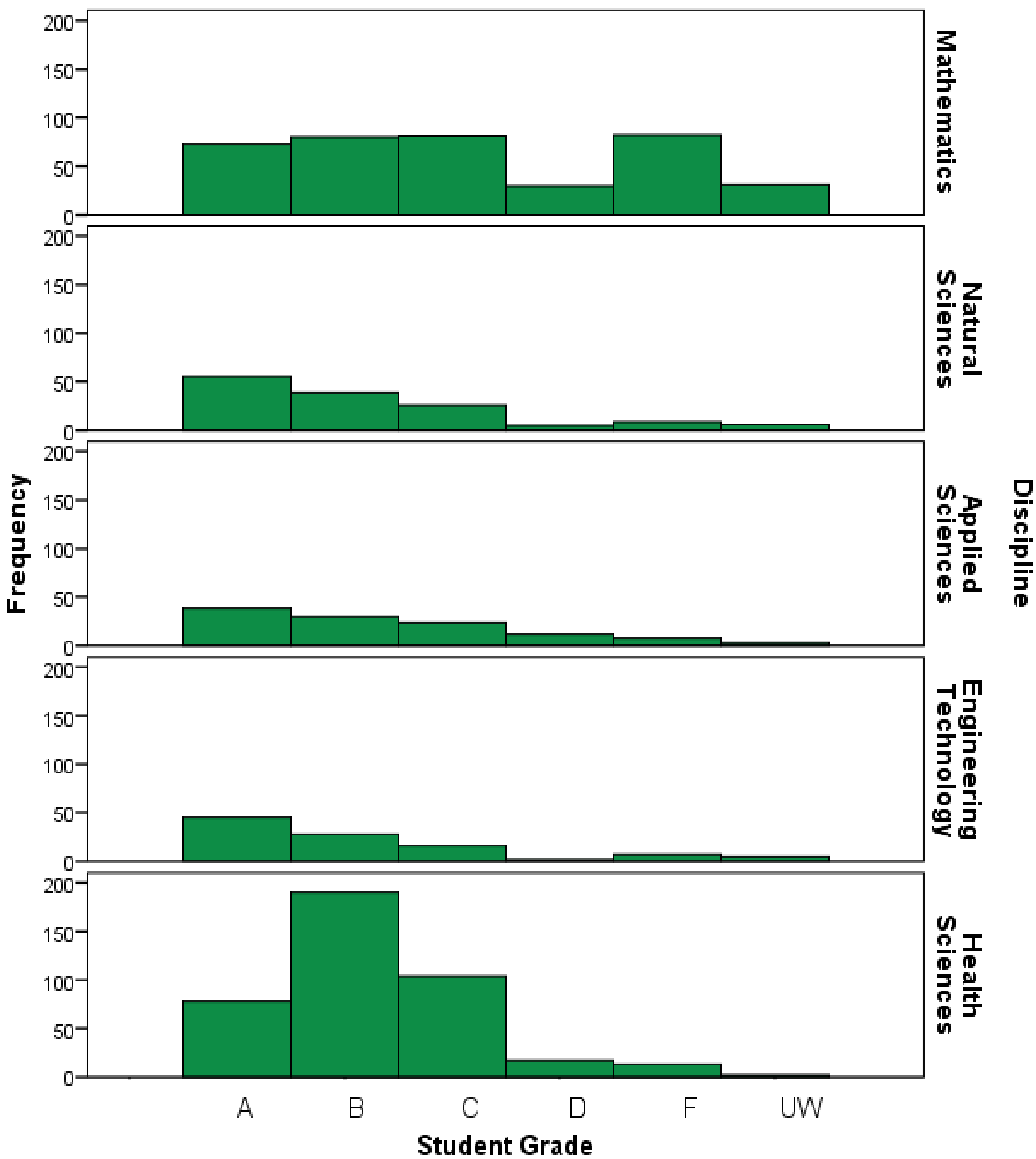

Figure 3. Grade distributions by discipline

Table 24

Averages of Individual ALM for the Total Sample and By Discipline (Top Five Most Used in Bold). ALM are listed in the order provided by the survey instrument.

ALM	All STEM	Mathematics	Natural Science	Applied Science	Engineering Technology	Health Sciences
Lecture	**3.11**	**3.81**	**2.27**	**3.1**	1.59	**3.36**
Interactive Lecture	**2.35**	**2.37**	**2.75**	2.3	**1.9**	**2.62**
Lab Activities	**1.68**	0.24	**2.51**	**3.0**	**3.03**	1.37
Quizzes	1.57	1.01	1.71	1.5	**1.72**	1.71
Q&A with clickers	0.23	0	0.40	0	0	0.43
Guest Lecture	0.26	0.09	0.04	0.3	0.51	0.36
Think/share/pair	0.74	0.19	1.35	0.40	0.50	1.62
Whole Group Discussion	**1.66**	**1.58**	1.55	1.4	0.69	**2.22**
Small Group Discussion	0.96	0.52	1.14	0.6	0.37	**1.77**
Minute Paper	0.11	0	0	0.3	0	0.09
Brainstorming	0.5	0.03	0.33	0.6	0.91	0.87
Student/Peer Teaching	0.65	0.19	0.56	0.3	0.51	1.69
Cooperative/Team-based	1.05	0.67	1.69	0.40	1.10	1.40
Lecture Note Share/Compare	0.74	0.89	0.41	0.10	0.51	0.92
Student Presentations	0.54	0	0.54	0.90	0.74	0.99
Demonstrations	1.26	0.44	**2.36**	1.20	1.07	1.31
Problem-based Learning	**1.85**	**1.96**	**2.77**	1.70	**1.63**	1.58
Role Play	0.24	0.08	0	0	0	0.58
Debates	0.12	0	0.22	0.50	0	0.07
Informal Writing	0.36	0.02	0.29	0.40	0.44	0.95
Review Sessions	1.42	**1.23**	2.17	0.60	0.75	1.62
Case Study	0.69	0	0.98	0.20	0.15	**2.15**
Literature Review	0.35	0.11	0.21	0.30	0.44	0.61
Original Research Proposal	0.11	0	0	0.3	0	0.22
Short Paper	0.18	0	0.29	0.50	0.16	0.14
Major Writing Project/Term Paper	0.20	0	0	0.5	0.16	0.53
Analysis and Design Project	0.34	0.02	0.29	0.4	**1.71**	0.06
App Develop/ Programming Project	0.31	0.18	0	0.40	0.74	0.39
Application Tutorial	0.47	0.12	0	1.10	**0.92**	0.52
Student-generated Exams/Quizzes	0.15	0.06	0.04	0	0.15	0.29
Concept Maps/Mind Maps	0.49	0.05	0.76	0	0.29	1.15
Student Attitude Survey	0.26	0.14	0.31	0	0.15	0.49
Campus Events	0.16	0.06	0.07	0	0.16	0.49
Video Critique	0.15	0.08	0	0.10	0	0.29

Annotated Bibliography	0.04	0	0	0.2	0	0.03
Personal Reflection Journal	0.27	0.02	0	0	0	1.11
Learning Portfolio	0.04	0	0	0	0.15	0.04
Field Trips	0.08	0	0	0	0.22	0.11
Service Learning	0.09	0	0	0	0.07	0.24
Video Creation	0.03	0	0.04	0.10	0	0
Student-Peer Assessment	0.26	0.08	0.14	0.50	0.37	0.42
Forums/ Online Discussions	0.32	0.06	0.37	0.80	0.46	0.15
Reflective Blogs	0.03	0	0	0	0	0.06
Formative Quizzes	0.99	0.22	1.6	1.8	0.15	0.88
Collaborative Projects	0.19	0.06	0.48	0.10	0.29	0.22
Online Lecture	0.74	0.11	0.44	**2.20**	0.54	1.16
Participation in Social Networking	0.07	0	0	0.10	0	0.11
E-portfolio	0.03	0	0	0	0.15	0.03
Computer-based Learning	1.08	0.22	1.41	**2.60**	0.87	1.49
Self-directed Learning	1.08	0.21	1.03	**3.30**	0.54	1.52
Background Knowledge Probe/JIT Teaching	0.24	0.14	0.32	0.40	0	0.08
Simulations/Games	0.61	0.02	0.97	1.50	0.15	0.56
Wikis	0.01	0	0	0	0	0.03
Modular/In-Course Remediation	0.46	0.03	0.59	0.10	0.15	1.25

Hausman-McFadden Test for IIA

Full Model

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1115.976	18.916	5	.002
Discipline	1122.048	24.988	5	.000
Introductory	1126.859	29.799	5	.000
ClassSize	1107.339	10.279	5	.068
Factor1	1133.128	36.068	5	.000
Factor2	1114.386	17.326	5	.004
Factor3	1112.274	15.214	5	.009
Factor4	1130.508	33.447	5	.000
Factor5	1113.587	16.527	5	.005
Factor6	1113.885	16.825	5	.005

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

Student Grade[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
A	Intercept	1.675	.551	9.252	1	.002			
	Discipline	.355	.109	10.639	1	.001	1.426	1.152	1.765
	Introductory	-1.345	.286	22.037	1	.000	.261	.149	.457
	ClassSize	-.038	.019	4.047	1	.044	.963	.927	.999
	Factor1	.004	.022	.028	1	.867	1.004	.961	1.048
	Factor2	.152	.068	4.955	1	.026	1.164	1.018	1.330
	Factor3	-.124	.067	3.413	1	.065	.883	.774	1.008
	Factor4	-.175	.058	9.014	1	.003	.839	.748	.941
	Factor5	.360	.132	7.476	1	.006	1.433	1.107	1.856
	Factor6	-.255	.191	1.789	1	.181	.775	.533	1.126
B	Intercept	1.125	.550	4.188	1	.041			
	Discipline	.300	.110	7.471	1	.006	1.350	1.089	1.675
	Introductory	-1.228	.293	17.612	1	.000	.293	.165	.520
	ClassSize	-.012	.019	.385	1	.535	.988	.953	1.025
	Factor1	.049	.022	5.032	1	.025	1.050	1.006	1.095
	Factor2	.201	.068	8.841	1	.003	1.222	1.071	1.395
	Factor3	-.234	.067	12.146	1	.000	.791	.694	.903
	Factor4	-.228	.058	15.362	1	.000	.796	.710	.892
	Factor5	.358	.131	7.440	1	.006	1.431	1.106	1.851
	Factor6	.080	.179	.203	1	.652	1.084	.764	1.538
C	Intercept	.621	.565	1.205	1	.272			
	Discipline	.262	.112	5.434	1	.020	1.299	1.043	1.619
	Introductory	-.789	.303	6.777	1	.009	.454	.251	.823
	ClassSize	-.022	.019	1.337	1	.248	.978	.942	1.015
	Factor1	.086	.022	15.770	1	.000	1.090	1.045	1.138
	Factor2	.154	.069	4.981	1	.026	1.167	1.019	1.337
	Factor3	-.171	.068	6.244	1	.012	.843	.737	.964
	Factor4	-.214	.059	13.030	1	.000	.807	.719	.907
	Factor5	.330	.132	6.223	1	.013	1.391	1.073	1.803
	Factor6	-.170	.183	.864	1	.353	.844	.589	1.208

D	Intercept	-.192	.732	.069	1	.793			
	Discipline	.230	.140	2.693	1	.101	1.258	.956	1.656
	Introductory	-.546	.388	1.974	1	.160	.579	.271	1.241
	ClassSize	-.015	.024	.361	1	.548	.985	.939	1.034
	Factor1	.025	.029	.737	1	.391	1.025	.969	1.084
	Factor2	.058	.088	.440	1	.507	1.060	.892	1.260
	Factor3	-.160	.090	3.196	1	.074	.852	.715	1.016
	Factor4	-.065	.075	.737	1	.391	.937	.809	1.087
	Factor5	.159	.163	.951	1	.329	1.172	.852	1.613
	Factor6	-.148	.244	.367	1	.545	.862	.534	1.392
UW	Intercept	.996	.827	1.449	1	.229			
	Discipline	-.308	.215	2.059	1	.151	.735	.483	1.119
	Introductory	-.788	.425	3.439	1	.064	.455	.198	1.046
	ClassSize	-.050	.030	2.746	1	.098	.951	.897	1.009
	Factor1	.045	.033	1.857	1	.173	1.046	.981	1.115
	Factor2	-.067	.117	.333	1	.564	.935	.744	1.175
	Factor3	-.110	.105	1.090	1	.296	.896	.729	1.101
	Factor4	.057	.100	.320	1	.572	1.058	.869	1.288
	Factor5	.158	.190	.692	1	.405	1.171	.807	1.699
	Factor6	.063	.318	.039	1	.844	1.065	.571	1.986

a. The reference category is: F.

Restricted Model

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	944.952	13.620	4	.009
Discipline	955.393	24.062	4	.000
Introductory	958.777	27.446	4	.000
ClassSize	940.816	9.485	4	.050
Factor1	967.337	36.006	4	.000
Factor2	946.970	15.638	4	.004
Factor3	946.404	15.073	4	.005
Factor4	961.389	30.058	4	.000
Factor5	945.211	13.880	4	.008
Factor6	947.778	16.447	4	.002

Parameter Estimates

Hausman-McFadden[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
A	Intercept	1.674	.555	9.111	1	.003			
	Discipline	.348	.109	10.257	1	.001	1.417	1.145	1.754
	Introductory	-1.340	.288	21.660	1	.000	.262	.149	.460
	ClassSize	-.038	.019	3.976	1	.046	.963	.927	.999
	Factor1	.006	.022	.079	1	.778	1.006	.964	1.051
	Factor2	.154	.069	4.975	1	.026	1.167	1.019	1.337
	Factor3	-.126	.068	3.482	1	.062	.881	.772	1.006
	Factor4	-.182	.059	9.560	1	.002	.833	.742	.935
	Factor5	.372	.133	7.872	1	.005	1.451	1.119	1.881
	Factor6	-.248	.191	1.695	1	.193	.780	.537	1.134
B	Intercept	1.135	.554	4.196	1	.041			
	Discipline	.296	.110	7.284	1	.007	1.345	1.085	1.668
	Introductory	-1.225	.294	17.358	1	.000	.294	.165	.523
	ClassSize	-.013	.019	.467	1	.494	.987	.951	1.024
	Factor1	.051	.022	5.566	1	.018	1.052	1.009	1.098
	Factor2	.207	.069	9.059	1	.003	1.230	1.075	1.407
	Factor3	-.235	.067	12.122	1	.000	.791	.693	.902
	Factor4	-.238	.059	16.380	1	.000	.788	.703	.885
	Factor5	.369	.132	7.786	1	.005	1.447	1.116	1.875
	Factor6	.087	.179	.238	1	.625	1.091	.769	1.549
C	Intercept	.630	.569	1.225	1	.268			
	Discipline	.259	.112	5.328	1	.021	1.296	1.040	1.615
	Introductory	-.789	.305	6.706	1	.010	.454	.250	.826
	ClassSize	-.023	.019	1.419	1	.234	.977	.941	1.015
	Factor1	.088	.022	16.437	1	.000	1.092	1.047	1.140
	Factor2	.159	.070	5.074	1	.024	1.172	1.021	1.345
	Factor3	-.172	.069	6.304	1	.012	.842	.736	.963
	Factor4	-.222	.060	13.836	1	.000	.801	.712	.900
	Factor5	.342	.133	6.576	1	.010	1.407	1.084	1.827
	Factor6	-.160	.183	.761	1	.383	.852	.595	1.221

uw	Intercept	1.011	.831	1.481	1	.224			
	Discipline	-.303	.214	2.007	1	.157	.738	.485	1.123
	Introductory	-.793	.426	3.468	1	.063	.452	.196	1.043
	ClassSize	-.051	.030	2.785	1	.095	.951	.896	1.009
	Factor1	.045	.033	1.919	1	.166	1.046	.981	1.116
	Factor2	-.067	.118	.322	1	.571	.935	.742	1.179
	Factor3	-.112	.106	1.118	1	.290	.894	.727	1.100
	Factor4	.052	.101	.264	1	.607	1.053	.864	1.284
	Factor5	.160	.190	.707	1	.400	1.174	.808	1.705
	Factor6	.066	.319	.043	1	.835	1.068	.572	1.996

a. The reference category is: F.

Box-Tidwell Transform Test for Multinomial Linearity

Case Processing Summary

		N	Marginal Percentage
Student Grade	A	290	25.4%
	B	367	32.2%
	C	251	22.0%
	D	66	5.8%
	F	119	10.4%
	UW	47	4.1%
Valid		1140	100.0%
Missing		0	
Total		1140	
Subpopulation		74	

Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	1410.351			
Final	1026.537	383.814	70	.000

Pseudo R-Square

Cox and Snell	.286
Nagelkerke	.299
McFadden	.107

Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	Df	Sig.
Intercept	1060.588	34.051	5	.000
ALM1BT	1035.872	9.335	5	.096
ALM2BT	1042.841	16.303	5	.006
ALM3BT	1050.282	23.745	5	.000
ALM4BT	1034.305	7.768	5	.169
ALM5BT	1043.800	17.262	5	.004
ALM6BT	1034.362	7.825	5	.166
ClassSize	1053.608	27.071	5	.000
Factor1	1034.105	7.568	5	.182
Factor2	1050.605	24.068	5	.000
Factor3	1047.927	21.390	5	.001
Factor4	1035.253	8.716	5	.121
Factor5	1051.769	25.232	5	.000
Factor6	1039.733	13.196	5	.022
ClasssizeBT	1055.211	28.674	5	.000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Parameter Estimates

Student Grade[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
A	Intercept	3.589	1.330	7.283	1	.007			
	ALM1BT	-.019	.040	.234	1	.628	.981	.908	1.060

	ALM2BT	.098	.100	.964	1	.326	1.103	.907	1.341
	ALM3BT	.243	.127	3.686	1	.055	1.275	.995	1.635
	ALM4BT	.010	.080	.016	1	.901	1.010	.864	1.181
	ALM5BT	-.121	.160	.574	1	.449	.886	.648	1.212
	ALM6BT	.261	.670	.151	1	.697	1.298	.349	4.829
	ClassSize	-.590	.260	5.153	1	.023	.555	.333	.923
	Factor1	.060	.134	.201	1	.654	1.062	.817	1.380
	Factor2	.072	.219	.109	1	.741	1.075	.699	1.653
	Factor3	-.639	.248	6.656	1	.010	.528	.325	.858
	Factor4	-.225	.198	1.293	1	.256	.798	.541	1.177
	Factor5	.719	.319	5.091	1	.024	2.053	1.099	3.834
	Factor6	-.482	.907	.283	1	.595	.617	.104	3.650
	ClasssizeBT	.150	.065	5.365	1	.021	1.162	1.023	1.319
B	Intercept	2.164	1.356	2.547	1	.111			
	ALM1BT	.023	.039	.355	1	.551	1.024	.948	1.106
	ALM2BT	-.023	.101	.051	1	.821	.977	.802	1.192
	ALM3BT	-.108	.129	.704	1	.401	.898	.697	1.155
	ALM4BT	-.021	.081	.067	1	.795	.979	.836	1.147
	ALM5BT	-.337	.159	4.514	1	.034	.714	.523	.974
	ALM6BT	-.448	.650	.475	1	.491	.639	.178	2.285
	ClassSize	-.468	.262	3.198	1	.074	.626	.375	1.046
	Factor1	-.041	.134	.095	1	.758	.959	.738	1.248
	Factor2	.382	.223	2.929	1	.087	1.465	.946	2.268
	Factor3	-.047	.253	.034	1	.854	.955	.581	1.568
	Factor4	-.204	.201	1.026	1	.311	.815	.550	1.210
	Factor5	1.095	.312	12.280	1	.000	2.988	1.620	5.511
	Factor6	.764	.885	.745	1	.388	2.146	.379	12.156
	ClasssizeBT	.124	.065	3.582	1	.058	1.132	.996	1.286
C	Intercept	.593	1.423	.174	1	.677			
	ALM1BT	.053	.040	1.703	1	.192	1.054	.974	1.140
	ALM2BT	-.008	.105	.005	1	.941	.992	.808	1.219
	ALM3BT	.085	.132	.418	1	.518	1.089	.841	1.410
	ALM4BT	-.045	.083	.293	1	.588	.956	.813	1.124
	ALM5BT	-.401	.162	6.126	1	.013	.670	.488	.920
	ALM6BT	.015	.671	.001	1	.982	1.015	.273	3.779

	ClassSize	.014	.275	.003	1	.958	1.015	.592	1.738
	Factor1	-.107	.137	.607	1	.436	.898	.686	1.176
	Factor2	.273	.230	1.400	1	.237	1.314	.836	2.064
	Factor3	-.445	.258	2.975	1	.085	.641	.386	1.063
	Factor4	-.152	.206	.547	1	.460	.859	.574	1.285
	Factor5	1.236	.319	14.985	1	.000	3.441	1.841	6.434
	Factor6	-.110	.911	.015	1	.903	.895	.150	5.338
	ClasssizeBT	-.002	.068	.001	1	.982	.998	.873	1.142
D	Intercept	-3.492	2.137	2.671	1	.102			
	ALM1BT	-.046	.055	.709	1	.400	.955	.858	1.063
	ALM2BT	.173	.128	1.844	1	.175	1.189	.926	1.528
	ALM3BT	-.193	.183	1.114	1	.291	.824	.576	1.180
	ALM4BT	-.200	.104	3.683	1	.055	.818	.667	1.004
	ALM5BT	-.184	.221	.693	1	.405	.832	.540	1.283
	ALM6BT	-.638	.883	.523	1	.470	.528	.094	2.981
	ClassSize	.451	.404	1.244	1	.265	1.570	.711	3.468
	Factor1	.194	.185	1.101	1	.294	1.214	.845	1.744
	Factor2	-.252	.291	.751	1	.386	.777	.440	1.374
	Factor3	.098	.348	.080	1	.778	1.103	.557	2.184
	Factor4	.405	.266	2.323	1	.127	1.500	.891	2.525
	Factor5	.619	.427	2.105	1	.147	1.858	.805	4.290
	Factor6	1.018	1.195	.726	1	.394	2.767	.266	28.782
	ClasssizeBT	-.111	.101	1.205	1	.272	.895	.735	1.091
UW	Intercept	-4.020	2.653	2.297	1	.130			
	ALM1BT	-.073	.069	1.101	1	.294	.930	.812	1.065
	ALM2BT	.465	.163	8.115	1	.004	1.593	1.156	2.194
	ALM3BT	-.144	.215	.449	1	.503	.866	.568	1.320
	ALM4BT	.097	.124	.613	1	.434	1.102	.864	1.406
	ALM5BT	.118	.271	.190	1	.663	1.126	.661	1.916
	ALM6BT	-.780	1.144	.465	1	.495	.458	.049	4.314
	ClassSize	.604	.537	1.266	1	.261	1.829	.639	5.238
	Factor1	.353	.234	2.271	1	.132	1.423	.899	2.252

	B	Std. Error	Wald	df	Sig.	Exp(B)	Lower Bound	Upper Bound
Factor2	-1.054	.389	7.347	1	.007	.349	.163	.747
Factor3	.315	.408	.596	1	.440	1.370	.616	3.049
Factor4	-.253	.324	.607	1	.436	.777	.411	1.467
Factor5	-.090	.551	.027	1	.870	.914	.310	2.690
Factor6	.655	1.510	.188	1	.664	1.926	.100	37.159
ClasssizeBT	-.169	.137	1.515	1	.218	.844	.645	1.105

a. The reference category is: F.

Final Model Statistical Results (Significant Results Highlighted)

Parameter Estimates

Student Grade[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
A	Intercept	1.675	.551	9.252	1	.002			
	Discipline	.355	.109	10.639	1	.001	1.426	1.152	1.765
	Introductory	-1.345	.286	22.037	1	.000	.261	.149	.457
	ClassSize	-.038	.019	4.047	1	.044	.963	.927	.999
	Factor1	.004	.022	.028	1	.867	1.004	.961	1.048
	Factor2	.152	.068	4.955	1	.026	1.164	1.018	1.330
	Factor3	-.124	.067	3.413	1	.065	.883	.774	1.008
	Factor4	-.175	.058	9.014	1	.003	.839	.748	.941
	Factor5	.360	.132	7.476	1	.006	1.433	1.107	1.856
	Factor6	-.255	.191	1.789	1	.181	.775	.533	1.126
B	Intercept	1.125	.550	4.188	1	.041			
	Discipline	.300	.110	7.471	1	.006	1.350	1.089	1.675
	Introductory	-1.228	.293	17.612	1	.000	.293	.165	.520
	ClassSize	-.012	.019	.385	1	.535	.988	.953	1.025
	Factor1	.049	.022	5.032	1	.025	1.050	1.006	1.095
	Factor2	.201	.068	8.841	1	.003	1.222	1.071	1.395
	Factor3	-.234	.067	12.146	1	.000	.791	.694	.903
	Factor4	-.228	.058	15.362	1	.000	.796	.710	.892

	Factor5	.358	.131	7.440	1	.006	1.431	1.106	1.851
	Factor6	.080	.179	.203	1	.652	1.084	.764	1.538
C	Intercept	.621	.565	1.205	1	.272			
	Discipline	.262	.112	5.434	1	.020	1.299	1.043	1.619
	Introductory	-.789	.303	6.777	1	.009	.454	.251	.823
	ClassSize	-.022	.019	1.337	1	.248	.978	.942	1.015
	Factor1	.086	.022	15.770	1	.000	1.090	1.045	1.138
	Factor2	.154	.069	4.981	1	.026	1.167	1.019	1.337
	Factor3	-.171	.068	6.244	1	.012	.843	.737	.964
	Factor4	-.214	.059	13.030	1	.000	.807	.719	.907
	Factor5	.330	.132	6.223	1	.013	1.391	1.073	1.803
	Factor6	-.170	.183	.864	1	.353	.844	.589	1.208
D	Intercept	-.192	.732	.069	1	.793			
	Discipline	.230	.140	2.693	1	.101	1.258	.956	1.656
	Introductory	-.546	.388	1.974	1	.160	.579	.271	1.241
	ClassSize	-.015	.024	.361	1	.548	.985	.939	1.034
	Factor1	.025	.029	.737	1	.391	1.025	.969	1.084
	Factor2	.058	.088	.440	1	.507	1.060	.892	1.260
	Factor3	-.160	.090	3.196	1	.074	.852	.715	1.016
	Factor4	-.065	.075	.737	1	.391	.937	.809	1.087
	Factor5	.159	.163	.951	1	.329	1.172	.852	1.613
	Factor6	-.148	.244	.367	1	.545	.862	.534	1.392
UW	Intercept	.996	.827	1.449	1	.229			
	Discipline	-.308	.215	2.059	1	.151	.735	.483	1.119
	Introductory	-.788	.425	3.439	1	.064	.455	.198	1.046
	ClassSize	-.050	.030	2.746	1	.098	.951	.897	1.009
	Factor1	.045	.033	1.857	1	.173	1.046	.981	1.115
	Factor2	-.067	.117	.333	1	.564	.935	.744	1.175
	Factor3	-.110	.105	1.090	1	.296	.896	.729	1.101
	Factor4	.057	.100	.320	1	.572	1.058	.869	1.288
	Factor5	.158	.190	.692	1	.405	1.171	.807	1.699
	Factor6	.063	.318	.039	1	.844	1.065	.571	1.986

a. The reference category is: F.