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## An Exploratory Comparison of a Traditional and an Adaptive Instructional Approach for College Algebra

Ryan Kasha  
*University of Central Florida*

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AN EXPLORATORY COMPARISON OF A TRADITIONAL AND AN ADAPTIVE  
INSTRUCTIONAL APPROACH FOR COLLEGE ALGEBRA

by

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Major Professor: John Kincaid

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## **ABSTRACT**

This research effort compared student learning gains and attitudinal changes through the implementation of two varying instructional approaches on the topic of functions in College Algebra. Attitudinal changes were measured based on the Attitude Towards Mathematics Inventory (ATMI). The ATMI also provided four sub-scales scores for self-confidence, value of learning, enjoyment, and motivation. Furthermore, this research explored and compared relationships between students' level of mastery and their actual level of learning.

This study implemented a quasi-experimental research design using a sample that consisted of 56 College Algebra students in a public, state college in Florida. The sample was enrolled in one of two College Algebra sections, in which one section followed a self-adaptive instructional approach using ALEKS (Assessment and Learning in Knowledge Space) and the other section followed a traditional approach using MyMathLab. Learning gains in each class were measured as the difference between the pre-test and post-test scores on the topic of functions in College Algebra. Attitude changes in each class were measured as the difference between the holistic scores on the ATMI, as well as each of the four sub-scale scores, which was administered once in the beginning of the semester and again after the unit of functions, approximately eight weeks into the course. Utilizing an independent t-test, results indicated that there was not a significant difference in actual learning gains for the compared instructional approaches. Additionally, independent t-test results indicated that there was not a statistical difference for attitude change holistically and on each of the four sub-scales for the compared instructional approaches. However, correlational analyses revealed a strong relationship between

students' level of mastery learning and their actual learning level for each class with the self-adaptive instructional approach having a stronger correlation than the non-adaptive section, as measured by an  $r$ -to- $z$  Fisher transformation test. The results of this study indicate that the self-adaptive instructional approach using ALEKS could more accurately report students' true level of learning compared to a non-adaptive instructional approach.

Overall, this study found the compared instructional approaches to be equivalent in terms of learning and effect on students' attitude. While not statistically different, the results of this study have implications for math educators, instructional designers, and software developers. For example, a non-adaptive instructional approach can be equivalent to a self-adaptive instructional approach in terms of learning with appropriate planning and design. Future recommendations include further case studies of self-adaptive technology in developmental and college mathematics in other modalities such as hybrid or on-line courses. Also, this study should be replicated on a larger scale with other self-adaptive math software in addition to focusing on other student populations, such as K - 12. There is much potential for intelligent tutoring to supplement different instructional approaches, but should not be viewed as a replacement for teacher-to-student interactions.

Dedicated to my grandfather,  
Dr. Herman Leon Kasha, M.D. (*Deceased*)

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## LIST OF ACRONYMS/ABBREVIATIONS

- AI** Artificial Intelligence – defined in this dissertation meaning technology that contains any level of adaptive properties within an expert system. This dissertation does not differentiate between the terms artificial intelligence and self-adaptation.
- ALEKS** Assessment and Learning in Knowledge Spaces – a software system by McGraw-Hills used for mathematics. This software provides students with a diagnostic assessment and develops a “learning pie” based on the student’s mastery level of learning. The homework objectives are chosen by the instructor. ALEKS develops specific homework assignments and gives random assessments to consistently update a student’s knowledge state. ALEKS was developed based on Knowledge Space Theory.
- AMATYC** American Mathematics Association of Two-Year Colleges – a national organization that focuses on the research and curriculum of mathematics in 2-year colleges. This organization has been an influence in the community college mathematics curriculum.
- ATMI** Attitudes Toward Mathematics Inventory. This inventory scale measures students’ attitude in mathematics in terms of their self-confidence, value, enjoyment, and motivation in mathematics as well as holistically. This scale was originally developed by Dr. Martha Tapias in 1996.

CAI	Computer-Assisted Instruction – where instruction is delivered in whole or part by an electronic interface via the Internet, CD, or mobile device.
CCRC	Community College Research Center
CCTCMIS	Community College and Technical Center Management Information Systems – agency that is part of the Florida Department of Education that collects data on Florida’s 28 colleges, does statistical analysis on the data, and furnish reports to the Florida Department of Education.
ITS	Intelligent Tutoring System
KST	Knowledge Space Thoery – a theory created by Jean-Claude Falmagne that assesses the knowledge structure of a system efficiently by assessing higher knowledge states. It assumes that problems that can be solved are a subset of the actual knowledge state and that inferences can be made about the knowledge state based on whether the question is answered correctly or incorrectly.
LMS	Learning Management System – a system created for on-line training and learning or to supplement a course with on-line support and a platform.  Blackboard is an example of a LMS.
MML	MyMathLab – a software package by Pearson developed for mathematics.  MyMathLab includes homework, quizzes, and exams. Assistance is made available through hints, examples, video tutorials, and the option of doing similar exercises.

MAT 1033C	Intermediate Algebra with lab. The student must complete Intermediate Algebra with a grade of C or higher to move on to College Algebra. As of July 1, 2014, students who are opting not to enroll in developmental mathematics can begin with this course. No placement exam is required for students who have graduated from a Florida high school 2003 or after or former military.
MAC 1105	College Algebra. Student entering this course must have passed MAT 1033C with a grade of C or higher or placement by the PERT exam.
N	Number (frequency)
NAEP	National Assessment of Educational Progress
NCTM	National Council of Teachers of Mathematics, which focuses on middle and high school mathematics curriculum
PERT	Postsecondary Education Readiness Test. This exam has been used to help determine students' placement into college-level or developmental reading, writing, and math courses since October, 2010.
SD	Standard deviation
TIMSS	Trends in International Mathematics and Science Study
ZPD	Zone of proximal development



## CHAPTER ONE: INTRODUCTION

### College Readiness

Achieving the Dream is a non-profit organization that is interested in helping community college students succeed through evidence-based practices (2013). According to this organization, the current generation of college-aged Americans will be less educated than their parents' generation for the first time in U.S. history while higher order skills are needed more than ever before in our workforce (2013). This phenomenon can be attributed to students entering colleges underprepared (2013). As a result, the percentage of high school students enrolling in college immediately following high school graduation has remained at 60% since the 1990s (Snyder, 2012). In addition, according to the Educational Testing Services, the number of students aged 25 to 29 completing four or more years of college has been around 25% for the past two decades (Burke, 2008). The Carnegie Foundation, an independent policy and research center for improvement of teaching, reports that 60% of students entering higher education in the United States are required to complete remedial courses (Strother, Van Campen, & Grunow, 2013; Taylor, 2008). In 2004, 1.2 million students took the ACT college-entrance examination, and less than 22% of these students were college-ready in mathematics according to the ACT testing board (Burke, 2008). Therefore, there are a large number of students required to complete remedial courses. However, 70% of all remedial students never complete the required math courses, "blocking their entry into higher education" (Strother, Van Campen, & Grunow, 2013, p. 3).

In addition to students not being college-ready, less than 30% of all community college students in the United States graduate with a degree (Bailey & Cho, 2010). The American Mathematics Association of Two-Year Colleges (AMATYC) reports that approximately 1.3 million students were enrolled in math courses at two-year colleges (Blair, 2006). In the fall of 2005, about 57% of students were enrolled in a developmental math course. In 2010, the percentage of students enrolled in developmental mathematics at two-year colleges stayed steady compared to the total number of mathematics courses offered at two-year colleges since 2005 (Blair, 2006). The Conference Board of the Mathematical Sciences (CBMS) reports that enrollment in developmental mathematics has increased by 19% since 2005 (Blair, Kirkman, & Maxwell, 2003, p. 1). In California, the second largest higher education system in the United States, over 70% of students are placed into remedial math courses (Brown & Niemi, 2007). The Florida Department of Education (2012) reports that only 31.8% of students in developmental math courses in the Florida's college system excluding public universities were successful during the 2007 – 2008 academic year, earning a grade of C or higher. In addition to developmental students having difficulty in completing their developmental requirements, only 20% of developmental students will earn a degree while 50% of non-developmental college students will earn a college degree (Thomas and Higbee, 2000).

Burke (2008) and Taylor (2008) attribute these statistics to an inadequate high school preparation for college-level math courses. The inadequate preparation is due to poor alignment between high school and colleges, often creating an “expectations gap” as described by the U.S. Secretary of Education Spelling's Commission on the Future of Higher Education (Burke, 2008,

p. 2). As a result of the misalignment between high schools and colleges, an enormous number of students are being placed into developmental math courses as well as developmental courses in reading and English (Bahr, 2008; Bahr, 2010a; Bahr, 2010b; Bahr, 2012; Bahr, 2013; Brown & Niemi, 2007; Fine, Duggan, & Braddy, 2009; Gallard, Albritton, & Morgan, 2010; Hern, 2012; Taylor, 2008). Currently, students that start in remedial college courses, particularly mathematics, have a slim chance in completing college-level courses and even a smaller chance of graduating with a certificate or degree (Bahr, 2010; Bailey & Cho, 2010; Brown & Niemi, 2007; The Carnegie Foundation, 2013). The lack of success in developmental math courses is due to the time that a developmental math student spends in these remedial courses. For example, students who successfully transferred to a university spent an average of five years in community college to get only one year worth of credit in California (Melguizo, Bos, & Prather, 2011).

### Developmental Education

Despite the high demand for remedial college courses, there is a huge debate on the success, benefit, and cost of developmental education (Melguizo, Bos, & Prather, 2011). Opponents of developmental math education argue that taxpayers should not have to pay again for students to learn skills that should have been obtained prior to entering college (Bahr, 2012). The cost of developmental math education is another criticism of developmental education (Bahr, 2008; Bahr, 2012; Melguizo, Bos, & Prather, 2011). The cost of developmental education is about \$1 to \$2 billion annually for public colleges (Bahr, 2008; Bahr, 2012; Melguizo, Bos, & Prather,

2011). If indirect costs were included, the total cost rise to \$17 billion annually (Bahr, 2008). In addition, opponents argue that developmental education is not working. Most students who begin the remedial sequence do not successfully exit college-level math courses following six years after initial college enrollment (Bahr, 2010). However, those that argue in favor of developmental education posit that it provides access to students to obtain prerequisite skills to prepare them for college-level coursework (Bahr, 2010). Developmental education provides a bridge to obtaining a college degree (Bahr, 2010). Supporters also argue that the U.S. economy is dependent on those that are competent with reading, writing, and basic, necessary math skills (Bahr, 2012). Moreover, remedial courses provide an opportunity for students to obtain necessary prerequisite skills needed for the work force (Bahr, 2012). Furthermore, McCabe (2000) argues that providing developmental education for underprepared students is essential to the mission of American higher education citing that over 80% of new jobs by 2020 will require some postsecondary education.

Despite the ongoing debate surrounding developmental education, “major changes are occurring in educational policies pertaining to postsecondary remediation” (Bahr, 2012, p. 178). Due to the low percentage of students exiting remedial college courses and the cost of developmental education, there is a national reform movement to help students accelerate their remedial education (Bahr, 2012; Brown & Niemi, 2007). The White House Summit Report (2011) provides some general recommendations on developmental reforms including modifying college schedules, creating specific course paths to shorten time to earn a degree, aligning developmental education with the learners’ diverse needs, increasing the use of cohort-based

education, and using technology to increase capacity. These suggestions are primarily focus on accelerating students' paths towards a college degree, modifying current instructional practices and using technology appropriately.

### Changes in Developmental Education

The Carnegie Foundation has worked with colleges to create shorter paths in mathematics that have focused on statistical and quantitative reasoning skills to give students an alternative path to complete their college degree (Merseeth, 2011). The shorter paths being implemented by the Carnegie Foundation colleges results in students completing their math requirements in two semesters instead of five semesters (Merseeth, 2011). For example, a community college in California developed “Path2Stats” where students take one semester of developmental mathematics, followed by a college-level statistics course (Hern, 2012). In this model, a just-in-time approach is used to present developmental math skills as they become relevant while learning Statistics. In essence, students are enrolled in a year-long Statistics course with included relevant developmental math lessons. The community college found that students in “Path2Stats” completed their math requirements at 4.5 times the rate of students placed on the traditional math path. The “Path2Stats” initiative led to the California Acceleration Project, which is advocating for a national acceleration movement in remedial education (Hern, 2012). Valencia College in Central Florida has offered students a similar path for students to complete their math requirements in two semesters. This alternative math pathway led students to College Statistics after one semester of developmental mathematics. Similar to “Path2Stats”, students

were learning Statistics with developmental math lessons presented when those skills became relevant. In another study, Sheldon and Durdella (2010) found that students in compressed courses were more likely to succeed than students who were not enrolled in accelerated developmental courses regardless of age, gender, or race.

Furthermore, other community colleges adopted accelerated programs by combining developmental math courses (Hern, 2012). For example, some community colleges in California combined elementary and intermediate algebra into one combined course to save time and reduce redundancy (Hern, 2012). Some colleges have eliminated remedial courses as prerequisite, offering students to enroll directly into college-level math courses. Additional support was provided through tutoring and math software. In California, several colleges follow this model, called the “mainstream model” (Hern, 2012).

Modularization serves as another way to accelerate students through their math requirements. Students in this model were assigned the topics they had to master relevant to their major at Jackson State Community College in Tennessee. Jackson State Community College had twelve distinct topics for developmental math, but only 7 of 41 course of study requires all modules to be completed. The topics to be learned were tailored to students’ course of study and math prerequisite skills needed for college-level courses. In addition to customizing students’ developmental study, the modules were self-paced and delivered through MyMathLabPlus, a math software system that offers on-line homework with assistance, examples, explanations, and practice assessments. This example of using computer-assisted instruction (CAI) for math raised the success rate from about 42% to about 59% for Jackson State Community College. Retention

rates (students staying in a course until the end without withdrawing) have increased by about 12% (Bassett & Frost, 2010).

As a result of the reported success of these accelerated programs in developmental mathematics, recent laws to change the delivery and option of developmental mathematics were passed in Florida (Senate Bill 1720 §1008.30, 2013). These law reforms, referred to as SB 1720, have dropped placement testing and remedial requirements for students who entered a Florida public high school as a 9<sup>th</sup> grader in 2003 or after and graduated with a standard high school diploma. Students with a recent Florida high school diploma can only be tested on a voluntary basis. Regardless of the student's placement test score, enrollment in developmental education courses is voluntary, not mandatory (Florida Department of Education, 2013). In addition, enrollment in remedial courses is voluntary in some colleges in New York that requires placement testing (Perin, 2004). As a result, more students will be entering college-level math courses without adequate remedial preparation. Furthermore, students depend on more tutoring services and math labs for additional assistance (Perin, 2004). However, resources at community colleges are limited in tutoring labs and may not always be supported by state funding (Perin, 2004).

In addition, the benefit of accelerating students' developmental education or eliminating developmental requirements altogether is unclear due to limited research in this area (Hordaras & Jaggars, 2014). In addition, faculty members may worry that "increased access to college-level courses will result in lower pass rates and dampen long-term student success" (Hordaras & Jaggars, 2014, p. 251). Hordaras and Jaggars (2014) conducted an analysis of accelerated

education in English and Mathematics. They compared shorter sequences of developmental courses and longer sequences of developmental courses. Results indicate that students going through a shorter sequence of mathematics compared to a longer sequence of mathematics, after accounting for student characteristics and cohorts, were only 1% more likely to earn an Associate degree over three years (Hordaras & Jaggars, 2014). This result was significant at the  $p < 0.10$  level (2014). In addition, Hordara and Jaggars (2014) concluded that accelerating developmental math education provides greater access to college-level courses, but there may be consequences in terms of student success in college-level courses.

The issue of underprepared students extends beyond developmental education and may affect college-credit courses and degree programs (Perin, 2004). For example, some institutions do not require or offer developmental education. Furthermore, only 25% of underprepared community college students enroll in developmental courses (Perin, 2004). Moreover, there are students who do not take math courses every semester, which contributes to the issue of students entering college-credit math courses underprepared. For these students, they have already completed their prerequisite requirements, but so much time has elapsed since their last math course, that there is information that has been forgotten and has to be relearned in order for them to be able to progress through college-level mathematics. In addition, older students returning to college may have forgotten much of their math skills and need some remediation. However, they may place into a college level math course based on older transcripts and records. Older students and students not completing math courses in successive semesters must be taken into consideration in addition to accelerated remedial students entering college mathematics.



In order for students to be successful in college-level math courses with the new reforms in place, a strategic plan must be developed and implemented with effective instructional strategies (Keup, 1998). For example, Black Hills State University redesigned their College Algebra course by adding a supplemental computer-based mastery learning program, incorporating more whole class discussion and cooperative learning activities, more application problems, and fewer lectures (Hargerty, Smith, & Goodwin, 2010). Black Hills State University's redesign of College Algebra resulted in a 21% increase in passing rate, a 300% increase in enrollment in the next sequential math course (trigonometry), 25% improvement in attendance rates, and a statistically significant increase in the Collegiate Assessment of Academic Proficiency scores. These improvements were made in response to a low number of math majors and a low enrollment rate for higher mathematics courses. In addition to the low enrollment in higher mathematics, calculus instructors reported that students did not understand the algebraic process. As a result, students could not successfully complete calculus problems. However, the redesign was not easy and took a few years to fully implement. Faculty required training and an understanding of the new approach to teaching college algebra. This redesign effort serves as a multi-faceted strategy example of helping students to be successful in college-level mathematics (Hargerty, Smith, & Goodwin, 2010).

However, there are no standardized best practices or approaches in place for community college math instruction (Thomas and Higbee, 2000). Currently, the main mode of instruction in college-level courses is primarily traditional lecture according to the CBMS 2010 report (Blair, 2006; Spradlin & Ackerman, 2010). For example, Calculus I sections taught in 2010 were 66%

lectures while Calculus II sections taught were 85% lecture (Blair, 2006). In addition, elementary statistics sections in 2010 were 81% lecture. Alternative or supplemental modes of instruction should be developed so that underprepared students can gain the knowledge and skills necessary to complete their post-secondary education (Spradin & Ackerman, 2010; Taylor, 2008).

### Instructional Media

A variety of instructional modalities are being implemented to better meet the needs of math students with deficiencies (Spradlin & Ackerman, 2010; Twigg, 2013). Additionally, on-line learning tools and distance education is in more demand due to technological advances and to make access to college more convenient for all students, especially part-time students with a busy schedule (Spradlin & Ackerman, 2010; Valentine & Bessett, 2013). In addition, many of these reform movements use computer-assisted instruction as a supplement or as the sole source of instruction to help students learn independently (Hern, 2012; Merseth, 2011; Moosavi, 2009). Moosavi (2009) reports that colleges and universities are investing money to develop and maintain computer labs to enhance instruction supplemented by computer-assisted instruction (CAI). As the demand for asynchronous learning continues to increase coupled with traditional lecture format being augmented or replaced by CAI, the use of CAI will continue to grow (Moosavi, 2009).

Twigg (2013) asserts that the use of instructional software is the key to the redesign in college math education since it provides content consistency, several instructional resources such

as hints, examples, videos, hyperlinks to relevant parts in the textbook, and provides timely, immediate feedback. CAI offers students the advantage of learning on their own schedule, to receive immediate feedback, and to receive instruction in a variety of ways to suit their learning needs (Spradlin & Ackerman, 2010). Computer assisted instruction (CAI) have become an integral part of higher education since it can reach a broader student audience, better address students' needs, and save money (Zavarella & Ignash, 2009). The focus is no longer on whether or not CAI should be integrated into the college curriculum, but how to use CAI effectively. The potential of computers and CAI is dependent on the instructors' use of such technological tools (Moosavi, 2009). Therefore, the use of math software should only be considered in light of the instructional approach being implemented.

Several studies (e.g. Fine, Duggan, & Braddy, 2009; Taylor, 2008; Xu, Meyer, & Morgan, 2008) confirm students in courses where CAI used as supplement to lecture or used in place of lecture perform equally well or better than the traditional lecture sections. However, these studies do not examine different instructional approaches with CAI involving the use of artificial intelligence compared to a traditional instructional approach with CAI.

Computer software such as MyMathLab and ALEKS are used predominantly in remedial and college-level math courses nationwide. With reform movements affecting students' math readiness and the pace at which they learn mathematics, alternative teaching methods including technology is being explored in developmental and college-level math courses throughout Florida and the country (Spradlin & Ackerman, 2010).

### Student Affect

Research has shown that students' level of motivation, attitude, locus of control, and their perception affects learning (Blair, 2006; Nunez-Pena, Suarez-Pellicioni, & Bono, 2013). Low grades were shown to be related to math anxiety and negative attitudes towards mathematics (Nunez-Pena, Suarez-Pellicioni, & Bono, 2013). For example, Nunez-Pena, Suarez-Pellicioni, and Bono (2013) explored the relationship between students' performance and their anxiety level in a research design course at the University of Barcelona. In addition, relationships between students' course grade and their attitude towards mathematics were also compared using an abbreviated Likert math anxiety scale (sMARS), where scores can range from 25 to 125 points. The math anxiety scale used provides scores in the area of math anxiety, math test anxiety, and math course anxiety. The math anxiety scale was internally validated and has shown strong internal consistency (Cronbach's  $\alpha = 0.94$ ) and a test-retest reliability of 0.72 (Nunez-Pena, Suarez-Pellicioni, & Bono, 2013). In addition to measuring math anxiety, attitudes toward mathematics were measured by a three-item questionnaire, which focused on enjoyment, self-confidence, and motivation. A sample of 193 students participated in this study. In this study, a significant relationship was found between students' final course grade and the variables under investigation regarding students' attitude, which included math anxiety, math test anxiety, math course anxiety, enjoyment of mathematics, self-confidence of mathematics, and motivation for mathematics. Post hoc comparisons showed that student who failed or received a lower grade had more math anxiety, more math test anxiety, and math course anxiety, and low enjoyment. In addition, these students reported low self-confidence and low motivation compared to students

who received a higher grade in the research design course. Students who obtained higher grades showed lower levels of math anxiety and had a higher level of self-confidence, motivation, and enjoyment. Nunez-Pena, Suarez-Pellicioni and Bono (2013) recommend taking the negative impact of attitudinal factors into consideration at all teaching levels (elementary, secondary, and post-secondary). Furthermore, programs or interventions that can mitigate negative impact of affect and can optimize student learning should also be incorporated.

Using technology, specifically CAI, can help to mitigate the negative impact of students' attitude. For instance, Elliott, Choi, and Friedline (2013) implemented an on-line statistics lab component as part of a research course for social work students to increase math literacy in the area of statistics and to create more positive attitude. Elliott, Choi, and Friedline (2013) reports that a majority of graduate students experience math anxiety and serves as a motivation for implementing an on-line statistics lab component. Students reviewed on-line lessons at their own pace and completed a weekly lab assignment relating to Statistics using SPSS. Data about students' attitudes towards the on-line Statistics lab was collected using a Posttest-only design. 68% of students were afraid to learn Statistics before the course began. However, no students were afraid to learn Statistics at the end of the course. This was statistically significant using the Fisher's exact test,  $p = 0.00$ . In addition, confidence levels in performing statistical analyses increased from 24% before the course to 80% of students being confident after the course. In addition, 100% of the students report being confident in reading and understanding scholarly articles after the course compared to 79% being confident before the course. This research study was limited primarily due to a lack of a comparison group and limited for using only a post-test

design. Therefore, these findings are descriptive in nature. The researchers suggest future investigation to actually determine the impact of the on-line statistics component of the research course.

Student affect has also been explored in younger students. For example, Cates and Rhymer (2003) examined the relationship between students' fluency in addition and their level of anxiety. Their study demonstrated that students with less math anxiety were able to complete more problems correct per minute for all four basic math operations (addition, subtraction, multiplication, division). Their findings support the notion that math anxiety may be related to the level of learning achieved (Cates & Rhymer, 2003). Some recommendations were made in reference to varying level of instruction and the rate of increasing instructional difficulties. The authors recommend that introducing students to topics that they are not yet ready for will lead to increased anxiety and decreased performance. For example, it is not wise to introduce students to regrouping in addition if students are having problems understanding addition without regrouping. The authors suggest that further research in this area may enhance educators' ability to prevent and treat math anxiety through more effective matching of instruction to student level of learning.

However, the finding of these research studies suggest that students' attitudes have been shown to be a contributing factor in whether students learn (Elliott, Choi, & Friedline, 2013; Gates and Rhymer, 2003). Furthermore, students' attitude and their level of learning was found to be positively affected by their confidence level, motivation level, anxiety level, level of persistence, and their overall attitude towards math and computer-assisted instruction in other

studies (Dabbagh & Blijd, 2010; Elliott & Friedline, 2013; Tapia & Marsh, 2004; Moosavi, 2009). In addition, Taylor (2008) has identified that self-confidence and self-esteem influence student learning. In response to these characteristics that affect student learning, it makes sense to develop effective instructional techniques that gives them support, opportunities to find academic success with positive feedback, and opportunities to increase their self-concept in general (Acelajado, 2004; Taylor, 2008). More specifically, math anxiety, negative attitudes, poor study skills, and lack of responsibility for learning should also be addressed in addition to math skills in remedial and college-level math courses (Spradlin & Ackerman, 2010). Since students' attitudes affect their learning experience, the effect of instructional approach on student affect should be considered. In fact, Spradlin and Ackerman (2010) recommend future studies investigating math anxiety levels with varying instructional approaches. Therefore, students' attitude levels will be measured in this current research study using Tapias's (1996) Attitudes Toward Mathematics Inventory (ATMI). The ATMI provides measures on students' confidence levels, value level, enjoyment level, and motivation level in addition to a holistic attitudinal score.

### Purpose of Study

The purpose of this study was to compare an adaptive instructional approach using ALEKS to a traditional instructional approach using MyMathLab in terms of their effect on learning gains on the topic of functions in College Algebra as well as their attitudinal changes. In addition, correlational analyses were performed to compare students' mastery learning levels

to their actual learning levels for each instructional approach. Another purpose was to compare this relationship between the instructional approaches.

College Algebra was chosen since it serves as a gateway courses for many students. In addition, student success in College Algebra is important for students to be successful in other disciplines (Hargerty, Smith, & Goodwin, 2010). College Algebra provides important concepts such as statistical analysis procedures and functions and processes such as modeling, problem solving, and analysis.

The research questions are as follows:

- 1) Is there a significant difference between learning gains on the topic of functions between the two College Algebra sections as a function of instructional approach (traditional vs. adaptive)?
- 2) Is there a significant difference between attitude changes between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?
- 3) Is there a stronger correlation between students' level of mastery learning (as reported by their respective software) vs. actual learning as a function of instructional approach (traditional vs. self-adaptive)?

### Summary

Florida and other states are reforming developmental education to make developmental education accelerated, offered only as a co-requisite, or not required for students that graduated



high school after 2003 according to Senate Bill 1720, which was signed into law on May 20, 2013 by Governor Rick Scott. The intent of developmental education reforms is to have students enter college-level courses sooner and to spend minimum time in developmental college courses. This reform movements taking place such as “Path2Stats” will give students greater access to college-level courses, but faculty fear that this will result in higher failure rates due to deficiencies and lack of preparedness (Hodara & Jaggars, 2014). CAI as a supplement to college-level math instruction is common (Zavarella & Ignash, 2009) and may be key to providing an alternative modality for students to learn, receive assistance, and to receive immediate feedback (Twig, 2013). Computer assisted instruction have yielded equal results to lecture-based math courses (e.g. Fine, Duggan, & Braddy, 2009; Taylor, 2008; Xu, Meyer, & Morgan, 2008). However, a self-adaptive instructional approach using CAI compared to a traditional instructional approach using CAI may yield greater learning gains and more positive attitude changes.

The purpose of this research effort is to determine whether there is a significant difference between a traditional approach using MyMathLab and an adaptive instructional approach using ALEKS, where there adjustments are automatically made based on the current knowledge state of students. Comparison of the two exploratory instructional approaches will be made based on students’ learning gains on the topic of function and on their attitude changes as measured by the ATMI (Attitudes Toward Mathematics Inventory). Measures for learning gains in functions between the two College Algebra sections is measured by the difference between the pre-test and post-test scores on function. In addition, attitude changes were measured between

the difference on the first administration and the last administration of the ATMI. Other measures collected include time spent completing homework on their respective software and the difference between actual learning (as measured by the post-test score on function) and the level at which course concepts were mastered (as reported by the respective software using homework scores).

### Organization of the study

The first chapter provides an introduction to current state of math education in postsecondary institutions, specifically community colleges. In addition, the first chapter reviews alternative modes of instruction being implemented in college math courses in response to controversy and reforms taking place regarding developmental math education. Chapter one also states the purpose of the study, specific research questions, and its potential benefits for stakeholders. Chapter two provides a literature review of math education and CAI, background of intelligent tutoring, discussion of Knowledge Space Theory (KST), and case studies that incorporated KST. Chapter three provides an in-depth description of the research design and how data was collected and analyzed. Chapter four provides the results of each research question followed by Chapter five, which provides the conclusion, implications, and future recommendations for extending this study.

### Potential Benefits

The aim of this study is to compare two instructional approaches with different CAIs where artificial intelligence is the focus of one of the CAI systems being analyzed coupled with

an adaptive approach in the classroom. Due to the nature of this research study, the results found can inform administrators, educators, and commercial software makers about the effects of self-adaptive technology used in an adaptive approach over different types of technology in traditional math instructional models. For example, ALEKS was the chosen software for the adaptive instructional approach due to its adaptive function. ALEKS is able to customize homework based on students' current knowledge state and can support an adaptive instructional approach. An adaptive instructional approach helps to individualize assignments based on students' current knowledge state. MyMathLab was chosen to accompany the traditional instructional approach since it supports the traditional lecture format. For example, each student is assigned the same homework assignments and same number of problems for each course objective. The results from this study can inform the features and functionalities that are best suited to optimize specific instructional approaches and the student learning experience in such learning environments.

## **CHAPTER TWO: LITERATURE REVIEW**

The purpose of this research study is to compare an adaptive and a traditional instructional approach both supplemented with CAI, where one CAI uses artificial intelligence to individualize a student's learning plan based on the course objectives. The two instructional approaches will be compared in terms of learning gains on the unit of functions in college algebra as measured by the difference between pre-test and post-test scores and in terms of students' attitude change based on total score and sub-scores from the ATMI. The ATMI was administered twice during the semester. Another purpose of this study was to examine and compare correlational relationships between students' level of mastery and their actual learning levels for both instructional approaches. Students' level of mastery is operationally defined as the homework grade on the unit of functions as reported by the student's respective software system. Students' actual learning level is operationally defined as the earned grade on the post-test for functions.

Chapter one covered some of the demographics of students entering colleges and some of the current reform movements taking place in community college math education. There are a large number of students entering colleges underprepared, more so in math compared to English or reading (Burke, 2008; Taylor, 2008; Strother, Van Campen, & Grunow, 2013). There are a small percentage of remedial college students earning their college degrees. A large number of students in remedial courses do not complete their college education. In addition, developmental education is surrounded with controversy due to its cost and low success rate (Bahr, 2008; Bahr, 2010; Bahr, 2012). As a result, national organizations such as the Carnegie Foundation,

Achieving the Dream, community colleges, state and national leaders are implementing alternative modes for college math instruction. Many of the alternative modes focus on accelerating the developmental path or remediation while enrolled in a college-level math course. Many of the accelerated models incorporate math software packages such as ALEKS or MyMathLab either as a supplement to traditional lecture classes or used solely for self-paced learning with the instructor being a facilitator. Computer-assisted instruction has been used in math education for decades. Several research studies (e.g. Fine, Duggan, & Braddy, 2009; Taylor, 2008; Xu, Meyer, & Morgan, 2008) have shown using CAI to be equally effective on student learning compared to traditional lecture alone. In some cases, the use of CAI has been shown to be more effective than traditional lecture alone.

This chapter will provide a brief history of math education and reforms. This chapter will also highlight some research studies that have used computer-assisted instruction and the results from those studies, followed by a discussion of intellectual tutoring, background of intelligent tutoring, and its impact in education. More specifically, this chapter will include a discussion of Knowledge Space Theory (KST). ALEKS, the self-adaptive software, is based on the Knowledge Space Theory. Research studies that have been done with different instructional approaches using knowledge space theory will also be included.

### Math Education

Reforms in math education are not novel (Huetinck & Munshin, 2000; Van de Walle, 2004). Some of the current alternatives being explored in college developmental mathematics

include shorter math paths, developmental math as a co-requisite, and CAI in mathematics. However, math reforms in the United States have been taking place for more than fifty years (Huetinck & Munshin, 2000; Van de Walle, 2004). The National Council of Teachers of Mathematics (NCTM), a math advocacy group focused on middle and high school mathematics curriculum, has guided the reform movement in mathematics since 1927 (Huetinck & Munshin, 2000). In 1927, the NCTM Yearbook, *Curriculum Problems in Teaching Mathematics*, identified that students were memorizing procedures without an understanding of the concept or applications of mathematics (Huetinck & Munshin, 2000). The traditional approach to mathematics instruction has been largely lecture-based since 1927 and still remains largely lecture-based (Blair, 2006; Van de Walle, 2004). The traditional lecture approach led to students not graduating with the necessary critical thinking skills in mathematics.

However, the Soviet Union successful launch of “Sputnik” in 1957 led to a major concern in the United States (Huetinck & Munshin, 2000). The Sputnik launched was a major impetus for the reform movements in mathematics instruction. In the 1960s, “New Math” was a reform movement that emphasized structural properties of mathematics (Huetinck & Munshin, 2000). Due to a lack of professional development and confusion over the “New Math” curriculum, this reform movement became discontinued before the 1980s. Piaget’s research played a role in the reform movement that took place in the 1970s. Piaget’s developmental stages of learning was incorporated into teaching training to enhance content knowledge and pedagogical skills, mainly at the elementary grade levels (Huetinck & Munshin, 2000). Manipulatives and hands-on activities were emphasized. In the 1980s, there was a “Back to

Basics” movement as a reaction to the “New Math” reform movement of the 1960s and 1970s (Huetinck & Munsin, 2000; Van de Walle, 2004). However, concerns over the state of math education in the United States continued into the 1980s.

In the mid-1980s, almost half of the students receiving doctoral degrees in mathematics were not Americans according to the National Research Council, 1985 (Huetinck & Munshin, 2000). There were concerns raised since there were very few native students who majored and graduated with degrees in mathematics. The decrease in the number of U.S. math majors graduating college led to a need to reform mathematics instruction (Huetinck & Munshin, 2000). The focus placed more emphasis on problem solving in the math curriculum and on how students could best learn mathematics rather than just focusing on the mathematics content (Huetinck & Munshin, 2000; Van de Walle, 2004).

The NCTM published *Curriculum and Evaluation Standards for School Mathematics* in 1989, which sparked a more persuasive, more widely accepted reform movement (Huetinck & Munshin, 2000; Van de Walle, 2004). According to Van de Walle (2004), the 1989 NCTM document had an enormous effect on the curriculum and approach to mathematics. The NCTM has published other documents that added to their 1989 publication. *Professional Standards for Teaching Mathematics* was published in 1991, and *Assessment Standards for School Mathematics* was published in 1995 (Huetinck & Munshin, 2000). The NCTM has also published *Principles and Standards for School Mathematics* in 2000, an updated document that encompassed the principles and standards from 1989 and includes the extension made in 1991

and 1995. According to Van de Walle (2004), the NCTM's standards in math education had a world-wide influence.

According to Huetinck and Munshin (2000), the need to have all high schools students prepared for the 21<sup>st</sup> century is what drives math reforms in education. All students should have the tools for independent learning and the tools to analyze information (2000). The NCTM lists five main goals for all students in mathematics. The goals are as follows, listed by Van de Walle (2004; p. 2):

- 1) Learn to value mathematics
- 2) Become confident in their [the student's] ability to do mathematics
- 3) Become mathematical problem solvers
- 4) Learn to communicate mathematics
- 5) Learn to reason mathematically

In addition to the goals for students, the NCTM has set forth six main principles that are important for "high-quality" mathematics education. These six principles center on high expectations and support for all students (equity); a coherent curriculum that is well articulated (curriculum); understanding what students know and need to learn and helping students learn it (teaching); students must learn mathematics with understanding, where new knowledge is built from prior knowledge and experience (learning); assessment support the learning of mathematics and provide useful information for both the teacher and the student (assessment); and technology is important in the teaching and learning of mathematics (technology). Technology should be adopted that best foster effective learning. Today, technology in mathematics is a tool that is



used. Technology in math has the potential to help students succeed in developmental mathematics, especially for mastery learning (Van de Walle, 2004).

In addition to the NCTM goals and principles, American Mathematical Association of Two-Year Colleges (AMATYC) (Blair, 2006) has set forth similar standards for college faculty to adopt. AMATYC's ultimate goals are to improve mathematics education and to encourage more students to study mathematics (Blair, 2006, p. 1). AMATYC advocates creating "creating an environment that optimizes the learning of mathematics for all students" (p. 27). To optimize the learning of mathematics for all students, AMATYC lists general characteristics to adopt for college faculty to reach this goal. Some of the characteristics listed include clearly defining high expectations and communicating those expectations to students, using a variety of instructional methods to address students' learning preferences, and providing a learning environment that supports the diverse needs of all learners. Furthermore, institutions should provide professional development regarding mathematics anxiety, multiple problem-solving strategies, and equipping classrooms that encourage active learning and the use of technology. Math anxiety and other factors influence learning in addition to the learning environment. AMATYC (Blair, 2006) states that confidence level, belief in the ability to learn, and attitude play major roles in how students learn mathematics. Math anxiety is described as a feeling or fear of failure when students learn or interact with math (p 23). Math anxiety can lead to the feeling of not be able to do math at all (p. 23). Since students' attitude, confidence level, and attitude can contribute to student learning, these factors should be addressed. AMATYC (Blair, 2006) suggest strategies such as doing homework on a regular schedule, asking questions in class, seeing the instructor or

a tutor for assistance, forming study groups, and using supplemental resources such as the Internet, books, or computer-assisted instruction.

However, the NCTM and AMATYC are not the only driving force in the math reform movements. National and international studies have contributed to the need of math reforms in the United States. In 1996, the Third International Mathematics and Science Study (TIMSS) was the largest study of mathematics and science education ever conducted (Van de Walle, 2004). The TIMSS study revealed that US students in 8<sup>th</sup> and 12<sup>th</sup> grades were below other countries such as Singapore, Korea, Japan, Hong Kong, Netherlands, and Austria (2004). This trend is still true from the most recent TIMSS study (NCES, 2013). A major finding of the TIMSS study showed that the US curriculum is unfocused, contains more topics than most countries, and involves more repetition than other countries. A major difference found was eighth grade math education in Japan is focused on helping students understand mathematical concepts while the focus for an eighth grader in the United States is on the procedures of solving math problems. According to the U.S. Department of Education in 1996 (as cited by Van de Walle, 2004, p. 7), “22% of the topics were developed while 78% of the topics were stated”. Based on this data, math reforms in the United States have focused on being globally competitive. Exploring and implementing alternative instructional methods and modalities to traditional lecture can play a role in improving math education according to the Van de Walle (2004), the NCTM (2000), and AMATYC (Blair, 2006).

### Technology and CAI in Mathematics

Several studies have found that CAI (computer assisted instruction) has enhanced learning (Hannafin, Dalton, & Hooper, 1987). According to Hannafin, Dalton, and Hooper (1987), there is increased pressure to “orient students to our fast-paced technologically oriented society” (p. 9). Technology in mathematics can refer to the use of graphing calculators, student response systems, mathematical software, simulations, multimedia, the Internet, and web-based instructional software (Blair, 2006). Computer and technology offers high potential to impact student learning, increase accessibility to information and can individualize instruction.

Advances in educational technology have made computers more powerful and less costly, which has resulted in more students having computer access (Spradlin & Ackerman, 2010). A majority of students in Spradlin and Ackerman’s study (2010) reported that computers have had a positive impact on their learning. In fact, the NCTM (National Council of Teachers of Mathematics) asserts that “technology is essential in teaching and learning mathematics; it influences the mathematics that is taught and enhance student learning” (2000). The use of technology to help students learn mathematics is an important focus for the NCTM due its inherent potential to improve the learning process (Heinich, Molenda, Russell & Smaldino, 1999; Van de Walle, 2004). In addition, CAI has been found to be more effective for elementary school, high school, and college than traditional teaching alone (House, 2011; Spradlin & Ackerman, 2010).

Traditional teaching in the literature refers to teaching methods, such as lecture, that is not supported by technology. According to Hannafin, Dalton, & Hooper (1987), publishers and companies have demonstrated CAI to be effective and engaging for learners. Chen (2009)

attributes success of CAI to its ability to help learners develop self-regulating learning behaviors. Chen (2009) points out that students in a traditional learning environment are passive learners since a teacher is in charge of delivering course content. Chen (2009) reports that “passive learners have low spontaneous learning abilities and do not know how to plan for autonomous learning (Chen, 2009, p. 8817). However, CAI has the potential to provide for more sophisticated, higher skills lessons such as writing, simulations, games, and application of computer as problem solvers (Hannafin, Dalton, and Hooper, 1987; Spradlin & Ackerman, 2010). A few case studies are discussed to highlight CAI and its effect on student learning and attitude.

Pilli and Aksu (2013) have shown CAI to be more effective on student learning and attitude compared to a lecture approach with the use of a textbook. Pilli and Aksu used Frizbi Mathematics Four, a mathematics drill-and-practice software, to teach fourth graders multiplication and division of natural numbers and operations with fractions (Pilli & Aksu, 2013). The experimental group of 29 students used this software while the control group of 26 students received only traditional lecture. Results of this study were obtained through a pre-test before the treatment, a post-test after the treatment, and another post-test four months later to assess retention. The mathematics attitudinal scale and computer assisted learning scale were both administered before and after the intervention (Pilli & Aksu, 2013). A series of ANOVAs revealed statistical significance at the  $p = 0.01$  level on achievement and attitude towards math and computer-assisted instruction (Pilli & Aksu, 2013). A significant difference for retention

was shown in favor of the experimental group for multiplying and dividing natural numbers, but not for fractions.

House (2011) conducted a meta-analysis of 1,978 tenth grade students to determine the effects of computer activities on math achievement. House (2011) used data from the Education Longitudinal Study of 2002. Students were given a questionnaire about how the computers were used in their class. Correlational analyses were conducted to compare each computer activity on the questionnaire to students' achievement scores on ELS: 2002 mathematics assessment, which consisted of algebra, geometry, data and probability, and advanced mathematical topics (House, 2011). Results indicate that a positive association existed between when a teacher uses technology to expand or introduce new ideas and students' achievement scores. In addition, students using technology for graphing or applications of what they learned to new problems tend to have higher achievement scores. These results indicate that the use of technology is effective for introducing new mathematical concepts (House, 2011).

However, using technology or CAI has not always been shown to be more effective than traditional lecture alone. For example, in Spradlin and Ackerman's study (2010), students in the traditional lecture section of Intermediate Algebra experienced similar learning gains to those students in an Intermediate Algebra with CAI. Therefore, a traditional instructional approach can be equivalent to an instructional approach with CAI. However, more research on the effectiveness of CAI is still needed (Spradlin & Ackerman, 2010). Furthermore, there is little research about how artificial intelligence impact students' attitude when compared to a non-adaptive approach with technology.

Overall, several case studies show that technology has the potential of improving student learning, for providing timely, effective feedback, and increasing student attitudes towards mathematics positively. However, educators must examine technology and media to determine its role and impact on student learning outcomes in order for technology to be effective (Heinich, Molenda, Russell, & Smaldino, 1999). According to the NCTM (2000) and AMATYC (2006), technology can be used to learn mathematics, do mathematics, and to communicate mathematical concepts. Technology enhances the learning of mathematics when used appropriately. Technology should be used to enhance conceptual understanding in addition to mastering math skills (Blair, 2006). This use of technology suggests that educators should choose technology appropriately and carefully to make certain that technology is truly enhance student learning (Blair, 2006). To truly enhance learning, technology should provide feedback, instructions on concepts and procedures, examples, tutorials, and a variety of problems to reinforce concepts and math skills (Blair, 2006).

Computer preparation software has been associated with increased test scores in standardized testing and linked to increased motivation (Relan, 1997). Relan (1997) attributes the increase in motivation to immediate feedback and individualized instruction that technology provides. Feedback is another attribute that increase students' motivation (Relan, 1997). Formative assessment of learning is meant to help students to improve (Bull, J., Stephens, D., 1999). The problem is that it is difficult for instructors to find time to provide meaningful formative feedback when needed (1999). Bull and Stephens (1999) have found that computer-assisted assessment (CAA) was effective in providing formative feedback to writing students.

Their study shows that a change to assessment strategies and procedures should be undertaken with attention on their effect on student learning.

Both CAI math software systems under study in this research effort provide students with immediate feedback and tutorial buttons for assistance. Due to the ability of math software to improve retention and motivation, AMATYC (Blair, 2006) recommends that college faculty integrate technology into their teaching of math, use technology tools that are aligned with instruction, and align technology platforms with those familiar to students. This researcher supports the notion that technology should not be considered in isolation, but should be aligned with an appropriate instructional approach to optimize student learning and experiences.

### Intelligent Tutoring

However, Baylari and Montazer (2009) reports that course content and domain structure are presented in a “static way, without taking into account the learners’ goals, their experiences, their existing knowledge and their abilities” (p. 8013). A static approach to web-based education leads to less feedback and support from the student’s instructor. The addition of intelligence and interactivity to educational technology is an important direction for research. Baylari and Montazer (2009) further argues that personalization is essential since learners have diverse backgrounds in terms of prior knowledge, age, experiences, culture, motivation, and goals. An individualized approach can cater a program to the learner’s strengths and weaknesses. With the growth of computing capabilities, the field of intelligent tutoring has emerged. Intelligent tutoring is focused on tailoring instruction and feedback to learners using intelligent agent

technology, which “facilitate the interaction between the students and the systems, and also generate the artificial intelligence model of learning, pattern recognition, and simulation such as the student model, task model, pedagogical model, and repository technology” (Baylari & Montazer, 2009, p. 8014). It is important to provide a background and framework of the field of intelligent tutoring.

Drawing from previous studies and research, Ma, Adesope, Nesbit, and Liu (2014) defines an intelligent tutoring system (abbreviated as ITS in the literature) as a computer system that performs tutoring, constructs a model of the student in terms of knowledge structure or psychological state, and uses the student modeling to adapt an appropriate tutoring strategy. Tutoring strategies can include asking questions, assigning a task, providing feedback or hints, answering questions, or providing appropriate prompts to engage the learner in a “cognitive, motivational or metacognitive change” (Ma, Adesope, Nesbit, & Liu, 2014, p. 902). There are four generally accepted components of an ITS. The four components must include an interface that communicates with the learner, a domain model that represents the knowledge that the student must learn, a student model that represent the student’s current knowledge or emotional state, and a tutor model that includes various tutoring strategies catered to the student model (Ma, Adesope, Nesbit, & Liu, 2014; Phobun, & Vicheanpanya, 2010).

Student modeling approaches can include model-tracing, probabilistic modeling, reconstructive bug modeling, and constraint-based modeling (Ma, Adesope, Nesbit, & Liu, 2014). Ma, Adesope, Nesbit, and Liu (2014) classified ITS as either expectation and misconception tailoring (EMT), model tracing, constraint-based modeling (CBM), or Bayesian



network modeling. EMT models student knowledge by matching students' responses to learning goals and anticipated misconception in the domain. EMT uses the results of the matching to provide scripted tutoring. The program AutoTutor is an example of an ITS that uses EMT. Model Tracing is based on the use of production rules which mimics how humans solve the problem in the specific discipline. Students select the appropriate operations in the discipline and a model-tracing process provides a series of production rules. Immediate feedback is also provided when errors are detected. After receiving feedback, students can choose a different operation. After the production rule is used, knowledge tracing is used to estimate the probability that the rule has been correctly learned. Model tracing is based on the ACT-R theory of human learning and cognition (Ma, Adesope, Nesbit, and Liu, 2014). CBM compares the student's responses to a set of constraints in the discipline. If a student does not violate a constraint, it is assumed that the student is on the right track. If a student violates a constraint, then feedback is given that reminds the student of the condition to follow. For example, suppose a student gives an answer to the square root of a negative number. A constraint rule could be in Algebra that the square root of a negative number does not exist in the real number system, therefore it is undefined. If a student provides an answer other than undefined in context of the real number system, feedback will be given to remind students that a square root of a negative number does not exist in the real number system. Bayesian networking the calculation of the probability that the student has learned or has the knowledge based on student's responses. Ma, Adesope, Nesbit, and Liu (2014) points out that the Bayesian networking model is flexible and

can be used to implement other types of student models. In addition, Bayesian networking modeling can lead to the creation of more complex models.

Intelligent tutoring has been shown to be generally successful when compared to other modes of instruction or non-intelligent CAI instructional approaches (Ma, Adesope, Nesbit, & Liu, 2014; Steenbergen-Hu & Cooper, 2014). Steenbergen-Hu and Cooper (2014) conducted a meta-analysis from thirty-five reports which contained 39 studies that assessed the effectiveness of intelligent tutoring systems (ITS) in higher education. They found that ITS had a moderate positive effect on college students' learning. However, ITS were found to be less effective than human tutoring but not at a statistically significant level. Moreover, ITS were found to be superior to all other instructional approaches including traditional lecture, computer-assisted instruction, and laboratory learning.

Both of Steenbergen-Hu and Cooper's meta-analyses both found a positive effect of ITS on student learning in mathematics in the K – 12 system (2013) and for college students (2014). Steenbergen-Hu and Cooper (2014) suggest that more research is needed to determine the impact of ITS. Some studies investigated ITS under a laboratory setting rather than a real learning environment. In addition, some studies used less popular ITS for short period of time, and some research studies used less rigorous designs compared to other studies. Steenbergen-Hu and Cooper (2014) concluded that ITS might be more appropriate for college students rather than K – 12 students due to the differences in age, experience, prior knowledge, motivation, and self-regulating skills. The results of these meta-analyses have limitations. For example, comparisons of different studies have other possible contributing factors that affect students learning where

ITS cannot be attributed solely to increased student learning. Factors such as different teachers or school environment might be contributing factors to the results found. Therefore, more controlled studies are needed to determine the actual impact of ITS on the K – 12 system and college. This study rectifies the issue of having different factors such as the instructor or different schools by providing a more controlled study for the comparison of two instructional approaches using ITS. Overall, ITS have shown to be effective more so than other instructional approaches that do not use ITS.

### Background of Intelligent Tutoring and Learning

The field of artificial intelligence became more popular and recognized when the 1997 world's renowned chess player Garry Kasparov lost against Deep Blue, an IBM supercomputer (Hamilton, 2000). As a result, the media had significant coverage and held this contest as significant for machine intelligence (Hamilton, 2000). However, artificial intelligence has been around for many decades and has been studied for its potential in various fields (Kline, 2011). Artificial intelligence was founded and officially recognized during the Dartmouth Summer Research Project Conference in 1956 (Kline, 2011; Hyman, 2012). In general, artificial intelligence can simply be described as computer that can think, understand, and exhibit expert behavior (Denning, 2003). Shaw (2008) simply describes AI as “an attempt to use computers to mimic the functioning of human intelligence, and may include knowledge acquisition, reasoning, and adaptation to experience” (p. 319). Intelligent tutoring is a sub-field of artificial intelligence with a goal of providing individualized instruction (Phobun & Vicheanpanya, 2010). An

intelligent tutoring system is defined as a computer system that performs tutoring functions where there is “real-time cognitive diagnosis (student modeling)” and the system provides “adaptive remediation” (Ma & Adesope, 2014, p. 902).

The field of intelligent tutoring dates back to 1924 with the introduction of the Pressey’s intelligence-testing machine (Petrina, 2004). The Pressey’s intelligence-testing machine provided users with a multiple choice exam from easy to hard where the counter on the machine only kept track of correct inputs. If the input was incorrect, the machine would go to the next question, but the counter would not register anything for that particular question. Pressey continued to develop his machine and eventually “changed its name to the Automatic Teacher” (Petrina, 2004, p. 311). In newer development of the Automatic Teacher, the machine would only advance to the next question after two correct responses, mimicking a drill-and-practice model of learning. Pressey claimed that the Automatic Teacher provided individualized instruction and immediate feedback more efficiently than a teacher could (Petrina, 2004). Pressey’s goal with the Automatic Teacher was to eliminate routine work for the teacher so that the teacher can individualize instruction for students (Petrina, 2004).

Pressey’s Automatic Teacher was based on the learning theories of Edward Thorndike (Petrina, 2004). Thorndike’s learning theory was based on three fundamental laws: 1) law of effect, 2) law of exercise, and 3) laws of acquired behavior or learning. (Petrina, 2004, p. 316). The law of effect refers to “connections between stimuli and response can be strengthened by rewards and weakened through punishment” (Petrina, 2004, p. 316). The law of exercise is that repetition strengthens connections while a lack of repetition weakens them (Petrina, 2004). The

goal of education for Thorndike was to individualize instruction through strengthening, eliminating, and modifying connections (Petrina, 2004).

Skinner, a prominent behaviorist, also had a similar goal to individualize instruction and provide prompt feedback in education (Casas, 2002). Skinner's operant conditioning theory was applied to the field of education based on Skinner's observation of the current education system in the 1950s. Skinner's operant theory was based on the premise that a specific behavior was either strengthened or weakened through immediate consequences that the behavior had on the environment, moving beyond the Stimuli-Response Model (Casas, 2002). In addition, immediate reinforcements must occur after the response in order to strengthen or weaken behavior. Skinner's programmed instruction was based on his operant learning theory (Casas, 2002).

Skinner's instructional approach was based on breaking the subject matter into a sequence of smaller steps where students could incrementally learn and master concepts before moving to more complex concepts and steps (Casas, 2002; Vargas, 2014). The student would respond to questions, receive immediate feedback, and the student would progress at his/her own pace. The student in this model would receive a low error rate. The emphasis of this instructional approach was on changing the learner rather than changing the subject matter. Furthermore, students' success of achieving a desired goal or behavior was based on the sequencing of instruction (Casas, 2002). Skinner believed that programmed instruction would lead to more efficiency and enable all students to learn at their individual pace.

The Skinner's Teaching Machine was created based on his operant theory of learning and programmed instructional approach. Skinner's teaching machine would present materials presented on a disk or tape, track the student's response, and reinforce correct behavior immediately by advancing to the next problem or by displaying the correct answer. Skinner viewed his Teaching Machine as a way to effectively supplement teachers. The Disk Machine was another teaching machine that implemented Skinner's programmed instructional approach.

Skinner referred to providing students individualized instruction as "shaping" (Vargas, 2014). Shaping refers to reinforcing actions that closely matched the desired behavior. Skinner's teaching machines could aid in the shaping process without the presence of a teacher (Vargas, 2014). Shaping took place through gradually teaching more complex steps incrementally. Skinner's research and programmed instruction led to improved instructional design (Heinich, Molenda, Russell, Smaldino, 1999). However, Skinner's teaching machine and the Pressey machine were mechanical and do not fit the current realm of intelligent tutoring as it is known presently. Intelligent tutoring is associated with computer-assisted instruction (Graesser, 2013).

The field of intelligent tutoring and artificial intelligence became popular during the 1950s (Kline, 2011). PLATO is an example of a computer user interface that led the computer revolution in the field of intelligent tutoring. PLATO, an acronym for Programmed Logic for Automated Teaching Operation, was invented by Don Bitzer at the University of Illinois (Lyman, 1968; Kroeker, 2010). PLATO has been used for education and training by schools, corporations, and the US government (Kroeker, 2010). PLATO emphasized an inquiry approach

to student learning (Lyman, 1968). In addition to allowing students to solve a problem using various strategies, the help feature in PLATO would offer a series of help pages dependent on their previous response (Lyman, 1968).

PLATO serves as an early application of Constructivism, a learning theory rooted in knowledge being constructed from the learner's experience and prior knowledge (Huetinck & Munshin, 2000). The idea of constructivism goes back to Piaget's belief that children are naturally curious about the world and organize information by schemas. Learners either assimilate new information into existing schemas or accommodate the new knowledge by modifying existing schemas. Learners will remain at what Piaget terms disequilibrium until the new knowledge has been assimilated or accommodated. Piaget believed that learners should actively participate in the learning process (Huetinck & Munshin, 2000).

Some researchers regard SCHOLAR as the first application of ITS (Ma, Adesope, Nesbit, & Liu, 2014). SCHOLAR was created by Jaime Carbonell in the 1970s. Carbonell contrast SCHOLAR from other CAI by emphasizing how a domain representation can model student knowledge. SCHOLAR's architecture represented domain knowledge separately from the natural language interface. The separate domain representation allowed SCHOLAR to generate and answer a large set of diverse questions for learners.

Cognitive Tutors serves as another example of an intelligent tutoring system that emphasize problem solving with specific feedback based to common mistakes and the provision of hints by user request (Koedinger & Alevan, 2007). The Cognitive Tutor is based on the ACT-R Theory of cognition and learning (Keodinger & Alevan, 2007). The Cognitive Tutors for high

school mathematics and Algebra have been successful in educational settings (Keodinger & Alevan, 2007; Chaudhri, Gunning, Lane, & Roschelle, 2013). The Cognitive Tutor for mathematics is used by more than 600,000 students in middle and high school (Chaudhri, Gunning, Lane, & Roschelle, 2013). Studies have demonstrated that Cognitive Tutor for Algebra resulted in better student learning compared to traditional Algebra courses. Each cognitive tutor provides students with a problem-solving environment with a variety of representational tools and real problem scenarios to solve. For example, the Cognitive Tutor for Algebra would provide students with a problem that requires algebraic thinking and would provide graphing paper or a symbolic equation solver as tools that can be used to help the student solve the problem. Students enter in specific steps to solve the problem. Feedback is received on each step with specific feedback relating to specific input errors. Hint buttons are provided, which explains the problem-solving strategies to apply. The hints are based on the student's input. For example, if a student uses  $t$  as a variable, the hint explanation will refer to the variable,  $t$ . Cognitive Tutors implement a mastery learning approach and keep tracks of the student's progress (Keodinger & Alevan, 2007).

Today, intelligent tutoring systems are enhancing student learning in the K – 12 system as well as the college system. However, there are debates surrounding the efficacy and capability to scale intelligent tutoring to meet broad needs in the educational system (Chaudhri, Gunning, Lane, & Roschelle, 2013). For example, Steenbergen-Hu and Cooper (2014) argues that each hour of instruction using ITS cost 200 hours of work to build. However, it is important to note that ITS are built to serve thousands of students, still making them cheaper than human



tutors for each individual student. Since the cost of building ITS is not cheap, it is worthwhile to investigate functions that make them effective and to compare specific ITS to other educational CAI. In addition, Craig, Driscoll, and Gholson (2004) found that an intelligent tutoring system, the AutoTutor, resulted in the most learning gains in an interactive condition compared to a passive condition, but learners in the interactive group was still answering about 50% of the questions on a post-test correctly. Current versions of the AutoTutor at the time this article was published (2004) implemented “unsophisticated tutoring strategies of untrained peers and paraprofessionals (Craig, Driscoll, & Gholson, 2004, p. 177). Improvements needed include “implementing Socratic tutoring strategies, modeling-scaffolding-fading, and other intellectual pedagogical techniques” (p. 177). However, Chaudhri, Gunning, Lane, & Roschelle, (2013) report that a system that models knowledge and uses that knowledge to assess, track, and guide learning is more effective than systems missing those features (2013). To improve student engagement and learning, multi-faceted approaches should be considered in addition to the educational tools be implemented. The use of intelligent tutoring has addressed the challenges of student learning and engagement through mimicking one-on-one tutoring (Chaudhri, Gunning, Lane, & Roschelle, 2013; Phobun & Vicheanpanya, 2010).

Intelligent tutoring is based on the premise that one-on-one tutoring yields the most effective results in terms of student learning. Bloom (1984) compared three varying instructional approaches. In Bloom’s research of varying instructional approaches in different grade levels, Bloom (1984) found that students under the tutoring condition were about two standard deviations above the average student in the conventional approach. Students under the mastery

learning approach were about one standard deviation above the average student in the conventional approach. In addition, Bloom (1984) reports that 90 percent of tutored students and 70 percent of mastery learning students attained achievement scores that were reached by only the highest 20 percent of students in the conventional approach. Furthermore, time on task was 90 percent or higher for the tutored approach and 75 percent for mastery learning approach compared to 65 percent for the conventional approach. Moreover, the relationship between entering achievement scores and summative achievements scored decreased from 0.60 for the conventional approach to 0.35 for mastery learning approach and 0.25 for the tutoring approach. In addition, Cohen, Kulik, and Kulik (1982) conducted a meta-analysis on numerous studies and found that the average learning gains with human tutors was 0.4 standard deviation units above a conventional approach with no tutors.

Bloom's research supports the conclusion that one-to-one tutoring has been shown to be the most effective in terms learning gains. Bloom (1984) concludes that the tutoring process demonstrates that students can reach a high level of learning. In addition, Bloom (1984) suggests further research in finding ways that can accomplish the same level of learning as tutoring through more practical means and less costly ways to implement on a larger scale. Bloom has coined this research challenge as the "2-sigma" problem (Bloom, 1984, p. 6). Bloom posits that the effectiveness of CAI should be determined in terms of student performance, completion rates, retention of learned material, and time required. Also, Bloom (1984) suggest measuring the effectiveness of CAI on student affect such as self-concept, interest in the subject, and desire to learn more with computer assisted technology.

Goodwin and Miller (2014) describe the application of Bloom's one-on-one tutoring to a larger scale such as a whole class as mastery learning. Mastery learning present new information and model new skills, provide students with practice opportunities, use formative feedback to check for students' understanding, use individualized interventions to reteach concepts, and check for understanding before moving forward (2014). Bloom's educational principles for one-on-one tutoring and for providing formative feedback are the philosophical basis for mastery learning (Hagerty & Smith, 2005). Mastery learning has been shown to be successful, but is hard to implement due to the required time commitment to develop and monitor a student's individualized plan (Hagerty & Smith, 2005). Goodwin and Miller (2014) cite that mastery learning can provide additional support for remedial students and has positive effects for low-achieving students. Despite these results, there are challenges associated with implementing mastery learning on a larger scale. For example, mastery learning may require educators to adopt or modify new instructional approaches to optimize student learning (Goodwin & Miller, 2014). Along with examining instructional and assessment approaches in a mastery learning model, there are technical challenges such as the development of formative assessments to align with remedial interventions. Despite these challenges, adaptive learning is becoming increasingly popular and widespread throughout the educational system. Moreover, most web-based CAI is based on the mastery learning model (Hagerty & Smith, 2005).

According to the DeVry Education Group, targeting instruction to the abilities and individual students' needs can reduce course drop-out rates, improve student outcome, accelerate learning, and assist instructors to focus on content where students are struggling the most

(Oxman & Wong, 2014). Adaptive learning systems are being used for on-line courses, supplements to on-line courses, for hybrid courses, and as supplements to traditional face-to-face courses. In addition, adaptive learning systems are expanding into e-books and are likely to increase at all educational levels in the United States (Oxman & Wong, 2014). DeVry Education Group believes that adaptive learning will become a standard and more expected in the future (Oxman & Wong, 2014).

### Learning and Scaffolding

Reform movements in mathematics have placed value on students' attitudes and the factors that affect students' attitude such as confidence, anxiety, motivation, attitude, and locus of control. According to Blair (2006) and Harriman (2006), adult students tend to prefer self-directed learning than children. The level of self-directed learning, interaction, and feedback can affect student learning and their attitudes (2006). Elliott, Eunhee, and Friedline (2013) argues that experiential learning is empowering since it encourages self-directed learning that leads to higher motivation, better retention, and the development of problem-solving skills. However, students with poor self-regulating behavior are not as successful academically as those learners with effective self-regulating behavior. Chen (2009) posits developing effective strategies that guide learners in actively processing learning behavior is an important endeavor for educators and instructional designers. Learners' self-regulating ability is an important factor that affects their learning since educators are usually not around to monitor students' attitude and behavior (Chen, 2009). However, self-directed learning can help students become more independent

learners and more confident. Adult learning, according to Harriman (2006), benefit with high levels of enthusiasm, when learning is self-directed, relevant to their prior experiences, and is interactive with immediate, meaningful feedback. Rowe (2010) claims that learners engaged in self-regulating activities tend to view those activities as useful and valuable.

Self-directed learning can be achieved through technology when students learn in their zone of proximal development (ZPD) (Snodin, 2013). The zone of proximal development is defined by Vygotsky (1978) to be the gap between a learner's independent level of performance and the learner's assisted level of performance; tasks and objectives that can be learned with assistance and support (p. 86). Scaffolding is the support that learners receive to complete tasks and goals within their ZPD (Gredler, 2012; Wass, Harland, & Mercer, 2011). Scaffolding strategies (Wood, Bruner, & Ross, 1976) can include providing examples, hints, prompts, and the use of learning strategies such as self-talk or index cards that can assist a learner in mastering a skill independently. These scaffolding strategies can help the learner master concepts and different learning objectives (Vygotsky, 1978; Wood, Bruner, & Ross, 1976). However, scaffolding must be tailored to the learner's individual needs to be optimally effective (McLeod, 2010). For example, Wood and Middleton (1975) observed how mothers interacted with their children to build 3-D models shown in a picture. The children in this study were 4 years old and the task given to them was too difficult to be completed by themselves. The results of this study showed that mothers were the most effective when they varied their strategy according to how the child was doing with the task. When the child was doing well, the mother offered less specific instruction and guidance while more specific instruction was provided when the child

was struggling with the task (Wood & Middleton, 1975). The appropriate type of scaffolding should be provided to college math students with remedial needs to optimize their chances of success (McLeod, 2010).

Delivering information and learning activities that are within a student's ZPD optimizes learning. In addition, scaffolding techniques within a student's ZPD can affect attitudes including self-confidence, motivation, and anxiety levels (Magliaro, Lockee, & Burton, 2005). For example, Dabbagh & Blijd (2010) found that degree of scaffolding influenced perception of learning. This research effort examined students' perception of their learning experience in a real world immersive environment, where learners were immersed in a real work situation. In the beginning of the project, there were confusion and anxiety due to initial disorientation and frustration. However, the anxiety and frustration lessened as students realized the benefit of being immersed in a real world project. Despite initial confusion in the beginning, it was found that students will persevere in a learning-by-doing environment when the scaffolding level matches students' level of learning (Dabbagh & Blijd, 2010).

Similarly, a study by Snodin (2013) found that a blended learning environment with a course management system (CMS) can help learners achieve greater autonomy (self-directed learning) when activities are carefully scaffold. Snodin collected data using a modified questionnaire, designed by Cotterall, student learning journal, interviews with students, and classroom observations. The results show that students viewed feedback and the "way they perceived themselves as learners" differently after the blended learning environment experience (p. 212). Snodin (2013) reports that students learned the importance of feedback and have

become more independent, more confident, and more experienced as a result of the feedback provided. The language learning program used provided the correct amount of scaffolding activities, which led to more self-regulated learning. After the blended learning experience, students began setting their own learning goals and spent extra time working on those goals independently. The blended learning environment helped students develop their own sense of autonomy within the confines of their ZPD. However, over-scaffolding might be possible and can lead to decrease independence (Chin, Dohmen, Cheng, Oppezzo, Chase, & Schwartz, 2010).

Chin, Dohmen, Cheng, Oppezzo, Chase, and Schwartz, (2010) state that technology may over-scaffold student learning, where students do not perform basic skills on their own. The controversy of using calculators in mathematics or spell checkers in word processing programs degrading writing skills are used as two examples of over-scaffolding. Chin, Dohmen, Cheng, Oppezzo, Chase, and Schwartz (2010) examined the type of learning produced by teachable agents and gather data about initial evidence on whether the teachable agents helped with learning new content after this instructional technology was removed. Their control group and the treatment group were given an opportunity to learn a new topic with no instructional technology. The study revealed that student learning improved significantly for casual relationships (Why questions) for those that used the teachable agents. This investigation took place with 134 fifth graders. Students were prepared for future learning by using TA technology (2010). The interactivity allowed students to reflect on their agent's thinking and accuracy, which allowed students to apply metacognition to their own understanding (Chin, Dohmen, Cheng, Oppezzo, Chase, and Schwartz, 2010, p.665). The researchers argue that using

interactive teachable agents will help prevent over-scaffolding and could guide the future of instructional technology. This study also suggests that assessments that include opportunities to learn as a part of that assessment to determine which instructional technology are valuable for learning. This study supports the notion that an adaptive instructional approach with CAI could potentially match a student's ZPD, help students develop autonomy, and improve their learning.

### Knowledge Space Theory and ALEKS

ALEKS (Assessment and Learning in Knowledge Spaces) was developed from research at New York University and the University of California with support from the National Science Foundation (ALEKS, n.d.). ALEKS is a math software system based on Knowledge Space Theory that use self-adaptive technology to enhance student learning. Knowledge Space Theory is a mathematical language that describes the ways in which particular elements of knowledge (concepts in Algebra, Mathematics, Accounting, and Statistics, for example) are organized to form distinct knowledge states. For example, arithmetic is regarded as a domain of roughly one hundred basic concepts, giving rise to a structure of approximately 40,000 knowledge states (ALEKS, n.d.; Stillson & Alsup, 2003). Computer algorithms have been developed to construct discipline-specific knowledge structures (known as "Knowledge Spaces") and apply them to assess knowledge states of individuals. Knowledge Space Theory was founded by Jean-Claude Falmagne (Falmagne, Doignon, Koppen, Villano, & Johannessen, 1990). The concept of KST is based on the fact that a knowledge state can be represented by a subset of problems that the participant can solve (1990). The researchers (1990) give the example that is a student can solve



a word problem that involved the long multiplication of decimals and fractions, then it can be deduced that students can multiply fractions and decimals and it is not necessary to assess the student on these skills separately. However, if a student was given a problem about multiplying one-digit numbers and does not perform correctly on such a problem, then it can be deduced that students probably cannot multiply two-digit numbers or three digit numbers (1990).

In ALEKS, the student is viewed as a system, and the KST algorithms in a computer program work to efficiently discover the current knowledge structure of the system in a specific discipline (1990). According to the ALEKS website, ALEKS (Assessment and Learning in Knowledge Spaces) “is a web-based, artificially intelligent assessment and learning system. Canfield (2001) classifies ALEKS as an intelligent tutor. ALEKS uses adaptive questioning to determine the student’s current knowledge state for a particular math course. ALEKS then assigns objectives that the student is most ready to learn. Once the student has mastered the assigned objectives, other objectives will become available to work on. ALEKS periodically reassesses the student to ensure that topics learned are also retained” as a student works through a course, (ALEKS, n.d.; Canfield, 2001). All questions types in ALEKS are short answer style.

According to ALEKS (n.d.) and Canfield (2001), “ALEKS delivers individualized student instructional paths and a continuous cycle of assessment and learning to increase student retention and course pass rates”. ALEKS claims that its artificial intelligence-based software has “delivered academic success to more than a million students” (Canfield, 2001, p. 3). ALEKS credits its artificial intelligence feature to targeting students’ strengths, weaknesses, and “pinpointing what a student knows and what he/she is ready to learn” (Canfield, 2001, p. 4).

This is very similar to how Vygotsky described scaffolding (Gredler, 2012). Other math software systems do contain adaptive properties based on other theories or algorithms. Recently, MyMathLab by Pearson offers an adaptive feature based on the Knewton Theory, which can support an adaptive instructional approach (Webley, 2013).

Both CAI in this research study offers assistance to students through generic hints, tutorial videos, and similar examples worked out step-by-step. Feedback might be generic or can be specific to the student's input. In the traditional approach, opportunities are given to students to self-correct or to do a similar exercise.

ALEKS offers a learning pie where students can visually see their current knowledge state and work on mastering assigned learning objectives. ALEKS homework assignments adjust based on a student's current knowledge state. A student's current knowledge state is adjusted through mastery of course objectives where a student must successfully complete homework problems three times in a row without any assistance. In addition, ALEKS will randomly (roughly every five hours) assign a random assessment to determine a student's current knowledge state. If student misses previously mastered problems, the corresponding objectives are re-added to a students' learning pie in ALEKS (Canfield, 2001). In ALEKS, the instructor selects the course objectives and problem types only. ALEKS has been shown to be successful in several studies as a supplement to class lecture, but none of the studies link any correlation of success to an adaptive instructional approach specifically.

### Case Studies of KST

In several studies, ALEKS used in conjunction with traditional instruction been shown to be at least as effective as or more effective than traditional lecture alone. For example, a university in the Mid-west used ALEKS as part of a program to help high school seniors place into college-level math courses. The focus of this study was on removing remediation requirements for incoming college freshmen. Three groups were compared in this study, which included a control group of 35 students who took no mathematics course during their senior year. The other two groups consisted of 55 students who took a non-ALEKS math course during their senior year while the other group consisted of 32 students who took an Intermediate Algebra course by using ALEKS. Remediation requirements were removed in one of three ways: ACT scores, COMPASS placement test or ALEKS assessment score in Intermediate Algebra. Fine, Duggan, and Bradley (2009) found that both intervention programs were successful at removing remediation requirements compared to not taking a math class at all during the senior year. The results of this study demonstrated that 60.0 percent of seniors taking a non-ALEKS math course and 46.9 percent of students in the ALEKS group did not require remedial mathematics compared to 14.3 percent in the control group. The results of this study indicate that taking a math course through ALEKS was equivalent to seniors taking Pre-Calculus and Calculus during their senior year in removing remediation requirements for graduating senior entering college as a freshman (Fine, Duggan, Bradley, 2009). The researchers note that ALEKS is an effective alternative when college bound math courses are not viable options, such as in rural areas.

Additionally, ALEKS has been shown to be successful for College Algebra compared to traditional pencil-and-paper sections. For example, a study in 2003 in a small university implemented ALEKS into four sections of College Algebra. Four other sections of College Algebra followed a traditional textbook-based approach using the same instructors who were also teaching the experimental sections. All instructors taught a traditional and an experimental section of College Algebra except for one. The sections taught by each instructor followed a similar day and time schedule. For example, an instructor taught a traditional section MWF 8:00 – 9:00 am section and a MWF 9:00 – 10:00 am section. Hargerty and Smith (2005) performed statistical analyses for class performance, influencing factors, and skill retention. Hargerty and Smith (2005) found that class performance was greater for the sections using ALEKS for three of the four instructors. The researchers studied the impact of influencing factors such as students' opinion of computers, students' opinion of their mathematics ability, the use or non-use of ALEKS, and whether the student was a traditional or non-traditional student (Hargerty & Smith, 2005). The results indicated “the use of ALEKS showed a statistically significant effect on the student's growth over the semester (Hargerty & Smith, 2005, p. 189). To analyze the researchers' third question on skill retention, a comparison was made for the CAAP exam, which is a state required exam for juniors. Hargerty and Smith (2005) reports that this exam is comprised of mainly college algebra questions. This question was analyzed for freshmen enrolled in College Algebra. There was a significant difference found in favor for those who were enrolled in the section that used ALEKS. It is important to note that the sample size for measuring skills retention dropped since the students must have been freshmen at the time of taking college

algebra and entering their junior year when completing the CAAP exam. The researchers concluded that students in the ALEKS section of College Algebra performed significantly better than students in a traditional textbook-based section. Hagerty and Smith (2005) recommended future research investigating if other software products are as effective as ALEKS. This research posit that comparing instructional approaches with different software is a more effective approach to examine since different math software naturally leads to a different learning experience. This current research effort is focused on comparing an adaptive instructional approach with ALEKS to a traditional approach using MyMathLab.

Furthermore, using ALEKS in lieu of traditional lecture has been shown to decrease anxiety and improve attitude. For example, a study of students in an Intermediate Algebra class in three colleges and two universities compared the use of ALEKS and traditional instruction (Taylor, 2008). Two independent groups were compared from a convenience sample of 93 students, 54 were in an experimental group and 39 were in a control group. Pre-tests and post-tests were administered to compare students' achievement using the National Achievement Test, First Year Algebra Test (NATFYAT), to compare students' anxiety levels using the Mathematics Anxiety Rating Scale (MARS), and compare students' general attitude using the Fennema and Sherman scales (F – S scales). Correlation coefficients comparison indicate that the experimental group had a greater correlation,  $r(52) = 0.41$ ,  $p = 0.002$  compared to the control group,  $r(37) = 0.203$ ,  $p = 0.213$  (Taylor, 2008). However, further analysis indicates the control group outperformed the experimental group, indicating that lecture is more effective for some students. Correlation coefficients comparisons on the pre-test and post-test on the F – S scale indicate a

stronger relationship for the experimental group,  $r(52) = 0.693$ ,  $p = 0.001$  compared to the control group,  $r(37) = 0.466$ ,  $p = 0.003$ . There was a statistical difference found for the control group between the pre-test and post-test on the F – S scales, but no statistical difference was found in favor for the experimental group. Even though not statistically different, attitudes towards mathematics did improve. Taylor (2008) points out that even though the results for the control group were statistically different; students' attitudes towards mathematics were not as good towards the end of the semester. Math anxiety did decrease at a greater rate for the experimental group. Taylor (2008) argues that a computer-based approach to Intermediate Algebra led students to more confidence and less math anxiety. In a college Statistics class that used ALEKS, the students felt that their analytical skills improved (Xu, Meyer, & Morgan, 2008). The use of ALEKS seems to indicate improvement in learning and increased perception of learning as measured by confidence level, anxiety level, and motivational level. In a comparison of using ALEKS in a College Algebra class, there was a significant difference in student performance (Hagerty and Smith, 2005). A redesign effort of college algebra at Black Hills State University used ALEKS as part of the redesign. The redesign was based on the mastery learning model and to develop a deep understanding of the concepts and processes of algebraic thinking (Hargerty, Smith, & Goodwin, 2010). This redesign effort resulted in a 21% increase in passing rate and a 300% enrollment increase in trigonometry, the next sequential course after college algebra. The results of this study showed that a multi-faceted instructional change incorporating ALEKS led to successful results compared to the conventional instructional approach, which was mainly lecture. Hagerty and Smith (2005) suggest that

ALEKS success is due to its nonlinear approach to math learning. ALEKS has been shown to be effective in terms of student performance and in terms of students' attitudes.

MyMathLab by Pearson and similar software packages has been shown to be effective also. For example, Moosavi (2009) did a comparison of two CAIs in terms of their effectiveness on student performance. Moosavi compared MyMathLab to Thinkwell. Both type of math software systems are similar in terms of content and how the software is used. It was found that the performance level to the two software systems were similar, where the Thinkwell software had slightly better performance scores than MyMathLab. Moosavi's study (2009) does not identify the underlying reasons for differences in performances between the two CAI groups. The researcher suggests that more research is needed in order to gain more insight into students' level of confidence, anxiety, and general perception of CAI. However, there have been no comparative studies focusing on the potential impact to students' achievement and impact of attitude using varying instructional approaches and CAI with artificial intelligence. This research effort will compare two varying instructional approaches to determine impact on student learning and their attitude towards mathematics.

In another study (Spradlin & Ackerman, 2010), traditional lecture was compared to traditional lecture with CAI in an Intermediate Algebra class. This study revealed that there was no significant difference between performance gains between the lecture only group and the lecture + CAI group. However, the gains were higher in the CAI group, but not statistically higher though. The researchers of the study suggest that teaching approach and format of the course might be more influential on student learning than just adding CAI to a class. This study

reveals that CAI does not always make a significant difference for student learning. One possible reason could be attributed to the fact that the homework problems were similar for both groups. The approach was also similar for both groups. However, the CAI provided immediate feedback, which could have contributed to the slightly higher performance than the lecture group. For the control group, the instructor returned all homework assignments with feedback the following class period, providing efficient feedback. Therefore, the essential difference between the traditional lecture group and the treatment group was that the outside assignments were computerized instead of delivered through the math textbook only. However, both groups did showed performance gains between the pretest and post-test using covariant analysis (ANCOVA) to control for entering behaviors. The performance gains can be due to learning and working with new content. Spradlin and Ackerman (2010) suggests that instructional technology have a great potential to improve learning and can be used to address the different learning styles and preferences for students, including modified class formats. The researchers suggest replicating this study with different instructional modes and to examine math anxiety levels in different modes of instruction.

According to Hagerty and Smith (2005), technology is a driving force in college math reform since it reduces cost in higher education and can provide students with formative feedback along the way. A barrier in higher education is the infeasibility to develop and monitor individualized learning plans for student (2005). An individualized learning plan would provide students with specific learning goals specific to his/her needs. An adaptive instructional approach using ALEKS, in essence, can develop an individualized learning plan while the



instructor provides specific, whole class assignments for every student to complete (Canfield, 2001). ALEKS is the math software under investigation due to its adaptive ability, which individualizes instruction for students based on their current level of learning and their appropriate zone of proximal development.

The purpose of this current study is to compare an adaptive instructional approach using ALEKS to a traditional instructional approach using MyMathLab in terms of learning gains and attitudinal changes for College Algebra. Learning gains will be examined on the unit of functions. Attitudinal changes will be measured using the ATMI. In addition, correlational analyses will be performed to measure the relationship between students' mastery learning levels and their actual learning levels for each instructional approach. Moreover, the two correlation coefficients will be compared for significant differences between the two instructional approaches. Chapter three will review the specific research questions and design. Chapter four will provide the results for each research question under investigation in this study. Chapter five will provide a discussion of the findings along with conclusions, implications, and recommendations for future research to expand upon this research effort.

## CHAPTER THREE: METHODOLOGY

The purpose of this research effort is to examine if an adaptive instructional approach is more effective compared to a traditional instructional approach in terms of learning gains on the topic of functions in College Algebra and also in terms of attitude changes as measured by the ATMI. The ATMI also provides sub-scores in the area of self-confidence, value, motivation, and enjoyment. In addition, this study seeks to measure any relationships between students' mastery learning score and actual post-test scores. The correlation between the two instructional approaches will also be compared using an  $r$ -to- $z$  Fisher transformation. More specifically, this research effort seeks to address the following questions:

- 1) Is there a significant difference between learning gains on the topic of functions between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?
- 2) Is there a significant difference between attitude changes between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?
- 3) Is there a stronger correlation between students' level of mastery learning (as reported by their respective software) vs. actual learning as a function of instructional approach (traditional vs. self-adaptive)?

## Design

This research effort is a quasi-experimental design due to a lack of random assignment. This research design is similar to a traditional pre-test/post-test experimental design (Leedy, 1997), but lacks random selection. Students self-selected the section in which to enroll in based on the section that best fit their schedule. However, the instructor was randomly assigned to two College Algebra sections, out of 45 sections, offered at the time of course scheduling. The instructor was assigned to two Monday, Wednesday, and Friday sections that met for 50 minutes during similar time of day. Section A was Monday, Wednesday, and Friday from 9:00 – 9:50 AM and Section B was Monday, Wednesday, and Friday from 10:00 – 10:50 AM. Students were not notified of the instructional approach and math software assigned until the first week of classes. The instructor was given a choice during the fall semester between using MyMathLab or ALEKS. The instructor randomly chose Section A to be assigned to ALEKS and would use a self-adaptive instructional approach. The self-adaptive instructional approach focused the lecture time on struggling concepts as reported by ALEKS. The instructor would focus the concepts of the lesson and do examples that matched problems that students were struggling with. The instructor for Section A took a flexible approach and catered lectures based on reports generated by ALEKS. Section B would be assigned to MyMathLab and would use a traditional instructional approach. The traditional approach as defined in this research study refers to a traditional pencil-and-paper lecture approach supplemented by non-intelligent CAI. The CAI in the traditional section was not set to track or adjust according to students' knowledge state. All assignments in the CAI for the traditional approach were the same for all students except for

algorithmic changes in numeric values. The instructor would spend some time in the beginning of the lesson addressing homework problems that students identified that they needed assistance with. The instructor delivered a fixed lecture after addressing students' homework problems. The instructor did not make any adjustments to the lecture notes. Section B was considered the control group in this study while Section A was the treatment group. Both sections were lecture-based and met face-to-face for the entire semester. This research effort was focused on comparing two instructional approaches with a focus on the impact of a self-adaptive approach.

Students can be placed into College Algebra by taking the Postsecondary Education Readiness Test (P.E.R.T.) and scoring 123 or higher. Florida began using the PERT as the placement test since October 2010. According to the Florida's Department of Education (2014), this test is aligned with postsecondary competencies that are necessary to be considered college-ready. "The PERT is comprised of three 25-item computer adaptive tests in reading, writing, and mathematics" (Florida Department of Education, 2014, p. 1). The topics and sample questions from the P.E.R.T. were obtained from McCann Associates (Retrieved from <http://www.fldoe.org/schools/pdf/PERT-studentstudyguide.pdf>, 2011). This information is provided in Appendix A. Students can also be placed based on their SAT, ACT, or CPT scores. Students must make a 500 or greater on the math section of the SAT, a 21 or greater on the ACT, or a 90 or greater on the CPT, which has not been administered in Florida since 2010. All entering students must be tested to place into College Algebra. An alternative way for students to be eligible to enroll in College Algebra is to complete the prerequisite, Intermediate Algebra

(MAT 1033) with a grade of C or higher. The course description at Valencia College follows below:

College Algebra is based on the study of functions and their role in problem solving. Topics in College Algebra include graphing the linear, quadratic, and exponential families of functions, and inverse functions. Students will be required to solve applied problems and communicate their findings effectively. Technology tools will be utilized in addition to analytical methods.

Specific topics and objectives for College Algebra are included in the course outline (Appendix B) and the sample syllabus (Appendix C). Students taking College Algebra must earn a grade of C or higher to progress to the next subsequent math course.

#### Descriptive Statistics

The Florida's FACTS report as of 2012 provides demographics statistics of all students registered in the state college system. There are a total of 28 public state colleges, which include all community colleges and state colleges. The 28 state colleges do not include four-year universities. According to the Florida's FACTS report of 2012, 46.12% are white, 18.08% are black, 23.87% are Hispanic, 2.99% are other minority, two or more races are 1.20% two or more races, and 6.40% are unknown ethnicities as of the beginning of Fall 2011. The Florida College System serves 478,130 students.

Valencia College serves about 69,422 students, where 59,958 are credit-seeking students as of the 2013-2014 academic year (Valencia College Facts, 2013). The average student's age at Valencia College is 24.1 years. 34.8% are Caucasian, 31.2% are Hispanic, 17.2% are African American, 11.7% are reported as other, 4.8% are Asian/Pacific Islander, and 0.3% are Native

American. 39.6% of students are considered full-time, and 60.4% of students are considered part-time. Full-time enrollment is defined as a student enrolled in 12 or more credit hours per semester, excluding summer semesters. Many courses are an average of 3 credit hours. A full-time student typically enrolls in four courses.

Demographic information was collected from my sections through a first-day questionnaire meant to identify this information (Appendix D). There were a total of 60 participants enrolled for this research study in the beginning of the term after the add/drop period. From the sample of 60 students, four students withdrew within the first couple of weeks in the course, leaving a total of 56 participants for this study (27 for Section A and 29 for Section B). Overall, there were 20 males (35.7%) and 36 females (64.3%). For Section A, there were 6 males (22.2%) and 21 females (77.8%). For Section B, there were 14 males (48.3%) and 15 females (51.7%). Overall in this study, there were 18 Caucasians (32.1%), 15 African Americans (26.8%), 10 Hispanics (17.9%), 6 (10.7%) Asians/Pacific Islander, 1 Native Indian (1.8%), and 6 (10.7%) reported as others. For Section A, there were 7 Caucasians (25.9%), 9 African Americans (33.3%), 4 Hispanics (14.8%), 3 Asians/Pacific Islander (11.1%), and 4 (14.8%) reported as others. For Section B, there were 11 Caucasians (37.9%), 6 (20.7%) African Americans, 6 Hispanics (20.7%), 3 (11.1%) Asians/Pacific Islander, 1 (3.4%) Native Indian, and 2 (6.9%) reported as others.

### Procedure

The instructor taught two College Algebra classes that met three times a week for 50 minutes per class session. The instructor holds a Master's degree in mathematics and meets Florida's requirement to teach undergraduate mathematics. College Algebra is primarily a course for first year community college students. Students normally are required to take an additional math course after College Algebra. The subsequent course will vary from student to student depending on their major and long-term academic goals. The class met face-to-face. During the first week of classes, students were oriented to the course including an orientation to their respective math software package. Additional training and assistance was offered to students during the instructor's office hours. In addition, students had free technical support through the software package. During the first week of classes, students were informed that features of their math software were being investigated and that they can take part of a voluntary research project. To avoid potential biases, the researcher chose not to explain which features were being investigated in their math software. The description in the informed consent form was generic and stated that certain features of the math software were being investigated in terms of how students learn. The students were given an informed consent form (see Appendix E). Permission to complete this research study was given by UCF and Valencia College (see Appendix F and G, respectively). The Attitudes Toward Mathematics Inventory (ATMI) was given during the first week of classes (see Appendix H). Permission to use the ATMI was granted by Martha Tapia (see Appendix I). The topic chosen was functions, which took place during the fourth through the eighth week of the semester. The topic of functions were chosen

since functions are a major topic in College Algebra that has to be mastered for students to be successful in the course and subsequent courses in mathematics. Functions also set the foundation of other topics studied in College Algebra. Students were given a pre-test on paper, prepared from TestGen by Pearson. The pretest covered the objectives of functions (see Appendix J). The students had to complete assigned homework in their respective software, which prepared them for the objectives covered on the exam. After completion of the course objectives on functions and homework, students were given the post-test on functions. The pre-test and post-test were identical except for algorithmic changes to number values. At the conclusion of the study of functions, students were administered the ATMI again. The basic steps are summarized below:

- 1) Course Introduction and Software Orientation (Week 1)
- 2) Informed Consent and ATMI administered (Week 1)
- 3) Pre-Test (paper and pencil) (Week 4)
- 4) In-class lectures on functions and assignments through software (Week 4, 5, 6, 7)
- 5) Practice exam through software (Week 7)
- 6) Post-Test (Week 8)
- 7) ATMI re-administered (Week 8)

#### Instructional and Software Differences

This research study was focused on comparing two instructional approaches supplemented with CAI. This section will provide some differences between the functionalities



of the two software systems and how those features were used to support the chosen instructional approach. The researcher informally interviewed colleagues who had experience with both ALEKS and MyMathLab to gain different perspectives on the similarities and differences between the two math software systems. The two math software systems are similar in terms of math content, but the approach is different. In the traditional section, the instructor lectures by topic, and each student receive exactly the same homework assignment and same number of problems. Students' assignments are not individualized. The instructor can program the same assignment for all students in MyMathLab for the traditional instructional approach. In MyMathLab, the students can do the homework and have resources available to them through the math software system. The students are able to view an example step-by-step solution on a similar problem, look at hints, view a video clip, or reference the textbook section to which the problem corresponds. The student is given three attempts to answer the problem correctly before it is marked incorrect. The student can do a similar problem to change it from being incorrect to correct. The change in the problem is algorithmic to the number value only. A screenshot of homework in MyMathLab is provided in Appendix K.

In the adaptive instructional approach, ALEKS was chosen. In the adaptive instructional approach, lectures are catered to students' difficulties and to problems that students are ready to learn. ALEKS provide a screen shot of the types of problems students are working on in a particular objective. The instructor can lecture on problems that students are struggling with, which is reported by the adaptive software. In addition, homework assignments are individualized for each student based on their current knowledge state of the course objective.

ALEKS, as discussed earlier, uses Knowledge Space Theory and assess the student's mastery of skills associated with the course objectives including any required prerequisites. The assessment is the first assignment students must complete in ALEKS and is approximately 30 short answer questions. This assessment self-adapts based on whether the student answers the previous question correctly or not. Once completed, students are assigned a learning pie with competencies that they must master that are relevant to the course objective being taught according to the schedule set by the instructor. The learning pie will include prerequisite skills. The learning pie will not include learning objectives that ALEKS deemed students are not ready to learn until certain objectives and skills have been mastered. Once a student gets the same problem correct three times without assistance, the objective is considered mastered. However, students are given an assessment periodically (about every 5 hours). If a student gets a mastered objective problem incorrect, the objective is added back the learning pie. These formative assessments are meant to maintain a current learning pie that matches the student's progress. The instructor programs the objectives of the course and schedules due dates for each objectives to be completed. The instructor is also able to program quizzes and examinations that match the course objectives. ALEKS also provide hints and instruction based on what the student types in for a math problem. A screenshot of ALEKS is provided in Appendix L.

Design for Research Question #1:

*Is there a significant difference between learning gains on the topic of functions between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?*

The goal of the first research question was to compare learning gains in the topic of functions as a function of instructional approach. To address this question, students were given a pre-test around week four and a post-test around week eight on the topic of functions. Functions is a pivotal topic in College Algebra. The topic of functions is difficult and new for most students. In addition, it is imperative for students to have an understanding of functions for subsequent topics covered in College Algebra and future college-level math courses. Both the pre-test and post-test is a paper-and-pencil test generated through TestGen by Pearson. Both tests were identical except algorithmic changes to number values. The pre-test was given the day before the topic is introduced. The post-test was given after the topic is completed with 1 day of review. The grading of the test was as follows: 1) multiple choice questions were marked as either incorrect or correct, 2) for short answer questions, the work was graded in addition to the final solution given and was graded as incorrect, partially correct, or correct. Questions marked as incorrect received 0 points, partially correct received  $\frac{1}{2}$  point, and correct received 1 full point. The fractional grade (total number correct over total number of questions) was changed to a percent grade. Independent t-test analyses was performed through SPSS (Statistical Package for Social Science) on mean pre-test scores and mean post-test scores for both sections, to measure for any significant differences. Learning gains was measured by subtracting the pre-test

score from the post-test for each student. The mean learning gains was compared with an independent t-test analysis for both sections. A dependent paired t-test analysis was also performed to measure the degree to which learning has taken place in each section.

### Design for Research Question #2

*Is there a significant difference between attitude changes between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?*

Students' attitudes were assessed using the Attitudes Toward Mathematics Inventory (ATMI) during the first week of classes and at the conclusion of this research effort (right after the post-test is given). The ATMI was originally developed by Tapia in 1996 and is a 40-item survey using a Likert-style scale designed to measure high school and college students' attitudes towards mathematics (Tapia & Marsh, 2004). Tapia and Marsh (2002) used confirmatory factor analysis to confirm that ATMI would hold true for U.S. college students (Tapia & Marsh, 2002) using a sample of 134 undergraduate college students, where the population consisted of 71 males, 58 females, 80% Caucasian, and 20% African Americans (Tapia & Marsh, 2002). The ATMI measures overall attitude in mathematics and four sub-factors of attitudes in mathematics: self-confidence, value, enjoyment, and motivation. Tapia and Marsh (2004) provide definitions for each of the four sub-factors. The self-confidence category measures students' confidence in mathematics and their self-concept (Tapia & Marsh, 2004). The value category measures feelings of anxiety (Tapia & Marsh, 2004). The enjoyment category measures the degree to which students enjoy working with mathematics, and the motivation category measures interest

and desire to pursue and study mathematics (Tapia & Marsh, 2004). Cronbach's alpha coefficients were found to be 0.96 for self-confidence, 0.93 for value, 0.88 for enjoyment, and 0.87 for motivation. Cronbach's alpha values above 0.70 are considered to be acceptable measures of internal reliability (Nunnally & Bernstein, 1994). The reliability of the scale is measured at 0.97 with college students. The content validity has also been established by Tapia and Marsh (2004).

Tapia and Marsh (2002) found items #9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22 and 40 to measure self-confidence, items #1, 2, 4, 5, 6, 7, 8, 35, 36, and 39 to measure value, items #3, 24, 25, 26, 27, 29, 30, 31, 37, and 38 to measure enjoyment, and items #23, 28, 32, 33, and 34 to measure motivation. Items #9, 10, 11, 12, 13, 14, 15, 20, 21, 25, and 28 are reverse items; items that make negative statements about mathematics. For example, item #12 states "Mathematics makes me feel uncomfortable". The researcher used Tapia's and Marsh's subscales to measure the four factors independently and examine significance difference in the before and after scores for each factor separately in addition to holistically.

The 40-item survey uses a Likert scale with the following response codes A - E, as developed by Tapia in 1996: A – strongly disagree, B –disagree, C – neutral, D – agree, and E – strongly agree. For quantifying data, A = 1, B = 2, C = 3, D = 4, and E = 5, giving a range of 40 to 200 points. Reverse items are interpreted using the formula  $6 - \text{reverse item's score}$ . For example, if a student picked E (strongly agree), this would normally be ranked as five for a positive statement. For these reverse items, the actual score for a ranking of E would be recorded as  $6 - 5 = 1$ , a low rating for this type of statement on the ATMI. The estimated

administration time is 20 minutes per administration. Both administrations took place during class time for the current study to investigate differences in students' attitude between the two instructional approaches. A copy of the actual questionnaire developed by Martha Tapia can be found in Appendix H.

Independent t-test analyses were performed using SPSS on pre-ATMI scores and on each of the four sub-scale scores. Independent t-test analyses were also performed on post-ATMI scores and on each of the four sub-scales scores. Attitude changes were calculated by subtracting the pre-ATMI scores from the post-ATMI scores for each student. The same was calculated for each of the 4 sub-scales scores respectively. Independent t-test analyses were performed to determine if there were a significant attitude change holistically and/or on each of the four sub-scales for each section.

### Design for Research Question #3:

*Is there a stronger correlation between students' level of mastery learning (as reported by their respective software) vs. actual learning as a function of instructional approach (traditional vs. self-adaptive)?*

The third question of this research effort sought to measure the relationship between students' level of mastery (as reported by the respective software) vs. actual learning (as measured by the post-test scores). The level of mastery was defined operationally as the homework score earned on the respective software. For the traditional section, once a homework problem is marked as correct, it stays correct. In general, the homework grade can only increase

in the traditional section since students' current learning state is not measured. For the self-adaptive section, homework grades could increase or decrease if the software determined that students lost previously mastered knowledge from the objective. The researcher recorded homework grades as reported by the software and used the homework grade as the representative score for mastery learning in the objective of functions. Pearson correlation analyses were performed to determine, if any, relationships between students' mastery scores on their respective software versus their actual learning (post-test scores) for each class type. The correlational analyses were compared between the two sections of College Algebra to determine if one instructional approach has a higher correlational relationship versus the other instructional approach using an  $r$ -to- $z$  Fisher transformation to test for statistical difference (Howell, 2011). There was a discussion about how scaffolding should match student's level of learning. Their mastery of learning as measured by the software should match their actual level of learning ideally. This part of this current research study is descriptive in nature. The pair of correlational analyses using the Pearson product moment correlation was computed through SPSS (Statistical Package for Social Sciences).

#### Assumptions and Limitations

According to Leedy (1997), no research can avoid biases and limitations that may influence the results of the data. Here were the assumptions and limitations for this current research study:

- 1) The sample was not a true, random sample. The sample used is a convenient sample based on students who enrolled in the 2 sections of College Algebra. In addition, class

schedules for the semester listed the instructor teaching the course approximately 3 months in advance of the semester. Students have a tendency to choose a section or to avoid a section based on the instructor teaching the course. Popular rating websites and word of mouth are two influences on how a student may or may not select a particular section being taught.

- 2) The sample size was limited to a total of about 60 students in two particular sections of College Algebra courses in a central Florida state college (30 students per section). The results presented may be true of the sample studied and similar populations. The results may not be generalizable to other colleges, different regions, or different demographics (such as an all-female institution). In addition, this study was at a state college, and is not applicable to universities due to different entrance requirements and differences in terms of class format and instruction delivery.
- 3) This research effort is narrowly focusing on one course objective in College Algebra, which limits interpretations of the results. For example, the results may differ for different topics or may differ if the whole course was studied. The reader should take this limitation into account when reviewing the results of the data in Chapter four.
- 4) Teaching contains confounding variables by the nature of teaching itself. The researcher controlled for as many variables as possible through offering the sections of College Algebra during the same time of day, same number of days, and same time length per class session. In addition, both sections had the same instructor and received similar lectures. Both sections received the same syllabus, course requirements and the same in-



class examinations. The students had equal access to the instructor during office hours. However, there are other factors that could influence a student's performance and attitude in any course including receiving additional tutoring, numbers of hours working, obligation to kids, and other obligations unaccounted for. According to Leedy (1997), each section being composed of different individuals and the inner dynamic can play a role and be an influence on the results of data (p. 220). The home environment can affect students' behavior and reactions in the class (p. 220). These are all variables not accounted for and could be influences on why students do well or don't do well on exams, which in turn can influence their attitude and perceptions of learning.

- 5) It was assumed that students entering College Algebra is representative of the population of students enrolled in College Algebra at public community and state colleges nationwide and, more specifically, Florida.
- 6) It was assumed that students entering College Algebra have competent computer literacy skills to use the math software and difference in computer literacy skills do not hinder or influence their progress in the course. The researcher gave the students two weeks to become acclimated and offered orientation to the software during the first week of classes as well as individual assistance during office hours. Research data in terms of the content was not collected until the fourth week in the course.

Chapter one introduced the purpose of the study along with rationale and potential benefits of this study. Chapter two included a literature review that focused on the reform movements in mathematics education, the history of artificial intelligence and intelligent tutoring, results of

studies with CAI, and a discussion of Knowledge Space Theory. Chapter three discussed the research design and the statistical tools that will be used to address the research questions posed. Chapter four will include all of the results from all research questions posed. A discussion of the results and conclusion with recommendations for future studies will be included in Chapter five.

## CHAPTER FOUR: RESULTS

### Overview of Research Design and Questions

The purpose of this research effort was to compare two instructional approaches (traditional versus self-adaptive) in terms of learning gains on the topic of functions and attitude changes as measured by the ATMI, including the four sub-scale scores in the areas of self-confidence, value, motivation, and enjoyment. In addition, this study sought to determine relationships between students' mastery of learning scores (homework scores) versus actual learning (post-test scores) through correlational analyses. More specifically, this research effort was focused on addressing the following questions:

- 1) Is there a significant difference between learning gains on the topic of functions between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?
- 2) Is there a significant difference between attitude changes between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?
- 3) Is there a stronger correlation between students' level of mastery learning (as reported by their respective software) vs. actual learning as a function of instructional approach (traditional vs. self-adaptive)?

### Participants

From the sample of 60 students, 6.7% of the sample (4 students) withdrew within the first couple of weeks in the course, leaving a total of 56 participants (27 for Section A and 29 for Section B). From the 56 participants left, four more students withdrew from the course. However, three of the four students agreed to complete the post-test on functions and the post-ATMI survey, so their data is complete. The other withdrawn student did not complete the post-test, but did complete the ATMI post survey. Consequently, this led to incomplete data for the post-test scores. However, Osborne (2013) suggests that estimating values for missing data will lead to more replicable findings than analyses that discard missing cases. Since it is better to retain cases and estimate value for missing data values (Osborne, 2013), the withdrawn student was assigned a post-test score equal to his/her earned pre-test score, which resulted in no learning gains for this student. Since all students who took the actual post-test performed higher when compared to their pre-test score, assigning a post-test score equal to the pre-test score was a conservative approach. It was safe to assume that the withdrawn student, at the very minimum, did not have any learning gains. However, the other 52 students did not withdraw from the course, and they participated in all aspects of the research, including the post-test test on functions and the post-ATMI survey. In Section A (adaptive instructional method), the mean age was 21.87 years while the mean age in Section B (traditional instructional method), was 23 years. The mean age of students in both sections was 22.43 years.

### Results of Research Question One

*Is there a significant difference between learning gains on the topic of functions between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?*

An independent sample t-test was computed to compare means on the unit pre-test and post-test for each class type (Section A and Section B). No statistical differences were revealed on test performance on the pre-test when comparing both instructional techniques ( $M = 32.22$  and  $SD = 10.789$ ) for Section A and ( $M = 35.38$  and  $SD = 11.378$ ) for Section B, with  $t(54) = -1.064$ ,  $p = 0.29$ . There was not a statistical difference found between the two instructional approaches for the post-test ( $M = 69.111$  and  $SD = 22.0303$ ) for Section A and ( $M = 70.966$  and  $SD = 17.6766$ ) for Section B, with  $t(54) = -0.349$ ,  $p = 0.729$ . The mean scores for the pre-test and post-test were similar between both sections as revealed by the independent t-tests. This t-test analysis indicates that both sections were not associated with significantly different means on the pre-test and post-test by class type, an indication of that both sections had similar knowledge about functions. Numerically, the post-test means were less than one point apart while the pre-test means were roughly about three points apart.

Prior to conducting the analysis, the assumption of normally distributed mean scores for the pre-test and post-test was examined. The distributions of mean scores were sufficiently normal for both sections on the pre-test and post-test. The skew and kurtosis levels for the pre-test were estimated at 0.08 and -0.097 respectively, for Section A, and 0.785 and 1.21 respectively, for Section B, which is less than the maximum allowable values for a t-test (i.e.,

skew  $< |2.0|$  and kurtosis  $< |9.0|$ ; Schmider, Ziegler, Danay, Beyer, & Bühner, 2010). For the post-test means, the skew and kurtosis levels were -0.554 and -0.702 respectively, for Section A and -0.418 and -0.971 respectively, for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.033$ ,  $p = 0.856$  for the pre-test and  $F(54) = 1.512$ ,  $p = 0.224$  for the post test.

In addition to comparing the pre-test and post-test mean scores, learning gains were measured by finding the difference between the post test and pre-test scores (Post-test – pre-test). An independent t-test was computed to compare means for learning gains by class type. No statistical differences were revealed for learning gains by class type ( $M = 36.889$  and  $SD = 18.0540$ ) for Section A and ( $M = 35.586$  and  $SD = 16.7620$ ) for Section B, with  $t(54) = .280$ ,  $p = 0.781$ . The skew and kurtosis levels were 0.056 and -0.686 respectively, for Section A, and 0.134 and -0.945 respectively, for Section B. The assumption of homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 0.174$ ,  $p = 0.678$  for learning gains.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the learning gains were statistically significant for each class section. The value  $t(26) = -10.62$ ,  $p < .001$  for section A and  $t(28) = -11.43$ ,  $p < .001$  for Section B. These paired t-test analyses indicate that both sections learned during the time period between the pre-test and post-test, but no one section had significantly greater learning gains than the other section as revealed from the independent t-test analysis. Pre-test score means, post-test score means, and learning gains means are presented in the table below by class type.

Table 1. Pre-test, Post-test, and Learning Gains Means by Class Type

<b>Class Type</b>	<b>Pre-Test Mean</b>	<b>Post Test Mean</b>	<b>Learning Gains Mean</b>
Section A ( <i>N</i> = 27)	32.22 ( <i>SD</i> =10.79)	69.11 ( <i>SD</i> = 22.03)	36.89 ( <i>SD</i> = 18.05)
Section B ( <i>N</i> = 29)	35.38 ( <i>SD</i> = 11.38)	70.97 ( <i>SD</i> = 17.68)	35.59 ( <i>SD</i> = 16.76)

Since there could be other benefits between the two instructional approaches in terms of time spent on homework, data regarding total time (in hours) spent on the topic was also collected. In addition, total time (in hours) spent on the software for the entire course was also collected. An independent t-test was computed on unit time spent as reported by the software and the total time spent for the semester for each class type. The independent samples t-tests were not associated with a statistically significant differences between mean unit time by class type ( $M = 11.582$  and  $SD = 10.2829$ ) for Section A and ( $M = 11.0245$  and  $SD = 7.93021$ ) for Section B, with  $t(54) = 0.228$ ,  $p = 0.820$ . There was not a significant difference between mean total time spent on the software by class type ( $M = 48.8707$  and  $SD = 37.67278$ ) for Section A and ( $M = 52.0886$  and  $SD = 34.88707$ ) for Section B, with  $t(54) = -0.332$ ,  $p = 0.741$ . This t-test analysis indicates that both sections were not associated with significantly different mean unit time and mean total time by class type, an indication of that both sections spent a similar mean amount of time on the unit and total time in the course.

Prior to conducting the analysis, the assumption of normally distributed mean time spent on functions and total time spent during the whole course were examined. The distributions of mean scores were sufficiently normal for both sections on unit time and total time. The skew and kurtosis levels were estimated at 1.129 and 0.920 respectively, for unit time for Section A,

and 0.514 and -0.930 respectively, for Section B. For the total time means, the skew and kurtosis levels were 1.019 and 1.781 respectively, for Section A, and 0.610 and -0.732 respectively, for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.799$ ,  $p = 0.375$  for unit time and  $F(54) = 0.004$ ,  $p = 0.947$  for total time. Unit time spent and total time means are presented in the table below by class type.

Table 2. Unit time and total time (in hours) means by Class Type

<b>Class Type</b>	<b>Unit Time Mean</b>	<b>Total Time Mean</b>
Section A ( $N = 27$ )	11.582 ( $SD = 10.2829$ )	48.8707 ( $SD = 37.67278$ )
Section B ( $N = 29$ )	11.0245 ( $SD = 7.93021$ )	52.0886 ( $SD = 34.88707$ )

### Results of Research Question Two

*Is there a significant difference between attitude changes between the two College Algebra sections as a function of instructional approach (traditional vs. self-adaptive)?*

An independent t-test was computed on the pre-ATMI scores and the post-ATMI scores for each class type. Independent t-tests were also computed for each of the 4 sub-factors (confidence, value, enjoyment, and motivation) of attitudes towards mathematics. The independent samples t-tests were not associated with statistically significant differences in means for mean pre-ATMI scores by class type ( $M = 129.96$  and  $SD = 29.57$ ) for Section A and ( $M = 136.276$  and  $SD = 30.1673$ ) for Section B, with  $t(54) = -0.790$ ,  $p = 0.433$ . There was not a statistically difference for mean post ATMI survey by class type ( $M = 133.11$  and  $SD = 30.33$ ) for Section A and ( $M = 136.55$  and  $SD = 30.04$ ) for Section B, with  $t(54) = -0.426$ ,  $p = 0.672$ .



This t-test analysis indicates that both sections were not associated with significantly different means on the pre-ATMI and post ATMI survey by class type, an indication of that both sections had similar mean attitude scores towards mathematics at both administration of the ATMI survey. Prior to conducting the analysis, the assumption of normally distributed mean scores for the pre-ATMI and post ATMI survey was examined. The distributions of mean scores were sufficiently normal for both sections on the pre-ATMI and post ATMI survey. The skew and kurtosis levels for pre-ATMI scores were estimated at -0.135 and -0.747 respectively for Section A and -0.821 and -0.267 respectively for Section B. For the mean post ATMI scores, the skew and kurtosis levels were -0.314 and -0.932 respectively for Section A and -1.02 and 0.724 respectively for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.028$ ,  $p = 0.868$  for the pre-ATMI scores and  $F(54) = 0.146$ ,  $p = 0.703$  for the post ATMI scores.

An independent t-test on the change in ATMI scores (Post score – Pre-ATMI score) revealed no significant difference between Section A and Section B. The mean ATMI change score was for Section A was 3.15 ( $SD = 29.21$ ), and the mean change score for Section B was 0.276 ( $SD = 16.34$ ), with  $t(54) = 0.458$ ,  $p = 0.649$ . For Section A, the skew and kurtosis levels were -1.13 and 4.29, respectively. For Section B, the skew and kurtosis levels were -0.28 and 0.154, respectively. The assumption of homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 2.822$ ,  $p = 0.099$  for ATMI change scores. It should be noted that even though there was not a significant statistical difference, students' ATMI scores increased slightly more for Section A while there was a negligible change ATMI scores for Section B.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the ATMI changes were statistically significant for each class section. The value  $t(26) = -0.56$ ,  $p = 0.5880$  for section A and  $t(28) = -0.091$ ,  $p = 0.928$  for Section B. These paired t-test analyses indicate that both sections were not associated with statistical change in mean ATMI scores during the time period between the pre-ATMI survey and post ATMI survey. Both sections had similar entering attitudes towards mathematics in the beginning of the semester and again during the second administration of the ATMI survey. Mean pre-ATMI scores, mean post-ATMI scores and mean change in ATMI scores are presented in the table below by class type.

Table 3. Pre-ATMI, Post ATMI and change means by Class Type

<b>Class Type</b>	<b>Pre-ATMI Mean</b>	<b>Post ATMI Mean</b>	<b>ATMI change mean</b>
Section A ( $N = 27$ )	129.96 ( $SD = 29.57$ )	133.11 ( $SD = 30.33$ )	3.15 ( $SD = 29.21$ )
Section B ( $N = 29$ )	136.28 ( $SD = 30.17$ )	136.55 ( $SD = 30.04$ )	0.276 ( $SD = 16.34$ )

Independent sample t-tests were computed for each of the sub-factor scores from the ATMI survey. The ATMI survey measured self-confidence, value, enjoyment, and motivation. No statistical differences were revealed for each of the individual sections of the ATMI. The t-test revealed no statistically significant difference between pre-self-confidence mean scores by class type ( $M = 49.037$  and  $SD = 13.25$ ) for Section A and ( $M = 49.828$  and  $SD = 14.2730$ ) for Section B, with  $t(54) = -0.214$ ,  $p = 0.831$ . There was not a statistical significant difference between mean post-self-confidence scores by class type ( $M = 49.111$  and  $SD = 15.27$ ) and ( $M = 49.966$  and  $SD = 13.2382$ ) for Section B, with  $t(54) = -0.224$ ,  $p = 0.823$ . This t-test analysis

indicates that both sections were not associated with significantly different means on pre-self-confidence and post self-confidence scores by class type, an indication of that both sections had similar mean self-confidence scores towards mathematics at both administration of the ATMI survey.

Prior to conducting the analysis, the assumption of normally distributed mean scores for the pre-confidence and post confidence scores was examined. The distributions of mean scores were sufficiently normal for both sections for pre-confidence and post confidence. For mean pre-self-confidence scores, the skew and kurtosis levels were estimated at -0.156 and -1.047 respectively, for Section A, and -0.497 and -0.380 respectively, for Section B. For the post confidence means, the skew and kurtosis levels were -0.686 and -0.606 respectively, for Section A, and -0.942 and 0.442 respectively, for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.084$ ,  $p = 0.773$  for the mean pre-self-confidence scores and  $F(54) = 1.009$ ,  $p = 0.320$  for the mean post self-confidence scores.

An independent  $t$ -test on the mean change in self-confidence scores (Post score – pre-score) revealed no statistical significant difference by class type ( $M = 0.0741$  and  $SD = 13.25$ ) for Section A and ( $M = 0.138$  and  $SD = 8.895$ ) for Section B, with  $t(54) = 0.028$ ,  $p = 0.978$ . For mean change in self-confidence, the skew and kurtosis levels were -1.55 and 5.485 respectively, for Section A, and 0.445 and 1.936 respectively, for Section B. The assumption of homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 0.825$ ,  $p = 0.368$  for mean

change in self-confidence scores. Both sections experience negligible changes to mean self-confidence scores.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the mean change in self-confidence were statistically significant for each class section. The value  $t(26) = -0.029$ ,  $p = 0.977$  for section A and  $t(28) = -0.084$ ,  $p = 0.934$  for Section B. These paired t-test analyses indicate that both sections were not associated with statistical change in self-confidence scores during the time period between the pre-ATMI survey and post ATMI survey. Both sections had similar entering self-confidence level towards mathematics in the beginning of the semester and again during the second administration of the ATMI survey. In addition, each section did not experience significant changes in self-confidence as indicated on the paired t-tests by class type. Pre-confidence means, post confidence means, and confidence change means are presented in the table below by class type.

Table 4. Pre-confidence Means, Post-confidence Means and Confidence Change Means by Class Type

<b>Class Type</b>	<b>Pre-confidence Mean</b>	<b>Post confidence Mean</b>	<b>Confidence change</b>
Section A ( $N = 27$ )	49.037 ( $SD = 13.25$ )	49.111 ( $SD = 15.27$ )	0.0741 ( $SD = 13.25$ )
Section B ( $N = 29$ )	49.828 ( $SD = 14.2730$ )	49.966 ( $SD = 13.2382$ )	0.138 ( $SD = 8.895$ )

Value is the next sub-factor analyzed. The independent samples t-tests were not associated with a statistically significant differences in means for the pre-value scores by class type ( $M = 36.926$  and  $SD = 10.1524$ ) for Section A and ( $M = 38.241$  and  $SD = 6.2829$ ) for Section B, with  $t(42.8) = -0.578$ ,  $p = 0.566$ . There was not a statistical difference for mean post-

value scores by class type ( $M = 36.667$  and  $SD = 6.9004$ ) for Section A and ( $M = 38.448$  and  $SD = 7.4190$ ) for Section B, with  $t(54) = -0.929$ ,  $p = 0.357$ . This t-test analysis indicates that both sections were not associated with significantly different means for pre-value and post-value scores by class type, an indication of that both sections had similar mean value mean scores towards mathematics at both administration of the ATMI survey.

Prior to conducting the analysis, the assumption of normally distributed mean pre-value and post-value scores examined. The distributions of mean scores were sufficiently normal for both sections for mean pre-value and post-value scores. For mean pre-value scores, the skew and kurtosis levels were estimated at  $-0.089$  and  $0.957$  respectively for Section A and  $-0.474$  and  $-0.884$  respectively for Section B. For mean post-value scores, the skew and kurtosis levels were  $-0.601$  and  $0.762$  respectively for Section A and  $-0.854$  and  $0.515$  respectively for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test for mean post-value scores, but was not satisfied for mean pre-value scores. A Welch's t-test value was used for mean pre-value scores since the assumption of homogeneity of variances was violated. The  $F$ -test,  $F(54) = 4.475$ ,  $p = 0.039$  for the pre-value mean scores and  $F(54) = 0.161$ ,  $p = 0.690$  for the post value mean scores.

An independent t-test on the change in value scores (Post-value – pre-value) revealed no significant difference between Section A and Section B. The mean value change score for Section A was  $-0.259$  ( $SD = 9.1889$ ), and the mean change score for Section B was  $0.2069$  ( $SD = 4.6933$ ), with  $t(54) = -0.259$ ,  $p = 0.797$ . The skew and kurtosis levels were  $-0.858$  and  $4.694$  respectively for Section A and  $-0.646$  and  $0.034$  respectively for Section B. The assumption of

homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 2.215$ ,  $p = 0.142$  for value change scores. Both sections experience negligible changes to mean value scores.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the mean value changes were statistically significant for each class section. The value  $t(26) = 0.147$ ,  $p = .885$  for section A and  $t(28) = -0.237$ ,  $p = .814$  for Section B. These paired t-test analyses indicate that both sections were not associated with statistical change in mean value scores during the time period between the pre-ATMI survey and post ATMI survey. Both sections had similar entering value level towards mathematics in the beginning of the semester and again during the second administration of the ATMI survey. Pre-value means, post value means, and value change means are presented in the table below by class type.

Table 5. Pre-value Means, Post value means, and value change means by Class Type

<b>Class Type</b>	<b>Pre-value Mean</b>	<b>Post value Mean</b>	<b>Value change</b>
Section A ( $N = 27$ )	36.926 ( $SD = 10.1524$ )	36.667 ( $SD = 6.9004$ )	-0.259 ( $SD = 9.1889$ )
Section B ( $N = 29$ )	38.241 ( $SD = 6.2829$ )	38.448 ( $SD = 7.4190$ )	0.2069 ( $SD = 4.6933$ )

Enjoyment was the next sub-factor analyzed. The independent samples t-tests were not associated with a statistically significant differences in means for pre-enjoyment scores by class type ( $M = 31.000$  and  $SD = 7.8935$ ) for Section A and ( $M = 33.276$  and  $SD = 9.0273$ ) for Section B, with  $t(54) = -1.001$ ,  $p = 0.321$ . There was not a statistically significant difference for mean post-enjoyment scores by class type ( $M = 33.074$  and  $SD = 7.9272$ ) for Section A and ( $M$

= 32.621 and SD = 8.1390) for Section B, with  $t(54) = 0.211$ ,  $p = 0.834$ . This t-test analysis indicates that both sections were not associated with significantly different means for pre-enjoyment and post enjoyment scores by class type, an indication of that both sections had similar mean enjoyment scores towards mathematics at both administration of the ATMI survey.

Prior to conducting the analysis, the assumption of normally distributed mean scores for mean pre-enjoyment and post enjoyment scores were examined. The distributions of mean scores were sufficiently normal for both sections for pre-enjoyment and post enjoyment. For pre-enjoyment, the skew and kurtosis levels were estimated at 0.076 and -0.089 respectively, for Section A, and -0.651 and -0.469 respectively, for Section B. For the post enjoyment means, the skew and kurtosis levels were 0.417 and -0.499 respectively for Section A and -1.085 and 0.713 respectively for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.660$ ,  $p = 0.420$  for pre-enjoyment means and  $F(54) = 0.002$ ,  $p = 0.963$  for post enjoyment means.

An independent t-test on the mean change in enjoyment scores revealed no significant difference by class type ( $M = 2.0741$  and  $SD = 8.0952$ ) for Section A and ( $M = -0.6552$  and  $SD = 4.85707$ ) for Section B, with  $t(54) = 1.542$ ,  $p = 0.129$ . The skew and kurtosis levels were 0.332 and 2.822 respectively, for Section A, and 0.077 and 0.162 respectively, for Section B. The assumption of homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 2.288$ ,  $p = 0.136$  for mean change in enjoyment scores. Even though the change mean score for enjoyment was not statistically significant, it should be noted that section A experienced a positive increase while section B experienced a negligible decrease.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the value changes were statistically significant for each class section. The value  $t(26) = -1.331$ ,  $p = 0.195$  for section A and  $t(28) = -0.726$ ,  $p = 0.474$  for Section B. These paired t-test analyses indicate that both sections were not associated with statistical change in enjoyment mean scores during the time period between the pre-ATMI survey and post ATMI survey. Both sections had similar entering enjoyment level towards mathematics in the beginning of the semester and again during the second administration of the ATMI survey. Pre-enjoyment means, post enjoyment means, and enjoyment change means are presented in the table below by class type.

Table 6. Pre-enjoyment Means, Post-enjoyment Means, and enjoyment change by Class Type

<b>Class Type</b>	<b>Pre-enjoyment Mean</b>	<b>Post enjoyment Mean</b>	<b>Enjoyment Change</b>
Section A ( $N = 27$ )	31.000 ( $SD = 7.8935$ )	33.074 ( $SD = 7.9272$ )	2.0741 ( $SD = 8.0952$ )
Section B ( $N = 29$ )	33.276 ( $SD = 9.0273$ )	32.621 ( $SD = 8.1390$ )	-0.6552 ( $SD = 4.85707$ )

Motivation was the last sub-factor analyzed. The independent samples t-tests were not associated with a statistically significant differences in means for pre-motivation scores by class type ( $M = 14.000$  and  $SD = 4.7878$ ) for Section A and ( $M = 14.931$  and  $SD = 4.7203$ ) for Section B, with  $t(54) = -0.732$ ,  $p = 0.467$ . There is not a statistical difference for mean post-motivation scores by class type ( $M = 14.222$  and  $SD = 4.6021$ ) for Section A and ( $M = 15.517$  and  $SD = 5.0471$ ) for Section B, with  $t(54) = -1.001$ ,  $p = 0.321$ . This t-test analysis indicates that both sections were not associated with significantly different means for pre-motivation and post motivation scores by class type, an indication that both sections had similar mean



motivation mean scores towards mathematics at both administrations of the ATMI survey. This result indicates that the pre-motivation and post motivation scores between both class types were similar.

Prior to conducting the analysis, the assumption of normally distributed mean scores for mean pre-motivation and post motivation scores were examined. The distributions of mean scores were sufficiently normal for both sections for mean pre-motivation and post motivation scores. For pre-motivation, the skew and kurtosis levels were estimated at 0.041 and -0.578 respectively for Section A and -0.208 and -0.417 for Section B. For the post motivation means, the skew and kurtosis levels were -0.228 and -0.695 respectively for Section A and 0.151 and -1.076 respectively for Section B. Additionally, the assumption of homogeneity of variances was also tested and satisfied via Levene's  $F$  test,  $F(54) = 0.017$ ,  $p = 0.895$  for pre-motivation means and  $F(54) = 0.958$ ,  $p = 0.332$  for post motivation means.

An independent t-test on the change in mean motivation scores revealed no significant difference by class type ( $M = 0.222$  and  $SD = 4.75017$ ) for Section A and ( $M = 0.5862$  and  $SD = 3.39661$ ) for Section B, with  $t(54) = -0.332$ ,  $p = 0.741$ . The skew and kurtosis levels were 2.086 and 7.956 respectively for Section A and -0.205 and 0.915 respectively for Section B. The assumption of homogeneity of variances was tested and satisfied with a Levene's  $F$  test,  $F(54) = 0.488$ ,  $p = 0.488$  for motivation change scores. Both sections experienced negligible change in motivation scores.

In addition to the independent sample t-tests, dependent paired t-tests were computed to measure whether the value changes were statistically significant for each class section. The

value  $t(26) = -0.243$ ,  $p = 0.810$  for section A and  $t(28) = -0.929$ ,  $p = 0.361$  for Section B. These paired t-test analyses indicate that both sections were not associated with statistical change in motivation mean scores during the time period between the pre-ATMI survey and post ATMI survey. Both sections had similar entering motivation level towards mathematics in the beginning of the semester and again during the second administration of the ATMI survey. Pre-motivation means, post motivation means, and motivation change means are presented in the table below by class type.

Table 7. Pre-motivation Means, Post Motivation Means, and Motivation change by Class Type

<b>Class Type</b>	<b>Pre-motivation Mean</b>	<b>Post Motivation Mean</b>	<b>Motivation Change</b>
Section A ( $N = 27$ )	14.000 ( $SD = 4.7878$ )	14.222 ( $SD = 4.6021$ )	0.2222 ( $SD = 4.75017$ )
Section B ( $N = 29$ )	14.931 ( $SD = 4.7203$ )	15.517 ( $SD = 5.0471$ )	0.5862 ( $SD = 3.39661$ )

#### ATMI Results Summary

From the above analyses, attitudinal scores towards mathematics were similar between both class types in the beginning of the semester and were similar during the second administration of the ATMI survey. In addition, the dependent paired t-test analyses revealed that there were no significant change in students' attitude between the beginning of the semester and at the end of the unit about functions for both class types, which was about eight weeks into the semester. Similar results were found for all four sub-factors of attitudes towards mathematics for both class types. Self-confidence, value, enjoyment, and motivation scores were similar in the beginning of the semester and again during the second administration of the ATMI survey. In addition, paired

t-test analyses revealed no significant changes in students' sub-factors attitude scores between the beginning of the semester and at the end of the unit about functions by class types.

### Results of Research Question Three

*Is there a stronger correlation between students' level of mastery learning (as reported by their respective software) vs. actual learning as a function of instructional approach (traditional vs. self-adaptive)?*

This research question is focused on the relationship between students' mastery level of learning and their actual learning. Students' mastery level of learning is operationally defined as their earned homework grade for the topic of functions as reported by the respective math software. Actual learning is operationally defined as the actual earned grade on the post-test for functions. The purpose was to determine relationships between these two variables and the extent of this relationship. In addition, a comparison of this relationship by class type might reveal if this relationship is stronger for one instructional approach versus the other. The relationship between students' level of mastery learning and actual learning was analyzed through two Pearson product-moment correlation coefficients by class type. There was positive correlation between students' level of mastery learning and their actual learning for Section A,  $r(27) = 0.84$ ,  $p < 0.01$  and  $r(29) = 0.56$ ,  $p < 0.01$  for Section B. These correlational analyses reveal a positive correlation between the students' level of mastery and actual learning for each class type with Section A have a stronger correlation than Section B. Using the Fisher  $r$ -to- $z$  transformation, the  $z$ -value = 2.08, corresponding  $p < 0.05$ , which shows that the difference

between these two correlation coefficients is statistically different. This means that students' homework grades are strongly correlated to their exam grade with a stronger relationship existing for the self-adaptive approach. This indicates that it is possible for the self-adaptive features of math software to more accurately represent students' learned knowledge. It is important to note that no causality can be concluded from a Pearson product-moment correlation coefficient.

Table 8. Pearson Product-moment Correlations between Mastery Learning and Actual Learning by Class Type

<b>Class Type</b>	<b>Correlation Coefficient</b>
Section A ( $N = 27$ )	0.84**
Section B ( $N = 29$ )	0.56**

*Note.* \*\*  $p < 0.01$  (2-tailed)

### Summary

This research study compared an adaptive and a traditional instructional approach in College Algebra. Three research questions were posed to explore and compare these two instructional approaches. The first question focused on learning gains between the pre-test and post-test on the topic of functions in College Algebra. The second research question focused on attitudinal changes between both administrations of the ATMI. In addition, the ATMI measured four sub-factors of attitude: self-confidence, value, enjoyment, and motivation. The third research question analyzed and compared Pearson moment-product correlation coefficients between students' mastery learning levels and their actual learning levels for each instructional

approach and between both instructional approaches. Students mastery learning levels was operationally defined as students' homework score as reported by the software. Actual learning level was operationally defined as students' post-test score on functions.

From the above analyses, students in both instructional approaches had similar entering knowledge about the topic of functions as indicated by independent t-tests on the pre-test. In addition, students in both instructional approaches had similar learned knowledge about functions as indicated by independent t-tests on the post-test. Similarly, students in both instructional approaches had similar learning gains. However, paired dependent sample t-tests revealed that learning gains were significant between the pre-test and post-test for each instructional approach.

In addition to the analyses on learning gains, students in both instructional approaches had similar entering attitudes and similar attitudes during the second administration of the ATMI. Furthermore, there was no significant attitude change between both administrations of the ATMI as measured by dependent sample t-test for each instructional approach. In addition, similar results were found for each of the four sub-factors. Students in both instructional approaches had similar self-confidence, value, enjoyment, and motivation scores for both administrations of the ATMI. Changes were negligible for self-confidence, value, and motivation. For enjoyment, the adaptive instructional approach experienced a 2.07 points increase while the traditional instructional approach experienced a negligible decrease. Even though enjoyment increased more for the adaptive instructional approach, this was not statistical significant.

The last research question calculated Pearson moment-product correlation coefficients between students' mastery learning level and their actual learning level for each instructional approach. The correlation coefficient for the adaptive instructional approach  $r(27) = 0.84$  and  $r(29) = 0.56$  for the traditional instructional approach. Both correlation coefficients were statistically significant,  $p < 0.001$ , but an  $r$ -to- $z$  Fisher transformation revealed that the correlation coefficient for the adaptive instructional approach was statistically significantly higher than the traditional instructional approach.

Overall, both instructional approaches were found to be equivalent in terms of learning gains and attitudinal changes. Both instructional approaches experienced equivalent learning gains. However, attitude did not change holistically or on any of the four sub-factors for both instructional approaches. Moreover, the correlational analyses suggest that the adaptive instructional approach might be more accurate in assessing students' true knowledge state and learning. Chapter five will include a discussion of the results along with conclusions. In addition, implications and suggestions for future studies will also be included.

## CHAPTER FIVE: CONCLUSION

### Overview

This research effort compared a traditional mode of instruction to a self-adaptive mode of instruction that used artificial intelligence. The traditional approach used MyMathLab as the supplemental software while the adaptive approach used ALEKS as the supplemental software. ALEKS was chosen for the self-adaptive approach since ALEKS was built around the premise of self-adaptive instruction using Knowledge Space Theory. ALEKS used the student's current knowledge state to adjust their learning goals and homework assignments. Both software systems had similar content for the unit of functions, but utilized different approaches for assignments. Two sections of College Algebra taught at a central Florida state college were compared in terms of students' gains in learning in the topic of functions, attitudinal gains holistically and by each of the four sub-factors as measured by the ATMI. The four sub-factors for attitude are self-confidence, value, enjoyment, and motivation. In addition, there was a comparison between students' level of mastery learning versus their actual learning level. Students' level of mastery learning was operationally defined as their homework score on the topic of functions as assigned by the respective software. Students' actual learning level was operationally defined as their post-test scores on functions. There were three research questions analyzed for this study.

The first research question compared learning gains between both sections based on a pre-test and post-test for the unit of functions. Independent t-test analyses were performed using SPSS on the pre-test, post-test, and learning gains. Learning gains were computed by subtracting

the pre-test score from the post-test score. The second research question compared attitudinal growth between both sections as measured by the ATMI. In addition, the ATMI provided scores for four sub-factors of students' overall attitude in self-confidence, value, motivation, and enjoyment. Independent t-test analyses were performed on students' entering attitudes, attitude after the completion on the function post-test, and changes in attitude using SPSS. The same t-test analyses were performed for each of the four sub-factors: self-confidence, value, enjoyment, and motivation. The third research question focused on correlational analysis between students' mastery level of learning as reported on the software versus actual level of learning, as measured on the post-test on the unit of functions. Pearson product-moment correlational analyses were performed to find if there was a significant relationship between students' mastery level of learning versus their actual level of learning for each class type. In addition, an *r*-to-*z* Fisher transformation was computed to measure for statistical significant difference between the two correlation coefficient between the two sections of College Algebra.

#### Assumptions, Delimitations, and Limitations of the Study

Several assumptions were made in this study. Specifically, students enrolled in both sections of College Algebra were computer literate and would be generally comfortable with the CAI software used. The researcher assumed that three weeks of acclimation to the software would allow enough time for participants to be proficient in the use of their respective CAI software. Participants in this study were assumed to be representative of both student population taking College Algebra found in state community colleges and in particular, representative of the



student population at Valencia College. It was also assumed that students placed into College Algebra was placed correctly by the PERT test or met the college's requirements to take College Algebra, based on alternative methods such as SAT or ACT scores or a review of a student's transcript showing that the minimum prerequisite requirements were met for College Algebra. The PERT test, SAT, ACT, and/or review of transcript are assumed to be valid and reliable methods for placing students into College Algebra. Pre-test and post-test were generated from TestGen software by Pearson. The questions selected for the topics of functions are assumed to be valid and reliable measure of their intended objective(s).

The scope of this study is narrow and focuses on learning gains and attitude changes based on quantitative measures only (Pre-Test scores, Post test scores, ATMI, and mastery scores as reported by the software). In addition, this study is delimited to measuring learning gains and attitudinal change between 2 sections of College Algebra measured by the change between pre-test and post-test and ATMI scores and sub-scores over a short, specific moment in time. It is delimited to community college students placed into College Algebra enrolled in a public, state college and placed into College Algebra by standardized placement test scores or by meeting prerequisites requirements as noted on students' transcript from other institutions or high school.

There were several limitations in this study. The first limitation was that the sample was nonrandom since students were able to self-select their College Algebra section. The sample size was limited to a total of 56 students (27 for traditional lecture approach and 29 for self-adaptive instructional approach). All participants were students enrolled at Valencia College in Central Florida, which limits generalizability to other community colleges in other geographic

areas as well as four-year colleges and universities. Another major limitation is that this study analyzed and compared only two instructional approaches with two popular CAI packages. This study did not analyze multiple adaptive software systems and was limited to the format and capabilities of ALEKS for the self-adaptive instructional approach. This study took place over a short period of time and focused on one unit topic in College Algebra. Furthermore, software format and modality was another limitation in this study. Although the course content and concepts were the same for both sections, with the same pre-test and post-test for the unit of functions; the mastery score as reported on the software were not reported in the same way for both sections. Homework scores were collected from both CAI software packages on the unit of functions, but the problems were not identical due to the adaptive features of ALEKS. In addition, a student's mastery score could actually decrease in ALEKS if a random assessment determined loss of mastery while a homework score in MyMathLab was based on accuracy of answering homework problems with no adjustments made later for the student's current knowledge state. The researcher recorded mastery scores as reported by ALEKS and MyMathLab on the unit homework with no adjustments. Finally, the lack of a randomized assignment of students to instructional approaches precludes definitive conclusions about the extent to which instructional approach may be causally linked to learning gains and attitude changes. The fact that the study design relies on the use of convenience samples in which all students enrolled in one of two College Algebra sections were assigned an instructional approach in a non-random manner places limits on the generalizability of results from this study. The use of non-random samples may result in biased estimates in which the magnitude of bias is

unknown. Thus, caution should be used in drawing conclusions about student groups beyond the scope of this study. Results are limited to providing insight and preliminary findings about the use of a self-adaptive instructional approach in College Algebra compared to a traditional approach using two different CAI math software systems for community college students. In addition, the analysis of self-adaptive instruction was limited to only one math software system in a face-to-face modality only. Other modalities, such as on-line or hybrid, were not considered. If other modalities were used, the results of this study could be different.

Knowledge of computer skills and previous experience with the respective software were not examined. Since MyMathLab is the default software used in previous math courses on the instructor's campus, students entering College Algebra from Intermediate Algebra had an advantage in the traditional section. Since ALEKS was a pilot software system for the purpose of this research effort and is not used in developmental mathematics courses on the instructor's campus, students entering the self-adaptive section of College Algebra might have had a greater learning curve compared to those students in the traditional section. Even though a few weeks to learn and become acclimated with the software was provided for both sections before data collection (pre-test and post-test on Functions), students' previous experience with their respective software could have biased their attitude towards the instructional approach adopted for their section. Students' comfort with the software could have influenced their performance in the chosen unit and in the course.

Finally, the self-adaptive feature in ALEKS was another limitation in this study. The artificial intelligence engine in ALEKS was developed based on Knowledge Space Theory and

provides homework based on the student's knowledge as measured by random assessments. A student's learning pie constantly adjusts and changes based on mastery of topics and re-assessment. However, the software did not adjust based on students' level of frustration or emotional state. Sottiliare and Proctor (2012) state that there is a need for tutors (ITS or humans) to be able to perceive and address the student's current affective state. Self-reported measures of affect could be biased based on the fact that students may not report their true affective state to conform to instructor's expectations (Sottiliare & Proctor, 2012). With an understanding of the student's affective state in addition to the student's knowledge state, ITS can select instructional strategies to optimize the learning experience (Sottiliare & Proctor, 2012). Future recommendations for future studies based on the listed limitations of this study are discussed later in this chapter.

### Discussion and Conclusions

For the first research question, there was no statistical difference found between the pre-test scores, post-test scores, or for learning gains as revealed by independent t-test analyses. These results indicate that both sections had similar entering knowledge about functions and that both sections had similar learning gains. Dependent paired t-test analyses for each class type were significant, an indication that both sections had significant learning gains between the pre-test and post-test on functions. A possible explanation for the reason behind both instructional approaches having similar learning gains might be due to the fact that college students tend to be more self-regulated learners (Blair, 2006). Both sections were face-to-face sections that met

three times weekly for a full semester, which made on campus tutoring and visiting the instructor during office hours more accessible. Therefore, students in the traditional section could have receiving scaffolding and extra assistance outside of their respective software as needed. The finding from this research question is in support of Spradlin and Ackerman's study (2010). Spradlin and Ackerman (2010) found that a traditional instructional approach for teaching Intermediate Algebra is equivalent to an instructional approach with CAI. Students in the traditional section of Intermediate Algebra of Spradlin and Ackerman's study had outside access to the instructor during officer hours and to tutors in a math lab. In the future, it would be interesting to note the time students spend seeking outside help from the instructor, math tutors, or other college resources to determine whether an instructional approach save students time from additional assistance or tutoring.

Another possible explanation for the result of this finding may be due to the instructional design of each section. For the traditional lecture section with CAI, the instructor designed homework assignments in MyMathLab that would provide for some scaffolding and review of important concepts for each unit. The scaffolding and review provided by the homework assignment set by the instructor in MyMathLab was a one-size-fit all approach, but the results of this study seems to suggest that this was equal to an adaptive assignment that would adjust according to the student's level of scaffolding that was needed. If the instructor just assigned problems relevant to the objective of functions without any provision of pre-requisite review problems, then it could have changed the results for this research question, possibly in favor of the adaptive instructional approach. However, not providing pre-requisite problems would not be

effective teaching practice. In conclusion, the adaptive approach may not provide additional benefits in terms of learning gains for the face-to-face courses due to students' access to on campus tutoring or to the instructor during on campus office hours. This type of access might have provided the additional scaffolding support that was needed.

Several studies have shown that CAI is an effective supplement in terms of learning and affect compared to traditional lecture alone (Fine, Duggan, & Braddy, 2009; Taylor, 2008; Xu, Meyer, & Morgan, 2008). Some studies examined MyMathLab compared to lecture alone while other studies examined ALEKS compared to lecture alone. Few studies have compared different CAI math software approaches (e.g. Moosavi, 2009), but no study to date has compared two instructional approaches with CAI math software, where one software utilized artificial intelligence. In Moosavi's study, which compared Thinkwell and MyMathLab (similar software), the two CAIs were found to be equivalent in terms of student performance on examinations. In Moosavi's study (2009), the two CAI courses were online and were compared to a traditional lecture class. Moosavi found that students in pre-calculus algebra had greater math achievements as measured on two exams and the final exams compared to students in a CAI section. Moosavi's ANOVA analysis revealed no statistical differences between the 2 CAI instructional methods. This current study is in support of Moosavi's findings, where there were no statistical difference found between students' learning gains between the two instructional approaches using CAI.

For the second research question, students in both sections had similar mean scores on the pre-ATMI, post-ATMI, and similar changes in attitude. There were no statistical differences

in attitudinal changes between both sections. In fact, both sections had similar attitude scores in the beginning of the semester and at the end of the unit, as measured by the ATMI. The same results were found for each of the 4 ATMI sub-factors (self-confidence, value, motivation, and enjoyment). An explanation for these results may be due to the fact that both instructional math software systems would not necessarily designed to improve student affect. This simple explanation could account for why there was no significant change in student affect holistically or in any of the four sub-factors. Another possible explanation for the results for this research question may simply be that the time period for attitudes to change was just too short. If this study was conducted with these two instructional approaches over a longer period of time or with multiple, sequential math courses, a difference in attitude might be discovered. For example, the adaptive section in this study experienced a slight increase of roughly 4% in enjoyment. Even though the increase for enjoyment was not statistical significant, it is possible for enjoyment and other attitudinal factors to have increased if studied over a longer period of time. However, it is important to note that the increase for enjoyment might be due to a few students marking a few questions higher than the first administration of the ATMI. This increase in enjoyment may not be really a true increase or change. Therefore, there were no significant changes for attitude for both instructional approaches. Moreover, Dalton and Hannafin (1988) had a similar finding for students' attitude. Even though differences were found for the CAI group, post-attitude scores after adjusting for entering attitudinal behavior were statistically equivalent. Therefore, Dalton and Hannafin (1988) concluded that initial positive attitude changes might be due to novelty rather than the computer's capabilities. In addition, Dalton and Hannafin (1988) reported that

students in their study were computer literate and have had substantially more computer exposure than students in previous studies. Furthermore, Dalton and Hannafin (1988) concluded that it was possible that students in their study were less susceptible to the influence of novelty on their attitudinal scores. In this current research study, it is possible that novelty was not an influencing factor due to students' everyday exposure to technology such as smart phones and tablets. Students' attitude scores in this study could be truly associated with their perceived mathematics ability as noted in Nunez-Pena, Suarez-Pellicioni and Bono's study (2013). In this current study, attitude did not change much holistically or in terms of the four sub-factors for each instructional approach. Furthermore, students' attitudinal scores were equivalent for both administration of the ATMI for each instructional approach.

The findings in this study suggest that a self-adaptive instructional approach utilizing a math software system with artificial intelligence may not offer any greater benefits in terms of attitudinal changes compared to a traditional instructional approach utilizing a math software system without using artificial intelligence. The findings in this study regarding attitudinal changes are in contrast to Pilli and Aksu's study (2013). In their study, the group of students in the CAI experimental group had statistically significant greater attitudinal gains as measured by the Mathematics Attitude Scale scores. Furthermore, students were able to retain learned skills over a four month period. A goal of educators, administrators, and decision makers is to improve students' attitude in mathematics (Nunez-Pena, Suarez-Pellicioni, & Bono, 2013; Tapia & Marsh, 1996). At the very least, using a specific instructional approach should not negatively impact students' attitudes. This study compared two varying instructional approaches with CAI.



The results of this study indicate that both instructional approaches did not have a negative impact on students' attitudes.

For the third research question, correlational analyses revealed a strong relationship between students' mastery level of learning and their actual level of learning for each instructional approach. An *r*-to-*z* Fisher transformation revealed that this relationship was stronger for the self-adaptive approach. This result indicates that the homework scores reported by ALEKS may be more representative of student's true knowledge state, since ALEKS is constantly updated a student's current knowledge state through random assessments. In addition, ALEKS does not mark a homework problem as correct until the student has successfully answered similar homework problems three times in a row without any assistance. Therefore, it is possible that correlation was higher in favor of the adaptive instructional approach due to the number of problems and frequency of assessments by ALEKS. For example, students may have completed more homework problems in ALEKS compared to MyMathLab. Moreover, ALEKS provided random assessments and adjusted the types and numbers of problems based on the results of the random assessments. In contrast, students immediately received credit in MyMathLab after getting a problem correct once (with or without assistance). A change in settings in MyMathLab where students had to get the homework problems correct without any assistance is possible, but this has to be manually set by the instructor. This could change the results of this research question or time spent completing homework on the software. Using the Knewton Theory setting in MyMathLab compared to the Knowledge Space Theory in ALEKS could also yield different results. In this current study, the time spent doing homework in the

respective software systems were similar for both class sections with no statistical difference as revealed by independent t-test analyses. The differences between time spent in the software systems could be affected if any of the changes mentioned previously were made.

### Implications

This study compared two instructional approaches, with one being a self-adaptive approach using ALEKS. The implications in this study for educator, administrators, software developers, and other stakeholders is focused on proper instructional planning, mitigating entering negative attitudes towards mathematics, and the use of assessment to help make decisions and to help students. In this study, no significant differences were found for learning gains between the two sections of College Algebra. It appears that since the instructional approach and the software systems were in sync with appropriate planning led to both sections having similar learning gains between the pre-test and the post-test. For example, since MyMathLab does not automatically offer prerequisite math problems as needed. Therefore, the instructor added some review and prerequisite problems that were pertinent to the current objective. Another example was that the instructor adjusted class lessons for the self-adaptive section based on reports of what students have mastered and what they are “ready to learn” as reported in ALEKS. The instructor was able to cater the lesson to the content that students were struggling with.

Many instructional approaches might utilize the use of technology or CAI as a supplement, but the focus should remain on the instructional approach, not on the software

system. According to Hirumi (2002), appropriate needs analysis and instructional planning is imperative for a student-centered learning environment to be optimal. Educators and administrators should select instructional software or technology that best matches a respective instructional approach. Proper planning of providing prerequisite problems for the traditional instructional approach led to learning gains being equivalent for both instructional approaches. This study confirms that no significant differences exist between a traditional instructional approach with CAI and a self-adaptive approach when properly planned and designed. In Hagerty, Smith, and Goodwin's study (2010), for example, College Algebra was redesigned. Even though the implementation of CAI was a fundamental component, the redesign effort included more discussion, application problems, interactive activities, and training for faculty. This multi-faceted approach led to a 21% improvement in pass rates for College Algebra for their study.

Another goal of this study was to investigate and compare attitudinal changes between both instructional approaches investigated. This study found no statistical significant differences between attitudinal changes between both instructional approaches. Furthermore, there were no statistical significant differences found for each of the four sub-factors (self-confidence, value, enjoyment, and motivation). Moreover, dependent sample t-test analyses indicated that there were no significant changes in attitude for each instructional approach. Each of the four sub-factors had similar results as the holistic attitudinal change for each instructional approach. Research has shown that there is an association between student achievement in mathematics and their attitude towards mathematics. For example, Cates and Rhymer (2003) found that math

anxiety was lower for students who could fluently perform math operations. Additionally, Nunez-Pena, Pollicioni, and Bono (2013) found that students with less math anxiety were associated with greater mathematic achievement and high self-confidence. Educators should use instructional strategies that mitigate students' entering attitude towards mathematics. Such strategies could include more collaborative projects, discussion, and more student-to-instructor interactions. In addition, software developers may want to design intelligent tutoring systems that measure student affect and adjust instructional strategies based on a student's current affect (Sottilaire & Proctor, 2012). In this particular study, both math software systems utilized were not necessarily designed to improve student affect. Tracking and utilizing student affect in addition to students' current knowledge state could enhance the student learning experience (Sottilaire & Proctor, 2012).

A third goal of this study was to compare the correlation coefficients between student mastery learning levels and their actual learning levels between both instructional approaches. The correlation for each instructional approach indicated a strong, positive association between students' mastery learning levels as reported by the software and their actual learning levels as measured by students' post-test scores on the topic of functions. Using an *r-to-z* Fisher transformation test, this association was stronger in favor of the adaptive instructional approach. This result indicate that intelligent tutoring systems might have a greater potential in more accurately reporting students' current knowledge state. This information would provide for more effective formative feedback that can be used by instructors to offer more specific assistance students, to modify lesson plans to focus on struggling concepts, or to help students make

informed decisions regarding their math knowledge. Perhaps, intelligent tutoring systems could be used as an “in-house” diagnostic tool and help make recommendations for placement or necessary remediation. In addition, software developers could focus on enhancing the tracking and monitoring of students’ knowledge state. However, these findings are preliminary in nature and more research is needed to determine the effect in which intelligent tutoring systems more accurately tracks and represents students’ knowledge state.

As student population grows with limited resources and a reduction in remedial math courses at the community college level, CAI can help students learn and review prerequisite skills for entering College Algebra students. Research has shown that CAI is more effective to use than lecture alone. In addition, CAI can provide students with more resources, practice, and immediate feedback (Twigg, 2013). Intelligent tutoring systems has a high potential to individualize and personalize the learning experience for students, but more development is still needed for it to reach its full potential. Intelligent tutoring systems can definitely provide students with instruction and feedback in a distance education environment when access to an instructor is limited. However, a human element stills makes a greater difference than the use of CAI math software systems alone. Math software systems that can report more accurate information regarding student learning can help professors and administrators.

CAI math software has become a regular supplement in many community and state colleges. Moosavi (2009) concluded that CAI methods should be learning tools “to promote higher-level cognitive activities” to result in greater student performance. Artificial intelligence provides an opportunity for individualized learning that can help promote higher level cognitive

activities through inquiry and constantly adapting to a student's level of learning. Development of math software with enhanced artificial intelligence that takes students' affect into consideration can help change students' overall attitude positively, which could impact student learning and performance. As promising as artificial intelligence can be, it should not be viewed as a substitute for human interaction and motivational advantages that a trained educator can bring into the learning environment (Moosavi, 2009). CAI math software should be chosen based on pedagogical design and delivery of a math course to be used as a supplemental resource to enhance the learning experience. Moosavi (2009) in his study reports that face-to-face pre-calculus algebra sections performed significantly better on assessments compared to CAI on-line sections. "Traditional instruction [(face-to-face)] contains a human element of student-teacher interaction not easily replicated in CAI. The teacher is able to impart enthusiasm, motivation, recognize students' struggles, and intervene appropriately" (Moosavi, 2009, p. 56). Furthermore, Spradlin and Ackerman (2010) points that a traditional instructional approach without CAI can yield positive learning results if enhanced with active learning activities such as cooperative learning, more class discussions, more relevant applications, and the use of peer tutoring. Therefore, it is important to consider the instructional approach in conjunction with CAI. Recommendations for future studies and developments are provided in the next section.

### Recommendations

There are several recommendations that would enhance or expand on this current study. Due to the limitations and delimitations in this study, future studies could more effectively

examine the results obtained from this study. This research study was quantitative in nature. The researcher recommends a qualitative study or a hybrid study in the future. The instructor received informal, verbal feedback from students about the self-adaptive approach to College Algebra. Some participants reported frustration and anxiety with the self-adaptive software. Others reported that the self-adaptive approach forced them to learn and master the concepts. Unfortunately, this data was not formally collected and could enhance this study by providing more insight into students' affect. Snodin (2013) states that "including qualitative instruments could be vital to providing a clearer, more complete picture of research findings" (p. 212).

Several issues that were beyond the scope of this current study on self-adaptive instruction in College Algebra might be of interest for future studies. Variables considered beyond the scope of this study included student use of tutors and other college resources outside of class, students' time spent for tutoring, or time spent in the math lab. It might be of interest to investigate students' time spent on tutoring, students' success in subsequent math courses, or gain students' insight through the use of journaling. Other future recommendations include comparison of other modes of instruction such as hybrid or on-line courses and analyses of other self-adaptive math software such as using the Knewton Theory in MyMathLab. The researcher of this current study also recommends a replication of this study using one software system for both sections where the setting can be changed to self-adaptive for the treatment group. This option was not available at the time of this study, but this feature has recently become an option some math software have been updated to incorporate more instructional modality choices. For example, MyMathLab provides such an option with self-adaptive assignments and paths based

on Knewton Theory (Pearson, n.d.). Another recommendation is to compare two self-adaptive instructional approaches for both software (MyMathLab and ALEKS) with a focus on comparing Knowledge Space Theory versus the Knewton Theory to see if one is more effective in terms of learning gains and attitudinal gains in College Algebra as well as correlational comparison between students' level of mastery learning versus their actual learning level.

Focusing on more College Algebra sections over a longer period of time during the semester could enhance this research design. In addition, focusing on other mathematics topics and concepts would also provide more information and insight. Another recommendation would be to replicate this study for Intermediate Algebra since Intermediate Algebra does not have any required prerequisite requirements. Intermediate Algebra would probably have entering students with diverse backgrounds in mathematics. It is possible that a self-adaptive instructional approach would help students with deficient backgrounds to remediate on missing mathematical skills. In addition, this study could be replicated for developmental mathematics. Since students learn at different pace and each student may have differing individual needs, a self-adaptive instructional approach with intelligent tutoring could provide students with the necessary remediation efficiently. Moreover, another recommendation for future studies would be to compare two different types of ITS where one perceived and adapted to student affect in a developmental or college-level math course. The ability to sense and predict emotions such as boredom, pleasure, or frustration would expand ITS's capabilities to optimize student learning and performance (Sottiliare & Proctor, 2012). As this feature develops for mainstream college math software, this can become a feasible future study.



This study found a significantly higher correlation coefficient in favor of the self-adaptive instructional approach between students' mastery learning level and actual learning level. However, the higher correlation coefficient could be the result of more homework problems or the frequency of assessments in ALEKS. Therefore, further analysis is recommended to investigate the extent to which this relationship exists. In addition, this relationship should be explored and compared for other math courses and for other student population.

The researcher suggests that this study be replicated with two on-line or hybrid sections. Under these two instructional approaches (on-line and hybrid), students may become more dependent on the software for scaffolding. Another recommendation is to replicate this study with self-adaptive software for students in K -12. Younger students are still developing their ability to self-regulate their learning. A difference could be discovered between the two instructional techniques with younger students. For example, younger students may not always know what they need assistance with, what they have to learn, or if they have mastered the topic. An adaptive instructional approach paired with intelligent CAI, such as ALEKS, could help regulate younger students' learning.

Ultimately, more research (quantitative and qualitative) is needed in the area of intellectual tutoring software for math and its impact on student learning and affect. The most effective approach is one that is well planned. Artificial intelligence is not the sole solution for providing students with effective instruction and tutoring. However, intelligent tutoring systems hold a high potential for making a difference for student learning in higher education as enrollment increases in community colleges with limited resources. As the demand for on-line

courses and distance education increases, the quality of on-line instruction with limited access to campus resources could be enhanced with intelligent tutoring systems.

## **APPENDIX A: P.E.R.T. MATH SAMPLE**

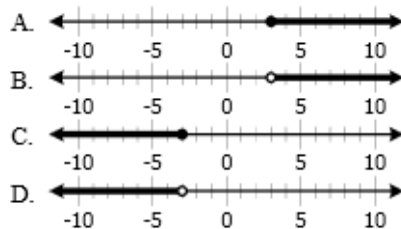
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**Math Sample Questions:**

1. Which of the following is a solution to the equation  $c + (4 - 3c) - 2 = 0$ ?

- A. -1
- B. 0
- C. 1
- D. 2

2. Graph the solution of  $y - 2 > 1$  on a number line.



3. Which of the following is a solution to the equation  $x^2 - 6x + 5 = 0$ ?

- A.  $x = -5$
- B.  $x = -1$
- C.  $x = \frac{1}{5}$
- D.  $x = 5$

4. What is the value of the algebraic expression if  $x = \frac{1}{2}$ ,  $y = -1$ , and  $z = 2$ ?

$$6x(y^2z)$$

- A. -12
- B. -6
- C. 1
- D. 6

5. Which of the following is equivalent to  $(8 - 5) \div 2^3$ ?

- A.  $\frac{3}{8}$
- B.  $\frac{19}{8}$
- C.  $\frac{27}{8}$
- D.  $\frac{1}{125}$

6. Factor completely:

$$x^2 - x - 6?$$

- A.  $(x - 2)(x + 3)$
- B.  $(x - 1)(x - 6)$
- C.  $(x + 2)(x - 3)$
- D.  $(x + 1)(x - 6)$

7. Simplify the following expression:

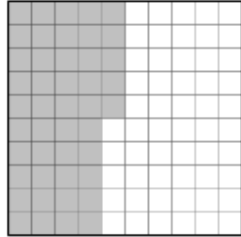
$$\frac{3x^4y^2}{xy^2}$$

- A.  $3x^3$
- B.  $3x^2y$
- C.  $3x^4y$
- D.  $\frac{3x^3y}{xy}$

8. Which of the following is equivalent to the expression  $(3ab)(-5ab)$ ?

- A.  $-2ab$
- B.  $-2a^2b^2$
- C.  $-15ab$
- D.  $-15a^2b^2$

9. What percent of the grid is shaded?



- A. 35%
- B. 40%
- C. 45%
- D. 55%

10. Which of the following is the equation of a line that passes through  $(-2, -1)$  and  $(-4, -3)$ ?

- A.  $y = \frac{1}{2}x + 1$
- B.  $y = x + 1$
- C.  $y = \frac{1}{2}x - 1$
- D.  $y = x - 1$

McCann Associates, 2011. Retrieved from

<http://www.fldoe.org/schools/pdf/PERT-studentstudyguide.pdf> on October 7,

2014.

## **APPENDIX B: COLLEGE COURSE OUTLINE AND DESCRIPTION**

## Major Topics/ Concepts/ Skills/ Issues

- Linear, Quadratic and Rational Functions
- Exponential and Logarithmic Properties, Functions and Equations
- Functions and Function Notation
- Graphs of Functions and Relations
- Systems of Equations and Inequalities
- Domains and Ranges of Functions
- Operations on Functions
- Inverse Functions
- Absolute Value and Radical Functions
- Applications (such as Curve Fitting, Modeling, Optimization, and Exponential Growth and Decay)

### Major Learning Outcomes with Corresponding Evidence of Learning

- A. Read and comprehend quantitative information describing real world situations at the college algebra level.
  - Use mathematical reasoning and common sense to evaluate answers as being possibly correct or definitely wrong. Complete a sequence of steps to a problem, and decide whether or not the answer is reasonable and logically support your conclusion.
  - Given a real-world situation described in words, answer comprehension questions based on the quantitative content in the reading.
- B. Use algebra to model real world situations.
  - Given a set of data, determine an appropriate function that models the data, and use that function to make predictions.
  - Given a real-world problem, model it using the appropriate tools, including algebraic equations or inequalities, a table of values, a graph, or a diagram. Use the model to solve the problem and interpret the results.
- C. Recognize the mathematical function concept and describe relationships between variables in real world situations. Use functions expressed verbally, numerically, graphically, and symbolically.
  - Given a functional expression, evaluate and interpret the expression in the context of an applied problem.
  - Given a function determine the domain and range.
  - Recognize the characteristics common to families of functions.
  - Demonstrate and explain how the inverse function can be used to reverse the roles of the independent and dependent variables.
  - Perform function operations including composition.



- D. Given the graph of a function, write its algebraic equation. Given an algebraic equation of a function, graph the function or a transformation of the function.
- Given the graph of a line, write an algebraic expression for the linear function.
  - Given the graph of a parabola which shows the vertex and another point, write an algebraic expression for the quadratic function.
  - Given the graph of an exponential function which shows the y-intercept and one other point, write an algebraic expression for the function.
  - Given the graph of a polynomial function that has only real roots, write a factored algebraic expression for the function.
  - Sketch basic graphs, including absolute value, radical, rational, piecewise, and power functions, and demonstrate how to transform them.
  - Recognize whether or not a given function increases or decreases, and model the behavior graphically.
- E. Recognize, model, and analyze linear functions in real world situations.
- Given a real-world problem about a quantity that changes at a constant rate and an initial value, write a linear function that models the quantity. Additionally, use the function and its graph to answer questions. The student should be able to write the function without using linear regression.
  - Given a real-world problem that gives at least two pairs of corresponding values for two variables that are linearly related, write a linear function that models the problem. Additionally, use the function and its graph to answer questions. The student should be able to write the function without using linear regression.
- F. Recognize, model, and analyze quadratic functions in real world situations.
- Given a real-world problem that is represented by a quadratic function, use the function and its graph to answer questions about corresponding values, the maximum or minimum value, and ranges of values (inequality).
  - Given a real-world problem that can be modeled by a quadratic function, find the equation of the function. The student should be able to write the function without using regression.
- G. Recognize, model, and analyze exponential and logarithmic functions in real world situations.
- Given a real-world problem that can be modeled by an exponential function, find the equation of the function. Additionally, use the function and its graph to answer questions. The student should be able to write the function without using regression.
  - Demonstrate the use of the definition and properties of logarithms to solve exponential equations.
- H. Given several concurrent quantitative conditions, express each condition algebraically, and find all possible solutions of the resulting system.
- Solve and graph a system of two equations in two variables and interpret the results.

- Solve and graph a system of inequalities in two variables and interpret the results.

**Obtained from Valencia's College Curriculum Committee website on October 7, 2014.  
Course objectives and corresponding evidence of learning is current as of April, 2014.**

## **APPENDIX C: SAMPLE SYLLABUS**

## Valencia College – WEST Campus

College General Phone: (407)-299-5000 College Website: [www.valenciacollege.edu](http://www.valenciacollege.edu)

### SYLLABUS – MAC 1105 (College Algebra) – Spring 2015

CRN 20124: Class - M/W/F 9:00 – 9:50 AM (Bd. 7, Room 233)

CRN 20125: Class - M/W/F 10:00 – 10:50 AM (Bd. 7, Room 233)

#### Instructor's Contact Information & Office Hours:

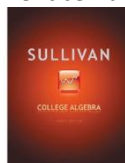
<b>Instructor:</b> Ryan Kasha, Ed.S. <b>E-mail:</b> <a href="mailto:rkasha@mail.valenciacollege.edu">rkasha@mail.valenciacollege.edu</a> <b>Math Lab and Tutoring/Phone:</b> Bldg. 7, Room 241/ (407)-582-1720 OR (407)-582-1780 OR (407)-582-1633 <b>Math Dept. Location/Phone:</b> Bldg. 7, Room 108/ (407)-582-1625 OR (407)-582-1848 <b>Office Hours:</b> Mon./Wed.: 11:00 AM – 1:00 PM; Tues./Thurs.: 8:45 AM – 10:00 AM; 11:45 AM – 12:45 PM Friday: 11:00 AM – 12:00 PM <b><i>I have an open door policy. I am also available by appointment. I am easy to find: Look for me in my office or Math Lab!</i></b>	<b>Office/Phone:</b> Bldg. 5, Room 247/ (407)-582-1475 <b>Instructor's website:</b> <a href="http://frontdoor.valenciacollege.edu/?rkasha">frontdoor.valenciacollege.edu/?rkasha</a>
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**Prerequisite:** MAT 1033 with a grade of “C” or higher; appropriate score on placement test; or placement by math department.

**Course Description/Topics:** This course is based on the study of functions and their role in problem solving. Topics include graphing, the linear, quadratic, and exponential families of functions, and inverse functions. Students will be required to solve applied problems and communicate their findings effectively. Technology tools will be utilized in addition to analytical methods. This is a Gordon Rule course requiring a minimum grade of C if MAC 1105 is used to satisfy Gordon Rule and general education requirements. Credit not given for both MAC 1105 and MAC 1102 nor for MAC 1105 and MAC 1104 nor for MAC 1105 and MAC 1132. If you have any questions regarding your math requirements, please see your advisor for further information. Your major and course of study may have different graduation requirements. **Credit Hours: 3**

#### **Required Course Materials:**

**Textbook:** *College Algebra* by Sullivan, 9<sup>th</sup> edition: Prentice Hall (Pearson), 2012. ISBN: 9780321716903



**Software:** MyMathLab Access Code/Kit (Included with new textbook purchase or can be purchased separately). MyMathLab access can also be purchased on-line from [www.mymathlab.com](http://www.mymathlab.com). Students are given a 17-day grace period before payment is required. Student repeating this course from last semester that have previously paid for access on the West Campus do not have to pay again for an access code - - see your instructor for course access & registration in MyMathLab.

**Other material:** 3-ring binder notebook with dividers, paper, graph paper, pencil, graphing calculator. A graphing calculator that does not perform symbolic manipulations is required. The TI-84+ (**highly recommended**) is used for in-class demonstrations and is particularly recommended. If you are receiving financial aid it may be possible to utilize some of your funds to purchase your calculator. Check with the financial aid office for more information. **No cell phone calculators permitted in this course!**

**Attendance and Make-Up Policy:** Experience has shown a high correlation between regular class attendance, participation, punctuality, and good grades. Students are expected to attend every class, be punctual, remain for the entire class period, and complete all assigned work. Students are responsible for all information presented and announcements/updates made in class whether you were present or not. Being absent is not an acceptable excuse for not being kept updated with any and all changes made. In-class activities may not be announced ahead of time, can NOT be “made-up” & can NOT be done in advance. All assignments must be done by their respective due dates. **Late work is not accepted and extensions are not given.** If you know you will be absent for a test, contact the instructor ahead of time to make arrangements. **If you are absent for a test without making prior arrangements, the test grade is a zero.** (Documented emergencies in which prior arrangements were not possible, as deemed by your instructor, are handled on a case-by-case basis SOLELY at your instructor’s discretion.) Examples of such emergencies include death in family, hospitalization, etc. Obligations to work, child care, traffic conditions, or not feeling well with no documentation, etc. are not considered excused absences and make-up examinations due to these reasons will NOT be permitted! **Take this policy seriously! There are no dropped grades for this course!**

**E-mail Policy:** The instructor will only correspond with you through your atlas e-mail ONLY. Students are expected to **check their atlas e-mail daily!** The instructor may send updates, announcements, changes, etc. to your atlas e-mail. Students are responsible for all messages sent to your atlas e-mail by the instructor. The instructor will not correspond with any other e-mail account, PDA, or cell phone. All e-mail correspondence must originate from your Valencia atlas account. Grades are discussed by appointment only or through your atlas e-mail. All e-mail by students and the instructor should be respectful and professional. Students should identify their name, class that they are in, and a complete message using respectful language. A subject line is mandatory. **The instructor does not check or use Blackboard e-mail!!**

**Cell Phones and Other Communication Devices:** During class, cell phones, pagers and other communication devices should be set such that they do not make noise. Ringing, beeping, buzzing, or a cell phone that suddenly plays a song is disruptive to the learning environment and is disrespectful to the instructor and your classmates. During a test, ALL such devices must be turned OFF (not on vibrate). If your communication device is audible during a test, your test may be collected and you may be asked to leave without an option for completion. Purposefully using a communication device during a test (talking, text messaging, etc.) is considered cheating. Your test will be picked up and you will receive a 0 on the test with the possibility of other academic sanctions such as F in the course and/or referral of the incident to Dean of Students.

**Valencia Core Competencies:** Valencia College have defined 4 interrelated competencies (**Think, Value, Communicate, Act**) that prepares students to succeed in the world community. These competencies are outlined in the College Catalog. In this course, you will further your mastery of those core competencies. Additional information is available on the college website at <http://valenciacollege.edu/competencies/>.

**Academic Honesty:** Students are expected to be in compliance with Valencia College’s policies on academic honesty. Cheating and academic dishonesty of any type will **NOT** be tolerated. You are expected to do your own work on exams, assignments, labs, etc. Talking or whispering during a test, providing/receiving exam content

information, use of electronic devices or calculators without prior instructor's approval, copying (including all take-home activities, examinations, and/or homework assignments), use of a cellular phone or other electronic device without prior permission, suspicious behavior, or failing to follow appropriate procedures for taking a test as prescribed by the instructor are all considered cheating. **Cheating will not be tolerated and will result in a zero on the exam/assignment. In addition, the instructor may refer this incident to the Dean of Students & Mathematics and can result in automatic removal from the course with a course grade of F.** The instructor reserves the right to determine appropriate penalties within Valencia policies.

**Students with Disabilities:** Students with disabilities who qualify for academic accommodations must provide a notification to Instructor (NTI) form from the Office for Students with Disabilities (OSD) and discuss specific needs with the professor, preferably during the first two weeks of class. The Office for Students with Disabilities determines accommodations based on appropriate documentation of disabilities. Contact information: West Campus SSB, Rm. 102 Phone: 407-582-1523 Fax: 407-582-1326 TTY: 407-582-1222

**Code of Conduct:** Valencia is dedicated not only to the advancement of knowledge and learning, but is concerned with the development of responsible personal and social conduct. The instructor believes that the classroom should be a safe learning environment for everyone. Actions or behaviors that intentionally or unintentionally create the perception of a hostile learning environment for others will not be tolerated. By enrolling at Valencia, a student assumes the responsibility for abiding by the general rules of conduct. Students who cause a disturbance to the learning environment as deemed by the instructor will be asked to leave class immediately. If you are asked to leave class for disruptive behavior, you may not return to any future classes until a private conference is completed with your instructor by appointment. You may also be required to arrange a conference with another college official before attending class again. Further information may be found in the current student handbook at: <http://valenciacollege.edu/studenthandbook.pdf>.

**Tutoring and Resources:** Free tutoring is available in the Math Support Center, Math Connections, and Hands-On Lab in Building 7, Room 240! In addition, you should meet regularly with your instructor, your SL leader (if applicable to your class), and form study groups with your fellow classmates. There is also tutoring videos and media presentations provided in MyMathLab software (Look in the multimedia library menu after logging in).

**Work Ethics and Tips for Success:** Students should maintain an organized notebook, complete homework regularly, get assistance as needed outside of class, and check their solutions to problems worked out. Students should plan to spend 2 – 3 hours daily on math homework and lab assignments. Students are expected to keep track of all due dates, exam dates, and should manage their time accordingly. Students should plan for the unexpected and should not wait until the last minute to complete assignments. Avoid last minute cramming and study, practice, and learn as we go along. This will lead to more effective learning and less stress! Students are expected to read ahead the sections that will be taught before class. The instructor will assume that students read ahead and previewed the main notes and examples in the section(s) that will be taught. Students that do not read ahead will be at a major disadvantage in terms of understanding and learning. Understanding math occurs with note taking, paying attention to lessons, asking questions, etc. Learning takes place when you actually “do” math, not just watch it. The most effective way to improve your math skills is through practice and more practice!

**Student Resource for Assistance:** **Valencia College is interested in making sure all our students have a rewarding and successful college experience. To that purpose, Valencia students can get immediate help with issues dealing with stress, anxiety, depression, adjustment difficulties, substance abuse, time management as well as relationship problems dealing with school, home or work. BayCare Behavioral Health Student Assistance**

**Program (SAP) services are free to all Valencia students and available 24 hours a day by calling (800) 878-5470. Free face-to-face counseling is also available.**

**GRADING POLICY:**

Requirements	Percent Weight
In-class exams (4 exams)	40%
Midterm Exam	15%
On-Line Lab Homework	15%
On-line Lab Quizzes	10%
Comprehensive Final Exam	20%
<i>Extra Credit Opportunities</i>	<i>Varies up to 3%</i>
<b>TOTAL for course:</b>	<b>100%</b>

**NOTE:** Failure to take the final exam will result in a course grade of F.

**Grading Scale:** A = 90.0 – 100%; B = 80.0 – 89.9%; C = 70.0 – 79.9%; D = 60.0 – 69.9%; F = below 60.0%

**NOTES:** It is the responsibility of the student to keep track of his/her grades throughout the semester and to understand his/her progress in the course at ALL times. **THERE ARE NO DROPPED EXAM GRADES IN THIS COURSE!!** All exam/quiz grades are rounded to the **nearest whole number** and final course grades are rounded to the nearest **tenth** of a percent!!

**I adhere to the highest standards of academic integrity, so please do not ask me to change (or expect me to change) your grade illegitimately or to bend or break rules for one person that will not apply to everyone. You are encouraged to take all course requirements seriously! Grades are earned – not given!!**

**Withdrawal Policy:** Students who do not attend class during the first week of class are considered “No Show” and will be automatically withdrawn during the “No Show” reporting period. These students will receive a grade of W in the course. Withdrawing from the course after the first week is the student’s responsibility. A student who withdraws by the withdrawal deadline will receive a grade of W. A student cannot withdraw after the withdrawal deadline and will receive a grade in accordance with the instructor’s grading policy. Any student that withdraws or is withdrawn during a third or subsequent attempt in the same course will be assigned a course grade of F. **The withdrawal deadline, if you are eligible to do so, is March 27, 2015 for full-term Spring classes.**

**Incomplete Grade Policy:** An Incomplete grade is not given except by exceptional circumstances with supporting documentation. An Incomplete grade will only be considered if requested by the student and the student has all class requirements fulfilled except for the final examination. The student must have a B average and must have supporting documentation. A student who is having difficulties completing the course requirements prior to the final exam must withdraw by the withdrawal deadline.

**Comprehensive Final Exam:** The final exam is a cumulative exam given at the end of the semester to assess all skills learned. Students that do not take the final exam will be given an automatic course grade of F, no matter the grade average in the course. There are NO retakes for the final exam. **Students must arrive on time to take the final exam. Students arriving late may not be permitted to take the final exam and will be given a grade of F for the course.**

**Lab HW:** Students can complete the on-line homework and have unlimited attempts until the problem is correct. The on-line homework will be averaged at the end of the semester and will count for a grade. All due dates are listed next to each assignment in the math software.

**Lab Quizzes:** You will be given lab quizzes for every few sections covered plus pre-test in the beginning each chapter, which will count as a quiz grade. The best way to prepare for the on-line quizzes is by taking notes in class and by doing the assigned homework. It is important to try your best on every quiz including the pre-tests! All due dates are listed next to each quiz in the math software.

**Notebook (Bonus 10 points towards lowest in-class exam):** A 3-ring organized notebook with subject dividers is required and should contain only math. You should have a section for class notes (labeled and written neatly), a section for all homework (on-line & textbook) labeled, numbered, all work shown, and checked for accuracy, a section for all lab quizzes (Each attempt on notebook paper with work shown, numbered, and done neatly), a section for your in-class exams with test corrections, and a section for all reviews & miscellaneous. Your test corrections should include redo of all missed problems and explanation of what was learned on separate piece of paper. Your syllabus should be in the front pocket or in the front, hole punched. Other methods of organization are allowed with instructor’s approval. Notebook must be organized and neat for grading! The notebook will be graded the week before finals or during the final exam period as announced in class.

**Extra Credit:** A few extra credit opportunities will be given throughout the semester. The purpose of extra credit is to reward hard work and to help students that become border-line between 2 letter grades at the end of the semester. The impact of extra credit will be a MAXIMUM of 3% of your total course grade. Pay attention to all extra credit opportunities as they can add up at the end of the semester.

There are plenty of opportunities for success in this course if you take this course seriously!

**Disclaimer:** Changes in the syllabus, class policies, evaluation process, and schedule may be made at any time to accommodate the needs of the class and at the discretion of the instructor. Students who are absent are responsible for any and all changes made to the syllabus or outline of this course. “Take responsibility for yourself!” Look for the outline that corresponds to when your class meets!!

**TENTATIVE OUTLINE(S)/SCHEDULE(S) (Subject to change):**

**M/W schedule:**

<b>WK #</b>	<b>Dates</b>	<b>Topics</b>	<b>Monday</b>	<b>Wednesday</b>
<b>1</b>	Jan 6/8	Course Introduction, Quadratic Equations, Complex Numbers	<b>Course Overview</b>	1.2, 1.3
<b>2</b>	Jan 13/15	Distance, Midpoint, Intercepts, Graphing, Symmetries, Circles, Variations	2.1, 2.2, 2.4	2.4, 2.5
<b>3</b>	Jan 20/22	CH 2 Review, HW questions	<b>MLK Holiday – NO CLASS!</b>	Review, 1.5
<b>4</b>	Jan 27/29	Functions, Graphs of Functions, Analyzing graphs	<b>CH 2 EXAM</b>	3.1, 3.2
<b>5</b>	Feb 3/5	Graphs of Functions, Properties of Functions, Library of Functions, Piece-wise Functions, Average rate of change, secant lines	3.2, 3.3	3.4
<b>6</b>	Feb 10/12	Transformations of Functions, Building	3.5, 3.6	<b>Review</b>



		functions from data		
<b>7</b>	Feb 17/19	Linear Functions, Quadratic Functions	<b>CH 3 EXAM</b>	4.1, 4.3
<b>8</b>	Feb 24/26	Quadratic Functions Applications, Quadratic Inequalities, Composite Functions, Inverse Functions	4.4, 4.5	6.1, 6.2
	March 3/5	<b>Spring Break!</b>	<b>NO CLASS!</b>	<b>NO CLASS!</b>
<b>9</b>	March 10/12	Review	<b>Review</b>	<b>CH 4, 6 EXAM</b>
<b>10</b>	March 17/19	Exponential Functions, Logarithmic Functions, Properties of Logarithms	6.3, 6.4	6.5, 6.6
<b>11</b>	March 24/26	Logarithmic and Exponential Equations, Compound Interest, Exponential Growth/Decay	6.7, 6.8	<b>Review</b>
<b>12</b>	March 31/ April 2	Polynomial and Rational Functions	<b>CH 6 EXAM</b>	5.1, 5.2, 5.3
<b>13</b>	April 7/9	Systems of Linear and Non-Linear Equations, Systems of Inequalities	8.1, 8.6, 8.7	<b>CH 5/8 EXAM</b>
<b>14</b>	April 14/16	Review for Final Exam	1.6, Final Review	Final Review
<b>15</b>	<b>April 21, 2014</b>	<b>Final Exam 1:00 – 3:30 PM (Monday)</b>	<b>Arrive on time or early!!</b>	
<b>All due dates for on-line HW and Quizzes are listed next to each assignment in MyMathLab! Keep track of all due dates!</b>				

**NOTE:**

January 19, 2015: Martin Luther King Jr. Holiday (No Classes – College Closed!)

**January 20, 2015: Drop/Refund Deadline 11:59 PM on atlas**

February 13, 2015: Learning Day (No Classes!)

March 9 – 15, 2015: Spring Break (NO CLASSES!)

**March 27, 2015: Withdrawal Deadline (Last Day to receive grade of W; must withdraw by 11:59 PM on atlas)**

April 26, 2015: Full Term Classes End

**April 27 – May 3, 2015: Final Exam Week**

**May 5, 2015: Final Course Grades viewable in Atlas**

## **APPENDIX D: DEMOGRAPHICS FORM**

**Instructions:** Thank you for agreeing to take part in this study. Please fill out the following form, which will help provide background information about yourself and some demographics.

**Name:** \_\_\_\_\_

**Age:** \_\_\_\_\_

**Circle one:** MALE                      FEMALE

**Circle your Race/Ethnicity:**

Caucasian/Non-Hispanic    Hispanic            African American    Asian            Native-Indian

Other

**Number of credits you are enrolled in for the semester:** \_\_\_\_\_

**Number of credits earned at Valencia College:** \_\_\_\_\_

## **APPENDIX E: INFORMED CONSENT FORM**



## Students' Perception of Learning Using Self-Adaptive Technology

**You must be 18 years of age or older to participate in this research.**

Principal Investigator: Ryan Kasha, Ph.D. student, Valencia Math Instructor.

Faculty Supervisor: Dr. Peter Kincaid, Ph. D.

Investigational Site(s): Valencia College, West Campus

**Introduction:** Researchers at the University of Central Florida (UCF) study many topics. To do this we need the help of people who agree to take part in a research study. You are being invited to take part in a research study which will include about 60 people enrolled in College Algebra math courses at Valencia College. You have been asked to take part in this research study because you are a student in one of these selected College Algebra sections. You must be 18 years of age or older to be included in the research study. Your participation will enhance the knowledge obtained from this research study.

The person doing this research is Ryan Kasha of Valencia College and a Ph.D. student from University of Central Florida. Because the researcher is a graduate student, he is being guided by Dr. Peter Kincaid, a UCF faculty supervisor in the Modeling and Simulation Department.

### What you should know about a research study:

- Someone will explain this research study to you.
- A research study is something you volunteer for.
- Whether or not you take part is up to you.
- You should take part in this study only because you want to.
- You can choose not to take part in the research study.
- You can agree to take part now and later change your mind.
- Whatever you decide it will not be held against you.
- Feel free to ask all the questions you want before you decide.

**Purpose of the research study:** The purpose of this study is to evaluate students' perception of the math software being used in College Algebra. Technology is being used very often in math courses either as a supplement to instruction. This study will focus on how certain features in the software

impact your performance and perception of learning. This research effort will help inform how certain features in commercial math software contribute to student learning and perception.

**What you will be asked to do in the study:** During your course, you will be asked to complete a demographic survey during the first week of classes, and the ATMI (Attitude Towards Mathematics Inventory) two times during the course. The ATMI will be administered during the first week of classes and around the 7<sup>th</sup> week during class time. In addition, the instructor will use some quiz/exam grades for data analysis. You will be asked to report how much you feel that you have mastered course material for a chosen course objective on before taking an in-class exam from a scale of 0% to 100%.

**Time required:** The time spent is no more or less than what is expected in a College Algebra class. All questionnaires, surveys, and testing will be completed during class time.

**Risks:** There are no reasonably foreseeable risks or discomforts involved in taking part in this study.

**Withdrawing from the study:** Your participation in this research study is strictly voluntary and is not required for this course. For students who wish not to participate or wish to withdraw from this study at any time can do so by anytime by contacting your instructor, Ryan Kasha. You can e-mail your instructor at [rkasha@valenciacollege.edu](mailto:rkasha@valenciacollege.edu) or call at (407) 582-1475. Your grade will NOT be adversely affected by refusing to participate or by withdrawing from the study. If you are under the age of 18, you cannot participate in this study.

**Compensation or payment:** There is no payment or compensation associated with taking part in this study.

**Confidentiality:** The instructor will limit your personal data collected in this study to people who have a need to review this information. The instructor cannot promise complete secrecy, but every effort will be made to keep your personal data confidential and private. All information will be handled in a strictly confidential manner, subject to disclosure requirements of Florida Sunshine Laws, so that nobody will be able to identify you when the results are reported. All data collected will be aggregated and no identification will be associated with any published or presented data. All information is subject to the Family Educational Rights and Privacy Act (FERPA) of 1974, which is designed to protect the privacy of educational records.

**Study contact for questions about the study or to report a problem:** If you have questions, concerns, or complaints, or think the research has hurt you, talk to Dr. Peter Kincaid, Faculty Supervisor, Modeling and Simulation Department at (407)-882-1330 or by e-mail at [pkincaid@ist.ucf.edu](mailto:pkincaid@ist.ucf.edu), and Russell Takashima, Dean of Mathematics of Valencia College, West Campus at (407)-582-1724 or by e-mail at [rtakashima@valenciacollege.edu](mailto:rtakashima@valenciacollege.edu)

**IRB contact about your rights in the study or to report a complaint:** Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (Valencia & UCF IRB). This research has been reviewed and approved by the IRB at Valencia College and University of Central Florida. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901. You can also contact Chair of Valencia's Institutional Review Board at [irb@valenciacollege.edu](mailto:irb@valenciacollege.edu).

VALENCIA IRB:  
Application # 15-0005  
Determination expedited J.B.  
Period 11/4/14 to 11/9/15

**APPENDIX F: IRB HUMAN SUBJECTS PERMISSION LETTER (UCF)**





University of Central Florida Institutional Review Board  
Office of Research & Commercialization  
12201 Research Parkway, Suite 501  
Orlando, Florida 32826-3246  
Telephone: 407-823-2901 or 407-882-2276  
[www.research.ucf.edu/compliance/irb.html](http://www.research.ucf.edu/compliance/irb.html)

## Approval of Human Research

From: **UCF Institutional Review Board #1**

**FWA00000351, IRB00001138**

To: **Ryan Kasha**

Date: **December 10, 2014**

Dear Researcher:

On 12/10/2014, the IRB approved the UCF Initial Review Submission Form  
following human participant research  
until 12/09/2015 inclusive: Type of

Review:

Project Title: Students' Perception of Learning with  
Self-Adaptive Technology

Investigator: Ryan Kasha  
IRB Number: SBE-14-10771

Funding Agency:

Grant Title:

Research ID: N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30 days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at <https://iris.research.ucf.edu>.

If continuing review approval is not granted before the expiration date of 12/09/2015, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

A handwritten signature in black ink that reads "Joanne Muratori". The signature is written in a cursive style with a large, sweeping initial "J".

Signature applied by Joanne Muratori on 12/10/2014 04:40:06 PM EST  
IRB Manager

**APPENDIX G: IRB HUMAN SUBJECTS PERMISSION LETTER (VC)**

VALENCIA COLLEGE  
Human Research Protection (HRP) Institutional Review Board (IRB)

IRB Determination Form

Title of Research Protocol: Students' Perception of Learning with Self-Adaptive Technology

Principal Investigator (PI): Ryan Kasha

Date Received by IRB Chair: 10/27/2014

IRB Number: 15-0005

Based on the IRB Protocol Initial Submission Form (or, as appropriate, the IRB Continuing Review/Termination Form or the IRB Addendum/Modification Form) submitted by the Principal Investigator and for the project identified above, the following determination has been made by the Valencia IRB:

- The research is exempt from IRB review. Exemption category: \_\_\_\_\_
- The research is eligible for expedited review and has been approved
- The research is eligible for expedited review but requires modifications and re-submission before approval can be given.
- The research is subject to full review and will be discussed at the next IRB meeting, currently scheduled for \_\_\_\_\_ (date)
- The research has been subjected to full review and has been approved.
- The research has been subjected to full review and has been disapproved.

Period of Approval: 11/5/14 to 11/5/15  
(cannot be retroactive)

Exemption from Valencia IRB review does not exempt the PI or Co-PI from compliance with all applicable institutional, Federal, State, and local rules, regulations, policies, and procedures.

Although the IRB has determined that this application is exempt from IRB review, the Principal Investigator is encouraged to read, understand, and apply the attached Investigator Responsibilities document, which is required of Principal Investigators whose research protocols are approved under the Valencia IRB full or expedited review process.

If you have any remaining questions about Valencia's IRB process, contact the IRB Chair at [irb@valenciacollege.edu](mailto:irb@valenciacollege.edu)

  
Signature of IRB Chair or Designated Representative

11/5/2014  
Date

C: IRB File, IRB Members, PI Supervisor/Administrator

## **APPENDIX H: ATTITUDES TOWARD MATHEMATICS INVENTORY**

## ATTITUDES TOWARD MATHEMATICS INVENTORY

Name \_\_\_\_\_ School \_\_\_\_\_

Teacher \_\_\_\_\_

Directions: This inventory consists of statements about your attitude toward mathematics. There are no correct or incorrect responses. Read each item carefully. Please think about how you feel about each item. Enter the letter that most closely corresponds to how each statement best describes your feelings. Please answer every question.

PLEASE USE THESE RESPONSE CODES:

- A – Strongly Disagree
- B – Disagree
- C – Neutral
- D – Agree
- E – Strongly Agree

1.	Mathematics is a very worthwhile and necessary subject.	
2.	I want to develop my mathematical skills.	
3.	I get a great deal of satisfaction out of solving a mathematics problem.	
4.	Mathematics helps develop the mind and teaches a person to think.	
5.	Mathematics is important in everyday life.	
6.	Mathematics is one of the most important subjects for people to study.	
7.	High school math courses would be very helpful no matter what I decide to study.	
8.	I can think of many ways that I use math outside of school.	
9.	Mathematics is one of my most dreaded subjects.	
10.	My mind goes blank and I am unable to think clearly when working with mathematics.	
11.	Studying mathematics makes me feel nervous.	
12.	Mathematics makes me feel uncomfortable.	
13.	I am always under a terrible strain in a math class.	
14.	When I hear the word mathematics, I have a feeling of dislike.	
15.	It makes me nervous to even think about having to do a mathematics problem.	
16.	Mathematics does not scare me at all.	
17.	I have a lot of self-confidence when it comes to mathematics.	
18.	I am able to solve mathematics problems without too much difficulty.	
19.	I expect to do fairly well in any math class I take.	
20.	I am always confused in my mathematics class.	
21.	I feel a sense of insecurity when attempting mathematics.	
22.	I learn mathematics easily.	
23.	I am confident that I could learn advanced mathematics.	
24.	I have usually enjoyed studying mathematics in school.	
25.	Mathematics is dull and boring.	
26.	I like to solve new problems in mathematics.	
27.	I would prefer to do an assignment in math than to write an essay.	
28.	I would like to avoid using mathematics in college.	
29.	I really like mathematics.	

30.	I am happier in a math class than in any other class.	
31.	Mathematics is a very interesting subject.	
32.	I am willing to take more than the required amount of mathematics.	
33.	I plan to take as much mathematics as I can during my education.	
34.	The challenge of math appeals to me.	
35.	I think studying advanced mathematics is useful.	
36.	I believe studying math helps me with problem solving in other areas.	
37.	I am comfortable expressing my own ideas on how to look for solutions to a difficult problem in math.	
38.	I am comfortable answering questions in math class.	
39.	A strong math background could help me in my professional life.	
40.	I believe I am good at solving math problems.	

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## **APPENDIX I: PERMISSION TO USE ATMI**



**Sent:** Saturday, October 25, 2014 12:40 AM

**To:** ryankasha [ryankasha@knights.ucf.edu]

Dear Ryan,

You have permission to use the Attitudes Toward Mathematics Inventory (ATMI) in your dissertation. If you have any question, please do not hesitate to ask me.

Please let me know of the findings in your study.

Sincerely,

Martha Tapia

Martha Tapia, Ph.D.  
Associate Professor  
Department of Mathematics and Computer Science  
Berry College  
P.O. Box 495014  
Mount. Berry, Georgia 30149-5014

## **APPENDIX J: PRE- AND POST-TEST FOR FUNCTIONS**

MAC 1105 (College Algebra)  
CH 3 EXAM

Name: \_\_\_\_\_ Spring 2015

Directions: Read each question carefully and perform the indicated operation(s). Provide all necessary work/explanation to receive credit. Clearly mark/circle your final answer. GOOD LUCK!!

**MULTIPLE CHOICE:** Perform the indicated operation(s) and choose the correct answer. There is only 1 correct answer.

Determine whether the relation represents a function. If it is a function, state the domain and range.

1)  $\{(-2, 6), (2, 5), (5, -5), (6, -1)\}$

A) function

domain:  $\{-2, 2, 5, 6\}$

range:  $\{6, 5, -5, -1\}$

B) function

domain:  $\{6, 5, -5, -1\}$

range:  $\{-2, 2, 5, 6\}$

C) not a function

Indicate whether the function is one-to-one.

2)  $\{(7, 2), (8, 2), (9, 3), (10, 9)\}$

A) Yes

B) No

Determine whether the equation defines  $y$  as a function of  $x$ . Show your work!!

3)  $x = |y|$

A) function

B) not a function

**SHORT ANSWER:** Perform the indicated operation(s), provide all work, and then clearly mark your final answer.

Find the value for the function.

4) Find  $f(-3)$  when  $f(x) = x^2 - 2x - 1$ .

Solve the problem.

5) If  $f(x) = 6x^3 + 7x^2 - x + C$  and  $f(2) = 1$ , what is the value of  $C$ ?

Find the domain of the function and express your answer using interval notation.

6)  $\frac{x}{\sqrt{x-5}}$

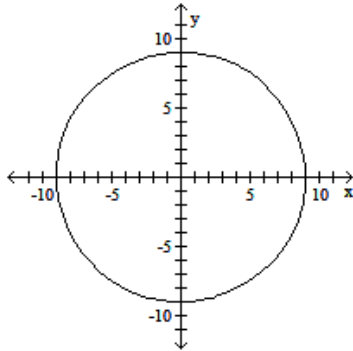
For the given functions  $f$  and  $g$ , find the requested composite function value.

7)  $f(x) = 2x + 4$ ,  $g(x) = 4x^2 + 3$ ; Find  $(g \circ f)(-3)$ .

Determine whether the graph is that of a function. Find the domain and range and all of the intercepts,



8)



Function (Yes/No)? \_\_\_\_\_

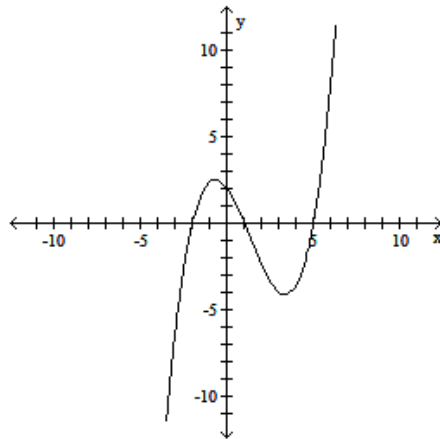
Domain (use interval notation): \_\_\_\_\_

Range (use interval notation): \_\_\_\_\_

List the intercepts of the graph as ordered pairs.



9)



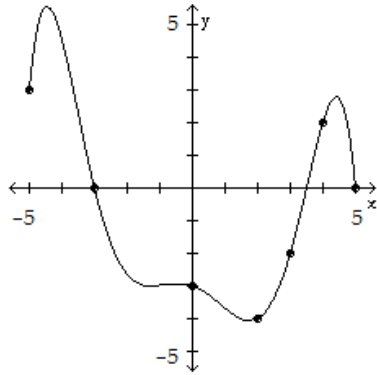
x-intercept(s): \_\_\_\_\_ y-intercept(s): \_\_\_\_\_

**MULTIPLE CHOICE:** Perform the indicated operation(s) and choose the correct answer. There is only 1 correct answer.

The graph of a function  $f$  is given. Use the graph to answer the question.



10) Is  $f(-5)$  positive or negative?



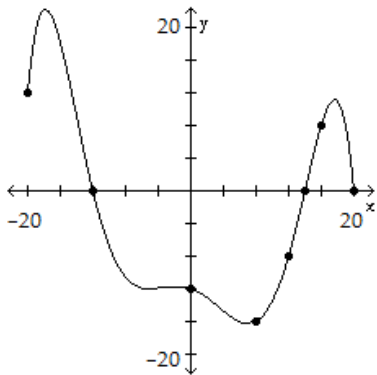
A) positive

B) negative

**SHORT ANSWER:** Perform the indicated operation(s), provide all work, and then clearly mark your final answer.



11) For what numbers  $x$  is  $f(x) < 0$ ? Express your solution using interval notation.

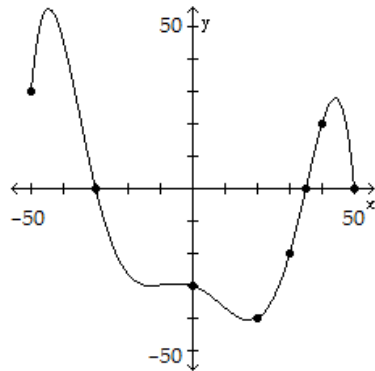


**Solution:** \_\_\_\_\_

**MULTIPLE CHOICE:** Perform the indicated operation(s) and choose the correct answer. There is only 1 correct answer.

**BI**

12) How often does the line  $y = -50$  intersect the graph?



- A) once       B) twice       C) three times       D) does not intersect

**Answer the question about the given function.**

**BI**

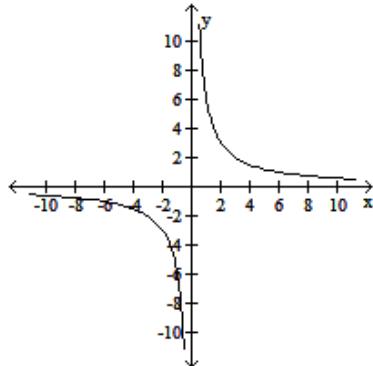
13) Given the function  $f(x) = -3x^2 + 6x - 1$ , is the point  $(2, -7)$  on the graph of  $f$ ? Show work!!

- A) Yes       B) No

**The graph of a function is given. Decide whether it is even, odd, or neither.**

**BI**

14)



- A) even       B) odd       C) neither

**Determine algebraically whether the function is even, odd, or neither.**

**BI**

15)  $f(x) = -3x^4 - x^2$

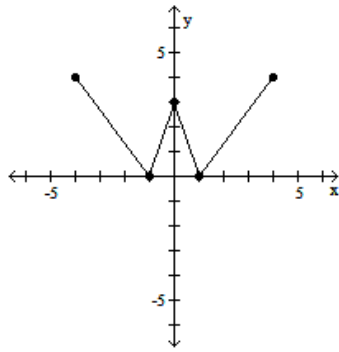
- A) even       B) odd       C) neither

SHORT ANSWER: Perform the indicated operation(s), provide all work, and then clearly mark your final answer.

The graph of a function is given. Determine where the function is increasing, decreasing, or constant. Write N/A if not applicable.

16)



Increasing (use interval notation): \_\_\_\_\_

Decreasing (use interval notation): \_\_\_\_\_

Constant (use interval notation): \_\_\_\_\_

Find the average rate of change for the function between the given values.

17)  $f(x) = x^2 + 2x$ ; from 9 to 5.

Find an equation of the secant line containing  $(1, f(1))$  and  $(2, f(2))$ . The equation will be in the form of  $y = mx + b$ .

18)  $f(x) = x^3 - x$

Find and simplify the difference quotient of  $f$ ,  $\frac{f(x+h) - f(x)}{h}$ ,  $h \neq 0$ , for the function.

19)  $f(x) = x^2 + 8x + 1$

Solve the problem.

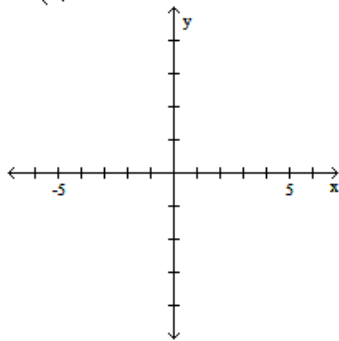


20) Jacey, a commissioned salesperson, earns \$360 base pay plus \$36 per item sold. Express Jacey's gross salary  $G$  as a function of the number  $x$  of items sold.

Graph the function, then find its domain, then evaluate the function given the values below.

21)

$$f(x) = \begin{cases} -x + 2 & x < 0 \\ \sqrt{x} + 3 & x \geq 0 \end{cases}$$



Domain (use interval notation): \_\_\_\_\_

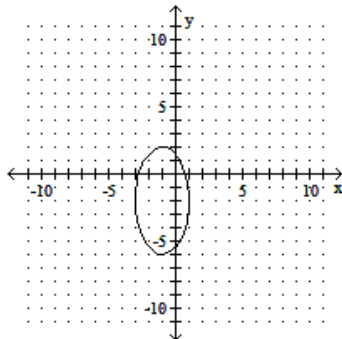
Find  $f(0)$ : \_\_\_\_\_ Find  $f(-10)$ : \_\_\_\_\_

**MULTIPLE CHOICE:** Perform the indicated operation(s) and choose the correct answer. There is only 1 correct answer.

Use the vertical line test to determine whether the graph is the graph of a function.



22)



A) not a function

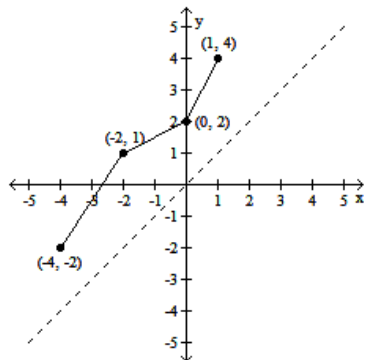
B) function



SHORT ANSWER: Perform the indicated operation(s), provide all work, and then clearly mark your final answer.

Use the graph of the given one-to-one function to sketch the graph of the inverse function. For convenience, the graph of  $y = x$  is also given.

23)



The function  $f$  is one-to-one. Find its inverse. Also state the domain of the function given below and the domain of its inverse. State the range for the function given below and the range of its inverse. Use interval notation when stating the domain and inverse.

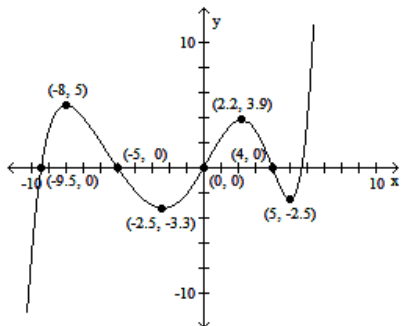


24)  $f(x) = \frac{2}{x+2}$

The graph of a function  $f$  is given. Use the graph to answer the question.



25)



State the ordered pairs for the local minima and local maxima.

Minima: \_\_\_\_\_

Maxima: \_\_\_\_\_

Note: Pre-Test and Post-Test were exactly the same except for algorithmic changes in numeric values. Created using TestGen by Pearson.

## **APPENDIX K: SCREENSHOT OF MYMATHLAB**

The screenshot shows a MyMathLab homework page. At the top right, the user's name "R Kasha" and the date "10/7/14 9:38 PM" are displayed. The page title is "Homework: CH 3 HW (3-1 to 3-3)". A navigation bar shows problem numbers 11 through 20, with 14 highlighted. The current problem is 3.1.49. The problem text is "Find the domain of the function." followed by the function  $f(x) = \frac{x}{x^2 + 1}$ . Below the function, the answer is given as "The domain is  $(-\infty, \infty)$ . (Type your answer in interval notation.)". The interface includes a calculator on the left, a sidebar with buttons for "Help Me Solve This", "View an Example", "Video", "Textbook", and "Print", and a bottom bar with "All parts showing", "Similar Exercise", and "Save" buttons. A status bar at the bottom indicates "Question is complete."

Screenshot of homework in MyMathLab (Pearson, n.d.).

Note: Assistance tools include viewing an example, receiving hints, watching a relevant video, and referencing the appropriate part of the textbook. Students can do a similar exercise for additional practice.

## **APPENDIX L: SCREENSHOT OF ALEKS**

The screenshot shows the ALEKS homework interface. At the top, there is a navigation bar with the ALEKS logo and links for HELP, WORKSHEET, INBOX, REPORT, OPTIONS, English, and EXIT. Below this is a secondary navigation bar with icons for MyPie, Review, Dictionary, Calculator, Homework, Gradebook, and Calendar, along with a subject dropdown menu set to 'Int. Algebra'. The main content area displays 'Question #8' and an 'Assessment Progress' indicator. The problem text reads: 'The diameter of a construction pipe is 7 ft . If the pipe is 29 ft long, what is its volume? (Use the value 3.14 for  $\pi$  , and round your answer to the nearest cubic foot. Be sure to include the correct unit in your answer.)'. A diagram of a cylinder is shown with a diameter of 7 ft and a length of 29 ft. Below the diagram is an input field containing '1115 ft<sup>3</sup>'. To the right of the input field are buttons for unit selection (ft, ft<sup>2</sup>, ft<sup>3</sup>), 'Clear', 'Undo', and 'Help'. At the bottom of the question area are 'Next >>' and 'I don't know' buttons.

Screenshot of homework in ALEKS (ALEKS, n.d.)

Note: Assistance includes a Help button with hints or a full explanation is available by clicking “I don’t know”. Students must get the same type of problems correct three times in a row without assistance.

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