Conditions that Promote the Academic Performance of College Students

in a Remedial Mathematics Course:

Academic Competence, Academic Resilience, and the Learning Environment

by

Cecile Mary Foshee

A Dissertation Presented in Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy

Approved May 2013 by the
Graduate Supervisory Committee:

Robert Atkinson, Chair
Stephen Elliott
John Horan

ARIZONA STATE UNIVERSITY

August 2013

ABSTRACT

Researchers have postulated that math academic achievement increases student success in college (Lee, 2012; Silverman & Seidman, 2011; Vigdor, 2013), yet 80% of universities and 98% of community colleges require many of their first-year students to be placed in remedial courses (Bettinger & Long, 2009). Many high school graduates are entering college ill prepared for the rigors of higher education, lacking understanding of basic and important principles (ACT, 2012). The desire to increase academic achievement is a wide held aspiration in education and the idea of adapting instruction to individuals is one approach to accomplish this goal (Lalley & Gentile, 2009a). Frequently, adaptive learning environments rely on a mastery learning approach, it is thought that when students are afforded the opportunity to master the material, deeper and more meaningful learning is likely to occur. Researchers generally agree that the learning environment, the teaching approach, and the students' attributes are all important to understanding the conditions that promote academic achievement (Bandura, 1977; Bloom, 1968; Guskey, 2010; Cassen, Feinstein & Graham, 2008; Changeiywo, Wambugu & Wachanga, 2011; Lee, 2012; Schunk, 1991; Van Dinther, Dochy & Segers, 2011). The present study investigated the role of college students' affective attributes and skills, such as academic competence and academic resilience, in an adaptive mastery-based learning environment on their academic performance, while enrolled in a remedial mathematics course. The results showed that the combined influence of students' affective attributes and academic resilience had a statistically significant effect on students' academic performance. Further, the mastery-based learning environment also had a significant effect on their academic competence and academic performance.

Lovingly dedicated to my husband

James, there are no words that could adequately express my gratitude. You gave me love, support, hope, and confidence. You took care of everything so that I could focus on my work. You made me laugh when I wanted to cry. You were even willing to put our lives on hold so that I could pursue my dream. Thank you for being my soul mate and my ally. Thank you for being my strength and my love! –Cecile

ACKNOWLEDGEMENTS

This is one of the most important accomplishments in my life, but I would not have made it without the help and support of many. To all of you who were always there for me, I give you my eternal gratitude. Now, I personally acknowledge some of you while some of you go unnamed; please know you are not unappreciated.

To Robert Atkinson. Thank you for allowing me to pursue my vision and enabling me to explore beyond our field. Thank you for not giving up on me when things did not work out the way I planned. Thank you for making your resources available to me. More importantly, thank you for finding an alternate road when I found myself at a dead end.

To Stephen Elliott. This could not have happened without you. Thank you for empowering me and giving me the opportunity to work with your research. Thank you for your mentorship and positive attitude. Mostly, thank you for all the time you so generously and without reservation gave to me.

To my committee, present and past: John Horan, Wilhelmina Savenye, and Joan Shapiro. Thank you for your willingness to stick with me down this long road, despite the many changes and difficulties. Your advice and support was greatly appreciated.

To my children, my mother, my sister, my family, and my friends. I know that many times it may have seemed that all I ever did was work. I missed many events, and though I was absent in body, I was never absent at heart. I am so thankful for your understanding, for your patience, and above all, for your unconditional love.

TABLE OF CONTENTS

CHAPTER Page

CHAPTER Page

APPENDIX Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

Chapter 1

INTRODUCTION

Thousands of high school graduates are not college ready (ACT, 2012; Bettinger & Long, 2009). A student who meets the *college readiness* criteria should be able to enroll in a first-year mathematics course at a college or university, right out of high school (ACT, 2012). The ACT research (2012) pointed to some dismal results: 25% of all ACT-tested high school students in the nation met all four benchmarks, English, reading, mathematics, and science; and 45% met the readiness benchmark in math. In 2011, the National Center for Educational Achievement (NCEA) identified the highest performing schools from over 300 school districts and drafted a report entitled *The 20 Non-Negotiable Characteristics of Higher Performing School Systems.* The NCEA identified various characteristics as signs of a successful school system: the most important was the alignment of the curriculum to the needs of students to properly introduce, develop, and master content; the second most important was the assessment of concepts at each grade level. Researchers have postulated that math academic achievement increases student success in college (Lee, 2012; Silverman & Seidman, 2011; Vigdor, 2013), yet 80% of universities and 98% of community colleges are placing a large number of first-year students in remedial courses to develop competence and help them attain college entry level skills (Bettinger & Long, 2009).

Efforts to improve math performance have prompted the development of adaptive learning programs such as Knewton Math Readiness (Knewton, 2012), MyMathLab (Stewart, 2012), Carnegie Learning Math Series (Ritter, 2011), and many others. In general, these computer-based programs address the needs of the student by using a mastery approach to learning. Knewton Math Readiness, for example, is a software program that automatically adapts the math content to the student's level of academic performance while providing the necessary information for students to develop competence and achieve mastery at their current level before moving on to the next level.

The efforts to improve math performance have also prompted much research on the need to improve the math skills nationwide; however, the research appears to be centered on the learning environments and how these environments impact learning or result in academic improvements (Bettinger & Long, 2009; Kim, 2012; Lee, 2010). While it is key to understand the dynamics that create effective learning environments, it is vital to understand the extent to which the students' individual strengths and limitations promote or inhibit academic performance.

Problem Statement

Although the variables that contribute to academic success are widely investigated, these are mostly explored in isolation (Dearnley & Matthew, 2007; Dumais, 2002; Jones & Jo, 2004; Kaighobadi & Allen, 2008; Meyer, 2011; Roosa et al., 2012; Silverman & Seidman, 2011; Strayhorn, 2010). Aspects or attributes thought to contribute to academic success or lack thereof (e.g., prior achievement, study skills, motivation, personalized learning, self-efficacy, remediation, socioeconomic status, gender, and ethnicity) are investigated independent of each other, without taking into account their possible interaction and its variable effects on individuals. Presently, it is not fully understood how these variables affect underperforming students. How much relative growth does a student experience when placed in a remedial math course? What aspects contribute to this growth? What role does the students' cognitive and affective attributes play in getting back on track? How much can be attributed to the students and how much is a product of the learning environment? The present study was intended to investigate various aspects of college students' academic competence, academic resilience, and academic performance, within a new adaptive learning environment. This new environment was developed by Knewton and math professors at Arizona State University (ASU), to enable college students to advance in disciplines requiring an understanding of mathematics.

The Research Literature

A review of the literature revealed a trend towards ethnic and gender disparities, though these issues were not the focus of the present study, they were deemed worthy of investigation. For example, college readiness scores have remained virtually stagnant for the last four years, with minority students meeting benchmarks at the lowest percentages (ACT, 2012). Nationwide, only 11% of American Indians, 13% of Hispanics, and 5% of African Americans met all four benchmarks. These minorities were also least likely to aspire to attain professional degrees. The level of preparedness is also a contributor to low academic performance; only 8% of students who took less than three years of math courses were able to meet the mathematics ACT benchmark—evidence of the importance of prior achievement on current or future achievement.

Strayhorn (2010) used Bourdieu's (1977) *cultural capital* as a construct to understand the minority disparity where cultural capital refers to the perceptions, behaviors, and attitudes towards education that are passed along within family circles and their social class. Strayhorn hypothesized that African American students enter schools with lower levels of cultural capital, and this phenomena seems accurate for most ethnic minorities. He surveyed 24,599 students (from the National Center for Education Statistics) of which 49% responded and the final selected sample was approximately 14% of the respondents (n = 1,766 Black students). Findings indicated that prior achievement was statistically significantly related, $r = .25$, to math achievement, $F(6, 1788) = 15.04$, $p < .01$ (e.g., predictors included in the model: gender, parent's level of education, and locus of control). He also found that background and family variables accounted for an additional 14% of the variance in math achievement. Gender and parents' level of education were also significant predictors. These findings validate the need for considering individual differences when addressing students' instructional needs and even more so when addressing the needs of remedial students. This was perhaps the most compelling reason for exploring personalized instruction, sometimes referred to or subsumed in the construct of adaptive learning.

Adaptive Learning

As the term indicates, adaptive learning refers to the process of adapting instruction to match the academic needs and abilities of the individual. This is typically accomplished through software programs that employ a range of approaches, from basic non-linear branching and response-based scaffolding to the more complex adaptive learning software programs. One such program is the Knewton Math Readiness Courseware, which uses a sophisticated system to respond to students' performance in real-time continually adapting the material to match students' known proficiencies (Knewton, 2012). The adaptation of instruction where students' proficiencies and deficiencies are continually taken into account is thought to create highly effective learning environments. The concept of individualized learning has been shown to be a key factor in academic success, particularly when the adaptation is based on the students' current and prior knowledge. It has long been established that prior-knowledge is a key component of learning, as it makes learning more meaningful and increases retention (Ebbinghaus, 1885; Ausubel, 1968). This can be particularly important for novice learners, who tend to organize new knowledge around explicit or literal pieces of known information.

Lalley and Gentile (2009a) examined the idea of adapting instruction to individuals. They found that the term was loosely defined and varied widely in application. Their aim was to identify variables that should be used as the guiding standards to adapt instruction. Lalley and Gentile posited that instruction should adapt to the learners' prior knowledge, content, and/or domain objectives. These researchers believed instruction should not be based on learning styles, brain-hemisphericity (e.g., right brain, left brain, or brain-based), multiple intelligences, and cognitive styles. They searched popular databases (e.g., Academic Search Premier, Psych INFO, ERIC, and Professional Development Collection) and discovered that only a fraction of the studies reviewed provided empirical support to back their claims. Out of the 3,299 articles on learning styles, 132 had indicators of empirical evidence. There were 120 brain-based articles, none of which matched Lalley and Gentile's empirical evidence criteria. The same was true for multiple intelligence, seven studies out of the 783 searched provided empirical evidence. Similarly, 110 out of 3,445 on cognitive style matched the empirical evidence criteria. Lalley and Gentile also evaluated and summarized the empirical evidence on various approaches and concluded that the evidence supported their assumptions on prior knowledge: "effective instruction should be tied to students' prior knowledge rather than students' traits" (p. 471). A key feature of well-designed adaptive learning environments is that instruction is closely aligned to what each student currently knows, as this alignment not only improves understanding, but it also enhances retention.

Adapting instruction is just one of the many ways educators aim to increase academic achievement. The desire to increase academic achievement is a widely held aspiration in education. This can be quickly verified by simply performing an academic search on the phrase *improving academic achievement*; the results matching this search criteria numbered in the thousands. Using Google Scholar to search for the same phrase, the search returned hundreds of thousands of matches. The aspiration to improve academic achievement has resulted in a variety of interventions and initiatives; including teacher-initiated motivational strategies to improve student performance. However, George (2010) cautions against the use of this approach with remedial math students. The concerns stem from the premise that teachers may inadvertently diminish students' autonomy when they cease to use standardized performance-based motivators such as grades, tests, and homework and opt for motivational strategies such as making personal attempts to engage the student in the course; a dangerous approach that can move beyond teacher-responsibilities and into subjective judgments. This is not to say that teachers should not care about their students' success, but in the case of remedial students, where vulnerabilities are at their highest, it is best to use standardized processes as much as possible. This may be a strong argument for considering the use of adaptive learning software programs as a means to systematically build skills, enhance self-efficacy, and fuel motivation without over tasking faculty or risking adverse effects to the students. Moreover, adaptive learning affords each student the time necessary to learn for mastery.

When students are able to stay on a topic until they have mastered it, deeper and more meaningful learning is likely to occur.

Learning for Mastery

In traditional instruction, concepts or topics are taught for a specific length of time and teachers move from topic to topic as defined by their curriculum schedule, rather than by the needs of the students (i.e., time-based). In a learning-for-mastery approach, instruction is driven by the students' academic needs and new topics are introduced only when the students have mastered the prerequisite topics (i.e., mastery-based). Instruction is bound by the mastery of content, which is intended to ensure that students fully understand concepts as they move through the curriculum.

Benjamin Bloom (1968) posited the concept of learning for mastery based in part on his belief (influenced by John Carroll, 1963) that given sufficient time and the appropriate learning conditions, 95% of students could achieve mastery. Bloom (1978) later stated that 80% of students in mastery-based classrooms performed equal to the top 20% of students in traditional classrooms. He held that the main factor separating the top performers from the low performers was time (Bloom, 1974). Since its inception, the mastery-based approach has been widely used and criticized (Chandler, 1982; Lalley & Gentile, 2009b). Bloom (1974) acknowledged that learning for mastery can be time prohibitive for some, but he also believed that if effective teaching strategies were used, this time could be reduced (e.g., frequent feedback with specific guidance). Arguably, the demands this instructional approach place on instructors may have limited its widespread adoption in traditional teacher-lead classrooms; however, with powerful software programs, this problem is now minimized. Software programs can be designed to excel at this task by quickly adapting to the individual learner's response and present examples and practice exercises that provide just the right balance of success and challenge.

There is a renewed interest in learning for mastery (Guskey, 2010), which may be a result of the current state of our education system; where thousands of students are completing courses but not mastering the content. High school graduates are entering college ill-prepared for the rigors of higher education, lacking understanding of basic and important principles (ACT, 2012). Nonetheless, some argue that learning for mastery is not a practical approach because it can lead to undesirable consequences. Senko and Miles (2008) investigated the premise that a mastery approach can harm students' likelihood of success, by allowing them to disproportionally focus their efforts on topics of more interest to them, or topics they find easier to attain. While these researchers admittedly acknowledged that mastery learning promotes deeper learning, they claimed that the path taken towards mastery leads to predicted lower grades in the class. They also held that mastery goal students reported using an interest-based approach, $n = 240$; $\beta = .16$, $p < .05$. These researchers contend that students with a mastery orientation measure their learning with self-referential subjective standards, whereas the performance oriented students measure their learning by outperforming their peers (e.g., being ranked in the top 10%). Several caveats are warranted about this research. For instance, one flaw in the basis of their argument is the assumption that mastery-learning environments do not use criterion-referenced measures (e.g., assignments, tests, competency assessments). Their argument also assumes that only performance-oriented students measure their performance with norm-referenced criteria and objective measures. This is not an accurate assumption; other possible explanations or alternatives were not explored by the authors, which one can argue weakens the validity of the original research.

Perhaps the most serious criticism of mastery learning is the lack of a formal assessment method (Chandler, 1982). The very nature of mastery learning makes standardized assessments problematic; when everyone is learning at a different pace and quite possibly different or new topics, teachers are faced with the challenge of systematically and objectively using a one-size-fits-all assessment tool. Diegelman-Parente (2011) proposed a logical approach that addresses this limitation. That is, the use of competency-based assessment tools in mastery-based environments. She suggests that students should demonstrate mastery of concepts that are deemed fundamental and meeting the criteria would earn a passing grade of C. Students can then be given the opportunity to earn extra points by completing additional enrichment activities; the extra points translate into mastery level grades. This approach seems a feasible compromise to allow faculty to maintain control over the learning process, while students are given the freedom to learn at their own pace, within the constraints of a semester, and achieve the level of mastery they desire.

Bloom (1968; 1978) posited that mastery learning could also provide other benefits, such as reduced anxiety. He argued that repeated academic success reduces anxiety about course achievement enabling students to better cope with academic demands. Van Dinther, Dochy, and Segers (2011) evaluated 39 empirical studies on the effects of self-efficacy and learning and found that mastery experiences were significantly correlated to the development of a strong sense of self-efficacy. It follows then that making progress towards a learning goal enhances students' sense of self-efficacy. According to Bandura (1977), self-efficacy is not only a predictor of academic success, but it also acts as a mediator of motivation and learning. When students have the opportunity to work on attainable tasks, they develop confidence in their abilities, this confidence then becomes a motivator to learn. Hence, mastery experiences motivate students to engage in activities that they perceive to be attainable, which in turn boosts their self-efficacy and fosters their self-regulation.

Self-efficacy, Self-regulation, and Motivation

Bandura's (1977) self-efficacy refers to the judgments individuals make about their ability or inability to take the necessary actions required to perform a given task. Moreover, individuals who have a low sense of self-efficacy about their ability to do a certain task, tend to avoid doing that task. Self-regulation acts as a monitoring mechanism of motivation to perform tasks through a goal system. Goals can help individuals overcome their hesitation to do something, due to low self-efficacy, by increasing their desire to attempt the task by focusing on goal attainment (Bandura, 1989); however, not all goals result in equal motivational benefits. For instance, proximal goals yield the highest motivation because they tend to have a more immediate fulfillment or are more readily attainable. Specific goals are better than general goals because the specific goals provide a plan of action. The level of difficulty of a goal can also serve as a personal motivator and gauge for accomplishment for postsecondary students, particularly when goals become increasingly difficult as skills become more developed (Schunk, 1991). Schunk explained that students assess their own capabilities based on cues they receive from others through vicarious experiences. When students see peers accomplish a task, they are better able to visualize themselves accomplishing similar tasks; however, the positive effects of vicarious experiences on self-efficacy are weak and can easily be offset by failure (Bandura, 1977). When students receive verbal encouragement from others about their ability to perform a task, their self-efficacy experiences a temporary boost. On the other hand, when students experience success through their own performance, the increase in self-efficacy has a stronger effect. Thus, when students set specific performance goals their sense of self-efficacy is reinforced as they attain those goals.

Affective and motivational factors traditionally have been overlooked in the evaluation of academic competence; however, the desire to understand these cognitive and affective relationships is rapidly increasing. In a recent experimental study, Changeiywo, Wambugu, and Wachanga (2011) compared the effects of a mastery learning approach against a traditional teaching approach on students' motivation to learn (n = 161). Their results indicated that students in the mastery group had significantly higher motivation than the students in the traditional group, $F(3, 157) = 36.3$, $P < 0.05$. In an informal review of research on motivation and engagement, published in the Educational Digest, the authors found that motivational factors were more likely to contribute to academic success when students experienced greater levels of autonomy and had frequent opportunities to demonstrate academic competence (Toshalis & Nakkula, 2012).

There have been studies where meaningful interactions between cognitive ability, motivation, and performance have not been clearly established, it is this very concept that prompted Hirschfeld, Lawson, and Mossholder (2004) to investigate the relationship between cognitive ability, performance and type of motivation. They evaluated how undergraduate students' academic performance was impacted by context-specific—academic achievement—motivation, general academic motivation, and cognitive ability (n = 364). The comparisons led the researchers to conclude that the relationship between cognitive ability and performance was moderated by academic achievement motivation, $\beta = 0.40$, $p < .01$. Furthermore, when achievement motivation was higher, cognitive ability was more predictive of performance, $\beta = 0.53$, $p < .01$. These results align with findings presented in a review of motivation in remedial mathematics, in which it was concluded that motivation was a key factor in determining students' math performance (George, 2010). Motivation has historically and intuitively been considered a key component in learning (Keller, 1979) and is critical to academic competence, academic resilience, and academic achievement. After all, it is a teacher's responsibility to know what to teach and when to teach it, but it is up to the students to decide if and how much they want to learn (Diegelman-Parente, 2011).

Academic Competence

DiPerna and Elliott (1999) defined academic competence "as a multi-dimensional construct composed of the skills, attitudes, and behaviors of a learner that contribute to academic success." (p. 208). Using this definition as a framework, they identified two domains that contributed to academic competence: academic skills and academic enablers. The academic skills domain relates to the basic cognitive abilities that enable students to function in an academic environment. This domain is comprised of three skill clusters: (a) mathematics and scientific inquiry, (b) reading and writing, and (c) critical thinking. The academic enablers domain relates to specific attitudes and behaviors in four skill clusters: interpersonal skills, study skills, motivation, and engagement. Figure

1 illustrates how each of these clusters contributes to a student's overall academic competence.

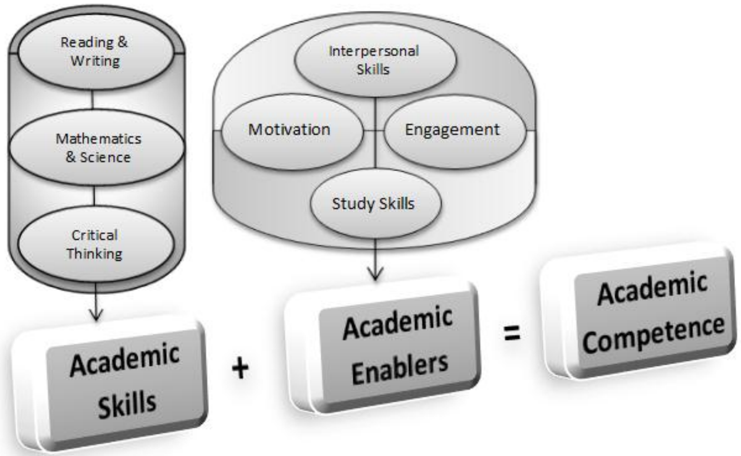


Figure 1. Visual representation of DiPerna and Elliott's (2001) Academic Competence model for college students.

The academic skills domain incorporates the students' perception of their understanding and level of command in: written language, mental math and problem solving, application of scientific concepts, and higher order thinking. The academic enablers domain takes into account the students' affective awareness: their view on their academic attitudes and behaviors towards peers and faculty; the approach they take when learning new material; and how they evaluate their persistence and their desire to learn. The cognitive abilities and affective attributes that are comprised in the academic competence construct closely align with the concepts and principles that constitute the building blocks of academic resilience: self-efficacy, self-regulation, motivation, and engagement. Self-efficacy aligns with the academic skills domain. Self-regulation, motivation, and engagement align with the academic enablers domain.

The literature review revealed that the learning environment, the teaching approach, and students' academic competence are important to academic success. It was also evident that most of these variables have been primarily investigated in isolation. To better understand the conditions that promote academic achievement, the intertwined nature of these variables cannot be dismissed. Thus, it is important to concurrently evaluate all aspects of students' academic performance: the learning method (i.e., teaching approach), the learning environment, academic competence, their affective attributes and academic resilience.

Before elaborating on academic resilience, it is important to first understand the underlying construct—resilience. Resilience refers to one's ability to bounce back (Herrman, Stewart, Diaz-Granados, Berger, Jackson & Yuen, 2011). When one thinks of resilience, the tendency is to think of this construct in terms of individuals being able to recover from adversity, distress, or even trauma. The ability to maintain mental health through positive adaptation despite adversity is the essence of resilience; whereas, academic resilience centers on students' self-efficacy, self-regulation, and motivation as key contributors to academic success (Morales, 2008; Scholar Centric, 2010).

Although resiliency is relevant in any academic subject, it could be argued that students may benefit most from resilient behaviors when studying mathematics. Johnston-Wilder and Lee (2010) argue that students have a harder time developing resiliency when learning mathematics due to the anxiety intrinsic to the subject. Students are typically expected to perform accurate and speedy calculations, but also their work is viewed as a reflection of their intelligence and their lack of performance is considered a failure. These judgments are at times self-inflicted, but more often than not, given by peers and sometimes teachers or even parents. Cassen, Feinstein, and Graham (2008) contend that resilience can be the one factor that can help counteract whatever risk factors that may be present and contribute to poor academic performance (e.g., intelligence, mental health, and environmental influences such as, family backgrounds, socioeconomic status, the learning environment, and the school system).

Academic Resilience

Martin and Marsh (2006) present a validated assessment of academic resilience. Much of their work builds upon the work of Andrew J. Martin who has over a number of years (2001-2006) examined motivation from various perspectives and have developed tools such as the motivation and engagement wheel. Based on this wheel, Martin and Marsh (2006) created their own model—the Student Motivation and Engagement Scale (SMES)—to evaluate predictors in adaptive and maladaptive dimensions related to motivation. They proceeded to validate this scale with a sample of 402 Australian high school students. The adaptive dimension of SMES included self-efficacy, mastery orientation, planning, valuing of school, study management, and persistence. The maladaptive dimension of SMES included anxiety, uncertain control, failure avoidance, and self-handicapping. Marin and Marsh found five of these predictors to statistically significantly predict academic resilience: self-efficacy, control, planning, low anxiety, and persistence. Of the five predictors, self-efficacy (r = .33) and anxiety (r = -.66) were the strongest. Martin and Marsh also found that academic resilience in turn predicted school enjoyment and class participation, both are thought to enhance commitment to learning.

The literature findings provided further support that the variables investigated in the present study: the learning environment, the teaching approach, the students' academic competence, and their academic resilience were consistently found to have positive effects on academic success.

Rationale for the Study

Purpose

The aim of this study was to investigate the role of academic competence and academic resilience, in an adaptive mastery-based learning environment, on the academic achievement of college students in need of remediation. Specifically, the focus of this investigation was on: (1) the academic performance of students in a remedial mathematics course, (2) the relationship between specific cognitive and affective attributes that were deemed central to resilient behavior, and (3) valued academic outcomes such as course completion.

Theoretical Framework

The conceptual framework to guide this investigation was based on the social ecology of resilience (Ungar, 2011). Ungar presented ecological resilience as a process where individuals dynamically interact with their environment based on the meaningfulness and relevance of their resources or opportunities, and the extent to which these opportunities meet their needs and personal capabilities. Figure 2 illustrates an expression of academic performance, inspired by Ungar's ecological resilience expression (Appendix C). This expression was used as the guiding theory in attempting to understand and assign meaning to the relationships revealed in this investigation. Academic performance (A_{p}) is a function (f) of affective attributes (A_{a}) relative to the level of resilient behavior (R_b) while holding cognitive ability (C_{a}) constant and the extent to which the learning environment supports or inhibits ($Env_{\mathrm{(s\text{-}i)]}}$) learning.

$$A_p = f \frac{C_a (A_a \cdot R_b)}{Env_{(s\text{-}i)l}}$$

Figure 2. Academic performance expression based on Michael Ungar's ecological resilience expression, 2011.

Ungar (2011) theorized the Social Ecology of Resilience as an attempt to demonstrate that resilience is both an internal and external process. He posited that an understanding of resilience would eliminate the cultural ambiguities associated with the construct. His view of resilience is based on the notion that the construct is essentially two processes: (1) A sequence of events by which individuals learn to be resilient; that is, when one has access to resources that sustain our wellbeing, then we become resilient, and (2) the extent to which an individual's social and physical ecology can provide those resources. In the present study, this view of resilience was used as a conceptual guide and an attempt to operationalize the model was also made. In this definition, resilience as a process can be thought of as the experiences through which one's attitudes are modified as one learns to be resilient. In contrast, resilience as an outcome can be thought of as the consequence of past experiences exhibited through behaviors. When one is learning to be resilient through a particularly difficult experience, the level of support the environment provides directly impacts one's attitude (i.e. process), which is evidenced in subsequent resilient behaviors (i.e. outcome). For example, if a student attempting to complete a particularly challenging homework problem is provided with appropriate resources that would allow the exploration of possible solutions, the student can spend enough time to figure out the problem and come up with the correct approach. If the student receives a favorable mark on this homework, the student's attitude towards difficult problems is modified, he or she might think: *That wasn't too bad, if I try hard enough, I can do this!* On the other hand, if the environment is ill suited and the student can't obtain timely answers, or have access to adequate resources, the student might take a best-guess approach. If the student receives an adverse mark on this assignment, the student's attitude towards difficult problems is negatively impacted and he or she might think: *That was way too hard, its no use trying, there is no way I can do this!* Thus, the outcome for each of these cases would be exhibited in the next assignment, when the student is faced with a similar problem he or she will either embrace it or avoid it.

Research Question

The present study was designed to answer this primary research question: How do cognitive ability and affective attributes moderate the mathematics academic performance of students in need of remediation? The following predictions are roughly illustrated in Figure 3.

Prediction one. It was anticipated that students' cognitive ability would have a direct relationship to their academic performance; however, this relationship was expected to vary as a function of their affective characteristics. Thus, students with effective study skills, who are highly motivated and highly engaged, would demonstrate superior academic performance to those with lower scores in those areas.

Prediction two. It was further hypothesized that resilient behavior would mark the difference between students who succeed in the class compared to those who did not. That is, successful students would display higher resilient behaviors throughout the course than did their counterparts.

Prediction three. It was hypothesized that a mastery approach to instruction would have a positive impact on the academic performance of remedial students while heightening their affective attributes. Consequently, it was expected that a positive change would be seen in students' academic competence. More specifically, by the end of the course: (1) a positive change was expected in engagement and motivation, (2) a reassessment of academic skills that better aligned with the students' actual performance was anticipated, and (3) no change was expected in interpersonal skills or study skills.

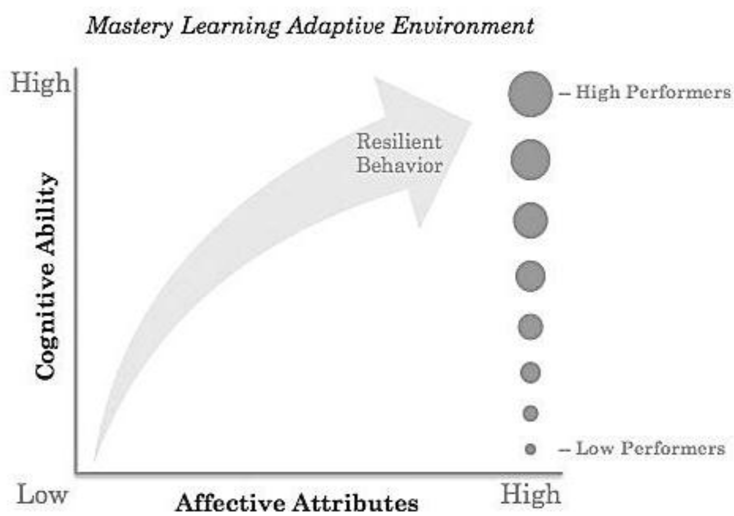


Figure 3. Graphic representation of predictions.

The findings from this study were used as a framework to refine an instructional model for remedial math students. Instructional designers and educators can use this model as a guide in the development of remedial math courses or to design interventions to improve the performance of remedial students. Teachers may also be able to use the model to better understand the performance of their students.

Chapter 2

METHODS

Participants

The present study utilized extant data collected as part of a concurrent research study entitled Student Success in Math—Longitudinal Study (data collected by ASU online staff). Institutional Review Board approval with exempt status was obtained for the Student Success in Math study (Protocol #: 1108006723; Appendix A). I was added to the study personnel of this protocol as a co-investigator. College students, who were enrolled at ASU during the period of 2010 to 2012, were invited to participate in the Student Success in Math study, which used an adaptive learning environment—the Knewton Readiness Math program. All students were presented with a consent form and given the opportunity to decline participation; a signed consent indicated they granted the research team access to their academic and institutional data (Appendix B). Multiple courses were observed over a period of two years as part of the Student Success in Math study, with a sampling population of over 12,000 students. However, due to matters beyond the scope of this study, the data accessible for this research were limited to the information gathered during the Fall 2012 semester, for the remedial course MAT 110 – Enhanced Freshman Mathematics.

Initially, 2,880 students were enrolled in this course, removing students who had no course data brought the sample down to 2,226 students, of those only 1,970 had an active enrolled status. To enroll in the first-year college algebra course students needed to earn a minimum of 40 points on the ALEKS (Assessment and Learning in Knowledge Spaces) placement test, and a minimum of 30 points for the college mathematics course.

Students who scored below these requirements were placed in MAT-110; however, students scoring beyond the minimum could also elect to enroll in the remedial course if they did not feel prepared for a first-year level course. Table 1 illustrates the Fall 2012 MAT-110 course's initial and final enrollment, as well as the passing rates.

Table 1

Remedial Course: MAT 110, Fall 2012 Semester

Enrollment status			F-2012	Gender		Course status	
Status	Initial *n*	Removed	*n*	Male	Female	Pass	Fail
	2,880		2,226	44%	57%	73%	1%
						2%[a]	
Enrolled			1,970[b]			18%[c]	
Missing		654[d]					
Dropped		95					
Withdrawn		161					

Note. [a]Percent of students marked as LC (learning complete: awaiting a passing grade processing). [b]Final enrollment number. [c]Percent of students marked as Z (in progress) which indicated they would continue the course the following semester. [d]Records with missing data.

Approximately 78% of students were 18 to 20 years of age, with a relatively proportional gender distribution, 56% females, 44% males. The ethnic distribution was less balanced, with Whites in the majority (52%), and the remaining students distributed among various races. Hispanics made up the larger minority group (26%) followed by the African American group (11%, see Figure 4). While the ethnic distribution did not appear to support the concerns for minority disparities found in the literature, when remedial enrollment is considered at the university level, then the minority disproportion aligns with the literature. That is, the Black enrollment in this course would in reality represent approximately 72% of the African-American freshmen population (comparison data obtained from the *2012-2013 Common Data Set*, http://uoia.asu.edu/sites/default/files/common/Common_Data_Set_2012-2013.pdf).

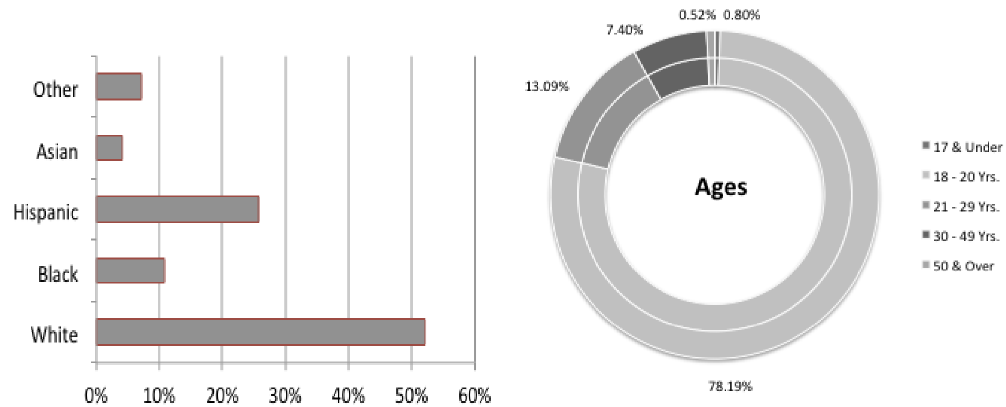


Figure 4. Ethnic and age distribution – Fall 2012 cohort.

The average SAT and GPA scores (*m* = 480; see Table 2 and Figure 5), appeared to be slightly below the typical first-year college students' SAT Math scores: *first quartile* = 490, *third quartile* = 630; GPA *m* = 3.42 (2012-2013 Common Data Set). Additionally, the initial enrollment in this course indicated that there were 2,880 students who were below the expected skill ability for a first-year college-level course during the Fall 2012 semester. The total freshmen enrollment for the 2012 year was approximately 10,600 students; thus, enrollment in the remedial course would represent roughly 27% of the freshmen student body. After remediation, 75% of the students who completed the remedial course were eligible to enter a first-year college level mathematics course.

Table 2
Summary of MAT 110 Scores Distribution

Scores	*N*	Missing	*M*	*SD*	*Variance*	Min	1st Quartile	*Mdn*	3rd Quartile	Max
Cum GPA	2,124	102	2.57	1.03	1.06	0.00	2.05	2.78	3.33	4.33
SAT I math	1,130	1,096	479.99	75.00	5,625.07	200	430.00	480.00	530.00	740.00
ALEKS	2,122	104	26.82	14.94	223.25	0.00	18.00	25.00	32.00	100.00
Final Exam	1,869	357	18.30	8.20	67.23	0.00	17.50	21.33	23.00	30.00

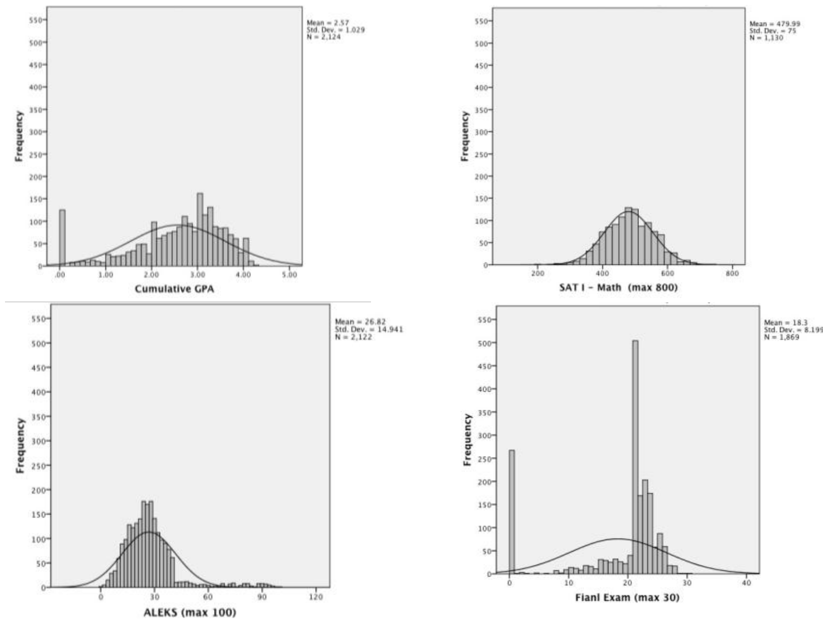


Figure 5. Normal distributions of MAT 110 scores

The focus of the present investigation was an attempt to understand the conditions that contribute to successful remediation and identify areas that may be further explored, which may prove helpful to remedial students.

Research Design

The present study utilized an extant dataset from a remedial mathematics course (MAT 110) offered during the Fall 2012 semester at ASU. All data were collected by the ASU online staff; however, at the time of the original data collection, random assignment and a true experimental design were deemed to be unethical given the population of interest and nature of the treatment. The evaluations of students and their performance in this course included correlational and comparative analyses within an intact group. The key dependent variable was academic performance as measured by within-course test scores and final course exam scores. The second dependent variable was academic competence, as measured by the ACES-College instrument. Two types of independent variables of importance were cognitive ability and affective attributes. GPA, ALEKS, and SAT scores were used to operationalize cognitive ability. The affective attributes and their associated measures were self-regulation (ACES-study skills), motivation (ACES-motivation), and engagement (ACES-engagement). Academic resilience was operationalized as resilient behavior measured by two indicators self-efficacy (ACES-academic skills) and course commitment—operationalized as perseverance (posttest attempt quantity), attendance (login frequency), and participation (lesson rate). Due to the enduring concerns about underperformance of minorities and women in mathematics courses (ACT, 2012), ethnicity and gender were also used as independent variables during the analyses.

Procedures

Data collection and evaluation design. The data gathered comprised a wide range of academic achievement determinants, such as institutional data, instructional data, evaluation data, and demographics. The data were collected during three phases: screening, instructional, and evaluation. The resulting evaluation design is illustrated in Figure 6. The institutional data included: SAT, GPA, final exam, and course grade. The instructional data included the Knewton embedded assessments and course engagement data (e.g., time records). The evaluation data included: ACES-College pretest and posttest scores. Missing data were removed using a listwise method; that is, all cases with missing values were removed from all analyses. Descriptive information regarding the missing data were summarized to determine whether a bias was present in the results.

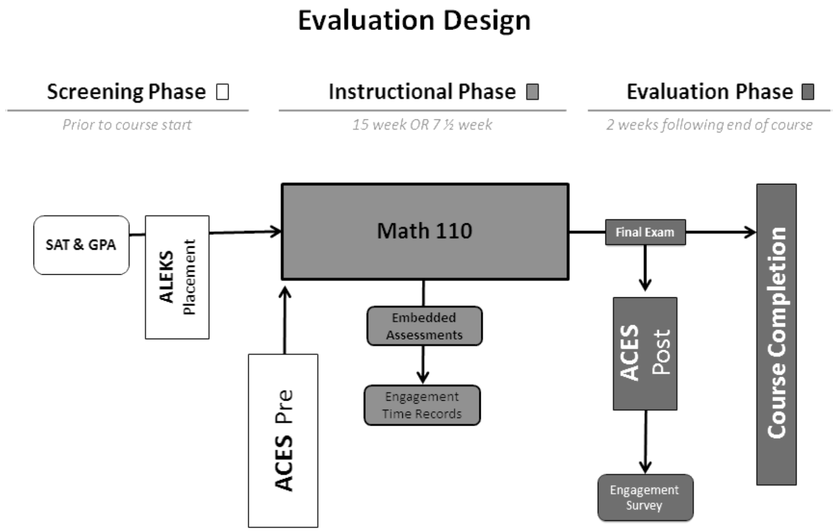


Figure 6. Evaluation model of the assessment types and assessment occasions for Math 110 taken during the Fall 2012 semester. Modified version of original evaluation model.

Data processing. An initial examination of the data revealed several noteworthy issues. For instance, it was possible that students took the ACES posttests in place of the ACES pretests and vice versa. There were no mechanisms in place to ensure students took one test before the other, they could take the same test multiple times and/or leave blank answers. This meant that further data processing was needed to arrive at a manageable, reliable, and consistent dataset. The process used for cleaning the data is described below.

Institutional data. The demographics data were already compiled into rosters for the entire semester. The rosters were matched to research IDs. A copy of the original roster file was made and all the fields that would not be used for the present study were removed. The information retained included: research ID, term, course number, enrollment status, course grade, GPA (e.g., current, cumulative, and transferred), ethnicity, and gender. The SAT scores, ALEKS scores and final exam scores were not part of the original data set, but were subsequently compiled by the ASU online staff.

Evaluation data. Two procedures were conducted: (1) duplicate records were marked but not removed; these were then evaluated against the three conditions, defined below, to determine if the records were true duplicates. (2) Each ACES sub-scale was evaluated for missing items and addressed according to the ACES-College manual (DiPerna & Elliott, 2001), then subscales were summed and domain totals computed. After initial conceptualization, the actual filtering and data consolidation were performed by automated custom scripts using Excel (Appendix D part 1). To start the cleanup process, a set of possible problem conditions were created along with a list of actions identifying how these conditions should be resolved when encountered. These conditions are identified in Table and a summary of actions follow.

Table 3

Possible ACES Pre- and Posttest Conditions

ACES test	Number of times a test was attempted									Record to be kept
Pre	0	1	1	0	> 1	> 1	> 1	0	1	First
Post	0	1	0	1	0	1	> 1	> 1	> 1	Last

Note. First and last records were verified by the start date.

Prior to running the scripts, the data were sorted by research ID and start date for both ACES pretest and ACES posttest.

First condition. If multiple tests were taken (pre- or post) on the same day, only the first test record was kept. This assumed that the first response may be less biased.

Second condition. If more than one test attempt was made on the same day and one of those attempts was incomplete, the incomplete record(s) was deleted. This assumes that there may have been some technical issue that prevented the student from completing the test. This excludes actual incomplete cases; that is, if there was only one test attempt made but the record was incomplete, then the record was kept.

Third condition. To address the possibility that posttests were mistakenly taken as pretests and vice versa, a rule of behavior was defined: When a duplicate pretest record was found and no posttest record existed, then the last pretest record was assumed to be the posttest. The opposite was done for the posttest: when a duplicate posttest record was found and no pretest record existed, then the first posttest record was assumed to be a pretest. A minimum five-day span between each test date attempt was set as the conditional criterion for the pretest versus posttest assumption. This reflected the absolute minimum number of days a student could conceivably go through the program.

Instructional data. The Knewton lesson session contains the in-course engagement information, which was tracked by number of logins. This file contained thousands of records. The same was true for the Knewton assessment data set, which contained the embedded assessments (lessons pretest and posttest scores) as well as the number of posttests attempted. Together these files required processing hundreds of thousands of records, this called for the development of a set of more complex scripts (Appendix E – part 2). These scripts matched each student ID with its corresponding lesson data, login data, and test data. Then files were stitched together with the institutional data and ACES data. Students who did not take a pretest or a posttest received a score of -100 respectively; for the analyses, these values were replaced with zeros. In addition, totals for each of the course commitment indicators (resilient behavior) were drawn from the Knewton dataset: total number of test attempts, total number of lessons taken and total number of logins. Another outcome of these custom scripts was the creation of a matrix of lessons taken by students; the intent was to use this matrix to map out the path students took to mastering the content and allow comparisons between students and the differing behaviors towards content mastery.

Instruments

While there were several indicators that quantified students' academic competencies, behaviors, and performance, only two of those were in an instrument format: The ACES-College and the engagement survey. The rest of the indicators were comprised of scores such as SAT, GPA, final exam, and course grades. Key performance information was also derived from the Knewton embedded assessments.

ACES-College. The Academic Competence Evaluation Scales—ACES-College was the primary instrument used during the original data collection and, as such, it was an indispensable instrument for this study. This scale was developed based on previous research and in accordance with the Standards for Educational and Psychological Testing (AERA, et al., 1999), as a means to systematically evaluate students' academic competence for intervention purposes (Appendix F). The information pertaining to this instrument was obtained directly from the ACES-College manual (DiPerna & Elliott, 2001).

The ACES-College is a 66-item questionnaire, written at a seventh-grade level using criterion-referenced ratings. Reliability evidence is very good (i.e, average internal consistency coefficient = .97; average retest coefficient = .92). The completion time for this instrument is estimated to be less than 20 minutes for both the Academic Skills and Academic Enablers domains. In the Academic Skills domain, students were asked to estimate their skill level within three subscales (reading and writing, mathematics and science, and critical thinking) in comparison to other students at their university. These ratings used a five-point Likert scale, where one was *Far Below* and five was *Far Above* (Figure 7). The skills in each of the subscales consisted of the most basic skills deemed necessary to be successful in school. Each skill rating, as envisioned by the authors, should have included an importance rating of each skill (i.e., *Not Important, Important, Critical*). Unfortunately, the importance ratings were not included or collected as part of the original data collection process (i.e., Success in Math Study) due to concerns about student time.

Academic Skills

Reading/Writing Skills	Far Below	Below	At Grade Level	Above	Far Above	Not Important	Important	Critical
1. Reading comprehension	1	2	3	4	5	1	2	3
2. Reading unfamiliar words by sounding out each of the letters	1	2	3	4	5	1	2	3

Mathematics/Science Skills	Far Below	Below	At Grade Level	Above	Far Above	Not Important	Important	Critical
11. Computation	1	2	3	4	5	1	2	3
12. Analyzing errors in information or processes	1	2	3	4	5	1	2	3

Critical Thinking Skills	Far Below	Below	At Grade Level	Above	Far Above	Not Important	Important	Critical
21. Synthesizing related information	1	2	3	4	5	1	2	3
22. Drawing conclusions from observations	1	2	3	4	5	1	2	3

Figure 7. Academic skills sample items.

In the Academic Enablers domain, students were asked to rate how often they used each skill within four subscales (interpersonal, engagement, motivation & study skills). These ratings used a five-point Likert scale, where one was *Never* and five was *Almost Always* (Figure 8) and a three-point importance rating; however, as stated earlier, the importance rating was left out from the original data collection. The questionnaire concluded with one open-ended question, which asked students to provide comments about themselves and how they learn best.

Academic Enablers

Interpersonal Skills	Never	Seldom	Sometimes	Often	Almost Always	Not Important	Important	Critical
31. I am considerate of others	1	2	3	4	5	1	2	3
32. I am willing to compromise	1	2	3	4	5	1	2	3

Engagement	Never	Seldom	Sometimes	Often	Almost Always	Not Important	Important	Critical
39. I use outlines to organize my written work	1	2	3	4	5	1	2	3
40. I speak in class when called upon	1	2	3	4	5	1	2	3

Motivation	Never	Seldom	Sometimes	Often	Almost Always	Not Important	Important	Critical
47. I am motivated to learn	1	2	3	4	5	1	2	3
48. I prefer challenging tasks	1	2	3	4	5	1	2	3

Study Skills	Never	Seldom	Sometimes	Often	Almost Always	Not Important	Important	Critical
57. I complete course assignments	1	2	3	4	5	1	2	3
58. I edit my work before I submit it	1	2	3	4	5	1	2	3

Figure 8. Academic enablers sample items.

The scoring process, outlined in the manual, directed to sum each subscale to obtain raw scores for each of the domains. These raw scores were then totaled to obtain the domain scores. That is, the raw scores for reading/writing, mathematics/science, and critical thinking were summed to obtain the score for the academic skills domain. The same was done with the academic enablers. Thus, the interpersonal skills, engagement, motivation, and study skills were summed to obtain the academic enablers domain score. Finally, academic domains skills and academic enablers were summed to yield the total academic competence score.

The manual also offered a process for dealing with missing data, when a student did not provide a rating for two or fewer items in any subscale, each of the missing items were given a score of 3, on the assumption that this value represented a conservative average skill rating at grade-level. When three or more item ratings were missing from a subscale, then the entire scale was omitted from the score and the domain to which the subscale belonged to was also omitted (pp. 18-20; DiPerna & Elliott, 2001).

The authors also defined three competence levels into the scoring process: *Developing*, *Competent*, and *Advanced*. These competence levels were easily identified by plotting the raw scores on the competence continuum for each scale and subscale (Figure 9). This competence continuum facilitated the construction of a confidence interval around students' scores, which provided the range of scores within which their actual scores were likely to fall.

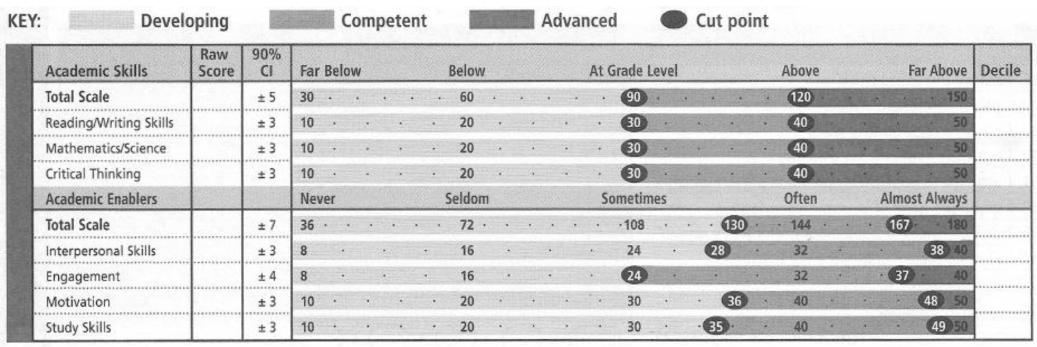


Figure 9. Competence levels for each of the ACES subscales.

For the purposes of this study, the information resulting from this instrument was used to evaluate self-efficacy, self-regulation, motivation, and engagement—academic competence. While one of the primary purposes of the ACES-College is to identify students' academic strengths and weaknesses to assist in the design of potential remedial interventions, the learning and self-management strategy portion of the scale, was not part of the data gathered during the original data collection process. Thus, the instrument could not provide a direct link for possible remediation interventions or instructional strategies. Nonetheless, due to the nature of the information gathered with the instrument and despite the missing strategy component, it still served as a strong source for remediation recommendations.

Engagement survey. Students were asked to estimate the number of hours they spent doing various activities during a typical week (e.g., preparing for the course, during and after class hours; working; and leisure activities). They were also asked to state the grade they were working towards and the grade they would expect to earn in the class. The survey consisted of 22 questions that, for the purpose of this study, were categorized into three clusters: time, grades, and engagement. The time clusters contained questions related to the amount of time students spent studying, time on-task, working for pay, and at leisure time. The grades cluster contained questions related to their desired grade and their actual grades. The engagement cluster contained all the Likert-type items (e.g., five-point scale; one being *Extremely Characteristic of Me* and five being *Not at All Characteristic of Me*), relating to students' homework and classroom behaviors. Figure 10 shows a sample question from the time cluster. The data gathered from this instrument were used to supplement the information given by the students in the Study Skills subscale (ACES-College) and to inform the revision of an instructional model for remedial students.

During the time you took this course, about how many hours in a typical 7-day week did you spend doing each of the following?

	0 Hours	1 - 5 Hours	6 - 10 Hours	11 - 15 Hours	16 - 30 Hours	21 - 25 Hours	26 - 30 Hours	More than 30 Hours
Preparing for **this course** (studying, reading, writing, doing homework, and other academic activities) outside of class time	○	○	○	○	○	○	○	○

Figure 10. Engagement survey sample question. For the entire survey, see appendix G

Knewton embedded assessments. The embedded assessments in the program consisted of content-specific quizzes within the lessons, and posttests to measure mastery (Figure 11). These tests determined which lesson was most suitable to the students' current knowledge level. All lessons were initially locked; a pretest had to be taken to unlock the lesson. Thus every lesson began with the *Show us What You Know* (SWYK) test. Once the test was taken the lesson was unlocked, irrespective of the score earned., Demonstrating 100% mastery on this test placed the student out of that lesson. That is, the student was not required to view the lesson and could move on to the next lesson. Those who did not demonstrate 100% mastery had the option to view the lesson first and then take a *Test your Skills* (TYS) posttest, or go directly to the posttest. Scoring a minimum of 70% on this first posttest would enable the student to move to the next lesson. Students earning anything below 70% were required to go through the lesson, at the end of which another TYS test was given. The same criteria applied for the second posttest, a student needed to earn 70% to move to the next lesson.

However, scoring below 70% on the second posttest, would put the course in *Focus Mode*. This meant the student would be taken to previous concepts, as far back as necessary to fill the knowledge gap, even to lessons out of which the student may have previously placed. At the end of the Focus Mode, the students were presented with the third TYS posttest. If a student did not earn the minimum 70% on this test, the student would remain in this lesson. However, the student was given the option to move to the next lesson, if desired, but had to at some point return to this lesson and earn the minimum passing score (70%). To complete the course, a passing score on all lessons was required and upon completion, access to the final exam was granted.

As mentioned previously, during the data collection, if a student was missing a test (either pretest or posttest) a score of -100 was assigned. The number of posttests was also meant to be an indicator of how much students may have interacted with the lesson. For example, a missing pretest could indicate that the student went straight to the posttest and skipped the lesson. If a student had one pretest and only took one posttest, it was possible that part of the lesson was skipped. If the student took two posttests, this indicated the student would have gone through the entire lesson. If a student had three posttests or more, then it was safely assumed the student was placed in Focus Mode. All posttests after the second posttest were identical.

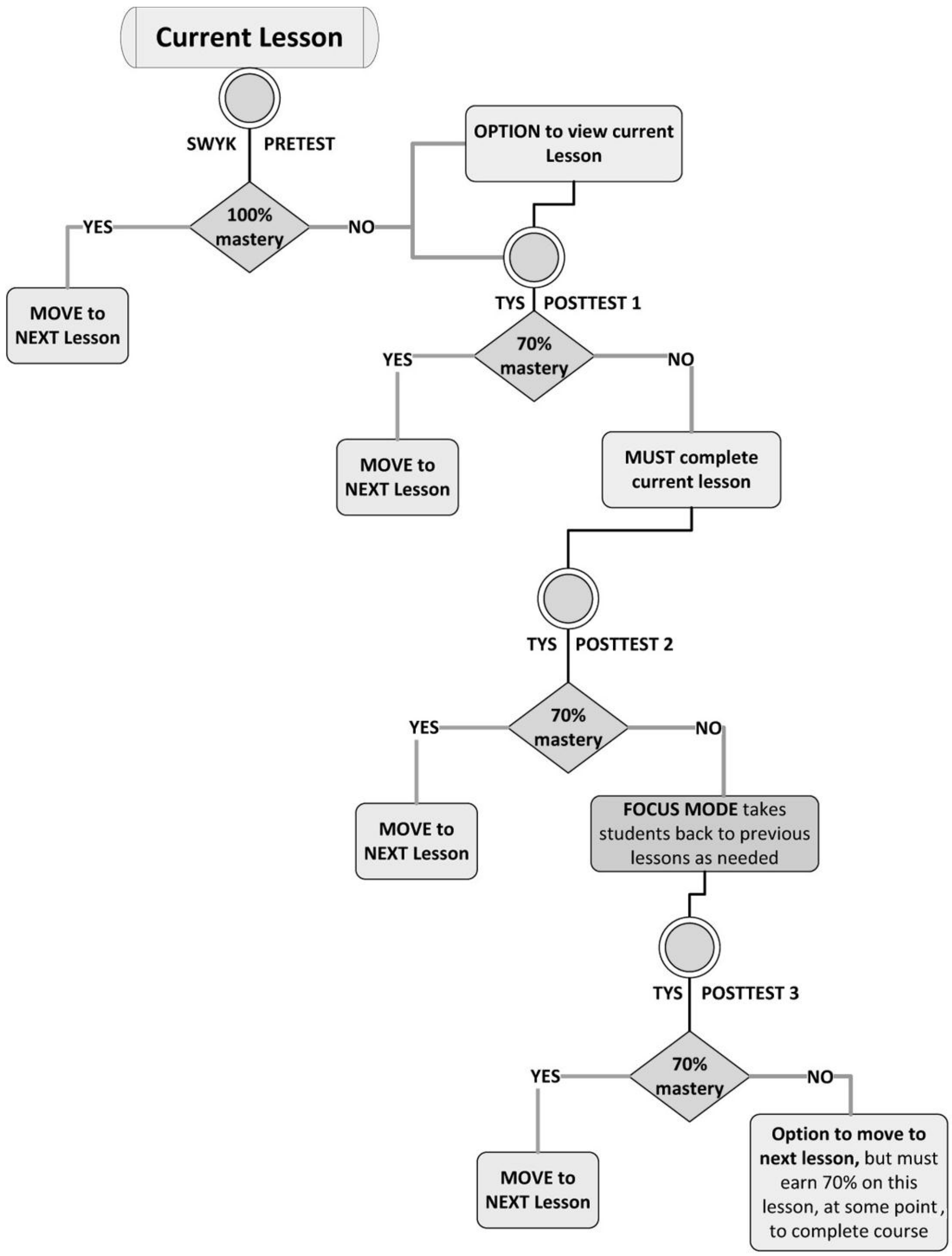


Figure 11. Diagram of Knewton embedded assessments

Knewton engagement time records. The students' level of engagement was tracked through session activity. A session constituted a single login/logout period; students were considered logged off after 15 minutes of inactivity. These session periods were only rough indicators of student activity, as some browser refresh rates may have caused the system to generate multiple logins. Additionally, if students were working on multiple lessons at once, their activity was only registered as a single session. Thus, this information was used with caution and checked against other indicators, such as *in-lesson* times (which started when the students began to view the content in the lesson and ended when they completed the posttest) and lessons posttests. Despite the limitations, these data were expected to provide a level of resilient behavior in the course.

The time records, along with the number of posttests taken, and the number of lessons completed, were used as a rough measure of course commitment (i.e., one of the indicators of resilient behavior). Resilient behavior was not part of the planned data collection; however, the existing data aligned with what could be defined as resilient behavior. For the purpose of this study, resilient behavior aimed to assess the level of academic resiliency exhibited by students during the course. Self-efficacy was found to be the strongest predictor of academic resilience (Martin & Marsh, 2006). Martin and Marsh hold that academically resilient students exhibit three specific behaviors: (1) they enjoy their courses, (2) they are more likely to participate, and (3) they have an enhanced commitment to learning. The Knewton records were intended to serve as indices of resilient behavior to operationalize this construct. Specifically: (1) course enjoyment was measured by attendance, operationalized as the frequency of logins, (2) participation was operationalized by the number of lessons viewed, and (3) commitment to learn was measured by perseverance, operationalized as the number of posttests taken. These indices collectively were referred to as course commitment.

Program: Remedial Adaptive Math Course

The remedial MAT 110 —Enhanced Freshman Mathematics course was developed to meet the needs and requirements of the university and to align with common core standards. The course used the Knewton adaptive learning software program—Knewton Math Readiness. The content was aligned with seven common core subjects: ratios and proportions, the number system, expressions and equations, geometry, statistics and probability, functions, and algebra. The purpose of the course was to help students develop the skills needed to enter the first-year college mathematics course required by their program of study. The enrollment in this course consisted of: students who were required to take MAT 117 but their ALEKS scores were between 0 – 29; students who were required to take MAT 142 and their ALEKS scores were between 0 – 39; and students who earned a passing score on ALEKS but did not feel ready to take a first-year college level mathematics course.

According to one of the math professors who teaches these courses at ASU (I. Bloom, personal communication, March 14, 2013), students placed in the remedial course typically fall into one of three broad placement-categories: (1) lack of knowledge base, students with many deficiencies, (2) explicit deficiency, students who struggle with a specific concept, (3) negligence, students who do not take the placement test seriously. These categories tend to result in a wide range of skill proficiencies and deficiencies within a single classroom, posing a real challenge for the traditional one-size-fits-all teaching approach. Professor Bloom believes the adaptive approach can be particularly beneficial in addressing this challenge by allowing students to progress through the lessons at their own pace and at a rigor best suited to their ability. She also believes that students are more likely to succeed in the course when faculty members utilize the information provided by the Knewton adaptive program to intervene as needed. Instructors who teach using the adaptive environment typically provide assistance during scheduled class times, and are able to use the Knewton student-progress information as a tool to determine the type of assistance to be given when it is most needed. For example, when students struggle with a specific concept, those students are placed in a *red zone,* alerting faculty of the problem area and flagging the students to watch (Figure 12). Faculty can then approach the student, or a small group of students to provide focused instruction and further explanation of the concept in question.

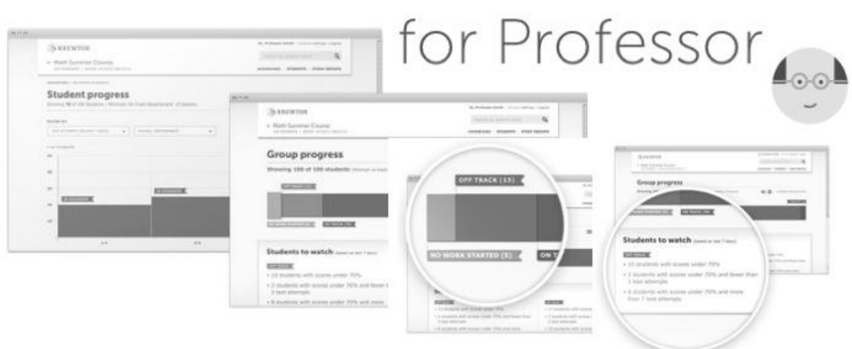


Figure 12. Knewton: faculty tools and resources.

The Knewton Math Readiness program uses a *learner analytics* adaptive engine to adapt instruction and create a self-paced system in which students' math abilities are continually assessed using multiple indicators to determine the most appropriate individualized learning path. The engine analyzes students behaviors and uses the students' diagnostic quizzes to adapt instruction as needed. Instruction is then personalized to students' current skill proficiencies, using Knewton's probabilistic model

(Figure 13), which identifies the specific content each student is most likely to master (Knewton, n.d.; 2012).

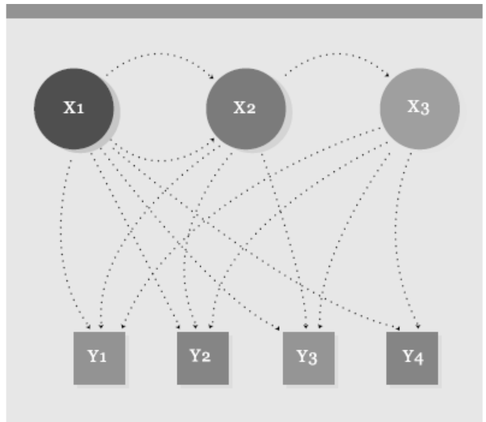


Figure 13. Knewton's probabilistic graphical model presented in their whitepaper, 2012. The model illustrates how relationships between concepts are determined.

The Knewton lessons could be conceptualized as having four key segments with multiple opportunities for students to demonstrate mastery of the lesson content at any point during the lesson—*Test your skills!* The first segment was a lesson introduction which presented the topic through a video lecture that provided a brisk high-level explanation. The second segment was a *Warm Up*, which quizzed students on the concepts presented in the lesson introduction. The third segment consisted of three or more *Workshops* depending on the topic; each of the workshops explained the key concepts discussed in the introduction in greater detail. The workshops were presented as video lectures with many real-world examples; at the end of each workshop students were given the opportunity to solve similar problems through workshop-based quizzes—*Now try it!* All questions in every quiz were followed by detailed explanatory feedback, using video or a step-by-step written format. Each activity took approximately 10-15 minutes to complete. The fourth segment was a *Wrap Up* which consisted of a lesson-based quiz. Students were able to view their current progress through a dashboard and workspace which contained all the information related to the course, from scores earned to lessons to be completed. Their dashboard also provided students access to lesson workshops previously viewed and feedback received on quizzes already taken (Figure 14).

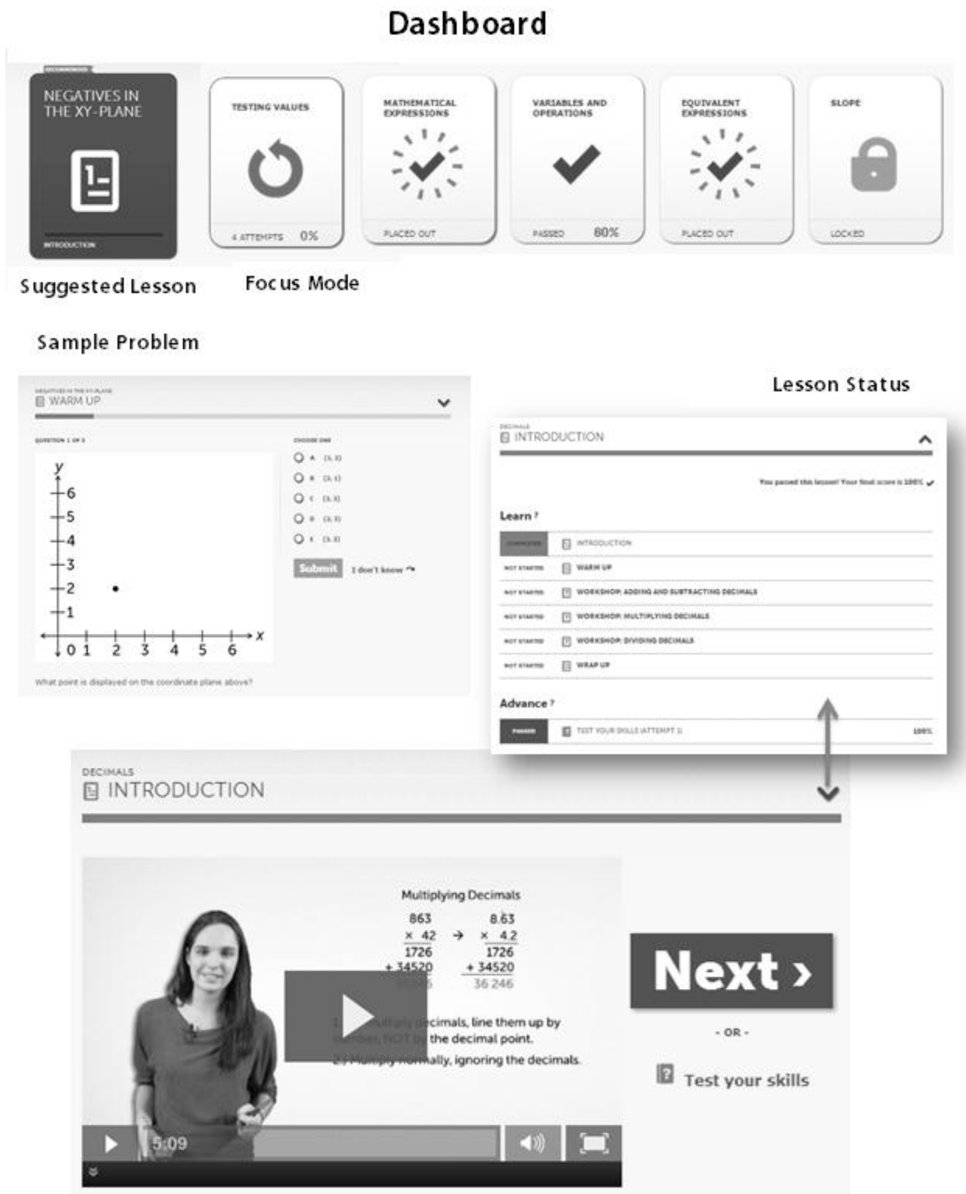


Figure 14. Knewton Dashboard: student tools and resources.

The modality of this course is typically hybrid (online and face-to-face). Most of the courses were offered for a period of 15 weeks, but there were also 7.5 week sessions. The course class time typically consisted of one 75-minute face-to-face period, and one open learning session per week. Regardless of the course session length, the actual course length was determined by the students' skill level as demonstrated by their mastery. A student, with few deficiencies, could conceivably complete the course in as little as two weeks, however all students are given two full semesters to complete the MAT 110 course. When students were not able to complete all the required lessons within the semester, a grade of Z (i.e., in progress) was given and those students would take the course again the following semester, with the course beginning where the students left off. It is important to note that the grade Z should not be equated with a failing grade, as a student receiving a Z would be simply utilizing the maximum length allowed by the university to complete the course. A student who continues on to the second semester and completes the course receives a mark of LC (i.e., learning complete); the instructor then assigns an actual grade through a grade-change process.

Successful completion of the remedial math course enabled students to advance to the appropriate first-year mathematics course in their program. The course was considered complete, when students passed all the core lessons (i.e., the minimum number of lessons required for their track). Specifically, track one had 52 core lessons and prepared students for MAT 117: *College Algebra.* Track two had 46 core lessons and prepared students for MAT 142: *College Mathematics*. The track was determined by the students' program of study. If a student was undeclared, by default, that student was placed in track one. While there were a minimum number of lessons to be completed, the content had up to 139 lessons, and students could take more or fewer lessons than the required minimum, depending on their skill level. Note that placing out of a lesson counted as completing that lesson—hence students could take less than the minimum number of lessons. The posttests generated from these lessons were the Knewton embedded assessments which were used as one of the performance indicators in this study.

Data Analysis

The academic performance expression presented earlier was used as a framework to answer the research question in this study (Figure 15). This expression was also used as a basis to form this study's predictions. To answer the research question (i.e., How do cognitive ability and affective attributes moderate the mathematics academic performance of students in need of remediation?) a series of hypotheses were tested, using hierarchical linear regressions and analyses of covariance. The breakdown in Table 4 shows the variables used in the correlational analysis conducted to evaluate the relationship amongst the predictor variables.

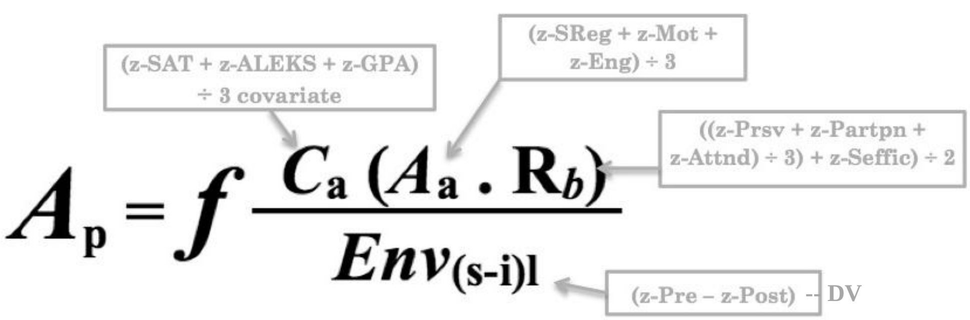


Figure 15. Academic performance expression (expanded from Figure 2).

Table 4

Statistical Analysis Breakdown – part 1

Rationale	Variables and analyses
	Correlations
Evaluation of the correlation amongst predictors: cognitive ability, affective attributes, and resilient behavior.	Cognitive Ability: SAT I (math) scores, ALEKS scores, and cumulative GPA scores Self-efficacy: ACES- pretest academic skills Motivation: ACES- pretest motivation Self-regulation: ACES- pretest: study skills Engagement: ACES- pretest: engagement Survey: Time: studying, on-task, at work, at play Grade: working towards, earned Engagement Resilient behavior: Perseverance: posttest frequency Participation: lesson completion rate Attendance: login frequency Ethnicity Gender

It was anticipated that students' cognitive ability would have a direct relationship to their academic performance, thus cognitive ability was used as a covariate throughout the analyses. Also, the use of covariates was an attempt to equalize differences among the students thereby partially addressing issues related to the use of intact groups (Maxwell & Delaney, 2004). The relationship between affective characteristics and academic performance was expected to vary as a function of resilient behavior. To this end, a hierarchical multiple regression analysis was conducted to evaluate whether an interaction existed between affective attributes, resilient behavior, and academic performance and whether the interaction impacted the academic performance or students in a remedial course (Table 5).

Table 5

Statistical Analysis Breakdown – part 2: *Prediction One*

Rationale	Variables	Analyses
Expression: Evaluating the expression: If academic performance was a function of cognitive ability (C_a) and affective attributes (A_a), then academic performance (A_p) was expected to significantly improve as cognitive ability and affective attributes increased; further this improvement was expected to vary as resilient behavior (R_b) varied. These analyses evaluated the relationship between cognitive ability, affective attributes, and academic performance; and the interaction between these variables and academic resilience, while controlling for cognitive ability.	**Control variables** Cognitive ability (C_a): Prior achievement: SAT, ALEKS & GPA scores **Independent variables** Affective attributes (A_a): Motivation: ACES- pre Motivation Self-regulation: ACES- pre Study skills Engagement: ACES- pre Engagement Resilient behavior (R_b): Self-efficacy: ACES- pre academic skills Course commitment: Perseverance: posttest quantity Participation: lesson rate Attendance: login frequency **Dependent variables**[a] Academic performance (A_p): Embedded quiz scores Final exam Course grade	Hierarchical multiple regression Control variables Cognitive ability (C_a) Predictors [a] Affective attributes (A_a) Resilient behavior (R_b) Dependent variables [a] Academic performance (A_p)

Note. [a]One analysis for each dependent variable.

It was further hypothesized that resilient behavior would mark the difference between the academic successes of students. To better understand this relationship, another multiple regression analysis was conducted. Table 6 shows the variables used for that analysis.

Table 6

Statistical Analysis Breakdown – part 3: Prediction Two

Rationale	Analyses
To evaluate whether students with higher performance scores also had higher resilient behaviors	**Repeated measures ANOVA** Within-subject factors: Resilient behavior (R_b) – pre / post Between-subject factors: Pass course & Fail course **One-way ANOVA** Factors : Resilient behavior (R_b) Between-subject factors: Pass final exam & Fail final exam

A final prediction was made that the mastery environment would have a positive impact on the academic performance and the academic competence of students in need of remediation. To this end, Analysis of covariance (ANCOVA) was conducted to evaluate how the learning environment affected each of the seven sub-scales of Academic Competence (Table 7). The variables gender and ethnicity were also used in this analysis to determine if the effects varied across these variables. To evaluate the performance component of prediction Three, the paths the students took within the course were also examined. That is, the way in which they approached the lesson content; the proportion of students that placed out of lessons and their corresponding performance scores compared to students who systematically went through every lesson and their corresponding performance scores.

Table 7

Statistical Analysis Breakdown – part 4: Prediction Three

Rationale	Variables	Analyses
Evaluation of the effects of the learning environment on students' academic competence, and whether the effects vary across gender and ethnicity and their academic performance.	**Covariates** Cognitive ability: ALEKS scores **Variables** ACES–pretests and posttests: Academic competence Academic Skills (self-efficacy) Academic enablers Affective attributes (self-regulation (study skills), engagement, motivation) Gender Ethnicity	Repeated measures ANCOVA Covariates Cognitive ability Within-subject factors ACES pre Knewton ACES post Knewton Between-subject factors Gender Ethnicity
	Mixed methods	
To evaluate the paths taken by students and to identify patterns within the lessons	**Descriptive** Proportion of lessons: Placed; one posttest; two posttests; and three posttests or higher. **Two-way ANOVA** Factors Lesson average attempts (0, 2, 3) Gain score **Independent samples *t*-Test** Variables Lesson average attempts (0, 2, 3) Grouping variable Pass exam / fail exam	

An additional descriptive analysis was conducted to evaluate the open-ended responses provided through the ACES instrument (Table 8), relating to students' learning preferences and their reflections on how they learn best. This information and the data gathered through the engagement survey were used to inform the recommendation made under the implications for practice section in Chapter Four.

Table 8

Variables for Additional Exploratory Analysis

Variables	Analyses
Independent measures	**Descriptive**
Pre and post ACES: open-ended question	
Cognitive ability: ALEKS scores	Summary of ACES responses
Engagement self-report Survey:	Summary of engagement responses
Cluster I	
Time spent preparing and studying	**Stepwise multiple regression** (backward method)
Time spent working	
Time spent playing	Control variables
Cluster II	Cognitive ability (C_a)
Grade working towards	Predictors
Grade earned	Time spent preparing and studying
Cluster III	Grade working towards
Rankings on the level of student engagement	Engagement ratings
	Dependent variables
Dependent measures	Academic performance (A_p)
Academic performance:	
Final exam	

Chapter 3

RESULTS

This study examined the relationship between the academic performance of college students, in a remedial mathematics course, and key variables considered to be contributors to their academic success—cognitive ability, affective attributes, and resilient behavior. Three predictions drove the examination of these variables and their relat1ionships. To this end, several hierarchical multiple regression analyses and an analysis of covariance were conducted. Before examining the results for each of these predictions, descriptive data for the key variables used throughout these analyses are presented in Table 9. The cognitive ability related variables were previously presented in Table 2.

Descriptive Data for Key Variables

Affective attributes is not a formal construct measured on the ACES-College but rather a composite variable comprised of engagement, motivation, and self-regulation (study skills). In this study, all three variables received ratings above grade level—engagement (M = 30.85, SD = 5.43, n = 1,317), motivation (M = 43.08, SD = 5.53, n = 1,315), and self-regulation (M = 43.60, SD = 5.47, n = 1,311)—indicating that students believed their affective attributes were at the high end of the competent level on the Competence Continuum of the ACES-College manual (see Figure 9). Engagement fell within the competent range on the competence continuum, 90% CI [26.84, 34.84]. Motivation and self-regulation were at the top end of the competent range, 90% CI [40.08, 46.08] and 90% CI [40.60, 46.60] respectively.

Resilient behavior was conceptualized as self-efficacy and class commitment. Overall, students rated their self-efficacy (academic skills) at grade level (M = 101.81, SD = 16.37, n = 1,317) falling well within the competent range on the competence continuum, 90% CI [96.81, 106.81]. The variables that comprised class commitment were significantly skewed (perseverance, Skew = 3.96, SE = .07, Kurtosis = 31.76, SE = .14; participation, Skew = -1.70, SE = .07, Kurtosis = 2.81, SE = .14; attendance, Skew = 3.54, SE = .07, Kurtosis = 20.55, SE = .14), therefore the median is presented to more meaningfully represent the sample. Perseverance was operationalized as the number of posttests taken. The median number of posttest taken was 53, with 37 posttests in the lower quartile, and 68 posttests in the upper quartile. The minimum number of posttests taken was zero and the maximum was 482. Participation was operationalized as the number of lessons completed. The median number of lessons completed was 56, with 47 lessons in the lower quartile, and 56 lessons in the upper quartile. Attendance was operationalized as the number of logins. The median number of logins was 88, with 61 logins in the lower quartile, and 130 logins in the upper quartile.

Academic success was operationalized through two key performance outcomes, final exam scores and the Knewton embedded assessment scores. The maximum possible score on the final exam was 30 points. Students needed to complete all the Knewton lessons before they gained access to this exam, thus not all students took the final exam (M = 18.30, SD = 8.20, n = 1,869). An examination of the quartiles indicated that at least 50% of the students passed the exam and 25% of the students scored 77% or higher. The Knewton embedded assessments were comprised of pretest scores and posttest scores for students' math skills.

The averaged pretest and posttest scores shown in Table 9 represent the raw scores. However, to compute the gain scores, *placed-out* students were taken into account. When a student placed-out of a lesson, by scoring 100% on a pretest, the data collection criterion systematically assigned a -100 score to that student's posttest. For the purposes of this study, these values were changed to zero to maintain students' actual score. The choice to use a value of zero instead of non-value (e.g., blank) was to ensure SPSS would not treat these cases as missing data. To avoid the misleading effects of leaving all the zeros in the data, before computing the gain score, all the pretests with a score of 100 were excluded and all the corresponding posttests with scores of zero were also excluded. This created a more accurate representation of a gain score as a result of going through the lessons (M = 40.61, SD = 11.86, n = 1,303). Students who placed-out of the lessons by definition already possessed the knowledge so they would not experience any gain; therefore, excluding these students from the gain scores was deemed appropriate.

Table 9

Means and Standard Deviations for the Scores of Key Variables

Variable	*n*	Missing	*M (SD)*	*Variance*	Min	Quartiles 1st	2nd	3rd	Max
				ACES pre					
Self-efficacy[a]	1317	909	101.81 (16.364)	267.78	29	91	101	112	150
Affective attributes[b]	1311	915	117.58 (13.77)	189.63	56	108	119	128	140
Academic enablers[c]	1311	915	151.12 (19.23)	369.63	40	140	153	165	180
Academic competence[d]	1309	917	252.93 (30.38)	923.18	73	236	253	272	330
				ACES post					
Self-efficacy	806	1420	106.44 (16.94)	286.99	30	93	105	118	150
Affective attributes[b]	803	1423	115.54 (16.17)	261.49	66	105	116	129	140
Academic enablers[c]	803	1423	149.39 (19.54)	381.96	90	137	150	165	180
Academic competence[d]	802	1424	255.77 (30.54)	932.86	169	236	255	274	330
				Resilient behavior					
Course commitment: Perseverance	1319	907	57.71 (38.28)	1465.48	0	37	53	68	482
Participation	1320	906	49.31 (13.43)	180.35	1	47	56	56	125
Attendance	1320	906	109.71 (90.15)	8126.99	0	61	88	130	909
				Academic success					
Knewton averaged pretest scores	1319	907	56.18 (14.75)	217.64	0	46.20	57.07	66.52	100
Knewton averaged posttest scores	1319	907	60.68 (12.78)	163.22	0	54.46	61.96	68.54	100
Knewton gain[g]	1303	923	40.60 (11.86)	140.78	-5	32.95	38.99	47.37	100
Final exam	1869	357	18.30 (8.20)	67.23	0.00	17.50	21.30	23.00	30.00
				Engagement survey					
Study – preparation [e]	451	1775	2.92 (1.40)	1.96	1	2	2	4	8
Time on-task [e]	450	1776	3.05 (1.60)	2.55	1	2	2	4	8
Overall engagement [f]	438	1788	3.66 (0.80)	0.64	2	3	1	1	5

Note. [a]Scores represent the summed ratings on student's ability in relation to other students at their grade level (e.g., 10 = Far Below and 50 = Far Above)—Academic Skills. [b]Scores represent the summed ratings of how often a given skill was used (e.g., Depending on the scale: engagement, motivation, or study skills) 8-10, = Never and 60-50 = Almost Always). [c]Scores Represent the total sum of the scales that make up the domain (e.g., academic skills: Reading/writing, math/science, and critical thinking. Academic enablers: Interpersonal skills, study skills, engagement, and motivation). [d] Scores represent the grand total of all the scores of all the scales (e.g., academic skills and academic enablers). [e]Scores represent a range of hours (e.g., 1 = 0 hrs. and 8 = more than 30 hrs.). [f]Scores represent averaged ratings (e.g., 1 = Not At All Engaged and 5 = Highly Engaged). [g]Scores represent the difference between the total pretest average and the total posttest average, excluding pretest scores of 100 and posttest scores of zero.

Missing data strategy. It is important to note that each of the analyses performed varied in sample size due to missing data. A Little's MCAR (Missing Completely at Random) test was conducted to determine if the missing values could be replaced with predicted values to retain a more consistent sample size throughout the analyses (Little, 1988). However, this approach was not a viable option for this study, as the MCAR test yielded significant results (Chi-Square = 2144.27, df = 1789, $p < .05$). Multiple regression and ANCOVA assumptions were tested (i.e., normality, homogeneity of variances, multicollinearity) as described below. All dependent measures were independent and continuous in nature.

Normality and data transformations. All variables were examined for normality and transformations were performed prior to conducting the statistical analyses. A number of variables exhibited some level of non-normality and while a large sample size is robust to this assumption, there were some variables that exhibited extreme skewness and kurtosis exceeding what might be considered problematic (i.e., skew values greater than 2.0; von Hippel, 2010). Some of the extreme scores contributed to the non-normality of the data; however, those extreme scores were not isolated cases and removing them may have meant removing some aspect that described the true population. Thus, transforming the variables to address this non-normality was necessary. Logarithmic (log) transformations, as described in the transformations section, were performed on variables that exceeded the *Skew* = 2 threshold (Field 2009).

The three variables ALEKS, cumulative GPA, and SAT were used as combined indicators of cognitive ability. Therefore, it was important to attempt normality and consistency among these variables. Additionally, all three indicators were measured on different metrics and transformation to a single scale was necessary. All three variables were transformed into Z-scores. The SAT variable was normally distributed so the only transformation performed on this variable was a Z-score transformation. The ALEKS variable had a pronounced positive skew and was kurtotic, *Skew* = 2.04, *SE* = .05, *Kurtosis* = 6.04, *SE* = .11, which exceeded the skewness criteria and thus log transformed. The cumulative GPA variable was less extreme and did not meet skewness criteria, *Skew* = -.94, *SE* = .05, *Kurtosis* = .37, *SE* = .11. Nonetheless, the desire to maintain consistency among these three variables was deemed more important and thus the cumulative GPA was also log transformed.

The same reasoning was used for the Final Exam variable, which exhibited a negative skew, *Skew* = -1.49, *SE* = .06, *Kurtosis* = .77, *SE* = .11. The resilient behavior variables perseverance, participation, and attendance also had non-normal distributions, all of which exceeded the skewness criteria and transformed accordingly (i.e., perseverance, *Skew* = 3.96, *SE* = .07, *Kurtosis* = 31.76, *SE* = .14; participation, *Skew* = -1.89, *SE* = .07, *Kurtosis* = 2.26, *SE* = .14; attendance, *Skew* = 3.55, *SE* = .07, *Kurtosis* = 20.59, *SE* = .14).

The assumptions of the statistical parametric tests that were used in this investigation are contingent on a normal distribution. A log transformation is believed to be particularly effective at addressing issues related to homogeneity of variance and normality (Field, 2009). Given the skewness of the data, log transformations were selected to obtain residuals approximately symmetrically distributed. Furthermore, all the variables that were transformed received the same type of transformation to avoid inconsistencies (Keene, 1995). Two forms of log transformations were used: log natural

(Ln = base-*e*; where *e* = 2.72) and log common (Log10 = base-10). The log natural transformation is suited for continuous variables whereas the log10 is better suited for ordinal data. The latter was used on the resilient behavior data, which measured number of logins, number of posttests and number of lessons.

Log transformations have specific rules that must be met for the procedure to work well; such as, the distributions should have a right skew, and all values contained in the variable must be greater than zero (e.g., no negative or zero values are accepted). Since the ALEKS variable was positively skewed, a log transformation was appropriate. However, this variable contained zero scores and negative scores, which resulted from the Z-score transformation. Consequently, a value of two was added to each score at the time of the transformation to satisfy the rules of the log transform procedure. The cumulative GPA, since it was standardized, violated the log transform rules on all accounts. Specifically, it had negative skewness, it contained zeros, and negative scores. This indicated that a reflection transformation needed to be included with the log transform. A reflection is the process of taking the largest score within the variable and adding a value of 1, and then every score is subtracted from the sum (highest score + 1). This method removes the negative values and the zeros, and then flips the distribution to the right. The resulting distributions for each of the transformed variables are shown in Figure 16.

Homogeneity of variance. Given the lack of randomization and lack of normality, Type I errors may have been at risk; however, the large sample size was expected to address this concern. An alpha level of .05 was used to perform all the analyses. To address the independence of scores, students' cognitive ability scores were used as covariates on all the statistical analyses to partially offset the use of intact groups. Moreover, Levene's tests (Levene, 1960 as cited in Gastwirth, Gel & Miao, 2009) were computed by using a one-way ANOVA with Final Exam as the dependent variable. The test of equality of error variances revealed that the error variance was equal across the key predictor variables. Cognitive ability, Levene's statistic: $F(14, 54) = 1.05$, $p = .42$. Affective attributes, Levene's statistic: $F(14, 54) = 1.78$, $p = .07$. Self-efficacy, Levene's statistic: $F(14, 54) = 1.01$, $p = .46$. Resilient behavior (course commitment) Levene's statistic: $F(14, 54) = 1.19$, $p = .31$.

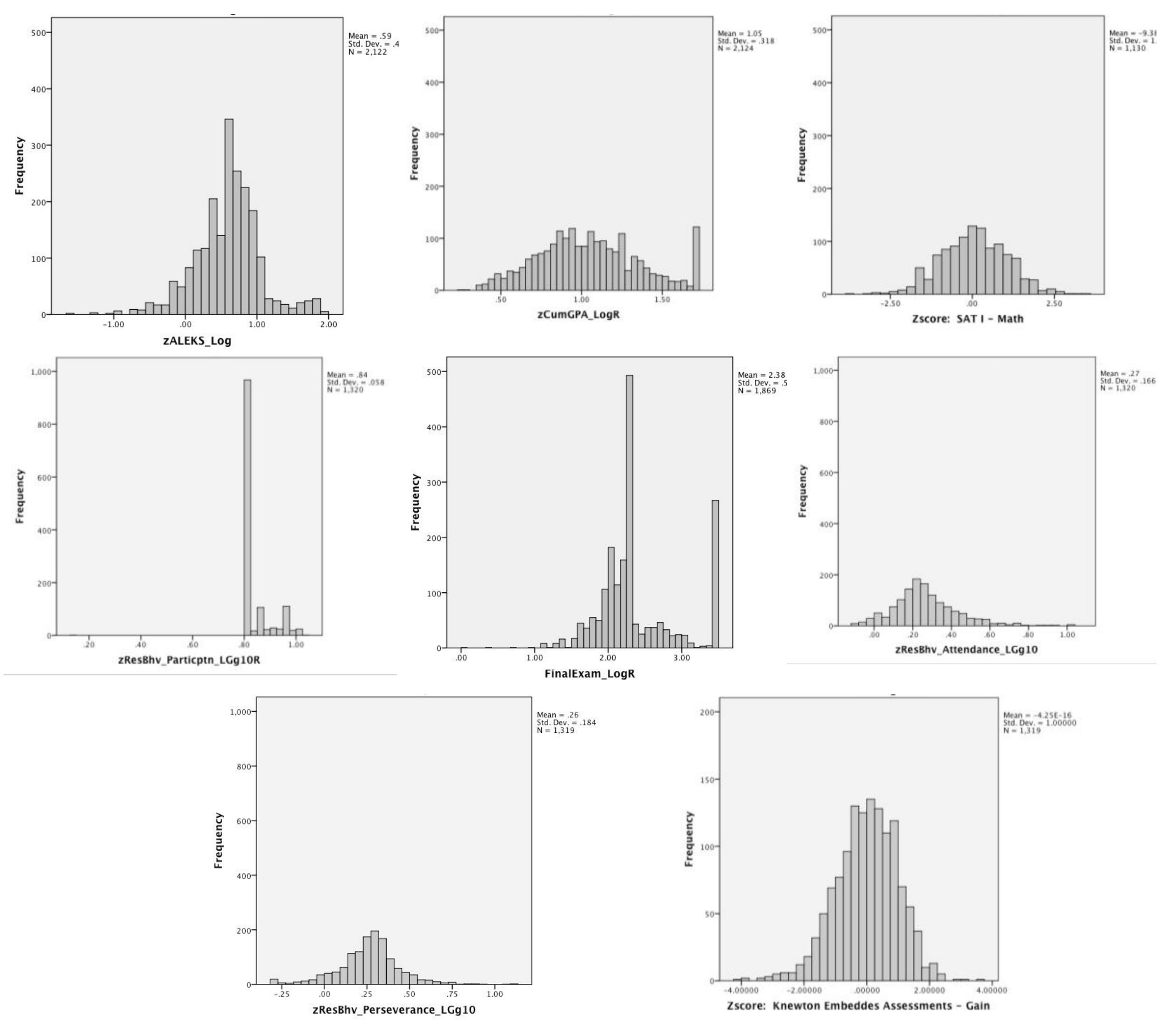


Figure 16. Distributions for transformed variables

Multicollinearity. A correlation analysis amongst the predictor variables was conducted. To address the non-normal distribution and the presence of outliers in the data, the Spearman's rho correlations analysis was used. This selection was based on the assumption that Spearman's correlations are more robust when dealing with non-normal data (Field, 2009). The untransformed versions of each of the variables were used for the correlation analysis. There was no indication of concern as most variables had relatively small correlations (Table 10). Self-efficacy and resilient behavior were negatively correlated, which may have resulted from the non-normal distributions, whereas affective attributes and resilient behavior were positively correlated. Featured results are: self-efficacy and perseverance, $r = -.09$, $p = .02$, $n = 607$; self-efficacy and participation, $r = -.03$, $p = .48$, $n = 608$; self-efficacy and attendance, $r = -.15$, $p < .01$, $n = 608$; affective attributes and perseverance, $r = .13$, $p < .01$, $n = 601$; affective attributes and participation, $r = .06$, $p = .17$, $n = 602$; affective attributes and attendance, $r = .12$, $p < .05$, $n = 602$; and self-efficacy and affective attributes, $r = .31$, $p < .01$, $n = 1{,}309$.

Table 10

Spearman rho Correlation Matrix of Key Predictor Variables

	r (*p*) *n*									
Variables	1	2	3	4	5	6	7	8	9	10
1. SAT	1 (.00)									
	1130									
2. ALEKS	.00 (.05)	1 (.00)								
	1128	2122								
3. Cum GPA	.05 (.11)	.12 (.00)	1 (.00)							
	1130	2122	2124							
4. Self-efficacy-AS	.20 (.00)	.15 (.00)	.04 (.16)	. 1 (.00)						
	658	1309	1310	1317						
5. Academic enablers[(a)]	-.12 (.00)	-.01 (.00)	.17 (.00)	.33 (.00)	1 (.00)					
	654	1303	1304	1309	1311					
6. Affective attributes[(b)]	-.13 (.00)	-.03 (.39)	.19 (.00)	.31 (.00)	.95 (.00)	1 (.00)				
	654	1303	1304	1309	1311	1311				
7. RB: Perseverance	-.41 (.00)	-.17 (.00)	.03 (.23)	-.09 (.02)	.12 (.00)	.13 (.00)	1 (.00)			
	716	1218	1220	607	601	601	1319			
8. RB: Participation	.08 (.05)	.23 (.00)	.32 (.00)	-.03 (.48)	.06 (.16)	.06 (.17)	.51 (.00)	1 (.00)		
	716	1219	1221	608	602	602	1319	1320		
9. RB: Attendance	-.45 (.00)	-.22 (.00)	-.07 (.01)	-.15 (.00)	.11 (.01)	.12 (.00)	.76 (.00)	.45 (.00)	1 (.00)	
	716	1219	1220	608	602	602	1319	1320	1320	
10. Survey: Engagement	-.04 (.56)	.06 (.17)	.17 (.00)	.07 (.23)	.32 (.00)	.33 (.00)	.00(.90)	-.02 (.73)	-.03 (.66)	1 (.00)
	240	435	436	324	324	324	245	245	245	438

Note. [a]Academic enablers are comprised of: interpersonal skills, engagement, motivation, and study skills. [b]Affective attributes is comprised of engagement, motivation, and study skills. These predictors were never used in the same analysis.

Prediction One: Supported

The prediction that college students' cognitive ability, affective attributes, and resilient behavior would have a direct relationship to their mathematics academic performance was analyzed with two linear hierarchical regressions using the transformed variables. A list-wise method was used to remove missing data across all three sets of predictors drastically reducing the sample size for each of the analyses. For each of the analysis, the predictors were entered in three steps, as outlined below, which resulted in three separate regression models for each analysis. The dependent variable for the first analysis was the final exam and the dependent variable for the second analysis was the Knewton embedded assessments (gain scores).

Regression variables:

1. Covariates: SAT I math, ALEKS, and Cumulative GPA.
2. Two sets of predictor variables:
    a. Affective attributes: engagement, motivation, and self-regulation.
    b. Resilient behavior:
        i. Self-efficacy: reading and writing, math and science, and critical thinking.
        ii. Class commitment: perseverance, participation, and attendance.
3. An interaction term: affective attributes-by-resilient behavior.

Regression analysis one, DV: final exam. The sample size for this analysis was 315 students. The first model yielded by this analysis contained the cognitive ability predictors, the second model contained the cognitive ability, affective attributes, and resilient behavior predictors, and the third model contained all the predictors plus the interaction term. The second model was the model of interest that addressed the prediction which yielded significant results, $R^2 = .41$, $F(12, 302) = 17.29$, $p < .01$. This result indicated that the linear combination of all the variables—cognitive ability, affective attributes, and resilient behavior—statistically significantly predicted the variability in the academic performance of students on the final exam (Table 11).

Affective attributes and resilient behavior accounted for and additional 16% of the variance in the academic performance on the final exam, beyond that accounted for by cognitive ability (Adjusted $R^2 = .38$, $\Delta F(9, 302) = 9.12$, $p < .01$). The prediction that affective attributes and resilient behavior would interact was also supported ($\Delta R^2 = .01$, $\Delta F(1, 301) = 7.27$, $p = .01$), the relationship between academic performance and affective attributes-by-resilient behaviors strengthens as these variables increase. It is inferred that students become more dedicated to their studies (e.g., more engaged, motivated, confident, and committed) as the slope of the relationship between affective attributes, resilient behavior, and academic performance become stronger $\beta = .05$, $SEB = .02$, p = .03, 95% CI for β [.004, .090]. In other words, above and beyond student's cognitive ability, their final exam scores increased by .05 units as their affective attributes and resilient behavior increased (Figure 17). This aligns with previous research on the factors that contribute to academic success (Bandura, 1977; Bloom, 1968, Schunk, 1991).

Table 11

Hierarchical Multiple Regression Coefficients. DV: Final Exam

Predictor	β (*SE*)	*p*	95% CI	ΔR^2
	Cognitive ability (institutional) constant			
SAT I - Math	-.047 (.025)	.068	[-.096, .003]	.006
ALEKS	-.014 (.066)	.831	[-.144, .116]	.000
Cumulative GPA	-.572 (.079)	.000	[.418, .727]	.103
	Affective attributes (ACES)			
Engagement	-.007 (.028)	.812	[-.061, .048]	.000
Motivation	.076 (.032)	.018	[.013, .140]	.011
Self-regulation	-.040 (.032)	.211	[-.102, .023]	.003
	Resilient behavior: self-efficacy (ACES)			
Reading and writing	-.074 (.033)	.024	[-.139, -.010]	.010
Math and science	-.061 (.030)	.042	[-.119, -.002]	.008
Critical thinking	.048 (.035)	.164	[-.020, .116]	.003
	Resilient behavior: class commitment (Knewton)			
Perseverance	.672 (.217)	.002	[.246, 1.098]	.018
Participation	7.305 (.937)	.000	[5.461, 9.149]	.119
Attendance	-.437 (.223)	.051	[-.876, .002]	.007

Note. All predictors were standardized prior to analysis.

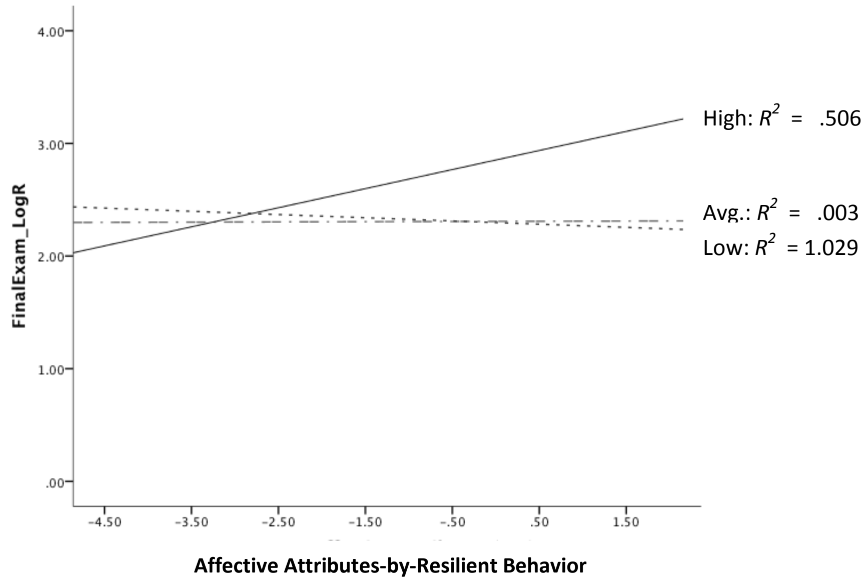


Figure 17. Graph of regression interaction effect

Regression analysis two, DV: Knewton embedded assessment. The sample size for this analysis was 327 students. The dependent variable was the Knewton gain score. The variables were entered in the same manner as with the final exam, thus three regression models were produced. The second model, containing the covariate and predictor variables (affective attributes and resilient behavior), was also significant, R^2 = .24, $F(12, 314) = 8.28$, $p < .01$. Once again, the prediction of the relationship between cognitive ability, affective attributes, resilient behavior, and the academic performance of students measured by their math skill gains (total average math posttest – total average math pretest) was supported. In this model, the linear combination of affective attributes and resilient behavior also proved to be a significant contributor to academic performance, accounting for an additional 5% of the variance in math skill gains (Adjusted R^2 = .21, ΔF (9, 314) = 2.50, p = .01).

The interaction prediction was not supported in this analysis (ΔR^2 = .002, ΔF (1, 313) = 1.01, p = .32) as documented in Table 12. To ensure that this discrepancy in the results was not potentially due to outliers in the resilient behavior data, a regression analysis was conducted excluding extreme values (n = 321). As anticipated, the results indicated that the outliers did not present a problem, for the analysis yielded similar results for the interaction term (ΔR^2 = .005, ΔF (1, 309) = 1.84, p = .18) and almost identical for the model of interest (R^2 = .23, F(10, 310) = 9.49, p < .01).

Table 12

Hierarchical Multiple Regression Coefficients, DV: Knewton Embedded Assessment

Predictor	β (*SE*)	*p*	95% CI	ΔR^2
Cognitive ability (institutional)				
SAT I – Math	-1.551 (.580)	.008	[-2.693, -.409]	.017
ALEKS	-4.918 (1.485)	.001	[-7.840, -1.995]	.026
Cumulative GPA	1.808 (1.729)	.296	[-1.593, 5.210]	.002
Affective attributes (ACES)				
Engagement	.144 (.115)	.212	[-.082, .369]	.003
Motivation	-.022 (.133)	.870	[-.283, .239]	.000
Self-regulation (study skills)	.097(.130)	.454	[-.158, .353]	.001
Resilient behavior: self-efficacy (ACES)				
Reading and writing	.054 (.119)	.651	[-.181, .289]	.000
Math and science	-.185 (.110)	.092	[-.401, .031]	.006
Critical thinking	-.108 (.122)	.375	[-.349, .132]	.001
Resilient behavior: class commitment (Knewton)				
Perseverance	2.252 (5.049)	.656	[-7.682, 12.186]	.000
Participation	1.596 (18.102)	.930	[-34.020, 37.212]	.000
Attendance	11.641 (5.269)	.028	[1.274, 22.007]	.011

Prediction Two: Not Supported

It was also predicted that resilient behavior would mark the difference between students who succeed in the class compared to those who did not. Success was defined as passing the course. From the perspective of testing this prediction, an examination of the resilient behavior between students who failed against those students who passed was not possible, as there were no resilient scores for those who failed. Conceivably, a comparison was still possible if all those students who did not pass the class were grouped into a category of *not-pass*. This category included students listed as *in progress*, students listed as learning complete, and students who withdrew from the course. It is important to note that the students being grouped under the not-pass category were not considered failing, but expected to have some differences which may have accounted for not having completed the course within one semester. Acknowledging that the results of an alternate analysis would only partially address the prediction, a repeated-measures ANOVA was conducted to compare the resilient behaviors of those who passed against those who did not pass. After removing cases with a list-wise method, the final sample size for this analysis was 607 students. The between-subject factor was course grade, with two levels: pass and not-pass. The within-subject factor was resilient behavior with four levels: self-efficacy, perseverance, participation, and attendance (Table 13).

The results of the between-subjects effects of the repeated measures ANOVA showed that the mean scores for resilient behavior between the pass and not-pass groups were not significantly different $F(1, 605) = 2.23$ $p = .14$, $\eta^2 = .004$, indicating no significant differences in the resilient behavior of those who passed the exam compared to those who did not pass the exam ($M = .04$, $SE = .03$, $p = .14$, 95% CI [-.01, .09]. These results align to the notion that the students in the not-pass group did not constitute failing students. Thus, Prediction Two was not supported by this alternate analysis.

Nonetheless, a more meaningful comparison was still possible if the exam scores were dichotomized into a group of students with scores of 19.5 points and higher into a pass-exam group (e.g., assuming a 65% score to pass the exam) and a second group of students with 19.4 points and below into the fail-exam group (n = 1163). Using these pass/fail criteria, 72% of students passed the final exam. A one-way ANOVA was conducted with the exam pass/fail category as the factor and resilient behavior as the dependent variable. The results were not significant, $F(1, 1161) = 3.31$ $p = .07$. There were no statistical differences in the academic resilience (self-efficacy, perseverance, participation, and attendance) mean scores between students who failed the exam and students who passed the exam. This established without any further doubt that Prediction Two was not supported.

Table 13

Statistics for Repeated Measures ANOVA

	Descriptive statistics		Resilient behavior	
Variables	Pass (n = x)	Not-pass (n = x)	Marginal means	
	M (SD)	*M(SD)*	*M(SE)*	95% CI
Self-efficacy	.01 (1.04)	-.54 (1.11)	-.022 (.054)	[-.129, .084]
RB: Perseverance	.30 (.13)	.20 (.24)	.252 (.008)	[.236, .268]
RB: Participation	.82 (.02)	.88 (.06)	.851 (.002)	[.848, .854]
RB: Attendance	.30 (.14)	.23 (.18)	.266 (.008)	[.251, .281]
Grade: pass			.316 (.024)	[.333, .380]
Grade: not-pass			.316 (.024)	[-.013, .013]

Note. All variables were standardized.

As part of Predictions Two and Three, an examination of the paths students took throughout the course was conducted. The intent was to understand the role of student's resilient behavior as students went through the lessons. It was also desired to investigate the impact of the learning environment on academic performance. Given that this exploration was going to be based on the relative performance of students, based on their pretest and posttest scores, a paired-sample t-test was conducted between the mean scores of these tests. The results indicated that the mean differences were significant, $t(1318) =$

8.76, $p < .01$, Cohen's $d = .29$ (corresponding to a small effect, Cohen 1992); thus, the qualitative analysis followed with the reassurance that these differences were not trivial.

Analysis of lesson paths: Predictions two and three. The lessons were reviewed to evaluate the impact of the environment on performance, and to identify patterns among the various student resilient behaviors: placing out of lessons, repeated posttest attempts, and viewing of entire lessons. As stated before, when students demonstrated 100% mastery on a lesson pretest, they did not have to view the lesson or take the posttest. Consequently, these students had zero posttest attempts and a score of zero on their posttests. As one might expect, these occurrences resulted in quite an unbalanced proportion of lower posttest scores compared to the pretest scores (Table 14), particularly in lessons were the placed-out rate was as high as 79%.

Table 14

Lessons with High Placed-out Rate: 40% and higher

Lessons in MAT 110-track-1 (117)	% Placed -out	Average mean scores *M* pre	*M* post	Max atmpts	*n*	*n* Placed-out
The number system						
1) Factors and multiples	40	77.00	53.00	1	1221	499
2) Negative quantities	48	81.27	44.60	1	1169	563
3) Decimals	66	88.60	33.48	0	1221	807
4) All about addition	79	92.97	21.42	0	1153	909
Equations and expression						
5) Independent and dependent variables	41	74.00	53.00	1	1197	495
6) Inequalities on the number line	44	79.11	50.38	1	1197	529
7) Testing values	45	81.73	47.44	1	1197	534
Ratios and proportions						
8) Fraction division	53	75.93	40.63	1	1212	642
9) Ratios and rates	55	83.46	42.71	1	1212	663

Note. The average number of attempts (atmpts) per lesson was 1. The 75th Percentile score = 90

This was not as evident in the lessons were the proportion of placed-out students was below 20%. Nevertheless, both of these circumstances evidenced the inverse relationship between placed-out rate and lesson difficulty (Figures 18-19), with a higher rate of students placing out of earlier lessons, up to 79% in the MAT 110-track-117 and as high as 90% in the MAT 100-track-142. Their perseverance (number of test attempts) did not follow this obvious pattern, as one would expect the difficult lessons requiring additional posttest attempts, yet the majority of lessons had an average of one posttest attempt—36 out 52 completed lessons in the 117 track and 12 out of 32 completed lessons in the 142 track (Table 15).

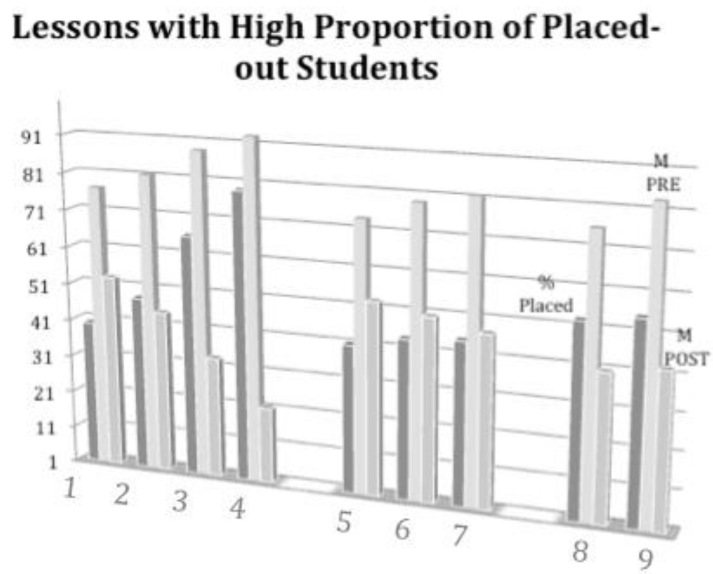


Figure 18. High proportion of placed-out students by lesson

Lesson names: 1) Factors and multiples. 2) Negative quantities. 3) Decimals. 4) All about addition. 5) Independent and dependent variables. 6) Inequalities on the number line. 7) Testing values. 8) Fraction division. 9) Ratios and rates (see Table 14)

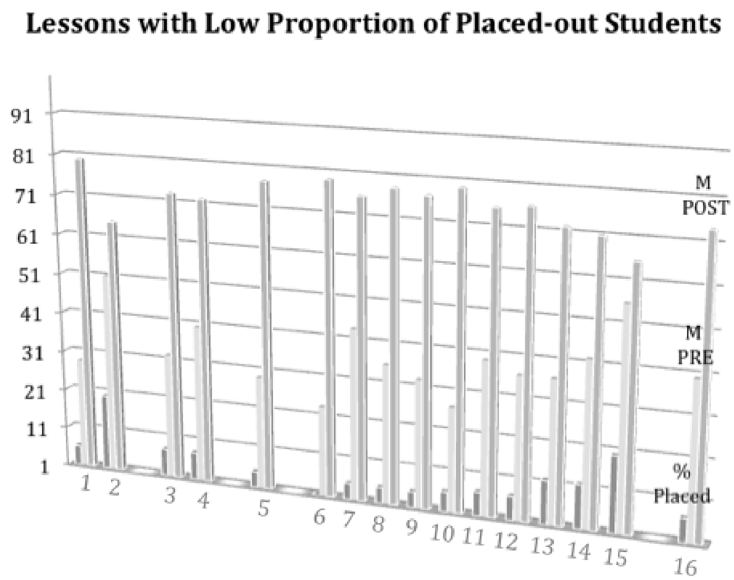


Figure 19. Low proportion of placed-out students by lesson

Lesson names: 1) Rational exponent rules. 2) Moving in the xy-plane. 3) Scientific notation. 4) Tricks of equality. Ratios and Proportions. 5) Ratios and fractions. 6) Domains and change 7) Understanding functions. 8) Functions in the world. 9) Linear functions. 10) Inverting linear functions. 11) Graphing quadratic and piece-wise functions. 12) Slope. 13) Composing functions. 14) Graphing radical and polynomial functions. 15) Building functions. 16) Linear and exponential expressions (see Table 16).

The number of posttests also served as a rough indicator of whether a student viewed the content or not. It is important to note that one test attempt may have indicated that the student did not go through the entire lesson or they could have skipped a lesson all together. It was not possible to know which option the student could have taken, as upon completing the pretest, and scoring under 100%, students had access to both, the lesson and the first posttest. With the majority of lessons having an average of one posttest attempt (77% for the 117 track and 63% for the 142 track), it rendered a great portion of this data impractical to evaluate, as the meaning of the results would be inconclusive.

Table 15

Lessons with an Average Posttest of One

Lessons in MAT 110-track-1 (117)	% Placed-out	Average mean scores *M* pre	*M* post	Posttest Score at 75P	Max atmpts	*n*	*n* Placed-out
		The number system					
1) Properties of math	17	61.28	67.92	80	21	1155	192
2) Fractions and decimals	25	64.20	62.57	90	8	1153	293
3) Negatives in the xy plane	28	71.43	59.73	90	12	1169	332
4) Long division	32	79.57	62.25	90	6	1202	394
		Equations and expression					
5) Irrational numbers	5	53.84	79.69	90	21	1082	57
6) Real world algebra	6	50.06	75.72	90	8	1188	66
7) Exponent rules	12	51.16	71.30	90	12	1166	142
8) Systems of linear equations	15	50.12	69.99	90	6	1029	151
9) Solving linear equations	15	51.29	72.93	90	21	1029	154
10) Mathematical expressions	26	67.74	58.68	80	8	1202	312
11) Square and cube roots	29	61.86	65.36	100	12	1166	333
12) Equivalent expressions	32	71.09	65.00	100	6	1202	386
13) Equations	37	73.96	60.18	100	21	1197	442
14) Variables and operations	38	73.65	56.74	90	8	1202	452
		Ratios and proportions					
15) Proportions	4	37.13	80.08	90	16	1177	44
16) Ratio applications	15	60.50	71.92	90	16	1212	178
17) Percents	19	55.38	75.35	100	15	1212	230
18) Ratios and percents	32	61.21	60.83	100	23	1177	375
		Functions					
19) Basic functions	16	55.44	73.93	90	22	1102	176
20) Features of linear and exponential functions	17	53.96	69.59	90	20	1017	171
21) Linear equations	18	46.84	69.20	90	22	1114	200
22) Features of quadratic functions	21	54.21	67.85	90	22	969	199
		Algebra					
23) Polynomial operations	4	54.65	64.41	90	13	1022	44
24) Using units	8	54.32	76.93	90	17	1128	90
25) Complex numbers	10	35.67	76.37	90	20	1022	104
26) Quadratic expressions	26	64.97	59.44	80	29	1022	268
27) Solving word problems	35	70.70	57.55	90	12	1128	397

Note. The average posttest attempt for all these lessons was 1.

Contrariwise, two attempts on the posttest had a more substantial interpretation. Two posttests indicated that the student viewed the lesson in its entirety, as the second posttest would have resulted when a student did not pass the minimum 70% score on the first posttest attempt. This would have required students to go through the lesson, at the end of which the second posttest would have been taken. Table 16 lists the lessons, which had a minimum average attempt of two posttests for the 117 track. Track 142 had a very small sample size in comparison (< 100), given that the topics were also different; this track was excluded from this part of the analysis to maintain consistency in the interpretations.

Similarly, three posttest attempts indicated the student would have been placed in focus mode and additional lessons would have been presented. Due to the possible number of lessons a student in focus mode could be exposed to (e.g., depending on the student's deficiencies) the only way to identify when a student was placed in this mode was by the number of posttest attempts (e.g., three or more posttests). Recalling that focus mode meant the student was not able to demonstrate at least 70% mastery of the content at the second posttest attempt. That is, even after having viewed the lesson in its entirety, the student was still struggling with the concepts. Only two lessons, in the 117 track, had an average of three posttests (e.g., Tricks of Equality and Understanding Functions). The scores in these lessons did not drastically differ from the other lessons with an average of two posttests, indicating that the overall performance was at some point leveled off (Table 16). It is worth noting that the maximum number of attempts in all lessons, except the ones with a high placed-out rate, was very high, but these high attempts were all below the lower quartile.

Table 16

Lessons that May Have Been Viewed in their Entirety - at least 2 posttest attempts

		Average Mean Scores		Posttest			
Lessons in MAT 110-R117	% Placed-out	M pre	M post	Score at 75P	Max atmpts	n	n Placed-out
		The number system					
1) Rational exponent rules	6	28.70	80.01	90	40	1047	59
2) Moving in the xy-plane	20	51.11	64.90	90	20	1169	231
		Equations and expression					
3) Scientific notation	8	32.42	73.12	90	34	1165	98
4) Tricks of equality[a]	8	40.38	72.25	80	38	1188	91
		Ratios and proportions					
5) Ratios and fractions	5	29.23	77.75	90	28	1177	54
		Functions					
6) Domains and change	1	23.60	79.17	90	30	1016	15
7) Understanding functions[a]	5	43.81	75.83	90	41	1017	50
8) Functions in the world	5	35.78	78.22	90	20	1102	50
9) Linear functions	5	33.03	77.08	90	44	1102	53
10) Inverting linear functions	6	27.10	79.39	100	35	986	60
11) Graphing quadratic and piece-wise functions	7	39.42	75.42	90	35	969	63
12) Slope	7	36.60	76.35	90	47	1114	75
13) Composing functions	12	36.68	72.29	90	44	987	119
14) Graphing radical and polynomial functions	12	42.20	70.90	90	46	958	172
15) Building functions	20	55.83	65.63	90	88	987	193
		Algebra					
16) Linear and exponential expressions	7	40.09	74.10	90	41	1054	

Note. [a]Average test attempts = 3. All other lessons average test attempts = 2.

In general, it appeared that students experienced a higher increase in their scores when they viewed the entire lesson, relative to those who had may not have viewed the lessons. The average gain for the lessons with two posttests was 37.49. Whereas the average gains for the lessons with one posttest was 9.08. To validate this notion of differences existing between the mean gain scores by the number of posttests taken, a two-way ANOVA was conducted.

Given the complexity of this dataset, to analyze this portion of the data, the total averaged gain scores were entered in a new file, along with their respective average test attempts. Three groups were entered, one for lessons with high placed-out rates, a second one for lessons that were viewed (average of two attempts), and the last group for lessons that may have been skipped (single attempt). The results indicated that the differences in students' gain scores were significantly related to the number of posttest taken, $F(2, 52) = 3.71$ $p = .03$, $\eta^2 = .136$. This in turn indicated that there may be differences in students' academic performance depending on whether they viewed entire lessons or not, the mean difference between these groups was $M = 25.91$ $SD = 6.30$, $p < .01$, 95% CI [13.23, 38.59].

To explore these differences deeper, five lessons were selected: (a) the two lessons that had an average of three posttest attempts, then randomly selected one of each of the following, (b) a lesson with a zero average posttest attempt, (c) a lesson with one average posttest attempt, and (d) a lesson with two average posttest attempts. An independent samples *t*-test was conducted. The grouping variable used was the pass-exam/fail-exam, established earlier, and the variables entered included: the five selected lessons' pretest and posttest scores, their resilient behavior (number of posttests), and cognitive ability variables. This yielded a sample of 595 students. The results indicated that the differences between those who passed the final exam and those who failed the exam, among the lesson categories were as follows:

1. There was a significant difference in pretest scores in the lesson with an average of two posttest attempts, $t(593) = 3.25$, $p <.01$.
2. There were significant differences in the pretest scores on both lessons with an average of three posttest attempts, $t(143) = 3.252$, $p < .01$ and $t(593) = 2.98$, $p < .01$.
3. There was a significant difference in posttest scores in the lesson with an average of zero posttest attempts, $t(141) = -3.01$, $p < .01$.
4. There were significant differences in the number of posttest attempts between the lessons with two posttest attempts and the lessons with one posttest attempt, $t(593) = .71$, $p < .01$.
5. There were significant differences in students' cognitive ability: ALEKS, $t(593) = 2.59$, $p = .01$, cumulative GPA, $t(593) = 8.57$, $p < .01$, and SAT, $t(593) = 7.00$, $p =< .01$.

These results would indicate that while some students started out with significant differences in their math skills, these differences appeared to dissipate when students viewed the entire lessons, despite the differences in cognitive ability (Table 17). This aligns with Bloom's theory of learning for mastery (1974).

Table 17

Independent Samples t-Tests

Variable	*t* (*df*)	*p*	*MD* (*SD*)	95% CI
		Cognitive ability		
ALEKS	2.592 (593)	.010	3.404 (1.313)	[.825, 5.983]
Cumulative GPA	8.468 (593)	.000	.707 (.083)	[.543, .871]
SAT	7.001 (593)	.000	54.965 (7.851)	[39.544, 70.385]
		Lessons – pretest scores		
All about addition[a]	-3.174 (125)[e]	.002	7.062 (2.225)	[2.656, 11.465]
Real world algebra[b]	2.877 (145)[e]	.005	7.872 (2.736)	[2.464, 13.279]
Composing functions[c]	3.254 (593)	.001	11.624 (3.572)	[4.609, 18.639]
Understanding function[d]	3.252 (143)[e]	.001	9.972 (3.066)	[3.911, 16.032]
Tricks of equality[d]	2.975 (593)	.003	8.425 (2.832)	[2.863, 13.987]
		Lessons – posttest scores		
All about addition[a]	-3.010 (141)[e]	.003	4.667 (-23.270)	[-23.270, -4.819]
Real world algebra[b]	.708 (593)	.479	1.635 (2.310)	[-2.902, 6.171]
Composing functions[c]	-.075 (593)	.941	-.254 (3.407)	[-6.945, 6.437]
Understanding functions[d]	-1.570 (593)	.117	-3.452 (2.198)	[-7.769, .866]
Tricks of equality[d]	-.930 (593)	.353	-2.297 92.471)	[-7.149, 2.556]
		Resilient behavior-Perseverance: number of posttests[f]		
All about addition[a]	-3.104 (139)[e]	.002	-1.62 (.052)	[-.265, -.059]
Real world algebra[b]	-2.592 (593)	.005	-.407 (.141)	[-.686, -.127]
Composing functions[c]	-.314 (593)	.754	-.120 (.382)	[-.870, .631]
Understanding functions[d]	-.377 (593)	.706	-.136 (.367)	[-.859, .582]
Tricks of equality[d]	-1.681 (593)	.093	-.542 (.322)	[-1.175, .091]

Note. [a]Lesson with 0 average posttest attempts. [b]Lesson with 1 average posttest attempt. [c]Lesson with 2 average posttest attempts. [d]Lesson with 3 average posttest attempts. [e]Equal variances not assumed. [f]Compared against 2 posttest attempts.

Prediction Three: Supported

It was hypothesized that a mastery approach to instruction would have a positive impact on the academic performance of remedial students while heightening their affective attributes. It was expected that specific areas that make up academic competence would exhibit a positive change by the end of the course. Specifically, it was predicted that a positive change would be seen in engagement and motivation, and students would reassess their academic skills based on their course experience. The self-paced, individualized nature of the Knewton course is not particularly designed to influence students' study skills or the way in which they interact with others, so no change was expected in interpersonal skills and study skills.

To test this hypothesis a repeated measures ANCOVA was conducted. Cognitive ability (SAT I Math, ALEKS, and Cumulative GPA) indicators were entered as covariates. These variables were minimally correlated to one another (see Table 10), thus it was deemed acceptable to use them together as covariates. Academic competence was the within-subjects variable, with each of the subscales as a level, for a total of 14 levels: (a) pre and post: reading and writing, (b) pre and post: math and science, (c) pre and post: critical thinking, (d) pre and post: interpersonal skills, (e) pre and post: engagement, (f) pre and post: motivation, and (g) pre and post: study skills. The between-subjects variables were gender and ethnicity and the dependent variable was the Knewton gain scores. The variable of grade was also added as a between-subjects factor to ensure students who had completed the course were added to the analysis, as records containing only ACES data and no Knewton course data existed in the dataset. A list-wise method was used to remove missing data across all variables resulting in 270 valid cases for the analysis including gender and ethnicity, and 581 cases for the within-subjects analysis.

The results of the multivariate tests of the ANCOVA repeated measures analysis, using the Wilks' lambda criterion (Λ), indicated that the academic competence means of students, before and after the Knewton course, were significantly different, $n = 270$, $\Lambda = F(13, 233) = 8.70$, $p < 0.01$, $\eta^2 = .33$. This analysis supported Prediction Three. The results indicated that the mastery environment had a significant effect on student's academic competence levels. However, according to the between-subject results, the significant main effect did not carry across gender, $F(1, 245) = .49$, $p = .48$, $\eta^2 = .002$, or ethnicity, $F(4, 245) = 1.62$, $p = .17$, $\eta^2 = .026$. Given that academic competence is comprised of seven subscales, follow up paired sample *t*-tests were conducted to evaluate which of the mean differences were significant (Table 18).

The comparisons were conducted to evaluate which pair of means was significantly different. Each of these subscales are independent of each other, thus each pairwise comparison had only two levels. The subscales were not being compared against each other. Consequently, it was deemed unnecessary to adjust the alpha for each of the comparisons (e.g., using a Holm's sequential Bonferroni procedure to control for Type I error). Thus, each of the comparisons was evaluated at the .05 level, $n = 581$.

Table 18

Mastery Environment Effects on Academic Competence

	Paired samples *t*-Test					
	Statistics		Paired differences			
ACES Subscale	*M* pre / *M* post	*SD* pre / *SD* post	*M* (*SD*)	*t*(580)	*p*	Cohen's *d*
Math and science	30.60 / 33.06	5.72 / 6.65	-2.461 (5.708)	-10.394	.000	-.40
Reading and writing	36.56 / 37.63	6.23 / 6.76	-1.076 (5.555)	-4.667	.000	-.17
Critical thinking	35.00 / 36.12	5.98 / 6.76	-1.124 (5.965)	-4.541	.000	-.18
Engagement	30.78 / 31.16	5.56 / 6.16	-.380 (5.034)	-1.821	.069	-.06
Motivation	43.14 / 42.60	5.64 / 6.23	.542 (5.341)	2.447	.015	.09
Interpersonal skills	34.39 / 33.93	4.30 / 4.86	.451 (4.593)	2.367	.018	.10
Study skills	43.99 / 42.95	5.55 / 6.30	1.041 (5.578)	4.500	.000	.18

All three subscales of the academic skills domain (self-efficacy) were statistically significant. Specifically, students experienced a significant increase in their judgment about their ability in math, $t(580) = -10.40$, $p < .01$, about their reading skills, $t(580) = -4.67$, $p < .01$, and their critical thinking, $t(580) = -4.54$, $p < .01$. The academic enablers (affective attributes) on the other hand, did not yield the expected results. Interpersonal skills had been predicted to remain the same, yet students experienced a significant negative change in this area, $t(580) = 2.37$, $p = .02$. Study skills (self-regulation) had also been anticipated to remain unchanged, still there was a significant decrease in the mean differences, $t(580) = 4.50$, $p < .01$. The increase in engagement was not significant as it had been anticipated, $t(580) = -1.82$, $p = .07$. Motivation appeared to move in the opposite direction by a significant decrease in mean differences, $t(580) = 2.45$, $p = .02$. The results of the comparison of academic enablers reflected that the mastery environment appeared to affect all areas of academic competence.

With the intent to verify the effects of the mastery environment on academic competence, an additional analysis was conducted. This was the second part of the lesson paths analysis conducted for Predictions Two and Three, the independent samples *t*-test was replicated using the same pass-exam/fail-exam grouping variables, the five selected lessons and all seven subscales of academic competence. The sample size for this analysis was 250 students. The results indicated that among the differences between those who passed the final exam and those who failed the exam, only two had significance within the subscales of academic competence, post math and science $t(34) = 2.43$, $p = .02$ (equal variances not assumed), and post study skills $t(248) = 2.80$, $p < .01$ (Table 19). These results confirmed that while the prediction about specific scales experiencing a change was partially supported by the statistically significant results, the effects of the learning environment on academic competence needed to be checked against the academic competence continuum to detect any shifts between competence levels.

Table 19

Differences in Academic Competence Within Selected Lessons

	Independent samples *t*-Test			
Variable	*t* (248)	*p*	*MD* (*SD*)	95% CI
		ACES pre scores		
Reading and writing	-.711	.478	-.946 (1.330)	[-3.565, 1.673]
Math and science	1.147	.253	1.294 (1.126)	[-.929, 3.516]
Critical thinking	.937	.350	1.183 (1.262)	[-1.304, 3.669]
Interpersonal skills	-.188	.851	-.174 (.926)	[-1.999, 1.651]
Engagement	1.401	.163	1.660 (1.185)	[-.674, 3.994]
Motivation	1.071	.285	1.376 (1.284)	[-1.154, 3.906]
Study skills	1.424	.156	1.763 (1.236)	[-.675, 4.201]
		ACES post scores		
Reading and writing	.099	.921	.142 (1.425)	[-2.665, 2.948]
Math and science	2.432[a]	.020	2.428 (.998)	[.400, 4.456]
Critical thinking	1.043	.298	1.470 (1.410)	[-1.307, 4.246]
Interpersonal skills	-.660	.510	-.672 (1.019)	[-2.676, 1.334]
Engagement	1.329	.185	1.829 (1.376)	[-.881, 4.539]
Motivation	.946	.345	1.343 (1.420)	[-1.453, 4.140]
Study skills	2.797	.006	3.879 (1.387)	[1.147, 6.612]

Note. [a]Equal variances not assumed. *df* = 34

Inspection of students' mean scores against the academic competence continuum revealed that the changes were negligible. With the exception of the subscale math and science, which had a small to medium effect size, Cohen's d = .40 (corresponding to a small-to-moderate effect size, Cohen, 1992) and moved from the developing range, 90% CI [27.06, 33.60], into the competent range, 90% CI [30.06, 36.06], all the other scales remained at their original range of competence (Figure 20). While the more meaningful implications were in the area of math ability, all the other subscales remained high in the academic continuum, based on normed data. These results suggest that the learning environment had a small but significant impact on academic competence.

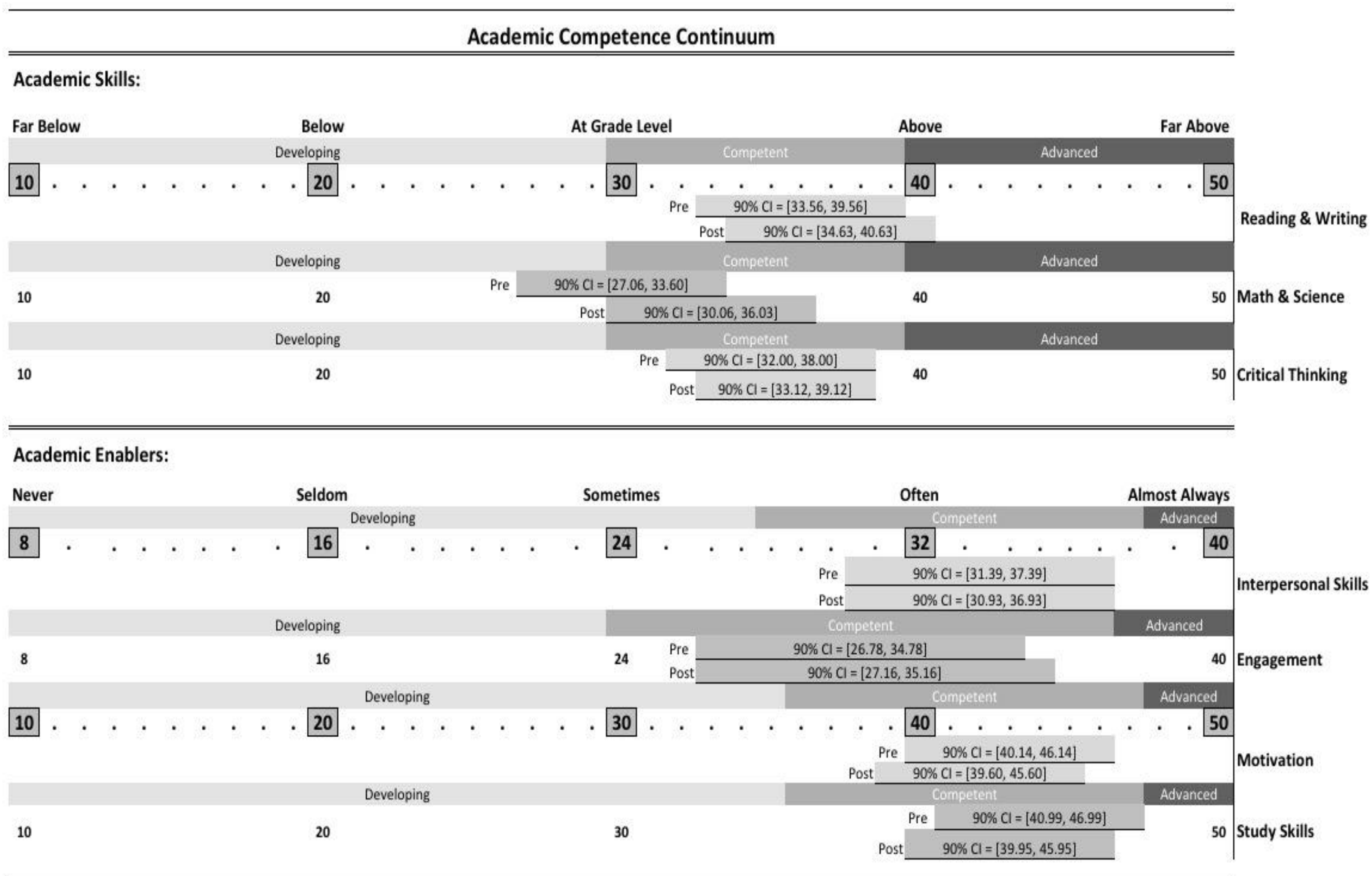


Figure 20. Academic Competence Continuum. Confidence intervals plotted based on mean scores for each subscale.

Exploratory Analyses

The qualitative data collected through the ACES open-ended questions and the information gathered through the engagement survey served as an additional source of information for instructional recommendations targeted at students in need of remediation. To this end, qualitative and quantitative analyses were performed.

The ACES open-ended question. "If you have any comments about yourself and how you learn best, please write them down in the space below" This question was presented at the pretest and posttest occasions; however, students either answered the question on the pretest and not the posttest, or vice versa. Some students offered a single comment, while others offered multiple comments. As a first step in summarizing this information, each comment was reviewed and shortened into concise and distinct statements. Once all the comments had been simplified, the statements were grouped into similar thoughts, or categories. Category labels were then created for each group to reflect the essence of the statements contained within. As a final step in the process, the statements were tabulated. From the 623 distinct statements that were offered, 20 categories emerged (Figure 21).

The top three categories were: (1) demonstrations—students felt they learned best from demonstrations and step-by-step explanations; (2) visual leaner—this statement was consistently offered with no further elaboration; and (3) hands-on learner—students felt they needed to do the work to learn and felt interacting with the teacher and the content was important. The responses were not as robust as anticipated; they tended to be more general in nature, which may be a result of the way the question was worded. It was not clear whether students felt their learning styles and needs had been met or how much these aspects would have enhanced their learning.

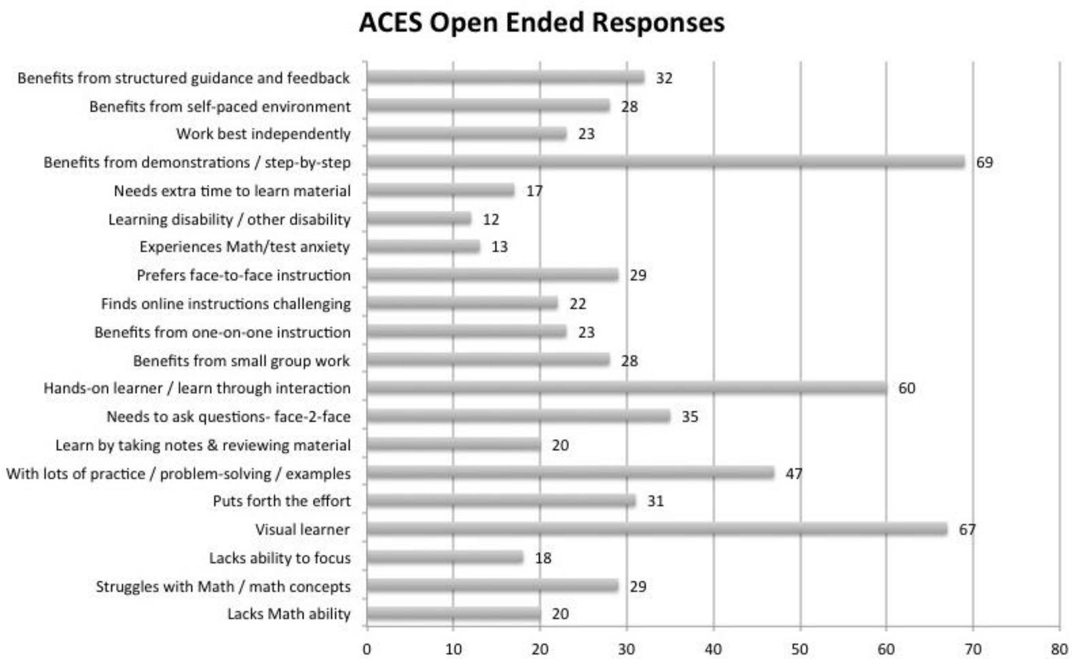


Figure 21. Response categories. Obtained from open-ended ACES question. Values represent frequency of responses within each category.

Qualitative analysis of the engagement survey. Data gathered through the engagement survey was grouped into clusters according to the type of responses each survey item prompted. The first cluster contained four questions related to the amount of time students spent engaged in a given activity. Two of those questions were related to studying and time on-task, conceivably a higher number would indicate higher engagement. The other two questions related to tasks that would compete with studying or course work (e.g., employment and leisure), thus a higher number could indicate lower engagement. The second cluster contained two questions related to the course grade they were working towards and the grade they earned (rated on a four-point Likert scale). Both of these questions were reverse scaled to fit the pattern of a higher number indicating higher engagement. The third cluster contained the rest of the questions (rated on a five-point Likert scale). This entire cluster, with the exception of question 19, was reverse scaled to ensure the higher values were indicative of higher engagement. Additionally, this third cluster was grouped into an overall scale to get a sense of the extent to which students were engaged with the course material (Figure 22).

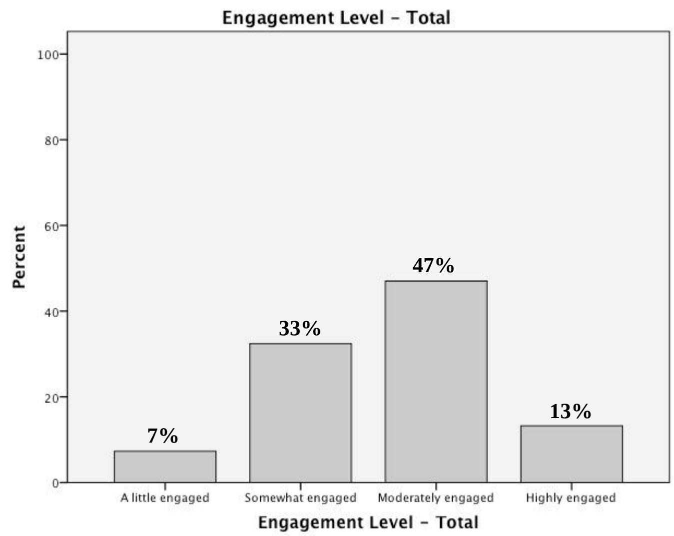


Figure 22. Engagement scale

A total of 457 students responded to the survey. The overall engagement scale, derived from cluster three, indicated that 80% of the respondents were somewhat engaged to moderately engaged with the course and course materials. The results of cluster one revealed that 56% of the respondents did not work for pay, 28% worked under 20 hours per week, and only 9% worked over 30 hours. On the leisure question, 62% reported playing video games and watching TV less than five hours per week. In terms of time-on task, in class (51%) and time studying or preparing for class (47%), the one- to five hour range was the average weekly amount devoted to coursework (Figure 23). Cluster two, indicated that 65% of students were working towards an A in the course, 30% towards a B and 5% towards a C, which suggested that for the most part students had a desire to be successful in the course.

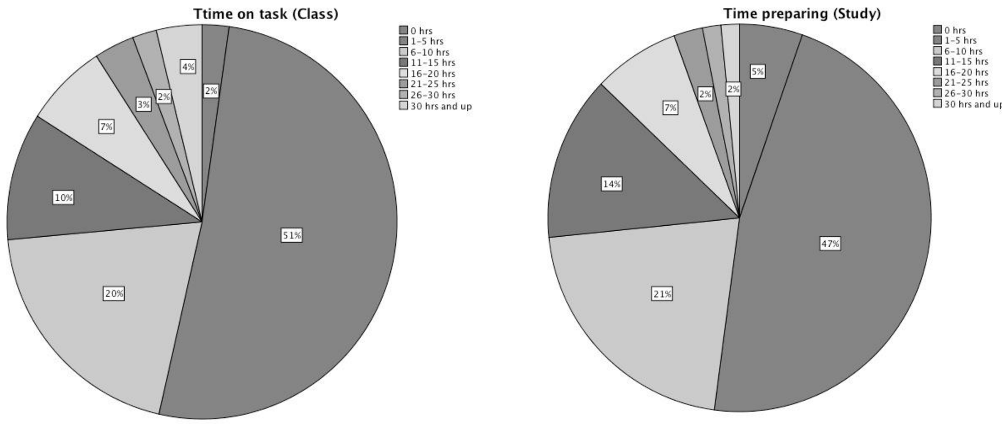


Figure 23. Time spent working on-task in class and time spent preparing and studying

Quantitative analysis of the engagement survey. This survey measured engagement level with actions that are commonly considered desired behaviors and characteristics of a good student (e.g., completed homework, came to class, put forth the effort, studied regularly, desire to learn material, etc.), see Table 15. The relationship between these behaviors and students' performance on the final exam, and which behavior could be considered a stronger contributor to the relationship was explored. To this end, a stepwise multiple regression analysis was conducted using selected survey questions as variables (Table 20).

Each question was evaluated for redundancy and relevance. For example, given that the majority of students spent a minimal amount of time at work or play, those items were excluded from the analysis. Another example of the process of elimination would involve the categories, grade working towards, and put forth the effort. Both of these variables are at the essence of many other variables. That is, when a student is motivated by earning an A, then the student will put forth the effort to achieve that goal; hence, the student will attend class, complete homework, and complete the readings. It followed that removing these items was a conservative approach.

Table 20

Means and Standard Deviations for Engagement Survey Questions

Variables[a]	*n*	Missing	*M (SD)*	*Variance*	Min	Quartiles 1st	2nd	3rd	Max
			Cluster I[b]						
Q1. Time preparing	451	1775	2.92 (1.40)	1.96	1	2	2	4	8
Q2. Time on-task	450	1776	3.05 (1.60)	2.55	1	2	2	4	8
Q3. Time at work	445	1781	2.67 (1.59)	5.70	1	1	1	4	8
Q4. Time at play	450	1776	2.67 (1.59)	2.53	1	2	2	3	8
			Cluster II[c]						
Q5. Grade desired	455	1771	3.60 (0.89)	0.35	2	3	4	4	4
Q6. Grade earned	443	1783	2.99 (0.89)	0.79	1	2	3	4	4
			Cluster III[d]						
Q7. Completed homework	451	1775	4.37 (0.855)	0.73	1	4	5	5	5
Q8. Came to class	451	1775	4.22 (0.89)	0.79	1	4	4	5	5
Q9. Thought about class	451	1775	3.75 (1.10)	1.22	1	3	4	5	5
Q10. Found ways to make interesting	450	1776	3.29 (1.22)	1.48	1	3	3	4	5
Q11. Desire to learn material	450	1776	3.47 (1.27)	1.60	1	3	4	4	5
Q12. Put forth effort	450	1776	4.18 (0.80)	0.80	1	4	4	5	5
Q13. Completed readings	450	1776	3.91 (1.06)	1.13	1	3	4	5	5
Q14. Had fun in class	450	1776	2.93 (1.30)	1.68	1	2	3	4	5
Q15. Studied regularly	450	1776	3.50 (1.12)	1.25	1	3	4	4	5
Q16. Applied material to life	450	1777	2.94 (1.29)	1.65	1	2	3	4	5
Q17. Paid attention in class	450	1776	3.86 (1.12)	1.26	1	3	4	5	5
Q18. Asked questions	449	1777	3.43 (1.30)	1.69	1	3	4	5	5
Q19. Did not complete homework	448	1778	3.46 (1.35)	1.82	1	2	3	5	5
Q20. Anticipated test material	449	1777	3.74 (1.05)	1.10	1	3	4	5	5
Q21. Quizzed self	448	1778	3.49 (1.18)	1.39	1	3	4	4	5
Q22. Discussed material with classmates	450	1776	3.24 (1.40)	1.94	1	2	3	4	5

Note. [a]All variables included in the regression analysis were z-scored. [b]Measured on an 8-point scale. [c]Measured on a 4-point scale. [c]Measured on a 5-point scale.

Utilizing the process of elimination described above, the final selection included 10 of the 22 survey questions: time preparing, time on-task, grade desired, found ways to make interesting, desire to learn material, put forth the effort, applied material to life, paid attention in class, quizzed self, and discussed with classmates. The use of a covariate for cognitive ability could not be dismissed (SAT, ALEKS, cumulative GPA); however, to simplify the model, the variable that had the highest correlation with total engagement level scale was selected, cumulative GPA, $r = .17$.

Variables were entered into the multiple regression analysis using a stepwise, backward method. The final exam was entered as the dependent variable. The list-wise method resulted in 404 students for this analysis. The criteria for inclusion and exclusion from the model were left at their default values—for the probability of entry into the model PIN = .05 and POUT = .10 for the criteria for the probability of exclusion from the model (Field, 2009). The analysis yielded a model with only three variables as its most parsimonious solution: cumulative GPA, grade desired, and effort put forth, $R^2 = .13$, F (3,400) = 20.62, $p < .01$. The variable of grade desired accounted for an additional 3% of the variance of the final exam scores, Adjusted $R^2 = .12$, ΔF (1,401) = 14.20, $p < .01$ and the variable of put forth the effort contributed an additional 1% of the variance, Adjusted $R^2 = .13$, ΔF (1,400) = 4.37, $p = .04$ (Table 21). While the selected variables were statistically significant, their contribution to the overall model seemed smaller than anticipated.

Table 21

Engagement Survey Variables

	Regression coefficients				
Variables	β	*SE*	*t*(401)	*p*	R^2
	Included in the model				
Cumulative GPA	.404	.068	5.92	.000	.063
Grade desired (working towards)	-.068	.020	-3.471	.001	.026
Put forth effort	-.041	.020	-2.09	.037	.009
	Excluded from the model				
	β In	*t*(401)	*p*	Partial *r*	Tolerance
Time preparing (studying)	-.021	-.445	.657	-.022	.965
Time on task	.050	1.054	.293	.053	.976
Found ways to make interesting	-.054	-.978	.329	-.049	.719
Desire to learn material	.011	.209	.834	.010	.769
Applied material to life	-.010	-.197	.844	-.010	.826
Paid attention in class	.055	.976	.330	.049	.690
Quizzed self	-.039	-.710	.478	-.036	.720
Discussed with classmates	.054	1.109	.268	.055	.926

Summary

In closing, the intent of this study was to understand the role of academic competence and academic resilience on performance and how the learning environment affected these variables. The results indicated that cognitive ability, affective attributes, and resilient behaviors predicted student's academic performance (Prediction One). The learning environment appeared to play a role in academic success, but it was not clear the extent to which other variables may have contributed to these changes (Prediction Two). Furthermore, students' academic competence levels experienced a significant, but small change after the mastery learning experience (Prediction Three). An in-depth discussion of these findings is presented in Chapter Four.

Chapter 4

DISCUSSION

This investigation was conducted with the primary goal of elucidating the conditions that promote or inhibit academic performance for college students in technology-driven remedial mathematics course. The process of investigating these conditions involved the evaluation of a number of variables: the learning environment, the teaching approach, affective attributes, and academic resilience, and how all these variables impacted students' academic performance, in a remedial mathematics course. The learning environment was an adaptive learning system, with a hybrid delivery. The teaching approach utilized a learning-for-mastery model. Students' academic competence was conceptualized to involve attributes of self-regulation, motivation, and engagement and students' academic resilience, which included self-efficacy and course commitment. Students' cognitive ability also was operationalized by prior academic achievement measures.

These learning conditions and student variables where investigated from a social ecology of resilience perspective. That is, the extent to which these conditions work together and interact with the environment to either promote or inhibit academic performance. As illustrated by the academic performance expression (Figures 2 & 15), it was hypothesized that the relationship between cognitive ability, affective attributes, and resilient behavior would vary as a function of the interaction between affective attributes-by-resilient behavior and the level of support and resources afforded by the learning environment.

The study was conducted to answer the following research question: How do cognitive ability and affective attributes moderate the mathematics performance of students in need of remediation? The research was conducted to investigate three fundamental predictions: (1) students with higher affective attributes and higher resilient behavior would exhibit higher performance; (2) more resilient students would fare better, academically, than less resilient students; (3) students' academic performance and academic competence, particularly self-efficacy, motivation, and engagement would be positively influenced by the mastery environment. Evidence based on robust samples of students was presented to support the first and third prediction. The interpretations and implications of these results are presented in this Chapter.

Discussion of Major Findings

Prediction One. As predicted, the results of this study confirmed a statistically significant relationship between the students' academic performance and their cognitive ability, affective characteristics, and level of academic resilience. This relationship indicates that in a mastery-based adaptive learning environment, the combined effects of the students' affective attributes (engagement, motivation, self-regulation) and their resilient behavior (self-efficacy, course commitment) can strengthen academic success. These effects were over and above the effects of the students' cognitive ability.

These results are not surprising given the well-established findings that cognitive ability is a key determinant in academic success and the conception that affective attributes are important to this success as well. Bandura (1977) established the importance of self-efficacy and self-regulation on students' ability to perform and these constructs are entwined with motivation (Bandura, 1989; Schunk, 1991). Motivation has been the subject of many investigations as it relates to academic achievement and has been put forth as an important factor in academic success (Changeiywo, Wambugu, & Wachanga, 2011; Diegelman-Parente, 2011; George, 2010; Hirschfeld, Lawson, & Mossholder, 2004). Likewise, the positive effects of engagement (Toshalis & Nakkula, 2012) and academic resilience have also been investigated and found to have a measureable influence on academic success (Johnston-Wilder & Lee, 2010; Martin & Marsh, 2006).

What was surprising about these findings was that the influences had such a small effect size. A potential explanation for this could be attributed to the learning environment itself. The benefits afforded by a mastery approach could have offset measurable differences among students. According to Bloom (1968, 1974, 1978), given enough time all students can perform equally well. Arguably, if all students perform at similar levels, then differences imparted by their affective attributes would be more difficult to detect, except in the more extreme cases; hence the small effect size.

An interaction was also predicted; it was expected that student's academic performance would increase as their affective attributes and academic resilience increased. This interaction, however, was detected only when the performance outcome was the final exam. Thus, this portion of the prediction was only partially supported by the evidence. That is, students exhibited a slight but significant increase in their final exam scores when their affective attributes and resilient behavior increased. This interaction did not appear to affect students' embedded assessments scores.

One possible reason the affective attributes-by-resilient behavior interaction was not present across both performance outcomes may have been a problem with the performance indicator itself. While the final exam was meant to assess the overall attainment of mastery of the content at the end of the course, the embedded assessments were ongoing measures of lesson mastery. It is quite likely that this was not an adequate outcome indicator of academic performance and its application should have been limited to assessing progress. For example, a student could have started with very low math skills, which would be reflected in the scores for the earlier lessons and as the student gained mastery of the material, the scores would increase over time. Thus, the overall embedded assessment scores would only reflect relative growth. That is, a student who experienced large learning gains could perform at the same level as someone who experienced minimal learning gains. As these gains only reflect the relative growth that needed to take place to bring both students to the same level. On the other hand, the final exam evaluated the final product and was not affected by the learning process or the relative growth. In hindsight, using the final exam as the primary performance outcome for this analysis would have been a better approach.

The resilient behavior measures also may have contributed to the discrepancy in the interaction results. Recalling that in the present study academic resilience was operationalized as resilient behaviors with two key measures: self-efficacy and course commitment. It is possible that the indicators were not sensitive enough. The indicator for participation was quantified by the number of lessons, perseverance by the number of posttest attempts, and attendance by the frequency of logins. The dynamics of the course were inconsistent with the intended purpose of these indicators. Specifically, students' had a core number of lessons to take for the course to be considered complete. Thus, the majority of students took approximately the same number of lessons; this may have caused a restriction of range for the participation indicator. Additionally, students could not move to the next lesson until they mastered the current one. In essence, the posttest attempts were a result of the course structure; hence, there would be negligible variability in the perseverance indicator. The same may be true for the attendance indicator, since students had to login to view a lesson and all lessons had to be completed, the differences in number of logins may only represent the amount of time each student had at any given point to devote to a lesson. In retrospect, these resilient behavior indicators did not appear to measure student attributes, as the behaviors were not self-initiated.

Furthermore, the combination of the limitation of the resilient behavior indicators along with the differences in variability on the outcome performance measures may have contributed to the disparity in the results. This explanation seems reasonable as it addresses the discrepancy on both performance outcomes. That is, one could infer that the limitations in the behavior measure underestimated the true interactions of both performance outcomes by: (1) yielding in a weak interaction between affective attributes-by-resilient behavior and the final exam performance, and (2) failing to detect an interaction between affective attributes-by-resilient behavior on the embedded assessments performance. Consequently, it could be concluded that using more accurate resilient behavior indicators (e.g., ACES self-efficacy and self-regulation) along with the outcome indicator with the highest variability (i.e., the final exam) would have increased the effect size of these findings.

Prediction Two. Academic resilience is an important attribute for students to have, particularly when learning math (Johnston-Wilder & Lee, 2010). Academic resilient students exhibit a high sense of self-efficacy, are not easily discouraged, and are motivated to attend and participate in class (Martin & Marsh, 2006). Thus, it was predicted that resilient behavior would be the distinguishing variable between successful and unsuccessful students. However, this prediction was not supported. There were no significant differences in resilient behaviors between the students who passed the course and those who had not passed the course within the one semester timeframe. Furthermore, the mean differences between the resilient behaviors of the students who passed the final exam compared to those who did not pass the final exam were not statistically significant either. It is important to recall that one posttest attempt suggested a student may or may not have viewed a lesson, and two posttests indicated that the entire lesson was viewed. Interestingly, on average the majority of students took only one posttest.

The non-significant findings are inconsistent with current research on academic resilience (Scholar Centric, 2010). With the exception of the self-efficacy, which is highly predictive of academic resilience, the course commitment resilience indicators (perseverance, participation, and attendance) had limitations, as explained earlier, that likely contributed to the lack of significance. The resilience indicators were intended to capture self-initiated behaviors that would be indicative of resilient attributes. For example, students who have high academic resilience tend to more actively participate in class, thus participation was measured by the number of lessons a student completed. This assumed that students completing a high number of lessons would represent those who were more involved with the course than students who completed fewer lessons. However, students were required to complete a core number of lessons to pass the course; hence, this indicator would not accurately capture a student's desire to learn more or engage with the course. Essentially, it captures the fulfillment of requirements needed to complete the course. Another example of a resilient attribute is perseverance, which was conceptualized as the students' willingness and fortitude to make repeated attempts at passing the embedded assessments despite persistent failures; thus, this attribute was measured by the number of posttests. However, the number of posttests was driven by the students ability to demonstrate mastery in the lesson content, which was typically achieved by the end of the lesson—two posttests. Such behavior would not be indicative of perseverance, but rather the ability to master the content within x number of attempts. It is worth noting that these issues were not discovered until after all the data were fully integrated, and not fully understood until thorough exploration and examination of the course itself had been completed. Both of these events took place too late in the process to allow for a redesign. In retrospection, the course commitment measures were inadequately posited as indicators of resilience, as they would have been better suited for capturing course completion and content mastery.

Nonetheless, it is important to acknowledge that an alternate justification may exist. That is, it may be possible that the nature of the mastery approach and the adaptive learning environment enables students to participate and engage with the content at such optimal levels that significant academic resilience differences are more difficult to detect. Specifically, if all students are exposed to content best suited for their current skill level; it follows that students are less likely to be discouraged and more likely to engage with the content. As students experience high levels of success resulting from their efforts, their self-efficacy and academic resilience are enhanced. However, these behaviors are being elicited by the learning environment and may not necessarily depend on the student to possess these attributes. It could then be inferred that academic resilience is a less important attribute of learners working in a mastery-based, adaptive learning environment. If this inference is accurate, non-significant academic resilience differences among students would be a logical outcome.

Prediction Three. This prediction stated that the mastery environment would have a positive effect on students' academic competence and students' academic performance. This prediction was supported by the results. That is, there was a statistically significant difference between students' academic performance ratings before and after going through the mastery environment. Due to continued interest in addressing disparities in academic performance among diverse populations (ACT, 2012; Strayhorn, 2010) the variables of ethnicity and gender were also investigated in this analysis. However, there were no significant differences among the various ethnic groups or gender.

Self-efficacy is enhanced by one's ability to successfully perform a task, particularly when the task is perceived as difficult or unattainable. A mastery-based environment affords students this opportunity through repeated experiential successes. Thus, it was predicted that the mastery environment would positively affect students' self-efficacy. It was also expected that these repeated successes would reduce anxiety and build confidence; hence motivation, and engagement were also expected to increase. The mastery environment was not expected to directly affect interpersonal and study skills; therefore, it was hypothesized that those skills would remain relatively unchanged. This prediction, however, was only partially supported. For the majority of students, their self-efficacy exhibited a significant gain; however, unexpectedly their motivation had a negative gain, and engagement had a positive gain.

Contrary to what was predicted, interpersonal skills and self-regulation (e.g., study skills), also exhibited gains. With the exception of the math and science subscale, the majority of students rated their academic skills at grade level and reported that they often used the behaviors indicative of strong affective attributes. This would indicate that students, going into their remedial course, were not as confident in their math skills as they were about other skills. This may also suggest that students have a more accurate perception of their math skills, as math ability is evaluated at all school levels; whereas, affective attributes are rarely addressed at schools. Thus students may not have an accurate perception of their affective attributes or may not be fully aware of these skills.

Parenthetically, math and science was the only subscale in which there was a shift in competence levels. This shift was statistically significant and it makes sense, considering students were taking a math course and one would expect students to reassess their skills after the course. Additionally, it is quite likely that students experienced a more measureable gain in this area because the learning environment affords students repeated experiential success; this in turn, would have enhanced their perceptions about their math ability which is consistent with Bandura' self-efficacy theories.

The results on the other subscales, while statistically significant, were quite marginal in terms of moving students from one ACES competence level into another. It is possible that students overestimated their affective skills and, after the course, reconsidered their ratings, thereby explaining the downward shifts or no shift at all on some of the subscales. Conceivably, changes may have taken place as a result of the mastery experience, and while students may have benefited or been inhibited by these experiences, the effects may not have been obvious or visible to them. Consequently, they would not necessarily report a drastic increase or change in the affected areas.

Another explanation focuses on the learning environment. As stated earlier, the mastery environment is designed to provide students many experiences that help strengthen the academic resilience and affective attributes investigated in this study. It had been anticipated that students' self-regulation skills (study skills) would remain the same, for it was not evident that the learning environment would promote this. Yet, students experienced a small but significant decrease in the area of study skills. This may have resulted from the realization, after going through the course that they needed to learn to manage their time better or take better notes. The structured approach of the learning environment may have indirectly altered students study habits and behaviors.

Lesson results: on performance. When looking at students' pretest and posttest scores independent of other variables, the mean scores were statistically significantly different. Students in lessons that were, on average, viewed in their entirety appeared to overcome their math skill deficiencies, as these students started off with significantly lower scores and by the end of the course had no significant differences with their peers on those lessons. This appears to align with previous findings supporting the positive effects of college remediation (Bettinger & Long, 2009). Additionally, there were statistically significant differences in gain scores between students who took two posttests and those who had only one posttest attempt. This would suggest that the learning environment can be a condition that enhances academic performance, which is consistent with learning for mastery theories.

Overall, the findings of this study speak to the possibility of the learning environment having imparted more influence on students' performance than what was formally measured and inferred. In addition to the benefits of the mastery-based approach (Bloom, 1968) and the notion of individualized learning (Lalley & Gentile, 2009a), students appeared to value many of the instructionally sound practices present in the Knewton learning environment. Instructional strategies such as step-by-step demonstrations, worked-out examples, the ability to work at their own pace, opportunities for practice, and explanatory feedback were all included in the students' descriptions of how they learned best. Additionally, many students appeared to be moderately engaged with the course, had the motivation to do well in the class, and put forth the effort. This indicated that the learning environment may also have influenced motivation and engagement. These results also underscore the important role of motivation in learning, particularly with computer-based learning systems (Keller, 2008).

Limitations

The most significant limitation for this study was the lack of a control or comparison group. Students' growth or lack thereof cannot be readily attributed to either the students' attributes or the learning environment, as there was no consistency of treatment. It is not possible to know the extent to which every student experienced the course under the same conditions, with the same limitations or resources. There may have been other influences, outside those investigated in this study that contributed to the students' academic success. The reasons why some students may have engaged in some lessons more than in others are unknown. For example, their actions could have been prompted by a previous lesson, by their prior knowledge, or the influence of a peer.

While statistically significant relationships have been established in this study, these findings should be carefully considered in light of this main limitation. Additionally, the study was conducted with data from an intact group, from one semester, from students taking the same course, at the same university. This sample may not constitute a representative sample of all remedial math students. Thus, these findings should not be generalized to the entire population of remedial math students. It is also possible that the positive effects of the learning environment are limited to this subject (i.e., mathematics).

Missing data was also a substantial limitation, although the overall sample was large. There were various categories that were missing substantial amounts of information. There were data missing at either the case level or item level. There were missing institutional records, incomplete cases that contained key variables, and a substantially smaller proportion of post measures compared to the pre measures. This not only greatly reduced the sample size, but more importantly, it prevented direct comparisons across all analyses. An important concern was whether these missing data might have biased the representatives of the sample. There were many possible reasons for these data to be missing: (1) students may have been unwilling to complete the surveys/tests; (2) students may have dropped out as a result of their failure in the course; (3) students may have found the course to be ill-suited for them or they may have been inadequately placed; (4) students may have experienced some external cause that prevented them from continuing with the course; (5) or they may have simply decided to quit. Numbers two and three represented the reasons of most concern, as these would have indicated a bias in the sample. However, there was no evidence that any of these reasons in particular might have been at the root of the problem. Nonetheless, an underestimate of the true variability in the sample may still exist. For the students who had complete data may have some underlying commonality not clearly identified in this study.

The constraints placed by the type of data were another limitation. Grades used a pass/fail criterion, which limited the possibility of evaluating various levels of performance. Also, there were many students that had pending grades (in-progress, learning complete) and others were missing grades. This prevented a true evaluation of the pass/fail categories. The Knewton data contained pretest and posttest scores; however, when students placed-out of a lesson, the posttest attempt would register as a zero. This meant that scores had to be examined in tandem, or a zero attempt resulting from a placed-out score could not be discerned from a true zero attempt. Given the size of this dataset, the evaluation of the individual lessons across all variables was impractical. Similarly, lesson data were only reported for core lessons. That is, there was no way of tracing the path a student took when placed in focus mode, and as a result the number of posttest attempts was used as a basic way of identifying those students.

Another limitation was the amount of "noise" in the data. That is, the number of logins operationalized students' attendance and could have been used as a measure of engagement during a given lesson. Unfortunately, there were many factors that were not controlled for: from the type of browser used, to the number of lessons a student could be running simultaneously. Ultimately, these data were used for attendance and provided only a glimpse at the students' true behaviors.

A final limitation related to the ACES pre- and post-tests, which collected information for the key variables in this study (self-efficacy, engagement, motivation, and self-regulation). The ACES pre- and post-tests did not appear to be rigorously administered. Mechanisms to ensure students took the pretest before a posttest were not in place and there was no enforcement to ensure students took the posttest after completion of the course. Due to time constraints and other conflicts, valuable parts of the ACES-College instrument were not included in the data collection, which weakened the rigor of the data.

Implications for Future Research and Practice

With the ongoing issue of the underperformance of high school graduates (ACT, 2012) and the nation's desire to improve math academic achievement (NCEA. 2011), it is certainly worthwhile to invest in developing skills beyond students' cognitive abilities. The results of the present study indicate that while cognitive ability is indeed the most important contributor to academic success, self-regulation, engagement, motivation, self-efficacy (i.e., academic competence), and academic resilience can strengthen this success and add to an understanding of students' learning. It is important to investigate the collective contribution of these variables and how they interact with the learning environment. Moving away from looking at the isolated effects of any given attribute and exploring complex relationships may complicate the research process, but it may bring us closer to fully understanding the conditions that promote academic success. Additionally, the finding of this study can provide support for future research aimed at promoting the shift from a time-based system towards a mastery-based system.

Future research. The most important research that could possibly follow from this study would be to compare the effects of a mastery adaptive learning environment on student's performance against the effects of a traditional, teacher-led classroom learning environment. Such a study should be conducted using an experimental design, and after carefully addressing the data limitations listed above. This type of research would be important not only to ground the results of the present study, but also yield generalizable findings. It would also be important to explore how much more math guidance, in the form of step-by-step demonstration, students get in the mastery-based adaptive environment, as opposed to the traditional classroom environment. Additionally, it may be interesting to explore if students who need additional time to learn and/or those who work best independently thrive in one environment compared to the other.

The suitability of a mastery-based, adaptive environment for students in need of remediation should also be investigated. The present study suggests successful remediation; however, to validate these findings, students' performance should be measured in subsequent courses to determine if their performance is at the same level as the performance of students who did not need remediation. The findings also indicated a significant impact on students' mathematics self-efficacy; thus, it would be important to explore whether their self-efficacy yields similar results in a subsequent course. Namely, do remediated students perform at the same level as students who did not need remediation? Do they also exhibit a gain in their self-efficacy? Do they exhibit a higher sense of self-efficacy than the non-remediated students? That is, if a student who was successfully remediated performs equally well on a subsequent course, then that student's perception of his or her mathematics ability would be further reinforced and a stronger more permanent change in self-efficacy would be expected.

Another possible research direction would be to investigate the impact of a hybrid approach compared to fully online instruction. Some students expressed the importance of having access to instructors face-to-face. It would be important to explore whether the lack of access, for the fully online group, adversely impacts students' performance. Yet another direction could be to explore the applicability of the ACES instrument and the theoretical academic performance model to other content areas. Finally, the addition of a resilience measure would strengthen the findings of any of these research directions. There are many validated instruments that could be used for this purpose, such as the Resilience Scale (Wagnild, 2009) or the Resilience Factor Inventory (Reivich & Shatte, 2002; available through AdaptivLearning.com), both of which measure overall resilience and are suitable for a variety of populations. Another approach would be to enlist the cooperation of programs geared towards assessing academic resilience, such as scholar centric (www.scholarcentri.com/research.html). In addition to a resilience measure, socioeconomic status indicators may also prove helpful in understanding the level of support and cultural capital the student has upon entering a course (Dumais, 2002; Strayhorn, 2010). That is, including information such as parental status (e.g., single parent) and parent's highest education level, in addition to ethnicity and gender, can help evaluate how well the students' background matches the academic culture they are entering (Morales, 2008; Roosa et al., 2012).

Implications for practice. It was speculated that variables would come to light that would inform the refinement of an instructional model for remedial math students. The results indicate that the combined effects of affective attributes and academic resilience strengthen predictions about students' academic performance. Thus, it may be wise to include items that address academic resilience (perseverance) in addition to self-efficacy, engagement motivation, and self-regulation in models targeted at college students in need of remediation. Additionally, the results of this study provide modest but valid evidence that the mastery-based environment plays a key role in students' academic success. These findings could be viewed as an opportunity to exploit the potential of making the highest and most positive impact. Recommendations to address the implications of these findings are provided below.

Recommendations for the ACES-College. The current ACES-College addresses most of the variables described above. That is, the academic skills domain assesses self-efficacy. The academic enablers domain assesses engagement, motivation, study skills (self-regulation and participation), and interpersonal skills. A strong recommendation to add a new subscale to the ACES-College instrument is presented here. The addition of a resilience subscale would enhance this instruments ability to better identify skills and behaviors that contribute to academic success. The academic skills and academic enabler domains already assess self-efficacy, motivation, self-regulation related skills, all of which are key components of academic resilience. Academic resilience has been put forth as a construct that is highly predictive of academic success (Howard & Johnson, 2000; Martin & Marsh, 2006). Thus, a resilience subscale would complement and strengthen this instrument (see Appendix H for a sample of the recommended scale).

In addition, a modified version of the current relationship model between academic competence and instruction is presented in Figure 24 (p.4; DiPerna & Elliott, 2001). This revised ACES-College instrument could help designers and practitioners better understand factors that should be accounted for, or included in the design of instructional interventions for remedial math students. The influences discovered by this study illustrate the relationship between the learning environment, students' academic competence (e.g., affective attributes and academic resilience) and their academic performance. The revised model provides practitioners with a simple guide to ensure they consider these aspects as they design interventions suitable for students in remedial courses.

Figure 24. Modified academic competence model. This model illustrates the relationship between academic competence and Instruction and academic outcomes.

Recommendations for Knewton. From an instructional design perspective, a couple of recommendations could be made to improve the already sound Knewton program. Currently, the lessons align to Merrill's (2013) "tell-ask-show" approach but it seems to fall short on the "do" (i.e., application) component. While students are asked to answer many problems, they are not given the opportunity to solve contextualized problems. That is, students would benefit from seeing how math skills can be applied to a real-world situation and the consequences of their decisions. For example, if a math problem was presented in a simulated professional scenario, say a nurse preparing the proper dose for a patient, and if the students miscalculate the dose, they should be able to see the patient go into a critical condition or something drastic. They could also be given the opportunity to experiment with answers and see the consequences of the different choices. An approach such as this would take the gamification component of this courseware beyond earning badges (Prof. K. Werbach, University of Pennsylvania, Gamification lectures [Coursera], October, 2012). The current system appears to do a marvelous job at matching content to the students' current skill, going beyond what can be done in a traditional classroom. However, asking students to solve math problems using the traditional approach of "tell-ask," simply replicates what can already be done in a classroom with pencil and paper. Thus, the opportunity to use the technology to truly engage the student with the content is not fully exploited.

Another recommendation would involve the focus mode process. It is clear that students benefit from the individualized learning afforded by the Knewton courseware. It is also clear that when students do view the entire lessons they benefit albeit, not all students are driven enough to work through the lessons. When students are placed on focus mode, they are evidently struggling with the content. The approach to start the remedial lessons with the "show us what you know" may not be the best approach for them. These students know they are not doing well, asking them to answer more questions may prove too frustrating and discouraging. It is acknowledged that these tests are the means for the system to determine what content to present. Nonetheless, struggling students may instead benefit from a set of choices, designed to foster a sense of self-determination, an important component of intrinsic motivation (Steinberg, 1989; Snow, 1992; Toshalis & Nakkula, 2012). That is, giving students the opportunity to choose from a list of topics. The list would be based on the last failed lesson, this way students are given a sense of control without risking that novice students might take the wrong path (Granger & Levine, 2010). Once the student has chosen a topic, they can then decide whether they know the content and attempt to place out by answering the "show us what you know" questions (see Appendix I).

A final recommendation is related to data gathering. It may be beneficial to collect more detailed information on student's actions throughout the lessons. At this point it is not clear whether a student viewed a lesson (e.g., partially, fully, or skipped) before making their first posttest attempt. Without this information, it is difficult to make solid conclusions about the extent to which the lessons benefit students. The results of this study indicated that students appeared to benefit from viewing the entire lessons; however, this could be a result of having already attempted a posttest and gained an insight as to the type of questions to expect. Similarly, it may also be beneficial to collect more detailed information relating to the number of lessons a student takes after being placed in focus mode. As it is not clear whether students are going around in circles on the same lesson, or further deficiencies are being identified along the way.

Recommendations for the academic performance expression. The findings also illustrate the role of the learning environment on students' academic competence and academic performance. These findings align with the ecological view of resilience, where the environment is believed to strongly influence the outcomes (Ungar, 2011). Consequently, a modified version of the academic expression, based on the current findings is presented in Figure 25. Where academic performance (A_{p}) is a function of students' cognitive ability (C_{a}), and the extent to which the learning environment (LEnv) supports their affective attributes (A_{a}) and resilient behavior (R_b). It is important to note that to operationalize this expression, terms should be entered into a hierarchical regression model as follows: $C_{\mathrm{a}} + A_{\mathrm{a}} + \mathrm{R}_b + (A_{\mathrm{a}} \,.\, \mathrm{R}_b)$, DV = performance indicator.

$$A_{\mathrm{p}} = \int_{LEnv} (C_{\mathrm{a}} (A_{\mathrm{a}} \cdot \mathrm{R}_{b}))$$

Figure 25. Modified academic performance expression. Based on the findings of the present study.

Conclusions

The overall results of the study highlight the importance of fostering self-efficacy, motivation, self-regulation, resiliency, and engagement in students in need of remediation, as these attributes play a small but significant role in their academic success in remedial mathematics. The findings of this study also suggest that a mastery adaptive learning environment may promote academic performance and directly or indirectly act as a vehicle to enhance affective attributes and resilient behaviors. These findings align to the theory that a mastery-based learning environment enhances academic performance (Bloom, 1976; Carroll, 1989). While the present investigation provided an explanation for these relationships, the evidence is modest and further investigation using a control group and randomization is needed to validate these results.

If a message were to be sought from these findings, it would be a recommendation that students' cognitive abilities continue to be the focus of instruction. That the learning environment be most concerned with implementing sound instructional design practices. And that students' self-efficacy, motivation, self-regulation, resiliency, and engagement be taken into account when designing and delivering instruction targeted at college students in need of remediation. As these appear to be the conditions that promote academic success.

In conclusion, given the mathematics underperformance problem in our nation, the findings of this study provide modest evidence and justification for future research exploring the benefits of adaptive, mastery-based environments for remedial mathematics courses. Furthermore, the findings of this study also suggest that an adaptive, mastery-based environment may be a condition that promotes academic performance and may indirectly or directly act as an agent to enhance affective attributes and resilient behaviors. Thus, it can be inferred that allowing students to work at a level consistent with their current skills and giving them the opportunity to learn through mastery experiences is an effective approach to promoting conditions for academic success.

REFERENCES

ACT, Report—National. (2012). *The condition of college & career readiness.* Retrieved from http://act.org/research-policy/college-career-readiness-report-2012/.

American Educational Research Association, American Psychological Association, National Council on Measurement in Education, American Educational Research Association. (1999). *Standards for Educational and Psychological Testing*. Washington DC: American Educational Research Association.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. doi: http://dx.doi.org/10.1037/0033-295X.84.2.191.

Bandura, A. (1989). Human agency in social cognitive theory. *The American Psychologist, 44*(9), 1175–1175. Retrieved from http://login.ezproxy1.lib.asu.edu/login?url=http://search.proquest.com/docview/212092576?accountid-4485.

Bettinger, E. & Long, B. (2009). Addressing the needs of underprepared students in higher education: Does college remediation work? *Journal of Human Resources, 44*(3), 736-771. doi: 10.1353/jhr.2009.0033.

Bloom, B. S. (1968). Learning for mastery. *Evaluation Comment UCLA-CSIEP, 1*(2), 1-12.

Bloom, B.S. (1974). Time and learning. *American Psychologist, 29*, 682−688.

Bloom, B.S. (1978). New views of the learner: Implications for instruction and curriculum. *Educational Leadership, 35*(7), 563-568, 570-576.

Bourdieu, P. (1977). Cultural reproduction and social reproduction. In J. Karabel & A. Halsey (Eds.*), Power and Ideology in Education* (pp. 487-510). New York: Oxford University Press.

Brown, K. G. (2001). Using computers to deliver training: which employees learn and why? *Personnel Psychology, 54*, 271–96.

Carroll, J. (1989). The Carrol model: A 25-year retrospective and prospective view. *American Educational Research Association, 18*(1), 26-31.

Cassen, R., Feinstein, L., & Graham, P. (2008). Educational outcomes: Adversity and resilience. *Social Policy & Society, 8*(1), 73-85. doi: 10.1017/S1474746408004600.

Chandler, T. A. (1982). An effective tool? Mastery learning: Pros and cons. *NASSP Bulletin, 66*(9). doi: 10.1177/019263658206645403.

Changeiywo, J. M., Wambugu, P. W., & Wachanga, S. W. (2011). Investigations of student's motivation towards learning secondary school physics through mastery learning approach. *International Journal of Science and Mathematics Education, 9*, 1333-1350.

Cohen J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155-159.

Connor, K. M. & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). *Depression and Anxiety, 18,*76-82.

Dearnley, C., & Matthew, B. (2007). Factors that contribute to undergraduate student success. *Teaching in Higher Education,12*(3), 377-391.

Diegelman-Parente, A. (2011). The use of mastery learning with competency-based grading in an organic chemistry course. *Journal of College Science Teaching, 40*(5), 50-58.

DiPerna, J. C. (2004). Structural and concurrent validity evidence for the academic competence evaluation scales-College edition. *Journal of College Counseling, 7*, 64-72.

DiPerna, J. C. (2006). Academic enablers and student achievement: Implications for assessment and intervention services in the schools. *Psychology in the Schools, 43*(1), 7-17. doi: 10.1002/pits.20125.

DiPerna, J. C., & Elliott, S. N. (1999). The development and validation of the Academic Competence Evaluation Scales. *Journal of Psychoeducational Assessment*, *17,* 207-225.

DiPerna, J. C., & Elliott, S. N. (2001). *The academic competence evaluation scales* college manual. San Antonio, TX: Pearson.

Dumais, S. A. (2002). Cultural capital, gender, and school success: The role of habitus. *Sociology of Education*, *75*(1), 44-68.

Field, A. (2009). *Discovering statistics using SPSS*, (3rd ed.). London: Sage.

Gastwirth, J. L., Gel, Y. R., & Miao, W. (2009). The impact of Levene's test of equality of variances on statistical theory and practice. *Statistical Science*, *24*(3), 343-360. doi: 10.1214/09-STS301.

George, M. (2010). Ethics and motivation in remedial mathematics education. *Community College Review, 38*(1), 82-92. doi: 10.1177/0091552110373385.

Granger. B. P. & Levine, E. L. (2010). The perplexing role of learner control in e-learning: will learning and transfer benefit or suffer? *International Journal of Training and Development, 14*(3), 180-197.

Guskey, T. R. (2010). Lessons of mastery learning. *Educational Leadership,68*(2), 52-57.

Herrman, H., Stewart, D., Diaz-Granados, N., Berger, E., Jackson, B., & Yuen, T. (2011). What is resilience? *Canadian Journal of Psychiatry, 56*(5), 258-265.

Hirschfeld, R., Lawson, L., & Mossholder, K. (2004). Moderators of the relationship between cognitive ability and performance: General versus context-specific achievement motivation. *Journal of Applied Social Psychology, 34*(11), 2389-2409.

Howard S. & Johnson, B. (2000). What makes the difference? Children and teachers talk about resilient outcomes for children 'at risk'. *Educational Studies, 26*(3), 321.337.

Johnston-Wilder, S., & Lee, C. (2010). Mathematical resilience. *Mathematics Teaching*, (218), 38-41.

Jones, V., & Jo, J.H. (2004). Ubiquitous learning environment: An adaptive teaching system using ubiquitous technology. In R. Atkinson, C. McBeath, D. Jonas-Dwyer & R. Phillips (Eds), *Beyond the comfort zone: Proceedings of the 21st ASCILITE Conference* (pp. 468-474). Perth, 5-8 December. Retrieved from http://www.ascilite.org.au/conferences/perth04/procs/jones.html.

Kaighobadi, M., & Allen, M. T. (2008). Investigating academic success factors for undergraduate business students. *Decision Sciences Journal of Innovative Education, 6*, 427-436. doi: 10.1111/j.1540-4609.2008.00184.x.

Keene, O. N. (1995). The log transformation is special. *Statistics in Medicine, 14,* 811-819.

Keller, J. M. (1979). Motivation and instructional design: A theoretical perspective. *Journal of Instructional Development, 2*(4), 26-36.

Keller, J. M. (2008). First principles of motivation to learn and e^3-learning. *Distance Education, 29*(2), 175-185. doi: 10.1080/01587910802154970.

Kim, CM. (2012). The role of affective and motivational factors in designing personalized learning environments. *Educational Technology, Research and Development, 60*, 563-584. doi: 10.1007/s11423-012-9253-6.

Knewton (n.d.). *Knewton math readiness.* Retrieved from http://www.knewton.com/wp-content/uploads/knewton-math-readiness.pdf

Knewton (2012). *Knewton adaptive learning, building the world's most powerful education recommendation engine* [White paper]. Retrieved from http://www.knewton.com/adaptive-learning-white-paper/.

Lalley, J. P., & Gentile, J. R. (2009a). Adapting instruction to individuals based on the evidence, what should it mean? *International Journal of Teaching and Learning in Higher Education, 20*(3), 462-475.

Lalley, J. P., & Gentile, J. R. (2009b). Classroom assessment and grading to assure mastery. *Theory into Practice, 48*, 28-35. doi: 10.1080/00405840802577577.

Lee, J. (2012). College for all: Gaps between desirable and actual P-12 math achievement trajectories for college readiness. *Educational Researcher, 41*(2), 43-55. doi: 10.3102/0013189X11432746.

Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association, 83*(404), 1198-1202.

Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: a construct validity approach. *Psychology in the Schools, 43*(3), 26-81. doi: 10.1002/pits.20149.

Maxwell, S. E., & Delaney, H. D. (2004). *Designing experiments and analyzing data: A model comparison perspective* (2nd ed., pp. 401-623). New York: Psychology Press.

Merrill, D. M. (2013). *First principles of instruction: Identifying and designing effective, efficient, and engaging instruction.* San Francisco: Pfeiffer.

Meyer, S. J. (2011). Factors affecting student success in postsecondary academic correctional education programs. *Journal of Correctional Education, 62*(2), 132-164.

Morales, E. E. (2008). The resilient mind: The psychology of academic resilience. *The Educational Forum, 72*, 152-167.

National Center for Educational Achievement. (2011). *The 20 non-negotiable characteristics of higher performing school systems.* Retrieved from http://www.nc4ea.org/resources/library/.

Reivich, K. & Shatte, A. (2002). *The resilience factor: 7 essential skills for overcoming life's inevitable obstacles.* New York: Broadway Books.

Ritter, S. (2011). *The research behind the carnegie learning math series* [White paper]. Retrieved from Carnegie Learning, Inc. http://www.carnegielearning.com/whitepapers/.

Roosa, M., O'Donnell, M., Cham, C., Gonzales, N., Zeiders, K., Tein, J.Y., Knight, G., Umaña-Taylor, A. (2012). A prospective study of Mexican American adolescent's academic success: Considering family and individual factors. *Journal of Youth and Adolescence,* 41(3), 307-319. doi: 10.1007/s10964-011-9707-x.

Senko, C., & Miles, K. (2008). Pursuing their own learning agenda: How mastery-oriented students jeopardize their class performance. *Contemporary Educational Psychology, 33,* 561-583.

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist, 26*(3-4), 207-231.

Scholar Centric. (2010). *Review of the Literature: Resiliency and academic performance* [White paper]. Retrieved from http://www.scholarcentric.com/research/SC_Resiliency_Dropout%20Prevention_WP_FNL.pdf.

Silverman, L. Seidman, A. (2011). Academic progress in developmental math courses: a comparative study of student retention. *Journal of College Student Retention: Research, Theory and Practice, 13*(3), 267-287.

Snow, R E. (1992). Aptitude Theory: Yesterday, today, and tomorrow. *Educational Psychologist, 27*(1), 5-32.

Steinberg, E. R. (1989). Cognition and learner control: a literature review, 1977–1988. *Journal of Computer Based Instruction*, *16*, 117-21.

Stewart, P. (2012, March). Closing the math achievement gap: Institutions find success with MyMathLab. *Diverse Issues in Higher Education, 29*(3). Retrieved from http://diverseeducation.com/article/16932/.

Strayhorn, T. L. (2010). The role of schools, families, and psychological variables on math achievement of black high school students [Project MUSE]. *The High School Journal, 93*(4), 177-194. doi: 10.1353/hsj.2010.0003.

Toshalis, E., & Nakkula, M. J. (2012). Motivation, engagement, and student voice. *The Education Digest, 78*(1), 29-35.

Ungar, M. (2011). The social ecology of resilience: addressing contextual and cultural ambiguity of a nascent construct. *American Journal of Orthopsychiatry, 81*(1), 1-17. doi: 10.1111/j.1939-0025.2010.01067.x.

Van Dinther, M., Dochy, F., & Segers, M. (2011). Factors affecting student's self-efficacy in higher education. *Educational Research Review, 6*(2), 95-108. doi:10.1016/j.edurev.2010.10.003.

Vigdor, J. (2013, January). Solving America's math problem. *Education Next, 13*(1). Retrieved from http://educationnext.org/solving-america%E2%80%99s-math-problem/.

Von Hippel, P. (2010). Skewness. In M. Lovric (Ed.), *International encyclopedia of statistical science*. New York: Springer.

Wagnild, G. M. (2009). The resilience scale user's guide for the US English version of the resilience scale and 14-item resilience scale (RS-14).

Young, G. L. (2003). Social ecology. In Bortman, M., Brimblecombe, P. & Cunningham, M.A. (Eds.), *Environmental Encyclopedia*, (Vol. 2, 3rd ed., p. 1308). Detroit: Gale.

APPENDIX A

IRB PROTOCOL

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Laura Brewer Sky Song 3
For **From:**	Mark Roosa, Chair Soc Beh IRB
Date:	08/08/2011
Committee Action:	**Exemption Granted**
IRB Action Date:	08/08/2011
IRB Protocol #:	1108006723
Study Title:	Student Success in Math - Longitudinal Study

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(1) (2) (4) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

APPENDIX B

CONSENT FORM

Success In ASU Math ARIZONA STATE UNIVERSITY

Evaluation Activity #1

ASU Success in Math - Study Information & Consent

This evaluation activity should take you only a couple of minutes to complete. You are required to read through the study information and then complete one yes/no question about your consent to have your data included in the study.

Student Information

It is important that you complete all of your student information so that you can get credit for completing this evaluation activity.

Please enter your first name and last name.

First Name:	
Last Name:	

Please enter your ASURITE ID.

Note: Your ASURITE User ID has 5-8 characters and it is the ID you use to login to myASU.

ASURITE ID:

Please select your class, instructor and schedule line number.

Note: You can find your schedule line number in the right corner your course web site. It has 5 digits.

Class

Instructor

Schedule Line Number

If you selected *Other-Staff above, please complete the following:

Instructor	
Schedule Line Number	

>> Next Page

Survey Powered By Qualtrics

ASU Student Success in Math
Study Information

****After you read through this information, you must complete the ONE yes-no question to earn credit on this evaluation activity****

As of fall 2011, ASU has adopted a web-based adaptive learning platform for its developmental math course (MAT 110) and its entry-level math courses (MAT 142, MAT 117). ASU Online and the Learning Sciences Institute (LSI) are working with the Math Department to study student success in these newly designed Math courses and to examine how students' experiences in these courses impact their success in subsequent math courses as well as longer-term persistence/retention to graduation from ASU.

The purpose of this research is to gather and analyze course and institutional data from students who are enrolled in MAT 110, MAT 142 and MAT 117 from Fall 2011 through Fall 2012. We are asking your consent to use your student data as part of this study. You will not be asked to complete additional materials as part of your participation. Participation only involves giving the research team access to your course data.

Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study at any time, there will be no penalty and it will not affect your grade in this course. You must be 18 years or older to participate in this study.

Your participation benefits the Math Department, ASU Online, and the Learning Sciences Institute at ASU in that your consent will allow the research teams from these units to examine student experiences with the new adaptive technology curriculum that was implemented in MAT 110, MAT 142 and MAT 117 beginning Fall 2011. There are no foreseeable risks or discomforts to your participation.

If you agree, the research team will gain access to your course experience data (i.e. results on assessments, surveys, course grades, and system data, like time spent on web-based course material). In addition, your ASURITE User ID will be used to facilitate matching demographic items (i.e., age, academic level, race, sex) and to track your experiences in subsequent math courses and your persistence to graduation from ASU (over the next 6 years). If you choose to participate your ID will be used solely for retrieving information from the student data warehouse and matching it to your course data. Once data is retrieved and matched your ASURITE User ID will be removed from all data files and will be replaced with a study ID that will allow the longer-term tracking of your experiences in future ASU Mathematics courses and your persistence to graduation (for up to 6 years or until you leave the University). All individually identifying information (like your name, ASURITE ID, ASU Student ID) will be removed from data files and files will be kept secure. The results of this study may be used in reports, presentations, or publications but your name will not be used. All study findings will be presented in the aggregate to further ensure confidentiality.

If you have any questions concerning the research study, please contact Kim Marrone Beckert, Ed.D. atkimberly.beckert@asu.edu or (480) 884-1917. If you have any questions about your rights as a subject/participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

ASU Student Success in Math Consent

Please indicate your decision to participate by answering "Yes" or "No" to the following consent statement. Note your agreement decision does not impact your course requirements in any way. In either case, you are responsible for completing the four evaluation activities and other course work.

I consent to have my MAT 110, MAT 142 or MAT 117 course data, student demographic data, as well as institutional data to track my enrollment and outcomes in subsequent math courses and my persistence/retention at ASU be used as part of the Student Success in Math Study.

- Yes
- No

Please select "Next Page" to submit.

<< Last Page >> Next Page

Survey Powered By Qualtrics

Success In ASU Math

ARIZONA STATE UNIVERSITY

Great job completing the ASU Student Success in Math Consent!

Your second evaluation activity is the ACES Pre-test and it should be done before you begin your coursework. The ACES Pre-test will take about 15 minutes to complete. Would you like to complete your next evaluation activity right now?

Click here to take the ACES Pre-test now.

Survey Powered By Qualtrics

APPENDIX C

ECOLOGICAL RESILIENCE EXPRESSION

BY MICHAEL UNGAR, 2011

$$R_{B(1,2,3\ldots)} = \frac{f(P_{SC}, E)}{(O_{Av}, O_{Ac})(M)}$$

“Behavior is the function of the person (P), including the person’s neurophysiological strengths and other personal capacities, interacting in dynamic but unspecified ways with an environment (E) that provides for his or her needs. …. A process-oriented and contextualized understanding of resilience and the behaviors associated with positive development under adversity (RB) requires sensitivity to the opportunity structure (O). …. The developmental pathways adopted depend on the availability (Av) and accessibility (Ac) of health-sustaining resources and the meaning (M) that is constructed for each within the child’s culture and context. …. These opportunities and their co-constructed meanings interact with the individual’s strengths (S) and challenges (C), though the influence of these is strongly mitigated by the opportunity structure that supports or suppresses their expression.” (pp. 11-12).

APPENDIX D

PART 1 –DATA FILTERING SAMPLE CODE

Data Filtering and Consolidating Code – partial sample

Code written by James P. Foshee 1/15/2013 updated 2/1/2013
===============================page 1 of 4 pages

```
Option Explicit

Public F11_Roster_col_start,
F11_Roster_col_end,
F11_Roster_row_start As Integer
Public F11_Roster_row_end As Double
Public number_of_students As Double
Public S12_Roster_col_start,
S12_Roster_col_end,
S12_Roster_row_start,
S12_Roster_row_end As Integer
Public ACE_startDate_col,
ACE_learn_col, Engage_startDate_col As
Integer
Public ACESpre_merge_complete,
ACESpost_merge_complete,
Engage_merge_complete As Boolean

' Roster and Datasheet names
Public roster_str, pre_datasheet_str,
post_datasheet_str, engm_datasheet_str
As String

' --------Scores-------
Public ACES_RW_label,
ACES_RW_Tlabel, ACES_MS_label,
ACES_MS_Tlabel As String
Public ACES_CT_label,
ACES_CT_Tlabel, ACES_DMAS_Tlabel
As String
Public ACES_IS_label, ACES_IS_Tlabel,
ACES_EG_label, ACES_EG_Tlabel,
ACES_MV_label, ACES_MV_Tlabel As
String
Public ACES_SS_label,
ACES_SS_Tlabel, ACES_DMAE_Tlabel,
ACES_Comp_label, open_Q_label As
String
'
Public ACES_RW_Qs, ACES_MS_Qs,
ACES_CT_Qs, ACES_IS_Qs,
ACES_EG_Qs, ACES_MV_Qs,
ACES_SS_Qs As Integer
'
Public ACES_IS_label_col,
ACES_RW_total_col,
ACES_MS_label_col,
ACES_MS_total_col As Integer
Public ACES_ENGM_label As String
Public ACES_ENGM_Qs As Integer
' Keeps track of the current column in the
merged Roster sheet.  Starts with column
4.
Public roster_col_index As Integer
' Set up Color for for when Pre or Post
datasheets have multiple entries
Public preColor As Integer
Public postColor As Integer

' Row Index of the current Research Id
Public ACESpre_Id_index,
ACESpost_Id_index, Engage_Id_index
As Integer
' Number of Research Id entries in each
Datasheet
Public ACESpre_Id_count,
ACESpost_Id_count, Engage_Id_count
As Integer
'
Public pre_head_1 As String
Public pre_head_2 As String
Public post_head_1 As String
Public post_head_2 As String
Public engm_head_1 As String
Public engm_head_2 As String
'
Sub get_globals()
Sheets("Instructions").Select
F11_Roster_row_start = Cells(21,
2).Value
'F11_Roster_row_end = Cells(21,
4).Value  ' computed
F11_Roster_col_start = Cells(22, 2).Value
F11_Roster_col_end = Cells(22, 4).Value

S12_Roster_row_start = Cells(23,
2).Value
'S12_Roster_row_end = Cells(24,
5).Value
S12_Roster_col_start = Cells(24,
2).Value
S12_Roster_col_end = Cells(24, 4).Value
' -------Roster Start Col --------
roster_col_index = Cells(25, 2).Value
' Roster End Col
'roster_col_index2 = Cells(25, 3).Value
' -------Pre Scores --------
'ACESpre_col_index1 = Cells(26,
2).Value
'ACESpre_col_index2 = Cells(26,
4).Value
' -------Post Scores-------
'ACESpost_col_index1 = Cells(27,
2).Value
'ACESpost_col_index2 = Cells(27,
4).Value
'-------- ACE Score Info-------
ACE_startDate_col = Cells(28, 2)
'ACE_num_cols = Cells(29, 2).Value
ACE_learn_col = Cells(30, 2)
' -------Engagement Scores--------
'Engage_col_index = Cells(32, 2).Value
Engage_startDate_col = Cells(33, 2)
'Engage_num_cols = Cells(34, 2).Value
' --------Scores-------
'ACES_label_col = Cells(32, 2).Value
' --------Read Write--------
ACES_RW_label = Cells(38, 2).Text
ACES_RW_Tlabel = Cells(39, 2).Text
ACES_RW_Qs = Cells(38, 4).Text
' --------Math Science--------
ACES_MS_label = Cells(40, 2).Text
ACES_MS_Tlabel = Cells(41, 2).Text
ACES_MS_Qs = Cells(40, 4).Text
' --------Crit Thinking-------
ACES_CT_label = Cells(42, 2).Text
ACES_CT_Tlabel = Cells(43, 2).Text
ACES_CT_Qs = Cells(42, 4).Text
' --------Acad Skills Domain--------
ACES_DMAS_Tlabel = Cells(44, 2).Text
' --------Interpersonal Skills-------
ACES_IS_label = Cells(45, 2).Text
ACES_IS_Tlabel = Cells(46, 2).Text
ACES_IS_Qs = Cells(45, 4).Text
' --------Engagement-------
ACES_EG_label = Cells(47, 2).Text
ACES_EG_Tlabel = Cells(48, 2).Text
ACES_EG_Qs = Cells(47, 4).Text
' --------Motivation--------
ACES_MV_label = Cells(49, 2).Text
ACES_MV_Tlabel = Cells(50, 2).Text
ACES_MV_Qs = Cells(49, 4).Text
' --------Study Skills-------
ACES_SS_label = Cells(51, 2).Text
ACES_SS_Tlabel = Cells(52, 2).Text
ACES_SS_Qs = Cells(51, 4).Text
' --------Academic Enablers Domain-------
ACES_DMAE_Tlabel = Cells(53, 2).Text
'-------- Academic Competence-------
ACES_Comp_label = Cells(54, 2).Text
'-------- Open Ended Question--------
open_Q_label = Cells(56, 2).Text
' --------Engagement-------
ACES_ENGM_label = Cells(60, 2).Text
ACES_ENGM_Qs = Cells(60, 4).Value

' Get the Roster and Datasheet names
roster_str = Cells(64, 2).Text
pre_datasheet_str = Cells(64, 3).Text
post_datasheet_str = Cells(64, 4).Text
engm_datasheet_str = Cells(64, 5).Text

====== end of sample =============
```

APPENDIX E

PART 2 –DATA CONSOLIDATION SAMPLE CODE

================================ Page 3 of 7 pages

```
current_id = 0
student_rowCount = 0
'ASU_roster_index =
 ASU_Roster_row_start
'ASU_GPA_index = ASU_GPA_row_start
pre_index = 2
post_index = 2
'online_index =
 ASU_OnlineEngage_row_start
'f2f_index = ASU_F2FEngage_row_start
'ASU_Fall2012_index =
 ASU_semester_row_start
asu_gpa_end = False
roster_end = False
' Loop through the Roster
'For ASU_roster_index =
 ASU_Roster_row_start To
 ASU_Roster_row_end
While (Not (roster_end))
 ' Change to the Roster Sheet
 Sheets(asu_roster_datasheet).Select
  ' Get the next Research Id, term, and
 course number
 research_id = Cells(ASU_roster_index,
 1).Value
 'course_num = Cells(ASU_roster_index,
 4).Text
' How many entries for this Student Id
 student_entries = 0
 '    Search 5 rows ahead of current index
 Set UserId_Range =
 Range(Cells(ASU_roster_index, 1),
 Cells(ASU_roster_index + 5, 1))
 student_entries =
 Application.WorksheetFunction.CountIf(Us
 erId_Range, research_id)
If (student_entries > 1) Then
  student_range = student_entries - 1
  enrl_entries = 0
  wdrw_entries = 0
  Set enroll_Range =
 Range(Cells(ASU_roster_index, 6),
 Cells(ASU_roster_index + student_range,
 6))
  enrl_entries =
 Application.WorksheetFunction.CountIf(en
 roll_Range, "ENRL")
  wdrw_entries =
 Application.WorksheetFunction.CountIf(en
 roll_Range, "WDRW")
  If (enrl_entries = 1) Then
   ' Find the position of the ENRL entry
   For x = 0 To student_range
     current_entry =
Trim(Cells(ASU_roster_index + x, 6).Text)
     If current_entry = "ENRL" Then
      ASU_roster_index =
ASU_roster_index + x
      enrlStatus =
Trim(Cells(ASU_roster_index, 6).Text)
     End If
    Next
  ElseIf (wdrw_entries >= 1) Then
    ' Find the position of the WDRW entry
    wdrw_count = 1
    For x = 0 To student_range
     current_entry =
Trim(Cells(ASU_roster_index + x, 6).Text)
' Current Enroll Status
     If ((current_entry = "WDRW") And
(wdrw_count = wdrw_entries)) Then
      ASU_roster_index =
ASU_roster_index + x
      wdrw_count = wdrw_count + 1
      enrlStatus =
Trim(Cells(ASU_roster_index, 6).Text)
     End If
    Next
  Else
    ' Just have DROP entries, pick the last
entry
    ASU_roster_index = ASU_roster_index
+ student_range
    enrlStatus =
Trim(Cells(ASU_roster_index, 6).Text)
  End If
 End If
' Copy the ASU Roster Info to the Semester
 Output Sheet
 ' ------------------------------------ Call
 get_asu_roster_info(asu_roster_datasheet
 , research_id, ASU_roster_index,
 output_datasheet, ASU_Fall2012_index)
++++++++++++++++++++++++++++++++
'       ASU Additional GPA Data
++++++++++++++++++++++++++++++++
 ' Change to the ASU GPA Sheet
 Sheets(asu_gpa_datasheet).Select
 asu_gpa_end = False
While (Not asu_gpa_end)
  gpa_Id = Cells(ASU_GPA_index,
 1).Value
  If (gpa_Id = research_id) Then
    ' Get the ASU Additional Data Info
    ' ------------------------------     Call
 get_asu_gpa_info(asu_gpa_datasheet,
 ASU_GPA_index, output_datasheet,
 ASU_Fall2012_index)
   asu_gpa_end = True
  ElseIf (gpa_Id > research_id) Then
   asu_gpa_end = True
  Else
   ASU_GPA_index = ASU_GPA_index +
1
  End If
Wend
++++++++++++++++++++++++++++++++
'       Determine the Research Id Row in
 ACESpre
+++++++++++++++++++++++++++   Call
 get_preResearch_Id_info(pre_datasheet,
 research_id, course_num)
++++++++++++++++++++++++++++++++
'       Determine the Research Id Row in
 ACESpost
 ++++++++++++++++++++++++++
 Call
 get_postResearch_Id_info(post_datasheet
 , research_id, course_num)
++++++++++++++++++++++++++++++++
'       Determine the Research Id Row in
 Engagement
++++++++++++++++++++++++++++++++
  online_student = "N"
  onlineEngage_entries = 0
  f2fEngage_entries = 0
' Is the Student Online
Sheets(onlineEngm_datasheet).Select
'    Search the Online Engagement Sheet
Set EngageId_Range =
Range("A1:A3000")
onlineEngage_entries =
Application.WorksheetFunction.CountIf(En
gageId_Range, research_id)
If onlineEngage_entries >= 1 Then
  online_student = "Y"
  Call
get_engmResearch_Id_info(onlineEngm_
datasheet, onlineEngage_Id_index,
onlineEngage_Id_count, research_id)
End If
' Is there a F2F entry for the current
student
Sheets(f2fEngm_datasheet).Select
'    Search the Online Engagement Sheet
Set EngageId_Range =
Range("A1:A3000")
f2fEngage_entries =
Application.WorksheetFunction.CountIf(
_index, post_index, "post")
```

APPENDIX F

ACADEMIC COMPETENCE EVALUATION SCALES: ACES-COLLEGE

Only Pre-test is shown here. Post-test questions are the same

ACES Pre-Test | Page 1 of 11

Success In ASU Math

Arizona State University

Evaluation Activity #2

ACES Pre-Test

This is your second evaluation activity in this course. The ACES Pre-test will take you approximately 15 minutes to complete and should be completed before you begin your course work.

Before you begin Evaluation Activity #2 - the ACES Pre-test, have you already completed Evaluation Activity #1 - Success in ASU Math Study Consent?

- ◯ Yes I have complete Evaluation Activity #1, please take me directly to the ACES Pre-test.
- ◯ No, I have not completed Evaluation Activity #1, please take me to there now. You will be able to link back to the ACES Pre-test after you complete the Success in ASU Math Study Consent.

>> Next Page

0% 100%

Survey Powered By Qualtrics

Academic Competence Evaluation Scales

James C. DiPerna and Stephen N. Elliott

College Form

Student Information

It is important that you include all of your student information so that you can get credit for completing this evaluation activity.

Please enter your first name and last name.

First Name:	
Last Name:	

Please enter your ASURITE ID.

Note: Your ASURITE User ID has 5-8 characters and it is the ID you use to login to myASU.

ASURITE ID:	

Please select your class, instructor and schedule line number.

Note: You can find your schedule line number in the right corner your course web site. It has 5 digits.

Class

Instructor

Schedule Line Number

If you selected *Other-Staff above, please complete the following:

Instructor	
Schedule Line Number	

<< Last Page   >> Next Page

0% 100%

ACES Pre-Test | Page 3 of 11

Directions

The Academic Competence Evaluation Scales assess a student's academic skills and academic enablers (interpersonal skills, engagement, motivation, and study skills). For each Academic Skill, provide a rating that is the best estimation of your skill level in comparison to other students at your college. For each Academic Enabling behavior, provide a rating that best describes the frequency with which you exhibit the behavior.

Please be sure to answer all of the questions on the following pages. There are no right or wrong answers, just your ideas about how often you use these skills.

Select "Next Page" to start the assessment.

<< Last Page >> Next Page

0% 100%

Survey Powered By Qualtrics

ACES Pre-Test | Page 4 of 11

Academic Skills

For each Academic Skill, provide a rating that is the best estimation of your skill level in comparison to other students at your college.

Reading/Writing Skills

	Far Below (1)	Below (2)	At Grade Level (3)	Above (4)	Far Above (5)
Reading Comprehension	○	○	○	○	○
Reading unfamiliar words by sounding out each of the letters	○	○	○	○	○
Vocabulary	○	○	○	○	○
Identifying a main idea	○	○	○	○	○
Reading fluency	○	○	○	○	○
Spelling	○	○	○	○	○
Punctuation	○	○	○	○	○
Grammar	○	○	○	○	○
Written communication	○	○	○	○	○
Drawing conclusions form written material	○	○	○	○	○

<< Last Page   >> Next Page

0% 100%

Survey Powered By Qualtrics

Academic Skills

For each Academic Skill, provide a rating that is the best estimation of your skill level in comparison to other students at your college.

Mathematics/Science Skills

	Far Below (1)	Below (2)	At Grade Level (3)	Above (4)	Far Above (5)
Computation	○	○	○	○	○
Analyzing errors in information or processes	○	○	○	○	○
Measurement	○	○	○	○	○
Understanding of spatial relationships	○	○	○	○	○
Mental Math	○	○	○	○	○
Using mathematical concepts solve daily problems	○	○	○	○	○
Testing hypothesis	○	○	○	○	○
Breaking down a complex problem	○	○	○	○	○
Identifying patterns from information	○	○	○	○	○
Problem-solving	○	○	○	○	○

<< Last Page | >> Next Page

0% 100%

Survey Powered By Qualtrics

Academic Skills

For each Academic Skill, provide a rating that is the best estimation of your skill level in comparison to other students at your college.

Critical Thinking Skills

	Far Below (1)	Below (2)	At Grade Level (3)	Above (4)	Far Above (5)
Synthesizing related information	○	○	○	○	○
Drawing conclusions from observations	○	○	○	○	○
Comparing similarities or differences among objects or ideas	○	○	○	○	○
Classifying objects or ideas into categories	○	○	○	○	○
Generalizing from information or experiences	○	○	○	○	○
Constructing support for or against a position or issue	○	○	○	○	○
Analyzing supporting and opposing viewpoints on an issue	○	○	○	○	○
Deciding among alternative solutions	○	○	○	○	○
Investigating a problem or issue	○	○	○	○	○
Developing a solution to a problem	○	○	○	○	○

<< Last Page >> Next Page

0% 100%

Survey Powered By Qualtrics

ACES Pre-Test | Page 7 of 11

Academic Enablers

For each Academic Enabling behavior, provide a rating that best describes the frequency with which you exhibit the behavior.

Interpersonal Skills

	Never (1)	Seldom (2)	Sometimes (3)	Often (4)	Almost Always (5)
I am considerate of others	○	○	○	○	○
I am willing to compromise	○	○	○	○	○
I express dissatisfaction appropriately	○	○	○	○	○
I accept suggestions from others	○	○	○	○	○
I work effectively in large group activities	○	○	○	○	○
I listen to what others have to say	○	○	○	○	○
I work effectively in small group activities	○	○	○	○	○
I interact appropriately with other students	○	○	○	○	○

<< Last Page | >> Next Page

0% 100%

Survey Powered By Qualtrics

ACES Pre-Test | Page 8 of 11

Academic Enablers

For each Academic Enabling behavior, provide a rating that best describes the frequency with which you exhibit the behavior.

Engagement

	Never (1)	Seldom (2)	Sometimes (3)	Often (4)	Almost Always (5)
I use outlines to organize my written work	○	○	○	○	○
I speak in class when called upon	○	○	○	○	○
I ask questions about exams or other assignments	○	○	○	○	○
I participate in class discussions	○	○	○	○	○
I volunteer answers to questions	○	○	○	○	○
I assume leadership in group discussions	○	○	○	○	○
I initiate conversations appropriately	○	○	○	○	○
I ask questions when I am confused	○	○	○	○	○

<< Last Page   >> Next Page

0% 100%

Survey Powered By Qualtrics

Academic Enablers

For each Academic Enabling behavior, provide a rating that best describes the frequency with which you exhibit the behavior.

Motivation

	Never (1)	Seldom (2)	Sometimes (3)	Often (4)	Almost Always (5)
I am motivated to learn	○	○	○	○	○
I prefer challenging tasks	○	○	○	○	○
I produce high-quality work	○	○	○	○	○
I critically evaluate my own work	○	○	○	○	○
I attempt to improve on previous performance	○	○	○	○	○
I make the most of learning experiences	○	○	○	○	○
I look forward to academically challenge myself	○	○	○	○	○
I assume responsibility for my learning	○	○	○	○	○
I pay attention in class	○	○	○	○	○
I am goal-oriented	○	○	○	○	○

<< Last Page | >> Next Page

0% 100%

Academic Enablers

For each Academic Enabling behavior, provide a rating that best describes the frequency with which you exhibit the behavior.

Study Skills

	Never (1)	Seldom (2)	Sometimes (3)	Often (4)	Almost Always (5)
I complete course assignments	○	○	○	○	○
I edit my work before I submit it	○	○	○	○	○
I finish my assignments on time	○	○	○	○	○
I take notes in class	○	○	○	○	○
I review notes and other class materials	○	○	○	○	○
I use strategies to remember information	○	○	○	○	○
I manage my time effectively	○	○	○	○	○
I prepare for exams	○	○	○	○	○
I prepare for class (e.g., complete readings, review notes)	○	○	○	○	○
I attend class	○	○	○	○	○

<< Last Page   >> Next Page

0% 100%

Survey Powered By Qualtrics

ACES Pre-Test | Page 11 of 11

If you have any comments about yourself and how you learn best, please write them in the space below.

PEARSON

Academic Competence Evaluation Scales (ACES).

PsychCorp

<< Last Page >> Next Page

0% 100%

Survey Powered By Qualtrics

Feedback page:

Success In ASU Math

Arizona State University

Great job completing the ACES Pre-Test!

Your third evaluation activity is the ACES Post-test and it should be completed after you complete all your coursework and before you begin your final exam.

0% 100%

Survey Powered By Qualtrics

APPENDIX G

ENGAGEMENT SURVEY

Success In ASU Math

Arizona State University

Evaluation Activity #4

Success In ASU Math - Engagement Survey

This is fourth and final evaluation activity in this course. The Success In ASU Math - Engagement Survey will take you approximately 5 minutes to complete and should be completed after you finish your course.

NOTE: If you did not get a chance to fully complete the ACES Post-test (Evaluation Activity #3 that was scheduled before your last exam), you will have an opportunity to go to that assessment once you complete this short survey.

Next Page >>

Survey Completion

0% 100%

Survey Powered By Qualtrics

Engagement Survey | Page 2 of 5

Student Information

It is important that you include all of your student information so that you can get credit for completing this evaluation activity.

Please enter your first name and last name

First Name:	
Last Name:	

Please enter your ASURITE ID.

Note: Your ASURITE User ID has 5-8 characters..typically includes a combination of letters from your first and last name.

ASURITE ID:

Please select your class, instructor and schedule line number.

Note: You can find your schedule line number in the right corner your course web site. It has 5 digits.

Class

Instructor

Schedule Line Number

If you selected *Other-Staff above, or you couldn't find your class schedule number in the drop-down, please complete the following:

Instructor	
Schedule Line Number	

<< Last Page   Next Page >>

Survey Completion

0% 100%

Survey Powered By Qualtrics

Engagement Survey | Page 3 of 5

Directions

Please read and answer each of the questions below.

During the time you took this course, about how many hours in a typical 7-day week did you spend doing each of the following?

	0 Hours	1 - 5 Hours	6 - 10 Hours	11 - 15 Hours	16 - 30 Hours	21 - 25 Hours	26 - 30 Hours	More than 30 Hours
Preparing for **this course** (studying, reading, writing, doing homework, and other academic activities) outside of class time	○	○	○	○	○	○	○	○
Working on course material during class time in **this course**	○	○	○	○	○	○	○	○
Working for pay	○	○	○	○	○	○	○	○
Watching non-educational TV and playing games	○	○	○	○	○	○	○	○

Using the grade scale A, B, C, D, how would you respond to the following items about your grade in this course?

	A	B	C	D
The grade I was working for was:	○	○	○	○
The grade I expect to get for this course is: (If you know your final course grade use that)	○	○	○	○

<< Last Page | Next Page >>

Survey Completion

0% 100%

Survey Powered By Qualtrics

Engagement Survey | Page 4 of 5

To what extent do the following behaviors, thoughts, and feelings describe you, in this course?

	Extremely characteristic of me	Moderately characteristic of me	Somewhat characteristic of me	A little characteristic of me	Not at all characteristic of me
Did almost all the homework problems	○	○	○	○	○
Logged in and participated in the course website as assigned	○	○	○	○	○
Thought about the course between the times I logged in and completed coursework	○	○	○	○	○
Found ways to make the course interesting to me	○	○	○	○	○
Desired to learn the material	○	○	○	○	○
Put forth effort	○	○	○	○	○
Stayed up with course readings	○	○	○	○	○
Had fun in class	○	○	○	○	○
Made sure to study on a regular basis	○	○	○	○	○
Applied course material to my life	○	○	○	○	○
Listened carefully in class	○	○	○	○	○
Asked questions in class or contributed to class discussions	○	○	○	○	○
Participated in class without completing readings or assignments	○	○	○	○	○
Anticipated what would be on the tests	○	○	○	○	○
Quizzed myself to determine readiness for a test	○	○	○	○	○
Discussed course content with a classmate	○	○	○	○	○

Thank you for taking the time to respond to this survey about your experience in your ASU Math course. We appreciate your participation in this study.

Please select "Next Page" to submit your answers to the Student Engagement survey.

<< Last Page   Next Page >>

Survey Completion

0% 100%

Survey Powered By Qualtrics

Success In ASU Math

ARIZONA STATE UNIVERSITY

Great job completing the ASU Student Success in Engagement Survey!

Fully completing all four evaluation activities is critical to the Success in Math study. Did you complete Evaluation Activity #3 before you last exam? Did you answer all the questions? If not, please click on the link below to access the ACES Post-test now. The ACES Post-test will take about 10-15 minutes to complete.

If you did not complete Evaluation Activity #3, the ACES Post-test, click here to take it now.

If you have already completed Evaluation Activity #3 the ACES Post-test - Thank You! Your response on the evaluation pieces will help us continue to improve this course.

Survey Completion

0% 100%

Survey Powered By Qualtrics

APPENDIX H

POSSIBLE ITEMS FOR THE ACES-COLLEGE

Following is a suggested set of possible items (Table 22) based on the resilience scale, RS-14 (Wagnild, 2009) and the resilience scale, CD-RISC10 (Connor & Davidson, 2003).

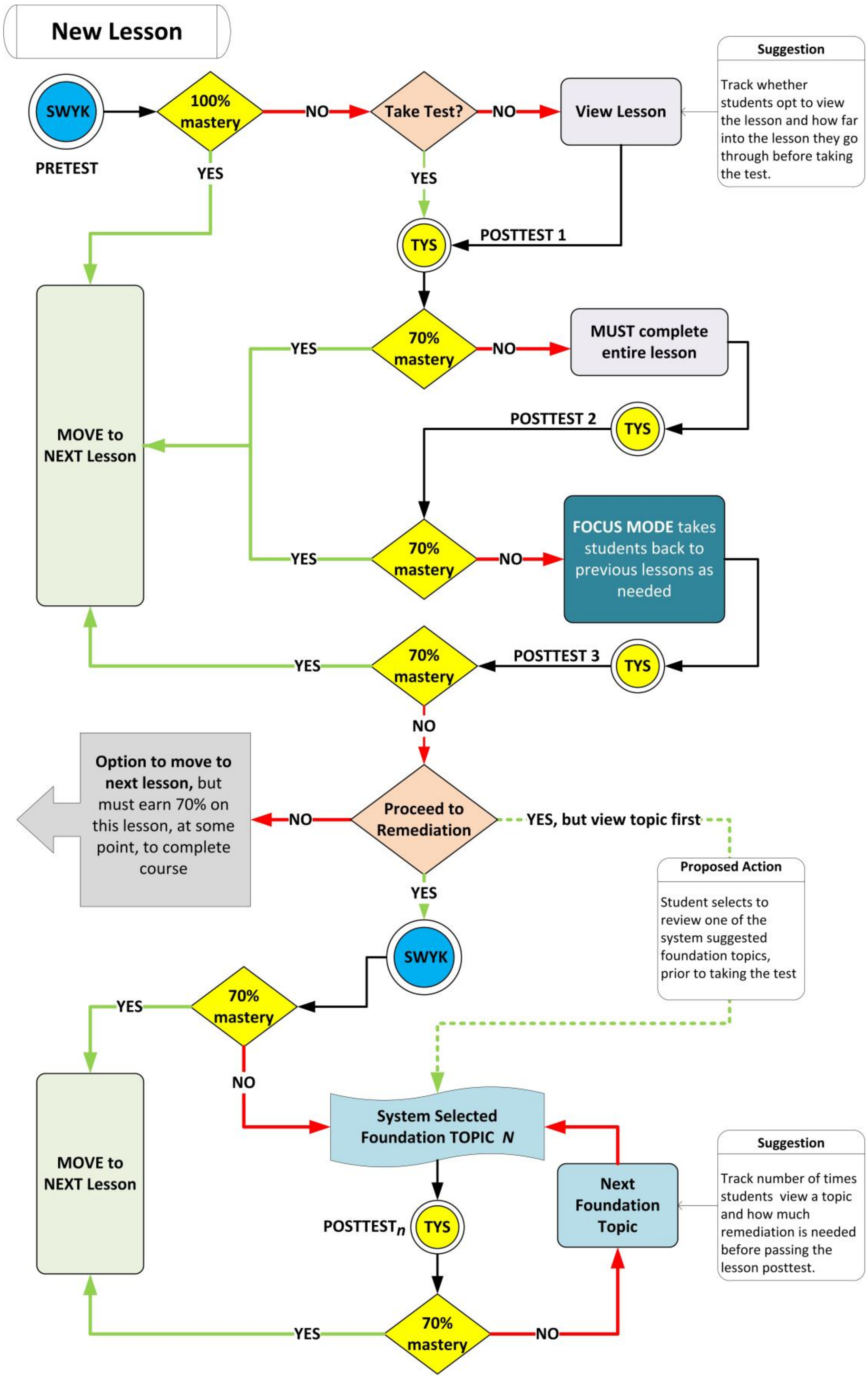
Suggested Resilience Subscale

Possible Items	Not True 1	Seldom True 2	Sometimes True 3	Often True 4	Very True 5
1. I am not easily discouraged.					
2. When I start something, I stick with it.					
3. I can handle multiple things at once.					
4. I am proud of my accomplishments.					
5. I get by one way or another.					
6. I am able to adapt.					
7. I can cope with stress.					
8. I have people I can count on.					

These items can be scored using the current scale values. The original resilience scales, used as a reference, apply a straightforward scoring system of low scores indicating low resilience and high scores indicating high resilience. Where the highest scores suggest students respond well to adversity and the lowest scores suggest students give up when faced with adversity. Needless to say, the validity of these items would need to be investigated and an appropriate confidence interval established.

APPENDIX I

PROPOSED KNEWTON FOCUS MODE BRANCHING


New Lesson
SWYK
PRETEST
100% mastery
NO
YES
Take Test?
NO
YES
View Lesson
Suggestion
Track whether students opt to view the lesson and how far into the lesson they go through before taking the test.
TYS
POSTTEST 1
70% mastery
YES
NO
MUST complete entire lesson
MOVE to NEXT Lesson
POSTTEST 2
TYS
70% mastery
YES
NO
FOCUS MODE takes students back to previous lessons as needed
70% mastery
YES
POSTTEST 3
TYS
NO
Option to move to next lesson, but must earn 70% on this lesson, at some point, to complete course
NO
Proceed to Remediation
YES, but view topic first
Proposed Action
Student selects to review one of the system suggested foundation topics, prior to taking the test
YES
SWYK
70% mastery
YES
NO
MOVE to NEXT Lesson
System Selected Foundation TOPIC N
Next Foundation Topic
Suggestion
Track number of times students view a topic and how much remediation is needed before passing the lesson posttest.
POSTTEST$_n$
TYS
70% mastery
YES
NO

APPENDIX I

ACES PERMISSION FOR USE

LEARNING SCIENCES INSTITUTE
ARIZONA STATE UNIVERSITY

April 22, 2013

Cecile Foshee
Graduate Student
MLFTC
Arizona State University
Tempe, AZ

Dear Cecile,

As an author of the **Academic Competence Evaluation Scales (ACES)**, I am pleased to acknowledge your use of the ACES in your dissertation research and give permission to reprint portions of the ACES in your dissertation to illustrate the measure and highlight scoring outcomes.

Sincerely,

Stephen N. Elliott, PhD