INVESTIGATIONS ON THE IMPACT OF SPATIAL ABILITY AND SCIENTIFIC REASONING OF STUDENT COMPREHENSION IN PHYSICS, STATE ASSESSMENT TESTS, AND STEM COURSES

by

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Abstract

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Physics examines topics that are highly spatial in nature. Students are required to visualize a system, manipulate that system, and then solve a given problem. Doing all of this simultaneously can lead to a cognitive overload, causing the student to be unable to correctly solve the problem. Some difficulties may be rooted in conceptual difficulties, whereas other difficulties may arise from issues with spatial intelligence and visual cognition. In some cases, students might have created an incorrect mental image of the problem to begin with, and itôs this misconception, not the lack of content knowledge, that has caused the student to arrive at an incorrect answer. This work focuses on several discrete investigations that relate to student learning in physics and the relationship to spatial ability and other factors, especially scientific reasoning. Specifically, we examine factors that might impact high school studentsô performance physics, state tests, and the SAT. We also compare spatial ability in students taking physics from high school through the beginning of upper division at the university level. Finally, we apply a novel approach from general systems performance theory to model student achievement on the SAT.

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Background

1.1 Background and Review of Physics Education

Is teaching an art or a science? Some consider it an art because it is a creative activity. Others consider it a science because it is a function of knowledge, art, and skill. The controversy has long existed. An article from the American Physics Teacher quotes F.K. Richtmyer as affirming, ñTeaching, I say, is an art and not a scienceò[Richtmyer, 1933]. In his view Physics is Physics. This debatable statement implies that science and education are completely separate. However, if this were so, would physics education research be conducted in physics departments? Richtmyerôs expression has been a main debate issue pertaining to the question of how to categorize Physics Education Research (PER) in accordance with the other fields of physics. Redish [1998] remarks how the creation of a body of knowledge in science is very similar to making a map. Redish [1998] compares the creation of our understanding of the physical universe, which is based on the accomplishments of individuals that have allowed for us to dig deeper into the realm of reality by providing segments of a physical map, to the formation of physics education. Each map is a segment of how an individual believes that the physical universe actually works. However, in the scientific community it is important to exchange and contribute ideas; therefore, a map is not made by only one person. Many researchers and a community have to agree that the general notions are correct. However, it is also important to be able to offer criticism in the scientific community that builds consensus knowledge. Redish [1998] further states that the making of the map is agreed upon by peer-reviewed publications. Therefore, like other disciplines, PER should be considered a science.

The foundations of the PER map are based on the learning process of the students. Redish [1999] also believes that because of this properly formed consensus community which includes experimentation and community consensus, the finding can be used by scientific educators. Tools are now available for scientists to use in the classroom setting. One was developed by Swiss psychologist Jean Piaget who came up with the idea of constructivism, which states that the ideas of how the world works come from the ñsensory dataò that we take in and is thus classified and categorized in order to develop associations with our physical universe [e.g., Piaget, 1977]. To make teaching a science entails being able to develop a controlled setting experiment. Redish [1999] explains that confusion takes place because ñpeople sometimes forget the role of the mind in doing physicsò and ñin order to do the best physics education research, we not only have to create an understanding of how people think, thereby possibly creating new cognitive science; we have to rethink and reformulate elements we take for granted.ò Thus, one must realize that including the mind is of utmost importance because our work and research is based on the studentsô ability to use their minds to create or handle mental images of abstract physics concepts.

Physics Educational Research has seen many advances during the past years. Lillian McDermott and her group from the University of Washington are mostly credited for this changes and cultural innovations. McDermott [2001] argues that the Physics Education Research community collects and reports findings in peer-reviewed journals and professional meetings like other sciences. McDermott describes the Physics Education Group at the University of Washington as having a research structure of ñan empirical applied science.ò She further suggests and supports the concept that science education research should be carried out by science professions in science departments since this would be discipline-based education research. One main reason for this is science professors have the content knowledge needed to truly understand the misconceptions created by the students that are being educated by them. This idea was embraced in a 1999 American Physical Society Council statement that states that PER is a branch of physics, and that PER faculty should be evaluated using the same metrics as any other branch of physics [http://www.aps.org/about/governance/committies/popa/1999.cfm].

In order to diminish the existence of misconceptions by the students, the PER group at the University of Washington focuses on identifying the misconceptions and creating interventions for the misconceptions (a list of about 115 misconceptions in physics is presented by McDermott and Redish [1999]). Their conceptual change strategies are used in the design of instructional materials that identify difficulties that students experience. The effectiveness of those materials is evaluated through pre-tests, posttests, and interviews with the students.

The studies on misconceptions have helped in the development of concept inventories, which are multiple-choice tests designed to evaluate a studentǿs comprehension of a given topic. It should be noted that one can not create a multiple-choice test and expect it to automatically become a concept inventory. It is a process that requires a number of steps. Beichner [1994] created the Test of Understanding Graphs in Kinematics (TUG-K0 and described a model for creating research- oriented multiple choice tests which can be used as tools for formative and summative evaluations of instruction. When a concept inventory is created, one must verify the content validity and reliability of the assessment. Beichner [1994] suggests that a test should have a mean of 50% in order to maximize the spread of scores, based on the field of educational assessment. He explains that validity is considered accuracy, which would indicate that the test actually measures what one wants it to measure. The precision of the measurement would be reliability. Since there are various different types of statistics that can be used to assess the reliability, validity is not actually calculated but established. The most commonly used statistical test is the KR-20 coefficient, named after Kuder and Richardson, the statisticians who developed it. If a test has a KR-20 Ó0.7, it is considered reliable [Kuder et. al, 1937].

Furthermore, different types of teaching have also been studied to understand the impact on student learning. Hake [1998] conducted a meta-analysis of many previous studies and datasets that showed quantitatively that there was a difference in the gain of understanding between two different styles of teaching. The two different methods of teaching that were used in the experiment were traditional methods and interactive engagement methods. Hake defined Interactive Engagement (IE) as methods designed, ñat least in part to promote conceptual understanding through interactive engagement of students in heads on and hands on activities which yield immediate feedback through discussion with peers and/or instructor, all as judged by their literature descriptions.ò He also defines the opposing view of teaching as traditional, which is according to Hake [1998] a course that relies on ñpassive student lectures, recipe labs, and algorithmic-problems exams.ò These two different methods of teaching were applied to three different groups in high school, college, and the university, respectively. To properly develop this into a scientific experiment, a quantitative measurement had to be taken to have as a baseline for comparison of both the beginning average and final average. Through this comparison, one could measure the gain that the students had in the courses where both methods of teaching were used.

The study analyzed the results of 62 introductory physics courses which had a total of N=6542 students. The study analyzed data from students who had taken concept inventories dealing with force and motion, particularly the Force Concept Inventory (FCI)

[Hestenes, 1992]. The author defined the following gain parameters for the classes he was investigating: high g are courses (g) Ó0.7, medium 0.7 > (g) Ó0.3 and low g are courses with (g) < 0.3. In order to have a reliable statistical interpretation of the results, the classes that had greater than 20 students were used in the study. However, if the courses had a homogenous student population smaller than 20 and consistent instruction, their weighted averages were included. Hake concluded that interactive engagement methods, which used a hands-on learning approach and provided the students with immediate feedback, produced better results than the more traditional methods style of teaching, which consisted of lectures and recipe labs. The determining factors and procedures were as follows: there were 14 courses that implemented traditional instruction in their classroom setting. These had the lowest gain where the student population was N=2084. In the IE courses, there was a greater percentage of students receiving a medium gain when the instructor would use the IE specific form of instruction with 85% (41 courses, N=3741) of the 48 IE courses, while only 15% (7 courses, N=717) in the low region. Quantitative answers are not the best indicators on how well a student understands the nature of physics.

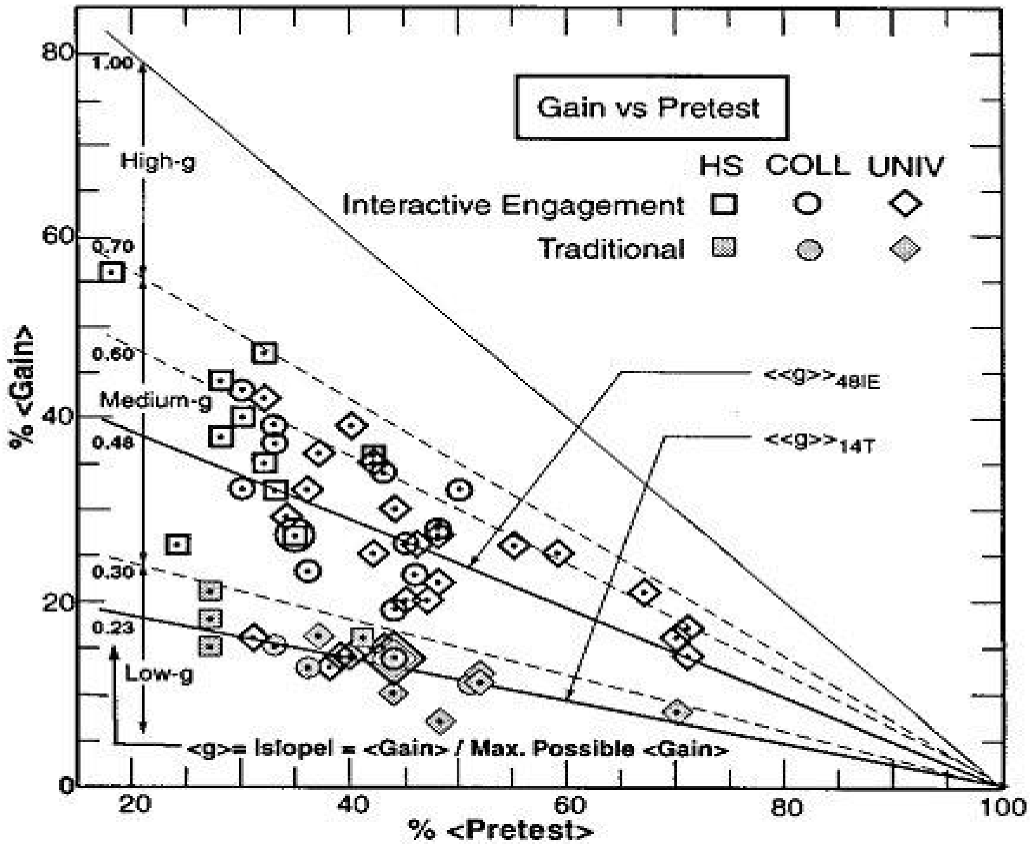

Figure 1.1 Hake Plot. Figure taken from Hake [1998], which shows that interactive engagement courses have a greater effect on student comprehension (as measured by the FCI) than non-active engagement courses.

In addition to concept inventories, tutorials have also been developed. According to a study that was conducted at the University of Washington, Lillian McDermott [2005] stated, ﾓStudents may understand the structure of an equation but may not know how to apply the equation in an experimental setting.ﾔ This can be found to be true in many classrooms. Therefore, the major objective of the study was to develop a set of tutorials for one- and two-dimensional motion for Physics by Inquiry and Tutorials in Introductory Physics. The tutorial consisted of a pretest, worksheet, homework, and posttest. Each tutorial session lasts for 50 minutes with an attendance of 20-25 students who worked in groups of 3 to 4. The study consisted of more than 20,000 students. Eleven thousand students were enrolled in a calculus based physics mechanics course. The subjects were given four exams at various times, the last one at the end of the course, which would probe their ability of distinguishing vector skills from conceptual skills. The first test examined their understanding of 1-D problems of colliding carts. The velocity vectors of the two carts were shown before and after, and the students were asked to determine the direction of the acceleration and to compare the magnitudes. This type of problem had no requirement of any formal knowledge of vectors. This problem was given to 5000 students; however, only 20% of the students gave the correct direction for both direction and magnitudes of the acceleration of the carts. The next two exams dealt with concept application and vector manipulation. In one of the problems the item posed was a cart striking the wall and rebounding. The student was then asked to determine the direction and magnitude of the average acceleration. The question was given to approximately N~360 students. In the next problem, however, the question was posed but without having any physical context. The only thing the students had to do was to subtract the vectors, and this problem was given to N~115 students. The problems were similar, but in one that involved only the calculation, 65% of students gave the correct response, while in the other group that had to deal with physical context, only 45% of students gave the correct response.

The next problem was a 2D vector manipulation posed to a calculus based course where N=100 students were given the problem. Ninety-five percent of the students got this question correct. It was concluded that vector manipulation was easier to grasp without any physical context. Probing conceptual understanding where explanations were required followed. The first was the 1D pretest of a ball moving up and down an inclined ramp. The students were required to draw both the velocity and acceleration vectors at various points along the plane. The question was posed to 20,000 students during the first to third weeks of class, and approximately 80% of the students were successful in answering the question correctly for velocity and 20 % for the acceleration. The second pretest was an object moving along a closed horizontal track. The students were required to draw velocity and acceleration vectors along the path of motion. Each second pretest was different; some tests had a constant speed setting, and others had increasing speed. These tests were given to 7000 students. The results showed that when speed was constant, 90% of the students gave correct responses for the velocity, but only 20% when the speed was changing.

To help the students with their difficulties, a set of tutorial systems was developed in understanding 1- and 2-dimensional motion. In the 1-D motion tutorial, the students were forced to confront motion of an object traveling up an incline. At the time the ball was traveling up the incline, they were asked to find the change in velocity over two specific instances. Then the student was asked to divide that quantity over rate and see how it related to instantaneous acceleration. In the homework, they then reflected over the visual and auditory representations of what was learned in the tutorial sessions. In the 2-D motion tutorial, the students were guided through the process of finding the acceleration through the use of vectors for an object moving along the oval at constant speed, increasing speed and decreasing speed. The tutorial then had the students take the post tutorial exams to examine their progress. The 1-D post-test had a problem of two pucks on a frictionless table. An improvement from 20% of N~5040 students answering correctly to 55 % of N~1845 students giving the correct response was seen. The next question was motion of two blocks up and down an inclined ramp. On the post-test, 75% of the N~575 students found the correct acceleration where only 20 % had gotten the correct answer in the pretest. In the 2-D tests, they had the students analyze the motion of an object with its speed changing along a closed horizontal trajectory. The test was divided into two segments with increasing speed and constant speed. When speed was constant 80% of the students were able to answer it correctly, as opposed to the pretest when only 20% of the students had answered it correctly. For increasing speed 35% of the students answered the question correctly, while only 5 % did so in the pretest. The next item was the pendulum problem where the student was asked to indicate the direction of the acceleration. The success went up to 15 % from 0% on the pretest. Even though many of the problems students had were mainly conceptual rather than mathematical, there was a direct correlation between tutorial implementation and improvement of students on physics understanding, which cannot be grasped in a traditional course setting. The tutorial set up for understanding of the formal definitions of velocity and acceleration was determined as beneficial.

However, modifications in learning don't only place in motion that occurs here on earth, but also conceptual understanding of how celestial mechanics work [e.g., Bailey and Slater 2004]. A tutorial system was developed that allowed for the students to have a better conceptual understanding of how the celestial objects behave. Stahly et al. [1999] developed an intervention type of tutorial system for US third graders which allowed them to probe into the lack of students understanding of the moon phases. The tutorial system was characterized as a three week "multiple component lessons" which used graphic models and explanations with more detailed examples, which showed a gain in their understanding. For older students, Lindell [2002] developed the Lunar Phases Concept Inventory (LPCI), which measured the gain of their understanding with the use of interviews. A test known as the Astronomy Diagnostic Test (ADT) [Zelik, et. al. 1997] was developed and it was multiple choice conceptual questions to probe students understanding in a quantitative way. The most unique part of this exam is it uses natural language as opposed to scientific language.

My research in the tradition of these aforementioned studies but with a focus on how students' spatial ability will impact their success in STEM courses. We used a statistical approach to correlate various resources with state assessments as well as grades the student received in their math and science courses.

1.2 Factors that Influence a Student's Success in STEM

1.2.1 Student Success in STEM

Nationally, there is now a greater demand to produce scientists and engineers, to be able to compete globally [Wang 2013]. The demand for students who are properly trained engineers and scientists has continued to rise. In fact, between the years 2004-2008, there was a 3.3% job growth in the sectors of science and engineering [Wang 2013]. There is a prediction that by the year 2018, 9 out of 10 occupations in the United States will be directly STEM related [Lacey et al., 2009]. This will require qualified scientists and engineers to be able to fill these new positions. However, there is still a national shortage of production of STEM majors who will able to not only initially enroll in a STEM program, but actually complete their degree. Furthermore, there is substantial evidence showing that minorities are underperforming in the STEM fields compared to their white/Asian counterparts [e.g., Blickenstaff, 2005; Clewell, et. al. 2002].

As stated above, there is a national need for more students to enter into the STEM fields and to be able to graduate with a degree. However, there are also many factors that contribute to a student's initial interest in science and engineering. A student's motivation to enter a STEM field is based on three internal factors that will later encourage them to enter a science and engineering related field [May et al., 2003]. The first factor is the students' confidence in their ability to solve complex math and science problems. The second factor is a senior's math achievement during his/her secondary education. The final factor is the amount of exposure to math and science courses. There are also external factors that contribute to a student's ability to compete at a college level environment. The main factors are social and financial. For example, the amount of financial aid that is given will determine a student's future academic choice such as college majors [Hackett et al., 1992]. The next is social, the amount of support they receive at the household, as well as the support they receive from teachers [Byars-Winston, 2010].

Another major factor that makes a direct impact on whether a student will enter a STEM field is the school they attend and the school they attend also makes an impact on how well a student's performs in STEM. Driven by the growing national need to retain more students in the fields of STEM, there has been a developing trend to open schools that serve to cater particular interests of students. Developed as intervention plan, magnet schools are developed with specific curriculums that allow for the students to further explore areas of interest, such as creative arts or science and engineering [Wiswall, 2014]. There is evidence that shows that the most underrepresented groups in the STEM fields are female and minority students [http://www.nsf.gov/statistics/wmpd/]. For female students, the years they travel through elementary education to secondary are normally a critical period. These are the years where female students begin to take less math and hard science courses, as opposed to their male counterparts. The magnet schools are developed to counter balance this situation by continually exposing them to math and science courses. The same can be applied to minorities such as Hispanic and Black students. These students, however, tend not to have the same socioeconomic background as their white counterparts. The parents also tend to be less educated, which usually plays a major part on minorities not being adequately exposed to a STEM related education.

Wiswall [2014] took a closer examination of how students will be affected by attending a magnet science school as opposed to students who weren't enrolled in a magnet school. There is direct evidence of the major impact attending a magnet school has on students compared to those who don't attend magnet schools. The study, compared math and science achievement for two groups of students, magnet and non-magnet students. It was found that there was no significant difference between magnet and non-magnet students who take Math A classes and Biology classes. However, as the students progressed in their high school career ladder, it was shown that non-magnet students were less likely to take the more advanced science and math classes.

In our study, our groups were both magnet and non-magnet students who were tested in a predominately Hispanic city in south Texas. We attempted to investigate the differences between magnet students and their non-magnet students using their spatial intelligence and their scientific reasoning skills. In addition, we also wanted to investigate the continuity of these students as they enter higher forms of education. There is a direct inequality at the university level between white/Asians and minority students who initially enter a STEM field to major in and those who are able to complete their degree program.

In 2010, there was a study conducted by the Higher Education Research Institute at UCLA that examined the initial enrollment rates of white/asian students to their minority counterparts to determine what field many were interested in entering [www.heri.ucla.edu]. In addition, the study also examined which ethnic groups were most likely to complete their STEM degree plans in 4 to 5 years. The study showed in 2009, white/asian students who enrolled as a STEM major was at 34.1% for underrepresented minorities and 34.3% for white/asian which indicates there is no statistical difference between both groups initial plans. The study also indicated that white/asian students who completed their degree plan within five years were at 46%, which far outpaced their minority counterparts who completed their degree plans within five years at only 26.8%. Therefore, we want to see if spatial ability also plays a role in how well students perform in the STEM fields at the university level.

It has been shown that secondary education makes a big impact on well a student will be prepared to enter into a STEM related field in college. According to a study examining the academic success of Hispanic students in STEM majors, [Cole et al., 2008], it has been shown that a Hispanic studentφs high school academic performance, such as a studentφs GPA, has a direct correlation on that students future decision to enter a STEM major and has a major impact on whether that student will continue on that particular degree path depending if that student acquired the necessary skills during their time in high school to compete at a college level. Furthermore, it was also shown that culturally, Hispanics tend to come from household where parents are normally less educated and tend not to understand on how to fully support their children in an academic sense. Also, once in college, Hispanic students tend to be more successful if they are supported by the faculty and if they have regular access to faculty members for mentoring [Cole et al., 2008].

1.2.2 Language in Science Education

As stated above, there is a national urgency for colleges to produce scientists and engineers. However, in the United States there is a cultural and language diversity that the classroom must be able to accommodate. Western Science is specifically designed linguistically to only serve the individuals who have grown with the language that is being used to convey the concept. According to the Digest of Educational Statistics [Synder, 1999], white students outperform minority students in the field science due to the disparity in the English language ability due to the cultural background of the household.

To be scientifically literate, one must not only know basic scientific facts, but also understand the discourse in which science is taught. Scientific literary is composed of two basic premises [Lee et al., 1998]. One is scientific knowledge and the other is scientific habits. The first is knowledge that a student must acquire, which includes scientific vocabulary and concepts as well as discourse that is used in the classroom. The second is a set of scientific habits, which is the student trying to understand and relate to the usefulness of science in their everyday lives. Therefore, language plays an essential role on how students not only learn in different disciplines, but also plays a major role on how they interpret scientific knowledge and its usefulness.

1.3 Cognitive Load

Sweller [1998] discussed that the memory that a person has in order to accomplish a task is finite and limited. Psychologists have also postulated that people only have a certain capacity of verbal memory such as words or sounds as well as limited amount of spatial ability, with the assumption that both the objects and sounds are not related [Baddeley, 2003].

In today's world, multitasking has become an integral part of how the world works and interacts. For this to be done, one must have an active memory for these tasks to be accomplished. For example, many adults and teenagers will be able to walk down the street, while eating a candybar, and texting on the phone. This was done because the person in this example has a good active memory. Therefore, the more active memory a person has the more tasks this person will be able to perform at the same time. [Konig et al., 2005]. However, Engle Engle [2002] insists that a persons active memory does not show the power of the person's actual memory; it actually only demonstrates how well a person can attend to several tasks without becoming distracted. This situation could well go hand in hand with the study of physics because as a student is attempting to solve a problem, the student must first visualize the problem, secondly think of the physical principle that can be applied to this problem and then begin to start applying the mathematical principle that pertains to this certain situation.

Students in classes at the university setting normally learn by listening to lectures by the professor on a particular subject, this is normally followed by guided practices, then the professor will allow for the student to perform independent practices. Throughout this procedure, one usually observes that some students have problems remaining focused because the more tasks that they need to perform, the more cognitive load that they have.

Mental rotations of images and other mental spatial operations require processing power [e.g. Shepard et al., 1971; Kosslyn, 1995]. This can add to student cognitive load. Representations may trigger activation of existing student knowledge in unanticipated ways leading to error, or even cause students to manufacture new erroneous ideas to fill a suddenly opened mental arena [Cid, et al. 2009]. The high spatial nature of physics normally causes for the cognitive load of a student to increase, especially when students have to digest visual information. Therefore, diagrams are used to help the students have a lighter cognitive load. When diagrams are shown to the students, the student does not have to visualize that picture although other mental tasks may be required in order to work with or use the diagram. Meltzer [2005] argues that abstract understanding of a physical concept does not exist. One gradually creates representations for abstract ideas in order to reach comprehension. Meltzer [2005] states that the ability to understand and use images is essential to the comprehension of concepts in physics; however, it should be noted that sometimes the images created for the purpose of increased conceptual understanding can actually create new misconceptions for students.

Conceptual misconceptions and misconceptions created by incorrect manipulation of mental images are not the same. For example, it has been found that the mental manipulation of 3-D images can produce cognitive load in addition to any cognitive load produced by understanding and applying a physics concept [Lopez and Hamed, 2004]. Students received a standard textbook figure of a complex current system that form in near Earth space during a geomagnetic disturbance called a substorm. The students were asked to determine the magnetic perturbation produced by the current system, but they had considerable difficulty with the task, Lopez and Hamed [2004] determined that the conceptual understanding what is the magnetic field of a given current was not what caused the difficulty in the assigned task. Rather, it was the manipulation of the mental images that prompted the students to make wrong conclusions pertaining to the magnetic disturbance produced by the current. Therefore, the error came cognitive load produced by creating a 3-D mental picture based on the 2-D textbook figure and the manipulation of that mental image in the mind of a student.

1.4 Visual Cognition and Spatial Ability

Visual cognition and spatial abilities bear different classifications as per cognitive scientists. In this presentation visual cognition is termed as the ability to see a mental image and be able to control that image with the mind [Kosslyn,1955]. Spatial ability is considered the mental manipulation of spatial information used to determine how a spatial configuration would be rotated, folded, repositioned, or transformed. This particular research is concerned with the rotation aspect, for it is basic spatial ability that is being utilized throughout this piece of research [Kosslyn, 1995]. Visual cognition and spatial abilities were tested by giving participants in the study1600 pairs of Tetris like objects, which were either pairs or mirror images of each other, to see how well the participants could match them up. The pairs that matched were rotated in what Shepard and Metzler [1971] term as ñpicture frameòor depth.

The participants were asked to pull a right lever if the pairs matched or a left lever if pairs did not match. In order to detect how long it took the subjects to determine whether the pairs were matched or not matched, participants were asked to pull a right lever if the pair matched or a left lever if the pair did not match, and pulling the lever stopped the clock. Interestingly, after comparing the time it took the subjects to make a decision with the angle through which the pairs were rotated, the researchers found a linear relation. It was determined that the more degrees through which an object is rotated, causes processing time for the brain to understand the association to become larger. Thus the cognitive load is increased when a task requires a larger mental rotation.

This clearly relates to students learning physics. Students studying a 2-dimensional image and trying to solve problems must use their visual and spatial abilities in order to visualize that system in 3 dimensions. If they are given a picture of an object drawn from a single perspective and asked to solve a problem that requires a different view of the object, or something that is perpendicular to the object, the students must rotate their mental image, which increases their cognitive load [Lopez and Hamed, 2005]. Thought experiments performed by Einstein and Newton proved visualizations are imperative to experiments using the imagination [Botzer and Reiner, 2005, and references therein].

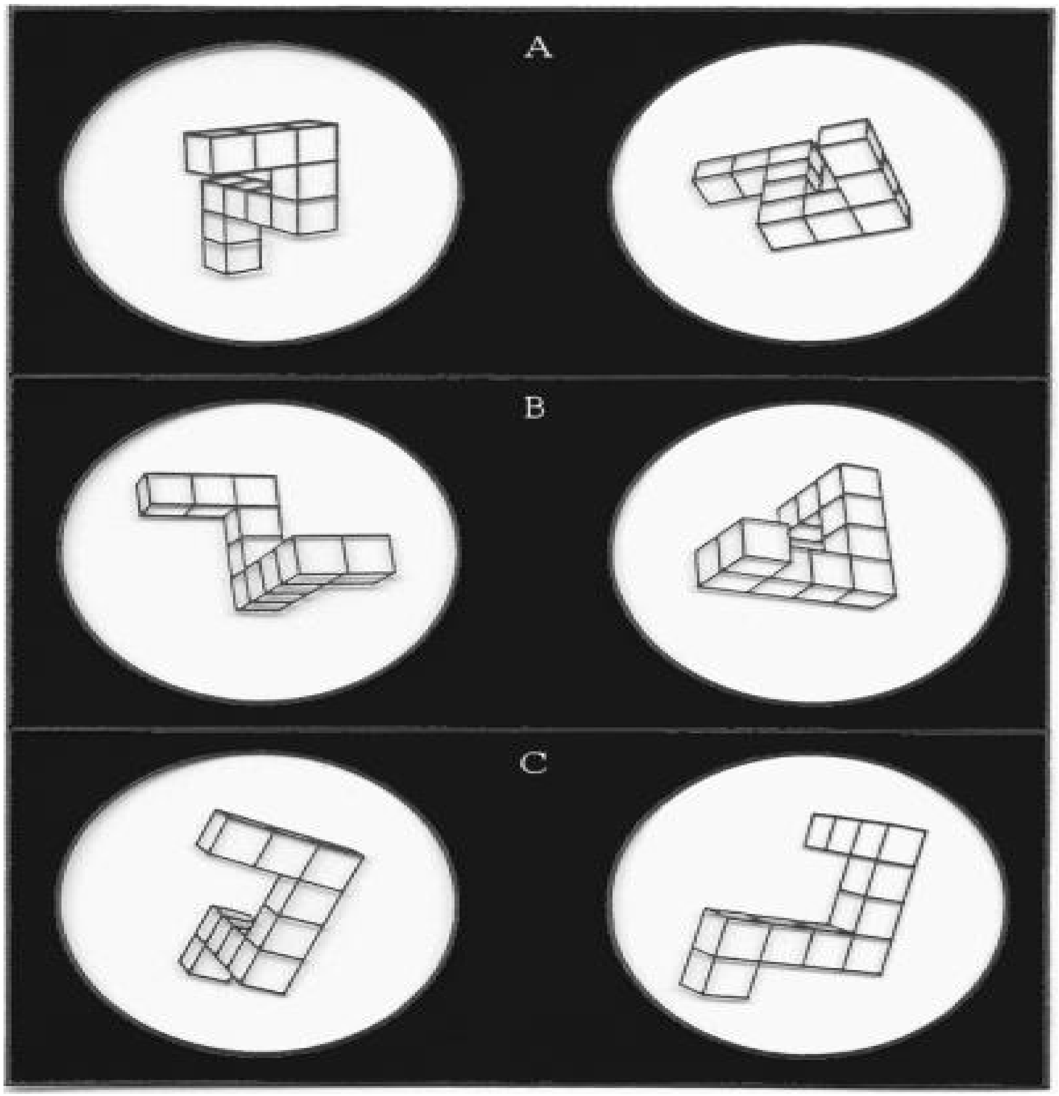

Figure 1.2 Shepard and Metzler Matched and Unmatched Pairs. The above figure shows three images where A and B have a matched pair. Image C shows an unmatched pair.

Science students are usually said to have a higher spatial ability in comparison to non-science students. However, students of physics have the highest spatial ability; geoscience students are second highest [Siemakowski and MacKnight, 1971].

According to Pallrand and Seeber [1984] visual spatial ability is required for students to succeed in courses like introductory physics, which Pallrand and Seeber [1984] found to be responsible for improving visual spatial ability. However, it is not known if students of physics have high spatial ability because they are taking physics or if it is because they possess high spatial ability that they are taking physics. To make a point, there is actually no conclusive evidence as to whether the spatial ability is improved because students choose to take physics or if taking physics gives the improved spatial ability to students.

Not much research has been done on the effects that spatial ability on student comprehension in the field of physics or space science. Kozhevnikov et. al. [2002] actually believes that a correlation does exist between individual differences in visual-spatial and the solving of kinematic type problems. In this respect, high visual spatial students may actually be able to understand concepts from actual life situations more easily than those students who have low visual spatial abilities. Both the low and high visual spatial students encounter the problems with the same misconceptions, but the high visual spatial students are able to figure out the conceptual information and acquire more correct answers on the conceptual assessment, according to Kozhevnikov et. al. [2002]. They also found that once conceptual knowledge is acquired then visual spatial ability ceases to be a predictor of performance on kinematic problems. However, in Science, Technology, Engineering, and Mathematics (STEM) fields is always a predictor of success and retention in introductory studies [Sorby, 1999;2005;2009; Sorby et al.,1996].

There has, however, been one particular longitudinal study that showed there is a correlation between spatial abilities and STEM classes such as chemistry, mathematics and physics. There have also been investigations on how spatial ability is correlated with college entrance exams such as the SAT-V and the SAT-M [Shea, 2001]. Nonetheless, there hasnôt been an investigation to how spatial abilities plays a role on how a child may succeed in a state assessment tests.

Wai et al. [2009] conducted an 11+ year, longitudinal study of 400,000 U.S. high school students in grades 9-12. Previous studies had used high ability students for their studies, but this study used a randomly selected population to determine how much of an impact spatial ability had on their success in entering STEM fields, as well as achievement in their STEM classes including up to the Ph.D. level. The motivation of this particular study was also to find the predictive value of spatial intelligence on finding if the students would be successful in STEM. In addition, the researchers wanted to see if by taking more rigorous STEM courses they would increase the studentsô spatial ability over time. The assessments for the study included testing their cognitive abilities that included their math, verbal, and spatial ability. The researchers also obtained information tests from the participants on content areas in various classes. The participants were also required to fill out a 398 questionnaire about their lives.

The most important results of the study showed that a studentôs spatial ability is a predicator of who may go on to obtain careers and degrees in a STEM field. It also showed that the previous study that only included students with high abilities were missing out on students that had aptitude to be successful in a STEM field. The study also provided a generalization of the human population as a whole. If a person has high spatial abilities, that person will likely also be successful in a STEM field. Following the findings Wai et al. [2009], we are interested in not only in how studentsô spatial ability is related to student success in their physics classes, but also the relationship to student scores on state assessments of student ability in science and mathematics.

1.5 Mental Rotation Test

In this study, The Mental Rotation Test (MRT) [Vandenberg and Kuse, 1978] will be used to measure and quantify spatial ability. It was selected because it is widely used in the literature. Some studies have shown that gender differences exist in the MRT [e.g., Linn and Peterson, 1985; Bors and Vigneau, 2011]. For instance, males generally score higher than females, but that is not important for our study. The MRT used was paper based since it is easier to take into a classroom and eliminates a location threat. The paper based MRT has 2 parts. Each part has questions and a time limit of three minutes. The students get a one-minute break between the two parts. It should be noted that if a student finishes before the 3-minute limit, he or she is allowed to check the work of that part only.

The structure of the questions is as follows: There is an image on the left and four images to the right. The student is to select the two images to the right that match the image to the left. Student must correctly identify the two images that match the image to the left in order to receive credit.

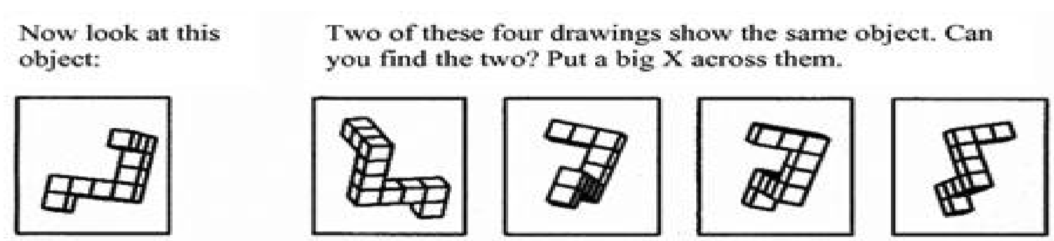

Figure 1.3 Example of MRT. Taken from MRT paper [Vandenburg and Kuse, 1971] and depicts an image on the left and four images to the right. The test taker is asked to choose two images that correctly matches the image to the right. The first and third images are the correct images. The second and fourth and not correct and are mirror images of the image on the left.

1.6 Experts vs. Novices

Studies have demonstrated that the storing of information in one's mind differs between experts and novices. Sweller [1994] explains that novices focus on the order of letters and the order of words, whereas experts don't pay attention words but to the entire message that is being presented. Sweller terms this as "automatic processing." In conscious processing the individual holds information in working memory. In automatic processing the individual mentally "downloads" the information that has already been stored in long-term memory while using working memory for courses of action. An adult's long-term memory stores information or words and, important information on details about the meaning of words. Therefore, they can use their working memory to assess what sentences or topics are expressing, instead of using it to denote the individual words.

"Chunking" is a technique used by experts in an effort to understand the meaning of the document. It means that experts are simply putting together the information found in different chunks of familiar or related information and using it as a single unit [Larkin et al., 1980]. This helps to reduce the load of their cognitive memory. If an expert is familiar with a word or words, he puts to use the stored information from the long-term memory. The working about that word or words is not used to understand words; it is used to understand chunks of word. On the other hand a novice, barely learning to read, uses particular letters as information and use more working memory to understand what is being read. Novices have simply not used their long-term memory to use chunks of sentences to understand meaning. Instead, they increase their cognitive load comprehension. Research has been done into the difference between experts and novice [Chapter 2 of How People, 2000].

There have been previous published studies that have demonstrated how ñchunkingò can be applied to other activities. In these studies, researchers attempted to understand the difference between chess masters and novices and how both groups use their memories differently [De Groot, 1978; Chase and Simon, 1978a; 1978b; Chi et al., 1981; Mestre, 1994]. If a chess master is given an active chess board where the pieces have been moved to certain positions, the expert will be able to determine the pattern (such as the Sicilian Defense) and easily remember the positions of the pieces. This is because the chess master has so much experience in the game of chess that they only have to put only one thing in short-term memory (ñSicilian defenseò) and then access their long-term memory for the distribution of pieces in the Sicilian defense. On the other hand, the novice does not have the advantage of the experience of so many different types of patterns, so they try to remember the exact position of each chess piece, overloading the short-term memory buffer.

Novices normally tend to focus on the surface features of the problem, like where each individual chess piece sits on the chess board. The expert on the other hand tends to focus more on the conceptual relationships that organize the positions of pieces into patterns. Studies have shown that this concept can also be applied when experts and novices attempt to solve physics problems. In a study conducted by Larkin et al. [1980], it was shown that experts tend to solve problems with the use of their hierarchical knowledge of the subject. This shows that experts have interlinked knowledge structures that provide a foundation for problem solving.

Novices attempt to solve problems based on surface features, for example, they look at a problem and identify it as a ñspring problemò or an ñinclined plane problemò, instead of realizing a broader physical principle, like conservation of energy or static equilibrium [e.g., Chi et al., 1981], which actually contains the elements of the solution (such as "energy at the beginning = energy at the end"). Also novices fail to make use of qualitative analysis to construct appropriate representations. For example, novices tend to use a reverse engineering technique to solve physics problems with a known variable as their objective that has to be reached. The expert will begin by examining the physical principles that the problem directly exhibits and then will be begin to use appropriate equations and not put numbers into the equation until the end.

1.7 Relationship between Visual and Spatial Abilities and Working Memory

As has been stated above, there is a strong relationship between working memory and how well a person performs specific tasks such as solving physics problems. However, it has not been clearly discussed on how working memory relates to visual and spatial abilities. Working memory is used to accomplish everyday tasks such as reading, calculation numerical values, etc [Miyake et al., 1999]. Working memory as defined by cognitive psychologists is the ability to maintain "task-relevant information" while performing a specific cognitive task Miyake et al. [1999]. Short-term memory is defined by Miyake et al. [1999] as being object oriented with no specific cognitive task associated with it.

In an attempt to understand how spatial and visual abilities are related to working memory, Miyake et al. [1999] developed a study where they found a relationship between working memory and three subfactors of traditional psychometric spatial abilities: Spatial Visualization, Spatial Relations, and Visuospatial Perceptual Speed. Spatial Visualization is defined as a process of apprehending, encoding, and mentally manipulating spatial forms [Miyake, 2001]. Spatial Relations is similar to Spatial Visualization [Miyake, 2001] but requires speed-based manipulation of 2-D objects. Visuospatial Perceptual Speed is defined by Miyake [2001] as a factor that "assess individual differences in the speed or efficiency with which one make relatively simple perceptual judgements."

The two spatial abilities that are to be investigated in this work are spatial visualizations as well as spatial relations. According to Miyake [2001], performing a task that involves spatial relations will use working memory and short-term memory due to the persons having to visualize the object in their mind. There is also a direct correlation that shows the more difficult the spatial task the more memory that will have to be used, therefore, creating a greater cognitive load. We will focus on how a studentõs spatial ability is related not only to performance in his/her STEM courses, as well as performance on state assessment tests. These require visualization of objects and mental manipulation of objects. The next section will explain how STEM fields use visual spatial ability to solve problems.

1.8 Spatial Abilities in Other STEM Fields

Previous research [Lopez and Hamed, 2004] has indicated that students sometimes have an inability in visualizing and manipulating visual images, rather than basic difficulties with physics concepts. Being successful in STEM depends in part on a studentõs ability to be able to visualize an image and for the student to be able to manipulate the image such as mental rotations using their mind, and then solve for a certain variable in that system. Mental rotation of images requires processing power [Shephard and Metzler, 1971; Kosslyn, 1995]. This will add to a studentõs cognitive load. There has been previous research into different areas of science and mathematics that explain how spatial ability and visual cognition plays a role in solving problems in various science fields, and we will review some of this research.

1.8.1 Chemistry

One of the branches of science that uses spatial ability is chemistry. A branch of chemistry known as organic chemistry, depends on the mental manipulation of molecular diagrams. Molecular diagrams can be represented in a variety of ways (depicted in figure

1.). In fact, a study conducted by Stieff [2007] revealed that students can be taught two different problem solving methods which are analytic and visuospatial problem solving. He found that students preferred solving organic chemistry problems using mental rotations for molecular diagams [Stieff, 2007]. However, since there is more than one branch of chemistry, the one that seems most relatable to visual ability is organic chemistry.

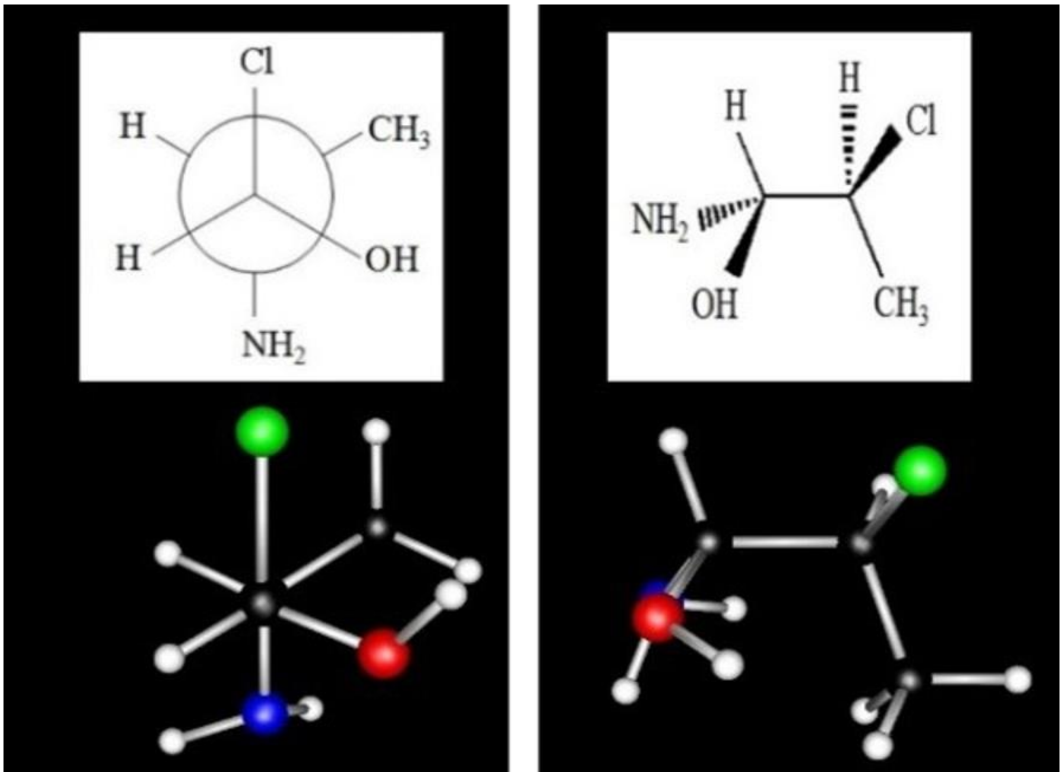

Figure 1.4 Examples of Molecular Diagrams. These are two examples of how molecular diagrams can be represented. This is an example that should give the reader an idea of how molecules can be represented differently.

1.9 Scientific Reasoning Test

Scientific reasoning is the backbone for all scientific research. In order to perform research, a person must be able to recognize a problem, hypothesize, formulate an experiment and be able to carry an analysis on the data that was acquired. Students are now placed in a more ñsimulated discovery context, in which they investigate a multivariable causal system through active or guided experimentation.ò[Zimmerman, 2007]. This sets a standard that students follow and allows one to measure how much reasoning has been obtained through their time in school.

In this particular study, the Test of Scientific Reasoning (which we refer to as SRT) developed by Lawson [1978] was chosen to assess a studentôs ability to reason through a variety of scientific problems. Test items were based on several categories of scientific reasoning including isolating variables, comparison reasoning, and proportional reasoning. SRT is widely used because of the ability to measure these particular qualities of student thinking. The SRT was used was paper based since is easier to take into a classroom and eliminates a location threat. The test is divided into 24 questions and the students the test is administered to are given twenty minutes to complete. Questions on a variety of math and science topics based on reasoning skills are administered. An example of the structure of a question in test is given:

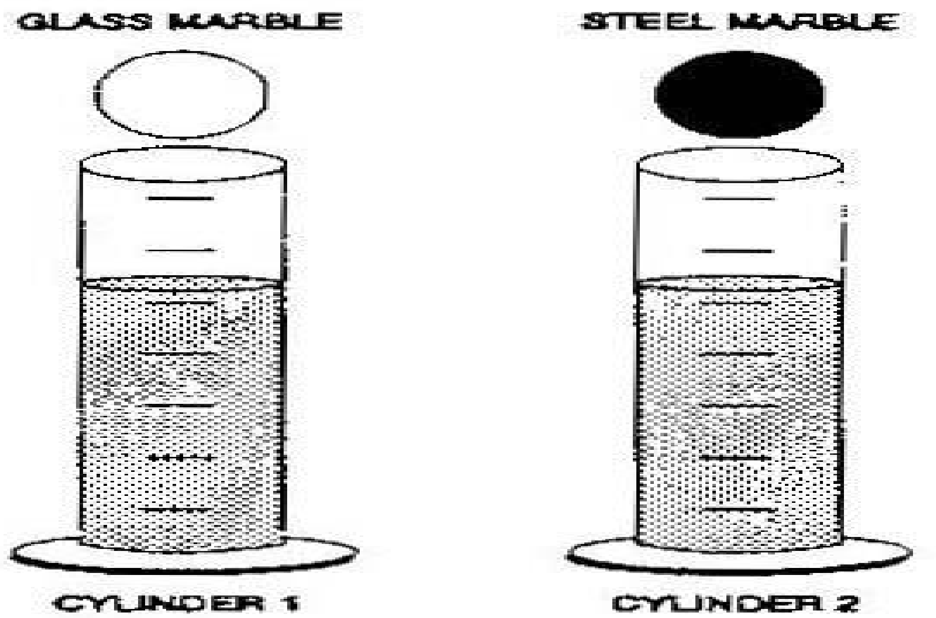

Figure 1.5 Figure taken from Lawson's Test of Scientific Reasoning. This shows two identical cylinders and the test taker is asked to determine which would exhibit a higher volume displacement based on the material the ball is made.

In the above question, the student is required to determine if the fluid will give different volume displacements depending on the material of the ball that enters the cylinder. Questions are paired. First there is the "content", then the "explanation." To get an item correct, student must select both the correct answer as well as the correct reason for the answer.

1.10 Texas Assessment of Knowledge and Skills

In 2003, Texas Education Agency and Texas educators collaborated together to develop the Texas Assessment of Knowledge and Skills (TAKS) test. Every year until 2013, Pearson INC. was the company used to develop the test questions based on these collaborations. Texas educators were asked to use the curriculum that the state mandates to develop objectives and the method of assessment of each of these objectives. TEA developed a blueprint and Pearson uses this to develop test questions each year. The TAKS were developed for course subjects that include math, science and English. This is was a major requirement for any student in Texas to graduate high school during the years of 2003-2013. The TAKS tests were designed to measure quantitatively how much was learned in each of the designated grade levels. The final TAKS tests were taken during a studentõs junior year [http://tea.texas.gov/student.assessment/taks/].

The three TAKS tests that were administered were math, science and English. Each of these tests had their own set of curriculum developed by the state. The science test had five objectives that had to be mastered by the student. This included scientific processes and skills, biology concepts, integrated physics and chemistry. The math test had ten objectives to be mastered by the student. These included algebra 1, geometry and measurement, probability and statistics, mathematical processes and tools. The English language arts tests had six objectives that included reading, written composition, and revising and editing.

Each test had a scaled score. A 2100 was required to pass, and a 2400 was required to earn commended status. This was a major requirement for graduation, however, if a student would score a satisfactory score on the SAT or ACT, the student would be allowed to replace this for their ELA or Math TAKS. In this research, we will use the TAKS test as a resource to determine any correlation between subject areas and classroom grades. In addition, we will also use this as a basic perf ormance resource when developing a model for the students SAT scores (See chapter 4).

Chapter 2

Student Spatial Intelligence, Scientific Reasoning, and the Impact on State Assesement Tests and STEM

2.1 Introduction

Important research has been conducted in the field of spatial ability, namely, how it impacts studentsôlearning in the STEM fields. Conclusive evidence indicates that the studentsôspatial ability is an important factor in their success in the STEM fields [Wai et al., 2009]. The objective of the study is to see, due to the intense visual nature of science and math, if spatial ability has a substantial impact on the studentsôsuccess, not only in their STEM classes, but also in their TAKS math and science test. This chapter outlines the project in greater detail and also provides a detailed explanation of the methodology used for this study. At the end of the chapter, a review of the data analysis method is presented.

2.2 Background for Study

There are specific studies that show that there is a correlation between spatial abilities and STEM classes, such as chemistry, mathematics and physics [Steiff, 2007; Casey, 1995]. Investigations have been carried out on how spatial ability is correlated with college entrance exams such as the SAT [Frey et al., 2004]. However, it hasnû been completely clarified how spatial abilities impact student scores on state assessment tests. Also, studies have shown students in different educational settings, such as a magnet school, may differ with their counterparts (non-magnet students) in spatial intelligence and success in their STEM courses [Wishwall et al., 2014].

A longitudinal study extending over 11+ years was conducted by Wai et al. [2009] on randomly selected 400,000 U.S. high school students in grades 9-12 whose cognitive abilities were tested. The major results of this study showed that students who have high spatial abilities tend to enter the STEM fields more often than those with a low spatial intelligence. In addition, the study demonstrated that previous studies missed students with high spatial intelligence because the studies had only focused on students with high academic abilities. Since the study included a random population sample, it could be inferred that if a person has a high spatial intelligence, he/she will likely go into a STEM field.

Furthermore, Ximena Cid in her dissertation [Cid, 2011] wanted to advance the research done by previous research studies. The first study that was used was a study conducted by Siemakowski and Macknight [1971] who found that science students had a higher spatial intelligence than non-science students. After that was established, they ranked the spatial intelligence of science majors and concluded that physics majors had the highest spatial intelligence in the STEM fields. The second study was research conducted by Pallrand and Seeber [1984]; in the study three different groups were examined to determine how spatial ability plays a role on the retention rate of students. It was found that students who dropped their STEM related course also had a lower spatial intelligence than those who remained in the class.

In our study, we examined how spatial intelligence plays a role in a student's success, not only in physics classes, but also in all STEM courses. We were interested in the relationship between student spatial ability and student scores on state assessment tests. Furthermore, we wanted to see if a significant difference between magnet students and non-magnet students existed in their spatial ability, and how this was related to their performance in their STEM classes and state tests.

Visual cognition is defined by Kosslyn [1995] as the ability to visualize an image in one's mind while being able to manipulate that image. All of these visualizations require processing power that can add to the student's cognitive load. In addition, representations of images may trigger activation of existing student knowledge in unanticipated ways. However, this may lead to error or even cause students to manufacture new erroneous ideas to fill a suddenly opened mental arena [Cid et al., 2009].

As has been previously demonstrated, physics and engineering involve 3-D concepts, some of which are quite abstract but are only represented with 2-D representations. 2-D drawings of 3-D systems, even with several minutes of explanations, can still leave students with misconceptions, and rotation of mental images adds to cognitive load when students are trying to determine the implications of 3-D systems [Lopez and Hamed, 2004]. Consequently, some of the difficulties students have may be due to their own spatial ability rather than other factors such as basic concepts like the ñright-hand rule.ò

Furthermore, as discussed in Chapter 1, it has also been shown that all STEM classes are spatial in nature. In addition, previous research [Cid, 2011] has revealed that studentsôspatial abilities can predict how successfully they will perform in some of their STEM classes. We were strongly interested in cognitive load; therefore, we investigated mental manipulation of spatial visual objects and how this will influence studentsôsuccess rates in high school physics, as well as how this can impact their grades in other STEM classes and their TAKS scores.

Therefore, as part of our research project, we chose a high school located in Laredo, Texas, a city that is situated about 150 miles south of San Antonio, Texas, and is on the border with the country of Mexico. The project became part of an initiative to introduce at United Independent School District (UISD) a new program called the Laredo United independent Research-based Achievement Study (LURAS), which is designed to investigate the impact spatial abilities have on studentsôSTEM classes as well as studentsô state assessment tests. LURAS is a collaboration between UISD and the UT-Arlington Department of Physics. The work presented in this section will focus on how spatial ability in mathematics, physics, chemistry and state assessment scores (TAKS) are correlated to determine success rates. The project involves the use of two different standard assessments, state assessment scores, and class grades in STEM classes.

2.3 Spatial Intelligence of Magnet Students and Non-Magnet Students

2.3.1 Selection of Magnet Students

The selection of magnet students is based on a systematic method developed by United Independent School District Advanced Academics Department [http://www.uisd.net]. For a student to be considered eligible for a magnet school within the district, that student must have a minimum GPA of 80 in core subject areas such as math, science, language arts, reading, and social studies in order to submit an application. Students are given the Cognitive Abilities Test (CogAT), which is a reasoning and problem-solving test developed by Riverside Publishing [http://www.riversidepublishing.com]. The test is divided into three different sections: verbal, quantitative, and nonverbal. The CogAT is not an IQ test; however, correlation has been found between innate ability and oneôs performance [http://www.riversidepublsihing.com]. The students are administered the test at different respective high schools within the school district and are given three hours to complete the test. Once the testing scores arrive at the studentsô respective schools, the students are then ranked on the district list based on overall composite scores. Parents are notified by phone during the month of April if the student qualifies for a magnet school spot. Within UISD, there are different magnet schools: engineering and technology, medicine and science, and business and information technology.

2.3.2 Methodology

The target population for this study included high school students in grades 11^{th} and 12^{th} taking a pre-AP Physics course. The accessible population included high school students enrolled at United High School, a part of the UISD and a public high school located in South Texas. The sample population for this study was drawn from magnet students (categorized high ability students) and non-magnet students (categorized non high ability students) enrolled at United High School. The accessible target populations will be the same for all presented data in this chapter, and they will be repeated for each experiment presented in this chapter. All data offered in this chapter was also collected ethically via the rules put forth by the Institutional Review Board (IRB) present at United High School, and only data from students and parents who signed the informed consents are presented here in conjunction with regulations at UISD.

The method for selecting the sample was semi-convenient. During the 2012 and 2013 school years, we collected data from the studentsôfinal course grades in Pre-AP Physics, Pre-AP Chemistry, Pre-AP Geometry, Pre-AP Algebra II. Additionally, in each course, we gave the MRT (Mental Rotation Test), which was administered toward the end of the month of April after the student took the state required assessment tests known as the TAKS. Also, we gave the SRT (Scientific Reasoning Test) at the same time the MRT was administered.

2.3.3 Data

Our operating hypothesis was that spatial abilities have a direct impact on the studentõs success in the STEM field as well as state assessment tests involving both math and science. Therefore, students with a high spatial intelligence are more likely to succeed in STEM classes [Siemakowski et. al., 1971]. In contrast, our null hypothesis was that there would be no significant difference in the spatial ability scores from students who are categorized as high academic ability students, compared to those who are not [Wai et al., 2009]. Table 2.1 exhibits the sample size for each course for both magnet and non-magnet studentsôMRT Test assessments. In addition, the table also includes the means and standard deviations for both magnet and non-magnet students. One thing to note is that the difference in sample size for the non-magnet students is greater than for magnet students. This is due to the parentsôwillingness to allow for their child to be tested.

Table 2.1: Means and Standard Deviation for MRT for both Magnet and Non-Magnet Students

N	Mean MRT Test	S.D. MRT Test
117-Total Number of Students	8.84	4.25
53-Magnet Students	9.87	3.74
64-Non-Magnet Students	8	4.49

2.3.4 Results

We were interested in reevaluating the Siemakowski and Macknight [1971] study. Their study used a different spatial ability assessment. If we look at Table 2.1, we can see there is a distinct difference for spatial ability as measured by the MRT. In order to analyze our data, we used a two-tailed related measures t-test. The table above shows both the means and standard deviation in the MRT test for both magnet and non-magnet students. The t-test disclosed that there was a significant difference in the studentsô spatial ability between the two groups, $t(115) = 2.6$, $p=.02$. Therefore, based on these results we can reject the null hypothesis. Thus, we found a definite difference in the spatial intelligence of magnet students as opposed to non-magnet students. We concluded that being in a magnet program is correlated with a higher spatial intelligence of students.

2.3.5 Discussion

From the data presented in Section 2.3.1, we can see that the specific spatial ability for both groups of students differs significantly. The magnet students will traditionally have a higher spatial intelligence because of the requirements that are necessary to enter the UETM (United Engineering Technology Magnet) program. However, as stated in previous studies, [e.g. Siemakowski, et al., 1971; Cid, 2011] students are more likely to have a higher spatial intelligence if they are in the fields of science as opposed to non-science majors. Also, Cid [2011] discussed that there is a difference even within the realm of science and engineering, with physics majors tending to have a higher spatial intelligence compared to other STEM majors.

Being in the magnet school seems to be related with the spatial intelligence of students. In this case, we saw the non-magnet students obtained an average MRT score of 8.84, which was lower than the magnet studentsô9.87. Therefore, we see that as a population in itself, magnet students did score higher, which shows a verification of Siemakowskiœ [1971] study. However, it must be further investigated if the magnet students have a higher spatial intelligence due to the selection process of the magnet program, or if itœ the magnet program itself that facilitated the studentsô spatial intelligence compared to non-magnet students. It could be that the selection of high ability students for the magnet program is also selecting for high spatial ability, or that the magnet program improves spatial ability by providing a more challenging curriculum, or both.

2.4 Spatial Ability Impact On Success in STEM Fields

In the previous section, we calculated that there was a statistical difference in the spatial ability of magnet students versus non-magnet students. In the Pallard and Seebers [1981] study, it was determined that there is a statistical difference in spatial intelligence between science students and liberal arts students. In addition, the Simankowski and MacKnight [1971] study showed that different students in different STEM fields have a different measured spatial intelligence. Therefore, it has been shown that there is a difference between the mean and s.d. (standard deviation) of magnet students and non-magnet studentsôspatial abilities; however, the effect of spatial intelligence on a studentsôperformance in a STEM class has not been demonstrated.

Cid [2011] showed that studentsôspatial ability is strongly influenced by the courses that the student is taking at the time by comparing MRT scores at the beginning and the end of the semester. In addition, her research showed that students taking physics had the strongest gain in spatial ability, compared to students who simply took an engineering course. We examined how the spatial ability of magnet students and non-magnet students will play a role on how successful they will be in a particular STEM class, and how successful they will be in a state assessment test. In addition, we will investigate if a pre-AP physics class makes an impact on studentôs spatial intelligence and their performance in an AP Physics B class.

2.4.1 Methodology

At the end of the 2012-2013 school year, two groups of students were administered the MRT test in a Pre-AP Physics class. We invited students who signed the informed consent form to participate in the LURAS study. We chose to include both magnet and non-magnet students for the study in order to have a diverse group. This allowed us to analyze and compare how their spatial intelligence would affect their performance in the STEM classes and state assessment tests. The justification for this study is that magnet students have shown to have a higher spatial intelligence compared to non-magnet students and should have a higher correlation to doing well in their STEM classes. These samples were drawn from equivalent courses from which the Section 2.4 was taken. Therefore, the variability should be the same.

At the end of the fall 2012 semester, we administered the MRT in the Pre-AP Physics classes. Again, the population was N=117 students, out of which 53 were magnet students and 64 were non-magnet students. The data for the test assessment is presented in the next section.

2.4.2 Data

For this data, our hypothesis was to show that there is a correlation between studentsôperformance in their STEM classes and their spatial abilities based on the study conducted by Cid [2011]. Our null hypothesis will show that there is no correlation between magnet students and non-magnet students.

Table 2.2 Means and Standard Deviations for grades in STEM Courses

Student Population	Mean/Standard Deviation
Magnet Student (N=53) Non-Magnet Student (N=64)	Algebra 2 (Mean=91, S.D.=7.30) Algebra 2 (Mean=87, S.D.=9.43)
Magnet Student (N=53) Non-Magnet Student (N=64)	Chemistry (Mean=89, S.D.=8.06) Chemistry (Mean=85, S.D.=7.69)
Magnet Student (N=53) Non-Magnet Student (N=64)	Geometry (Mean=88, S.D.=6.67) Geometry (Mean=85, S.D.=7.18)
Magnet Student (N=53) Non-Magnet Student (N=64)	Physics (Mean=88, S.D.=6.91) Physics (Mean=86, S.D.=10.66)
Magnet Student (N=53) Non-Magnet Student (N=64)	TAKS 2012 MATH (Mean=2426,S.D.=210.59) TAKS 2012 MATH (Mean=2245, S.D.=120.63)
Magnet Student (N=53) Non-Magnet Student (N=64)	TAKS 2012 SCIENCE (Mean=2400, S.D.=160) TAKS 2012 SCIENCE (Mean=2258, S.D.=100.58)

Correlations

Magnet Students		MRT	chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english
MRT	Pearson Correlation	1	.075	.053	.102	.390**	.322*	.306*	.248
	Sig. (2-tailed)		.595	.708	.466	.004	.019	.026	.073
	N	53	53	53	53	53	53	53	53
chemistry	Pearson Correlation	.075	1	.711**	.870**	.509**	.532**	.744**	.405**
	Sig. (2-tailed)	.595		.000	.000	.000	.000	.000	.003
	N	53	53	53	53	53	53	53	53
geometry	Pearson Correlation	.053	.711**	1	.678**	.563**	.524**	.663**	.451**
	Sig. (2-tailed)	.708	.000		.000	.000	.000	.000	.001
	N	53	53	53	53	53	53	53	53
algebra 2	Pearson Correlation	.102	.870**	.678**	1	.431**	.434**	.743**	.320*
	Sig. (2-tailed)	.466	.000	.000		.001	.001	.000	.019
	N	53	53	53	53	53	53	53	53
2012 taks math	Pearson Correlation	.390**	.509**	.563**	.431**	1	.706**	.574**	.564**
	Sig. (2-tailed)	.004	.000	.000	.001		.000	.000	.000
	N	53	53	53	53	53	53	53	53
2012 taks science	Pearson Correlation	.322*	.532**	.524**	.434**	.706**	1	.629**	.511**
	Sig. (2-tailed)	.019	.000	.000	.001	.000		.000	.000
	N	53	53	53	53	53	53	53	53
physics	Pearson Correlation	.306*	.744**	.663**	.743**	.574**	.629**	1	.532**
	Sig. (2-tailed)	.026	.000	.000	.000	.000	.000		.000
	N	53	53	53	53	53	53	53	53
2012 taks english	Pearson Correlation	.248	.405**	.451**	.320*	.564**	.511**	.532**	1
	Sig. (2-tailed)	.073	.003	.001	.019	.000	.000	.000	
	N	53	53	53	53	53	53	53	53

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

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 2.1 Correlations between MRT and STEM Courses for Magnet Students

Correlations

Non Magnet Students		MRT	chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english
MRT	Pearson Correlation	1	.228	.207	.221	.450**	.374**	.204	.225
	Sig. (2-tailed)		.070	.100	.079	.000	.002	.106	.073
	N	64	64	64	64	64	64	64	64
chemistry	Pearson Correlation	.228	1	.575**	.560**	.438**	.125	.471**	.199
	Sig. (2-tailed)	.070		.000	.000	.000	.325	.000	.116
	N	64	64	64	64	64	64	64	64
geometry	Pearson Correlation	.207	.575**	1	.542**	.420**	.171	.386**	.228
	Sig. (2-tailed)	.100	.000		.000	.001	.177	.002	.070
	N	64	64	64	64	64	64	64	64
algebra 2	Pearson Correlation	.221	.560**	.542**	1	.252*	.182	.747**	.256*
	Sig. (2-tailed)	.079	.000	.000		.045	.149	.000	.041
	N	64	64	64	64	64	64	64	64
2012 taks math	Pearson Correlation	.450**	.438**	.420**	.252*	1	.557**	.158	.555**
	Sig. (2-tailed)	.000	.000	.001	.045		.000	.213	.000
	N	64	64	64	64	64	64	64	64
2012 taks science	Pearson Correlation	.374**	.125	.171	.182	.557**	1	.164	.572**
	Sig. (2-tailed)	.002	.325	.177	.149	.000		.195	.000
	N	64	64	64	64	64	64	64	64
physics	Pearson Correlation	.204	.471**	.386**	.747**	.158	.164	1	.264*
	Sig. (2-tailed)	.106	.000	.002	.000	.213	.195		.035
	N	64	64	64	64	64	64	64	64
2012 taks english	Pearson Correlation	.225	.199	.228	.256*	.555**	.572**	.264*	1
	Sig. (2-tailed)	.073	.116	.070	.041	.000	.000	.035	
	N	64	64	64	64	64	64	64	64

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

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 2.2 Correlations between MRT and STEM courses for Non-Magnet Students

2.4.3 Results

We were interested in expanding the study conducted by Cid [2011], which used the Mental Rotation Test [Vandenburg and Kuse, 1978], a timed test that requests for the test taker to match two out of four objects to a given shape, and the shapes that you have to match are given to you at different angles. Cid [2011] found no correlation (r^2=0.0173, N=50) between grades in introductory calculus-based physics and the studentsôMRT score. The same can be concluded for the non-magnet population in this study. The correlation matrix is symmetric; therefore, we only looked above or below the diagonal. If we look for the data for MRT, in figures 2.1 and 2.2, ignoring the correlations for each assessment with itself, for the confidence level of $\alpha=0.05$, one can see that that there is no significant correlation with the STEM courses for both magnet and non-magnet students, except for magnet students enrolled in physics. Therefore, the factor of spatial intelligence for non-magnet students didn't have a significant impact on the success the students would have in their science and math courses.

2.5 Correlation between Spatial Ability of general population and STEM courses and State Assessment Tests

We conducted a similar experiment to the one in Section 2.5, but this time we did not distinguish between magnet and non-magnet students and treated it as a random population model. Previous work suggests that there is a correlation between spatial ability of students and their level of achievement in STEM courses even if in individual courses there is no correlation [Cid, 2011]. In this section, we examine how spatial ability is correlated with student performance on the Texas Assessment of Knowledge and Skills (TAKS) and with their STEM course grades.

2.5.1 Methodology

Our sample population was taken from the same United High School population that was described in Section 2.4.1. Again, this represents both the magnet and the non-magnet students that attended the same high school during the same time period. Both groups were restricted to the same graduation requirements. Our sample size will remain the same size for this section. This data was collected during the 2012-2013 school year. We gave students in the different introductory physics courses the MRT at the end of the semester. Therefore, we will present the data of the two different populations of both non-magnet students and magnet students as a whole.

2.5.2 Data for Total Population and STEM courses

We did a correlation study between MRT data for all magnet and non-magnet STEM class grades and TAKS scores. We then collected final grades for each student who signed the informed consent and participated in the study. In addition, we collected all studentsôTAKS scores in terms of actual numerical values. The sample means and standard deviations are presented in Table 2.3, and correlations are shown in Figure 2.3.

Table 2.3 Means and Standard Deviations for General Population

Assessments	N	Mean	Standard Deviation
MRT Scores	117	8.98	4.64
Physics Grades	117	87.03	7.95
Algebra 2 Grades	117	89.92	7.89
Chemistry Grades	117	87.56	8.18
Geometry Grades	117	86.99	6.74
Biology Grades	117	88.81	8.06

Correlations

Magnet Students		MRT	chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english
MRT	Pearson Correlation	1	.075	.053	.102	.390**	.322*	.306*	.248
	Sig. (2-tailed)		.595	.708	.466	.004	.019	.026	.073
	N	53	53	53	53	53	53	53	53
chemistry	Pearson Correlation	.075	1	.711**	.870**	.509**	.532**	.744**	.405**
	Sig. (2-tailed)	.595		.000	.000	.000	.000	.000	.003
	N	53	53	53	53	53	53	53	53
geometry	Pearson Correlation	.053	.711**	1	.678**	.563**	.524**	.663**	.451**
	Sig. (2-tailed)	.708	.000		.000	.000	.000	.000	.001
	N	53	53	53	53	53	53	53	53
algebra 2	Pearson Correlation	.102	.870**	.678**	1	.431**	.434**	.743**	.320*
	Sig. (2-tailed)	.466	.000	.000		.001	.001	.000	.019
	N	53	53	53	53	53	53	53	53
2012 taks math	Pearson Correlation	.390**	.509**	.563**	.431**	1	.706**	.574**	.564**
	Sig. (2-tailed)	.004	.000	.000	.001		.000	.000	.000
	N	53	53	53	53	53	53	53	53
2012 taks science	Pearson Correlation	.322*	.532**	.524**	.434**	.706**	1	.629**	.511**
	Sig. (2-tailed)	.019	.000	.000	.001	.000		.000	.000
	N	53	53	53	53	53	53	53	53
physics	Pearson Correlation	.306*	.744**	.663**	.743**	.574**	.629**	1	.532**
	Sig. (2-tailed)	.026	.000	.000	.000	.000	.000		.000
	N	53	53	53	53	53	53	53	53
2012 taks english	Pearson Correlation	.248	.405**	.451**	.320*	.564**	.511**	.532**	1
	Sig. (2-tailed)	.073	.003	.001	.019	.000	.000	.000	
	N	53	53	53	53	53	53	53	53

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

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 2.3 Correlations between MRT and STEM courses for General Population (non-magnet)

2.5.3 Results

The correlation matrix is symmetric; therefore, we only need to look above or below the diagonal. If we look at the data for MRT, ignoring the correlations for each assessment with itself, for the confidence level of Ŭ=0.05 and Ŭ=0.01, one can see that all variables have a correlation with all STEM courses except for geometry, although for most of the courses the effect size is weak. In previous studies conducted on spatial abilities and physics, [Cid 2011] it was shown that there was essentially no correlation between physics final grades and the MRT. However, looking at figure 2.4 below and treating magnet students and non-magnet students as a whole population, one can see that there is a weak positive correlation (4%-6%) between studentsôfinal grades and their spatial ability.

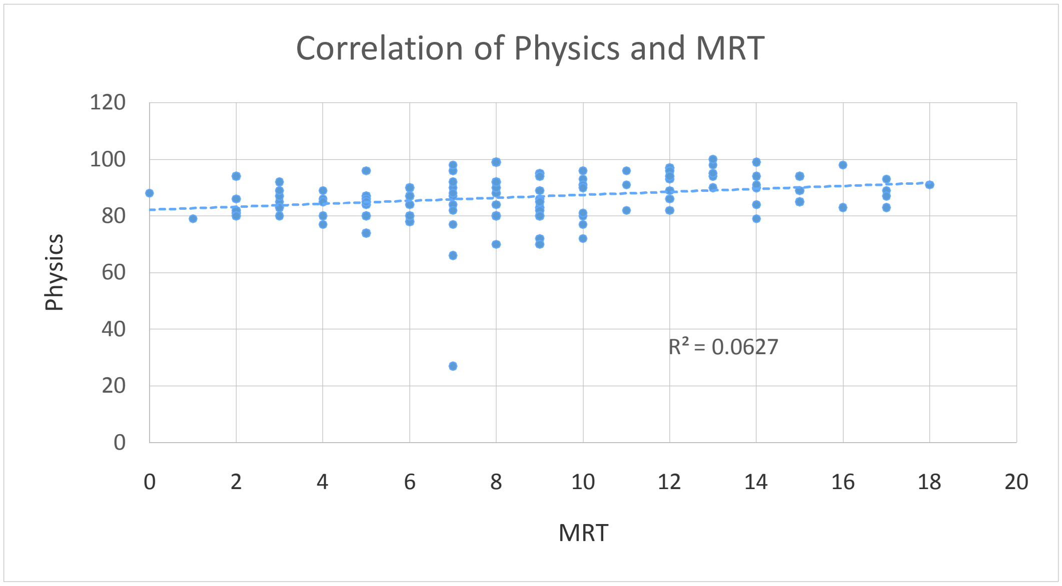

Figure 2.4 Graphical Representation of Correlation between Physics and MRT. Graph shows that there is an effect that spatial intelligence has on the performance of students in physics.

In this particular study, by looking at figure 2.3 and figure 2.4, we see that the Pearson correlation coefficient for physics is r(117)=.25, p=.006 that is significant at Ŭ=0.01, with an r^2=0.0627, so 6% of the variation in the grade is explained be spatial ability.

The data in section 2.4 shows that the average scores for magnet students were higher on average in both their math and science courses. This can be observed by comparing figures 2.1 and 2.2. Non-magnet students showed that there was a positive correlation between their spatial intelligence and their performance in the Science-TAKS test, Pearsonôs r(64)=.374, p=.002. In addition, the Math-TAKS test also showed a positive correlation r(64)=.450, p=.000. This means that a non-magnet studentôs spatial ability, as measured by the MRT, has an effect for predicting studentsôperformance in Science-TAKS.

Interestingly, there was a positive correlation between magnet students and their TAKS-Math scores and TAKS-Science scores. Science-TAKS test showed a positive correlation r(53)=.322, p=0.019 and Math-TAKS, Pearson r(53)=.390, p=.004. Also, magnet students showed a positive correlation between their spatial ability and physics, Pearson correlation r(53)=.306, p=.026. Also, by studying figure 2.5, figure 2.6, figure 2.7 and figure 2.8 of the state assessment tests and the student spatial intelligence, one can find that there is a general trend line that is being produced by both groups of magnet and non-magnet students. In addition, if we look at the table 2.4, table 2.5, table 2.6, and table 2.7 we see that both regression lines lie within the same standard of error; we can infer that for both groups spatial intelligence is having the similar impact on their performance in the TAKS tests by comparing the linear regression equations.

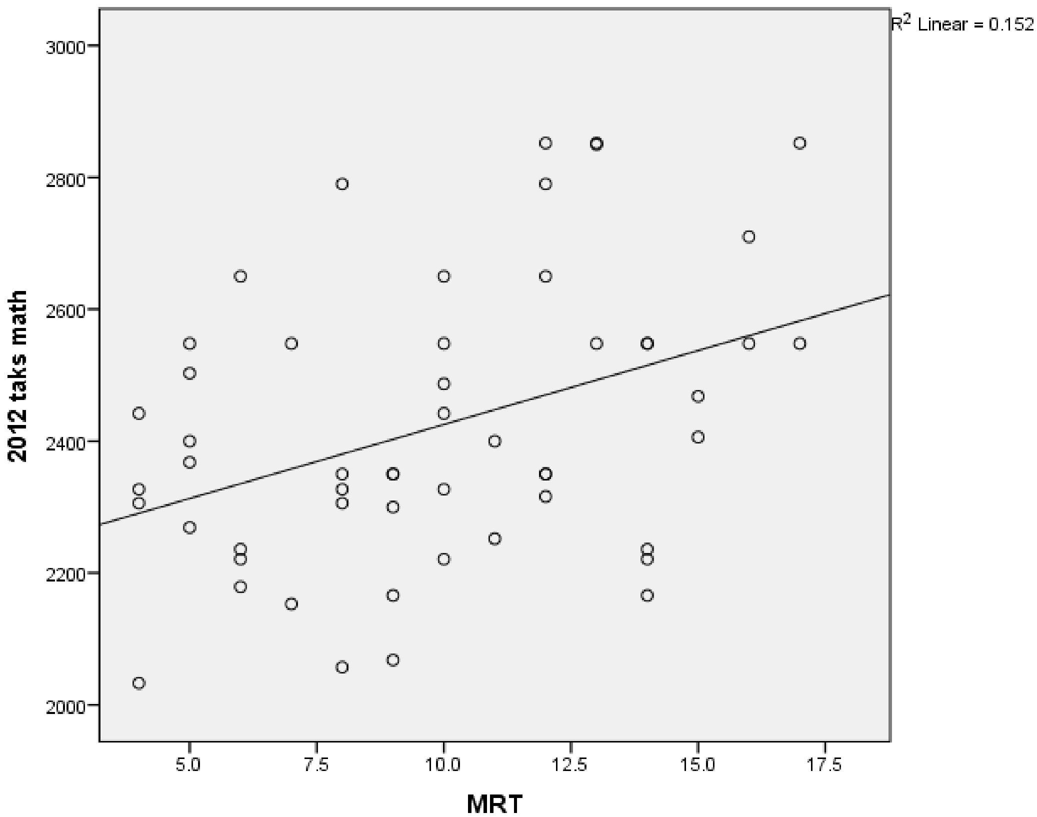

Figure 2.5 Graphical Representation of Correlation between 2012 math-TAKS and MRT. It is shown that there is an effect that spatial intelligence has on the performance of magnet students in 2012 math-TAKS.

Table 2.4 Coefficient Table for MRT and dependent variable 2012 math-TAKS

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2200.868	78.263		28.122	.000
	MRT	22.442	7.425	.390	3.023	.004

a. Dependent Variable: 2012 TAKS math

In addition, we also saw a positive correlation on studentsôspatial ability and their success in their state assessment tests. We decided to investigate further how spatial intelligence impacts student success in their state assessment tests. Therefore, we plotted both the math-TAKS and science TAKS of each student population separately to see the effect size MRT has and then compare the effect size with each separate population. The first plot found in figure 2.5, is the math-TAKS versus spatial ability of the magnet student population, N=53. Therefore, by looking at table 2.4 and figure 2.5, we see that r^2=.152, which shows that MRT has a medium effect on the performance of magnet students in 2012 math-TAKS. In table 2.4, the regression linear equation is y=22.44x+2201. Therefore, spatial intelligence accounts for 15.2% of the variation in the math-TAKS scores for the magnet students.

Now letÕs take a look at the same population of magnet students, N=53. We again will plot their spatial intelligence as measured by the MRT, and this time will investigate the variance and regression of this particular population in the science-TAKS.

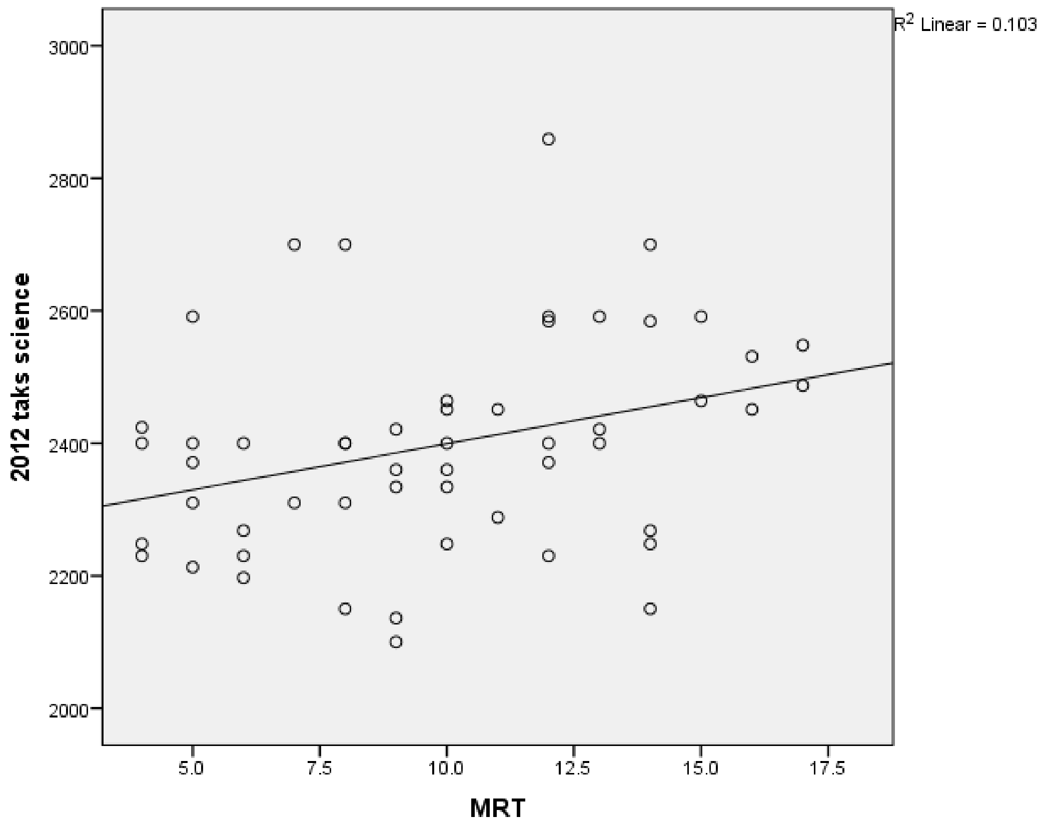

Figure 2.6 Graphical Representation of Correlation between 2012 science-TAKS and MRT. It is shown that there is an effect that spatial intelligence has on the performance of magnet students in 2012 science-TAKS.

Table 2.5 Coefficient Table for MRT and dependent variable 2012 science-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2260.327	60.410		37.417	.000
	MRT	13.902	5.731	.322	2.426	.019

a. Dependent Variable: 2012 taks science

In table 2.5, the regression linear equation is $y=13.9x+2260$, where $r^2=0.103$, which shows spatial ability accounts for 10.3% of the variation in the science TAKS scores for the magnet students.

Now we can take a look at the other student population of non-magnet students N=64. We will again plot their spatial intelligence measured by the MRT versus their state assessment scores and will examine the regression and variance in the sample.

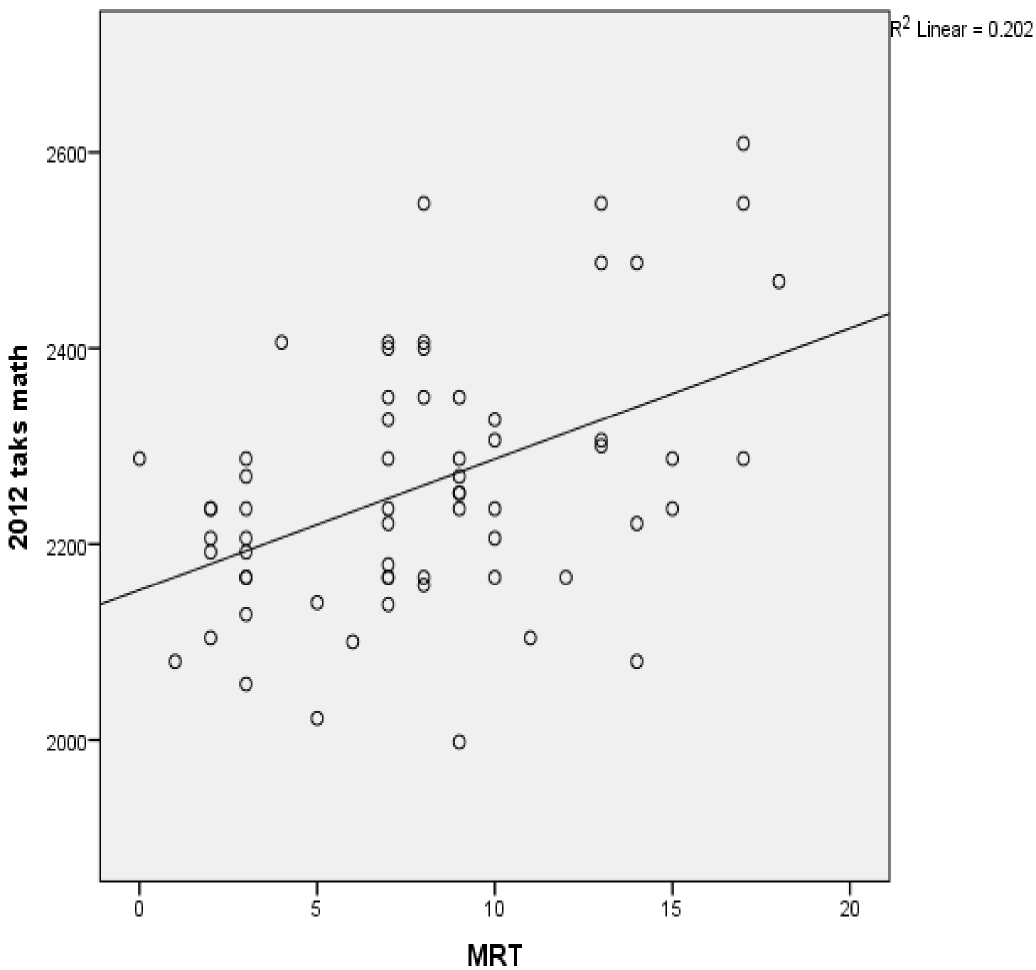

Figure 2.7 Graphical Representation of Correlation between 2012 math-TAKS and MRT. It is shown that there is an effect that spatial intelligence has on the performance of non-magnet students in 2012 math-TAKS.

Table 2.6 Coefficient Table for MRT and dependent variable 2012 math-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2153.038	30.862		69.762	.000
	MRT	13.368	3.371	.450	3.966	.000

a. Dependent Variable: 2012 taks math

In table 2.6, the regression linear equation is y=13.4x+2153, where r^2=0.202, and which means that spatial ability accounts for 20% of the variation in the Math TAKS scores for non-magnet students. In addition, it shows that there is a medium correlation effect happening on the non-magnet students.

Now we , examine the science TAKS, and we again plot the spatial intelligence measured by the MRT and plot it against the scores of the non-magnet students on the science TAKS.

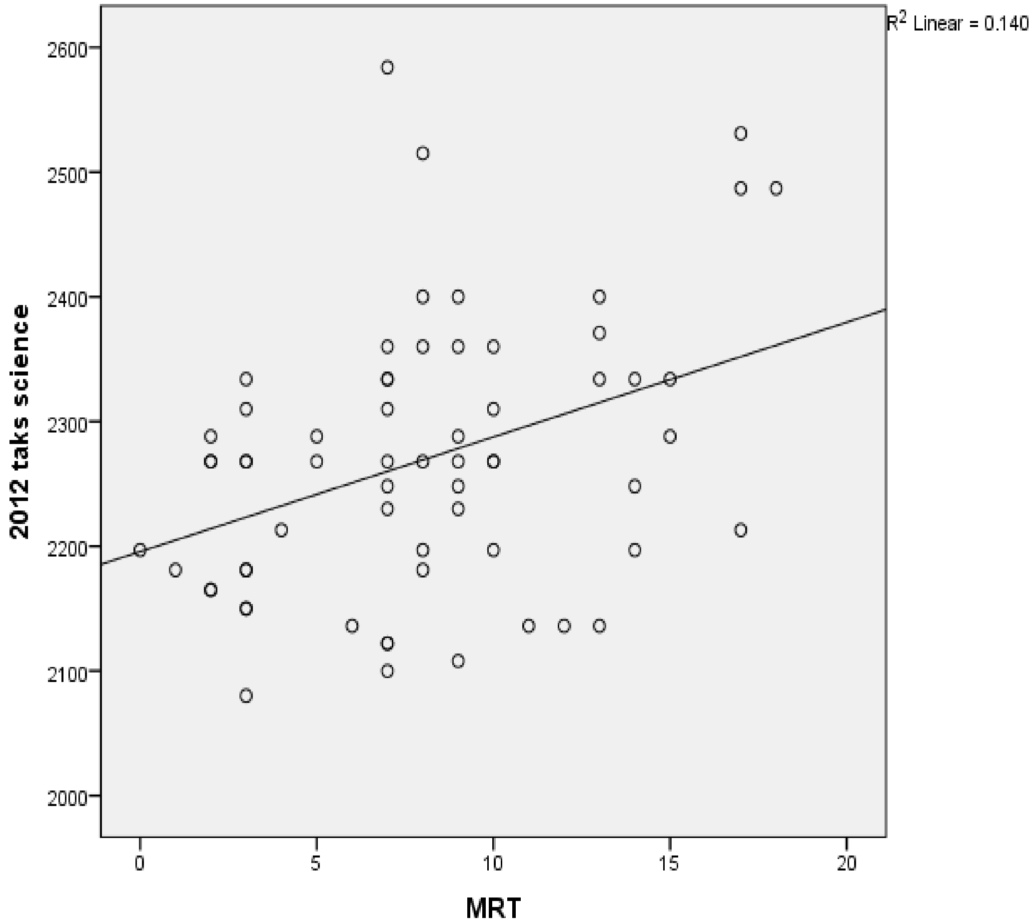

Figure 2.8 Graphical Representation of Correlation between 2012 science-TAKS and MRT. It is shown that there is an effect that spatial intelligence has on the performance of non-magnet students in 2012 science-TAKS.

Table 2.7 Coefficient Table for MRT and dependent variable 2012 science-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2195.632	26.516		82.803	.000
	MRT	9.196	2.896	.374	3.175	.002

a. Dependent Variable: 2012 taks science

In table 2.7, the regression linear equation is y=9.2x+2196, where r^2=0.140, which indicates spatial ability accounts for 14% of the variantion in the science TAKS scores for non-magnet students in the performance in science-TAKS.

2.5.4 Discussion

In this section, we saw that spatial ability is weakly related to scores in high school science and math classes, but that it is more significantly related to their scores on the TAKS for both populations, magnet and non-magnet. An interesting finding was that we saw that spatial intelligence had more of a predictive factor for non-magnet students, as opposed to magnet students, who scored higher in their MRT. We decided to investigate the two populations separately to see how both were affected by their spatial intelligence. We saw that both were positively affected, and that spatial intelligence had some impact on both populations. In addition, we saw that both had similar impact values by comparing the linear regression fits for both magnet and non-magnet students. Therefore, spatial intelligence actually had a similar effect on both populations when taking their state assessment tests in science and math.

2.6 Lawson's Test of Scientific Reasoning and State Assessment Exams

Recently, there has been an overhaul in the educational system in the state of Texas. For a student to be properly prepared, he/she must not only understand the major components of the life and physical sciences; indeed, a child must also learn how to acquire and develop reasoning skills through math and science courses. [http://tea.state.tx.us]. These basic skills involve learning quantitative reasoning as well as analytical reasoning that are acquired through the implementation of the Texas Essential Knowledge and Skills (TEKS). In addition, reasoning skills are also learned not only in a traditional classroom setting, but also in a laboratory setting where experimentation and hands on learning help the student better grasp these concepts. This will allow for students to be better prepared for the tasks of future careers involving math and science.

During the course of this research, we also included Lawson's Test of Scientific Reasoning (which we refer to below as the SRT) as part of our assessments. Previous research suggests that during the course of education that takes place in the classroom, reasoning abilities may be enhanced. The question that was presented in a particular study conducted by Lawson [1978] was if there should there be more of a direct involvement in students developing their formal reasoning skills. One of the primary conclusions was that sometimes formal reasoning is hindered by the environment that may not be as nourishing to allowing for a student's mind to develop formal reasoning as part of their everyday tasks. Therefore, I want to determine if there is a primary difference on how reasoning is taught in the two different classroom settings of magnet versus non-magnet students. Also, I want to determine how much of a relationship reasoning has on being successful in state assessment tests, and if there will be a correlation in their respective STEM classes.

2.6.1 Methodology

As previously mentioned, at the end of the 2012-2013 school year, two groups of students were administered the MRT test in a Pre-AP Physics class. We chose to include both magnet and non-magnet students in order for the study to have a diverse group so we could analyze and compare how their spatial intelligence would affect how they would perform in the STEM classes and state assessment tests. However, we also wanted to see the impact scientific reasoning would have on their success in STEM courses and their state assessment tests. The justification is that Lawson [1978] has shown that scientific reasoning can be developed and acquired through the use of methods developed in the classroom. Our operating hypothesis is that there will be a significant difference between magnet students and non-magnet students. Our null hypothesis is that there is no difference between the two groups of students. Also, we wanted to see if scientific reasoning had any correlation on their performance in their STEM classes and state assessment tests.

At the end of the fall 2012 semester we administered the SRT assessment in two Pre-AP Physics classes. Again the population was N=117 students, out of which 53 were magnet students and 64 were non-magnet students. The data are presented in the next section.

2.6.2 Data

Table 2.8 Mean and Standard Deviation for SRT for both Magnet and Non-Magnet Students

N	Mean SRT Test	S.D. SRT Test
117-Total Number of Students	5.25	2.79
53-Magnet Students	6	2.59
64-Non-Magnet Students	4.53	2.80

2.6.3 Results

From the above table 2.8, one can see that the average SRT score for a magnet student is significantly higher than a non-magnet student. A t-test revealed that there is a statistical difference (t(115)=2.92, p = 0) between these two populations. Therefore, we can determine that there is a difference between the scientific reasoning of magnet students and non-magnet students.

In order to test if the SRT is a predictor of success in STEM courses and state assessment tests, we did a correlation study. In addition, if we look forward at the data tables, figures 2.13, 2.14, 2.15, the correlation matrices are symmetric; therefore, we only need to look above or below the diagonal. If we look at the data for SRT for the student population as a whole, in figure 2.13, ignoring the correlations for each assessment with itself, for the confidence level of Ŭ=0.05 and 0.01, one can see that the SRT has a direct correlation with all variables except for physics. There is a high correlation for both the science and math TAKS tests with a correlation r=.552 and r=.603, respectively. By looking at the figures 2.9, 2.10, 2.11, 2.12 below, we see a high positive correlation between Lawsonõs Test of Scientific Reasoning and both math and science TAKS. Therefore, we can infer that SRT will act as good predictor on how well a student will perform on the TAKS tests and also shows by an independent measue that Texas is assessing student reasonaing along with the specific TEKS content in these state tests.

To promote our investigation on how scientific reasoning has a factor in the students success in their state assessment tests we plotted both the math-TAKS and science TAKS of each student population separately to see the effect size and then compare the effect size that scientific reasoning has on each separate population. The first plot, figure 2.9, is the math-TAKS versus scientific reasoning of the magnet student population N=53. In table 2.9, the regression linear equation is y=23.40x+2065.55, where r^2=0.431, which indicates scientific reasoning accounts for 43% of the variation in the math TAKS scores for magnet students.

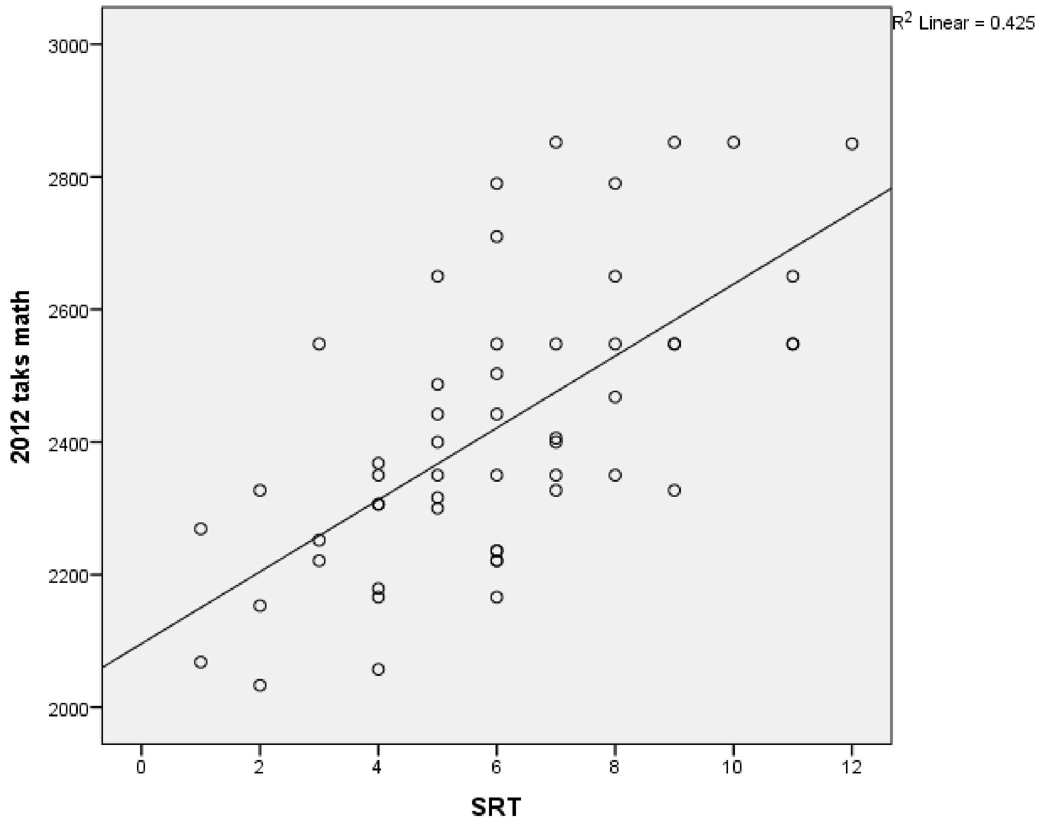

Figure 2.9 Graphical Representation of Correlation between 2012 math-TAKS and SRT. It is shown that there is an effect that scientific reasoning has on the performance of magnet students in 2012 math-TAKS

Table 2.9 Coefficient Table between SRT and math-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2095.893	57.762		36.285	.000
	SRT	54.234	8.828	.652	6.143	.000

a. Dependent Variable: 2012 taks math

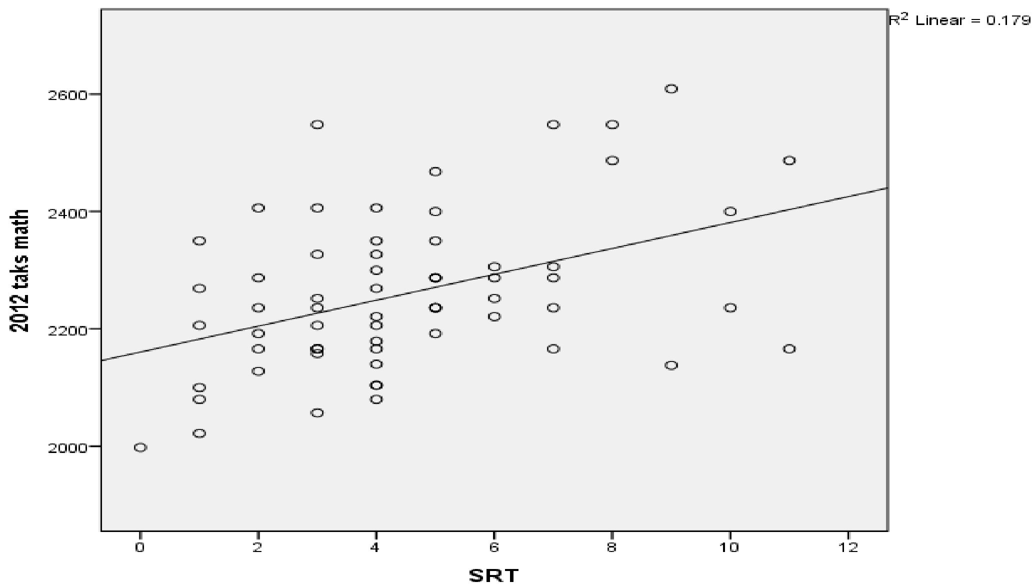

Figure 2.10 Graphical Representation of Correlation between 2012 math-TAKS and SRT. It is shown that there is an effect that scientific reasoning has on the performance of non-magnet students in 2012 math-TAKS

The next population is the non-magnet students N=64. The first plot, figure 2.10, is math-TAKS versus their scientific reasoning to be able to investigate the impact this measure had on their state assessment test. In table 2.10, the regression linear equation is y=12.9x+2122, where r^2=.179, which shows scientific reasoning accounts for 17.9% of the variation in the math TAKS scores of non-magnet students. Figure 2.11, is science-

TAKS versus their scientific reasoning. In table 2.11, the regression linear equation is y=13.1x+2209, where r^2=.093 thus, scientific reasoning ability accounts for 9.3% of the variation in the science TAKS scores for non-magnet students.

Table 2.10 Coefficient Table of 2012 math-TAKS and SR

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2209.955	26.953		81.992	.000
	SRT	13.166	5.217	.305	2.524	.014

a. Dependent Variable: 2012 taks science

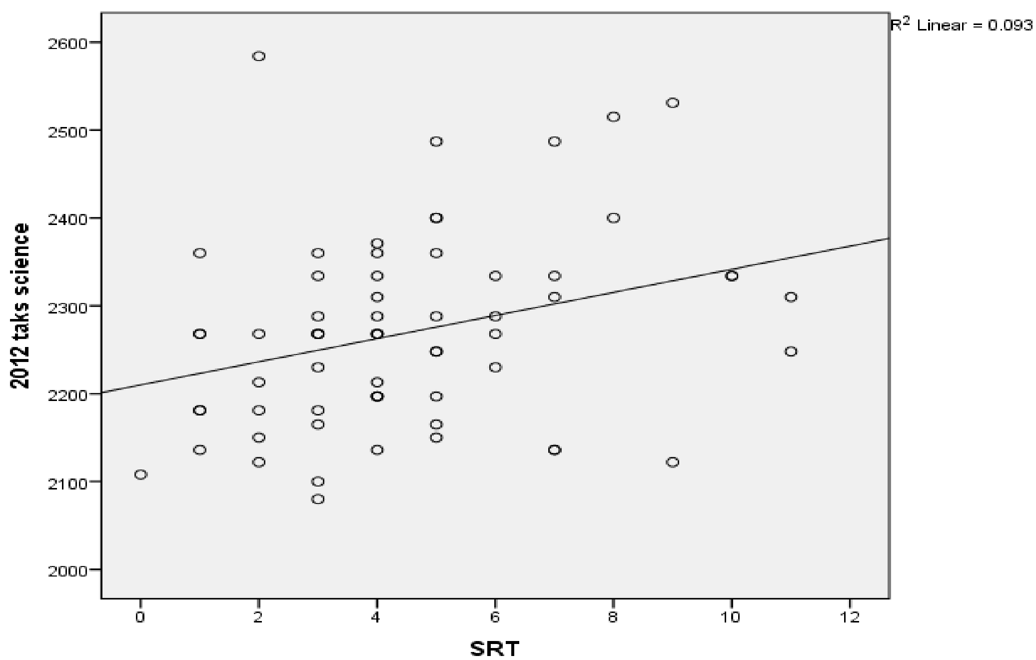

Figure 2.11 Graphical Representation of Correlation between 2012 science-TAKS and SRT. It is shown that there is an effect that scientific reasoning has on the performance of non-magnet students in 2012 science-TAKS

Table 2.11 Coefficient Table of 2012 science-TAKS and SRT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2209.955	26.953		81.992	.000
	SRT	13.166	5.217	.305	2.524	.014

a. Dependent Variable: 2012 taks science

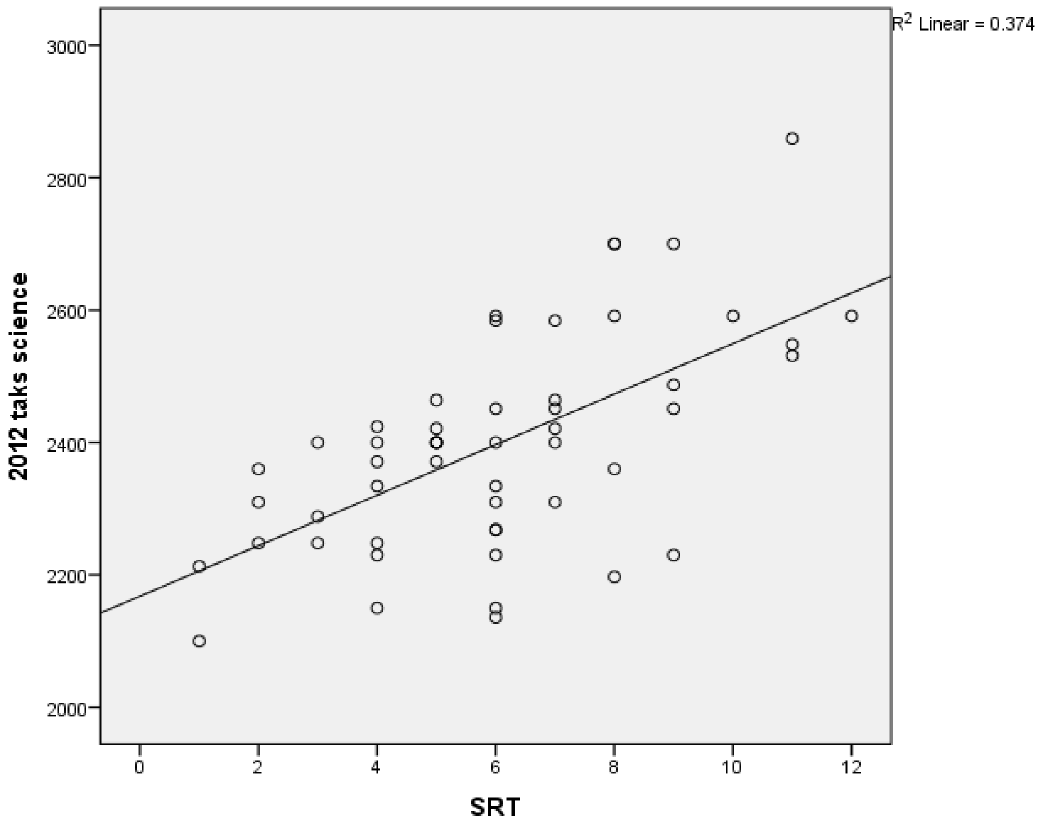

Figure 2.12 Graphical Representation of Correlation between 2012 science-TAKS and SRT. It is shown that there is an effect that scientific reasoning has on the performance of magnet students in 2012 science-TAKS

Table 2.12 Coefficient Table of 2012 science-TAKS and SRT

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2167.823	45.271		47.885	.000
	SRT	38.161	6.919	.611	5.515	.000

a. Dependent Variable: 2012 taks science

Figure 2.12 shows the relationship between the science TAKS scores and the scores on the SRT for the magnet students. In table 2.12, the regression linear equation is y=38.16x+2167, where r^2=.374, so that scientific reasoning ability accounts for 37% of the variation in the science TAKS scores of the magnet students.

Correlations

General Population		chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english	SRT
chemistry	Pearson Correlation	1	.651**	.704**	.524**	.422**	.565**	.359**	.277**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000	.002
	N	117	117	117	117	117	117	117	117
geometry	Pearson Correlation	.651**	1	.608**	.505**	.388**	.486**	.367**	.336**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000	.000
	N	117	117	117	117	117	117	117	117
algebra 2	Pearson Correlation	.704**	.608**	1	.388**	.362**	.741**	.326**	.273**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.003
	N	117	117	117	117	117	117	117	117
2012 taks math	Pearson Correlation	.524**	.505**	.388**	1	.717**	.336**	.601**	.607**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000	.000
	N	117	117	117	117	117	117	117	117
2012 taks science	Pearson Correlation	.422**	.388**	.362**	.717**	1	.357**	.581**	.577**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000	.000
	N	117	117	117	117	117	117	117	117
physics	Pearson Correlation	.565**	.486**	.741**	.336**	.357**	1	.371**	.151
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000	.104
	N	117	117	117	117	117	117	117	117
2012 taks english	Pearson Correlation	.359**	.367**	.326**	.601**	.581**	.371**	1	.374**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000
	N	117	117	117	117	117	117	117	117
SRT	Pearson Correlation	.277**	.336**	.273**	.607**	.577**	.151	.374**	1
	Sig. (2-tailed)	.002	.000	.003	.000	.000	.104	.000	
	N	117	117	117	117	117	117	117	135

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

Figure 2.13 Correlation Table for SRT and STEM courses and state assessment tests.

A correlative analysis for the scientific reasoning test for the entire population was conducted. It was correlated against all their STEM courses and their state assessment tests, treating our sample size as a general population as shown in figure 2.13 and explained in section 2.6.3.

The next correlative analysis, shown in figure 2.14, was conducted for only magnet students, and we examined their SRT scores against all their STEM courses and state assessment tests. The results were explained in section 2.6.3. Lastly, we conducted a correlative analysis with all non-magnet students and their STEM courses and state assessment tests, as shown in figure 2.15 and explained in section 2.6.3.

Correlations

Magnet Students		SRT	chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english
SRT	Pearson Correlation	1	.363**	.530**	.326*	.652**	.611**	.505**	.359**
	Sig. (2-tailed)		.008	.000	.017	.000	.000	.000	.008
	N	71	53	53	53	53	53	53	53
chemistry	Pearson Correlation	.363**	1	.711**	.870**	.509**	.532**	.744**	.405**
	Sig. (2-tailed)	.008		.000	.000	.000	.000	.000	.003
	N	53	53	53	53	53	53	53	53
geometry	Pearson Correlation	.530**	.711**	1	.678**	.563**	.524**	.663**	.451**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000	.001
	N	53	53	53	53	53	53	53	53
algebra 2	Pearson Correlation	.326*	.870**	.678**	1	.431**	.434**	.743**	.320*
	Sig. (2-tailed)	.017	.000	.000		.001	.001	.000	.019
	N	53	53	53	53	53	53	53	53
2012 taks math	Pearson Correlation	.652**	.509**	.563**	.431**	1	.706**	.574**	.564**
	Sig. (2-tailed)	.000	.000	.000	.001		.000	.000	.000
	N	53	53	53	53	53	53	53	53
2012 taks science	Pearson Correlation	.611**	.532**	.524**	.434**	.706**	1	.629**	.511**
	Sig. (2-tailed)	.000	.000	.000	.001	.000		.000	.000
	N	53	53	53	53	53	53	53	53
physics	Pearson Correlation	.505**	.744**	.663**	.743**	.574**	.629**	1	.532**
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000
	N	53	53	53	53	53	53	53	53
2012 taks english	Pearson Correlation	.359**	.405**	.451**	.320*	.564**	.511**	.532**	1
	Sig. (2-tailed)	.008	.003	.001	.019	.000	.000	.000	
	N	53	53	53	53	53	53	53	53

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

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 2.14 Correlation Table for SRT and STEM Courses and state assessments for Magnet Students

Correlations

Non-Magnet Students		SRT	chemistry	geometry	algebra 2	2012 taks math	2012 taks science	physics	2012 taks english
SRT	Pearson Correlation	1	.026	.198	.053	.423**	.305*	-.071	.258*
	Sig. (2-tailed)		.838	.117	.679	.000	.014	.575	.040
	N	82	64	64	64	64	64	64	64
chemistry	Pearson Correlation	.026	1	.575**	.560**	.438**	.125	.471**	.199
	Sig. (2-tailed)	.838		.000	.000	.000	.325	.000	.116
	N	64	64	64	64	64	64	64	64
geometry	Pearson Correlation	.198	.575**	1	.542**	.420**	.171	.386**	.228
	Sig. (2-tailed)	.117	.000		.000	.001	.177	.002	.070
	N	64	64	64	64	64	64	64	64
algebra 2	Pearson Correlation	.053	.560**	.542**	1	.252*	.182	.747**	.256*
	Sig. (2-tailed)	.679	.000	.000		.045	.149	.000	.041
	N	64	64	64	64	64	64	64	64
2012 taks math	Pearson Correlation	.423**	.438**	.420**	.252*	1	.557**	.158	.555**
	Sig. (2-tailed)	.000	.000	.001	.045		.000	.213	.000
	N	64	64	64	64	64	64	64	64
2012 taks science	Pearson Correlation	.305*	.125	.171	.182	.557**	1	.164	.572**
	Sig. (2-tailed)	.014	.325	.177	.149	.000		.195	.000
	N	64	64	64	64	64	64	64	64
physics	Pearson Correlation	-.071	.471**	.386**	.747**	.158	.164	1	.264*
	Sig. (2-tailed)	.575	.000	.002	.000	.213	.195		.035
	N	64	64	64	64	64	64	64	64
2012 taks english	Pearson Correlation	.258*	.199	.228	.256*	.555**	.572**	.264*	1
	Sig. (2-tailed)	.040	.116	.070	.041	.000	.000	.035	
	N	64	64	64	64	64	64	64	64

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

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 2.15 Correlation Table for SRT and STEM courses and state assessments for non-magnet students

If we look at the individual correlation matrices for both magnet and non-magnet students, we only need to look above or below the diagonal. If we look at the data for the SRT for the magnet student population, ignoring the correlations for each assessment with itself, for the confidence level of Ŭ=0.05 and 0.01, one can see that SRT has a direct correlation with all variables including physics. The Pearson correlation r(53)=.505, p=.000 for physics shows that scientific reasoning has a predictive value on how well a student will perform in that particular course. Now, if we look at the data for the SRT for the non-magnet students population, ignoring the correlations for each assessment with itself, for the confidence level of Ŭ=0.05 and 0.01, one can see the SRT has no correlation on any of the STEM courses; however, it does show a positive correlation on their state assessment tests.

Now, if we look at the students, magnet and non-magnet, as a general population, we see that scientific reasoning has a direct impact on all state assessment tests, including the ELA-TAKS test. This shows that scientific reasoning is a factor that is important in being successful in those particular areas. In addition, it shows that the state of Texas does measure how much reasoning a student knows when they are being tested with state assessments and what is taught in the courses the students are taking. However, from individual populations we see that there is a difference between scientific reasoning in the magnet population compared to the non-magnet population. Interestingly, magnet students had higher Pearson correlation coefficients in SRT for both the science and math TAKS state tests compared to their non-magnet counterparts which implies magnet students used their reasoning skills heavily compared to their non-magnet students.

2.7 Factors Affecting Performance in Physics

The entire chapter has been dedicated to how spatial ability makes a major impact on how successful students will be in their STEM courses. However, we are really interested in the idea of how spatial ability acts as a predictor in their success in physics. In addition, we want to see if physics played a role in the success of other assessments such as the TAKS tests. Furthermore, we want to examine if after taking pre-AP physics, a studentøs spatial intelligence was affected.

2.7.1 Methodology

As stated in previous sections, our target population for the study was magnet students and non-magnet students at a high school located in Laredo, Texas. The high school is a part of the United Independent School District System and has an engineering magnet program located within the high school. The students were administered the same set of tests such as the MRT and SRT during the 2012-2013 school year. In addition, we also included a group of 30 students who were in an AP Physics B class who were given the same assessments. In this set of data, we only conducted statistical analysis on both groups of students.

2.7.2 Data for Magnet and Non-Magnet Students

Table 2.13 Means and Standard Deviations for Physics Grades for general population, magnet students and non-magnet students

Student Population N=117	Mean Physics Grades	S.D. Physics Grades
General Population (N=117)	86.84	9.05
Magnet Population (N=53)	87.88	6.91
Non-Magnet Population (N=64)	85.87	10.66

2.7.3 Results

In table 2.13, we can see that the magnet students on average scored higher than their non-magnet counterparts. However, to determine if this result is statistically significant, we must peform a t-test on the two samples, $t(115)=1.0$, $p=.31$. According to this result, there is no significant difference between magnet students and non-magnet students. However, we would like to see what impact their grades may have had in other areas such as the science TAKS.

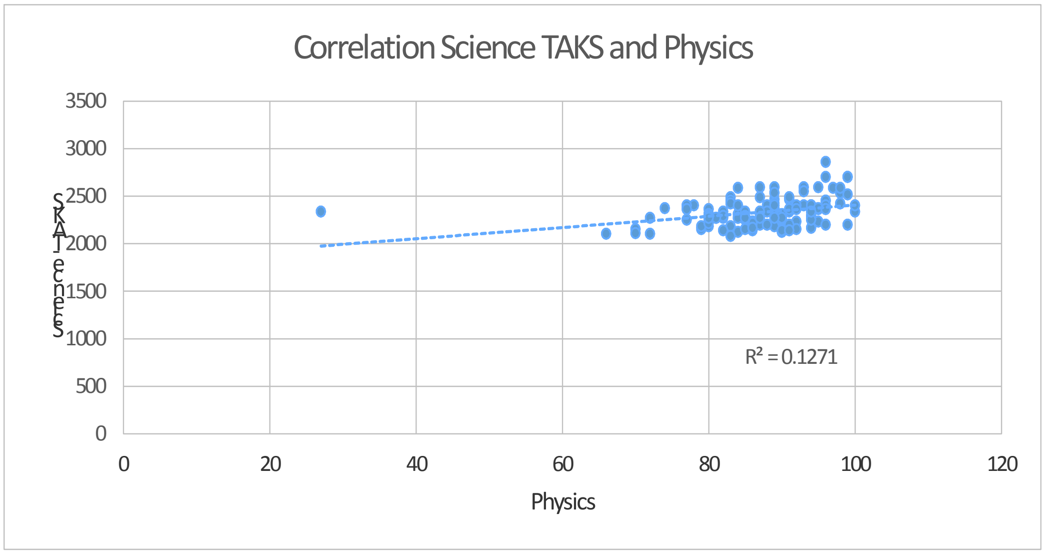

Figure 2.16 Graphical Representation of correlation between science TAKS and Physics

From the above figure 2.16, we can see a medium effect that physics played as a predictor on how successful students would be in their success in science TAKS.

However, we wanted to examine the impact spatial intelligence, scientific reasoning and language had on the grades of both populations of students. The first graph that we examined, figure 2.17, expresses to what extent spatial intelligence impacted studentsôgrades in physics.

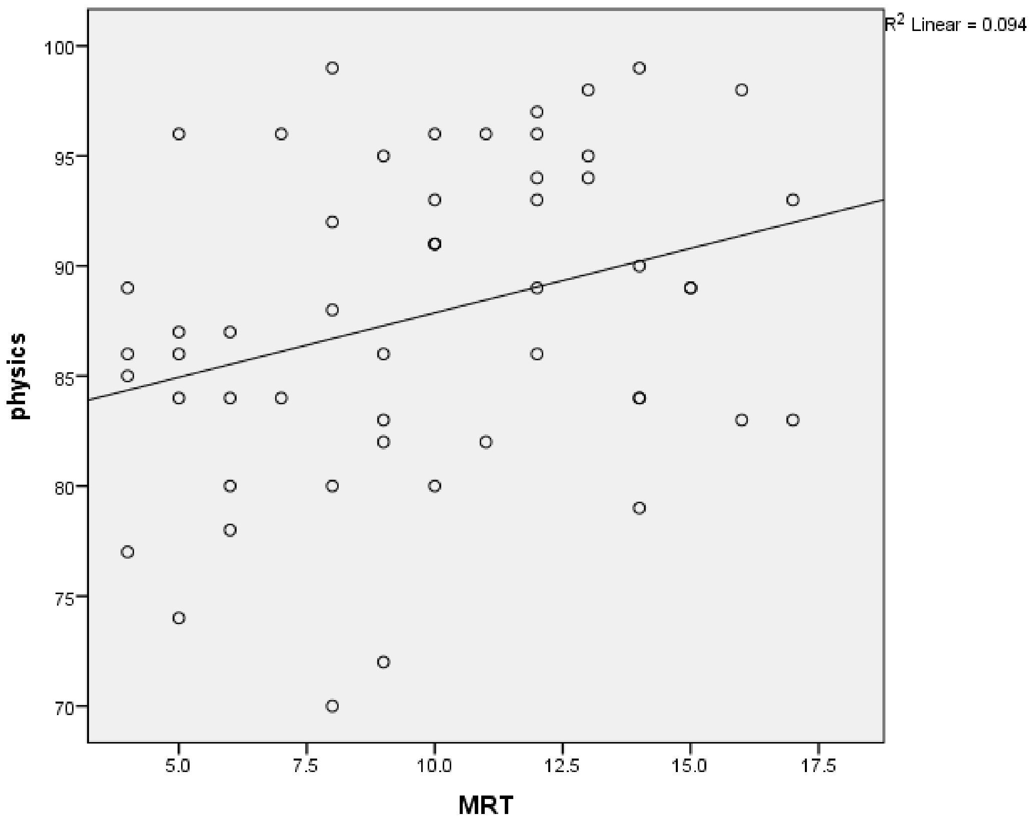

Figure 2.17 Graphical Representation of correlation between physics and MRT

Table 2.14 Coeffiecient Table of MRT and dependent variable Physics

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	82.011	2.686		30.534	.000
	MRT	.586	.255	.306	2.299	.026

a. Dependent Variable: physics

Table 2.14 shows the regression linear equation is y=.586x+82.01, where r^2=.094 so that spatial intelligence accounts for 9.4% of the variation in the Physics scores of the magnet student population.

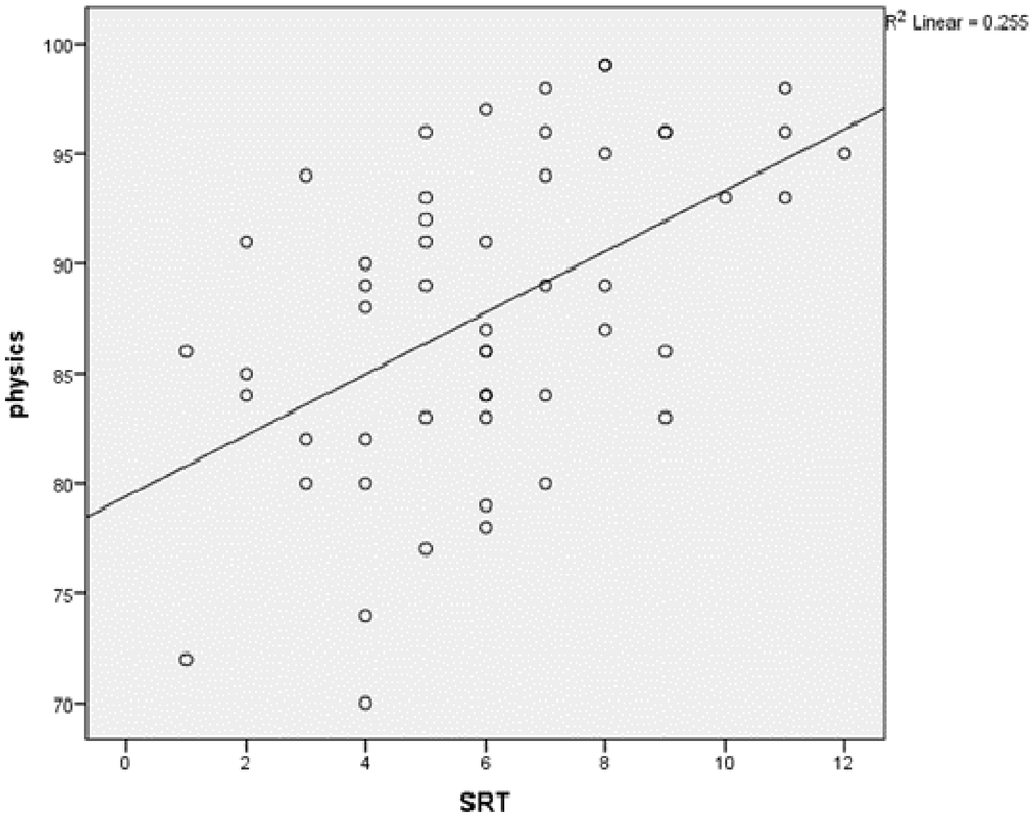

Figure 2.18 Graphical Representation of correlation between SRT and physics

Table 2.15 Coefficient Table of SRT and dependent variable Physics

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	79.407	2.184		36.355	.000
	SRT	1.393	.334	.505	4.174	.000

a. Dependent Variable: physics

In table 2.15, the regression line is y=1.39x+79.407, r^2 =.255, so that scientific reasoning ability accounts for 25.5% of the variation in the physics scores of the magnet students. Now we compare the other population, non-magnet students.

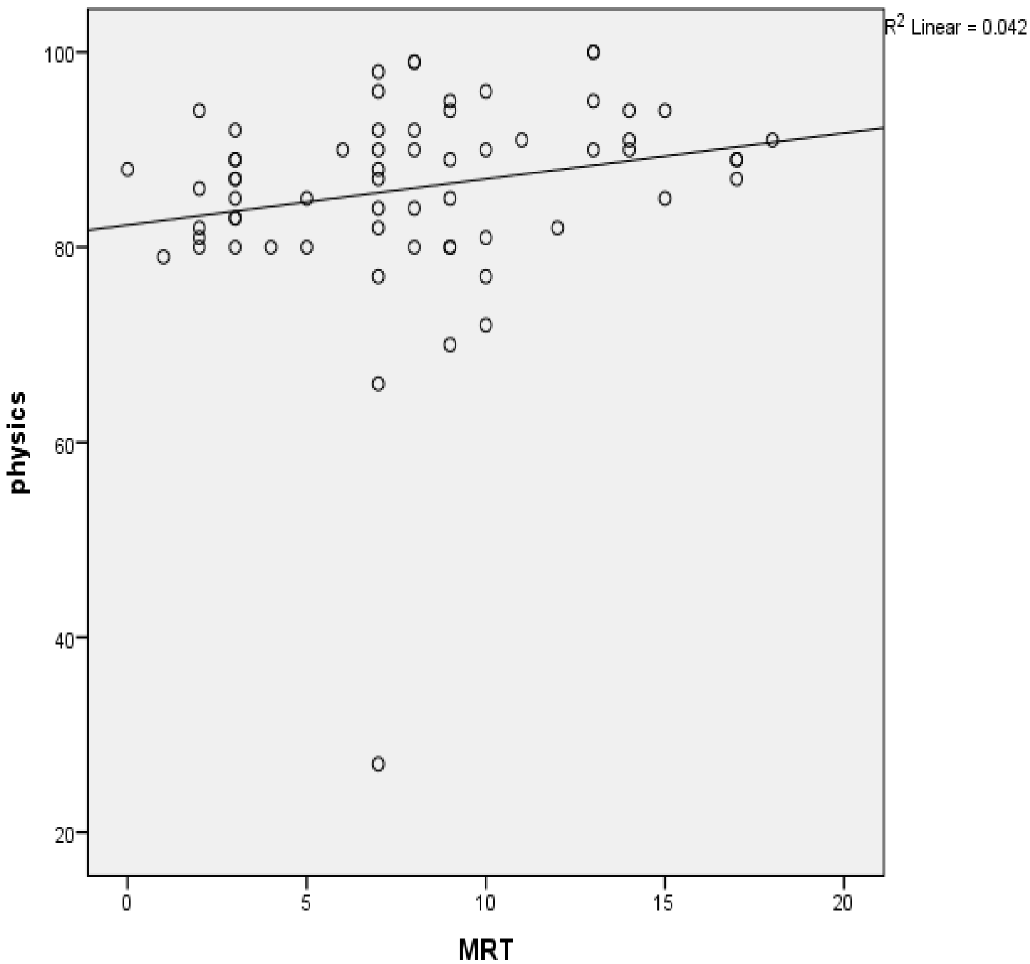

Figure 2.19 Graphical Representation of correlation between physics and MRT, non-magnet students

Table 2.16 Coefficient Table of MRT and dependent variable physics, non-

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	82.296	2.626		31.333	.000
	MRT	.471	.287	.204	1.641	.106

a. Dependent Variable: physics

magnet students

In table 2.16, the linear regression equation is y=.471x+82.30, r^2=.042, so that spatial ability accounts for 4.2% of the variation in physics grades of the non-magnet students. The next graph is scientific reasoning plotted against their physics scores for non-magnet students.

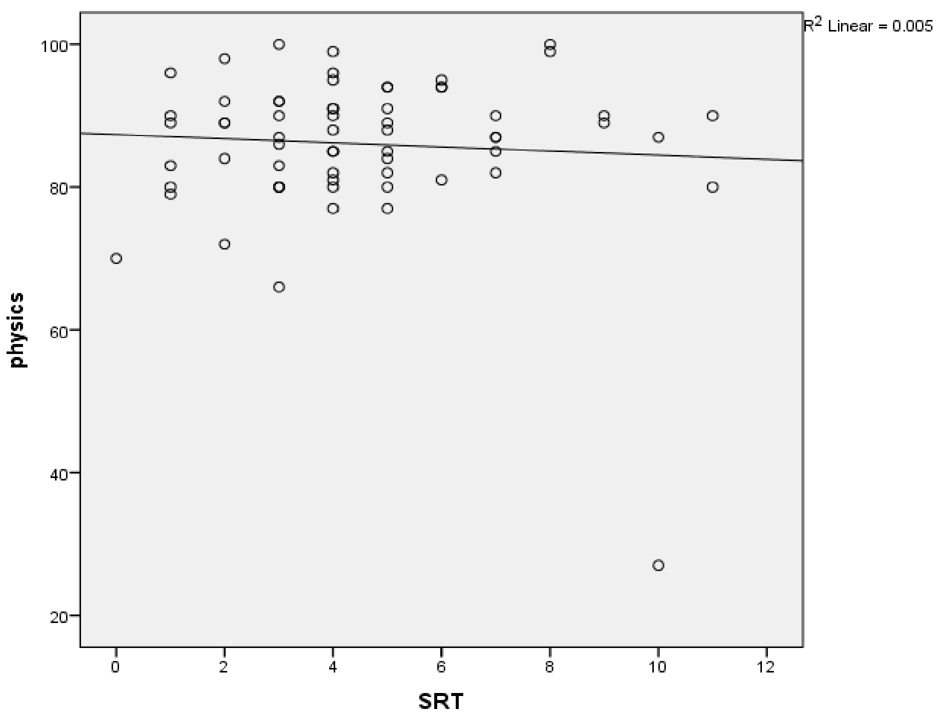

Figure 2.20 Graphical Representation of correlation of physics and SRT for non-magnet students

Table 2.17 Coefficient Table for SRT and dependent variable physics for non-magnet students

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	87.362	2.649		32.977	.000
	SRT	-.289	.513	-.071	-.563	.575

a. Dependent Variable: physics

The above graph, figure 2.20 , presents no correlation between non-magnet students scientific reasoning scores and their physics grades. In table 2.17, the regression linear equation is y=-.289x+87.36, where r^2=.005 so that scientific reasoning ability accounts for 0.5% of the variation in the physics scores of non-magnet students. Therefore, we can infer that scientific reasoning didn't have an impact on how well the non-magnet students would perform in their physics class, which is a very different result from the result with the magnet students.

2.7.4 Discussion

The results show that spatial ability was a factor in the performance of both magnet and non-magnet students. This could be due to the spatial nature that physics requires in addition to the cognitive load that is required for students to be successful in the class. The most interesting result was that again magnet students scored higher in their reasoning tests, and this seemed to have had an effect on how well the students performed in the physics class. The non-magnet students scientific reasoning didn't have an impact at all on their physics scores. In addition, by comparing the two regression equations for both magnet and non-magnet students, we see that using the standard error coefficients both equations lie within the same range. Therefore, spatial intelligence had the same impact for both groups of students.

2.7.5 Comparison of Pre-AP Students and AP Students Spatial Intelligence

Now we want to see if after taking a pre-AP physics course, studentsôspatial intelligence was affected. Below, we will show the mean and standard deviation of spatial intelligence of pre-AP physics students and AP physics students.

Table 2.18 Mean and Standard Deviation for MRT scores for Pre-AP Physics and AP Physics B

Student Population	Mean MRT Score	S.D. MRT
Pre-AP Physics (N=117)	8.84	4.25
AP Physics B (N=30)	11.9	3.72

Table 2.18, shown above, demonstrates that the AP students had a higher measured spatial intelligence compared to their pre-AP counterparts. To determine if this is a significant difference between both populations, we will perform a t-test. The test shows t=3 and p=0.00, which shows that the difference between the two populations is significant. It has been shown [Cid, 2011], that due to the high spatial nature of physics, students tend to have a higher MRT score after having taken a physics course. This could be the effect that is being shown here.

Now we can compare the results obtained by Cid [2011] in her dissertation, by looking at the AP-Physics B students and comparing them to in the incoming freshmen taking PHYS 1443, which is an introductory calculus based physics course. Using the data, from Cid [2011], we see that incoming freshmen obtained an average MRT score of 10.20 with a S.D. of 4.54; however, it must be noted that these scores were acquired during the beginning of the semester. Now by looking at table 2.17, AP-Physics B students had an average score of 11.9 on their MRT score with a S.D. of 4.54. Now, to see if these scores are significantly different, we performed a t-test which revealed a t

(78) = 1.7, p =.08, which is not quite statistically significant. Now, it must also be noted that the AP-Physics B students took the MRT at the end of the semester. This is important to show, since these are students who on average attend state universities such as the University of Texas at Arlington.

2.8 Language Barrier and Student Success in STEM

As stated in the previous chapter, Synder [1999] stated white students tend to outperform minority students in the field of science due to the language barriers posed by the students cultural differences. Western science has been designed to serve indiviudals who have grown with the language used in that particular discipline. To be scientifically literate, one must not only know basic scientific facts, but also understand the discourse in which science is taught. Scientific literary is composed of two basic premises [Lee, et. al., 1998], one is scientific knowledge and the other is scientific habits.

2.8.1 Methodology

As previously mentioned, at the end of the 2012-2013 school year, two groups of students were administered the MRT test in a Pre-AP Physics class. We chose to include both magnet and non-magnet students for the study to have a diverse group so we could analyze and compare how their spatial intelligence would affect how they would perform in the STEM classes and state assessment tests. However, we also wanted to examine if the language barrier of the students had any impact on how well the students perform in their STEM courses. It has been shown that magnet students have higher spatial intelligences compared to their non-magnet studentøs counterparts, and there is a distinguishing factor in how well these two groups performed in state assessment tests. We want to examine if this is because of the studentøs spatial ability, and what effect language is playing in their performance. Also, we want to examine if language is also playing a role in how well the students will do in their physics courses.

At the end of the spring 2013 semester, the state of Texas administered the ELA-TAKS assessment to measure English language skills. Again the population was N=117 students, out of which 53 were magnet students, and 64 were non-magnet students, which are part of this particular study. The data for the test assessment is presented in the next section.

2.8.2 Data

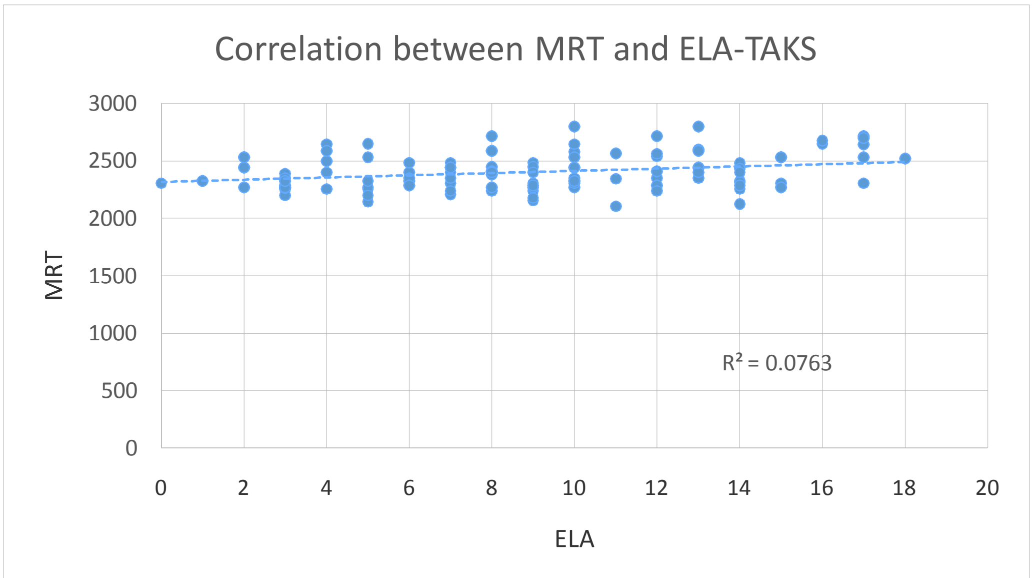

Figure 2.21 Graphical Representation of Correlation between MRT and ELA-TAKS.

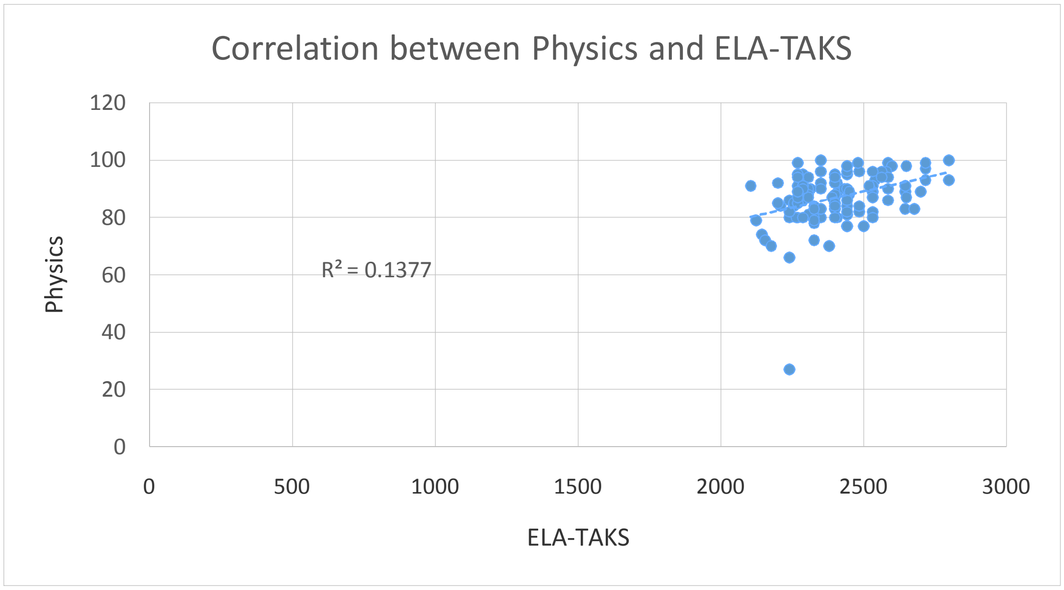

Figure 2.22 Graphical Representation of Correlation between Physics and ELA-TAKS

2.8.3 Results

From the above figure 2.21, we can observe that there is a weak positive correlation between the language ability of students and the spatial intelligence of students. Therefore, language does have a small predictive value on how well a student will perform on the MRT test. If we look at figures 2.1 and 2.2, we can see that spatial ability doesnơt show a correlation between ELA and MRT for both non-magnet students and magnet students. However, if treated as a population as a whole, see figure 2.3, MRT shows a positive correlation with ELA-TAKS. ELA-TAKS and MRT have a Pearson correlation r(117)=.276, p=.002. Therefore, language ability doesnơt have an impact on how a studentǒs spatial intelligence for individual magnet and non-magnet populations, but we do see an effect spatial intelligence has if treating both populations as a whole.

In addition, we examined the impact that ELA posed for both the magnet and non-magnet population in their state assessment tests. The first group we examined is the magnet students and how ELA impacted their math-TAKS, as shown in figure 2.23.

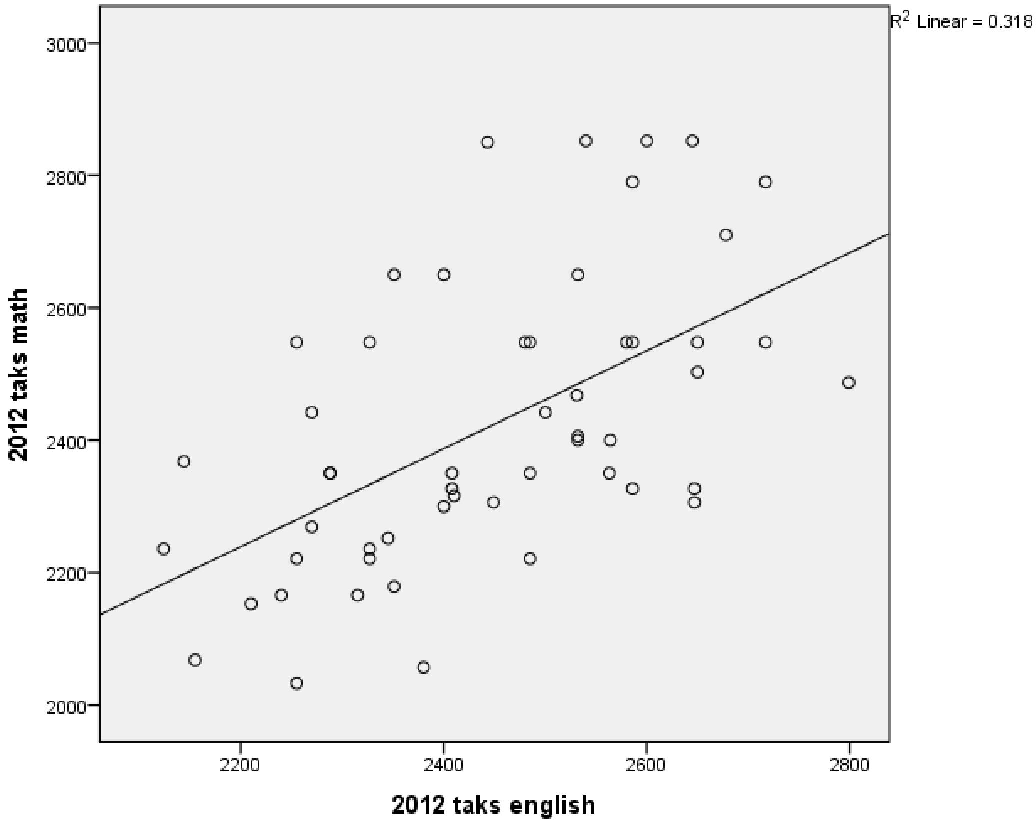

Figure 2.23 Graphical Representation of correlation between 2012 math-TAKS and ELA-TAKS for magnet students

Table 2.19 Coefficient Table for 2012 ELA-TAKS and dependent variable 2012 math-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	611.619	371.868		1.645	.106
	2012 taks english	.740	.152	.564	4.880	.000

a. Dependent Variable: 2012 taks math

In table 2.19, the regression linear equation is y=.740x+611.62, where r^2=.318, so that English Language Arts accounts for 32% of the variation in the math-TAKS scores of the magnet students.

The next graph, figure 2.24, exhibits the magnet science-TAKS scores versus their ELA-TAKS scores, to see how language impacted their science-TAKS scores.

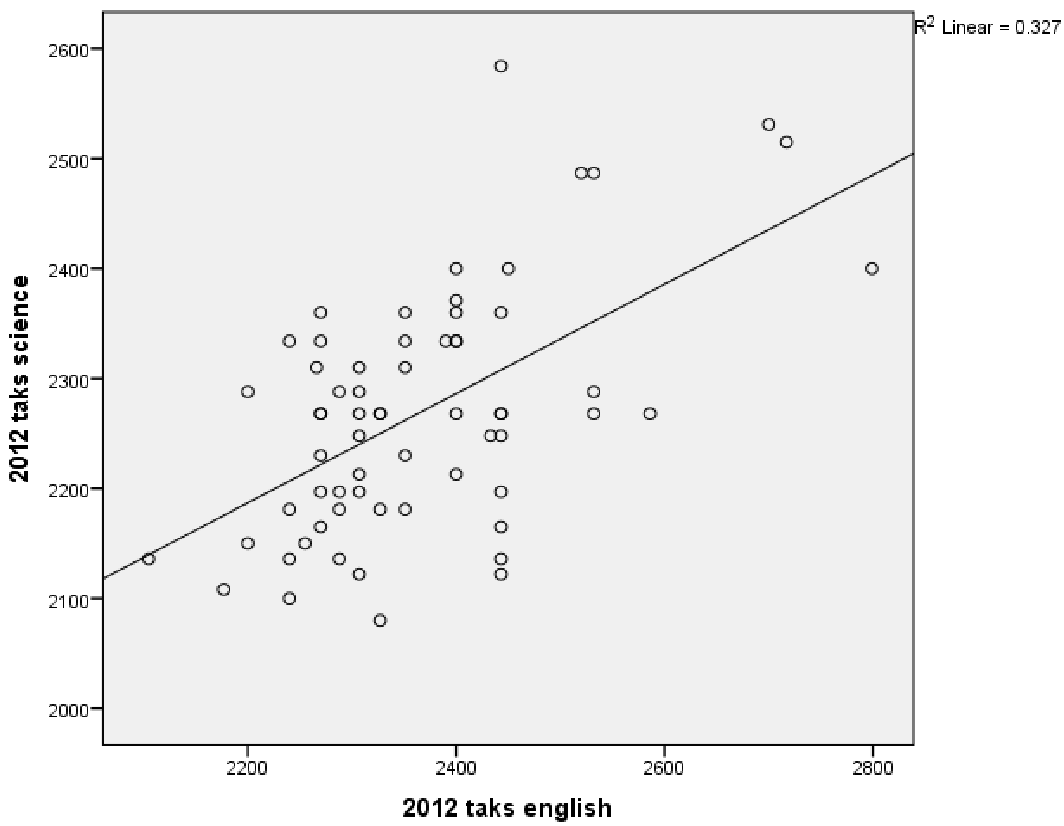

Figure 2.24 Graphical Representation of correlation between 2012 science-TAKS and 2012 ELA-TAKS for magnet students

Table 2.20 Coefficient Table of 2012 ELA-TAKS and dependent variable 2012 science-TAKS for magnet students

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1093.204	214.366		5.100	.000
	2012 taks english	.497	.090	.572	5.494	.000

a. Dependent Variable: 2012 taks science

In table 2.20, the linear regression line for 2012 science-TAKS score is $y=.497x+1093.20$,where $r^2=.327$ so that ELA accounts for 33% of the variation in the science TAKS scores of the magnet students.

The next group that we examined was the non-magnet students. The first graph, figure 2.25, is the math-TAKS versus the students ELA-TAKS scores. The graph will show a linear fit as well as a variance coeffienct.

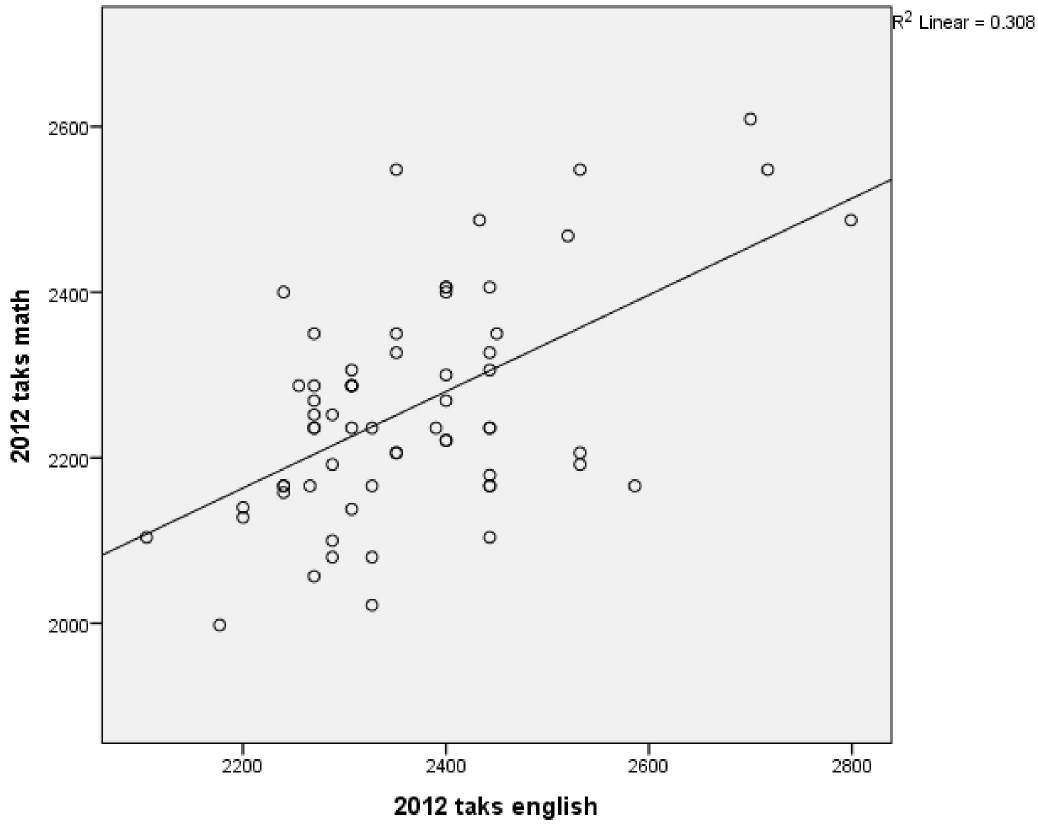

Figure 2.25 Graphical Representation of correlation between 2012 math-TAKS and 2012 ELA-TAKS for non-magnet students

Table 2.21 Coefficient Table of 2012 ELA-TAKS and dependent variable 2012 math-TAKS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	880.815	262.743		3.352	.001
	2012 taks english	.583	.111	.555	5.257	.000

a. Dependent Variable: 2012 taks math

In table 2.21, the regression linear equation is y=.583x+880.82, where r^2=.31 so that ELA account for 31% of the variation in the math TAKS scores of the non-magnet students.

2.8.4 Discussion

For both the magnet and non-magnet students, ELA-TAKS was a significant factor in how well the students would perform in the math-TAKS tests. Futhermore, looking at the regression line equations, both groups lied within the same realm due to the standard error for both the slope and intercepts. This means that ELA impacted the students equally.

2.9 General Conclusions

We have collected data from two different high school populations: magnet and non-magnet students. We were looking to reproduce various aspects of the study conducted Cid[2011]. A comparison between magnet students and non-magnet students showed that there is a statistical difference between their respective MRT scores. This leads us to the claim that magnet students, due to their selection process, are bound to have a higher spatial abiltiy than students enrolled as non-magnet students.

We were trying to extend the results shown in the dissertation presented by Ximena Cid [2011] in her investigation of using spatial intelligence as a predictor for rentention and success in STEM classes. The spatial intelligence did play a role for magnet students in their TAKS-Math scores and for non-magnet students in their TAKS-science scores. In addition,it also played a role on state assessment tests in both math and science. However, spatial ability was not a large factor in student performance in their high school classes.

Another aspect of our study was the role of scientific reasoning ability as measured by Lawsonøs [1971] Test of Scientific Reasoning (SRT). We saw there was a significant correlation between the SRT of the general population and all aspects of the STEM courses and assessments. Interestingly, however, there was no significant correlation between physics and SRT. In magnet students there was a significant correlation between the success in their assessments and the score they received in the SRT. In addition, magnet students had a significant correlation in their success in physics and the SRT. However, we didnôt see the same effect SRT had on non-magnet students compared to their magnet counterparts.

We found scientific reasoning had more of an impact on the studentsô success in state exams than compared to the impact the STEM courses had on their success in TAKS tests. Also, we saw that language does play a role on how successful students will be in their physics courses, and this could be a factor on how successful a student will be in other STEM courses. Also, language was a contributing factor in how well the students performed in the state exams.

Chapter 3

The Relationship between of Student Spatial Intelligence and the Progression in Physics Courses from High School to University

3.1 Intoduction

As discussed in chapter 2, spatial ability can have a significant impact on how well students will perform in their state assessment tests such as the TAKS. In addition, we saw that spatial ability had a correlative factor in the performance of physics in the magnet student population group. Furthermore, we saw that there was a statistical difference between the two populations that were studied, magnet and non-magnet. The magnet students had on average a statistically significant higher MRT score to their non-magnet counterparts. Also, students who were enrolled in an AP Physics course scored higher on the MRT test compared to students who were enrolled in a pre-AP Physics course. The purpose of this chapter is to examine how spatial ability changes as students go on to higher level physics courses in university.

3.2 Background for Study

Cid [2011] studied how taking physics class affected the spatial intelligence of students. In mathematics and engineering, spatial ability had a correlative factor that showed MRT was able to predict how well a student would perform in their class and if that student would remain in that class. In physics, it was shown that the final grade in physics doesn't correlate significantly with their MRT score. Therefore, MRT has no predictive value on how well students will perform in their physics courses.

In addition, Cid [2011] replicated the results that were obtained in a study conducted by Pallrand and Sieber [1984], where it was demonstrated that taking a physics course had a bigger impact on a student's spatial ability than an taking an engineering course. Cid [2011] showed that taking physics had the biggest impact on a studentô s spatial intelligence compared to introductory calculus and engineering courses. She concluded that the reason is because the problems in physics have the most content that involves the most spatial intelligence used, compared to the other fields. In this chapter, we want to compare data on spatial intelligence, among group of students in high school and college, and examine how studentsô spatial intelligence changes (on average) as they proceed through STEM education.

3.3 Methodology

The target populations of this study were students in high school and college level freshmen and upper classmen. All students in high school were either taking a pre-AP physics course or an AP-Physics course. The accessible high school student population were students that were enrolled at a high school in Laredo, Texas. The current study population was drawn from juniors and seniors enrolled at United High School. The group was composed of a mixture of students that were enrolled at the United Engineering and Technology Magnet (UETM) School and students that were not enrolled in any magnet program. The UETM is independent of the administrative responsibilities of the larger school in which it is housed. During the 2012- 2013 school years, we measured their spatial intelligence using the Mental Rotation Test.

The method for collecting was convenient. We used one AP Physics class with students that had already taken the necessary prerequisite of Pre-AP Physics. The AP Physics classes were an introductory algebra based physics class composed mainly of seniors who were prepared to graduate from high school. In total, there were 30 students (5 females), ranging between the ages of 16-18 who took all three state assessment tests. In addition, we also had a sample of 117 juniors who were enrolled in a pre-AP physics course. From this sample size, there were 53 magnet students and 64 non-magnet students.

These students were invited to participate in the study and were all taking AP Physics at the time they were tested. Before the test could be administered to the students in the classroom, an IRB board had to convene to approve the study. In addition, since the majority of the students were minors, the parents had to be notified with the use of consent forms that their children would be administered tests, grades would be collected for research purposes, and their state assessment scores would also be used for research purposes.

For the other sample size, we are using data from students at University of Texas at Arlington. One set of data that were collected by Cid [2011] comes from students who were taking PHYS 1443 (calculus-based introductory mechanics) and students taking ENGR 1105 (introduction to engineering, a course all engineering students take their first semester). The MRT was administered at the beginning and the end of the semester. Additional data were taken from juniors and seniors who were enrolled in PHYS 3313 (modern physics, with an introduction to special relativity, quantum mechanics, particle physics, and cosmology). These data were collected in 2011 as part of an ongoing research project, extending the work of Cid [2011] and have not been previously used in any publication.

3.4 Data

We used basic statistical analysis and correlative analysis to analyzed the data. The variables that were used were their final physics grades and their MRT scores. Our operating hypothesis is that studentô s spatial intelligence will increase with every class that the student takes. Our null hypothesis is that there will be no difference between the studentsôspatial intelligence. Table 3.1 shows the sample size for each course for both magnet and non-magnet studentsôMRT Test assessments. It also shows the additional information obtained from the introduction to engineering, the calculus based introductory physics. and modern physics. The number of students in each sample is indicated. Furthermore, the table also includes the means and standard deviations for all different physics students.

Table 3.1 Means and Standard Deviations for MRT Scores

N	Mean MRT Test	S.D. MRT Test
117-Pre-AP Physics (Post)	8.84	4.25
30-AP Physics B (Post)	11.9	3.72
104-ENGR 1105 (Pre)	9.66	5.10
65-ENGR 1105 (Post)	11.34	5.21
50-PHYS 1443 (Pre)	10.20	4.54
39-PHYS 1443 (Post)	13.54	4.27

TABLE 3.1-Continued

30-PHYS 3313 (Pre)	13.13	4.63

The labels (Pre) and (Post) refer to whether the MRT was given at the beginning or the end of the semester. Figures 3.1 and 3.2 shows how the MRT scores increased as the students went from a secondary education setting to a college education setting, from lower level courses to higher level course.

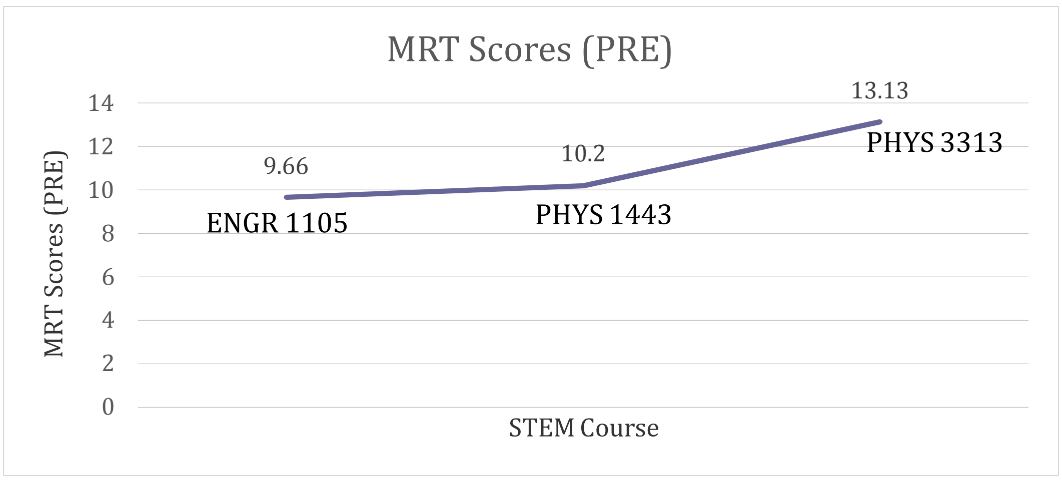

Figure 3.1 Graphical Representation of STEM Classes and Pre-MRT scores. It is shown that there is an effect that spatial intelligence has on the performance of students in their respective classes.

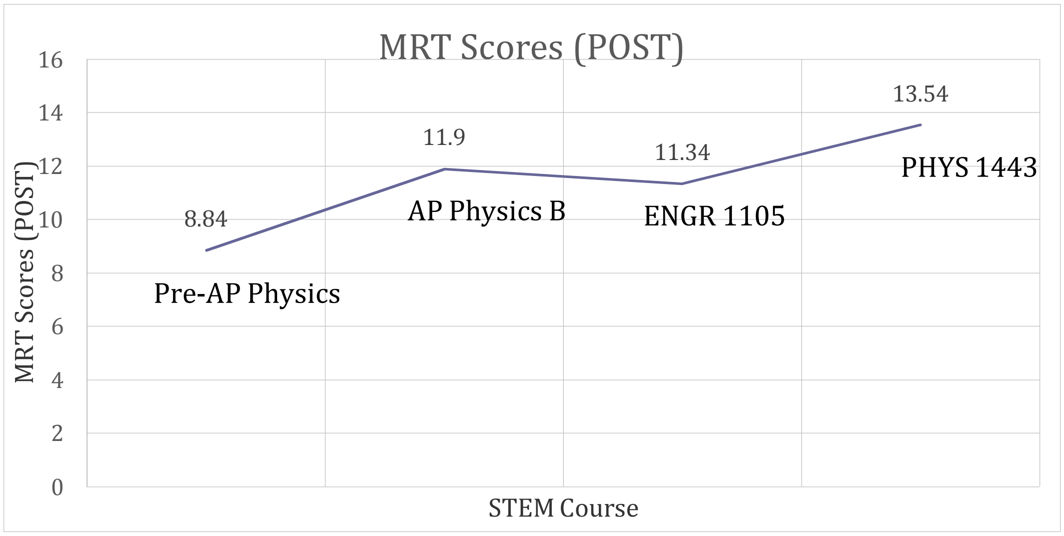

Figure 3.2 Graphical Representation of STEM Classes and Post-MRT scores. It is shown that there is an effect that spatial intelligence has on the performance of students in their respective classes.

3.5 Results

It has been shown using the data in table 3.1 that students tend to have a higher MRT score after having taken a physics or engineering course [Cid, 2011]. Therefore we have to compare students taking the MRT at the same point in the semester. From the table above, we can see that the AP students had a higher measured spatial intelligence compared to their pre-AP counterparts, and both took the exam at the end of the semester, so we can compare them. To determine if the difference between the populations is significant, we performed a t-test. The test showed $t(145)=3$ and $p=0.00$, which indicates that the difference between the two populations is significant. The next population we can compare is the students taking ENGR 1105 and PHYS 1443. By taking those classes, we saw that their spatial intelligence increased. To see if these results are significant, we will perform a t-test for those individual classes. It must be noted that during the course of that semester the student population decreased due to students dropping out, which may have had an effect on the average MRT score. By looking first at ENGR 1105, we performed a t test which revealed that the increase to be statistically significant, t (167) = 2.06, p =.04. The next course is PHYS 1443, we performed a t-test which revealed t (87) = 3.53, p =.0007, which is a extremely statistically significant result. Therefore, a studentõs spatial intelligence will increase significantly by taking a physics or engineering course.

In general, we see a trend that both the pre and the post scores increase as the students progress to higher levels. To see if this was a significant results, we again performed a t-test with the AP Physics B (post) scores to entering PHYS 1443 freshmen (post) scores. The t-test showed t (67) = 1.67, p =.09, which shows that the increase is not quite statistically significant but is still considered significant. It should be noted, this is not a true longitudinal study ï these are not the same students. However, they are representative of the student population. However, the spatial intelligence score changes are significant. For example, comparing the PHYS 1443 (pre), and modern physics PHYS 3313 (pre), the t-test shows t (78) = 2.77, p =.0069 which is a statistically significant result. Therefore we can conclude that the spatial ability of the populations taking physics classes increases as they take more advanced physic classes, all the way from high school through undergraduate education.

3.6 Physics Grades and Spatial Intelligence

We examine the data that was obtained from both high school and college students to determine the relationship between spatial intelligence and how well the students performed in their respective physics courses. Therefore, we want to how this relationship varies across physics course in high school and college, taking into account that Cid [2009] found essentially no correlation between MRT scores and grades in PHYS 1443.

3.7 Methodology

Our sample size was the same as described in section 3.4, all students are represented by their respective courses. The courses that are examined in this section were pre-AP physics, AP Physics B, and Modern Physics obtained from upperclassmen attending UTA. Our sample size was the same as in previous sections for all respective physics classes. The data for high school students was obtained during 2012 and 2013. For the modern physics class, the data was obtained during the 2010 school year.

3.8 Data

We did a correlative study with MRT data for all physics data. We then collected final grades for each student who signed an informed consent and participated in the study. The first group that was examined were the pre-AP physics students, in figure 3.3.

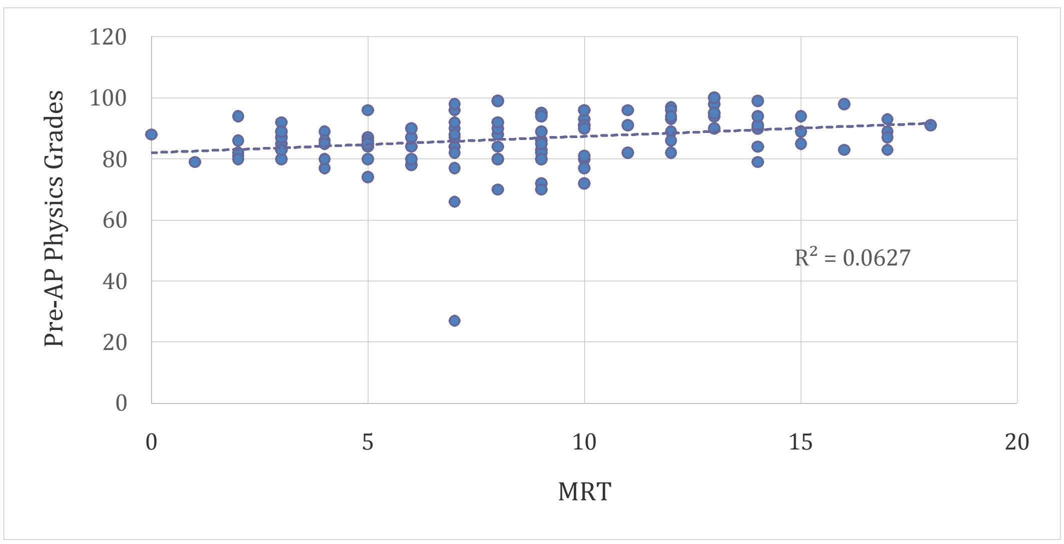

Figure 3.3 Graphical Representation of Correlation between PRE-AP Physics and MRT. It is shown that there is an effect that spatial intelligence has on the performance of students in physics

The next group that is examined are the students who are taking AP Physics B, figure 3.4

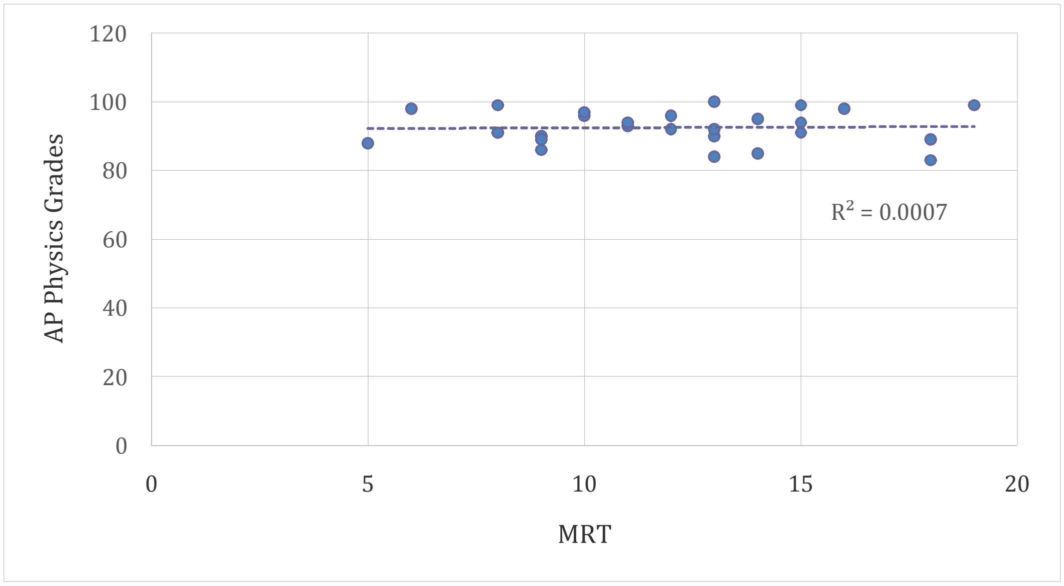

Figure 3.4 Graphical Representation of Correlation between AP Physics B and MRT. It is shown that there is no effect that spatial intelligence has on the performance of students in AP Physics B

The last class that was examined was the modern physics class, figure 3.5.

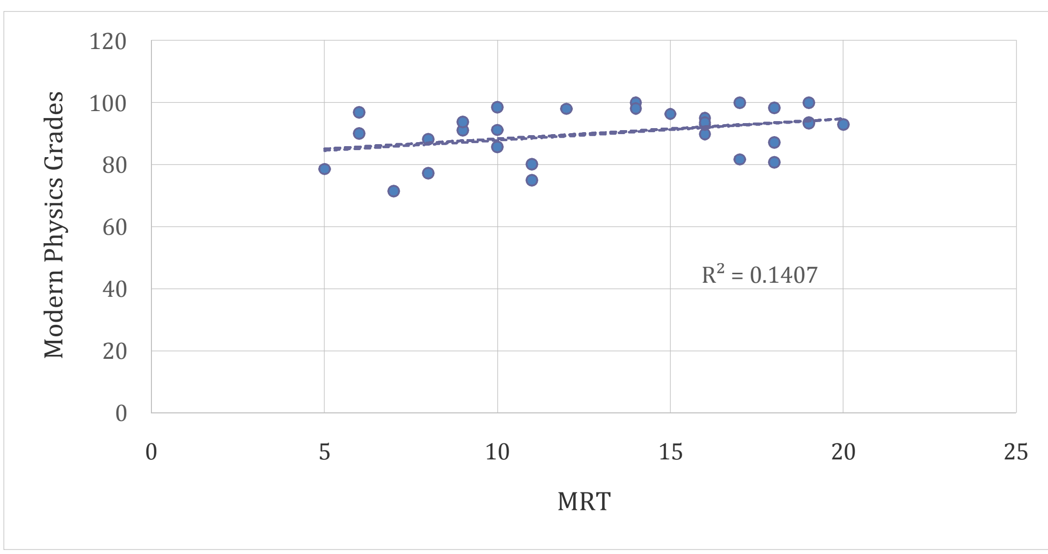

Figure 3.5 Graphical Representation of Correlation between Modern Physics and MRT. The graph indicates that spatial intelligence does have an effect on the performance of students in the modern physics class.

3.9 Results

By looking at figure 3.3, we can see that there is a weak correlation r (117) =.250 between the pre-AP physics and MRT score. By looking at the next graph, figure 3.4, the data between AP Physics B and their respective MRT score has r (30) =.03, which indicates there is no correlation between the students grades and their MRT scores. On the other hand there is a correlation in figure 3.5 , of r (30) =.38 for the modern physics class. Thus for modern physics class there is a medium effect of the MRT on physics scores for those students.

3.10 Discussion

From looking at section 3.4, we see that there is a statistically significant increase of the MRT scores as the student goes from pre-AP Physics to AP Physics B to various physics courses at the University of Texas at Arlington. This can be seen as the average of the students MRT scores consistently are increasing through high school and on to freshmen level college physics, and modern physics (as a representative of upper division physics). However, by looking at Table 3.1, we see that if we treat or look upon the different groups of students as a general population, AP-Physics B (post) has a higher average than the students in PHYS 1443 (pre) and ENGR 1105 (pre), but the story with the MRT scores at the end of the semester were different, with the college students having the same or higher scores. This suggests that after taking a course, the improved spatial ability starts to relax to lower values, unless it is reinforced by something (like taking more courses).

In addition we see that beginning engineering students are very similar in their MRT scores to high school students in pre-AP and AP physics. This makes sense, since it is students in those courses who are the likely population to go on to universities to major in engineering. However, in subsequent courses we see that the average MRT increases and the differences are statistically significant. This progression of higher levels of spatial intelligence being correlated with higher levels of STEM achievement is consistent with the results of Wai et al. [2009].

Another finding that is interesting is that, for the most part, there is little correlation between grades in physics courses and score on the MRT. However, the spatial ability of students increases as they take more physics courses, and the population that goes on to take higher level physics courses has a better spatial ability as measured by the MRT. This is consistent with Wai et al. [2009], but it leaves us without a clear selection mechanism. If grades were correlated with MRT, the answer would be simple. Only students with better grades go on to take more physics. The real story must be more complicated than that. Perhaps spatial ability is acting as some kind of limiting factor for the top levels students and highest grades. We will explore that possibility in the next chapter.

Chapter 4

Applying General Systems Performance Theory to Determine the Relationship between Basic Abilities, including Spatial Intelligence, on Student Performance on the SAT

4.1 Introduction

From Chapter 2, we learned that spatial ability makes an impact on how successful students will be in their STEM courses, including physics. In addition, we saw that taking a pre-AP physics course may make an effect on the studentsôspatial intelligence. Furthermore, we observed the effect spatial intelligence had on the studentsôsuccess on state assessment tests. In Chapter 3 we saw that studentsôspatial ability increases as the move up to higher level physics courses. However, there is not a strong correlation between studentsôgrades and their spatial intelligence as measured by the MRT. So what is the selection mechanism? One possible answer is that students with MRT above some minimum do fine in physics, but that other factors, such as math skills are the real determining factor.

The aforementioned results used traditional analysis such as linear correlation and basic statistical analysis. This chapter presents research using a different method for analyzing data known as Nonlinear Resource Casual Analysis (NRCA). The NRCA method will demonstrate how a studentõs success in any particular task is divided into basic performance resources, and if a student has a deficit in one or more resources, this resource will make an impact on their achievement in this task. This might allow us to better quantify the factors that determine student performance, if we can show that the method works. We will use data on student performance on the SAT to investigate the application of NRCA to our data.

4.2 Background for Study

4.2.1 General Cognitive Ability and Scholastic Achievement

Important factors have gradually come together to dictate the demands that students must meet in order to comply with college entrance requirements. To begin with, the competitive nature of college has placed more importance on college entrance exams such as the SAT. Colleges now place as much weight on the SAT as they do on the studentsôgrades [Marchant, 2005]. The SAT, an exam administered and developed by the College Entrance Examination Board, tests the student on verbal and mathematical reasoning, and a writing section has also been added to the test that is currently being used by the College Board. [https://www.collegeboard.org/]. College Board members concur on the theory that a combination of both the studentsôSAT scores and grades received during their time in high school will provide a stronger indicator on how well the students will perform in college. However, the SAT does not reflect how well students did in their high school classes ï it is a predictor how well they will be able to perform in college [Marchant et al., 2005].

The current SAT, as of 2005, is a test administered eight times annually and consists of three different assessments: writing, critical thinking, and mathematics. The SAT takes 3 hours and 45 minutes to finish. The SAT scores range from 600 to 2400, which is a combination that results from the three possible 800 point sections. The mathematics section tests arithmetic operations, algebra, geometry, statistics and probability. However, as opposed to previous exams, the 2005 version of the SAT test now requires the student to apply high-level mathematics, such as algebra II and scatter plots. The critical reading section includes reading passages and sentence completions. The writing section includes a short essay and multiple choice questions on identifying errors and improving grammar and usage. According to the College Board, the SAT doesnọt test logic or a studentọs reasoning ability; rather, it tests the skills that were acquired during oneọs time in high school [http://www.collegeboard.org].

There have been general studies that have demonstrated that cognitive ability tests correlated with a personọs general mental ability for overall educational achievement in such tests such as the SAT [Deary et al., 2007]. Interestingly, there is also evidence of a direct link between general intelligence and the score a student receives on the SAT test [Frey et al., 2004]. In this particular study, two major findings were revealed. The first showed that the SAT is an adequate measure of intelligence. The second finding is that the test is also able to measure general cognitive functioning.

However, knowledge also counts for how well a person will perform at specific tasks. A person who is highly gifted intellectually canọt perform a task they have never seen before such as make an omelet if they have never cooked before, for example. The abilities that a person has can be viewed as resources that are brought to bear when asked to perform a task. Therefore, we wish to understand the link between what resources are used during the SAT test and what will be a limiting resource for each of the students.

4.2.2 Cognitive Abilities and Science Teaching

Learning is a collective effort and is viewed as õactive, constructive, cumulative and goal oriented.ö [Shuell, 1986]. By learning, one acquires two different types of knowledge: general and specific. Specific knowledge is defined as rules about disciplines on how to handle specific situations. General knowledge is defined as applicable strategies for problem solving, inventive thinking, decision-making, learning, and good mental management. Physics is a discipline that is based on a specific type of knowledge skills that allow for one to learn about how the universe works; however, the same strategies and logic that physics uses can also be applied to other disciplines.

Science is a discipline that allows for a teacher to teach students formal operational logic through inquisition [Lawson et al., 1978]. According to Jean Piagetôs cognitive developmental theory, when a student enters high school, on average at the age of 15, they have entered the last stage of their intellectual development, formal operational thought [Piaget, 1977]. For a physics teacher, the laboratory is a primary location to allow for a student to become inquisitive. The laboratory has the materials for actual involvement that allows for students to find things out for themselves. [Lawson et al., 1978]. Therefore, physics can act as a catalyst that allows for students to develop their cognitive skills, such as dealing with abstract concepts and mutiple variables, both hallmarks of formal operational thinking.

In addition, physics can also promote intellectual development by allowing for more formal reasoning. Formal reasoning is fundamental to developing a meaningful understanding of mathematics, as well as the sciences [Fuller et al., 1977]. Physics promotes the use of functional relationships that allow the student to describe and interpret dependencies on different variables. Equally, exploration of the physical world and discussion can allow for students to gain experience and knowledge of the physical world in which they live. Since the SAT measures student skills, acquired during their time in school, we also want to examine if there is a relationship to this in general science education, particularly physics, and how this impacts studentsô cognitive abilities and their SAT scores.

4.2.3 General System Performance Theory

General Systems Performance Theory (GSPT) is a framework that allows one to model systems, tasks, and their interfaces. [Kondraske, 2011]. GSPT considers that all systems have a function, and to perform these functions a resource must be used to complete a specified task. A resource is traditionally defined as any tangible resource that can be quantitatively measured. According to Kondraske [2011] a resource is defined not necessarily by quantitative terms, but by terms that will define on how well a task can be executed. Kondraske [2011] further states that for a task to be executed, the amount of resources must be greater than or equal to the amount of the resources that the task demands. GSPT seeks to establish what Basic Performance Resources (BPRs) are required to execute a High Level Task (HLT). By using this technique, this will allow for us to determine the resources the students used in taking the SAT exam (which we define to be the HLT), and what resources are the limiting BPRs.

Traditional analysis of data often uses linear analysis where one finds a correlation between the two separate variables to show the causal relationship. In GSPT (general systems performance theory), two variables will many times demonstrate that there is a direct correlation between high HLT and high BPR and low HLT and low BPR. However, sometimes there are samples that demonstrate that there may be a high HLT with a low BPR and low HLT with high BPR. In these particular cases, HLT performance is limited by another, different, BPR.

Nonlinear Casual Resource Analysis (NRCA) is a method that was developed to estimate the degree of performance in a HLT (High Level Task) supported by a set of BPRs (Basic Performance Resources). Customary examples include flying, driving, etc. Such HLTֹs have several variables that make them possible. These BPRs may include, for example, visual processing speed. Consider the case where we define driving down the road as our HLT. To drive the car successfully there are several factors or abilities that are needed for this task. The driver must have a certain level of visual acuity, hand-eye coordination, hearing ability to determine if there are emergency vehicles coming down the road, etc. These would be the BPRs for the driving HLT. The success rate of driving is dependent on all these basic performance resources. The better the quality of these resources, the better one may drive, but at some point, one of these BPRs is going to limit the driving skill. This approach has also been taken in other areas to examine basic performance resources [Gettman et al., 2003].

There has never been an investigation based into what resources are required for students to be successful in the SAT exam using the NRCA model. The task explained is divided into a reading comprehension and a math reasoning section. If a task requires a resource of R_o, then a deficit in that resource would not allow for the student to be successful in completing the Higher Level Task. In this particular study, we are going to consider examining how spatial ability will act as a basic performance resource (BPR) that will act as a limiting factor along with other variables that will provide the limiting value for student success on the SAT test.

4.3 Methodology

The target populations of this study were students that were focused and oriented towards taking advanced science and math courses. The accessible student population was comprised of students that were enrolled at a high school in Laredo, Texas. The current study population was drawn from juniors and seniors enrolled at United High School. The group was composed of a mixture of students that were enrolled at the United Engineering and Technology Magnet (UETM) School and students that were not enrolled in any magnet program. The UETM is independent of the administrative responsibilities of the larger school in which it is housed.

The method for collecting data was convenient. We used one AP Physics class with students that had already taken the necessary prerequisite of pre-AP Physics. The AP Physics classes were an introductory algebra-based physics class composed mainly of seniors who were prepared to graduate from high school. In total, there were 30 students, ranging between the ages of 16-18 who took all three state assessment tests. Five of these were females. These students were invited to participate in the study and were all taking AP Physics at the time they were tested, and informed consent was obtained in accord with the IRB approved for this study.

The resources that were used in the study included the students STEM grades, state assessment tests, and two exams that were chosen independently by the researchers. The state assessment tests were high-stakes. The students were required to pass with an acceptable state mandated score to graduate from high school and receive a diploma. For this research study, TAKS in the fields of science, math, and English Language Arts (ELA) were used to represent a portion of the studentsôbasic performance resource used in the SAT. Interestingly, an alternative method for graduating from a Texas high school during the years 2003-2013 was to use the SAT as a measurement tool for both the math and English portion of the TAKS tests. If the students received a minimum score on both the SAT-M and SAT-V, they would be allowed to use these scores towards their TAKS requirement for completing high school. The SAT scores are considered to be the high level task (HLT) for the purpose of this analysis.

The studentsôAP Physics grades were one of the BPRs. Not all students who took the class were required to take the AP Physics test, but four students took the test and were successful by receiving a grade ranging between 3-5 of the sample population. In addition, all student grades from the math courses were taken as a composite basic performance resource. This included geometry, Algebra 2, and pre-calculus. These courses were all pre-AP classes. Furthermore, twenty six of the twenty nine students took AP Calculus. The studentsôscience grades were also included as BPRs. This included biology, chemistry and physics. These were all again pre-AP classes. The other two assessments that were administered were the Mental Rotation Test (MRT) and Lawson's Test of Scientific Reasoning (SRT), discussed in earlier chapters, and we include these as BPRs.

4.4 Constructing the SAT model

The first step in the NRCA analysis is to generate a scatter plot of the BPR as a function of the HLT, and from the plot determine the lower bounds on the BPR. The lower bound of the distribution of the data determines the amount of basic performance resource necessary to accomplish the HLT. The second step is to determine the Resource Demand Function (RDF) by drawing a one or more set of straight lines that represent the bounds of the data. The RDF (generally expressed as a piecewise linear fit) represents the limiting value of the HLT for the given BPR value. To understand how the RDFs were generated, we must first understand what the line means. The RDF is how much of a BPR will be needed to achieve a given HLT score. It represents the relationship between the amount of resource a student has and the quantity of the HLT a student can achieve. The resource demand function is graphed using a straight line in the form of y=mx+b. The constant m is the slope of the demand function and shows how the basic resources of the students affect the HLT demanded. Finally, the model is constructed by combining the set of resource demand functions to determine for each set of BPR data representing one student what is the minimum HLT (in the case SAT score) that would be generated by the available BPRs for that student. This minimum HLT is the limiting HLT and the corresponding BPR is the limiting BPR.

The first BPR we examine is the MRT. Figure 4.1 presents the MRT data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource (spatial ability measured by the MRT) on the y-axis. The distribution shows no strong correlation, which is to be expected since the SAT does not measure spatial intelligence [Wai, et al., 2009]. There is a lower bound of data that suggests that spatial ability behaves as a threshold for student performance on the SAT for the four students that lie directly on the BPR function. The threshold is the RDF, indicated by the line. For example, no student got a 2050 on the SAT unless they have a score on the MRT of 11 or better. The student who had a 15 on the MRT and a 2050 on the SAT had some other resource that was a limiting factor for the SAT because a 15 on the MRT would imply that student should score a 2250 on the SAT if the only thing limiting the student is spatial ability. The RDF was placed at the lower bounds of the BPR data, which represents the limiting resource factor for those four particular individuals. The corresponding linear equation for the RDF is $y=0.02x-39.2$.

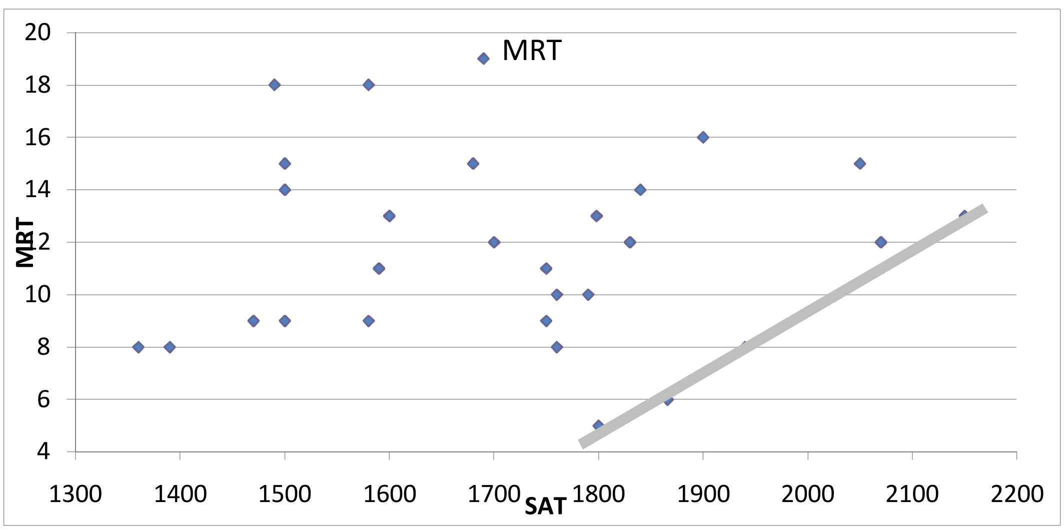

Figure 4.1 Graphical Representation of performance model for SAT scores and MRT scores, each being HLT and BPR, respectively. The line represents the resource demand function.

Figure 4.2 presents the SRT data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource (scientific reasoning measured by the SRT) on the y-axis. There is a lower bound of data that indicates that scientific reasoning behaves as a threshold for 3 students, with 3 other students close to the line (distance is measured in the x-direction). In addition, one can see in outlier with a SAT score of 1900 and a SRT score of 10. Therefore, the student over performed this particular model for predicting their SAT score, or alternatively the student got a SRT score that is really not an accurate measure of the studentǿs reasoning ability for whatever reason (such as goofing off on the SRT, not getting much sleep the night before taking the SRT, etc.). The RDF was placed at the lower bounds of the BPR data that represents the limiting resource factor for those particular individuals. The corresponding linear equation for the RDF is y=.03x-41.9.

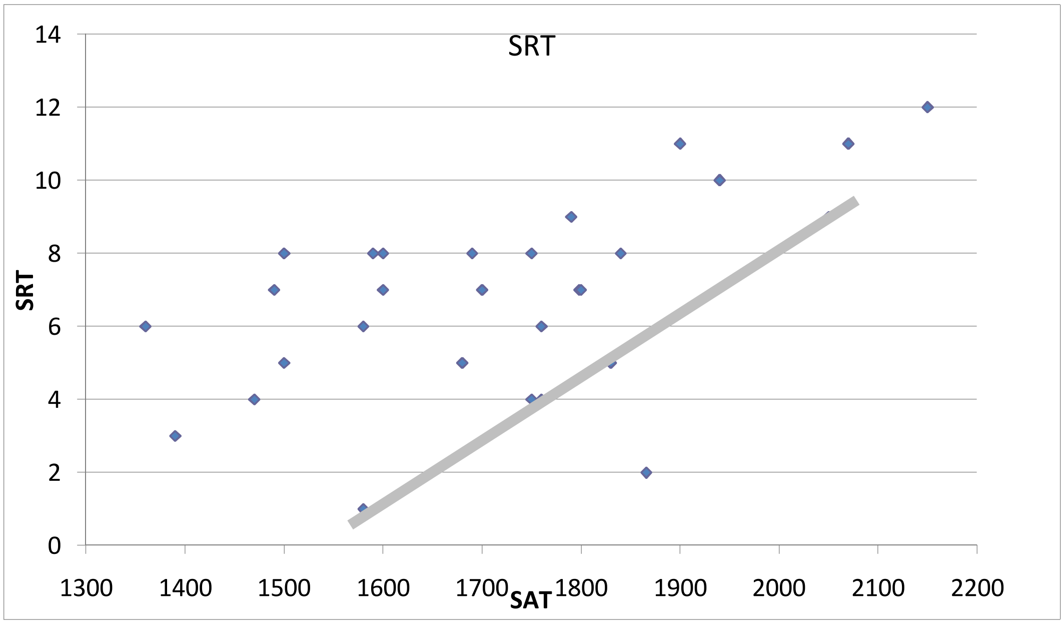

Figure 4.2 Graphical Representation of performance model for SAT scores and SRT scores, each being HLT and BPR, respectively. The line represents the resource demand function. An outlier can be seen to the right of the line.

The third BPR we examine is the Math TAKS. Figure 4.3 presents the Math TAKS data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource on the y-axis. To represent the lower boundary of the ditribution, a piecewise function was necessary to properly incorporate all students that were both high and low performers. The first half has a linear equation of $y=.32x+1808.7$ at $x<1600$ and $x>1600$ is $y=1.45x-205.8$. Also, one can see that one outlier does exist with a SAT score of 2070, and that student over performed relative to the RDF.

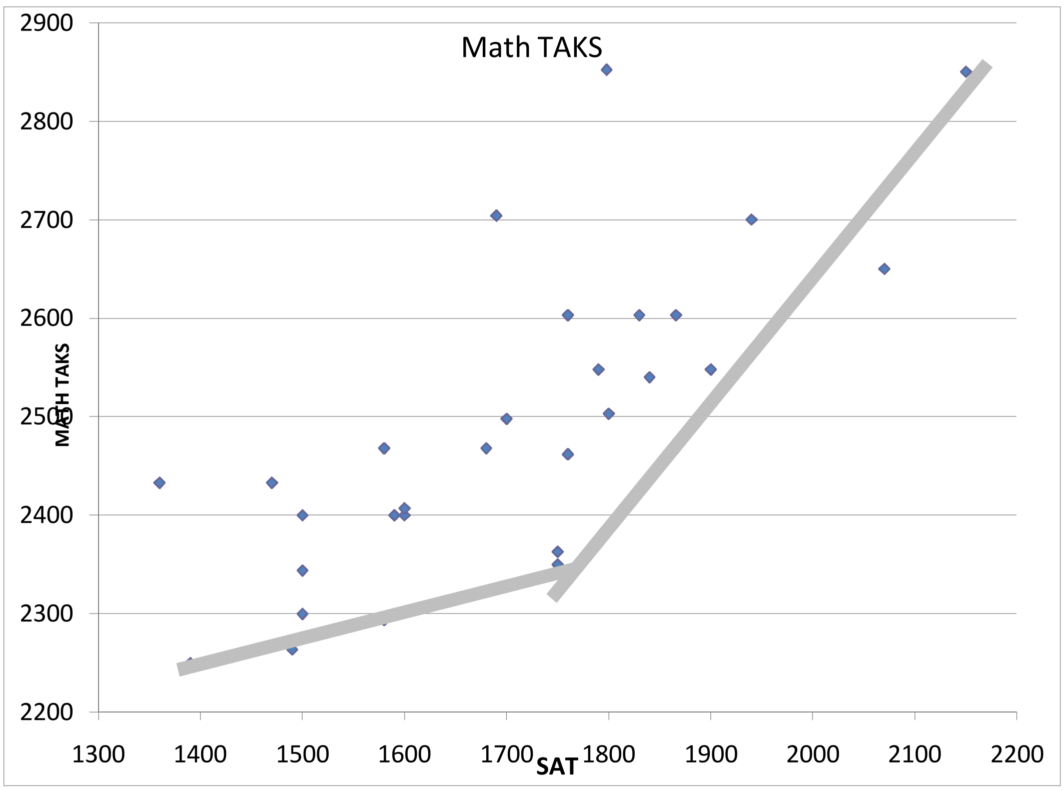

Figure 4.3 Graphical Representation of performance model for Math TAKS scores and SAT scores each being BPR and HLT, respectively. The lines represent the resource demand function that is modeled as a piecewise fit. One outlier point can be seen.

Figure 4.4 presents the ELA TAKS data with the high level performance (SAT scores) plotted on the x-axis. It was necessary to break it up the RDF into a piecewise function. However, the piecewise function was not able to include two outliers in the group. One of the outliers had a SAT score of 1900 and another had a score of 2090, which meant these two over performed the RDF. The equation for the RDF is y=.68+1087.11 (x<1880) and (x>1880) is y=1.27x-11.9. It is also possible that the RDF is actually the other single, thin line, in which case there are no outliers, where the RDF is y=.78x+825.8. To some degree, these RDFs are subjective due to the relatively small amount of data, but for the time being, we will use the first set of lines as the RDF.

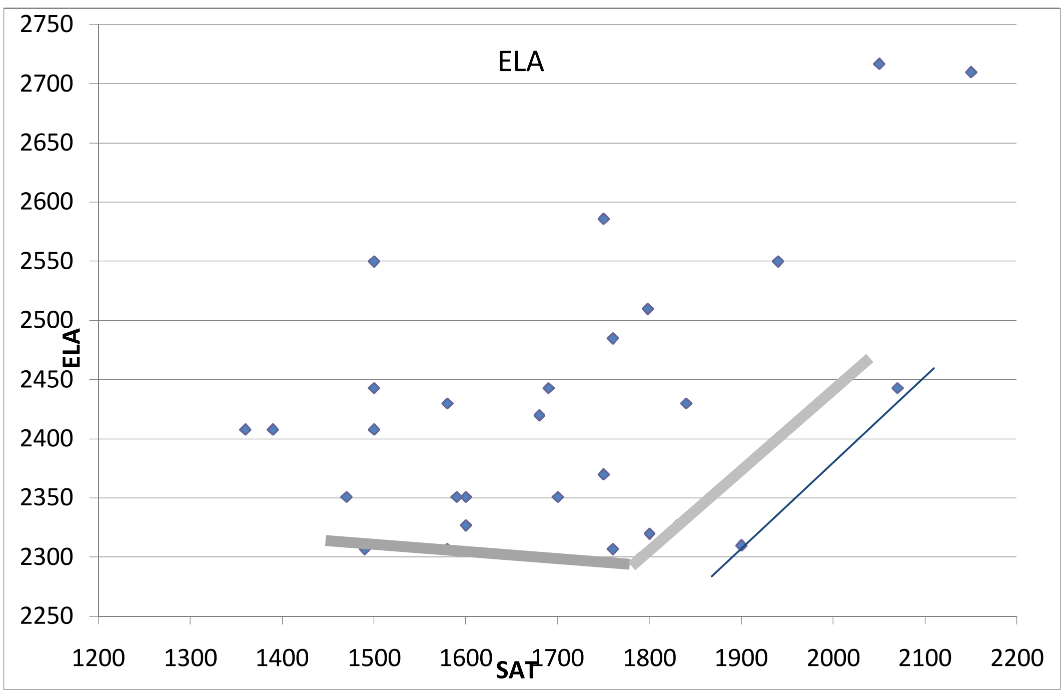

Figure 4.4 Graphical Representation of performance model for ELA TAKS scores and SAT scores each being BPR and HLT, respectively. The resource demand function is modeled as a piecewise fit with two domains and two outlier points. An alternative RDF is drawn as well as a single, thin line.

Figure 4.5 presents the AP-Physics B data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource on the y-axis. The resource demand function has 4 students very close to or on the curve. However, we see that there is one outlier in the graph. The corresponding linear equation for the RDF is y=.02x+51.99.

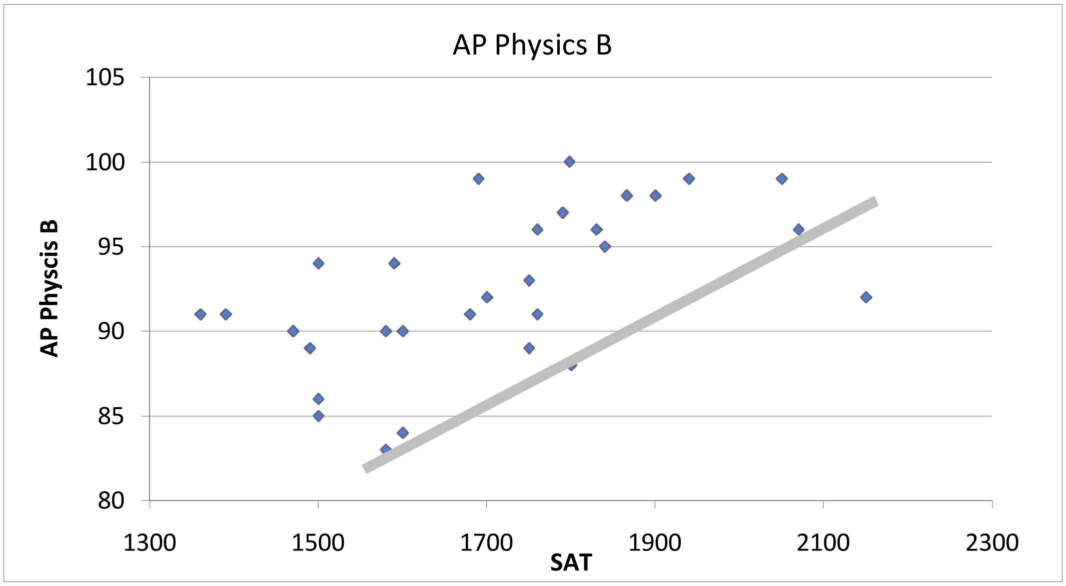

Figure 4.5 Graphical Representation of performance model for SAT scores and AP Physics grades, each being HLT and BPR, respectively. The line represents the resource demand function. An outlier can be seen to the right of the line.

The sixth BPR we examine is the Science TAKS. Figure 4.6 presents the Science TAKS data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource on the y-axis. The resource demand function here was placed at the lower bounds of the data set and has three students lying directly on the curve. The RDF was placed at the extreme lower bound of the BPR data for those individuals. The corresponding linear equation for the RDF is y=.92x+620.04.

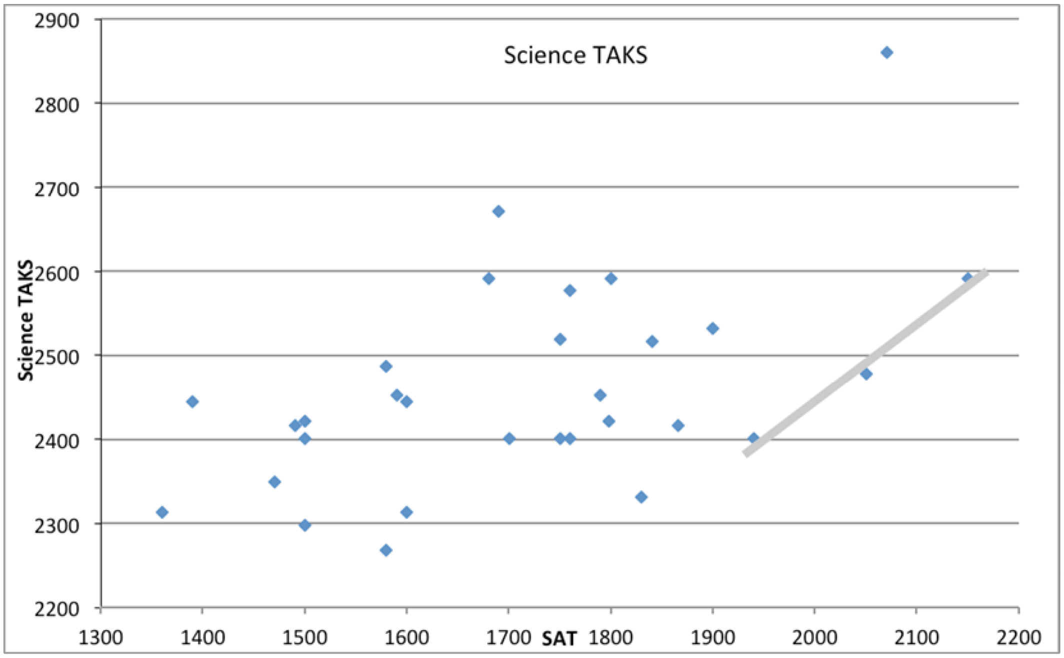

Figure 4.6 Graphical Representation of performance model for Science TAKS scores and SAT scores each being BPR and HLT, respectively. The line represents the resourse demand function.

Figure 4.7 presents the average math grades data with the high level performance (SAT) plotted on the x-axis and the basic performance resource on the y-axis. The RDF and has four students lying on the curve. The corresponding linear equation for the RDF is y=.02x+48.1.

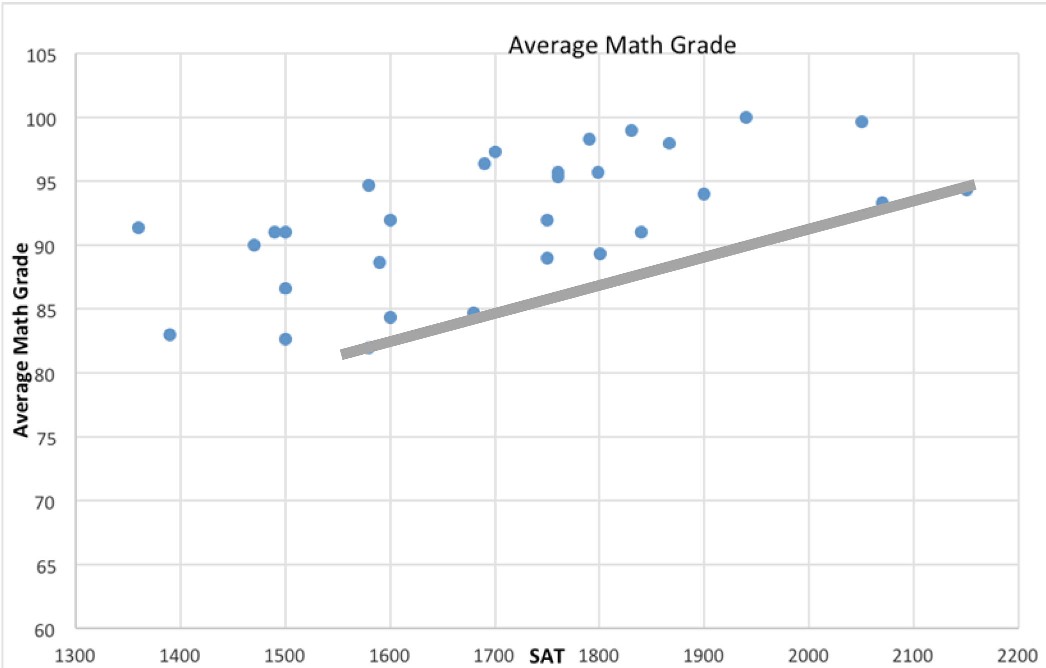

Figure 4.7 Graphical Representation of Performance model for average math grades and SAT scores each being BPR and HLT, respectively. The line represents the resource demand function.

The eighth BPR that was examined was the average science grades. Figure 4.8 presents the average science grades data with the high level performance (SAT scores) plotted on the x-axis and the basic performance resource on the y-axis. The resource demand function was placed at the lower ends of the data points. Here the curve lies directly on three student grades. The RDF was placed at the extreme lower bound of the BPR data for those individuals. The corresponding linear equation for the RDF is y=0.02+57.3.

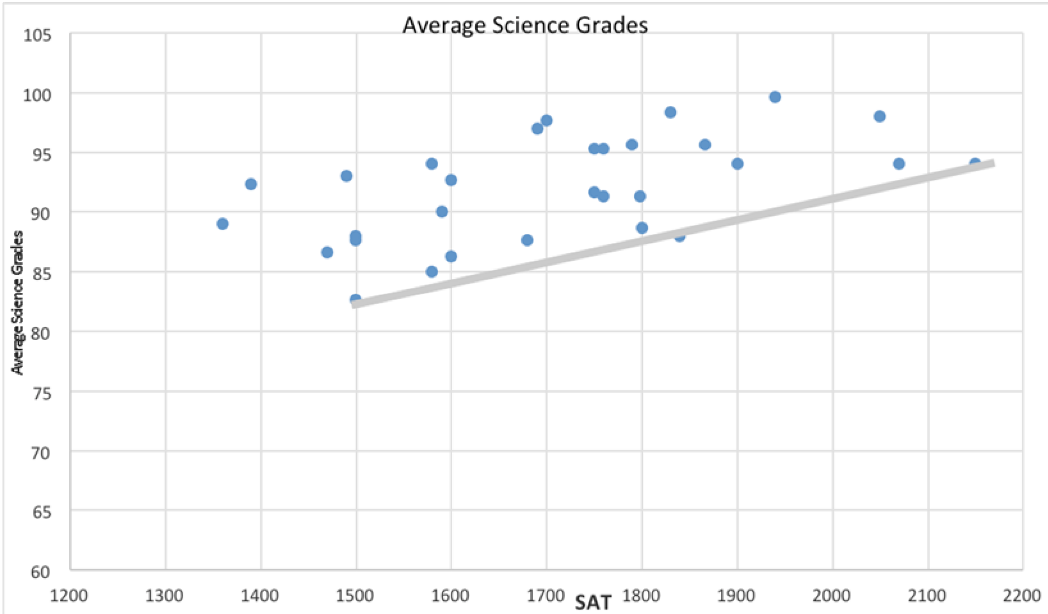

Figure 4.8 Graphical Representation of performance model for average science scores and SAT scores each being BPR and HLT, respectively. The line represents the resource demand function.

4.5 Interpreting the SAT model

Using the resource demand functions, student SAT performance predictions were made for each subject. The relationship between the NCRA model based SAT predictions and actual SAT scores are shown in figure 4.9. It is interesting to note that according to the College Board website [http://professionals.collegeboard.com/testing/sat-reasoning/scores/sat-data-tables] the standard error of difference can be taken into account if there is a 60 point difference. There is no statistical difference in the ability of a student who for example scores a 450 and 510. Therefore, 14 students fall within that range which means that the NCRA was able to predict HLT performance with very statistical accuracy for 63% of the students.

There are 11 students whose NRCA predicted SAT values are either being overestimated or underestimated by the current model. In the case that students that were found to have overestimated SAT values, we suggest that they likely had a performance resource that was not included in the study. That is to say that the resources for which we had data indicate that the student should achieve a certain SAT score, but they scored lower. In GSPT, this suggests that there was another BPR not included in the model. And it was that BPR which was the one that was really the factor that limited the student performance.

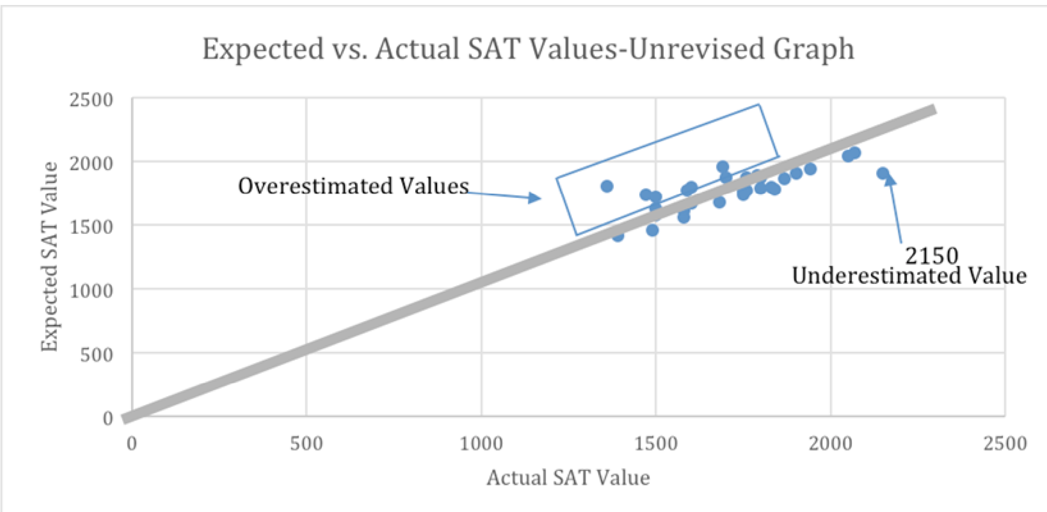

Figure 4.9 Relationship between Actual SAT scores and NRCA predicted SAT performance values-non-normalized

For the cases of underestimated values, the quantity of limiting resources may not have been not the true measure of that resource for that student. For example, if one looks at figure 4.9, one student received a score of 2150, as pointed by the arrow in the graph. According to our model, this student's limiting resource should be AP Physics B. However, by looking at figure 4.2, we see that 2150 sits below the resource demand function, and that student was the outlier. Even though the RDF would suggest that the student should have had a lower score, the student scored higher. This can be explained if the student's grade in AP Physics B is not a realistic reflect of their ability (maybe the student did not take the class seriously, had a bad days on exam days, etc.) so that that student underperformed in the AP Physics B course. Therefore, we chose the next limiting resource as the "true" limiting function. We did this for all students who were outliers assuming that the measure of that BPR for the students was not a correct measure. With that change we can recalculate the expected SAT scores.

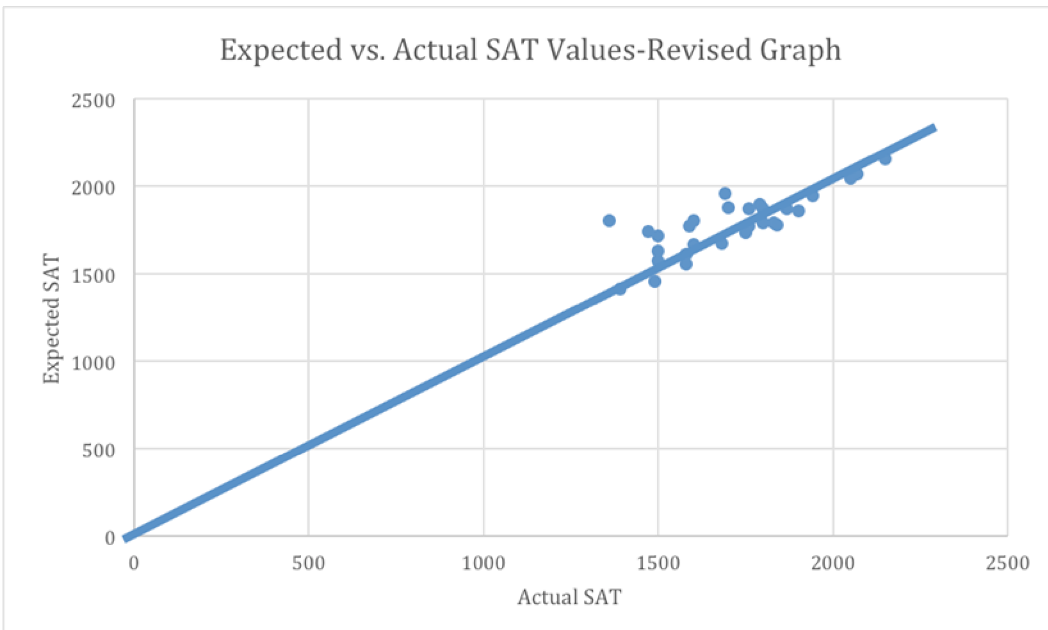

Figure 4.10 Relationship between Actual SAT scores and NRCA predicted SAT performance values

In figure 4.10, we see that the method that we used was successful in being able to predict for 70% of the students. That is to say, for 70% of the students (21/30) the NCRA model yields a predicted SAT score that is within 60 points of the actual SAT score. The remaining 30% of the students were students for whom the current model did not work within the limit of validity of the SAT. One possible reason for this is that we used a total of only 8 basic performance resources to develop our current model. This group of students may have had had other performance resources that we do not include or measure, and it was one of these that limited the students to a score on the SAT that was lower than predicted.

4.6 Discussion

Kondraske [2011] states that a definition for model is ñthe most appropriate misrepresentations of the truth that allows one to accomplish something useful.ò This implies that a model only provides us with a limited view on what resources are being actually utilized. Clearly, a studentøs performance on the SAT depends on many different basic performance resources. Our study has implications on what resources a student will use during the SAT exam. Figure 4.10 demonstrates that there is a direct correlation between the values that the students received and the values that the students were expected to receive based on the NRCA model. The correlation between these two values was found to be $r^2 = 0.64$, N=30. Figure 4.10, also shows that there were eleven data points that were over predicted. These over predictions can be explained by seeing that the 8 BPRøs used in this study are not the limiting factors for these students. Some other resource must exist that was not measured quantitatively.

Table 4.1 was constructed to show the students and their respective limiting factors

Student	Basic Performance Resource
Student 1	ELA TAKS
Student 2	MATH TAKS
Student 3	SCIENCE TAKS
Student 4	MATH TAKS
Student 5	SRT
Student 6	PHYSICS
Student 7	MATH TAKS
Student 8	MATH TAKS
Student 9	MRT
Student 10	MATH TAKS
Student 11	MRT
Student 12	ELA TAKS
Student 13	ELA TAKS
Student 14	SRT
Student 15	SRT, ELA TAKS
Student 16	SRT
Student 17	SCIENCE
Student 18	MATH TAKS
Student 19	PHYSICS
Student 20	MRT
Student 21	MATH TAKS
Student 22	MATH TAKS

Table 4.1-Continued

Student 23	MATH
Student 24	ELA TAKS
Student 25	SRT
Student 26	MATH
Student 27	MRT
Student 28	PHYSICS AND MATH
Student 29	MATH TAKS
Student 30	SRT

Here we see that only 4 students had their spatial ability as a limiting BPR. This is consistent with previous studies [Wai et al., 2009] that spatial ability doesn't play an essential role in how well a student will perform on the SAT. The BPR that was the limiting factor for the largest number of students is the Math TAKS with 9 students. This implies that math ability (as measured by the TAKS) did play a major role on how well a student was going to perform on the SAT. The SRT and ELA TAKS also played a big role on how well a student was going to perform, being the limiting factor for 6 and 5 students, respectively.

4.7 Generalized Approach to NRCA

Nonlinear Casual Resource Analysis (NRCA) is a method for determining the performance of a HLT (Higher Level Task) supported by a BPR (Basic Performance Resources) in the field of education. We know that using select basic performance resources, such as school grades and state assessments such as the TAKS test and using these resources in a student's test taking ability in the SAT, we can determine a high correlative value in predicting student's SAT value against their actual SAT value.

There are specific studies that show there is generalized success in using these methods in other fields of research. [Kondraske et al., 2002]

In our previous section, we demonstrated that using a series of basic performance resources, we could determine which would be the limiting factors for a studentφs success in performing a high level task such as the SAT. However, we want to see how the theory would predict other high level tasks, and whether the predictions and models are consistent from one group to another. In this section, we examined other basic performance resources that were taken by two groups of students, engineering magnet students and non-magnet students. We again took several BPRφs and plotted them against a state assessment test that was taken in the spring of 2012 as the HLT. From the two groups of students there were two resources that were independent of the assessment available from the school district: Lawsonφs Test of Scientific Reasoning (SRT) and the Mental Rotation Test. The other resources were their class grades; however, since their individual classes were geared towards their perspective class types and taught by different teachers we canφt use them as a generalized BPR.

4.8 Methodology

The target population for this study included high school students in 11th grade taking a Pre-AP Physics course. The accessible population included high school students enrolled at United High School. The sample population for this study was drawn from Magnet students and non-magnet students enrolled at United High School. The accessible target populations will be the same for all presented in this section. All data presented in this chapter was also collected ethically via the rules put forth by the Institutional Review Board (IRB) present at United High School, and only data from students and parents who signed the informed consents is presented here in conjunction with regulations at UISD.

The method for selecting the sample was semi-convenient. Our sample size is 117 students who were juniors at United High School in Laredo, Texas. The sample size is divided into 53 magnet students and 64 non-magnet students. During the 2012 and 2013 school year, both groups of students were administered the TAKS test for science, math, and English as part of their graduation requirement. The MRT and the SRT were administered towards the end of the month of April after the student took the TAKS .

4.9 Data

For the high level task, we take three measures of performance: Math-TAKS, Science TAKS and their respective physics grades. The basic performance resources that are being used in this section are the MRT, SRT, and ELA-TAKS. However, now we create one plot for each population, magnet and non-magnet, so that we can compare the RDFs of the two populations.

Figure 4.11 presents the MRT data with the HLT (Math ï TAKS) plotted on the x-axis and the basic performance resource (MRT) on the y-axis for the magnet students. The distribution shows no strong correlation between MRT and the Math-TAKS. There is lower bound of data that suggests that spatial ability did play a role in the threshold for student performance on the Math-TAKS for five students. For this particular RDF, two lines were required to make a piecewise function. The first half has a linear equation of $y=.01x-24.29$ $x<2790$ and the second, for $x>2790$, is $y=.18x-486.8$.

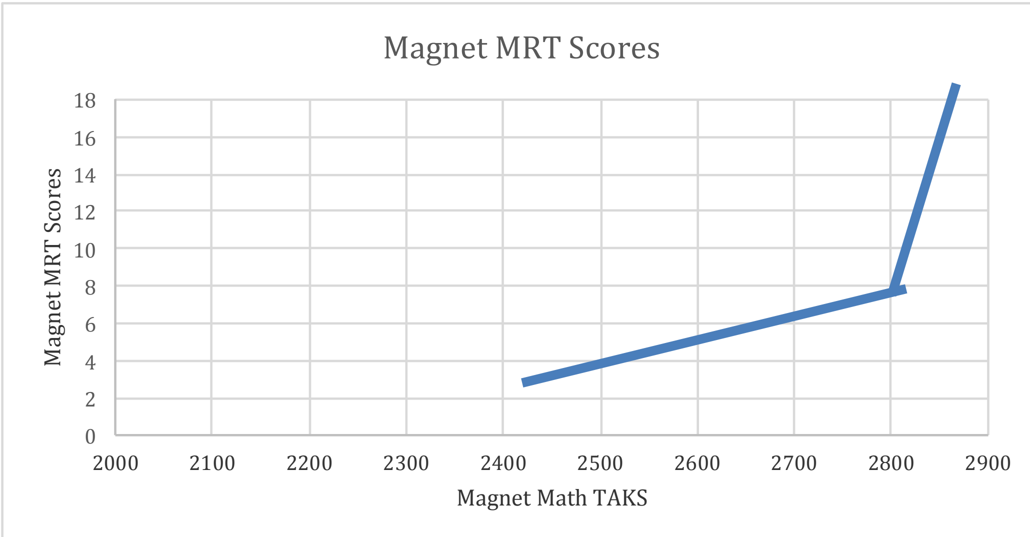

Figure 4.11 Graphical Representation of performance model for Magnet MRT Scores and Magnet Math-TAKS scores.

Figure 4.12 presents the MRT data for the students with HLT (math-TAKS) plotted on the x-axis and the MRT data on the y-axis. Spatial ability was the limiting factor for 3 students. The corresponding equation for the RDF is y=.03x - 64.4.

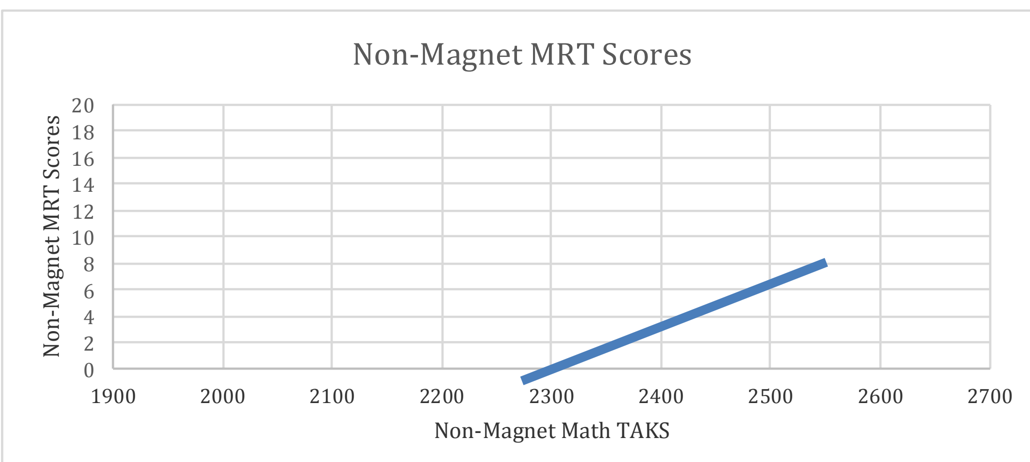

Figure 4.12 Graphical Representation of performance model for non-magnet mrt scores and non-magnet math-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.13 presents the SRT data for the students with the high level task (math-TAKS) plotted on the x-axis and the SRT data on the y-axis. The distribution shows a correlation that exists between the two variables, which is to be expected since the TAKS test was designed to test a studentȇs scientific reasoning skills (as discussed in Chapter 2). SRT played a limiting role for 3 students. The corresponding linear equation for the RDF is y=.013x-30.7.

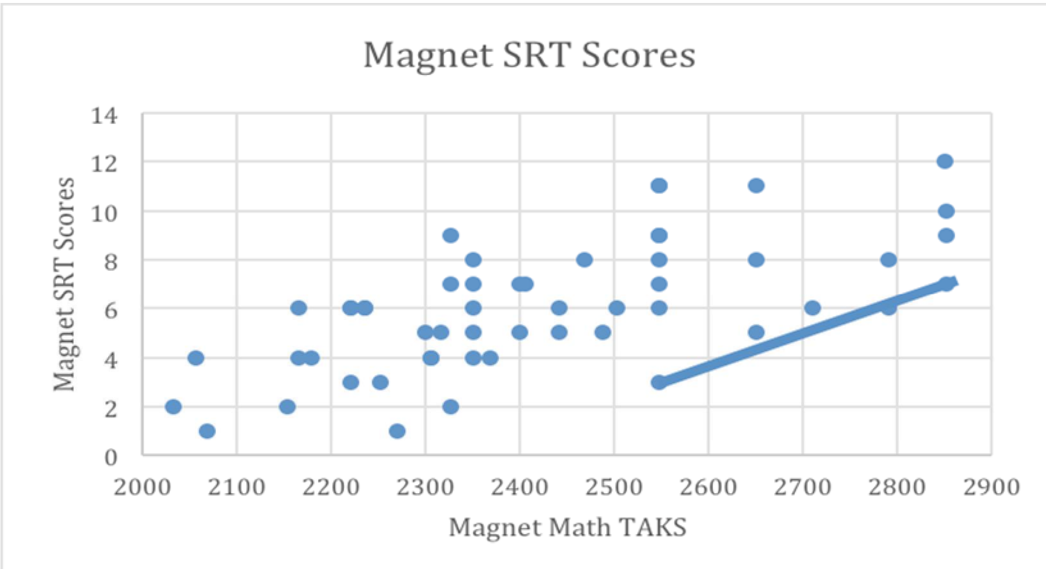

Figure 4.13 Graphical Representation of performance model for magnet srt scores and magnet math-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.14 presents the SRT data for non-magnet students with the HLT (math-TAKS) plotted on the x-axis and the SRT data on the y-axis. Scientific reasoning did limit six student performances, and there is one outlier. The RDF was placed at the lower bound of the BPR data, and the corresponding linear equation for the RDF is y=.03x-76.05.

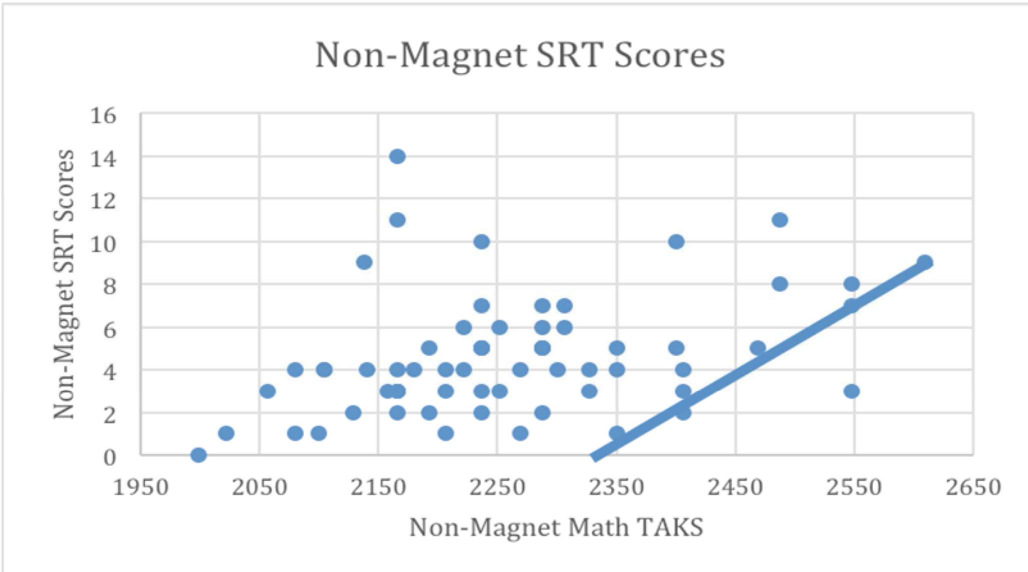

Figure 4.14 Graphical Representation of performance model for non-magnet scores and non-magnet math-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.15 presents the ELA-TAKS data for magnet students with the high level task (Math-TAKS) plotted on the x-axis and the ELA-TAKS data on the y-axis. The distribution shows no correlation between the magnet studentsôMath-TAKS and their respective ELA-TAKS scores. ELA-TAKS did limit 5 students, with one outlier. The RDF was placed at the lower bound of the BPR data, and the corresponding linear equation for the RDF is y=.34x+1445.4.

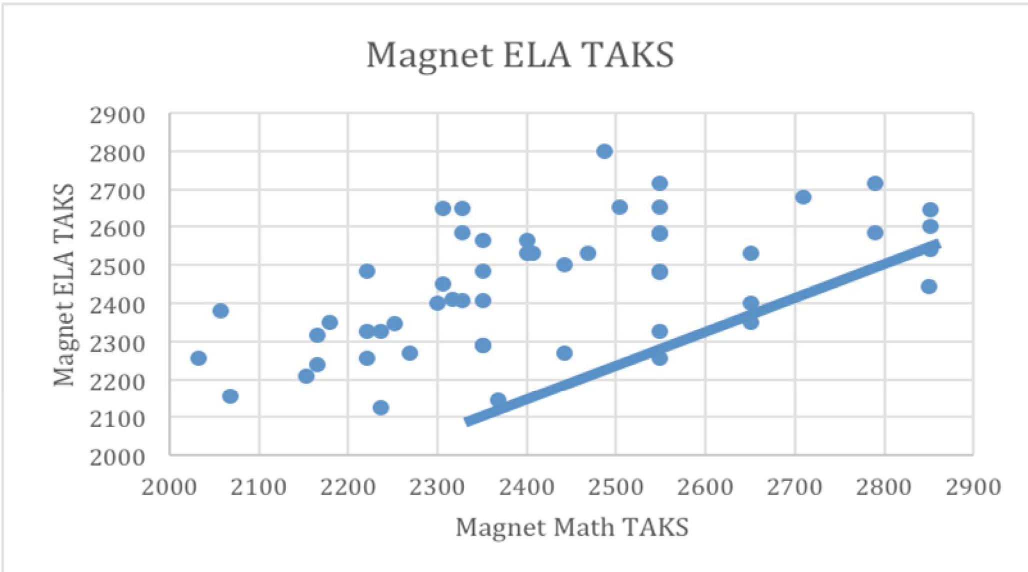

Figure 4.15 Graphical Representation of performance model for magnet ELA-TAKS scores and magnet math-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.16 presents the ELA-TAKS data for non-magnet students with the higher level task (math-TAKS) plotted on the x axis and the ELA-TAKS data on the y-axis. ELA-TAKS did play a role in 2 studentsôperformances. The RDF equation is y=.75x+442.5.

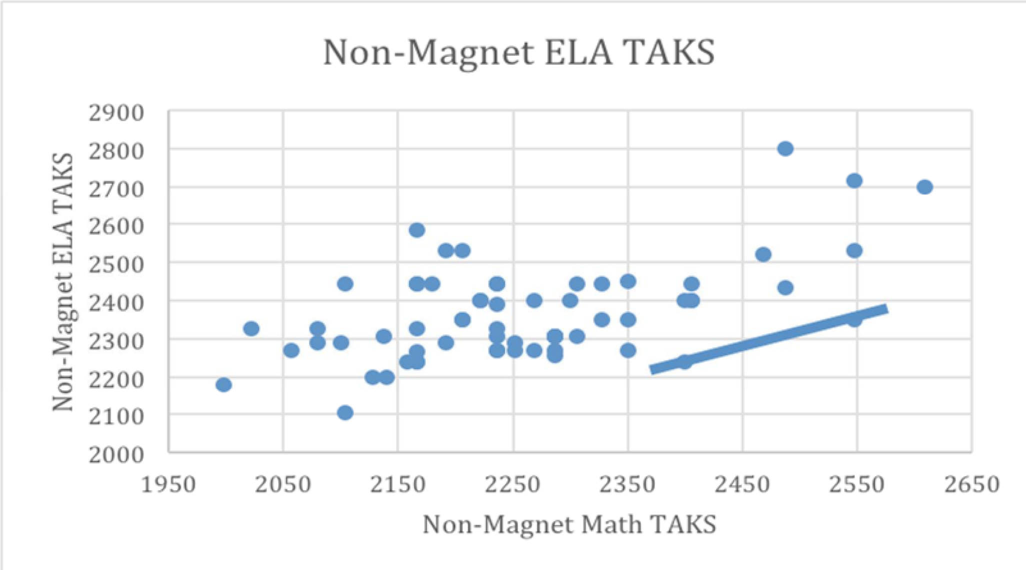

Figure 4.16 Graphical Representation of performance model for non-magnet ELA-TAKS scores and non-magnet math-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.17 presents the MRT data from magnet students with the high level performance (Science ï TAKS) plotted on the x-axis and the basic performance resource (MRT) on the y-axis. There is lower bound of data that suggests that spatial ability did play a limiting role for student performance on the Science-TAKS for 3 students. The RDF is y=.01x-20.11.

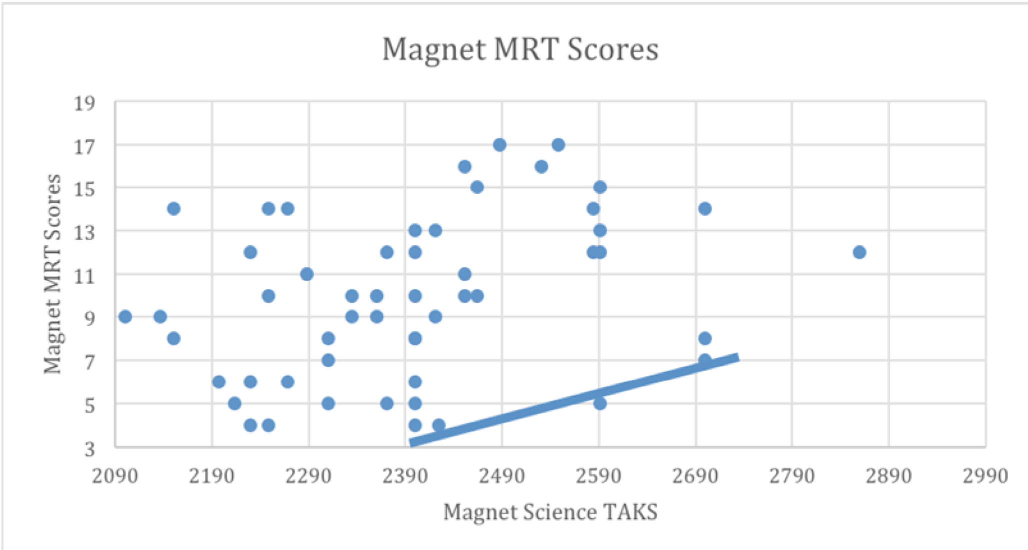

Figure 4.17 Graphical Representation of performance model for Magnet MRT Scores and Magnet science-TAKS scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.18 presents the MRT data for the students with the HLT (Science-TAKS) plotted on the x axis and the MRT data on the y-axis. The distribution shows no correlation between the spatial ability of students and their performance in their Science-TAKS scores. Spatial ability did play a role in 7 studentsôperformances. The corresponding linear equation for the RDF is y=.02x-31.85.

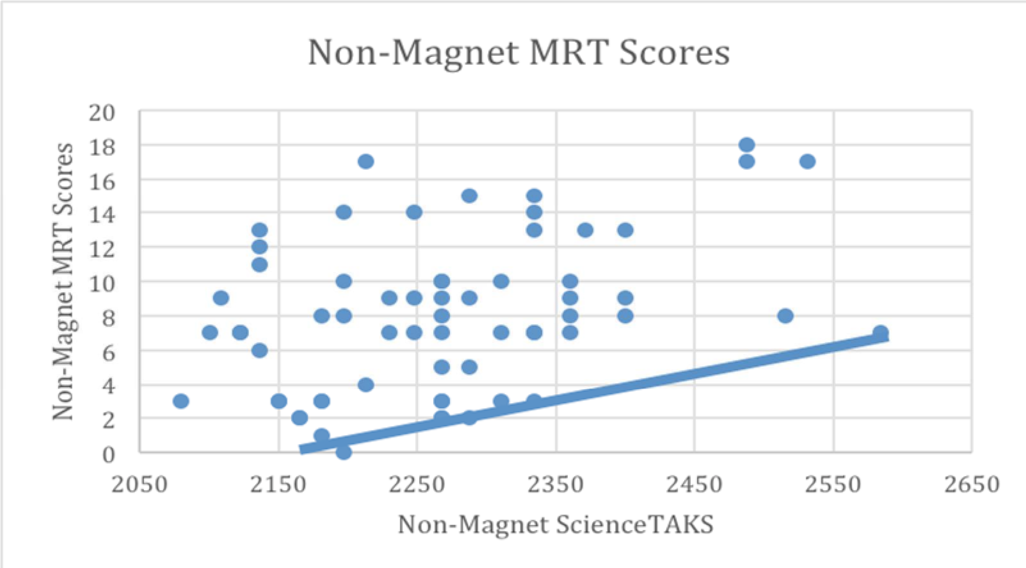

Figure 4.18 Graphical Representation of performance model for Non-Magnet MRT Scores and Non-Magnet Science-TAKS scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.19 presents the SRT data for the magnet students with the HLT (Science-TAKS) plotted on the x-axis and the SRT data on the y-axis. The distribution shows a correlation that exists between the two variables of magnet students SRT and Science-TAKS, which is to be expected since the TAKS test was designed to test a studentꞌs scientific reasoning skills, as discussed in chapter 2. SRT played a limiting role for 5 students. The corresponding linear equation for the RDF is y=.02x-40.73.

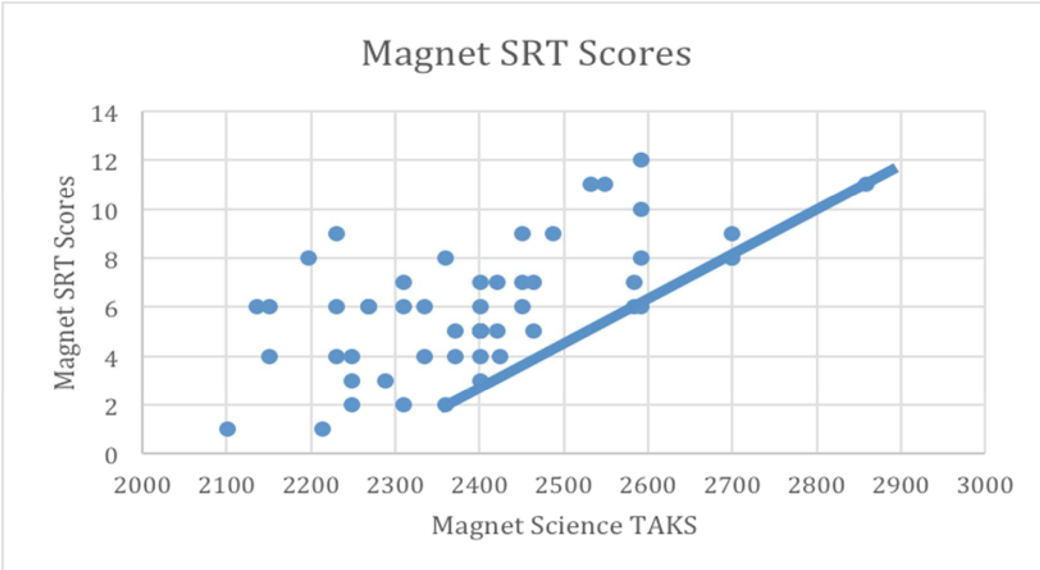

Figure 4.19 Graphical Representation of performance model for non-magnet SRT scores and non-magnet science-TAKS scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.20 presents the SRT data for the non-magnet students with the HLT (Science-TAKS) plotted on the x-axis and the SRT data on the y-axis. SRT had a limiting role for 2 students, with one outlier. The corresponding equation for the RDF is y=.03x-73.17.

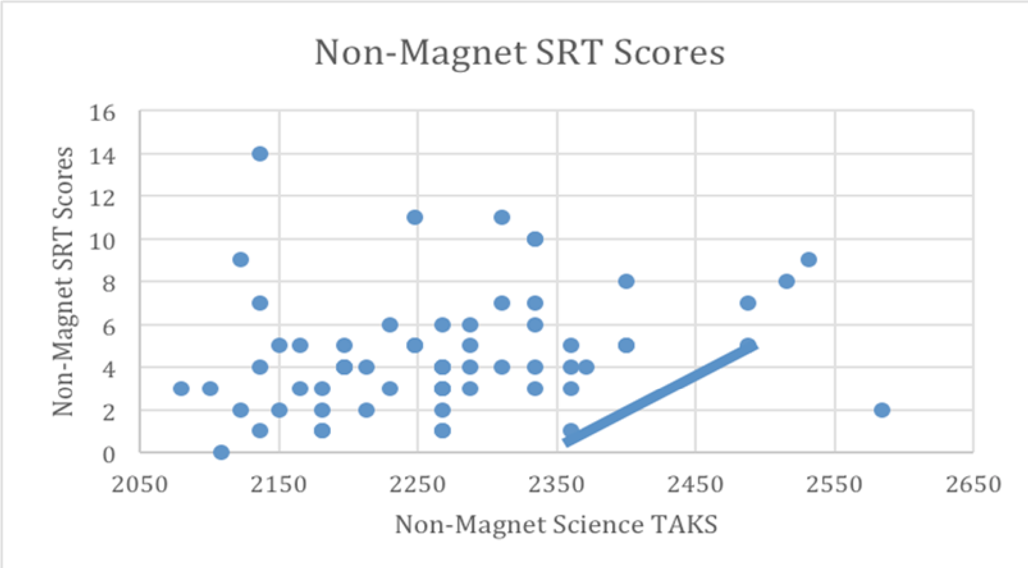

Figure 4.20 Graphical Representation of performance model for non-magnet srt scores and non-magnet science-TAKS scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.21 presents the ELA-TAKS data for the students with the HLT (Science-TAKS) plotted on the x-axis and the ELA-TAKS on the y-axis. ELA-TAKS had a limiting effect for two students, with one outlier. The corresponding linear equation for the RDF is y=1.02x-308.

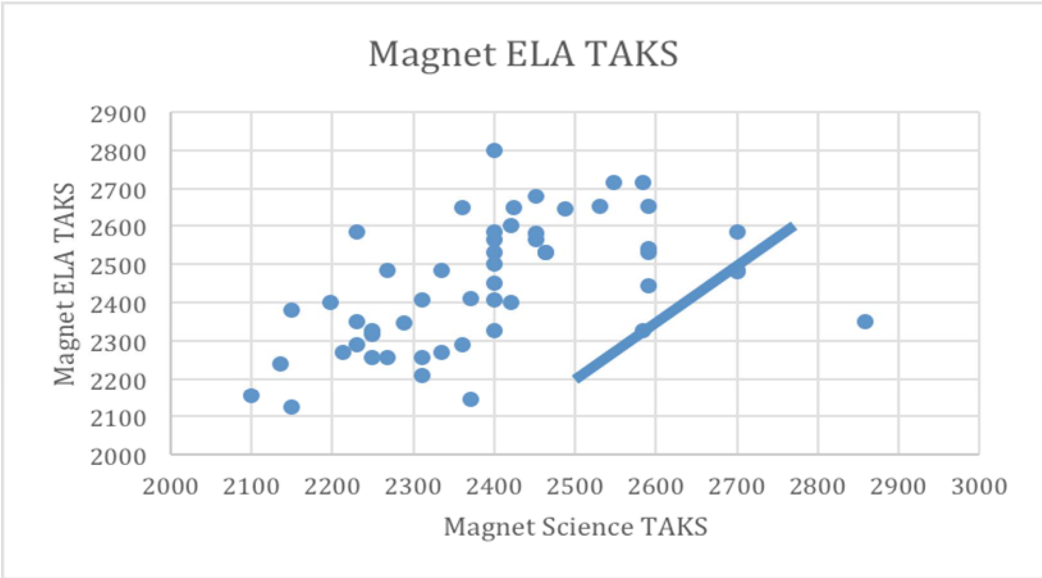

Figure 4.21 Graphical Representation of performance model for magnet ELA-TAKS scores and magnet science-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.22 presents the ELA-TAKS data for the students with the higher level task (science-TAKS) plotted on the x-axis and the ELA-TAKS on the y-axis. ELA-TAKS had a limiting effect for five students. The corresponding equation for the RDF is $y=.30x+1495.21$.

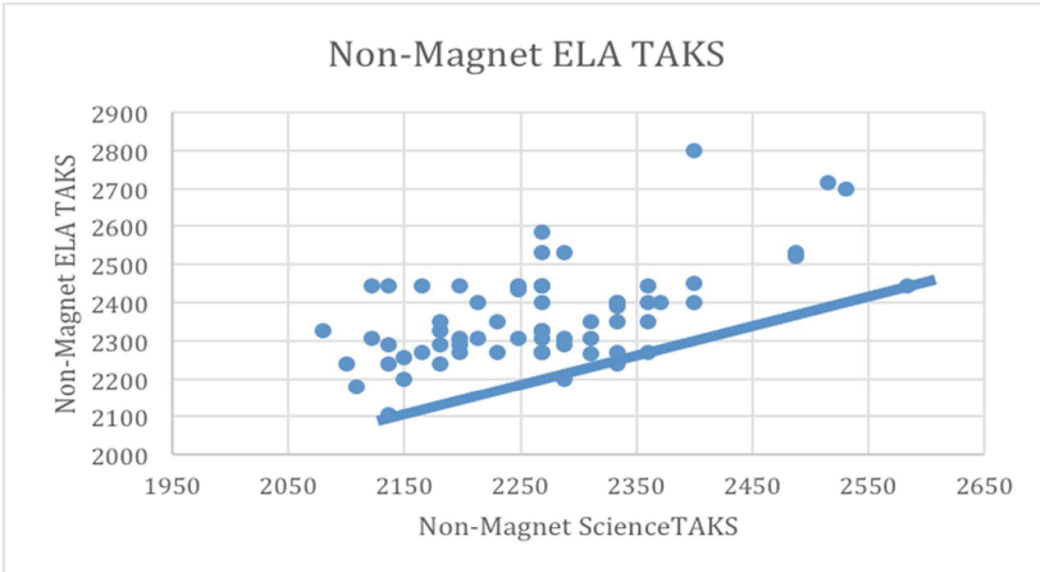

Figure 4.22 Graphical Representation of performance model for non-magnet ELA-TAKS scores and non-magnet science-taks scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.23 presents the MRT data for the magnet students with the HLT (physics) plotted on the x-axis and the MRT on the y-axis. MRT had a limiting effect for three students, with one outlier. The linear equation for the RDF is y=.4x-31.4.

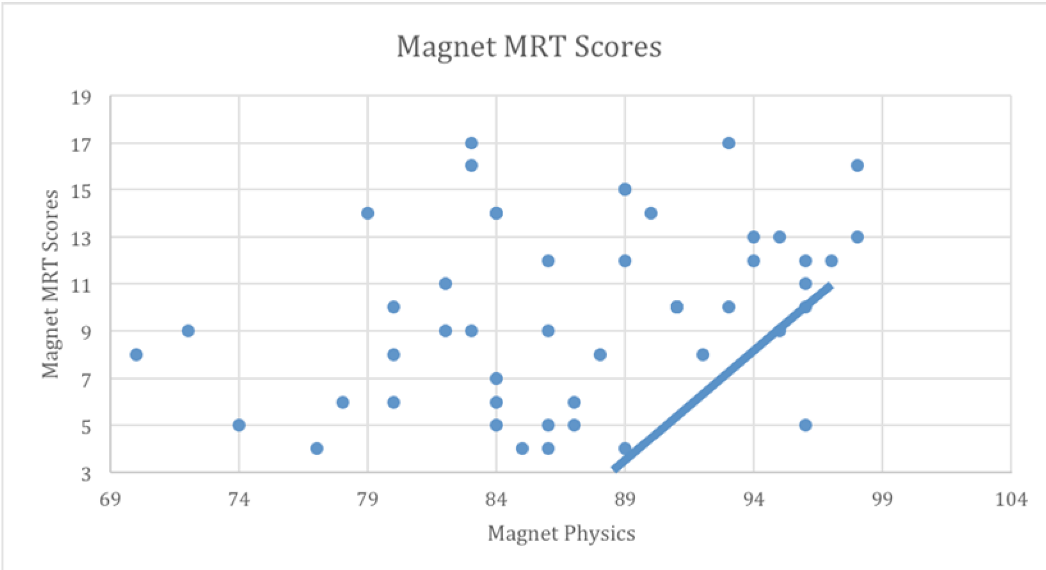

Figure 4.23 Graphical Representation of performance model for Magnet MRT Scores and Magnet Physics scores each being BPR and HLT, respectively. The line represents the resource demand function

Figure 4.24 presents the MRT data for the non-magnet students with the higher level task (physics) on the x-axis and the MRT on the y-axis.. The BPR curve lies directly over the performance for 3 students and the corresponding linear equation for the RDF is y=x-92.

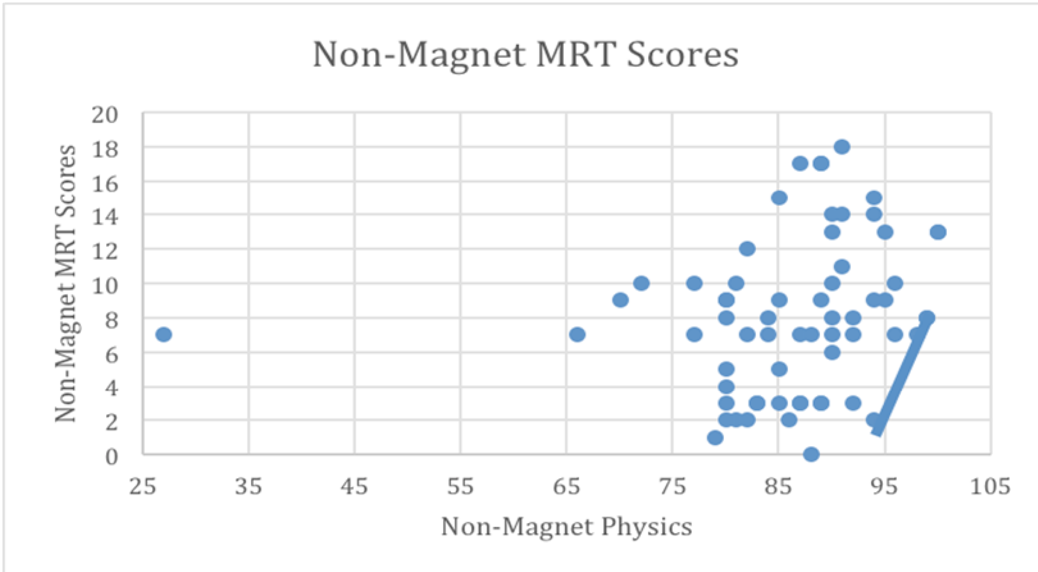

Figure 4.24 Graphical Representation of performance model for Non-Magnet MRT Scores and Non-Magnet Physics scores each being BPR and HLT, respectively. The line represents the resource demand function

Figure 4.25 presents SRT on the y-axis and HLT (physics) on the x-axis for the magnet students. This required a piecewise RDF, with $x<91$, $y=.11x-4.35$ and $x>91$ $y=1.38x-129.72$.

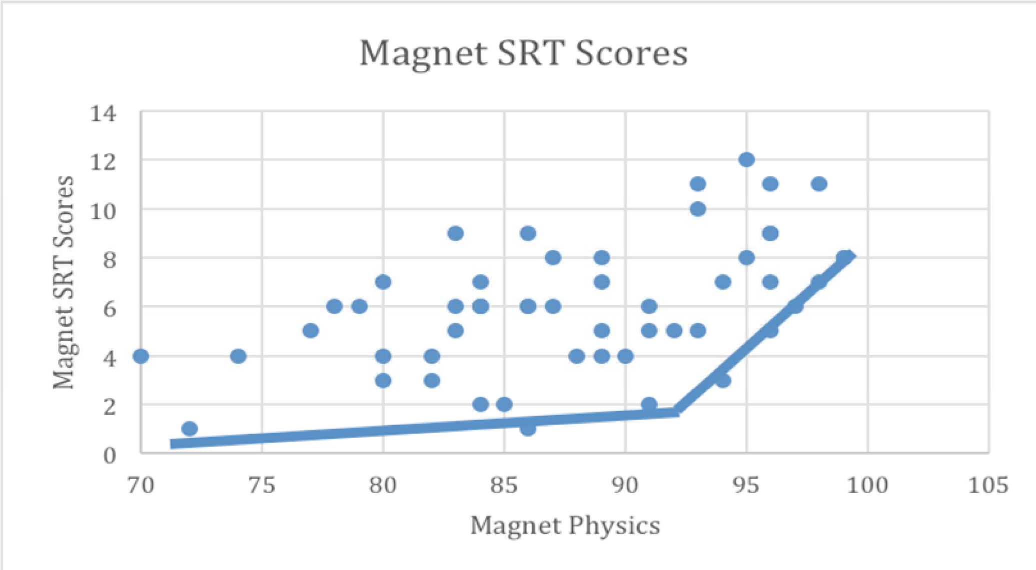

Figure 4.25 Graphical Representation of performance model for magnet srt scores and magnet physics scores each being BPR and HLT, respectively. The line represents the resource demand function.

Figure 4.26 presents the SRT data on the y-axis with physics as the HLT on the x-axis, for the non-magnet students. The corresponding RDF is y=0.5x-47.

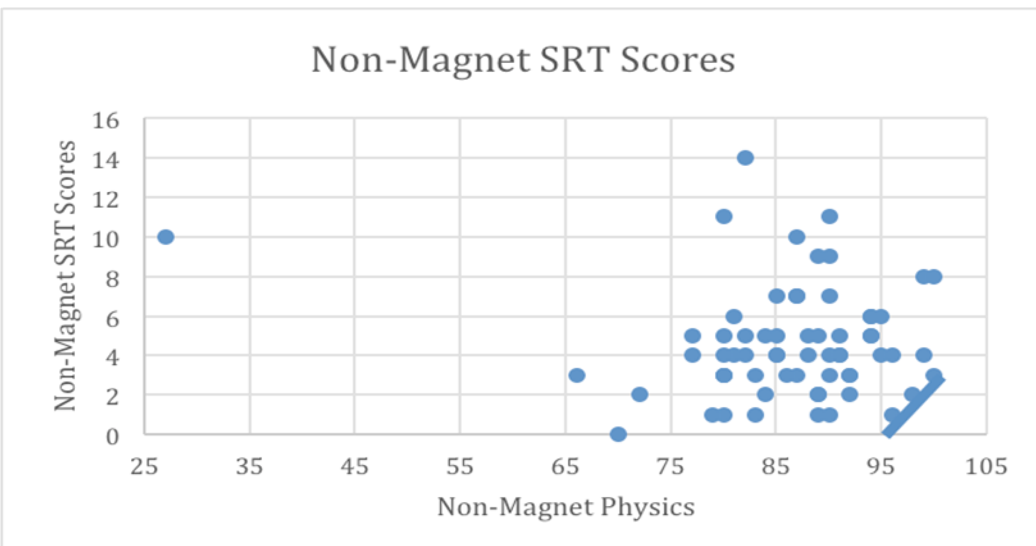

Figure 4.26 Graphical Representation of performance model for non-magnet SRT scores and non-magnet physics. The line represents the resource demand function.

The ELA-TAKS scores are plotted on the Y-axis, and Physics grades are on the y-axis in figure 4.27. The RDF curve is placed directly over 8 students. The corresponding functions is y=.098x+2191.4 when x< 95, y=.02x+2349.1 when x >95.

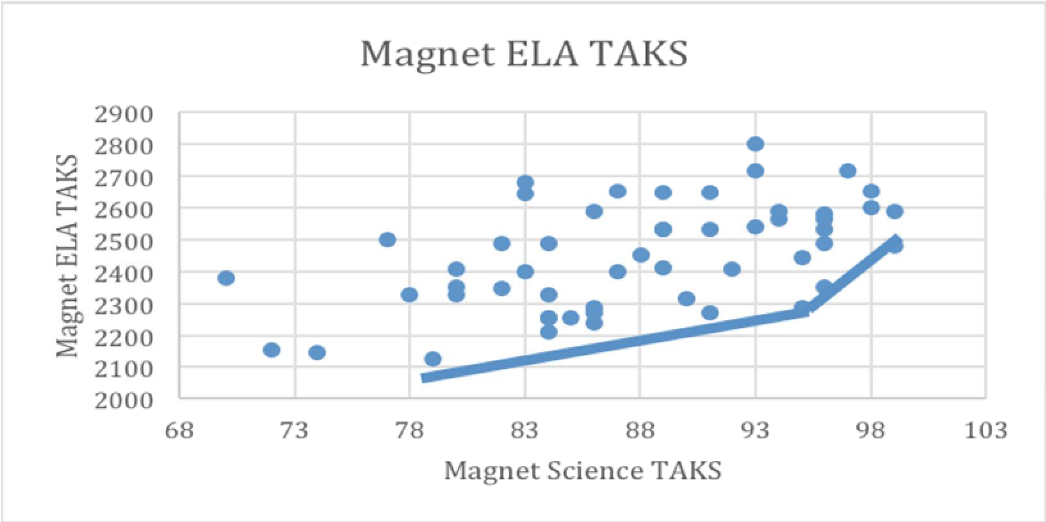

Figure 4.27 Graphical Representation of performance model for magnet ELA-TAKS scores and magnet physics scores each being BPR and HLT, respectively. The line represents the resource demand function.

The BPR for the non-magnet students is the ELA-TAKS and HLT is their respective physics grades, plotted on the y-axis and x-axis, respectively, in Figure 4.28. The BPR curve lies directly on three students with one outlier. The corresponding RDF is y=4.89x+1783.

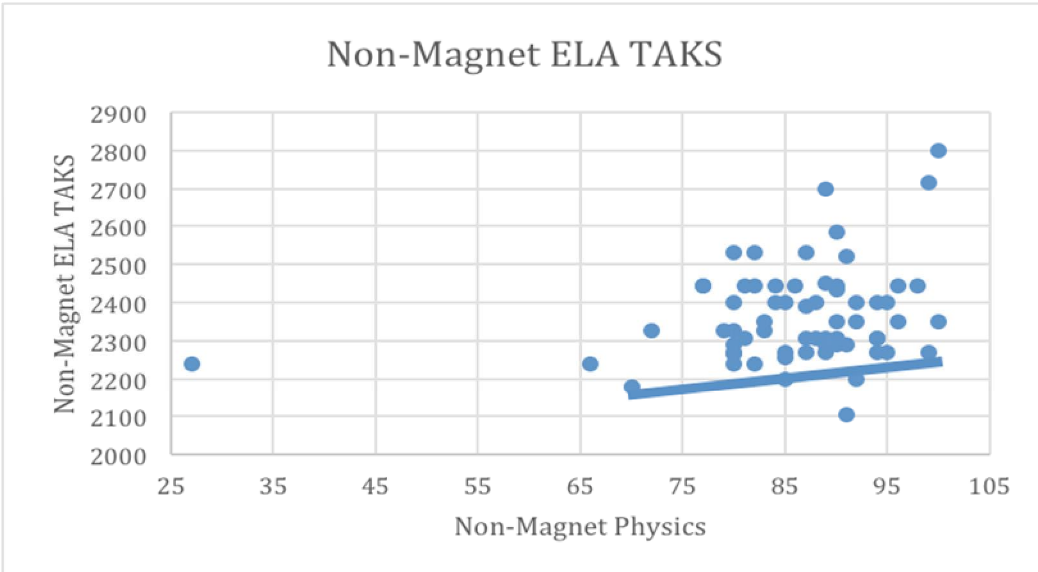

Figure 4.28 Graphical Representation of performance model for non-magnet ELA-TAKS scores and non-magnet physics scores each being BPR and HLT, respectively. The line represents the resource demand function.

4.10 Discussion

To determine if we can use the same RDFs on the two populations, we can look at figure 4.17 and figure 4.18 where the HLT is math TAKS and the BPR is spatial intelligence measured by the MRT. The corresponding equations for those figures donõt have the same slope and y intercepts. Therefore, one RDF function cannot be used for both populations and so a single NCRA model cannot describe both populations be. Another example is with physics grades as HLT using spatial intelligence as a BPR (figures 4.23 and 4.24). The corresponding equations for those figures also do not have the same linear equations, therefore, no generalizable equation can be used to describe both populations in physics.

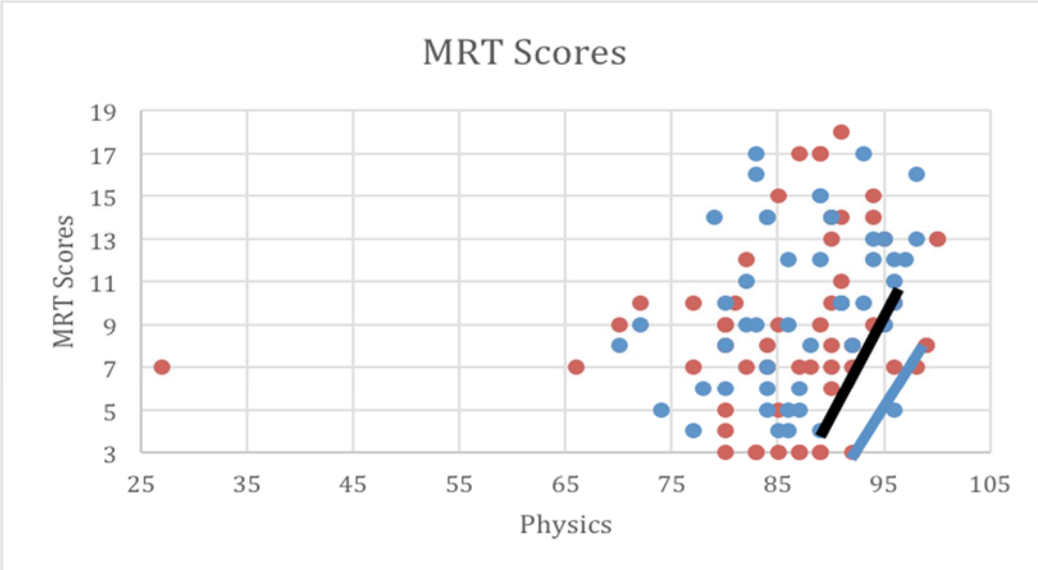

Figure 4.29 Graphical Representation of performance model for MRT scores and physics scores each being BPR and HLT, respectively. The lines represent the resource demand function for each individual group.

By looking at fig. 4.29, we see that the RDFs are not the same for both populations. However, we do note that the blue outlier lies on the RDF for the orange population (blue line). So perhaps the reason that that RDFs are not the same is because the RDF for the blue (magnet) population was constructed with insufficient data. Moreover, inspecting Figures 4.19 and 4.20, and looking at the corresponding RDFs (SRT and Science TAKS), the RDFs are not too dissimilar in slope and intercept. Therefore we cannot dismiss the possibility that with enough data one might be able to create a predictive NCRA model for student performance on state assessments like TAKS, or national tests like the SAT.

4.11 Conclusions

The first part of chapter 4 showed that a model could be created that would accurately predict the SAT scores of the students, but only on the condition that the score would be known beforehand. Therefore, a model could only be created when one knows the score of the Higher Level Task, in this case, the SAT. The question is if such a model can be applied to a different population and used to predict student performance. To investigate this, we compared RDF's for both magnet students and non-magnet students for a variety of HLTs and found that there was no general RDF's that can be applied to either population of students, with one possible exception (SRT/Science TAKS). We also found an indication that the issue may be the amount of data used to construct the RDF.

Chapter 5

SUMMARY OF RESULTS AND FUTURE WORK

5.1 Summary of Results

One major focus of the research was to investigate the relationship between spatial intelligence student achievement in their individual STEM courses and state assessment scores. In the study, the population was divided into a magnet population and non-magnet population. Since there is a cognitive assessment requirement to be accepted into a magnet program, when the students were tested the magnet students tested at a significantly higher level compared to the non-magnet students. Correlative and statistical assessments were then used to assess how the student's spatial intelligence impacted their state assessment courses and STEM courses. The results showed that the spatial ability of students correlated weakly with their science and math class grades. However, there was a significant correlation to their TAKS scores for both student populations and their spatial intelligence. Interestingly, spatial intelligence played a similar role, for both magnet and non-magnet, in the success of their state assessment scores.

In addition to the role of spatial intelligence, we investigated the role of scientific reasoning in high school student achievement. The assessment that was used in this portion of the work was Lawson's Test of Scientific Reasoning, referred to in the text as the SRT. The results showed that magnet students had a higher scientific reasoning score compared to their non-magnet counterparts. It can be inferred this could be a combination of the selection effect of the magnet program, the result of the different educational setting and the difference in the curriculum of magnet students, or a combination of both factors. Correlative analysis showed the SRT, had a significant impact on how well the students, both magnet and non-magnet, performed on their state assessment scores, which indicates that the state exams actually do measure, in part, student reasoning ability.

The next major analysis was done in chapter 3. This chapter examined the spatial intelligence of different student populations as they go from a secondary education setting to a college education setting. This chapter showed that MRT scores were consistently increasing as a student went from high school to college level physics, up through modern physics (which is a junior/senior level course). One reason for this increase is simply by taking a physics course, a student's spatial intelligence will increase. Another possibility is that students with higher spatial ability take higher level physics course, even though course grade is not strongly correlated with MRT scores. Also, the high school students who were enrolled in a pre-AP or AP physics course had similar MRT values to entering freshmen at the University of Texas at Arlington. This makes sense because these are the kind of students who will enroll in state universities in a STEM major. The major question that arises is the mechanism by which spatial intelligence is selected for in physics courses, since it does not determine grades. This suggests that the effect may be subtler that a simple correlation, with spatial intelligence acting more as a limiting factor. This led us to the work in chapter 4.

In chapter 4, we used an approach called NRCA (Non-linear resource casual analysis), which identifies what basic performance resource will be used in a high level task and which performance resource is the limiting factor that sets the level of achievement on the high level task. The high level task in this study was the SAT, and eight basic performance resources were used to determine which one was the limiting the student that set the maximum value one would expect for the SAT for a given student. We used this approach because it seems that considering spatial intelligence as a limiting factor is a more productive approach that viewing it as a controlling factor, given that there is not a strong correlation between MRT scores and physics grades. The model that was created was accurate at producing a correlation with student SAT scores; however, it was examined if this approach could be used with two different populations with the same HLT (High Level Task). This approach was not successful because it was unclear that we would be able to create Resource Demand Functions for one group that could be applied to another group. Therefore the NRCA model would not be a true predictive model since you could not use it with a new population and expect to get a reasonable answer. However, there are some indications that with much more data, robust RDFs could be created and the approach could produce predictive models

5.2 Future Work

More studies have to be conducted to examine the effect STEM courses have on a studentφs spatial intelligence. This has to be done through a wide range of STEM courses to get an accurate depiction of how a given class affects a studentφs spatial intelligence. In addition, the NRCA model should be revisited to see if a by sampling a much larger student population and by including more basic performance resources we could identify generalizable RDFφs that would work for different populations and create a model that would be truly predictive for a given high level task (not necessarily the SAT).

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Biography

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He earned a Bachelor of Science degree in Physics in 2005 and a Master of Science degree in Physics in 2008 from the University of Texas in Arlington. He became a high school teacher of physics for the United Independent School District in 2011 where he continues to teach at the magnet school.