Elasticity Theory of Learning Growth in the 21st Century

BY

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THESIS

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SUMMARY

My study provides a framework that is based on the ecological framework to understand the dynamic interrelations among various personal and environmental factors. I developed a theory in this dissertation that has the potential to include all the variables (+6000 variables) that the National Education Longitudinal Study of 2002, NELS: 2002, contains. The NELS:2002 data includes surveys from students, teachers, parents, principals, and administrators in a sequence of data collection.

The Meinshausen-Bühlmann, MB, algorithm (high-dimensional graph model) selects the variables that can predict a target variable of choice through a lasso regression process. The MB algorithm produces a graph that demonstrates the conditional dependence and independence across all the variables under study. In order to connect funding to learning, the elasticity theory analysis will provide guidelines in the process of selecting the elements that have the highest return on investment.

The framework in this dissertation provides a broad scale of data analysis and different approaches to interpret statistics based on the variable's elasticity. The theory in this dissertation provides a new approach to the analysis of complex data such as the NELS:2002 (+6000 variables, and 16179 entries). This new approach has the potential to change the traditional data analytics landscape across all industries especially in education by including the elasticity theory as an additional factor to interpret the statistical results.

Chapter 1 Introduction

The tendency to underestimate the complexity of educational cause-and-effect relationships can undermine efforts to improve educational outcomes. School administrators, parents, policymakers, and teachers' efforts to improve students' learning all make a difference. Education is an accumulating process, and therefore, in order to have successful results, one needs time, funding and efforts from all parties. The education system is a large puzzle with many pieces that are intertwined, and cannot be separated. The debate over different factors, such as class size, teacher qualifications, principal leadership, and family engagement that influence student achievement is demonstrated in over 40 years of literature. Each school of thought defends its paradigm about the best solution for education improvement. All the various formulas for success are important. After evaluating some of the literature, especially articles reporting studies regarding small class size, it becomes apparent that all of the factors combined contribute to making a successful student. In other words, promoting the interactions of all factors will turn the school into an efficient organization that not only will promote learning, but also improve students' social skills, such as personal growth.

Most members of society have a stake in education, with different goals. Parents, teachers, principals, policymakers, and researchers all agree that a student in the 21st century needs something different than what was required 50 years ago. What was considered a good education 50 years ago is no longer enough for today's market. A high school diploma 40 years ago was more than sufficient to earn a solid middle-class income and to assure good employment prospects. Today, a college degree doesn't guarantee a high-paying job. As technology is changing rapidly, the need for higher skills in math and science is becoming a necessity rather than a luxury. The globalization impact on our society is enormous, and therefore, the extra skills that a child in the early grades requires is rapidly changing and it is getting more and more challenging. According to Bryk, Gomez, Grunow, and LeMahieu (2015) “literature textbooks, previously taught in college courses, have been pushed down into high school grades; and introductory statistics that was a graduate course is now taught in middle school. The question remains, do we have enough trained teachers to cope with this challenge?” (p. 62).

The imbalance in the distribution of education resources, funds, and others are hindering the education development, impacting education quality, and increasing the illiteracy rate in poor neighborhood schools; as a result, the poor neighborhoods suffer from slow economic growth. In order to guarantee an efficient allocation of resources in education, the Pareto principle should be considered. The Pareto principle is a technique that identifies the top 20% of reasons that requires to resolve the 80% of the difficulties. In other words, the allocation of funds and resources needs to be studied carefully before making any decision to guarantee that no party will suffer when promoting one factor over another. All the factors are important and play a simultaneous role in student’s learning. The reduction of class size didn’t yield a good return on investment in most cases.

Class size reduction has been one of the most influential factors in American K-12 education. In recent times, a lot of states have encouraged the reduction of class size. For example, increasing the student/teacher ratio in the USA by one pupil would lower the cost by $12 billion per year in teacher salary expenses alone (Whitehurst & Chingos, 2011).

The emphasis of this study is to demonstrate that the positive interaction of the different elements can create a combustible learning environment that will promote learning for students. In other words, all the factors need to work congruently in order to make a difference in the student achievement and the promotion of education. The impact of the interaction among the different elements that this literature review is examining is crucial to reach optimum results. The lack of not considering interaction among these elements will result in a waste of effort and resources.

In the United States market, the desperate need for skilled professionals forced employers to attract people from outside the USA to meet the economic market demand of consumers. Accordingly, a college graduate in the USA finds himself competing with cheaper and more skilled foreign labor. Therefore, some have argued the US education system should undergo drastic reform in order to meet the new challenges imposed by the economic globalization (Bowles & Gintis, 2011).

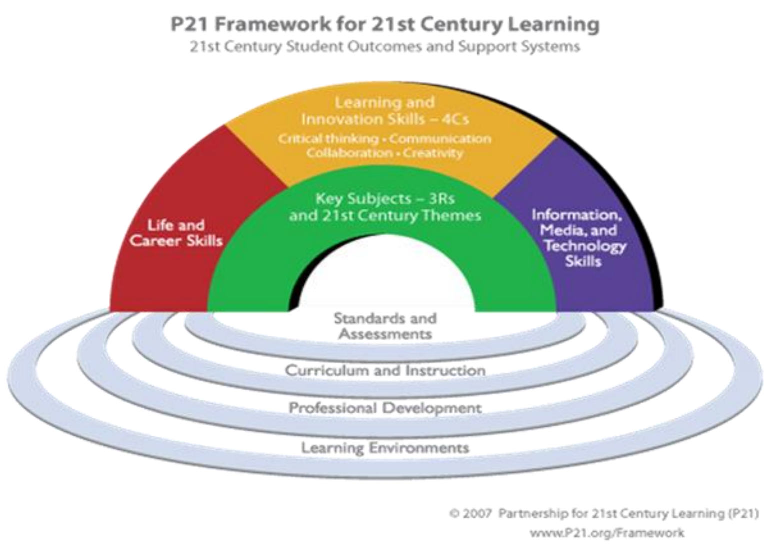

Figure 1-1 Learning Framework for 21st Century

Background

Education is the backbone of any society that is interested in thriving. The United States is facing a tremendous challenge to prepare children, teachers, and schools for the 21st century in order to maintain its status as a superpower. Nations around the world and especially Western countries are undertaking wide-ranging reforms to better prepare students to work and compete in a 21st-century economy. Scotland, for example, took a drastic measure in preparation for the 21st century and reached the McCrone agreement, which was aimed at improving teachers' work, modernizing teaching profession, and preparing the teaching profession for the 21st Century (Scottish Executive, 2000)

The globalization of the world economy and the rapid change in technology require a new set of skills needed by the workforce. It is becoming a mandate that the USA education system adopt a new model of learning that will cope with all the challenges that face the new generation of children. The burden of all these demands cannot be placed solely on the shoulders of the teacher but has to be shared by all the parties involved in the school education system. The selection and training of these parties are crucial to bear this kind of responsibility. The collaboration and the positive interaction among the different parties that make the school system are crucial to guarantee an optimum result for student achievement. Schools fail because of the absence of leadership and the lack of cooperation among the different players. A good example of school and community interacting positively together is Hancock High School in Chicago. The efforts of Bonnie Whitmore, the principal of Hancock, resulted in a significant improvement in student achievement. Bonnie Whitmore's leadership brought the school and community together, encouraged learning, and provided the best training for teachers. The bottom line:

Bonnie Whitmore was able to turn a failed school into a very successful school system (Bryk, Sebring, Allensworth, Easton, & Luppescu, 2010).

The 21st-century competitive skills include critical thinking, collaboration, communication skills, and creativity. Additionally, life skills are equally important and include capacity for lifelong learning, technological and financial literacy, global awareness, and skills for effective civic engagement (Harvard University advanced leadership initiative think tank, 2014, Executive Summary; Scott, 2015). A 21st-century successful individual must always be engaged in learning, acquiring new skills, adapting to a new environment, and adjusting to a new culture as the world is becoming like a small village. A student who graduated from college in the USA is competing with international students for a competitive spot in graduate school, and an equally challenging position in the workforce. The education system in the USA from early grades has to be at least at the same level as the rest of the advanced world.

International students are displacing USA students in most graduate schools, especially the schools that are based on math and science. Heller (2001) found that the most influential predictor of graduate school enrollment is the undergraduate academic characteristics, and not the undergraduate financial burden. According to Mahroum (2000), the dependency on international students is growing every year. Anderson (2014) showed that USA universities dependency on international students to conduct research, recruit and retain teaching talent is on the rise. Anderson added that many universities will not even survive without international students. The numbers of international students are staggering, according to an NSF survey conducted in 2011 on graduate students from 153 universities. The survey found that international students represents 71% of the full-time graduate students in electrical engineering, 65% in computer science, 61% in industrial engineering, and more than 50% in economics, chemical engineering, materials engineering, and mechanical engineering compared with the situation in year 1982 where international students accounted for only 44% of the full-time graduate students and 35% in computer science.

International students are key to supporting research, helping retain and attracting top faculty at USA universities, Additionally, many USA universities rely on international students to maintain their graduate school programs (Anderson, 2014). Although international students are becoming a vital resource to maintain the graduate programs in many universities, I found that this research is alarming because the education system in the USA is failing to attract American students to graduate schools especially African American students (Allen & Epps, 1991).

In summary, researchers such as Bryk and Dorothy Wallace (USA), Rick Muir and Jonathan Clifton (England), Michael Fullan and Ben Levin (Canada) and many others approached education as a whole system. Actually, my model is influenced primarily by the Bryk model. The Maestro picture that I chose for the principal is dedicated to Bonnie Whitmore, principal of Hancock High School. Bryk made principal Whitmore the example of the principal who pulled all the pieces together to produce successful students.

The difference in my approach compared with other researchers is the use of a structured framework, the general ecological model. It is a model that is widely used in psychological and medical research. The ecological model is important in education because it helps to organize our thoughts, knowledge, and identify opportunities for intervention. The ecological model illustrates the relativeness of each factor in relation to the target factor. In my case, the target factor is student achievement.

The Bayesian network provides a statistical modeling that enables analysis and the integration with the ecological model. Bayesian network model quantifies the relationships among the factors described in the ecological model. The idea of using a Bayesian network stems from Bryk and others researchers who stated that “We cannot improve at scale what we cannot measure” (Bryk et al., 2015 p. 111).

I have benefited from other researchers that focused on one factor because without their contribution I would not have been able to claim that all factors are significant. One factor means one band in my general ecological model, e.g. teacher effect. The teacher effect is a band in the general ecological model, which is comprised of multiple factors that interact with each other. A teacher effect can make a separate ecological model that is nested within the general ecological model, and that goes for every band or a factor that researchers have studied. The nesting of each band can go down to many levels and that is the reason for the complexity of the education system. In other words, each band can be made of multiple levels of ecological models. The ecological model that I am introducing provides a better approach to illustrate researchers’ studies.

In my thesis, I will highlight some of the big pieces of the education puzzle in this literature review to shed some light on their crucial role in promoting students’ learning and the importance of their interaction to guarantee the optimum result. The literature review presented next focuses on the following factors: (1) Family and Community Engagement; (2) Teacher Quality and Effects; (3) Teacher Supply, Teacher Retention, and Teacher Quality; and (4) Principal Leadership. All factors contribute in a certain way to promote education and student learning.

Chapter 2 LITERATURE REVIEW

2.1 Introduction

In this literature review, I depict a cross-sectional picture of what impacts student achievement on a daily basis. I selected the factors that influence student achievement directly and indirectly according to most researchers in the field of education. The purpose of this literature review is to investigate the factors that affect student achievements, such as class size reduction, teacher quality, peer effect, teacher-student relationship, and principal leadership in the USA and other countries around the world. Researchers have identified in some studies five essential factors that influence school improvement: (1) comprehensible and challenging instructions; (2) quality/effective teachers committed to the school and teaching; (3) continuous teacher and principal qualification improvement; (4) strong interconnections between families, community, and the school; and (5) a supportive student-centered learning environment, and inclusive leadership involving principals collaborating with faculty, parents, and community (Bryk et al., 2010; Roderick, Easton, & Sebring, 2009; Sebring, Allensworth, Bryk, Easton, & Luppescu, 2006).

The goal of this literature review is to examine existing research on how the interaction among the different factors is the most important to the study as opposed to studying each factor in isolation of the others. My theory is that the existence of one factor or the contribution of one factor will not be significant without the existence of the other factors, even though one factor may contribute as high as 90% in the student achievement. The presence of 10% plays a role in making the other factors reach the 90% impact on student learning. A good example of this analogy is the teacher-principal relationship. The teacher may contribute up to 90% in the student success; however, without the 10% principal contribution, the 90% might not even exist.

This literature review will examine the role of salient factors that contribute to students' learning and academic success in order to prepare students for the 21st century. Illustrative factors that are frequently examined by researchers and according to them influence student achievement to include: (1) family and community engagement; (2) class size effect; (3) cost benefit and the economics of class size reduction; (4) teacher quality and its impact, (5) teacher supply and demand; and (6) principal leadership. The elasticity theory explains the behavior of the outcome of student achievement due to one specific treatment, for example, class size reduction. The Pareto efficiency is a principle that creates a balance of resource distribution. Recall that Pareto efficiency/principle is a technique that helps to identify the top 20% of causes that needs to be addressed to resolve the 80% of the problems.

2.2 Family and Community Engagement

Researchers over the years found a significant association between family involvement in education and students' academic achievement and students' success. Parents are an essential element in a child's development and success. Research has demonstrated positive effects of family involvement on children in promoting learning and developing their well being. The parent's real involvement includes attending parent-teacher conferences, volunteering at school, helping with homework, or simply encouraging their children achievement. Parent involvement also includes sports and parent expectation. Parental involvement is an involvement that covers all levels of school life.

Coleman (1966) concluded that family social economic status, family education, and peers are more important than schools and teachers in defining the outcomes of student achievement (cited by Aaronson et al., 2007). Parents have full control of their child's life. They can depend on their social economic status ("SES") and make decisions to improve their child's success. In fact, some parents move to another state for their children. Parents can do a myriad of things to influence the lives of their children. They do not necessarily need to wait for a better teacher or a better principal; and accordingly, they can take actions based on their financial ability and education level, such as moving their child from a public to a private school, switching schools, paying for a private tutor, or moving to a different location for a better school.

Researchers concluded that parent involvement has positive effects in promoting academic achievement, improving school attendance, ameliorating classroom behavior, and lowering dropout rates (Epstein, 1992; Greenwood & Hickman, 1991b). In many cases, parental involvement varies and does not depend necessarily on the parent's financial status. Sui-Chu and Willms (1996) defined four types of parental engagement: two focused on home engagement (discussion and supervision) and the other two focused on family engagement in school education (contact with the school and volunteering/PTO meetings, etc.). To get the perception of family engagement across schools nationwide, Sui-Chu and Willms sampled 24,599 eighth graders from the NELS survey. The outcome of the regression model using the NELS data revealed that home involvement represents all SES levels; however, school involvement varied with respect to SES. The outcome of the regression determined that the level of parent participation in their child's school depends on the school's overall SES and not on the individual SES.

The effectiveness of parents' involvement in their child's success is influenced by their level of education. Researchers found that there is a strong correlation between the parent's level of education and student achievement. Parents with high education background can help their children with their homework and can help them with any school education challenge. Balli, Demo, and Wedman (1998) explored the family engagement effects on students' mathematics homework assignments. They compared three types of parental engagement on homework assignment categorized into three groups. In the first group, parents were not urged to be involved; in the second group, students were encouraged to involve their parents; and in the third group both students and parents were prompted to engage family members in the mathematics homework. The data used in this study is comprised of 74 Caucasian sixth graders (31 boys and 43 girls). Balli established that students in group 3 have the highest score followed by students in group 2 and then group 1. They also found a positive correlation between parents' education level and mathematics post-test. Although the sample is small and it is hard to generalize, it gives an indication of the importance of family engagement.

Sheldon and Epstein (2005) also suggested that there is a positive correlation between parent involvement and student outcome in mathematics. They surveyed 18 schools across Ohio, Maryland, Wisconsin, Minnesota, and California to examine the relationship between students' mathematics score and parents' involvement. The three practices that schools performed to get family engaged were: making teachers contact information accessible for the parents, holding meetings with parents whose kids struggle in math, and giving detailed feedback about the student's progress in the report card. Sheldon emphasized that these approaches helped increase family engagement, and consequently, improved mathematics test scores. Sheldon and Epstein cited other research that supported the same result (Epstein & Van Voorhis, 2001; Sheldon & Epstein, 2005). The results of the research suggested that if schools are interested in increasing students' test score, they should encourage and enable family involvement with their children's education. Bakker, Denessen, and Brus-Laeven (2007) also noticed that students with a high level of achievement have some sort of parental involvement. Parental involvement has to be sustained and not sporadic in order to have a positive impact on children's academic achievement (Brandt, 1979; Ekstrom, 1986; Salerno & Fink, 1992).

Student absenteeism and truancy represent one of the major problems in any school district and in particular in poor neighborhood schools. The research found that there is an inverse correlation between students' attendance and students' dropout rate. In a longitudinal study that included 18 schools (12 elementary, and six secondaries) from urban and rural areas, Epstein and Sheldon (2002) examined the relationship between school programs and parental involvement on student attendance. The study used longitudinal data which was gathered during the school year 1996-1997. Epstein and Sheldon found that when family and community are engaged in school activities, attendance rose, and truancy rates declined.

The way parents interact with their children impacts the child's behavior at school. Denham et al. (2000) indicated that parents with proactive behavior, such as supportive presence, clear instruction, and limit setting for their children can have a positive effect on their children behavior.

The role of parents is an essential component in their child's attainment. The lack of parental involvement manifests itself more in urban areas where the likelihood of students living with single parents is higher. Jeynes (2005), in his meta-analysis study, examined three components of parent involvement: (1) the overall parent involvement and parent involvement programs; (2) the relationship between parent involvement (e.g., parent expectations, participation in school events) and their children's achievement; and (3) the relationship between parent engagement and their kids' achievement by race and gender. The meta-analysis included 41 studies that are primarily dedicated to elementary school in urban areas. Jeynes found that parent involvement is a function of parent expectation. He also noticed that, contrary to expectation, parents in urban areas are more involved with their children than parents in suburban areas, especially in elementary schools. Furthermore, he found that the parents' reading level and parents expectations are the most important components that influence student achievement.

Parent engagement sets the stage for the child's success at school in the child's elementary school years. A student, whose parents are involved in the early years of his life, is likely to be more successful than a student who does not get quality attention. Barnard (2004) examined the impact of the family early involvement in student's life. He found that family engagement plays a big role in helping their children transition to high school successfully. In his study, Barnard used data from the Chicago public schools that included 1165 students. Barnard concluded that parents involved in their children's early years education, and development reduce the likelihood of their dropout at high-school by 21%. On the other hand, Bronstein, Ginsburg, and Herrera (2005), stressed that there is an association between family involvement and student academic achievement.

To measure the impact of family involvement, Bogenschneider (1997) tested the following three questions: (1) Does family engagement relates to promoting learning? (2) Does parents' education level associated with school engagement? And (3) Does family structure (e.g., biological mother and father, a single mother, and mother and stepfather) has any correlation with school involvement? He used data from a survey administered in California, and Wisconsin during the 1987-1988 school year in nine schools that included 10,000 students in grades 9 through 12. The schools were selected such that diverse ethnicity, and the socioeconomic background was guaranteed. Bogenschneider determined that family education level is positively correlated with school engagement. Additionally, he found that the level of engagement is more significant for biological parents and families that included both parents (husband & wife).

The family structure plays a vital role in the student's life, and achievement. Among the 27 industrialized countries studied by the Organization for Economic Cooperation and Development, the statistics showed that in the USA 25.8% of children are raised by a single parent compared with an average of 14.9% across the other countries. The statistics also showed that among African American the percentage of children raised by a single parent can reach 72%. According to the same organization, the USA does not have policies in place to support families, such as childcare and national paid maternity leave. As a consequence, the kids don't get a great deal of positive parental attention for appropriate behavior at school. The attention that the parents give to their children is crucial to offset any attention deficit at school, and in return, helps to create a balanced child. In contrast, a balanced emotional child will be more likely to focus on learning. Policymakers should follow the example of some industrialized countries who provide child support and make it a priority in their budget allocation.

Overall, the relationship between the school and the community is an essential component in the success of any student. Bryk et al. (2010), found that the local community effects on student achievement are significant. They also noted that among the five essential components for school improvement that researchers agreed on are strong interconnections among families, and inclusive leadership involving principals collaborating with faculty, parents, and community. Students with a single parent can lack to a great extent the adequate attention that a kid will need.

School curriculum is becoming more challenging every year and in particular math, for example, the math that was taught at the college level is now taught at the middle-school level.

Mathematics curriculum for parents is becoming more challenging with a subject like probability theory. There a high percentage of parents that didn’t study difficult math subjects at school, and as consequence, they can’t help their children with their homework. This is a hurdle that is hindering parents from getting engaged with their children and their homework. The parents with their busy schedule and the lack of knowledge are relying more and more on the school to help their children, which, as a result, has put more burden on the school.

In a research conference was held in Melbourne Australia on building teaching quality, Eliot (2003) argued that teaching quality, and therefore, student’ learning improves as a school parent partnership focuses on learning. In addition, Eliot found that students’ learning increases and student achievement rise when the teacher engages student-family/caregiver in school learning. Moreover, he claimed that student learning can be maximized if educators establish a teacher-parent relationship based on student learning and skill development.

In conclusion, family involvement plays a vital role in any student's success but it is not as easy as someone thinks. It requires constant dedication, knowledge, and most important time. The evidence that researchers found on the effects of parents on promoting academic achievement, improving school attendance, improving classroom behavior, and lessen drop-out rates are overwhelming (Epstein, 1992; Greenwood & Hickman, 1991a). The involvement is maximized when there is a relationship between the teacher and the parents. Eliot (2003) found that student achievement rises when the teacher engages student-family/caregiver in school learning. The amount of support and the smart involvement of parents in their child’s school life has a significant influence on their success. Dufur, Parcel, and Troutman (2013) argued that the social capital at home is much more significant than the one provided at school if it even exists. The family level of education influences the quality of family engagement and the kind of support that families exercise on their children, while family structure plays a big role in the emotional stability of the child, which impacts the student positively in his/her school endeavor (Bogenschneider, 1997).

2.3 Teacher Quality and Effects

Teaching is a profession that it is not for everybody. It requires passion, patience, the ability to deliver instruction in ingenious ways and many other skills. In my twenty plus years of teaching, I never followed the same rule to teach in every class. My main challenge with every group of students is to find the most appropriate way to deliver the instruction and the proper approach to building bridges between the students and myself. I discovered that every group of students is different. Students can have the same skills, same SES, but every class culture is always different from the interaction among the students throughout the year develops. The dynamic change in the class culture required a constant adjustment in teaching throughout the school year.

In a study conducted in Oslo requested by the Ministry of Education and Research, Nordenbo, Larsen, Tiftikçi, Wendt, and Østergaard (2008) found that there are three main criteria that influence the relationship between the teacher and the students: (1) teachers must possess interpersonal skills to build bridges with the students; (2) teachers must have the qualification and the capability to teach; and (3) teachers must have a command and the expertise on how to engage students in the class. In addition, Palardy and Rumberger (2008) recognized three factors that influence a teacher effectiveness: teacher background and training, teacher attitude towards children, and the instructional practices for student learning. They examined these factors in first grade using the Early Childhood Longitudinal Study data and claimed that instruction practices are the most significant factor among the three factors of teacher effects, and contrary to expectation, they found that background and training are not significant in teacher's effectiveness. Palardy and Rumberger concluded that there is no direct correlation between teacher qualification and student achievement. They clarified that teacher degrees and training do not guarantee that a student will receive comprehensible instruction in class.

Sanders and Rivers (1996) used the Tennessee Value-Added Assessment System ("TVAAS"), which is a method to determine teacher's influence on the academic growth rate for students (Bock, Wolfe, & Fisher, 1996; Sanders & Horn, 1994; Sanders, Saxton, & Horn, 1997). According to the Tennessee Education Department, TN Department of Education, TVAAS assesses schools and teachers' effects on students' academic achievement and student learning growth. In addition, TVAAS provide educators with the tools to select and implement the programs that promote student learning. According to Sanders and Rivers, the instrumental procedure that TVAAS uses to measure teacher effectiveness are: a testing method that creates a scale associated with the curriculum and in which it covers all the grade levels, a longitudinal database that monitors continuous development and building, and a multivariate and longitudinal statistical process that produce the desired teacher effects without bias. The TVAAS database is about three million records, which includes Tennessee's entire grades 2-6 student population and offers complete information about student achievement in mathematics, reading, languages, science and social studies from 1999 until the production of this research (1996). The TVAAS database allows the examination of the cumulation effects of teachers on student academic achievement over all grade levels. Sanders et al. found that teacher effectiveness contributed to an increase of fifty percentile points in student achievement based on three years of teaching. They added that teacher effectiveness benefited all students from all ethnic backgrounds and, in particular, low achievers.

In addition to a teacher's natural ability to teach and in order to produce a high-quality teacher, some training/mentoring must be provided to gain the necessary skills for the job. Algozzine, Gretes, Queen, and Cowan-Hathcock (2007) argued that a skilled teacher is a major factor in promoting student achievement and induction support programs are essential to produce high-qualified teachers especially in the first two years of the teacher's career.

Teacher preparation programs vary from one state to another. Some find that a certified teacher is vital to student achievement, and therefore, they stiffened teacher qualification criteria for the job. There are two examples of teacher certification programs, the "alternative teacher certification" (AC), and the traditional certification (TC) programs. The first allows a teacher to start teaching before completing the program, and the second has to be completed before teachers can begin teaching. Boyd, Goldhaber, Lankford, and Wyckoff (2007) found that traditional teacher preparation did not have a huge impact on students' outcome compared with the less demanding policy, AC. They found that some schools were successful in attracting and selecting great teachers without the need to go through these demanding preparation programs. They argued that there is no significant evidence to suggest a difference between both policies on student achievement. Mentoring is another preparation program that is used in one large urban district. There are two kinds of mentoring programs, full-release and site-based. Fletcher and Strong (2009) stated that teachers who underwent the full-release program had a higher impact on students' outcome. In addition, Fletcher, Strong, and Villar (2008) found evidence that student test scores in math have improved, especially when math was taught by teachers who underwent a mentoring program.

Consideration of teacher certifications and teacher licenses is different from one state to another; some states mandate that teachers should hold a certification to teach and other do not require it. Policymakers constantly tried to improve teacher effectiveness by raising the requirement to enter the teaching profession; however, this policy failed to identify quality teachers (Gordon, Kane, & Staiger, 2006). Gordon et al (2006) suggested that highly qualified teachers should be paid more by the federal government as an incentive to attract highly qualified teachers. They also recommended that states should allow potential teachers (people who didn't pursue teaching careers or didn't get the specific training at school) that did not get the necessary certification to enter the profession provided that they show great skills in teaching. Overall, measuring teacher effectiveness is a very daunting task. Some researchers used preparation program/certification as an indication of teacher quality, and therefore, effectiveness. On the other hand, other researchers found that certification by itself is not a good indication, and what is more reliable is the teacher's performance in his/her first two years of teaching (Kane, Rockoff, & Staiger, 2008).

Goldhaber and Brewer (2000) examined empirically the impact of different kinds of certifications (probationary certification, emergency certification, private school certification, or no certification) on 12th-grade students. They noticed that students taught by teachers who earned a standard certification tend to have a better math score compared with the students who were taught by teachers who hold private school or no certification. In addition, they found no difference between math and science students who were educated by teachers who hold standard certification or emergency certification.

Furthermore, Goldhaber and Anthony (2007) examined the efficiency of the certification of teachers by the National Board for Professional Teaching Standards ("NBPTS") in identifying effective teachers among potential teachers. They also examined if the completion of the NBPTS assessment process could improve teacher quality. Goldhaber and Anthony (2007), used data provided by the NBPTS on National Board teacher candidates. D. Goldhaber and Anthony found that the NBPTS effect was significant in recognizing quality teachers, however, this outcome was not consistent across different grade levels and student characteristics. They also noted that the certification does not improve teacher quality or teacher effectiveness. Moreover, Goldhaber and Anthony examined the effect of the NBPTS teacher certification on student achievement. They used a sample of 390,449 students from which 9,000 students were taught by teachers, who were undergoing their NBPTS assessment process, and 6,000 students were taught by teachers who already received their NBPTS certification. They showed that students with certified teachers enjoyed a growth of 6.18 points in reading and 10.21 points in math, which was larger and statistically significant than students with uncertified teachers (5.83 in reading and 9.14 in math). On the other hand, scores for students who were taught by non-applicant teachers increased by only 5.69 points in reading and 9.75 points in math. Overall Goldhaber and Anthony reported that the difference between certified and noncertified teachers account for a fourteen percent of standard deviation or one-point increase in math score.

Teacher quality plays a big role in improving student test score regardless of the composition of the students in the classroom. Aaronson, Barrow, and Sander (2007) examined teacher effectiveness in the Chicago public schools. They used matched student-teacher administrative data. Aaronson found that the effect size of improving teacher quality in math by one standard deviation increased student test score in math by 0.13 grade, which is equivalent to 20% average yearly gains. The finding was not affected by the type of students or students' score level. In addition, Aaronson claimed that after adjusting for the teacher quality dispersion problem, two standard deviations of improving teacher quality increased students test score by

0.3-0.5 grade, which is equivalent to an average yearly gain of 25% to 45% in student math score performance.

Measuring teacher effectiveness is a challenging task. The need to measure teacher effectiveness is extremely important to improve teaching quality and without the ability to measure teacher effectiveness accurately there is no hope for teacher improvement. The discrepancy in research data used to measure teacher effectiveness is large and so is the outcome of research. Gallagher, Rabinowitz, and Yeagley (2011) suggested that policymakers and educators should consider as much data sources as possible before drawing any conclusion (Herman, Baker, & Linn, 2004; Stone & Lane, 2003; cited by Gallagher et al. 2011).

Gallagher, et al recommended the use of the statewide achievement testing data, because it is administered in a standardized fashion. They found that the data is reliable, valid, and fair to assess teacher effectiveness (Toch & Rothman, 2008; cited by Gallagher, 2011). In addition, Gallagher, et al found that data collected from statewide testing is adequate when statistical analysis of growth is used to identify teacher impact on student learning, especially in the case of value-added modeling (Braun, 2005; Goldhaber & Hansen, 2010; Hanushek & Rivkin, 2010; Harris, 2009; Kane et al., 2008; cited by Gallagher, 2011).

In conclusion, teaching is an art (Brophy, 1988) and will continue to be an art because every group of students creates a particular culture within a classroom. The different composition of each class requires the development of an appropriate teaching style to suit the different cultures that could exist in a classroom. Brophy (1988) argued that there is no one systematic teaching way that can fit all kinds of students or as he put it in medical terms, “there is no one pill that can fix all ill people”. Teacher relationships with the students are based on three criterion: interpersonal skills, high training/qualification, and management (Nordenbo et al., 2008). A sound relationship with students is extremely important to achieve effective teaching (Palardy & Rumberger, 2008). The second criteria for teaching skills that Nordenbo et al revealed, was training and this is achieved through induction and mentoring programs, especially in the first two years of the teaching career. The training and induction problem not only helps teachers at the beginning of their careers but also supports the teachers who face overwhelming challenges at the beginning of their careers. All these training programs contributed to improving teacher performance; as a result, the training programs helped to advance student achievement (Fletcher & Strong, 2009). Overall, teacher quality has a major effect on student achievement regardless of the student level, student social economic status, or class composition (Aaronson et al., 2007).

2.4 Teacher Supply, Teacher Retention, and Teacher Quality

Although class size reduction improved student achievement across all demographic groups according to most researchers, the implementation of this policy across schools led to a significant reduction in instruction quality due to the shortage of high-quality teachers, especially in math and science (Jepsen & Rivkin, 2009). The question remains: Do we have enough trained teachers to cope with this challenge of expansion? According to Sutcher, Darling-Hammond, and Carver-Thomas (2016), the USA is headed toward a serious teacher shortage. Sutcher et al. (2016) defined a shortage of teachers as “the inability to staff vacancies at current wages with individuals qualified to teach in the fields needed.” Sutcher et al used several federal databases, which included: Schools and Staffing Surveys, Teacher Follow-up Survey databases from 2012 and 2013, the Baccalaureate and Beyond 2008:2012 databases, the Higher Education Act Title-II data from 2005 through 2014, and more recent data from the State of California. The analysis of data indicated that the teachers’ shortage will get worse by 2017-2018.

Additionally, the modeling of the new teacher supplies and demand showed a current (2016) shortage of 64,000 new teachers, which is by 2020, and according to the model will be around the 300,000 teachers per year. The model also demonstrates that by 2025, this shortage will amount to 316,000 per year. Sutcher recommends a drastic measure should be taken in order to solve this problem.   Despite this currently projected shortage, Sutcher found that the enrollment in teacher preparation programs dropped from 691,000 in 2009 to 451,000 in 2014, a 35% decline, which of course adds to the shortage problem.

The problem is not only a shortage of teacher supply but also teacher retention, which is another factor that affects the shortage of teachers supply. Teachers' shortage is the most challenging problem that faces educators, and policymakers at all levels (state & federal), who are constantly pursuing the hiring of new teachers to offset the huge deficit in teachers supply. Based on Ingersoll's (2001, 2002) analysis of teacher retention, and the National Commission on Teaching & America's Future (NCTAF), Ingersoll reported that teacher retention was a "national crisis" (p. 21), and the retention is more severe in poor and minority areas (Cochran-Smith, 2004). According to Cochran-Smith, high-qualified teachers are predominately entering the profession out of love for the job and love for children; however, he acknowledged that that is not enough to retain teachers for the long-haul as the competition with the open market does not favor the teaching profession.

Historically, the teaching profession was not a first choice career for college graduates. This is primarily due to the low salary of teachers compared with other jobs in the market. Starting with the twentieth century, Sedlak and Schlossman (1986) found that the teaching profession is becoming more appealing as teachers started to enjoy more liberty, independence, and higher wages; however, despite this appeal, he added that schools failed to attract a large number of qualified teachers. In addition, they argued that despite the fact that women and minorities replaced the shortage of male teachers, the open market lured women to the less stressful and higher paying job.

The responsibilities that first-year teacher bears don’t differ much from a veteran teacher. The workload, the stress from students and the many other challenges that a teacher faces on a daily basis do not differ depending on the teacher’s years of experience. Therefore, an adequate support system is vital for first- and second-year teachers until they are more comfortable with the numerous challenges that they face every single day. Mentoring and induction programs are essential to keep teachers from leaving the profession early in their career. Comprehension Mentoring and induction programs play a big role in teachers’ retention especially for the first two years of the teacher career. Smith and Ingersoll (2004) examined the impact of teacher induction and mentoring on teacher retention. They used the National Center for Education Statistics’ (NCES) Schools and Staffing Survey (SASS) along with its supplement, and the Teacher Follow-up Survey (TFS) data, the largest data on teachers staffing, to analyze the effects of mentoring and induction programs. According to Ingersoll and Smith, teachers who undergo a mentoring & induction program in their first two years are more likely to remain on the job. They added that attrition rate among new teachers can reach up to 50% in their early years of teaching (1-5 years) (Huling-Austin, 1990; Ingersoll & Smith, 2004). In addition, Duke, Karson, and Wheeler (2006) examined the mentoring and induction program effect on teachers’ teacher retention. They used the 1999-2000 schools and staffing survey data. The logistic regression that they performed on the data showed that teachers who went through the mentoring and induction programs are more likely to stay on the job. Moreover, the mentoring and induction program also benefited teachers who did not earn an education degree (see also Strong, 2005).

The challenge of offsetting the deficit of teacher attrition is compounded as states are adopting the class size reduction policy and as more teachers are required to accommodate special needs students. According to Clement (2000), the number of teachers needed in the United States due to the rise in school enrollment, reduction in class size, accommodating students with special needs, and teachers' attrition mounts to two million in the next ten years. Smaller class size can make a difference in the child's learning behavior; however, smaller class size requires additional qualified teachers, which is a big challenge that faces school administrators due to the short supply qualified teachers. There is a shortage of teachers in key subjects, such as math and science. According to Ingersoll and Perda (2009), the problem is not in the supply as much as in the rise in attrition rate, which is due primarily to job dissatisfaction on one hand and the pursuit of higher paying and less demanding jobs on the other hand.

According to Ingersoll (2003), staffing qualified teachers is one of the main problems that face school administrators. He explained that the shortage of qualified teachers affects school effectiveness and teaching performance. He added that the surge in retirement and the increase in student enrollment caused this current shortage of teachers. In his examination, Ingersoll used data from the Schools and Staffing Survey and its supplement, and the Teacher Follow-up Survey conducted by the National Center for Education Statistics. He found that teacher shortage is caused by teacher's who exit the profession to pursue one that is less stressful and higher in pay and not due to retirement as was believed. He noted that the problem is more serious because most of the teachers that are quitting are the highly qualified teachers.

In conclusion, teachers' shortage is one of the biggest problems facing schools especially after most school districts across the nation started to adopt the idea of smaller class size and also with the increase in student enrollment. The problem is not just in the supply but also in the quality of teachers (Jepsen & Rivkin, 2009). The problem with teachers' supply is not just the funds necessary to hire new teachers, but also the time that is required to train new teachers before they begin teaching. The USA is facing a large shortage in teachers' supply and the deficit in the number of teachers is on the rise (Sutcher et al., 2016). Despite the fact that teachers' retention rates have improved due to the Comprehension Mentoring and Induction Program (Smith & Ingersoll, 2004), the number of teachers needed by 2020 will be around the 300,000 teachers per year. And by 2025, this shortage will amount to 316,000 per year (Sutcher et al, 2016). The challenging process of hiring a teacher and to bring this teacher up to speed is enormous. The other next challenge is searching for the optimal strategies that can impact increasing the teachers' retention rates; as teachers and especially the highly qualified ones tend to leave the profession for less stressful and higher paying jobs (Ingersoll, 2001, 2002). The shortage in teachers' supply led to the increase in the number of teachers that are not qualified in major subject areas like math and science, and therefore, lacked detailed knowledge of the curriculum. The unqualified teachers negatively affect students in the long run.

2.5 Principal Leadership

A school principal is a catalyst for any school organization. He is the one that liaises with all of the parties involved, including parents, teachers, and students and student district administrators. The leadership of the school principal is an essential component in the success of any school as a unit. A school can have all the successful components, such as great teachers, excellent curriculum, and resources; however, the absence of capable leadership will decrease the likelihood of improving learning. A school principal creates the liaison among all the stakeholders of any school organization like teachers, students, parents, and the whole community. Principals contribute indirectly in promoting student learning. Principals create the environment of any school and influence the culture of the school in general. New teachers cannot succeed without the leadership and the support of the principal. Principals are responsible for teacher motivation, setting school goals, and interacting with parents and the community. The bottom line is that the principal leadership is a very important piece of the school puzzle. The example of successful principals is given in Bryk's book "Learning to Improve: How America's Schools Can Get Better at Getting Better". Bryk et al. (2015), showed that among the many challenges of preparing any career person for the 21st century is the continuous learning and improvement and school principals and teachers are no exceptions. The school principal needs to constantly work on improving student achievement, supporting teachers, searching for innovative ways to enhance learning, engaging parents, managing school budgets, and a host of other skills. In order to succeed in the 21st century, there is a very high level of standard and expectation, and a new breed of leadership is required to meet and be accountable for such a challenge.

Figure 2-1 The Principal is the School Maestro

The principal is the school Maestro. He is the one that is responsible for the success and failure of the whole school. The leadership of a principal is like a shock absorber at the doorstep of every school where all the challenges come knocking. The principal is like the captain of a ship or the pilot. He is responsible for steering the ship and directs it towards success and safety.

Waters, Marzano, and McNulty (2003) examined the impact of leadership practice on student achievement. In their meta-analysis, they selected 70 studies out of 5,000 studies that directly met their research criteria for design, control, and data analysis. Waters, Marzano, and McNulty reported that researchers established a framework called “a balanced leadership framework”, which included knowledge, skills, strategies, resources and educational tools. They found through the analysis of the data from this meta-analysis that an average positive correlation between school leadership duties (twenty-one different duties) and student learning is of .25. The twenty-one leadership duties that researchers established are “culture, order, discipline, resources, curriculum, instruction, assessment, focus, knowledge of curriculum, instruction assessment, contingent rewards, communication, Outreach, input, affirmation, relationship, change, ideals/beliefs, monitors/evaluates, flexibility, situational awareness, intellectual stimulation.”

Any organization, even the smallest one in the society, cannot exist, survive, and succeed without the presence of a leader. A leader can make or break any institution. Leadership is a key to the success or failure of any organization starting from the smallest unit (husband and wife) to the biggest organization, which includes academic institutions. The bottom line is that schools cannot be successful without the leadership and efficiency of principals. In order to improve principals effectiveness and their impact on student achievement, their leadership has to be measured. The importance of finding the proper tools to measure principals’ effectiveness was the focus of researchers for many years. Measuring principals' effectiveness will help identify the proper skills that a principal would need to develop and progress. In order to assess the principal's effectiveness to improve teaching and learning in their schools, shaping a vision of academic success for all students, Branch et al. (2012) examined the impact of principals' effectiveness on students learning growth. The growth measure is measured using the value-added measure model (VAM). The VAM is a way to detach the real influence of a teacher or a principal on student learning from all others factors that might influence the outcome of student achievement like family socioeconomic status, student ability, school environment, parents' education level, peer groups influence, and other factors that can have any sort of impact on student learning. In this study, Branch, Hanushek, and Rivkin estimated the principal value-added on student learning by using the fixed effect regression model; the principal fixed effect is the result of the regression of the mathematics achievement on lagged achievement, principal demographic characteristics, student demographic characteristics, and measures of student mobility. The growth measure/value-added was computed for every school and for every grade level using the Texas Assessment of Academic Skills, and TAAS data, which was collected by the University of Texas at Dallas. The data included 7,420 principals from 1995-2000. The TAAS focused on measuring the level of proficiency in three areas: reading, writing, and math. Branch, Hanushek, and Rivkin found that the principal effectiveness is surprisingly very high and it amounts to 0.207 standard deviations. In addition, Branch, Hanushek, and Rivkin discovered that poor neighborhood schools are deprived of experienced principals. In general, principals in poor neighborhoods tend to be inexperienced. There is an increased likelihood that a principal in a poor neighborhood will move to another job after the first year on the job.

On the other hand, Branch reported that experienced principals would likely improve school quality, teacher effectiveness, tend to improve the school environment, attract a new teacher, and improve the rate of retention among teachers. Furthermore, Hallinger, Bickman, and Davis (1996) studied the impact of school principals' leadership on school effectiveness. They used the Tennessee School Improvement Incentives Project data, which included 87 elementary schools in Tennessee between 1983 and 1985. They found that the effect of principals is directly related to school social economic status, the amount of family engagement, and teacher expectations for student learning. In contrast, Hallinger, Bickman, and Davis reported no direct effect of principals' leadership on student learning; however, they acknowledge that there is an indirect effect. In general, they found that principals are responsible for setting the school environment, which in turn helps teachers and students to progress.

Principal and teacher roles are intertwined with student learning. The overlap between principal and teacher responsibilities to ensure instructional leadership throughout the school is crucial in promoting learning. The idea that a qualified teacher is more important than a principal is ludicrous; they both complement each other. The principal is not the only instructional leader but the "leader of instructional leaders" (Glickman, 1989). Teachers depend on principals for support, direction and other very important matters. There are two types of leadership: (1) transformation leadership, which focuses on motivating and inspiring people in the organization; and (2) instructional leadership, which is a partnership between the principal and the teacher. The focus of the instructional leadership is to find new ideas to improve school effectiveness and student achievement. the instructional leadership focuses on curriculum, instruction, and assessment (Marks & Printy, 2003).

In addition, Marks and Printy (2003) examined the correlation between the two kinds of leadership and school attainment assessed in terms of student achievement and teaching/instructional quality. They chose twenty-four elementary, middle and high schools that had school-based management (Newmann, Marks, & Gamoran, 1996; cited by Marks & Louis, 1997; Marks & Printy, 2003). The schools selected were eight elementary, eight middle, and eight high schools. In these types of schools, teachers have discretion over curriculum, instruction, and assessment (Marks & Louis, 1997); cited by Marks & Printy, 2003). They used the hierarchical linear modeling (HLM) to analyze the data. Marks and Printy revealed that transformation leadership by itself is not sufficient to have any impact on school performance; however, they claimed that the interaction of both types of leadership had a significant impact on student achievement and teaching quality (see also Louis, Leithwood, Wahlstrom, & Anderson, 2010).

There are some detractors of the principal role in student learning (Murphy, 1988; Hallinger & Heck, 1996, p. 1; Bosker & Witziers, 1996; Scheerens & Bosker, 1997; Grift, 1990; Van de Grift & Houtveen, 1999a; cited by Witziers, Bosker, & Krüger, 2003). Murphy claimed that the number of research conducted on principals' leadership is very limited and is of poor quality. It is therefore not reliable in assessing the relationship between the principal role in student learning. Hallinger and Heck determined that the studies conducted in the USA and UK lacked sufficient evidence of principal effectiveness in student achievement, and in the Netherlands, Bosker and Witziers (1996); Van de Grift and Houtveen (1999b) found no significant correlation between principal leadership and student learning.

Moreover, Witziers et al. (2003) conducted a quantitative meta-analysis study, which included studies conducted between 1986 and 1990 on the impact of principals' leadership on student achievement. They used studies that were based on research that focused directly on the relationship between principals and student achievement (37 research from 25 countries). The student achievement measure excluded all factors that are not directly related to the student performance. Witziers found that the associations between leadership and student achievement are small (below .10), which was not a surprising outcome since the principal leadership impact directly teacher effectiveness, school climate and indirectly student achievement.

It should be noted that all of the studies cited above, showing reservations about the correlation between leadership and student learning, were conducted before the year 2000, after which more conclusive research emerged. For example, Robinson, Lloyd, and Rowe (2008) conducted a meta-analysis (22 studies) that examined the impact of transformation leadership, and instruction leadership on student achievement. They found that on average instruction leadership was three to four times the impact of transformation leadership on student achievement.

In addition, Robinson et al. (2008) conducted another meta-analysis (12 studies) that examined five different kinds of leadership practice on students' achievement: "establishing goals and expectations; resourcing strategically";" planning, coordinating, and evaluating teaching and the curriculum"; "promoting and participating in teacher learning and development, and ensuring an orderly and supportive environment". Robinson found that the involvement and promotion and participation in teacher learning have a significant effect on student achievement; however, he realized that the planning, the goal setting, and the teaching and curriculum evaluation have a medium effect.

The advocates for the role of principal leadership outnumber the opponents by far. I am a big proponent of principal leadership. Many researchers have proven that leaders can make or break any organization.

In conclusion, principal leadership plays a big role in the success of any school organization. The leadership of any organization can make or break this organization. The principal of any school has the ability and the skills to select and hire teachers, evaluate and improve teacher effectiveness, defines curriculum and set the benchmark goals for students and teacher expectation (Branch et al., 2012).

In addition, principals serve as a liaison between the parents/community and the school. Principal leadership promotes student learning, student support, and develops staff and serves as the building blocks for school organizational structure. Waters et al (2003) found a strong correlation between the twenty-one leadership duties for a principal and student achievement. Schools in the poor neighborhood do not just suffer from low-quality teachers, but they are also deprived of experienced leadership (Branch et al., 2012).

Furthermore, the contribution of the principal is positively correlated with the overall school social economic status, family engagement, and teacher expectations (Hallinger et al, 1996). The two kinds of principal leadership, transformation, and instructional leadership proved to be positively correlated with student achievement and teaching quality (Marks & Printy, 2003).

There were early detractors of the importance of the principal leadership, and these researchers claimed that there was not enough evidence to prove the correlation between student achievement and principal leadership (Murphy, 1988; Hallinger & Heck, 1996, p. 1; Bosker & Witziers, 1996; Scheerens & Bosker, 1997; Van de Grift, 1990; Van de Grift & Houtveen, 1999).

2.6 Explanation of the Discrepancy in the Literature

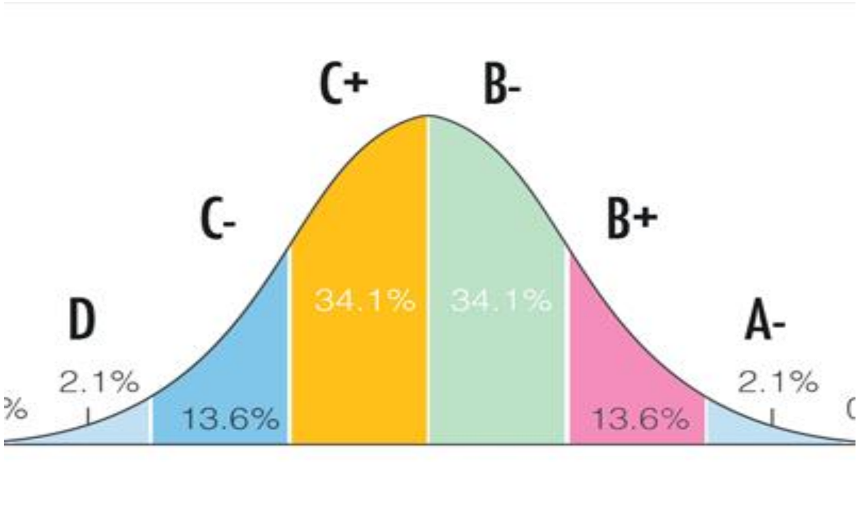

Figure 2-2 Bell-shaped Curve Distribution

2.6.1 Elasticity Theory in Statistical Analysis

In most of the literature that I reviewed, the focus was on how the mean of student achievement has improved. The mean is not a good yardstick to measure student achievement. The mean is a very sensitive parameter, which can be influenced by just one outlier and can give a false indication of any outcome. The idea of closing the gap between the top students (white) and bottom students (African and Latino), in my opinion, is a political statement and has nothing to do with what the students need.

In the majority of the literature, I noticed that the outcomes for individuals at the bottom of the sample distribution are more significant than individual at the top. In other words, the bottom subsample always benefited more from the intervention/treatment, such as the case with smaller class size studies. In addition, researchers always suggested that low achievers benefited more from the intervention than high achievers. The consensus of researchers concluded that the gap between low achiever and high achiever decreased due to smaller class sizes, which is not necessarily true. These conclusions do not necessarily explain how the treatment influenced the behavior of the data in the study. The assumption was made that all students on the distribution had the same responsiveness to treatment, which is not necessarily true because each one has a different elasticity, and therefore, different responsiveness. The responsiveness is a function of prior knowledge and many other variables that were not included in the study.

In a random sample represents data around the population mean. In this random sample, students on the low side of the distribution tend to have more elastic behavior in terms of responsiveness to treatment than students at the top of the distribution. Some researchers suggested in the case of a smaller class size, teachers tend to give more attention to low-achievers than high achievers, and therefore, low-achievers benefit more from the treatment, which is again not true. As a matter of fact, the elasticity theory will give a much better interpretation of the different outcomes of any potential treatment.

The elasticity theory does not treat all data points with the same weight in terms of responsiveness. In general, and depending on the position of the data point in the distribution, the elasticity of the data point will differ in terms of responsiveness to treatment. In general, the outcome of a treatment should be different for every data point depending on the sample. The idea of a random sample does not mean much and does not give all the facts that will help the interpretation of the outcome. If the sample is selected randomly, the data is probably around the middle of the students' population. A random sample will likely include students in the zones C-, C+, B-, and B+. In this case, the elasticity of grades for low-achiever is higher than the elasticity of grades to high-achiever (see graph below), and therefore for the same amount of effort, low-achiever could gain more points than a high-achiever.

The inaccurate assessment of the impact of the treatment is due to the fact that the statistics used are not the appropriate one that can reflect the impact of a treatment. As an example of the miss use of statistics is the use of the mean and standard deviation in everything. For example, high-achiever might gain fewer points on the scale and could result in a non-significant result; however, they could gain on the percentile scale more significant results when their grade point average is improved. The percentile or the ranking is the statistics that reflect the impact of a treatment, which is not the kind of figure that the mean or the standard deviation provides.

Even though the gap is narrower using the statistics of the mean, the percentile will show that the gap doesn’t in most cases change. In other words, the high-achiever might, in reality, benefit more than the low-achiever. The low-achiever might have gained certain points but did not move up in the ranking, and therefore, there was no gain. In general, the elasticity theory can help explain the behavior of the result of intervention than simply relying on the statistical laws, which do not rely on the overarching fact that the elasticity. The dependency on the mean and standard deviation to interpret the output of the experiment for both low-achiever and high-achiever is sometimes lead to wrong conclusions. Therefore, it is imperative to include elasticity theory in explaining the behavior of statistical results, because the conclusion could be incorrect or not accurate. An inaccurate diagnosis of a problem will result in making the wrong decision.

Again, elasticity is a measurement of how responsive a variable is to a change in another variable. Elasticity can be negative or positive, linear or not linear. The following are the possible absolute values of elasticity:

If |E| is close to zero this means that the variable is not responsive to the change in the other variable. The smaller the elasticity, the smaller the response and vice versa.

If |E| is very large, very elastic the variable is very responsive to the change in the other variable.

|E| < 1 this is inelastic means a lot of effort must be put to make a small change, or (relatively unresponsive)

|E| > 1 is elastic means small effort will make a considerable change, or (relatively responsive)

Elasticity can be also a nonlinear factor.

In education, student grade elasticity is a measure of how responsive a student's grade to the amount of effort put by a student/teacher/principal to influence student grades.

This is an example of elasticity that is linear. It can have different values or different slopes:

E1 represents individual at the bottom of the sample

E2 represents individual at the top of the sample

N.B. curves in economics are sometimes in reverse to the norm, the independent variable is the y-axis and the dependent variable is on the x-axis.

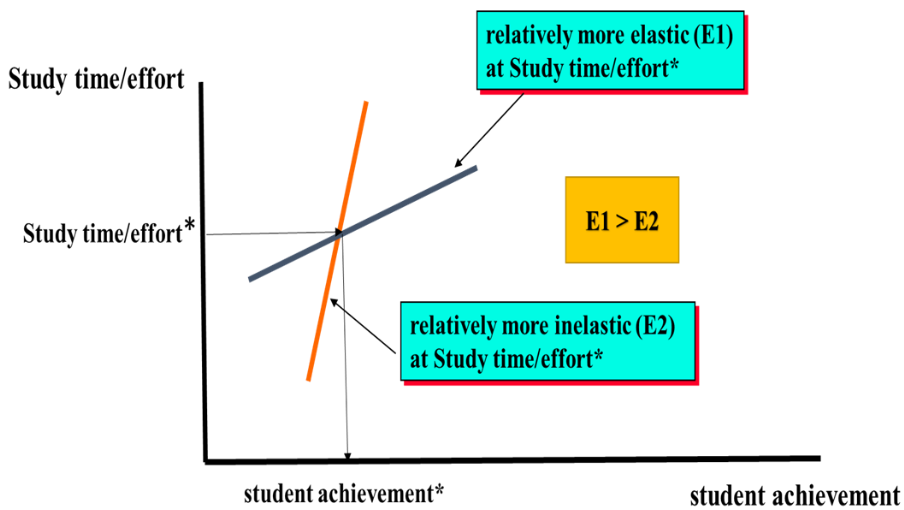

Figure 2-3 Elasticity Curve

$$\text{Elasticity of grade} = \frac{\Delta G}{\Delta S}$$

ΔG= change student achievement

ΔS= time spent to influence grade outcome or efforts put to influence grade outcome

Another example of elasticity is the elasticity of learning. The elasticity of learning is the ratio of the learning gain over the change in the amount of effort. The elasticity will be able to explain the behavior a variable under some treatment, in other words, elasticity will be able to explain the responsiveness due to certain intervention. In my 30 years of experience in education as a student, an instructor, and a coach, I found that the behavior of elasticity follows to a certain extent the bell-shaped curve above. At the bottom of spectrum things start slow, inelastic (not responsive) and as things start to move, elasticity increases (responsiveness increase) until things hit the middle region where the elasticity starts to taper again (less responsiveness) until things get closer to the top of the distribution where things start to be inelastic again. At the inelastic space, it is required a lot of effort to make a very small change. One can take basketball as an example to illustrate the elasticity theory. The players in the starting lineup players play the beginning and the closing minutes of the game because the beginning and the end of the game are always inelastic; however, the bench players play the middle minutes, because they are elastic. The end of the game, in particular, requires a lot of effort to score one point.

In general, starting something new is always cumbersome/inelastic and at that stage, the amount of effort is not proportional to the gain (high effort and low gain). As things move towards the middle, the amount of effort becomes proportional to the gain, and this is the best place to use the laws of statistics as the size of efforts are directly proportional to the outcome and the elasticity in this region is close to one; however, as thing moves towards the top or bottom of the distribution, the amount of effort used does not correspond to the gain. In other words, the amount of effort and the outcome are not proportional and this is where the laws of statistics fail to explain the behavior of these two regions. In basketball, for example, there is a lot of effort taken by players to finish the game. There can be a lot of focus and energy to make just one shot, but this one shot will make the difference between winning and losing the game.

The elasticity theory explains why teachers /coaches require a certain kind of talent and skills to teach/coach students at the bottom and at the top of the scale. This also explains the challenge that teachers face to teach students in poor neighborhood schools where most of the students are in zones D, and C-, as the size of efforts does not correspond to the student achievement gain at the end of the school year. Additionally, teachers are not fairly evaluated due to the small gain that they made in student achievement, ignoring the fact that these teachers made a tremendous amount of effort during a whole year. The non-proportionality in the relation between efforts and gain is another reason why teachers do not last in poor neighborhood schools (high effort and low gain). First, they are discouraged, and second, they are not fairly evaluated.

In doing statistical analysis, I noticed that statistical theories do not explain the behavior of the data at the extremes of the spectrum, as the laws of statistics are much more suited to the data that lies around the mean of the population where the relationship between input and output is directly proportional, or where elasticity is almost equal to one. Scientists in engineering tend to use truncated normal distribution (the truncated normal probability distribution is a normal probability distribution truncated into a finite interval) because the behavior at the extremes of the distribution does not guarantee an unbiased estimator (Pender, 2015).

Elasticity theory and percentile in some analysis are in my opinion much better tools to interpret data behavior especially if the data are at the extremes of the spectrum where elasticity is less than one or inelastic. There are a lot of applications in education, medical, and pharmaceutical fields where the interest of research is targeting extreme cases. The laws of statistics by itself can't be a good tool to illustrate the significance of a treatment, especially when the elasticity of these cases is one.

In the case of the top students, every extra point gained can give a student a precedence over another. In other words, a difference of one point would never be statistically significant, when comparing test scores of two students, but this one point can give precedence to one student. Students with top grades face fierce competition due to the inelasticity of the grades, as each extra point can move him/her few percentiles, which could be enough to win a spot at a top college. This extra point would require a significant amount of effort, but it will be the difference between winning something substantial or losing. The significance is not the statistical difference, but whether one reaches his goal or not, whether the treatment improved the person ranking or not. There is no point in claiming a significant and nonsignificant status if the individual doesn't reach his/her goal. The benefit of using elasticity theory and percentile for evaluating outcome in cases of student achievement is extremely important because it can show if the ranking of the student among his peers has improved. Student achievement should be measured by the improvement in the student's ranking. The idea that a student gained some standard deviation in his test score doesn't mean much because at the end what counts is the ranking of this student among other.

A very good example of inelasticity case is Michael Phelps (Olympian swimming champion) times. Phelps put extraordinary effort for a long period of time just to improve his time by 0.1 seconds. Michael Phelps is at the top of the scale and any minor improvement in his time requires a substantial amount of effort. The behavior at the top of the scale will not necessarily be noticed by statistics like the mean and standard deviation. Again, in order for

Phelps to improve his time in one race by 0.1 seconds, he has to put a significant amount of effort to accomplish this goal. His coach and everybody involved with his training have to put a lot of effort so that he can improve his time by only 0.1 seconds, which is extremely small. The very small difference of time makes the difference between a gold medal winner and a silver medal winner.

The mean difference between Phelps' times will not be noticed by the laws of statistics, but winning a gold medal by itself shows that the improvement by this 0.1 seconds is significant. The situation of an individual or a group of individuals at the top of the scale is considered inelastic. The elasticity of this group of individuals would be different as we go from top to bottom. The top ones will be the less elastic, and as we go down, the elasticity increases until it hits the middle and then starts to taper again as things start to move towards the bottom. It is a lot easier for a student in zone B- to gain 10 points compared to a student in the A- zone to gain one extra point, simply because the B- grade is a lot more elastic than the situation at the A-, where things are inelastic.

The following is an example to explain the behavior of a student's grades at the bottom of the distribution (grades D and C-) when a treatment like a smaller class size is applied to this group. The figure below illustrates the behavior of a sample at the bottom of the grades distribution (grades D and C-) for students before and after a treatment like the smaller class size.

In figure 2-4, the bubbles represent the distribution of students grades before and after the treatment. The lowest grade in the distribution has the lowest elasticity, and therefore, the lowest responsiveness/elasticity to treatment. In contrast, the highest grade in the distribution has the highest responsiveness/elasticity to treatment. The student's grade with the highest elasticity will improve relatively more than the student with the lowest grade due to the elasticity of grades. In this example, if the intervention is successful, the mean grades after the intervention, M2, will be higher than the mean grades, M1, before the intervention. Also, the variance before the treatment V1 is lower than the variance after the treatment, V2. The change in the dispersion of grades after the treatment is due to the difference in elasticity/responsiveness among all students' grade.

The positive effect of treatment caused an increase in the dispersion of students' skills, and this is due to the difference in elasticities among the student's grades, and therefore we might get into a situation where the mean didn't change. The variance can increase due to the different responsiveness of students to the treatment. The new distribution of the data can have a similar mean with a higher variance, which can cause a none significant result even though some students have improved. The figure below illustrates the situation before and after the treatment:

Figure 2-4 Elasticity Theory of Student Response before and after Treatment

If we apply a treatment to the student's grades from zone B+ to A-; as a result, the mean might be higher and the variance might be smaller. In the categories of B+ to A- the B+ students will have a much higher elasticity than students with the A-. Therefore, when conducting data analysis, it is important to identify the elasticity associated with the data in order to be able to interpret the result accurately without the rush to label some outcome as significant or not significant. It is crucial to understand the behavior of the data in the different zones to interpret the outcome correctly.

Elasticity is a widely used tool in economics that determines a lot of the business decision making that involves billions of dollars. I believe that this tool can also be used in education to help deduce the behaviors of different data points, which statistics (mean and standard deviation) will fail short to interpret these outcomes accurately.

2.6.2 Percentile and Standard Deviation

When the outcome reveals a specific standard deviation of improvement, it does not reveal to the reader any relevant information. The intervention goal is to improve student test score relative to other students. The intervention in the case of education is done for ranking improvement, for order improvement, and therefore, the percentile is an adequate statistic to emphasize the size effect. Again, for a very small standard deviation of improvement, a student can improve significantly on the percentile scale. This is the reason why parents send their kids to a private school where class size is smaller, in order to improve their chances to get ahead of the others, and therefore, increase their chances in a better place whether in education or jobs. The statistics should be selected based on the goal of the treatment. The idea that the mean and standard deviation is good for every study is ludicrous.

2.7 General Conclusion, and Dissertation Research Plan

The graphs below depict the relationships among the different factors that influence student achievement with a breakdown that was discussed in the literature.

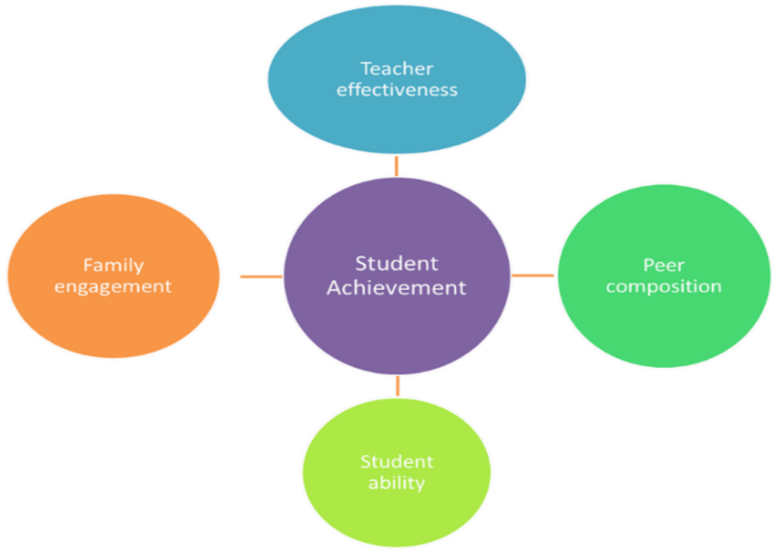

Figure 2-5 Selected Factors Influencing Student Achievement

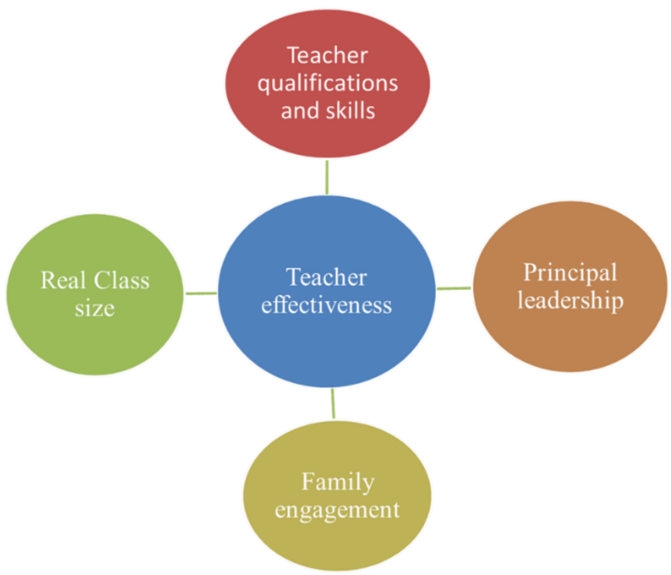

Figure 2-6 Selected Factors Influencing Teacher Effectiveness

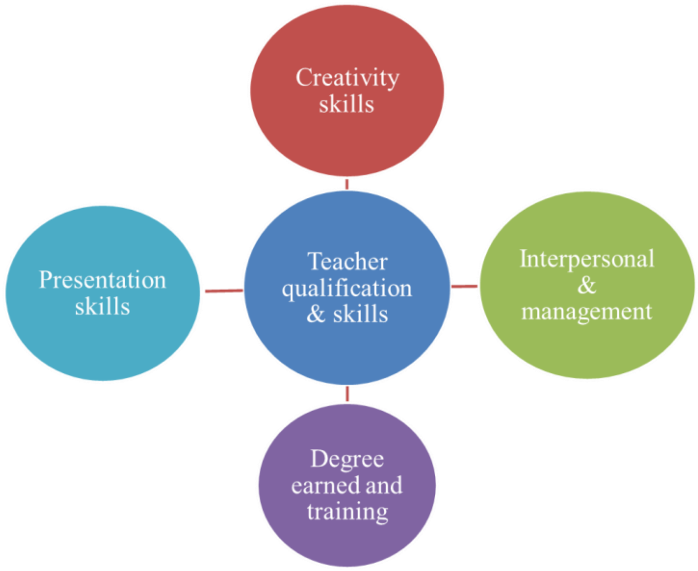

Figure 2-7 Selected Factors Influencing Teacher Qualification & Skills

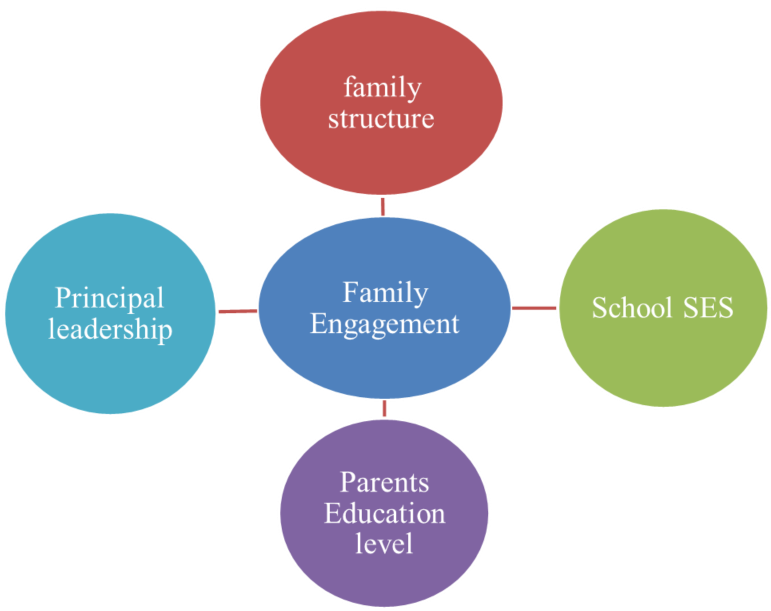

Figure 2-8 Selected Factors Influencing Family Engagement

The above diagrams depict the complexity of the relationships and interactions among all of the factors, as has been demonstrated in the literature. All of the factors described above in the body of the literature (family influence, class size, teacher effectiveness, principal leadership) contribute to a certain degree of student achievement. It is absolutely not possible to isolate one factor from the rest of the factors because all of the factors are intertwined. The absence of any factor will jeopardize the whole system; as a result, the student achievement would suffer. All of the factors are extremely important, despite the fact that one-factor influence might have a small direct contribution to student achievement. The ineffectiveness of this factor could crumble other factors that directly depend on it, and again the performance of the school would suffer. The positive interaction among these factors is essential to make the student achievement progress possible.

The student’s day is split between school and parents, and both have an equal responsibility for achieving success. The school and parents participate directly in the progress of student achievement, and therefore, there has to be a congruous relationship between the school and the parents to promote student learning. Successful projects, such as the STAR project, the Wisconsin projects, and others would not have led to positive results without the contribution of all stakeholders. Unfortunately, researchers have ignored all efforts used by all stakeholders to make small class size successful. They focused only on the benefit of small class size, which cannot by itself be the only solution for student improvement. The congruous relationships among all the stakeholders were essential in achieving the goal of improving student learning and improving student achievement. On the other hand, the absence of the harmony among these factors would make any improvement a very difficult task and can have a counter effect.

In looking at class size policy and implementation outside of the USA, Japan has an average of 32 students per class. It may still be considered one of the best school systems in the world. They argue, is that the most important factor that influences student achievement is a quality teacher and not a smaller class size.

The teacher is the backbone of education. There is no education without an effective and talented teacher. The teacher is the one who delivers the instruction. If the instructions are not clear and comprehensible, the student will learn nothing. All the factors, such as smaller real class size, principal leadership, peer effect, family involvement, in addition to the composition of the students in the class, are impacting either directly or indirectly teacher's effectiveness. The teacher is front and center of the success of any education system (see diagram above).

Resources have to be allocated in a smart way to reinforce the interaction among all contributors that make up the school fabric in an effort to achieve an optimum system for education. A solution solely focusing on one factor to improve the education system is the wrong approach because all of the factors contribute to the success of the student. Accordingly, policymakers and administrators should consider improving the school system from a "Pareto efficiency" perspective.

As mentioned earlier, Pareto efficiency is a state where resources are allocated in the most efficient manner such that if any attempt to reallocate the resources to improve one individual or a group, the result should not be worse off for the rest of the individuals or groups. I am certain that our school system is not Pareto efficient, and therefore, there is ample room for improvement within the same budget for a more holistic approach by considering all factors.

The discrepancy in measuring variables like teacher-effectiveness, principal-leadership and other latent variable made the possibility of implementing research finds extremely hard to impossible. The non-standardization of measuring these latent variables create a noncoherent atmosphere among researchers, and therefore research results are not consistent. The standardization of measuring the latent variables in education will create a more reliable data pool that can be used by all researchers and can produce robust results. At the same time, researchers can compare their findings on the same ground.

The challenge to prepare a student for the 21st-century global economy is not an easy task and requires the collaboration of all stakeholders. The world that we live in now has no economic barriers, labor can move freely anywhere. The search for skills and talents doesn't stop at the border of any country. There is no question that smaller class size promotes learning, improves student academic achievement, makes the teacher more effective in their classroom, and lessens class disruption. However, the consideration of class size reduction in isolation of other factors in the school system will doom the benefit of the class size reduction intervention. The success of the STAR project laid on the fact that all stakeholders (policy makers, legislators, principals, parents, teachers, etc.) collaborated to make the very idea of small class size successful.

The purpose of this study is to demonstrate that in order to improve our education system, one has to focus on the system as a whole and optimize the resources available in order to meet the challenges that the nation faces preparing the students for the 21st challenges. The idea of the one factor like a smaller class can by itself pull it off is not real.

Nations around the world are undertaking a wide range of reforms to better prepare children for the higher educational demands of life and work in the 21st century. The skills that a child needs in this rapidly changing world and the competencies that teachers need to effectively teach those skills are a big challenge and should be the focus of future research. Therefore, Principal leadership and teacher professional development should be front and center of research because they are the backbone of the education system.

Another research focus should be on students at the top and the bottom of the spectrum, students who are either below or above the two standard deviations from the population mean. Researchers have ignored to a certain extent these two groups of students. The students at the top of the spectrum, the A+ students, are tomorrow's design leaders. They are the one who will carry the baton in innovation, science, engineering, and math. On the other hand, the investment in the D students will create more employment opportunities, raise the value of real estate over time, neighborhoods with fewer violent and property crimes, consequently, the economy will flourish.

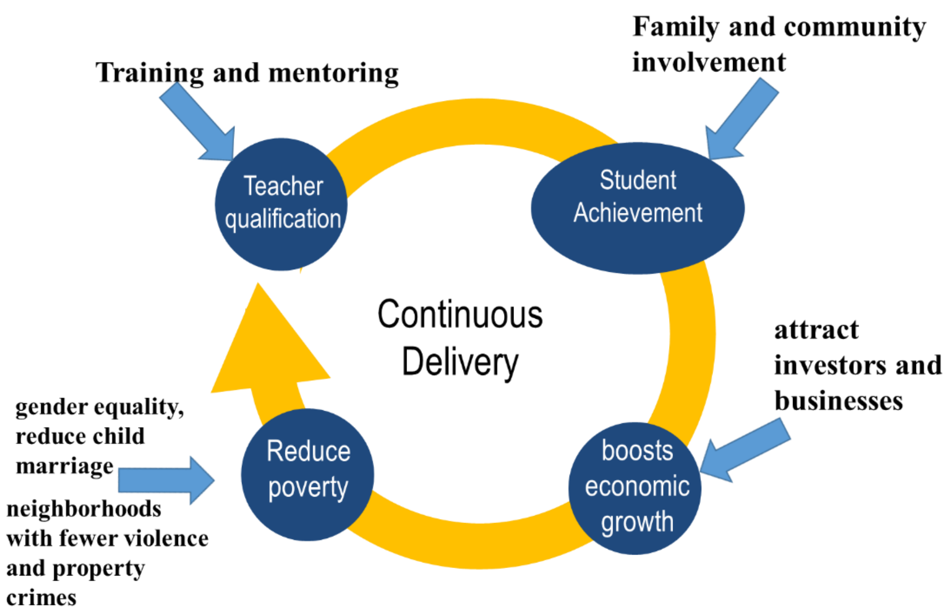

Figure 2-9 Investment in Low Income Neighborhood Schools

Finally, ranking the different factors that affect student achievement is completely out of context. All of the factors interact with each other to produce the education system. The idea of ranking the different factors undermines the impact of one factor over the other.

2.8 Meinshausen-Bühlmann (MB) Structure Learning

The Meinshausen-Bühlmann (2006) algorithm uses the neighborhood lasso regression which imposes an ℓ_1 relaxation. Therefore, we are solving an optimization problem with ℓ_1

regularization. The neighborhood lasso uses lasso regression to perform neighborhood selection for each node in the graph (Tibshirani, 1996). This approach sets a subset of regression coefficients to zero, and so automatically performs model selection.

The neighborhood lasso takes each random variable individually and estimates the best neighborhood using the ℓ_1-regularized sample-based least squares loss. It will begin with node 1 and it will estimate its neighborhoods and then node 2 then node 3, and then it will combine these neighborhoods for the overall structure estimate.

Chapter 3 Methodology

3.1 Introduction

In the previous chapters, I focused on the complexity and interrelated nature of the major factors that ultimately influence students' learning opportunities and achievement. The graphical representation of the ecological framework is the best model to illustrate the relationships and the interplay of all the variables that have been introduced in the previous chapter. The Graphical modeling enables the integration of information from diverse factors and is well suited to undertake the challenges of complex ecological problems. Direct graph or undirected graph modeling enables the assessment of the potential impacts of the different factors on student achievement.

3.2 The Ecological Framework

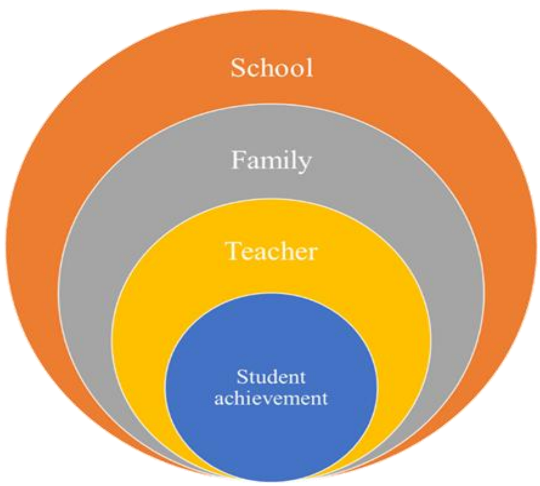

Figure 3-1 Ecological Model for Education

The ecological model provides a powerful analytical framework for understanding student achievement. The ecological model is a model of education that illustrates the linkages and relationships among multiple factors (or determinants) affecting education, and therefore, student achievement. The ecological framework provides a mechanism for understanding the interconnection and the complex interactions that occur across the multiple levels of the school community (Berkes, Folke, & Colding, 2000). According to Christenson (2004), the ecological models are used by psychologists to study and develop the partnership between families and school personnel to improve student learning.

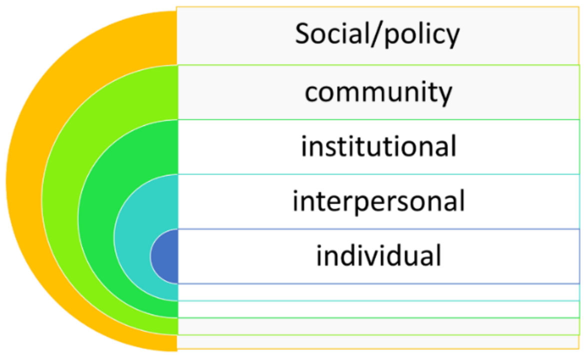

Figure 3-2 General Ecological Model

The recent development in the business world on managing data and information became so vital in projecting business growth. The process of converting data to information, and converting information into knowledge influenced companies' decisions and helped business stakeholders to make critical decisions about a company's plans (Petrides & Guiney, 2002). Petrides added that an ecological framework can take advantage of the abundance of available data and turn it into the knowledge that can help improve learning. Furthermore, he clarified that knowledge ecology is a framework to demonstrate the intersection between the goals of a school and the goal of a student. According to Fullan (2002), schools and school systems require knowledge building and knowledge management in order for the leadership to advance learning and improve students' success. According to Du Plessis (2007), knowledge management is the vehicle that drives change, innovation, and improvement in any company or organization. Knowledge management includes multiple factors, such as personal practice, resources, culture, and organization structure, which is crucial given the abundance of data available in education. The ecological model will facilitate data management, and guide decision-makers to reach a more informed decision. Chen, Liang, and Lin (2010) concluded that that the knowledge management attainment in any organization relies on preserving a healthy knowledge ecology.

According to Argyris and Schön (1996), the ecological framework is a concept that contains a broad range of disciplines that are overlapped and intertwined. The ecological framework allows for a broad range of factors to be envisioned together. The ecological framework highlights the essence of community and the importance of leadership (Community Intelligence Labs, 2000). According to Brown and Duguid (2000); Brown (1999), ecological framework overreaches the boundaries of the learning community and allows the widespread knowledge and learning within the community. He added that the ecological framework helps the dissemination of ideas, knowledge, and information that develops within the school and impacts the external community. The ecological model will help us understand the effects of the factors that impact the social and physical environment on student's learning (Patrick, Ryan, & Kaplan, 2007).

According to Bronfenbrenner (1994), the child's environment influences his growth and development. He explained that the ecological system is made of four socially structured subsystems that guide and support human growth which includes (a) microsystem, (b) mesosystem, (c) exosystem, and (d) macrosystem. The microsystem, which has the closest relationship, is the most influential. The microsystem is the one that depicts the direct relationship between the student and school, and between student and family. The mesosystem explains the different parts of the person's microsystem which has a direct effect on the individual. The exosystem includes places that the child does not have a direct contact with, such as the parent's work. Parents' type of work and work stress have an indirect effect on parent-children conflict (Crouter, Bumpus, Maguire, & McHale, 1999). Finally, the macrosystem is the overarching system that influences the child from a distance, such as cultural values, the economy, and wars. Wars and the collapse of an economy have a tremendous impact on the children psychological well-being and their future development (Hick, 2001).

An ecological model of health can describe the multiple factors that can cause a knee pain. The factors that have an effect on knee pain are ankle flexibility and hips strength and stability (Lutter, 1980; Wang, Chen, Shiang, Jan, & Lin, 2006). The use of statistical and analytical techniques or a combination of both are used in ecological models. The knee pain creates other problems; as other muscles start to compensate for this deficiency; as a result, the knee develops a bad pattern of movement. Knee pain causes limping, and limping can slow down walking. Similarly, as knee pain can cause limping and slows down the person, bullying is a psychological disorder that can threaten the learning environment at school. School bullying is a major problem in the USA and has a great impact on the school environment as a whole. An increase in bullying impacts students learning and increases the number of absentees' students (Espelage & Swearer Napolitano, 2003). According to Espelage, Gutgsell, and Swearer (2004), a social-ecological framework can best describe the different factors that identify the social behavior of bullying students which helps decision-makers to diagnose the problem properly and reach the adequate decisions. The ecological framework focuses on all of the variables that are linked to the issue of the study to provide a complete picture for decision-makers.

According to Ruderman, Stifel, O'Malley, and Jimerson (2013), the ecological framework has its origins in the fields of psychology and human development. In the mid-20th-century, Bronfenbrenner (1994); Lewin (1943), began their work to understand the interplay of the individual and the environmental factors. They suggested that researchers used the ecological framework as a model for studying health promotion, health psychology, epidemiology, and maternal child health. The ecological model is a model that can be used in education to emphasize and explain the linkages, causation, and relationships among the enabling factors, or determinants (i.e., school committees, teachers, administrators) that are affecting student achievement. The ecological framework assists in providing shape, structure, clarity of purpose and direction for a combination of factors that influence learning and therefore student achievement.

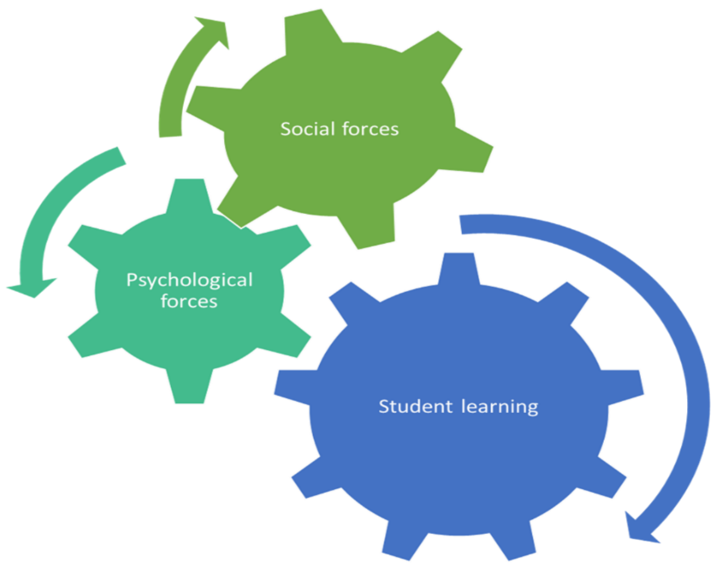

Figure 3-3 Forces Impacting Student Learning

The ecological model is important in education because it helps to organize our thoughts, knowledge, and identify opportunities for intervention (Naeem, Loreau, & Inchausti, 2002). The model also helps in the assessment of any interventions and whether it has reached the desired effects (Almond, Mislevy, Steinberg, Yan, & Williamson, 2015).

The main factors that influence student learning (Reynolds, 1991; Reynolds & Walberg, 1992) are ability, motivation, effort, instruction (quality and quantity), social and psychological environment. Furthermore, researchers have agreed that motivation is the number one factor that advances academic achievement (Banks, McQuater, & Hubbard, 1978; DeCharms, 1984; Dweck, 1986). Academic engagement is a result of the student motivation which further improves student learning (Newmann, 1992). Furthermore, Pintrich (2003) determined that the factors that influence student learning are motivation, interest (Tobias, 1994), ability and aptitude (Garavalia & Gredler, 2002), attention (Kane, Conway, Hambrick, & Engle, 2007), health and nutrition (Alderman, Behrman, Lavy, & Menon, 2001; Behrman, 1996; Blumenshine, Vann, Gizlice, & Lee, 2008; Fowler, Johnson, & Atkinson, 1985; Jackson, Vann, Kotch, Pahel, & Lee, 2011), and prior knowledge and achievement (Garavalia & Gredler, 2002; Hewson, 1982; Tobias, 1994). All these psychological factors and the interplay among them have a stake in any student's readiness. The factors that influence student learning are important predictors of general academic achievement for any student.

Prior knowledge gained by the student determines his efficiency in learning new concepts. In fact, Reynolds (1991) found that prior knowledge is a central factor in a student future achievement. The grade that an 8^{th}-grade student receives in math is a measure of the amount of knowledge that the student has acquired since he began going to school and not just in that particular year.

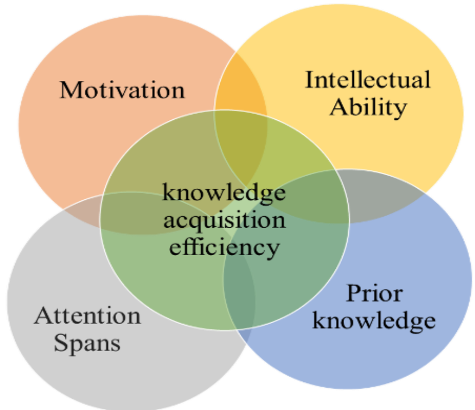

Figure 3-4 Factors Impacting Knowledge Acquisition

The graph above shows how psychological forces, such as motivation, attention span, prior knowledge, and intellectual ability influence student learning. The combination of these factors influences to a great extent the efficiency of the knowledge acquisition.

The acquisition of a new concept in math or any other subject at one period of time depends on prior knowledge. The knowledge gained over the years of schooling and learning influences the potential for success of any student. A student who fails to understand a concept at a certain period during his years of education could make the acquisition of a new concept harder. Student prior knowledge is crucial when a student is attempting to learn a new concept (Svinicki,1994). Svinicki added that when prior knowledge is complete (i.e., stimulated, adequate, applicable, and precise) it enhances learning; however, when it is not complete (i.e., disabled, lacking, wrong, and erroneous), it impedes learning.

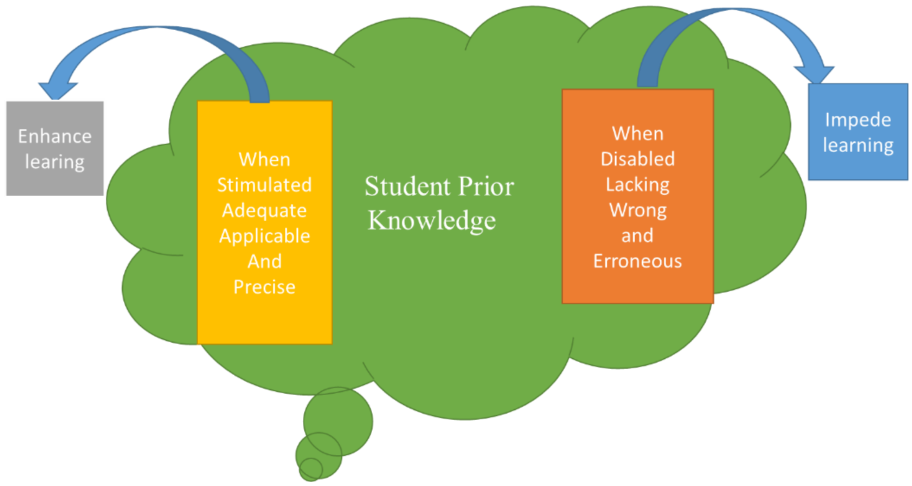

Figure 3-5 Prior Knowledge Effect

Lack of prior knowledge increases the difficulty of learning new concepts; as a result, the achievement gap will widen, and the catch up will become increasingly difficult. In other words, as the efficiency of acquiring new knowledge drops, the problem gets compounded, especially when other topics like physics and chemistry rely on prior math knowledge. Svinicki stressed that prior knowledge impacts the process of acquiring new knowledge. Beyer (1991) stressed that every student comes to class with the knowledge accumulated from previous experiences whether this knowledge has been gained from education or from real life. Therefore, the score that a student earns is a function of his current and prior knowledge.

Psychological factors, such as motivation, are affected by social forces presented by the attitudes of parents and teachers towards children (Singh, Granville, & Dika, 2002). The social forces presented in the graph below are the factors that influence the psychological factors that affect student learning.

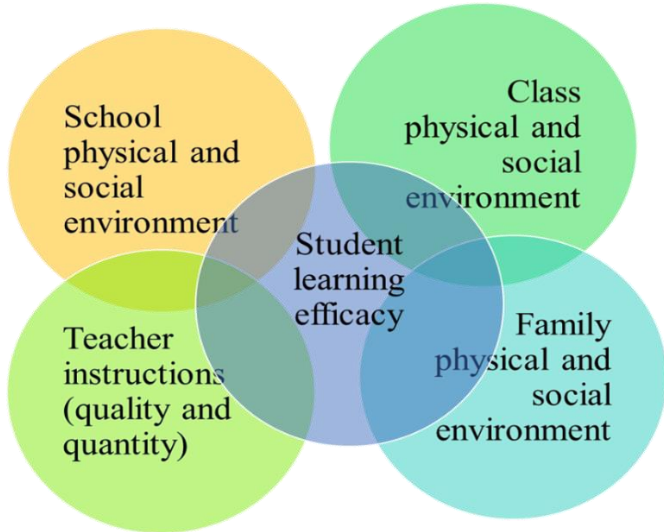

Figure 3-6 Factor Impacting Student Learning Efficacy

The factors that influence the psychological factors of student's learning are directly impacted by the student's environment, whether it is physical or social. The interest that a student has in learning, acquiring knowledge, and going to school depends on the family, teacher, class physical and social environment, and school physical and social environment. Literature has overwhelmingly indicated that each factor will either empower or inhibit the student to learn and therefore, impact the accumulation of knowledge over time. Fraser, Walberg, Welch, and Hattie (1987) stated that the social and physical environment at home plays a big role in the advance of student learning. They added that the physical and social environment at schools, such as student-teacher relationships, and relations among peers that play a significant role in student's motivation. They concluded that social factors, as a result, affect future achievement.

The complexity of all the factors that I mentioned above makes it very hard to envision how they impact student learning. The ecological framework provides a graph that encompasses all the factors; it explains how these factors are interconnected and allow researchers to explain to stakeholders the importance of each factor in relation to other factors. Furthermore, the ecological model shows the distance between each factor and another. In other words, it explains whether a factor has a direct or indirect effect on a certain variable. The bottom line: one graph can capture everything. In this thesis, my focus is on learning the interplay of the relationships of the enabling factors in education and their contribution to student achievement. I will compile the information into a consistent mesh that may be used to describe the influence of each factor in tracking student achievement. The meshes or networks are of cause-effect relationships that will allow one to learn about the interaction of these factors in a causal model.

In conclusion, the goal of the education researchers and practitioners is to improve education. The multiple levels of the ecological model are the preferred method because it offers a better understanding of the complex environment surrounding the student. A positive school environment has a significant influence on student motivation and learning. Student's learning is a very complicated process as it reflects the combinations of multiple influences on behavior. The ecological model is about how the student relates to the multiple layers of factors that influence his behavior. The ecological model allows us to address the factors that can help a student to advance in his education. The strategies to improve student learning can be used at each level of the ecological model to address the different factors. Each level in the ecological model can be thought of as a level of influence and also as a key point for education improvement. It offers a framework for researchers and practitioners to determine how to focus on accelerating progress in education.

The Bayesian network is the best fit for the ecological framework. Bayesian network models are useful tools to model ecological complex data that has high-dimensionality. The graphical models and their applications are best suited for the analysis of social problems and scientific problems are best described by ecological models because of the multiple factors that could impact the variable or variables of interest. The Bayesian network creates the graphical system that best describes the structure of the data variables, and develops the joint probability distributions of the interplay of these variables.

3.3 Elasticity Theory

The ecological factors that influence students' learning are physical, social and psychological forces. Any student is exposed to these factors every day and that impact his learning. The forces that students are exposed to every day are the catalyst factors that influence the efficiency of his learning. The accumulation effects of these forces impact the amount of knowledge a student will acquire over time. Therefore, the amount of knowledge gained over time is a function of all these forces. The amount of knowledge a person hold reflects on his ability to acquire new knowledge. On the other hand, the efficiency of student learning is a function of the student's prior knowledge.

The elasticity of learning new knowledge is a measure of the relationship between a change in the amount of knowledge acquired and the change in the amount of prior knowledge gained. the elasticity measure is also a measure of the amount of unit gain in new knowledge gained given a change of one unit in any of the catalyst factors (physical, social and psychological forces). For example, the elasticity of knowledge change with respect to a unit change in class size

$$\mathrm{E} = \frac{\%change\ in\ Knowledge\ level}{\%\ change\ in\ class\ size}$$

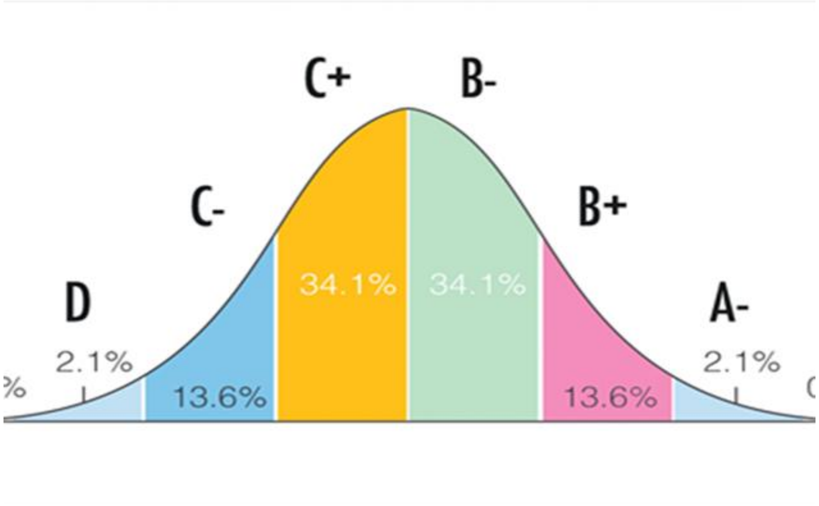

Figure 3-7 Bell-shaped Distribution

The graph above is a breakdown of different regions in the spectrum and each region represents a certain elasticity of learning. The bottom part of the spectrum, “D”, and the very top “A” has the lowest elasticity. The regions in the middle represent a much higher elasticity. In other words, the responsiveness of students to any positive change in these regions will result in higher responsiveness, i.e., a higher score gain.

The percentage change in knowledge level is a function of prior knowledge. The relationship of elasticity to prior knowledge will be almost linear in the regions “C-” to “B+”; however, the region of “D” where prior knowledge is very poor, the elasticity of acquiring a new knowledge is inelastic; in other words, the responsiveness to learning a new concept will be small.. In the “A-” and up regions, the elasticity will depend on the program and curriculum. If the curriculum is used the elasticity will be low and there is no room for improvement; however, a challenging curriculum can give more room for these students to advance in their learning, as the elasticity will be higher. The group of students of “A-” and higher has a high level of prior knowledge, and therefore, moving to a more challenging environment will have a better chance to reach a much higher level.

The elasticity coefficient is normally a coefficient that is suggested by practitioners, e.g. teachers. Teachers can tell from their experience the responsiveness that they can anticipate from a certain group of people. The parameters of the elasticity distribution can also be recommended by practitioners. This another opportunity that researchers can collaborate with practitioners. In order to predict the impact of certain percentage change of a class size on student score

$$\%change\ in\ Knowledge\ level = \mathrm{E} * \%\ change\ in\ class\ size$$

The Elasticity coefficient, E, is a unitless ratio. and it is independent of the type of quantities being varied.

Even though I am willing to change class size, the elasticity will be the factor that will influence the impact of class size on the score. If the elasticity is low the score change will be small, and vice versa.

In economics for example,

$$\mathrm{E} = \frac{\%volume\ of\ sales}{\%\ price\ change}$$

Price elasticity of demand is a measure of the relationship between a change in the volume of sales of a particular good and a change in its price. Price elasticity of demand is a term in economics often used when discussing price sensitivity

The reduction in price will not automatically increase the volume of sales. The volume of sales depends on the elasticity factor. If the elasticity is high then any change of the price will be translated into a significant amount in volume sales, and if the elasticity is low, the reduction in price will contribute in a minimal change in sales. For example, the elasticity of purchasing soda downtown Chicago is less elastic compared with the elasticity of purchasing sodas in the suburb. In the suburb the reduction of price entices the people to purchase more because they have space; however, in the downtown, people live in condominiums and a lower price does not translate to higher sales like the case in the suburb; therefore, the reduction in price will not automatically impact sales volume. The aim of reducing the price is to achieve the maximum purchasing power of the customer. The elasticity coefficient gives an indication of how much the seller can lower its price to get the maximum purchasing power of the client. If the price is discounted to level and the sales don't match this reduction in price, the business will not be profitable. The same analogy can be used in class size. If the group of students in a class or a school has a low elasticity of learning, the reduction in class size will not have a significant change in their achievement. There have to be other factors to be considered first in order to increase this elasticity before deciding to reduce class size. The benefit of using the ecology model can indicate the factors that can influence the elasticity of learning, and therefore, a change in class size can reflect on student achievement.

3.4 Graphical Models

A graphical model is a way of representing probabilistic relationships between random variables. The graphical models describe and model multivariate systems that cover conditional independence, several types of independence graphs (Whittaker, 2009)

3.4.1 Directed Graphical Models

In a directed graph model edges give causality relationships (Bayesian network or Directed Graphical Model)

3.4.1.1 Bayesian Networks/Bayesian Belief Networks

Bayesian networks or Bayesian belief networks (BBNs) (Aguilera et al., 2011a) are probabilistic models that are transparent. BBNs structure model is comprised of two main components: (1) a directed acyclic graph (DAG) that represents the dependencies and independencies among the model variables; and (2) the strengths of the links between the nodes is demonstrated by conditional probability tables (CPTs). The direct acyclic graph (DAG) according to Nielsen and Jensen (2009), is the qualitative component where each vertex denotes one variable in the model. On the other hand, the edges are the links between the nodes and represent the probabilistic dependencies among the corresponding nodes. These conditional dependencies in the graph are often estimated by using known statistical and computational methods. Bayesian networks denote the joint probability distribution of a set of random variables with a possible mutual causal relationship among them**.**

The graph below shows a Bayesian network for variables X_1, X_2, X_3, X_4, X_5. The joint distribution, P (X1, X2, X3, X4, X5), in this case, will be:

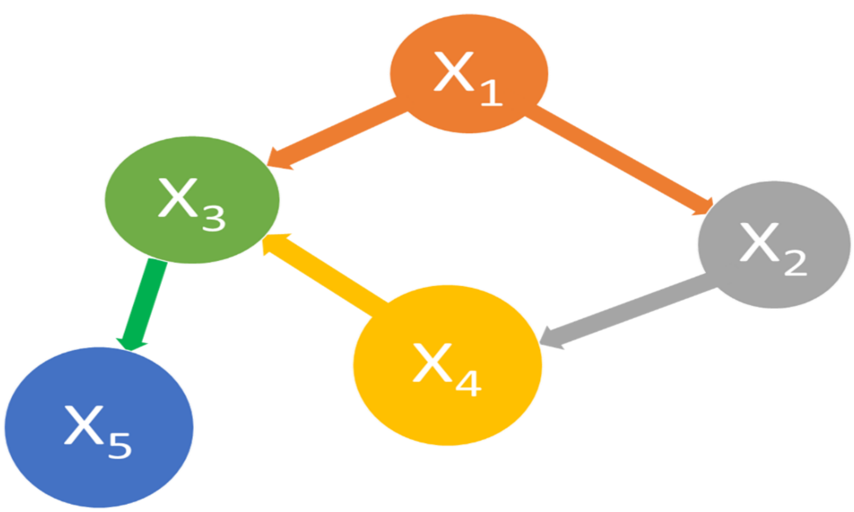

Figure 3-8 Acyclic Graph

$P(X_1, X_2, X_3, X_4, X_5) = P(X_1) * P(X_2|X_1) * P(X_3|X_1) * P(X_4|X_2, X_3)$ and $P(X_5|X_3)$

The quantitative component takes into account the independency encoded by the network structure which is the joint distribution of the variables represented in the model. The joint distribution is equal to the product of the conditional distributions associated with each node.

The Bayesian network's model can create the link between qualitative (graph) and quantitative (conditional probability associated with each node) methods since it can offer a joined modeling framework that agrees with a broad range of ecological systems (Landuyt et al., 2013).

The probabilistic approach is becoming more popular than certainty factors, fuzzy sets, and Dempster-Shafer theory for reasoning with uncertain knowledge and belief (Zhang & Poole, 1996). Bayesian networks are the best-known representation framework for the probabilistic approach (Howard, 1981; Pearl, 1988). Bayesian networks is a structure and a model that represents the joint distribution over propositional variables of interest in terms of their conditional and prior distributions. Bayesian networks are founded on Bayesian views of statistics. The probability distribution of a certain variable captures the knowledge of uncertainty around this variable. The knowledge represented by the Bayesian networks is the state of the joint distribution of all variables making the network (Almond et al., 2015).

Bayesian networks (BNs) are a directed acyclic graphical model (DAG) that encodes the independence properties of a joint density. A DAG model is comprised of a set of nodes that each represents a random variable, and the edges signify the direct influence between the variables. The absence of an edge between two variables indicates that these two variables are independent. There are two assumptions for the independence encoding in the Bayesian network: (1) the local Markov assumption that states that a node X in a Bayesian networks are independent of its non-descendants given its parents; and (2) Markov Blanket that states that a node X is conditionally independent of all other nodes given its parents, children, and children's parents (Pearl, 1988).

A DAG model illustrates the conditional independence between the variables of interest from their parametric forms (Ghahramani & Beal, 2000). The conditional independence can lead to a significant reduction in computation cost, especially in the complex Bayesian network structure. According to Boutilier et al (1996), Bayesian networks allow qualitative representation of conditional independence properties of a distribution; as a result, it offers a normal and condensed representation of the distribution. It simplifies knowledge acquisition and makes the algorithm inference more efficient.

A graphical model (Ben-Gal, 2007; Jordan, 1998) is a marriage of graph theory and probability theory. Jordan added that the union of both the probability theory and graph theory allows the representation of the variables in interest in a compact and efficient way, especially when their probability distribution is conditionally independent. Jordan stressed that uncertainty and complexity are the main problems that arise in applied mathematics, engineering, and machine learning. He demonstrated that probability theory connects the different parts together, ensures the consistency of the system, and provides ways to link the models to the data. The graph theory can provide the interface that can model a complex set of variables.

Bayesian networks or belief networks, also known as the causal network, are the method of choice for uncertain reasoning in artificial intelligence and expert system because of its bidirectional inference capabilities and its probability foundation (Heckerman, 1998; Jensen, 1996). Bayesian network with its underlying graphical model is an excellent tool to model uncertainty (Holmes, 2008). According to Pearl (2011), Bayesian network nodes indicate the variables of interest (e.g. students' grades, teacher years of experience, family SES, etc.). The edges or links denotes the causal or informational dependencies among the variables. Pearl added that the conditional probability for each node given its parents quantifies the dependency between the nodes.

According to Heckerman (1998), there are many advantages to using the graphical model: (1) BN is not sensitive to missing data unlike frequentist approaches like regression; (2) Bayesian networks can learn the structure of the network, and therefore, identify causality and dependency among the nodes or variables, and therefore, can realize the problem space. It can also predict the result if an intervention is introduced; (3) Bayesian networks can combine prior information with data because its causal and probabilistic nature; and (4) Bayesian networks with Bayesian statistical model avoid data overfitting. Heckerman explained that BNs in handling incomplete data can avoid the inaccurate prediction that frequentist approaches can mistakenly make when data is missing. Learning about the causal relationship among all the nodes is one of the biggest benefits of Bayesian networks (Heckerman, 1998; Murphy, 1998).

Bayesian networks models have been used by all disciplines including medicine, engineering, information technology, biology and recently education which is the best modeling tool used in a complex environment full of uncertainty like education and learning (Pollino & Henderson, 2010). Bayesian networks can help decision makers to explore and predict students' test scores given the student's educational history, teacher effectiveness, school environment, and numerous other variables of interest. They added that Bayesian networks models satisfy model integration (data types and qualitative information), prioritization (ranking variables, and cost-benefit), flexibility (configuration change, and knowledge update), and communication (easy to understand). The graphical nature of Bayesian networks allows the seizing of the cause and effect between the variables in the diagram. The strength of the relationships between the nodes is manifested by the use of probabilities which is illustrated through the use of both quantitative and quantitative information. The outcome of the model can be assessed quantitatively and through a strict process.

The Bayesian networks configuration adopted in my thesis is the Causal Bayesian Networks, which uses the Causal Markov Condition as defined by Pearl (2009). In the Markovian causal model, each variable is independent of all its non-descendants given its parents. Pearl demonstrated that in causal networks each parent-child relationship is a stable and autonomous unit, which means that any manipulation in any relationship will impact the organization of other relationships. The configuration of the network based on causality allows predicting the impact of any external treatment, e.g. new policy, without the need to repeat the experiment. The other benefit of Causal Bayesian networks is the flexibility to make any changes to the network on the fly to study the impact of removing one variable from the configuration. For example, to represent a disabled variable, one can simply delete all links that are connected to this node, and study the impact. Pearl illustrated that a joint distribution expresses the probability of every event, and a causal model explains the probability change as a consequence of external intervention.

3.4.1.2 Bayesian Network Limitation

A Bayesian networks statistical inference have two versions of uncertainties models (1) a model of uncertainty in the data range, and (2) a model uncertainty outside the data range (Fygenson, 2008). Fygenson stressed that undertaking the extrapolation problem (prediction outside or inference outside the data range) is problematic. The distribution outside the data range is unknown and Fygenson recommended the use of non-parametric models. An example of the complexity of handling extrapolation model uncertainty in prediction contributed to the disaster of the 1986 Challenger space shuttle. Niedermayer (2003) indicated that one of the limitations of the Bayesian networks is the alteration of the probability distribution upon which the system is built. In other words, the change of the probability parameters outside the data range can cause serious problems. The problem of changing probability parameters outside the data range will misrepresent the prior knowledge and jeopardize the validity of the whole network.

In the case of education, there are many forces that influence student achievement (1) social forces, (2) psychological forces, (3) the incremental nature of learning, and (4) space and time. The interaction of these forces are very complex in nature, and therefore, extrapolating distribution outside the data range can cause significant problems. An example of extrapolation in education was the implementation of class size reduction in California from 1998-2001. The rush to adopt this new policy resulted in a significant decline in teachers' effectiveness on average due to the sudden need for more teachers and additional classroom space. The implementation of the class size reduction compounded the prevailing teaching deficiency problem. The implementation of this new policy required an increase of 38% more teachers in two years (Stecher, Bohrnstedt, Kirst, McRobbie, & Williams, 2001). This 38% increase in teachers resulted in hiring new teachers that did not have the appropriate credentials. The teachers that did not have sufficient credentials consisted of 1.8% of K-3 teachers in 1995; however, by 1997, the percentage of unqualified teachers increased to 12.5% as the demand increased due to CSR (Stecher & Bohrnstedt, 2002).

Another big factor to consider in addition to extrapolation is time. The time it takes for a system to absorb and adjust to a new treatment has to be analyzed. The implementation of a new policy or an intervention should take into consideration the social and psychological forces that impact students, teachers, and administrators. The idea that implementing a new policy will have an immediate impact is false. In electrical engineering, for example, the implementation of a new change will disrupt the whole system and send the system to a transient state. The transient state is a state where voltage and current can fluctuate with no specific pattern. In other words, the transient behavior of a system is unpredictable when it is subject to any intervention. The unpredictable nature of the transient state requires electric circuit designers to protect the circuit against extreme changes that might destroy the circuit. A high magnitude of overvoltage, also called spike, can cause damage, and precautions should be taken to protect the circuit. Similarly, in economics, any market decision that is taken by the Feds will have an immediate impact on the stock market. For example, any change in interest rate creates an instant shock to the market. The change can derail the market, such as the case when the Feds rose the interest rate to a level that the market couldn't sustain; as a result, the market collapsed at the end of 1999.

A similar situation can happen in a school system because the intervention can cause a shock to the system. A new policy, such as the reduction of class size, can cause a spike and may create turmoil and disruption to the school system, as the case in California. The complexity of variables that are involved in a school system make the change more difficult and requires caution. In cases where a new policy is implemented, there will be a period of unrest. The duration of this unrest is unknown and unpredictable and depends solely on the severity of the treatment. The transient period becomes more problematic as more variables are involved in the process. As an example, reducing class size will cause (1) instruction adjustment for smaller class size, teaching a smaller class size is not like teaching a large class size; (2) the need to hire and train new teachers; (3) the increase of the number of classrooms; and (4) adjustment of peer social relations, because larger classes tend to be normally distributed. Therefore, a treatment in the form of class size reduction can cause a shock to the system. Therefore, a prediction from a model under intervention needs to take into consideration all the turmoil that can happen at the beginning of applying such a treatment. Intervention into the system should take into consideration two things (1) the elasticity of learning, and (2) sensitivity of the change.

3.4.1.2.1 Bayesian Network Example

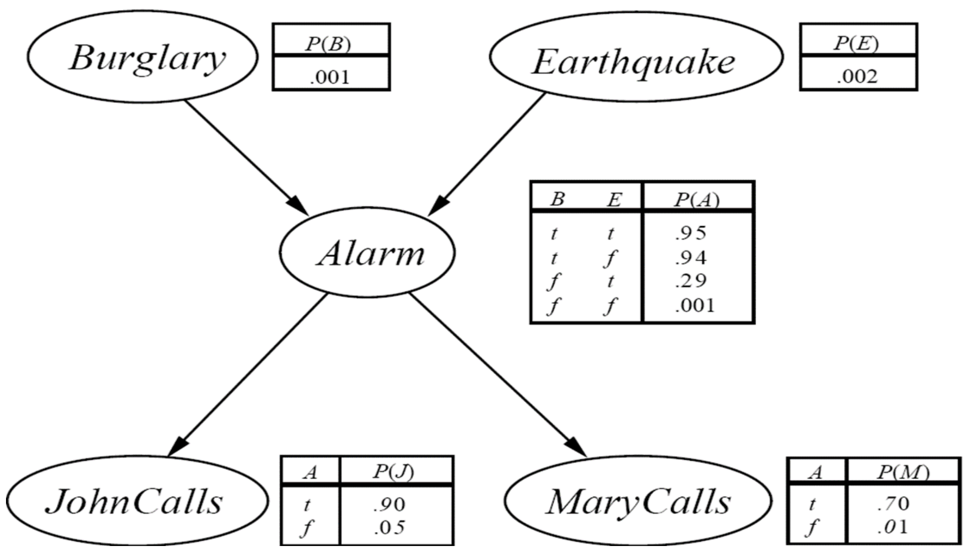

Figure 3-9 Bayesian Network Example

The graph above shows a Bayesian network with 5 random variables: Burglary (B), Earthquake (E), Alarm (A), JohnCalls (J), and MaryCalls (M). A variable X is independent of its non-descendants given (only) its parents. The network topology reflects causal knowledge as follows:

- A burglar can set the alarm off
- An earthquake can set the alarm off
- The alarm can cause Mary to call
- The alarm can cause John to call

In the example above “Earthquake” and “Burglary” causes “JohnCalls”, and/or “MaryCalls” only through the sounding of “Alarm”.

The alarm is set off in case there is a burglary and/or an earthquake. Mary and John are the neighbors. If the alarm sounds, then either, or both, or none of them would call.

There is a probability distribution table associated with each node of the graphs, which gives all the possible probability values. The graph also shows the links between the variables. In other words, it demonstrates the dependencies between the nodes. Conditional probability distribution table, CPD for each node X_i describes the probability of the certain event of X_i given the parent's variables, $P(X_i \mid Pa(X_i))$.

A Bayesian network can represent the joint distributions of the following form

$$p(x) = \prod_{k=1}^{K} p(x_k \mid pa_k)$$

In the above graph, the Bayesian networks represent the joint probability distribution of all the variables in the network. It gives a statistical measure of the likelihood of two or more events occurring at the same point in time.

The combinatorial approach of the joint probability distribution computation implies that the joint distribution goes through all combinations of the variable values as follows:

P(J, M, A, E, B) = P(B) P(B | E) P(A | E, B) P(J | A, B, E) P(M | A,B,E,J)

Number of computation= $(2^5 - 1) = 31$

In the Bayesian networks approach and by establishing the Markov assumptions we have:

- B and E are independent,
- J and M are independent

- J is independent of B and E gave A, in other words, if A does not occur than J is independent of B and E
- M is independent of B, E, and J given A, in other words, if A does not occur than M is independent of B, E, and J

Therefore,

P(B | E) is reduced to P(B)

P(J | A, B, E) is reduced to P(J | A)

P(M | A, B, E, J) is reduced to P(M | A)

As a result, the joint probability distribution of the Bayesian network is

P(J, M, A, E, B) = P(B) P(E) P(A | E, B) P(J | A) P(M | A)

Number of computation= 1+1+4+2+2= 10

The number of computations is the entries of each CPD table in the graph above.

As the number of distribution values increases along with the increase in the number of variables, the number of values will grow exponentially.

The Bayesian networks will help answer the owner's question: If he receives a phone call from Mary and no calls from John, what is the probability that there is a burglar in the house? In other words, what is P(B | M, J)?

P(b | m, ¬j) , i.e., P(B=true | M=true ∧ J=false)

By definition of Bayesian

$$P(B \mid M, J) = \frac{\text{Area of "B, M, J" region}}{\text{Area of" M, J " region}}$$

$$P(b \mid m, j) = \frac{P(b = true, j = \ false, m = true)}{P(j = \ false, m = true)}$$

$P(b, m, \neg j) = \Sigma A \in [a,\neg a] \Sigma E \in [e,\neg e]\ P(\neg j, m, A, E, b)$;marginal

$P(J, M, A, E, B) \approx P(J \mid A)\ P(M \mid A)\ P(A \mid E, B)\ P(E)\ P(B)$; conditional independence.

$P(\neg j, m, A, E, b) \approx P(\neg j \mid A)\ P(m \mid A)\ P(A \mid E, b)\ P(E)\ P(b)$

In this case there is no earthquake; therefore $A=a \wedge E=\neg e$

$P(\neg j, m, a, \neg e, b) \approx P(\neg j \mid a)\ P(m \mid a)\ P(a \mid \neg e, b)\ P(\neg e)\ P(b)$

$\approx 0.10 \times 0.70 \times 0.94 \times 0.998 \times 0.001$

Note in the equation above: small letter denotes the value of the random variable. A capital letter denotes all possible values of the random variables.

Bayesian networks possible probability values depend on the number of variables, and the number of values in the distribution. In an unconstrained joint distribution (going through all possible combinations), it requires $O(2^n)$ probabilities. In the case of a Bayesian network with k parents, it requires $O(n\ 2^k)$ probabilities.

Example: a full unconstrained joint distribution

$n = 30$: need 10^9 probabilities for full joint distribution

Bayesian network joint distribution will require

$n = 30$, $k = 4$: need 480 probabilities

3.4.2 Undirected Graphical Models

In an undirected graph model edges simply give correlations between variables (Markov Random Field or Undirected Graphical model)

3.4.2.1 Meinshausen-Bühlmann Graphical Model

The method that I used in the analysis is the high-dimensional graphs and variable selection with the LASSO. The method has been developed by Meinshausen and Bühlmann (2006) to provide an algorithm for performing model selection in a structure learning problem while controlling the number of false discoveries. This method is used to solve problems with a very large number of features and complex datasets. The high-dimensional graphs and variable selection with the LASSO is a great tool to analyze complex systems like the education system, where the factors that impact the student performance is extremely intertwined (see fig 4-1). The big advantage of this method is in its ability to select the most influential variables among a large number of variables, especially when the data is large in the number of features and small in the number of entries. The algorithm is applicable to engineering, genetics analysis, time series analysis, network and scheduling (Boyd, Parikh, Chu, Peleato, & Eckstein, 2010). My focus in this study is on the statistical learning problem. The examples below provide a snapshot of selected variables to analyze the issues related to the factors that influence student achievement.

An undirected graphical model, UGM, is defined by a graph of a set of variables (nodes) that are connected by bidirected edges (links). I will now show how to construct and estimate an undirected graphical model, UGM, from a set of data, using least-squares linear regression, according to the method of Meinshausen and Bühlmann (2006).

Recall that, for n sample data observations $\mathbf{y}_n = (y_i)_{n\times 1}$ of a dependent variable Y corresponding to sample observations $\mathrm{X}_n = ((1,\mathbf{x}_i))_{n\times(p+1)}$ of p predictor variables $X_1,\ldots, X_p$ (including a constant (1) term), the linear regression model is defined by:

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i, \text{ for } i = 1,\ldots,n,$$

where β_0 is the real-valued intercept parameter, $\beta_1,\ldots,\beta_p$ are the real-valued effects of the p predictors (resp.), and the ε_i (for $i = 1,\ldots,n$) are regression errors assumed to be independently and identically distributed with mean zero and variance σ^2. As a side note, the linear regression model can be specified to handle nonlinear effects by employing nonlinear transformations of the p predictors, such as polynomial expansions. Also recall that given a sample set of data $(\mathbf{X}_n, \mathbf{y}_n)$, the ordinary least-squares (OLS) estimate of the population parameters $\boldsymbol{\beta} = (\beta_0, \beta_1, \ldots, \beta_p)$ is the (p+1) dimensional value $\boldsymbol{\beta}$ that minimizes the residual sums of squares (RSS):

$$\mathrm{RSS} = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2$$

As an alternative to OLS regression, the LASSO (Tibshirani, 1996)estimation procedure can be used to estimate the parameters $\boldsymbol{\beta}$ while performing automatic predictor selection to identify the subset of significant predictors among the p total predictors. Assume that the data of each of the p predictors have been rescaled to have mean zero. Then the LASSO least-squares estimator of the coefficients is the value of $\boldsymbol{\beta}$ which minimizes a penalized residual sums of squares (PRSS), defined as follows:

$$\sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| = \mathrm{RSS} + \lambda \sum_{j=1}^{p} |\beta_j|$$

while employing a ℓ_1 penalty term, $\lambda \geq 0$. As the tuning parameter λ increases the coefficient estimates shrink towards zero. Each fixed value of the penalty term λ has the effect of forcing the coefficients of insignificant predictors to take on a value of exactly zero. In summary, the LASSO approach to least-squares regression automatically combines coefficient estimation with predictor selection in a single algorithm, and it tends to produce simpler and more interpretable models that involve only a significant-predictor subset of the p total predictors. Also, when $\lambda = 0$ (zero penalties), the LASSO estimation procedure is equivalent to OLS estimation. Finally, given a set of data $(\mathbf{X}_n, \mathbf{y}_n)$, the optimal estimate of the penalty can be found at the value of λ that minimizes the AIC criterion AIC = PRSS + 2d, where d ($\leq p$) refers to the number of non-zero LASSO coefficient estimates.

For a given dataset of observations of *K* variables $X_1,...,X_p$, the Meinshausen and Bühlmann (2006) approach to estimating an undirected graphical model , UGM, is based on performing a LASSO regression of each variable on all other variables, in turn for each of the *K* variables, while in each instance the AIC criterion is used to estimate the penalty λ. In summary, this undirected graphical network model estimation approach is based on a sequence of *K* LASSO regression estimations combined with predictor selections. Then the undirected network graph is estimated (constructed) according to what these *K* LASSO regressions determine as significant predictors from the data.

3.4.2.1.1 Undirected Graphical Model Pilot Study

I now illustrate this Meinshausen and Bühlmann (2006) procedure through the undirected graphical network analysis of NELS pilot data, involving 1996 sample observations of the following 12 variables: Dropout, Sex, Race, Math test Score, Science test Score, Reading test Score, Social Science test Score, Type of School, Teacher interest in Student, Teacher praising student for good work, Student-Teacher relationship, School Spirit). The table below presents the results of the *K* LASSO regressions combined with predictor selection, where an insignificant predictor of a given dependent variable is indicated by a coefficient value of zero (Meinshausen & Bühlmann, 2006).

		Predictors											
		Dropout	SEX	RACE	ReadingST	MathSTD	ScienceSTD	SocialScienceSTD	SchoolType	SRelationT	schoolspirit	TinterestedSt	SpraisedByT
Dependent variables	Dropout	0.000	0.000	0.000	0.000	**-0.073**	**-0.005**	0.000	0.000	**0.356**	**0.112**	**0.087**	**0.037**
	SEX	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**-0.017**	0.000	0.000	0.000	0.000
	RACE	**0.016**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	ReadingSTD	0.000	0.000	0.000	0.000	**0.335**	**0.293**	**0.283**	0.000	0.000	0.000	0.000	0.000
	MathSTD	**-0.021**	0.000	0.000	**0.325**	0.000	0.402	**0.186**	0.000	0.000	0.000	0.000	0.000
	ScienceSTD	0.000	0.000	0.000	**0.269**	**0.385**	0.000	**0.250**	0.000	0.000	0.000	0.000	0.000
	SocialScienceSTD	0.000	0.000	0.000	**0.331**	**0.226**	**0.324**	0.000	**0.025**	0.000	0.000	0.000	0.000
	SchoolType	0.000	**-0.039**	**-0.005**	0.030	0.000	**-0.108**	**0.112**	0.000	0.000	**0.105**	**-0.019**	**-0.074**
	SRelationT	**0.055**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.330**	**0.353**	**0.250**
	Schoolspirit	**0.011**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.491**	0.000	**0.183**	**0.235**
	TinterestedSt	**0.012**	0.000	0.000	0.000	0.000	0.000	**-0.012**	0.000	**0.441**	**0.157**	0.000	**0.340**
	SpraisedByT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.346**	**0.219**	**0.371**	0.000

Table 3-1 Pilot K LASSO Regressions Results with Predictor Selection, NELS:88 Data

From this table, it is possible to construct (estimate) an undirected network graph that shows the relationships among the 11 NELS variables. This graph is presented in the figure below. In this graph, the link between school spirit and Dropout is present because either schoolspirit significantly predicted Dropout (with a non-zero coefficient estimate), or Dropout significantly predicted schoolspirit (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table. In the same graph, the link between school spirit and MATHSTD is absent because either schoolspirit did not significantly predict MATHSTD (with a zero coefficient estimate), or Dropout did not significantly predict MATHSTD (with a zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

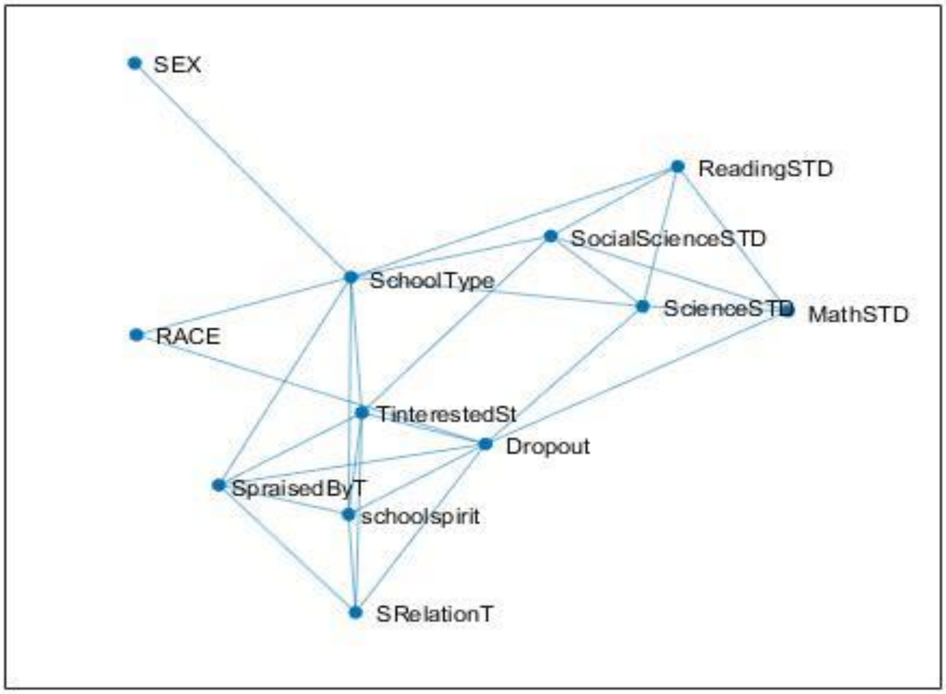

Figure 3-10 The Undirected Network Graph from the Pilot NELS Data Estimate, based on the results of the K LASSO regressions combined with predictor selection (given in the previous table).

3.5 Description of the NELS: 2002 Data

The NELS:2002 surveys included pupils reporting on school, work, experiences at home, educational resources, peers and parents' role in education, environment around the school, educational and occupational objectives, and other student insights. In addition, the surveys included the student-teachers' relationship, parents, and school administrators. High school and postsecondary transcripts data available for research on course taking and grades. The fifty states and the District of Columbia were included in this data.

3.5.1 Purpose of NELS:2002

The 2002 National Education Longitudinal Study focused on the major factors that impacted students' learning growth and included students' integration, students' dropouts, parents, teachers, and school studies (Scott, 1995). Scott illustrated that the initial focus of the NELS: 2002 was on 10th-grade cohort students with two years' follow-ups. He also pointed out that the data includes all kind of demographic distinct subgroups, and the data is also connected to previous longitudinal studies. Another goal of the data is to explain to all stakeholders all the changes in the educational system operations and illustrate the impact of the different elements that influence student achievement. The data included:

- Students' academic progress, the parents, community around the school, school social and physical environment, and classroom elements that influence student achievement.
- The challenge that faces students when moving from 8th grade to secondary school, and later from secondary to college.
- The impact of courses taken on student learning growth.
- The effect and the consequence of students' dropout, and its impact on the school system.
- The curriculum that is constantly changing and its impact on students and parents.
- The goal of the school to help and promote student learning.
- Language issues for minority student and the impact on academic performance.

The NELS 2002 survey data consists of the five questionnaires data sets:

I. The data by student describes the following categories:
   1. background
   2. language in use

3. family
4. opinion about oneself
5. plan for the future
6. jobs and chores
7. school life
8. school work
9. activities

II. Data by parent describes the following categories:

1. Family background
2. Child's school life
3. Child's family life
4. Opinion about the child at school
5. Eight-grade future
6. Financial information and educational costs

III. Data by teacher describes the following categories:

1. Student information
2. Class information
3. Teacher background

IV. School administrators' data describes the following categories:

1. School characteristics
2. Student characteristics
3. Teaching staff characteristics
4. School policies and practices

5. Grading or/and testing structure
6. School programs
7. School climate

V. The student's drop out data describes the following categories:

1. Student's address
2. School experiences and activities
3. Language use
4. Student opinion about oneself and his attitude
5. Background information
6. Money and work

The detailed description of the National Education Longitudinal Studies, NELS:2002, data can be found at National Center for Education Statistics (NCES) website https://nces.ed.gov/surveys/els2002/avail_data.asp

Chapter 4 Results

4.1 Introduction

The aim of this research is to provide a theoretical framework to decode the complexity of the education system. The number of variables that influences student performance is very large, with direct and indirect impacts on student success. The framework recommended in this thesis will provide the procedures to analyze a large number of variables simultaneously, and therefore provide a clear picture of the relationships across the key elements in the education system.

The NELS 2002 original dataset contains 6,571 variables with a mixture of categorical and continuous attributes. I chose 74 variables in total to conduct this study out of the 6000 variables. The only reason to choose this substantially complex subset is to illustrate how my theory applies in practice. The subset that I chose doesn't have any evidence that these variables were necessarily more important than other variables. The 74 variables are a mix of categorical and continuous variables. The number of entries for each variable is 16,197. In an attempt to preserve as much data as possible, I converted every subcategory in any categorical variable into a number of dummy variables. In other words, the number of dummy variables computed represents all the categories in each categorical variable. I assigned a zero category to both the missing data and non-informative data categories in each categorical variable. The resulting number of variables in total is 196 variables.

The full LASSO-based network graph analysis of the196 variables with 16,197 entries took about 2.5 hours on an Intel i5 computer. The total number of variables can increase depending on the nature of the study.

The variables selected reflect student sex, student ethnicity, parent education, parent ethnicity, parent occupation, grandparent education, teacher education, principal involvement in curriculum, principal influencing hiring and firing, and student performance represented in the math and reading scores.

My model examines 10 variables at a time to avoid clutter; a busy graph is hard to read. The choice of 10 variables is an attempt to zero-in on a smaller subset of "interesting" variables, but this selection is illustrative, not definitive. It is plausible from the literature that these variables are influential, but there is no claim that these are the most influential. The selection of variables in each snapshot under study has only one subcategory of each categorical variable. Each snapshot of variables is associated with a table of LASSO regression coefficient and a UNG (Undirected Network Graph). The number of possible combinations is equal to:

$$C(n,r) = \frac{n!}{r!(n-r)!}$$

Where r is equal to the number of variables in a snapshot (10 variables), and n is the total number of variables (196 variables).

$$C(196,10) = \frac{196!}{10!(196-10)!}$$

In each graph, the edge (link) between any two variables in a given graph (see figure 4-2), for example, between grandparent education and math standard score, is present because either grandparent education significantly predicted math scores (with a non-zero coefficient estimate), or math scores significantly predicted grandparent education (with a non-zero coefficient estimate). Each node in the graph represents a variable and the LASSO regression identifies the variables that can predict this particular variable. In other words, the LASSO regression selected the variables that influence that particular variable. The algorithm performs the LASSO regression of each of the *p* variables on the other *p*-1 variables on stages. In each cycle, a regression is performed on one of the *p* variables against all the other *p*-1 variables. In other words, each variable takes a turn and is regressed against the rest of the *p*-1 variables.

The corresponding table for each graph tabulates all the coefficients that resulted from the full LASSO-based regression (a non-zero value means that the variables can predict each other, however, a zero coefficient indicates no relationship). The magnitude of the coefficient represents the strength of the relationship between two variables. In any table, a regression coefficient in red denotes a negative coefficient, whereas a coefficient in black denotes a positive coefficient. For example, see table 4-1. A LASSO regression coefficient in any of the examples below which is computed given all 196 variables selected in this study. In other words, the values of the coefficients are influenced by all 196 variables.

4.2 Results

The tables and graphs below are based on the results of the K LASSO regressions combined with the predictors' selection. The tables in this chapter show a side-by-side comparison of the estimated LASSO regression coefficients, LRC, from the method developed by Meinshausen and Bühlmann (the high-dimensional graphs and variable selection with the LASSO). In addition, the algorithm creates a graph associated with every table using the same data set selected.

The LASSO estimated regression coefficient matrix presented in each table is not symmetric due to the nature of the computation used. In addition, if there is a dependent variable in a matrix (10 variables) that has no significant direct predictors, it does not necessarily signify that this dependent variable has no predictors (see Hispanic_St in table 4-3 and figure 4-4). In addition, this dependent variable could also have an indirect connection to the same variables, which can be depicted from the graphs presented below. The dependent variable could have other predictors among the 196 variables. In general, the estimated LASSO regression coefficient that comes out of any subsample is highly variable in terms of which subset of variables is chosen. The result that comes out when repeating the same target of variables with a new subsample is not fixed. The underlying reason is that there is a structural diversity among different sparse models that all yield close to the optimal predictive performance.

The graphs below starting from figure 4-2 to figure 4-11 show the relationships between [variables] of different sets of variables. A direct link between two variables signifies a direct relationship, whereas if the connection is through multiple links then this signifies indirect association between the two variables. In other words, the pairwise connection strength between every pair of variables depends on the number of links that separate these two variables. The graphs are a demonstration of the ecological system described in the literature review section and in Chapter 3 of this thesis (see figure 3-1 and figure 3-2). The closer the relationship between the two variables the more impact one variable has on the other variable. The relationship starts to weaken as the layers are farther away from each other.

The detailed description of the selected variables and their indices can be found in Appendix I, and II.

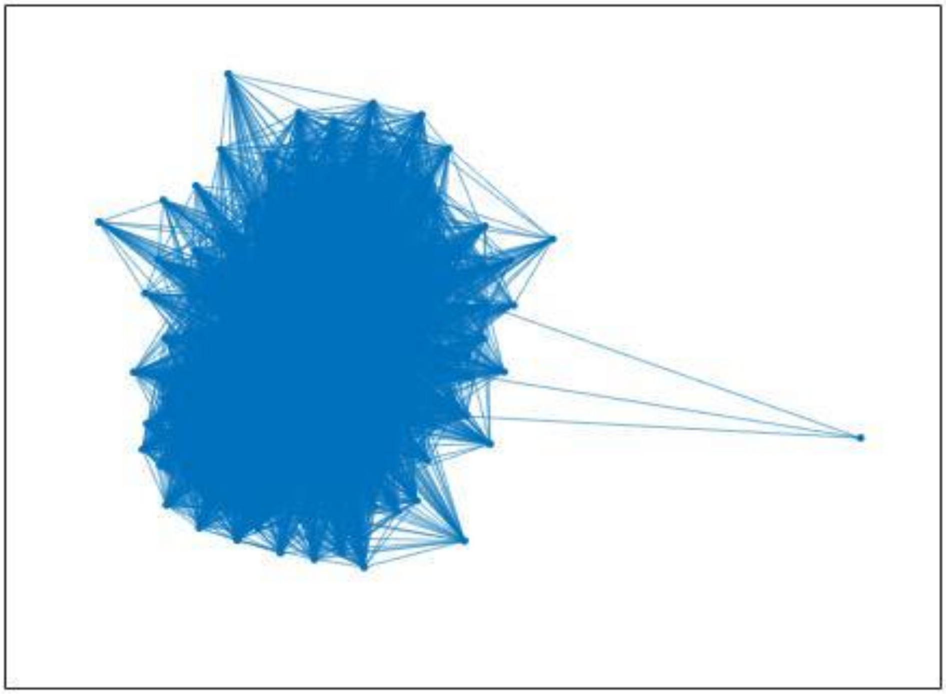

Figure 4-1 The Undirected Network Graph, UNG, from the NELS 2002 Data Estimate, based on the results of the K LASSO Regressions of all the 196 variables

		Predictors									
Dependent Variables		Male_St	EnglishNative_L	MathStdScore	FC_Mo& Father	MEduc_2 YschoolGr ad	FEduc_4Y CollegeNDe	GPEduc_ GED	MOCCU _Manager	PaExp_4Y_Col	MathSelfEffi_B aseY
	Male_St	0.0000	0.6068	0.2842	0.2357	0.0000	0.0000	0.0000	0.0000	0.5921	0.0009
	EnglishNative_L	0.1252	0.0000	0.0249	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathStdScore	2.1152	1.7850	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.1522	0.0013
	FC_Mo&Father	0.3109	0.1349	0.0000	0.0000	0.1201	0.0000	0.0000	0.0005	0.0000	0.0000
	MEduc_2YschoolGrad	0.1639	0.2115	0.0000	1.1573	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	FEduc_4YCollegeNDe	0.1805	0.5124	0.0000	0.7919	0.0177	0.0000	0.0000	0.0000	0.0000	0.0000
	GPEduc_GED	0.0000	0.0252	0.0097	0.0105	0.0000	0.0020	0.0000	0.0017	0.0000	0.0000
	MOCCU_Manager	0.0993	0.0000	0.0049	0.3074	0.0158	0.0246	0.0090	0.0000	0.0015	0.0124
	PaExp_4Y_Col	0.8288	0.6734	0.3855	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
	MathSelfEffi_BaseY	0.0608	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-1 LRC for Variables with Indices [2,7,13,19,36,45,50,61,104,162].

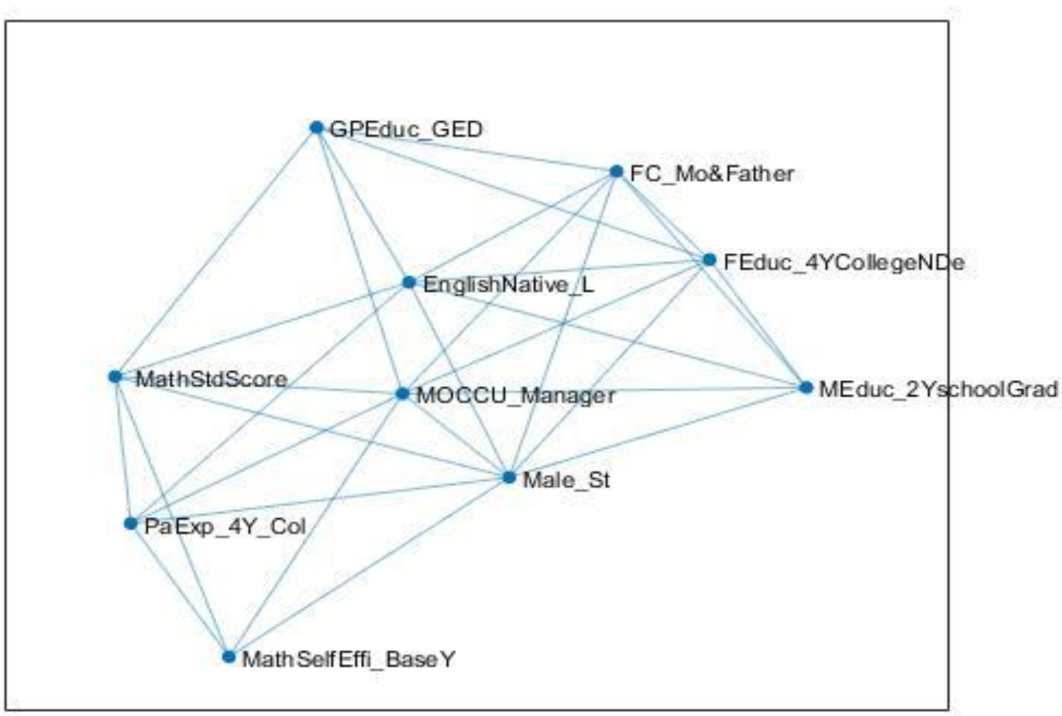

Figure 4-2 A UNG Representation Based on the Outcomes in Table 4-1

Table 4-1, shows that a male student (Male_St) is positively influenced by his parents' native languages and in this case English. English native parents contribute to children's proficiency in both English and their native language proficiency. The family composition influences a male student’s success rate in school, and a family composition of a mother and father (FC_Mo&Father) has a positive influence on a male student. Parents who commit to sending their children to college have a positive influence on the child’s success in school (PaExp_4Y_Col). A male student does not perform well in math (MathStdScore), because of a negative approach towards math (Hannula, 2002). Therefore, MathStdScore, EnglishNative_L, MathSelfEffi_BaseY, and PaExp_4Y_Col impact the performance of a male student.

A math standard score is positively influenced by PaExp_4Y_Col, EnglishNative_L, and Student self-efficacy. Literature agrees with the same result (Hailikari, Nevgi, & Komulainen, 2008). In addition, male students (Male_St) tend to have a negative attitude towards mathematics (Zan & Di Martino, 2007).

Figure 4-2 shows the constructed undirected network graph with the different relationships among the 10 variables selected. In this graph, the link between GPEduc_GED and MathStdScore, is present because either GPEduc_GED significantly predicted MathStdScore (with a non-zero coefficient estimate), or GPEduc_GED significantly predicted MathStdScore (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

The significance of the grandparents’ education in the math score is a new trend that shows a correlation between grandparents and grandchildren’s education.

In the same graph, the edge between the two variables, FC_Mo&Father and MathStdScore, is absent because either FC_Mo&Father cannot directly predict MathStdScore (with a zero coefficient estimate), or vice versa. However, there is an indirect connection between FC_Mo&Father and MathStdScore through any of the following four nodes: EnglishNative_L, MOCCU_Manager, Male_St, and GPEduc_GED.

		Predictors									
		Female_St	Black_St	MathStdScore	ParFluent_E	FC_Mother Only	PEduc_No HiSchool	GPEduc_No HiSchool	MOCCU _Services	FamIncome_ B_$10&15	StuEvalTch_N
Dependent Variables	Female_St	0.0000	0.0000	0.2915	0.0031	0.1707	0.0000	0.0000	0.0005	0.0000	0.0000
	Black_St	0.0000	0.0000	0.0000	0.0000	0.0011	0.0000	0.0000	0.0008	0.0000	0.0000
	MathStdScore	2.1178	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	ParFluent_E	0.0000	0.0000	0.0021	0.0000	0.0000	0.0028	0.0000	0.0034	0.0000	0.0000
	FC_MotherOnly	0.2914	0.0000	0.0000	0.0067	0.0000	0.2717	0.0001	0.0031	0.0008	0.0000
	PEduc_NoHiSchool	0.0734	0.0000	0.0000	0.0032	1.1696	0.0000	0.0000	0.0017	0.0004	0.0001
	GPEduc_NoHiSchool	0.0000	0.0000	0.0041	0.0110	0.0085	0.0012	0.0000	0.0059	0.0042	0.0000
	MOCCU_Services	0.0132	0.0155	0.0118	0.0910	0.5210	0.0313	0.0031	0.0000	0.0872	0.0137
	FamIncome_B_$10&15	0.0000	0.0000	0.0000	0.0000	0.0025	0.0000	0.0000	0.0000	0.0000	0.0000
	StuEvalTch_N	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000	0.0007	0.0000	0.0000	0.0000

Table 4-2 LRC for Variables with Indices [1,4,13,17,23,25,49,59,80,174].

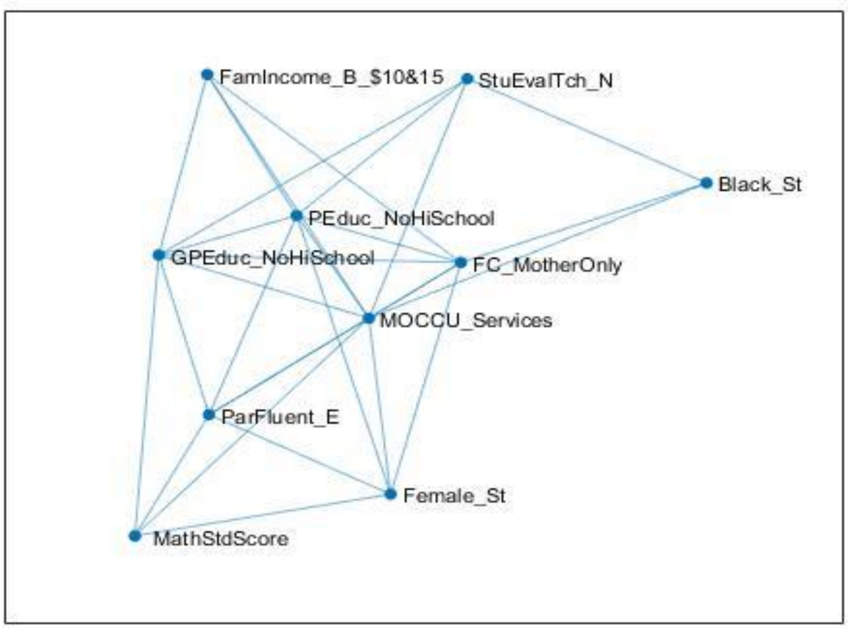

Figure 4-3 A UNG Representation Based on the Outcomes in Table 4-2

Table 4-2 shows that a female student (female_St) is positively influenced by parents' fluency in English (ParFluent_E). The proficiency in the English language contributes to children's proficiency in both math and reading (Kiplinger, Haug, & Abedi, 2000). The family composition influences a female student's success in school. For example, a family that consists of only a mother (FC_MotherOnly) has a positive influence on a female student. However, it seems that a family composition of mother and father has a superior positive influence (LRC = 0.2357, see table 4-1) than that of a mother only (LRC= 0.1707).

A female student tends to have an increasingly negative attitude towards math (LRC = 0.2915) compared with a male student's attitude towards math (LRC= 0.2842, see table 4-1).

A mother employed in service career (MOCCU_Services) is more likely to have a positive effect on her daughter's school performance.

Overall, it seems that MathStdScore, ParFluent_E, FC_MotherOnly, and MOCCU_Services are associated with a female student.

Table 4-2 also shows that a low-income family that earns between $10,000 and $15,000 per year (FamIncome_B_$10&15) is associated with a family composition consisting of only a single mother (FC_MotherOnly).

Figure 4-3 shows the constructed undirected network graph with the different relationships among the 10 variables selected. In this graph, the link between ParFluent_E and MathStdScore is present because either ParFluent_E significantly predicted MathStdScore (with a non-zero coefficient estimate), or ParFluent_E significantly predicted MathStdScore (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, the link between the two variables, FamIncome_B_$10&15 and MathStdScore, is absent because either FamIncome_B_$10&15 did not directly predict

MathStdScore (with a zero coefficient estimate), or vice versa. The graph illustrates that FamIncome_B_$10&15 is connected indirectly to MathStdScore through the variable, GPEduc_NoHiSchool. In addition, there are more connections between the two variables through multiple nodes as the graph illustrates.

		Predictors									
Dependent Variables		Hispanic_St	MathStdScore	ParNotFluent_E	FC_Fa&FemaleG	MEduc_2YschoolGrad	MathTeachEd_Dip&MA	TchAccInternet_Yes	GoodTchAward_No	MathBaseY_L1	ReadProf_L1
	Hispanic_St	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathStdScore	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0007	0.2314	0.0012
	ParNotFluent_E	0.0050	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	FC_Fa&FemaleG	0.0000	0.0000	0.0078	0.0000	0.3519	0.0008	0.0000	0.0004	0.0000	0.0000
	MEduc_2YschoolGrad	0.0000	0.0000	0.0051	0.3992	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathTeachEd_Dip&MA	0.0000	0.0000	0.0000	0.0000	0.0033	0.0000	0.0000	0.0000	0.0000	0.0000
	TchAccInternet_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0017	0.0000	0.0000
	GoodTchAward_No	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0884	0.0000	0.0000	0.0000
	MathBaseY_L1	0.0704	3.1822	0.0066	0.0028	0.0024	0.0001	0.0000	0.0140	0.0000	0.0516
	ReadProf_L1	0.0000	0.0000	0.0015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0533	0.0000

Table 4-3 LRC for Variables with Indices [5,13,18,21,36,111,135,145,147,159].

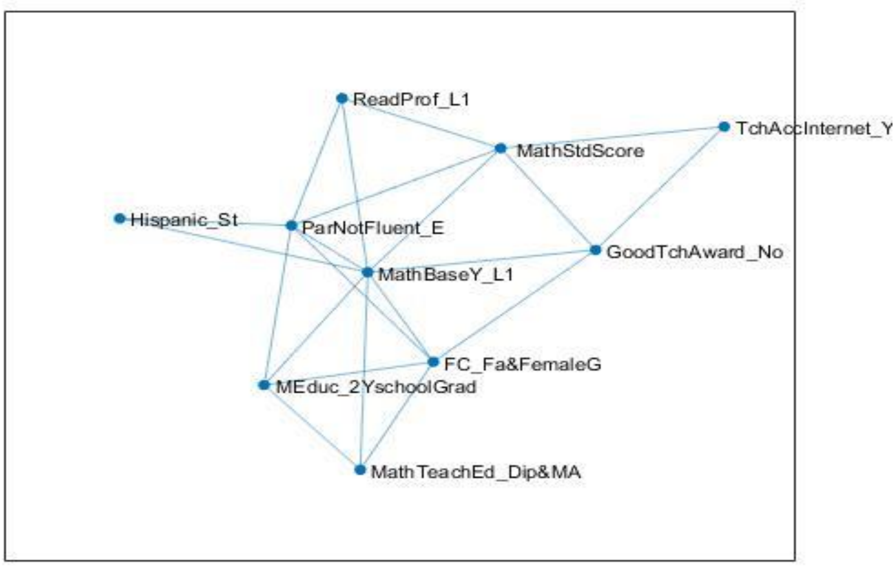

Figure 4-4 A UNG Representation Based on the Outcomes in Table 4-3

Table 4-3 shows again that family composition that consists of a father and a female guardian (FC_Fa&FemaleG) has no direct impact on MathStdScore as the literature has suggested. However, the graph in figure 4-4 shows that there is an indirect connection through any of the nodes: GoodTchAward_No, ParNotFluent_E, and MathBaseY_L1. On the other hand, the graph in figure 4-4 depicts that a teacher that has access to the internet influences directly a student's math score (MathStdScore).

Figure 4-4 also shows a surprising outcome which is that a math teacher with a diploma or a master degree, MathteachEd_Dip&MA, does not directly impact a student's MathStdScore, but impacts it indirectly.

The factors that predict MathStdScore and vice versa are TchAccInternet_Yes, GoodTchAward_No, MathBaseY_L1, and ReadProf_L1. The relationship between MathBaseY_L1 and MathStdScore suggests the importance of prior knowledge (Hailikari et al., 2008).

Figure 4-4 shows the constructed undirected network graph with the different relationships among the 10 variables selected. In this graph, the link between MathBaseY_L1 and ReadProf_L1 is present because either MathBaseY_L1 significantly predicted ReadProf_L1 (with a non-zero coefficient estimate), or ReadProf_L1 significantly predicted MathBaseY_L1 (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, the edge between the two variables, Hispanic_St and ReadProf_L1, is absent because either Hispanic_St did not directly predict ReadProf_L1 (with a zero coefficient estimate), or vice versa. The graph also depicts that there is an indirect link between Hispanic_St and ReadProf_L1 through any of the two nodes, ParNotFluent_E and MathBaseY_L1. In addition, there are other connections between the two variables through multiple nodes as the graph shows.

Dependent Variables		Predictors									
		FC_Mo&MaleG	MEduc_CollegeGrad	FamIncome_B_$75&100	HomeLiRe_50+	PaExp_MA	EngTeachEd_Dip&MA	TchAccComp_Yes	MathF1Y_L1	StuExp_BaseY	MathCo_4Y
	FC_Mo&MaleG	0.0000	0.2638	0.0000	0.0000	0.0000	0.0000	0.0000	0.0009	0.0000	0.0000
	MEduc_CollegeGrad	0.5029	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	FamIncome_B_$75&100	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	HomeLiRe_50+	0.0000	0.0000	0.0012	0.0000	0.0000	0.0032	0.0000	0.0170	0.0243	0.0000
	PaExp_MA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	0.0010	0.0000	0.0000
	EngTeachEd_Dip&MA	0.0000	0.0000	0.0006	0.0038	0.0035	0.0000	0.0000	0.0013	0.0000	0.0036
	TchAccComp_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathF1Y_L1	0.0036	0.0000	0.0000	0.0028	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	StuExp_BaseY	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathCo_4Y	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-4 LRC for Variables with Indices[20,38,86,96,105,108,125,152,164,196]

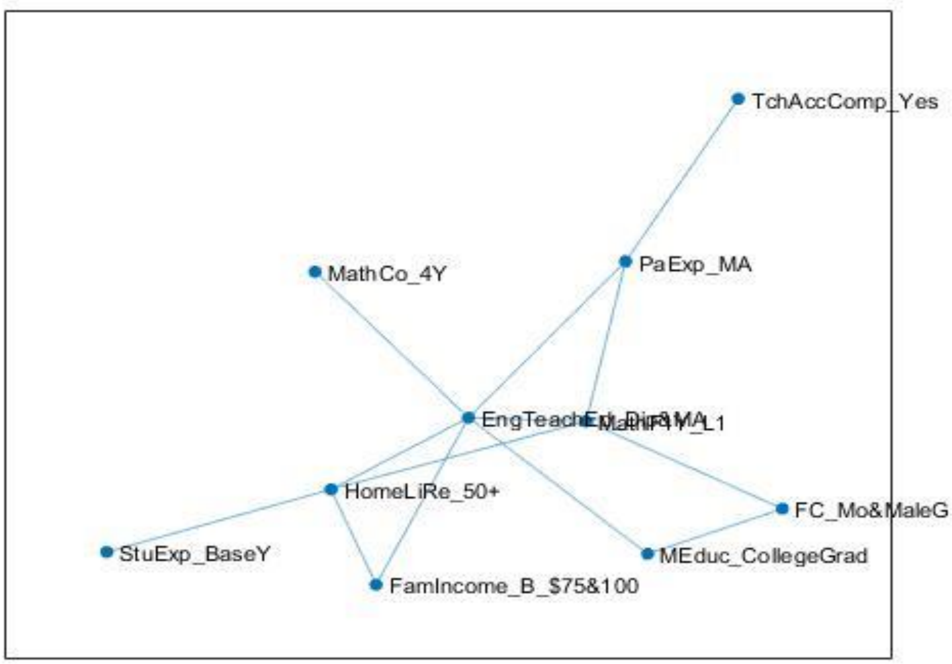

Figure 4-5 A UNG Representation Based on the Outcomes in Table 4-4

Table 4-4 shows that a home that has a collection of over 50 books, daily paper, and regular magazines (HomeLiRe_50+) is associated with family income that is between $75,000 and $100,000 (FamIncome_B_$75&100), English teacher education with a master degree or a diploma (EngTeachEd_Dip&MA), level 1 math that focuses on geometry and algebra (MathF1Y_L1), and the student education goal (StuExp_BaseY).

Figure 4-5 shows the constructed undirected network graph with the different relationships among the 10 variables selected. In this graph, the link between FC_Mo&MaleG and MEduc_CollegeGrad is present because either FC_Mo&MaleG significantly predicted MEduc_CollegeGrad (with a non-zero coefficient estimate), or MEduc_CollegeGrad significantly predicted FC_Mo&MaleG (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, the link between the two variables, FamIncome_B_$75&100 and PaExp_MA, is absent because either FamIncome_B_$75&100 cannot predict PaExp_MA (with a zero coefficient estimate), or vice versa. However, the graph shows that there is an indirect link between FamIncome_B_$75&100 and PaExp_MA through EngTeachEd_Dip&MA. In addition, there are indirect connections between the two variables through multiple nodes as the graph shows.

		Predictors									
		MultiRace_P	FC_Guardians	MathStd Score	PEduc_ PhD	GPEduc_ MasterD	MOCCU _Prof	FOCCU_ Prof	PaExp_PhD	TchAccInternet _Yes	StuExp_BaseY
Dependent Variables	MultiRace_P	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	FC_Guardians	0.0006	0.0000	0.0000	0.6173	0.0000	0.0028	0.0005	0.0000	0.0000	0.0000
	MathStdScore	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.8058	0.0004	0.0000
	PEduc_PhD	0.0000	0.4890	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	GPEduc_MasterD	0.0682	0.0192	0.0050	0.0000	0.0000	0.0017	0.0088	0.0000	0.0000	0.0000
	MOCCU_Prof	0.0000	0.0016	0.0000	0.0186	0.0000	0.0000	0.0214	0.0014	0.0000	0.0041
	FOCCU_Prof	0.0000	0.0018	0.0000	0.0000	0.0049	0.0241	0.0000	0.0000	0.0000	0.0103
	PaExp_PhD	0.0000	0.0000	0.4494	0.0000	0.0000	0.0000	0.0000	0.0000	0.0034	0.0000
	TchAccInternet_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	StuExp_BaseY	0.0000	0.0000	0.0029	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-5 LRC for Variables with Indices [12,22,13,32,55,60,70,106,135,164].

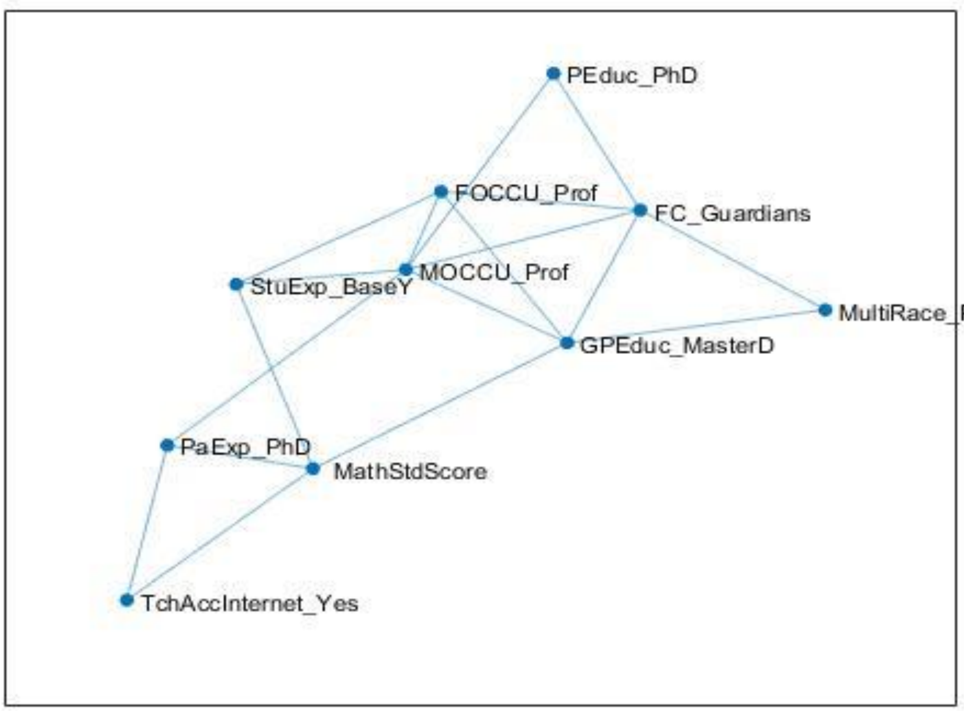

Figure 4-6 A UNG Representation Based on the Outcomes in Table 4-5

Table 4-5 shows that parental expectations for children's academic achievement such as in this case parents expecting that their children should get a Ph.D. (PaExp_PhD) directly impacts a student's math performance (MathStdScore). Similarly, MathStdScore is associated with PaExp_PhD and TchAccInternet_Yes.

The graph in figure 4-6 shows that an edge (link) between FC_Guardians and PEduc_PhD, is present because either FC_Guardians significantly predicted PEduc_PhD (with a non-zero coefficient estimate), or PEduc_PhD significantly predicted FC_Guardians (with a non-zero coefficient estimate), for the two of the *p* LASSO regressions presented in the table.

In the same graph, the edge between the two variables MathStdScore and PEduc_PhD is absent because either MathStdScore did not directly predict PEduc_PhD (with a zero coefficient estimate), or MathStdScore did not directly predict PEduc_PhD. However, there are indirect connections between the two factors through multiple nodes as the graph shows, which doesn't suggest that parents' education have a weak influence on student's school performance. Parents' education might not have a direct impact on student homework, but parents' education has a very strong impact on the overall student academic achievement.

		Predictors									
		ParNotFluent_E	PEduc_MasterD	MOCCU_NoJob	FamIncome_B_$100&200	FOCCU_Military	EngTeachEd_PhD	PrinEvalStdTest_Great	PaExp_MA	EngSelfEffi_BaseY	StuEvalTch_N
Dependent Variables	ParNotFluent_E	0.0000	0.0000	0.0281	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	PEduc_MasterD	0.0053	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0009
	MOCCU_NoJob	0.1267	0.0725	0.0000	0.0350	0.0052	0.0066	0.0000	0.0000	0.0000	0.0000
	FamIncome_B_$100&200	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	FOCCU_Military	0.0169	0.0644	0.0094	0.0000	0.0000	0.0007	0.0115	0.0109	0.0085	0.0295
	EngTeachEd_PhD	0.0051	0.0049	0.0038	0.0104	0.0001	0.0000	0.0000	0.0100	0.0077	0.0140
	PrinEvalStdTest_Great	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0383
	PaExp_MA	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003
	EngSelfEffi_BaseY	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0050	0.0000	0.0000
	StuEvalTch_N	0.0000	0.0000	0.0000	0.0003	0.0005	0.0000	0.0081	0.0000	0.0000	0.0000

Table 4-6 LRC for Variables with Indices [18,31,57,87,73,109,144,105,163,174].

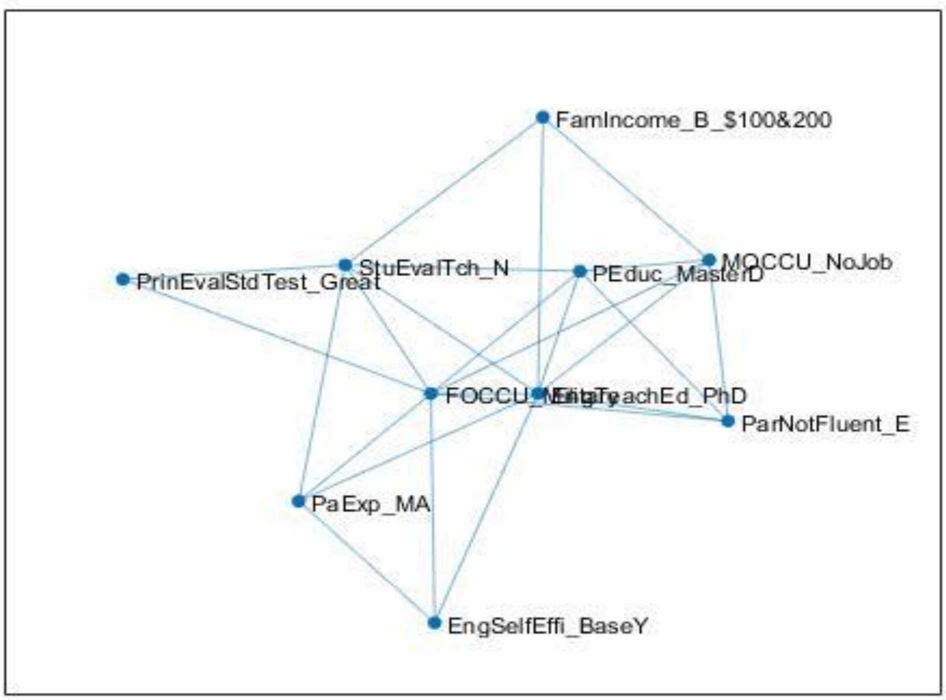

Figure 4-7 A UNG Representation Based on the Outcomes in Table 4-6

Table 4-6 shows that a mother without a job (MOCCU_NoJob) is associated with the following variables: ParNotFluent_E, PEduc_MasterD, FamIncome_B_$100&200, FOCCU_Military, EngTeachEd_PhD. A mother without a job (MOCCU_NoJob) can also predict any of the previous variables. The table also shows that parental expectations for children's academic achievement can influence Student English self-efficacy (EngSelfEffi_BaseY).

Table 4-6 also demonstrates that a student is encouraged to evaluate his teacher when these factors are present: parents' income is between $100,000 and $200,000 (FamIncome_B_$100&200), a father serving in the military (FOCCU_Military), and when the principal acknowledges the importance of standardized tests (PrinEvalStdTest_Great).

The graph in figure 4-7 depicts the link between EngSelfEffi_BaseY and PaExp_MA is present because either EngSelfEffi_BaseY can significantly predict PaExp_MA (with a non-zero coefficient estimate), or PaExp_MA can significantly predict EngSelfEffi_BaseY (with a non-zero coefficient estimate), for two of the p LASSO regressions presented in the table.

In the same graph, the edge between EngTeachEd_PhD and PrinEvalStdTest_Great is absent because either EngTeachEd_PhD did not directly predict PrinEvalStdTest_Great (with a zero coefficient estimate), or EngTeachEd_PhD did not directly predict PrinEvalStdTest_Great. On the other hand, the two variables are linked indirectly through any of the two nodes (FOCCU_Military, StuEvalTch_N). In addition, the two variables are connected indirectly through multiples nodes as the graph illustrates.

		Predictors									
		White_P	FC_Fa&FemaleG	PEduc_ MasterD	GPEduc_2Y schoolGrad	MOCCU_ Teacher	FOCCU_ Manager	SES_MHigh	MathStdScore	MathTeachEd_ BA	MathCo_B_3&4Y
Dependent Variables	White_P	0.0000	0.0000	0.0000	0.0101	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	FC_Fa&FemaleG	0.0000	0.0000	0.8746	0.0000	0.0015	0.0007	0.0034	0.0000	0.0000	0.0000
	PEduc_MasterD	0.0000	0.3503	0.0000	0.0000	0.0002	0.0009	0.0064	0.0000	0.0000	0.0000
	GPEduc_2YschoolGrad	0.2418	0.0000	0.0000	0.0000	0.0070	0.0000	0.0125	0.0121	0.0000	0.0000
	MOCCU_Teacher	0.0145	0.0000	0.0652	0.0000	0.0000	0.0218	0.0000	0.0000	0.0141	0.0000
	FOCCU_Manager	0.0000	0.0036	0.0281	0.0022	0.0192	0.0000	0.0000	0.0000	0.0000	0.0000
	SES_MHigh	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0025	0.0000	0.0000
	MathStdScore	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MathTeachEd_BA	0.0157	0.0000	0.0000	0.0000	0.0036	0.0005	0.0000	0.0000	0.0000	0.0192
	MathCo_B_3&4Y	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-7 LRC for Variables with Indices [9,21,31,52,62,71,91,13,110,195].

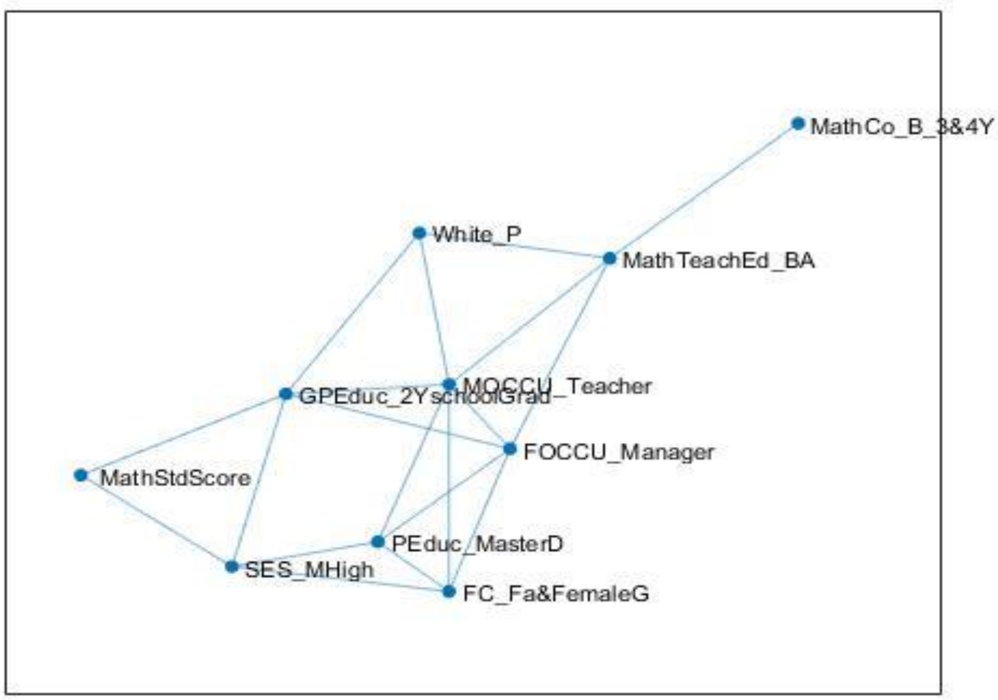

Figure 4-8 A UNG Representation Based on the Outcomes in Table 4-7

Table 4-7 shows that a family SES (SES_MHigh) has a positive relationship with student math performance (MathStdScore), as has been suggested by the literature. A math teacher with a BA (MathTeachEd_BA) has an association with white parents (White_P), a mother's occupation as a teacher (MOCCU_Teach), and a father occupation as a manager (FOCCU_Manager). In addition, a math teacher with a BA is negatively influenced by the number of years of mathematics coursework required for a student to graduate (Co_B_3&4Y).

The graph in figure 4-8 shows the link between SES_MHigh and MathStdScoreis present because either SES_MHigh significantly predicted MathStdScore (with a non-zero coefficient estimate), or MathStdScore significantly predicted SES_MHigh (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, the edge between MathCo_B_3&4Y and FOCCU_Manager is absent because either MathCo_B_3&4Y did not directly predict FOCCU_Manager (with a zero coefficient estimate), or FOCCU_Manager did not directly predict MathCo_B_3&4Y (with a zero coefficient estimate). The graph shows that the two variables are connected indirectly through MathTeachEd_BA. In addition, the two variables are indirectly connected through multiple nodes as the graph illustrates.

		Predictors									
		Male_St	PEduc_PhD	ParNatL_Others	MOCCU_Prof	FOCCU_Prof	PaExp_PhD	FamIncome_G_$200	HSDiplomatest_Yes	GoodTchAward_Yes	MathCo_B_2&3Y
Dependent Variables	Male_St	0.0000	0.0000	0.0000	0.0000	0.0000	0.4964	0.0000	0.0000	0.0000	0.0000
	PEduc_PhD	0.0528	0.0000	0.0000	0.0000	0.0000	0.0000	0.0006	0.0000	0.0000	0.0000
	ParNatL_Others	0.0000	0.0000	0.0000	0.0000	0.0000	0.0062	0.0000	0.0058	0.0000	0.0000
	MOCCU_Prof	0.2990	0.0186	0.0000	0.0000	0.0214	0.0014	0.0475	0.0000	0.0030	0.0024
	FOCCU_Prof	0.1057	0.0000	0.0059	0.0241	0.0000	0.0000	0.0396	0.0000	0.0000	0.0014
	PaExp_PhD	0.9493	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0004
	FamIncome_G_$200	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	HSDiplomatest_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	GoodTchAward_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005
	MathCo_B_2&3Y	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-8 LRC for Variables with Indices [2,32,16,60,70,106,88,114,146,194].

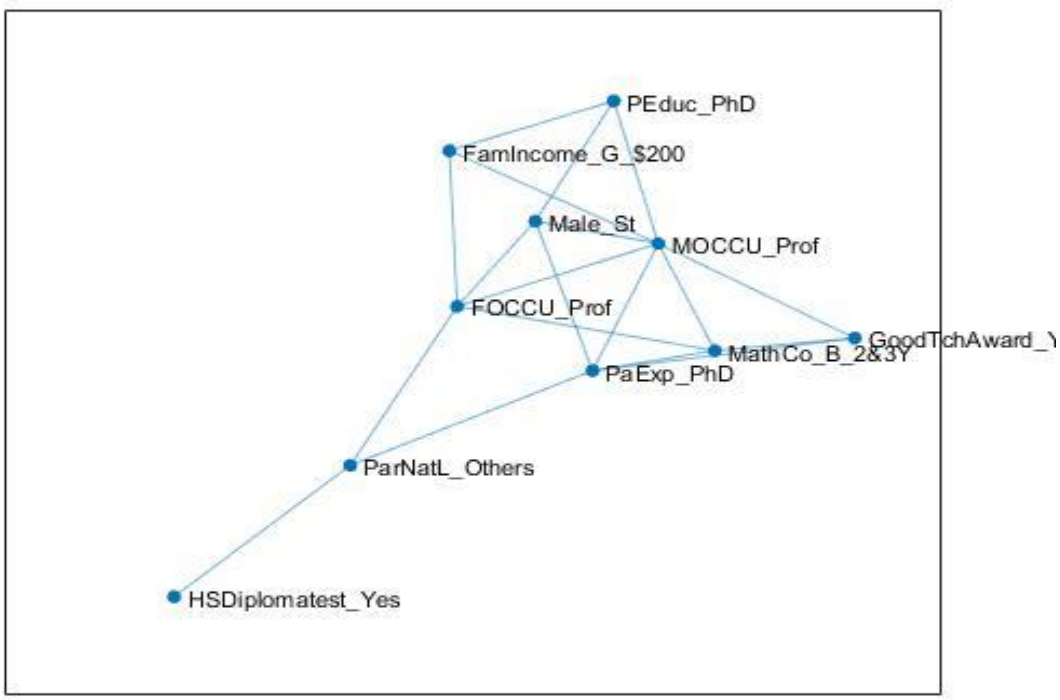

Figure 4-9 A UNG Representation Based on the Outcomes in Table 4-8

Table 4-8 shows that a father with a professional career is influenced by or can be predicted by the variables male student (Male_St), parents' native language is not English or Spanish (ParNatL_Others), mother's occupation professional (MOCCU_Prof), family income greater than $200,000 (FamIncome_G_$200), and math coursework required for graduation (MathCo_B_2&3Y).

The graph in figure 4-9 displays the link between FOCCU_Prof and MOCCU_Prof present because either FOCCU_Prof significantly predicted MOCCU_Prof (with a non-zero coefficient estimate), or MOCCU_Prof significantly predicted FOCCU_Prof (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, an edge between MathCo_B_2&3Y and HSDiplomatest_Yes is absent because either MathCo_B_2&3Y did not directly predict HSDiplomatest_Yes (with a zero coefficient estimate), or HSDiplomatest_Yes did not directly predict MathCo_B_2&3Y. The two variables are connected indirectly through multiple links as the graph demonstrates. This shows that the relationship between the two variables is weak, or the two variables have a low impact on each other.

		Predictors									
		FC_Mo&Father	ParFluent_E	MEduc_NoHiSchool	MOCCU_Clerk	MathStdSc	ProcPaDiscPolicy_	MathTeachEd_BA	MathF1Y_L1	MathF1Y_L5	TchAccComp_Yes
Dependent Variables	FC_Mo&Father	0.0000	0.0082	0.1305	0.0018	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000
	ParFluent_E	0.0002	0.0000	0.0000	0.0000	0.0021	0.0000	0.0000	0.0000	0.0000	0.0000
	MEduc_NoHiSchool	0.9835	0.0048	0.0000	0.0007	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MOCCU_Clerk	0.5868	0.0174	0.0181	0.0000	0.0022	0.0000	0.0000	0.0065	0.0172	0.0000
	MathStdScore	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0045	0.0146	0.0025
	ProcPaDiscPolicy_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0210
	MathTeachEd_BA	0.0032	0.0036	0.0000	0.0000	0.0000	0.0000	0.0000	0.0071	0.0030	0.0139
	MathF1Y_L1	0.0000	0.0000	0.0000	0.0000	0.0698	0.0000	0.0000	0.0000	0.0000	0.0000
	MathF1Y_L5	0.0004	0.0218	0.0093	0.0223	0.8083	0.0338	0.0168	0.0017	0.0000	0.0000
	TchAccComp_Yes	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-9 LRC for Variables with Indices [19,17,33,64,13,129,110,152,156,125].

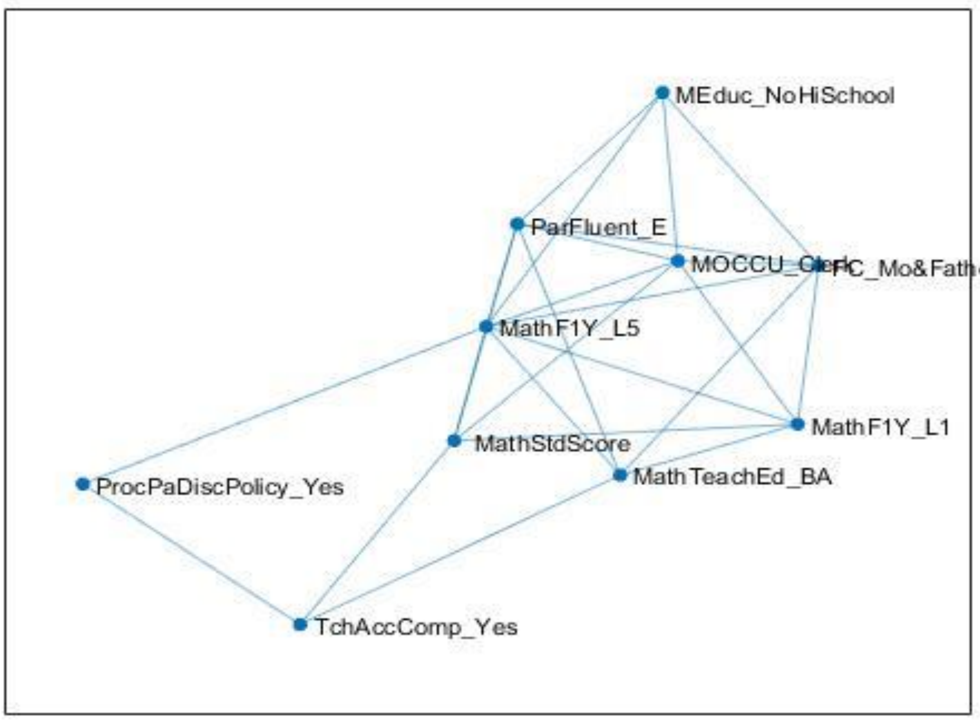

Figure 4-10 A UNG Representation Based on the Outcomes in Table 4-9

Table 4-9 shows that a math teacher with a bachelor degree (MathTeachEd_BA) is positively influenced by the family composition that consists of a father and a mother (FC_Mo&Father), parents' fluency in English (ParFluent_E), the student mathematics proficiency probability at level 1 (MathF1Y_L1), and the teacher has access to a computer in the classroom (TchAccComp_Yes).

A math teacher with a bachelor degree is negatively impacted by the mathematics proficiency probability at level 5 (MathF1Y_L5). In addition, MathStdScore is predicted by, MathF1Y_L1, MathF1Y_L5, TchAccComp_Yes. This is another indication of the influence of prior knowledge.

The graph in figure 4-10 shows the link between MOCCU_Clerk and MathStdScore. The link is present because either MOCCU_Clerk significantly predicted MathStdScore (with a non-zero coefficient estimate), or MathStdScore significantly predicted MOCCU_Clerk (with a non-zero coefficient estimate), for two of the *p* LASSO regressions presented in the table.

In the same graph, an edge between TchAccComp_Yes and MOCCU_Clerk is absent because either TchAccComp_Yes did not directly predict MOCCU_Clerk (with a zero coefficient estimate), or MOCCU_Clerk did not directly predict TchAccComp_Yes. However, the two variables are linked indirectly through the factor, MathStdScore. In addition, the two variables are connected indirectly through multiple nodes.

		Predictors									
Dependent Variables		Female_St	Hispanic_P	PEduc_GED	MOCCU_Services	FamIncome_B_$20&25	HomeLiRe_two	StEdGoal_4Y_Col	ContSTD&Perf_No	GoodTchAward_No	MathCo_4Y
	Female_St	0.0000	0.0000	0.0000	0.0005	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
	Hispanic_P	0.0000	0.0000	0.0000	0.0071	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	PEduc_GED	0.1661	0.0000	0.0000	0.0009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	MOCCU_Services	0.0132	0.0364	0.0000	0.0000	0.0575	0.0014	0.0018	0.0000	0.0000	0.0003
	FamIncome_B_$20&25	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	HomeLiRe_two	0.0434	0.0000	0.0000	0.0000	0.0000	0.0000	0.0053	0.0000	0.0000	0.0002
	StEdGoal_4Y_Col	0.0042	0.0000	0.0000	0.0000	0.0000	0.0042	0.0000	0.0000	0.0000	0.0045
	ContSTD&Perf_No	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	GoodTchAward_No	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0055	0.0000	0.0031
	MathCo_4Y	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 4-10 LRC for Variables with Indices [1,11,26,59,82,95,99,117,145,196]

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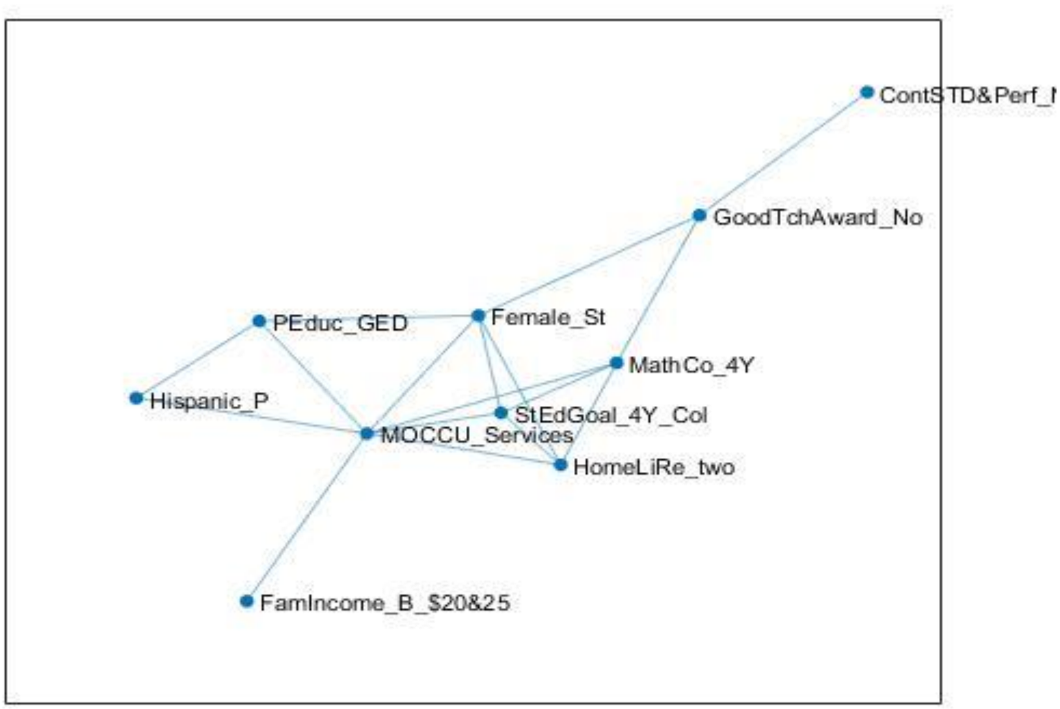

Figure 4-11 A UNG Representation Based on the Outcomes in Table 4-10

Table 4-10 shows that a student goal to attend a four-year college (StEdGoal_4Y_Col) is predicted by the variables female student (Female_St), HomeLiRe_two, and MathCo_4Y. The literature shows that the number of females interested to earn a college degree is on the rise (DiPrete & Buchmann, 2013).

Table 4-10 also shows that a mother's career in the service sector is positively influenced by the variables Female_St, and StEdGoal_4Y_Col. She is negatively impacted by Hispanic_P, FamIncome_B_$20&25, HomeLiRe_two, and MathCo_4Y.

The graph in figure 4-11 represents the link between PEduc_GED and Female_St present because either PEduc_GED significantly predicted Female_St (with a non-zero coefficient estimate), or Female_St significantly predicted PEduc_GED (with a non-zero coefficient estimate).

In the same graph, the edge between GoodTchAward_No and Hispanic_P is absent because either GoodTchAward_No did not directly predict Hispanic_P (with a zero coefficient estimate), or Hispanic_P did not directly predict GoodTchAward_No. However, the two variables are connected together through multiple nodes, which shows that the relationship between the two variables is weak.

In summary, the results above demonstrate the relationships among the designated variables and the strength of these relationships across the variables selected. The tables tabulated the LASSO regression coefficients of the selected variables. The graphs illustrated the relationships between the selected variables.

The ecological figure below summarizes the findings of this study with respect to the target variables: math and reading performance. In figure 4-12, each variable within a band in the graph has some influence that permeates through the layer(s)/band(s) down to the target variable.

The advantage of using an undirected graphical model is that it allows the use of any variable as a target variable. The ecological model is therefore built around this target variable depending on the number of links that separate this target variable from the other variable.

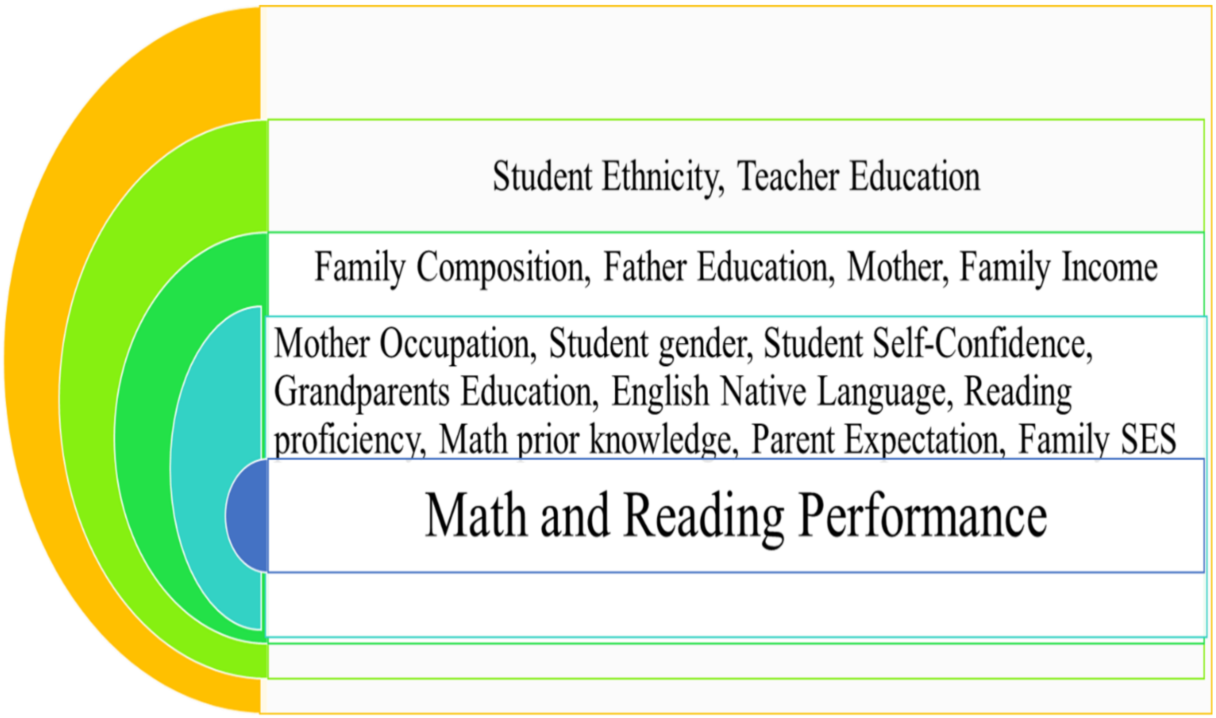

Figure 4-12 The Ecological Model of Student Learning

The figure above shows the ecological model and how the four levels are interrelated and what they each constitute. The ecological model summarizes the results of the association and relationships among the multiple factors affecting student performance. It illustrates the interrelated systems at the four levels that impact the student performance. In addition, it encompasses the relationships of all the factors, both direct and indirect, that affect the performance of a student and the school system at large.

The findings of this study demonstrated that grandparents' education has a direct impact on the grandchildren's success in school; however, parents' education has an indirect effect, but again that doesn't undermine parents' impact, which is much greater than just being involved in helping their kids doing the homework. Parents overall make the ultimate decision for the children. Family SES has a direct impact on a student's achievement, however, family income has an indirect impact on a student's performance. Student ethnicity dropped way at the back (level 4) in terms of its influence on student performance. Native English-speakers' parents have a direct impact on a student's performance. In addition, a student's self-confidence has a direct impact on a student's performance.

Chapter 5 Conclusion

This study aimed to develop a theory to analyze complex systems, such as the education system. The theory developed will guide researchers and policymakers to identify the determinants of student achievement based on the ecological model. Finally, the theory developed will demonstrate that key variables can, in theory, be identified to have the most influence on student performance. In addition, the selection of these variables will be based on the economic value and the return on investment of each of the variables selected.

The education systems data is comprised of thousands of factors (+6000 variables in the NELS 2002 data) that impact student learning. The high-dimensional graphs and variable selection method with the LASSO identified the variables that best predict a target variable, such as math standard score. In order to visualize the relationships of certain variables, snapshots were taken from the whole graph (figure 4-1). The snapshots in Chapter 4 served as examples to demonstrate the relationship between some selected variables. The theory developed in this thesis is comprised of two main steps: 1) variable selection, and 2) model selection and data fitting.

The figures below describe an example of mapping an undirected graph to an ecological model. This example will serve as a guide to show the relationships between the variables in the context of the ecological model.

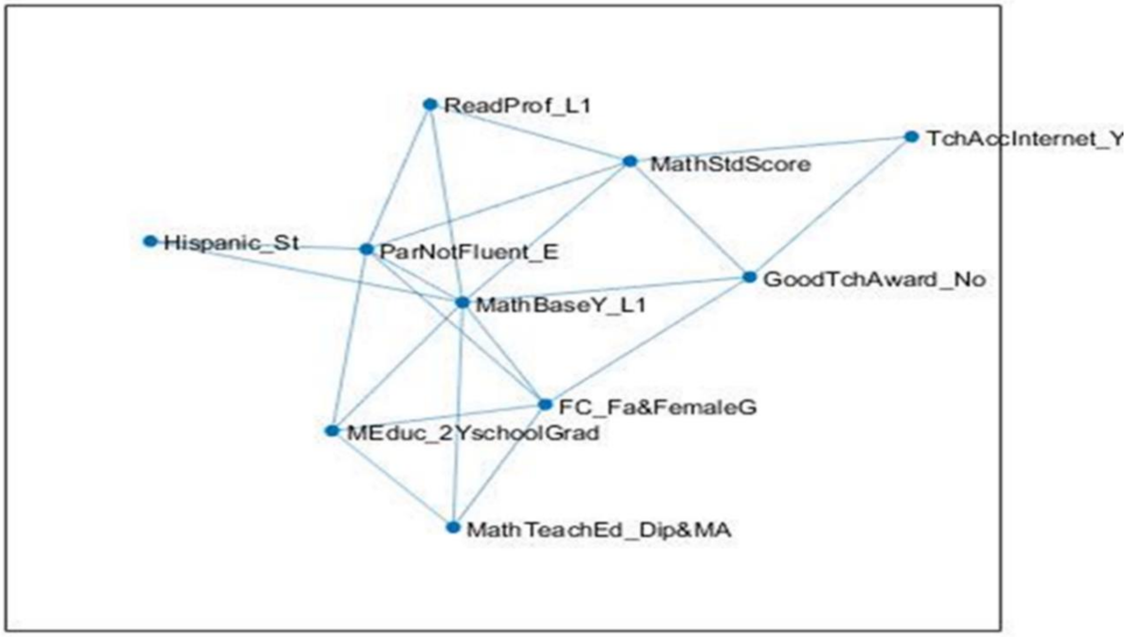

Figure 5-1 Undirected Graph Example (figure 4-4)

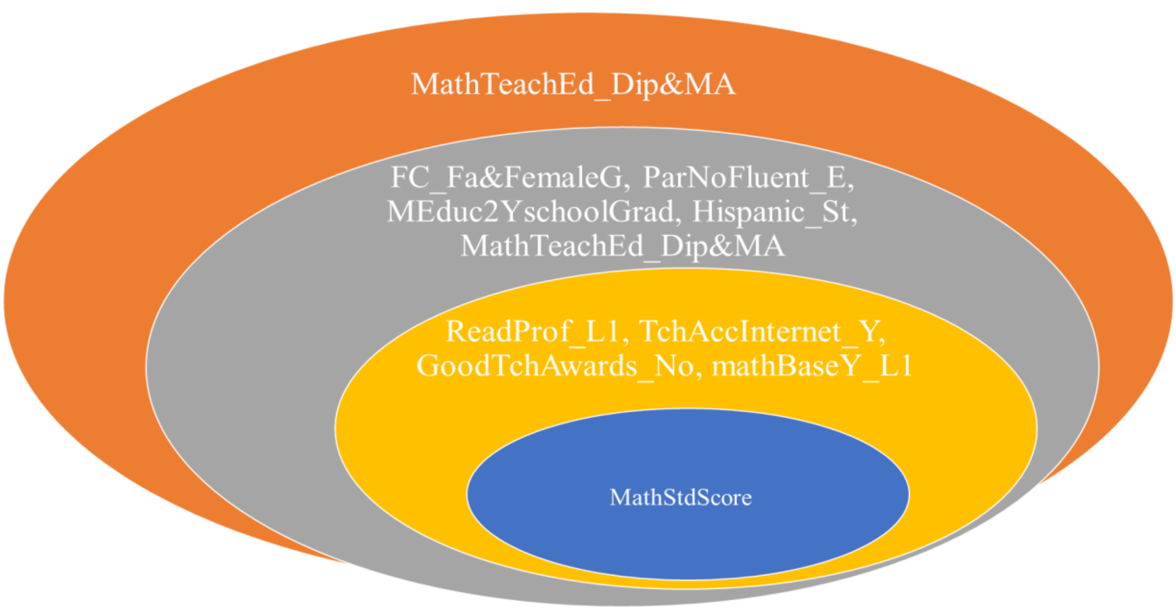

Figure 5-2 Direct Mapping of Figure 5-1 into the Ecological Model

Figure 5-2 depicts the overlapping bands in the ecological model, and how the ecological model above illustrates the interactions among the different levels. In addition of helping in clarifying these factors, the model also suggests that in order to influence math and reading performance, it is required to act among all levels of the model simultaneously.

Here is a description of the two steps, which includes an example from the result obtained in Chapter 4.

Step 1: Variable selection

1. High graph model variable selection

    a) Run the high dimensional model to select the significant predictors for every dependent variable of interest. Every dependent variable will be predicted by all the selected independent variable(s).

    b) Select a set of variables that comprise the variables of interest among all the variables. The number of snapshots is C (n, r). where n is the total number of variables, and r is the subset that comprises only the variables of interest.

    c) Generate the network graph that is composed of nodes (variables) and edges (connections). The networks graph will show the connection or a flow between the variables. The network graph will illustrate the degrees of separation between the different the nodes (variables).

2. **Elasticity analysis**

   Select the variables that have the highest return on investment by examining the elasticity of each variable. The variables that have the highest return on investment are the variables with the highest elasticity. Higher elasticity means high outcome with less input. In this step, not all variables can be subject to this kind of analysis, e.g. family composition.

3. **Sensitivity analysis**

   Run a sensitivity analysis to explore the range of change of each of the variables within the elasticity range explored in the previous step.

4. Repeat step 4 and 5 as necessary to obtain the optimum set of variables.
5. Chose the paths from the graph that include the variables with the highest elasticity.

   The different paths make the potential models. Step 5 and 6 can be repeated to revisit the selection of these paths.

Step 2: Model Selection and Data Fitting

The models that fit the ecological framework are numerous. I would recommend either the Bayesian network model or the multilevel regression model. Both of these models will be a great fit for an ecological system. The dependent or the target variable under study will be the variable to be modeled. The selection of the variables that enter the model are the predictors selected from the previous steps. In this step, the original data will be used.

The resulting model will be a description of a system under study. The information provided in this model will demonstrate how the change in any of the predictors will impact the target value. The change in the variable is now subject to the guideline of the previous steps in the variable selection. A researcher will know the range of potential changes based on the elasticity and the sensitivity analysis conducted before. Therefore, the famous word of increasing or decreasing one unit will not be used in any prediction.

Future research

Future research should focus on the impact of student promotion to the next grade on knowledge acquisition especially math. There are eighteen (18) states that force an assessment to determine student eligibility for promotion or retention. There are twelve (12) states that require state tests. In addition, there are three (3) that require a combination of state and local assessments (Zinth, 2005).

The second area of research should focus on the interaction between curriculum and instruction. There should be a focus on how the math teacher interacts with mathematics curricula and the impact on the student knowledge acquisition.

The third area of research is the use of technology. Students are glued to their phones and learning math by interaction should be the focus of research. How to use technology to improve learning? The study showed that the use of the computer in instruction improved math standard score.

The fourth area should focus on how teachers can reduce disparities among students when students’ skills are different. Students in one class are widely different in skill levels in core subjects. The initial prior knowledge differences often translate into systematic disparities in achievement over time.

The fifth area of research should focus on improving student assessment. Student assessment procedures should provide students with the prospect to reveal their abilities, and should be considered an integral part of the learning-teaching process.

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Appendices

Appendix I List of Variables and Indices

Index	Variable CategoriesName	Variables
1	Female_St	Gender of student (male or female).
2	Male_St	
3	White_St	Student's race/ethnicity-composite
4	Black_St	
5	Hispanic_St	
6	MultiRace_St	
7	EnglishNative_L	Whether English is student's native language-composite
8	N_EnglishNative_L	
9	White_P	Parent's race/ethnicity-composite
10	Black_P	
11	Hispanic_P	
12	MultiRace_P	
13	MathStdScore	Math test standardized score
14	ParNatL_E	Parent's native language-composite
15	ParNatL_Sp	
16	ParNatL_Others	
17	ParFluent_E	Parent’s English fluency
18	ParNotFluent_E	
19	FC_Mo&Father	Family Composition
20	FC_Mo&MaleG	
21	FC_Fa&FemaleG	
22	FC_Guardians	
23	FC_MotherOnly	
24	FC_FatherOnly	
25	PEduc_NoHiSchool	Parents' highest level of education
26	PEduc_GED	
27	PEduc_2YSchoolNDe	
28	PEduc_2YSchoolGrad	
29	PEduc_4YCollegeNDe	
30	PEduc_CollegeGrad	
31	PEduc_MasterD	
32	PEduc_PhD	

33	MEduc_NoHiSchool	Mother's highest level of education-composite
34	MEduc_GED	
35	MEduc_2YschoolNDe	
36	MEduc_2YschoolGrad	
37	MEduc_4YCollegeNDe	
38	MEduc_CollegeGrad	
39	MEduc_MasterD	
40	MEduc_PhD	
41	FEduc_NoHiSchool	Father's highest level of education-composite
42	FEduc_GED	
43	FEduc_2YSchoolNDe	
44	FEduc_2YSchoolGrad	
45	FEduc_4YCollegeNDe	
46	FEduc_CollegeGrad	
47	FEduc_MasterD	
48	FEduc_PhD	
49	GPEduc_NoHiSchool	Grandparents Education
50	GPEduc_GED	
51	GPEduc_2YschoolNDe	
52	GPEduc_2YschoolGrad	
53	GPEduc_4YCollegeNDe	
54	GPEduc_CollegeGrad	
55	GPEduc_MasterD	
56	GPEduc_PhD	
57	MOCCU_NoJob	Mother/female guardian's occupation-composite
58	MOCCU_Crafts	
59	MOCCU_Services	
60	MOCCU_Prof	
61	MOCCU_Manager	
62	MOCCU_Teacher	
63	MOCCU_Military	
64	MOCCU_Clerk	
65	MOCCU_Sales	
66	MOCCU_Farmer	
67	FOCCU_NoJob	Father/male guardian's occupation-composite
68	FOCCU_Crafts	
69	FOCCU_Services	

70	FOCCU_Prof	
71	FOCCU_Manager	
72	FOCCU_Teacher	
73	FOCCU_Military	
74	FOCCU_Clerk	
75	FOCCU_Sales	
76	FOCCU_Farmer	
77	FamIncome_L_$1	Total family income from all sources 2001-composite
78	FamIncome_B_$1&5	
79	FamIncome_B_$5&10	
80	FamIncome_B_$10&15	
81	FamIncome_B_$15&20	
82	FamIncome_B_$20&25	
83	FamIncome_B_$25&30	
84	FamIncome_B_$35&50	
85	FamIncome_B_$50&75	
86	FamIncome_B_$75&100	
87	FamIncome_B_$100&200	
88	FamIncome_G_$200	
89	SES_Low	Quartile coding of SES1 variable
90	SES_MLow	
91	SES_MHigh	
92	SES_High	
93	HomeLiRe_None	BY home literacy resources
94	HomeLitRe_One	
95	HomeLiRe_two	
96	HomeLiRe_50+	
97	StEdGoal_HighS	
98	StEdGoal_2Y_Col	How far in school student thinks will get-composite
99	StEdGoal_4Y_Col	
100	StEdGoal_MA	
101	StEdGoal_PhD	
102	PaExp_HighS	How far in school parent wants 10th-grader to go-composite
103	PaExp_2Y_Col	
104	PaExp_4Y_Col	
105	PaExp_MA	
106	PaExp_PhD	

107	EngTeachEd_BA	Highest degree earned by the English teacher
108	EngTeachEd_Dip&MA	
109	EngTeachEd_PhD	
110	MathTeachEd_BA	Highest degree earned by math teacher
111	MathTeachEd_Dip&MA	
112	MathTeachEd_PhD	
113	HSDiplomatest_No	Students must pass a test for high school
114	HSDiplomatest_Yes	
115	AcaSTDCont_No	Content standards for academic subjects
116	AcaSTDCont_Yes	
117	ContSTD&Perf_No	Content standards linked with performance standards
118	ContSTD&Perf_Yes	
119	HSDiplomatest_No	Students must pass a test for high school diploma
120	HSDiplomatest_Yes	
121	PrinInflTchHorF_No	Principal's influence on hiring/firing teachers
122	PrinInflTchHorF_Some	
123	PrinInflTchHorF_Major	
124	TchAccComp_No	Teachers Access computers
125	TchAccComp_Yes	
126	TchCompInstr_No	Teachers use computers as instructional tools
127	TchCompInstr_Yes	
128	ProcPaDiscPolicy_No	Process to get parent input on discipline policies
129	ProcPaDiscPolicy_Yes	
130	TrPaBehProb_No	Training parents to deal with problem behavior
131	TrPaBehProb_Yes	
132	PaidSecSchHrs_No	Use paid security at any time during school hours
133	PaidSecSchHrs_Yes	
134	TchAccInternet_No	Teachers have access to the Internet
135	TchAccInternet_Yes	
136	TchAccCableTV_No	Teachers have access to cable TV
137	TchAccCableTV_Yes	
138	TchAccCCTV_No	Teachers have access to closed-circuit TV
139	TchAccCCTV_Yes	
140	TchAccDVD_No	Teachers have access to videodisc player/VCR/DVD
141	TchAccDVD _Yes	
142	PrinEvalStdTest_No	Principal evaluated on standardized test scores
143	PrinEvalStdTest_Minor	

144	PrinEvalStdTest_Great	
145	GoodTchAward_No	Good teachers given a special award
146	GoodTchAward_Yes	
147	MathBaseY_L1	Mathematics—level 1
148	MathBaseY_L2	Mathematics—level 2
149	MathBaseY_L3	Mathematics—level 3
150	MathBaseY_L4	Mathematics—level 4
151	MathBaseY_L5	Mathematics—level 5
152	MathF1Y_L1	Mathematics—level 1 First year
153	MathF1Y_L2	Mathematics—level 2 First year
154	MathF1Y_L3	Mathematics—level 3 First year
155	MathF1Y_L4	Mathematics—level 4 First year
156	MathF1Y_L5	Mathematics—level 5 First year
157	ReadIRT_R	Reading IRT estimated number right
158	ReadSTDScore	Reading test standardized score
159	ReadProf_L1	Reading proficiency probability at level 1
160	ReadProf_L2	Reading proficiency probability at level 2
161	ReadProf_L3	Reading proficiency probability at level 3
162	MathSelfEffi_BaseY	Student self-efficacy in math in the base year
163	EngSelfEffi_BaseY	Student self-efficacy in Eng in the base year
164	StuExp_BaseY	Control expectation scale
165	StuUInterest_BaseY	Instrumental motivation (utility interest) scale
166	ActionEffort	General effort and persistence scale
167	ClassPrep	Class preparation scale
168	StuWrAbility	Student writing ability
169	SES_F1	F1 socio-economic status composite
170	Dropout_N	Student Dropout
171	Dropout_Yes	
172	TchEvalTch_N	Teachers Evaluate Teachers
173	TchEvalTch_Yes	
174	StuEvalTch_N	Students Evaluate Teachers
175	StuEvalTch_Yes	
176	TchVideoCam_No	Teacher have access to a video camera
177	TchVideoCam _Yes	
178	TchVideoPrdStdio_No	Teacher have access to a production studio
179	TchVideoPrdStdio _Yes	
180	Bulling_daily	How often student bullying a problem at school

181	Bulling_weekly	
182	Bulling_monthly	
183	Bulling_never	
184	TchVAbuse_daily	How often verbal abuse of teachers a problem at school
185	TchVAbuse_weekly	
186	TchVAbuse_monthly	
187	TchVAbuse_never	
188	ClassDisorder_weekly	How often disorder in classrooms a problem at school
189	ClassDisorder_monthly	
190	ClassDisorder_never	
191	EngCo_L_4Y	Years of English coursework required to graduate
192	EngCo_4Y	
193	MathCo_B_!&2Y	Years of mathematics coursework required to graduate
194	MathCo_B_2&3Y	
195	MathCo_B_3&4Y	
196	MathCourse_4Y	

Appendix II List of Variables and Explanation

Original Variable name	Modified Variable Names and the categories represented	Variable description and original categories
BYSEX	Female_St (2) Male_St (1)	Gender of student (male or female). Category / Label / Frequency Unweighted / Percent Unweighted ------------------- -- ------------------- 1 Male 7,653 47.25 2 Female 7,717 47.64 -8 Survey component skipped 179 1.11 -4 No respondent 648 4.00 TOTAL 16,197 100.00
BYRACE	White_St (7) Black_St (3) Hispanic_St (4, 5) MultiRace_St (1, 2, 6)	Student's race/ethnicity-composite Category / Label / Frequency Unweighted / Percent Unweighted ------------------- -- ------------------- 1 Amer. Indian/Alaska Native, non-Hispanic 130 0.80 2 Asian, Hawaii/Pac. Islander,non-Hispanic 1,460 9.01 3 Black or African American, non-Hispanic 2,020 12.47 4 Hispanic, no race specified 996 6.15 5 Hispanic, race specified 1,221 7.54 6 More than one race, non-Hispanic 735 4.54 7 White, non-Hispanic 8,682 53.60 -8 Survey component legitimate skip/NA 305 1.88 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYSTLANG	EnglishNative_L (1) N_EnglishNative_L (0)	Whether English is student's native language-composite Category / Label / Frequency Unweighted / Percent Unweighted ------------------- -- ------------------- 0 No 2,586 15.97 1 Yes 12,658 78.15 -8 Survey component legitimate skip/NA 305 1.88 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYPARACE	White_P (7) Black_P (3) Hispanic_P (4, 5) MultiRace_P (1, 2, 6)	Parent's race/ethnicity-composite Category / Label / Frequency Unweighted / Percent Unweighted ------------------- -- ------------------- 1 Amer. Indian/Alaska Native, non-Hispanic 107 0.66 2 Asian, Hawaii/Pac. Islander, non-Hispanic 1,254 7.74 3 Black or African-American, non-Hispanic 1,736 10.72 4 Hispanic, no race specified 688 4.25

		5 Hispanic, race specified 984 6.08 6 More than one race, non-Hispanic 195 1.20 7 White, non-Hispanic 8,321 51.37 -9 Missing 2,085 12.87 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYPARLNG	ParNatL_E (1) ParNatL_Sp (2) ParNatL_Others (3, 4, 5, 6)	Parent's native language-composite Category / Label / Frequency Unweighted / Percent Unweighted ------------------ ------------------------------------- ------------------- 1 English 10,917 67.40 2 Spanish 1,045 6.45 3 Other European language 91 0.56 4 West/South Asian language 176 1.09 5 Pacific Asian/Southeast Asian 574 3.54 6 Other language 222 1.37 -9 Missing 2,345 14.48 -8 Survey component legitimate 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYPLANG	ParFluent_E ParNotFluent_E	Parent's English fluency Category / Label / Frequency Unweighted / Percent Unweighted ------------------ ------------------------------------- ------------------- 0 Not fluent 889 5.49 1 Partially fluent 122 0.75 2 Fluent 1,094 6.75 3 Non-native Engl speaker, fluency unknown 334 2.06 4 Native English speaker 10,917 67.40 -9 Missing 126 0.78 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 2,536 15.66 TOTAL 16,197 100.00
BYFCOMP	FC_Mo&Father (1) FC_Mo&MaleG (2) FC_Fa&FemaleG (3) FC_Guardians (4, 7, 8, 9) FC_MotherOnly (5) FC_FatherOnly (6)	Family composition Category / Label / Frequency Unweighted / Percent Unweighted ------------------ ------------------------------------- ------------------- 1 Mother and father 9,100 56.18 2 Mother and male guardian 1,880 11.61 3 Father and female guardian 492 3.04 4 Two guardians 266 1.64 5 Mother only 2,751 16.98 6 Father only 452 2.79 7 Female guardian only 190 1.17 8 Male guardian only 49 0.30

		9 Lives with student less than half time 145 0.90 -9 Missing 45 0.28 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYPARED	PEduc_NoHiSchool (1) PEduc_GED (2) PEduc_2YschoolNDe (3) PEduc_2YschoolGrad (4) PEduc_4YCollegeNDe (5) PEduc_CollegeGrad (6) PEduc_MasterD (7) PEduc_PhD (8)	Parents' highest level of education Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------- 1 Did not finish high school 944 5.83 2 Graduated from high school or GED 3,053 18.85 3 Attended 2-year school, no degree 1,666 10.29 4 Graduated from 2-year school 1,597 9.86 5 Attended college, no 4-year degree 1,758 10.85 6 Graduated from college 3,468 21.41 7 Completed Master's degree or equivalent 1,786 11.03 8 Completed PhD, MD, other advanced degree 1,049 6.48 -9 Missing 49 0.30 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYMOTHED	MEduc_NoHiSchool (1) MEduc_GED (2) MEduc_2YschoolNDe (3) MEduc_2YschoolGrad (4) MEduc_4YCollegeNDe (5) MEduc_CollegeGrad (6) MEduc_MasterD (7) MEduc_PhD (8)	Mother's highest level of education-composite Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------- 1 Did not finish high school 1,942 11.99 2 Graduated from high school or GED 4,122 25.45 3 Attended 2-year school, no degree 1,852 11.43 4 Graduated from 2-year school 1,621 10.01 5 Attended college, no 4-year degree 1,589 9.81 6 Graduated from college 2,820 17.41 7 Completed Master's degree or equivalent 1,061 6.55 8 Completed PhD, MD, other advanced degree 311 1.92 -9 Missing 52 0.32 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYFATHED	FEduc_NoHiSchool (1) FEduc_GED (2) FEduc_2YschoolNDe (3) FEduc_2YschoolGrad (4) FEduc_4YCollegeNDe	Father's highest level of education-composite Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------- 1 Did not finish high school 2,043 12.61 2 Graduated from high school or GED 4,323 26.69 3 Attended 2-year school, no degree 1,439 8.88 4 Graduated from 2-year school 1,194 7.37 5 Attended college, no 4-year degree 1,418 8.75

	(5) FEduc_CollegeGrad (6) FEduc_MasterD (7) FEduc_PhD (8)	6 Graduated from college 2,737 16.90 7 Completed Master's degree or equivalent 1,282 7.92 8 Completed PhD, MD, other advanced degree 865 5.34 -9 Missing 69 0.43 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYGPARED	GPEduc_NoHiSchool (1) GPEduc_GED (2) GPEduc_2YschoolNDe (3) GPEduc_2YschoolGrad (4) GPEduc_4YCollegeNDe (5) GPEduc_CollegeGrad (6) GPEduc_MasterD (7) GPEduc_PhD (8)	Highest reported level of education among parents^ parents Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 1 Did not finish high school 1,949 12.03 2 Graduated from high school or GED 4,258 26.29 3 Attended 2-year school, no degree 643 3.97 4 Graduated from 2-year school 780 4.82 5 Attended college, no 4-year degree 645 3.98 6 Graduated from college 2,003 12.37 7 Completed Master's degree or equivalent 820 5.06 8 Completed PhD, MD, advanced degree 631 3.90 -9 Missing 1,753 10.82 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 2,536 15.66 TOTAL 16,197 100.00
BYOCCUM	MOCCU_NoJob (0) MOCCU_Crafts (2, 5, 8, 16) MOCCU_Services (4, 12, 15) MOCCU_Prof (9, 10) MOCCU_Manager (3, 11) MOCCU_teacher (14) MOCCU_Military (7) MOCCU_Clerk (1) MOCCU_Sales (13) MOCCU_farmer (3)	Mother/female guardian's occupation-composite Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 0 No job for pay 621 3.83 1 Clerical 2,468 15.24 2 Craftsperson 337 2.08 3 Farmer, farm manager 85 0.52 4 Homemaker 751 4.64 5 Laborer 684 4.22 6 Manager, administrator 1,661 10.26 7 Military 28 0.17 8 Operative 637 3.93 9 Professional A 2,178 13.45 10 Professional B 607 3.75 11 Proprietor, owner 364 2.25 12 Protective service 114 0.70 13 Sales 653 4.03 14 School teacher 1,004 6.20 15 Service 2,360 14.57 16 Technical 771 4.76 -9 Missing 47 0.29 -8 Survey component legitimate skip 179 1.11

		-4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYOCCUF	FOCCU_NoJob (0) FOCCU_Crafts (2, 5, 8, 16) FOCCU_Services (4, 12, 15) FOCCU_Prof (9, 10) FOCCU_Manager (3, 11) FOCCU_teacher (14) FOCCU_Military (7) FOCCU_Clerk (1) FOCCU_Sales (13) FOCCU_farmer (3)	Father/male guardian's occupation-composite Category / Label / Frequency Unweighted / Percent Unweighted 0 No job for pay 177 1.09 1 Clerical 365 2.25 2 Craftsperson 1,944 12.00 3 Farmer, farm manager 292 1.80 4 Homemaker 387 2.39 5 Laborer 1,611 9.95 6 Manager, administrator 2,251 13.90 7 Military 202 1.25 8 Operative 1,763 10.88 9 Professional A 1,630 10.06 10 Professional B 899 5.55 11 Proprietor, owner 922 5.69 12 Protective service 519 3.20 13 Sales 797 4.92 14 School teacher 217 1.34 15 Service 614 3.79 16 Technical 713 4.40 -9 Missing 66 0.41 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 -1 Don't know 1 0.01 TOTAL 16,197 100.00

BYINCOME	FamIncome_L_$1 (1, 2) FamIncome_B_$1&5 (3) FamIncome_B_$5&10 (4) FamIncome_B_$10&15 (5) FamIncome_B_$15&20 (6) FamIncome_B_$20&25 (7) FamIncome_B_$25&30 (8) FamIncome_B_$35&50 (9) FamIncome_B_$50&75 (10) FamIncome_B_$75&100 (11) FamIncome_B_$100&200 (12) FamIncome_G_$200 (13)	Total family income from all sources 2001-composite Category Label Frequency Unweighted Percent Unweighted ------------------ -- ------------------- 1 None 80 0.49 2 $1,000 or less 178 1.10 3 $1,001-$5,000 305 1.88 4 $5,001-$10,000 351 2.17 5 $10,001-$15,000 699 4.32 6 $15,001-$20,000 782 4.83 7 $20,001-$25,000 1,000 6.17 8 $25,001-$35,000 1,894 11.69 9 $35,001-$50,000 3,022 18.66 10 $50,001-$75,000 3,316 20.47 11 $75,001-$100,000 2,178 13.45 12 $100,001-$200,000 1,810 11.17 13 $200,001 or more 582 3.59 TOTAL 16,197 100.00
BYSES1QU	SES_Low (1) SES_MLow (2) SES_MHigh (3) SES_High (4)	Quartile coding of SES1 variable Category Label Frequency Unweighted Percent Unweighted ------------------ -- ------------------- 1 Lowest quartile 3,608 22.28 2 Second quartile 3,604 22.25 3 Third quartile 3,731 23.04 4 Highest quartile 4,301 26.55 -8 Survey component legitimate skip/NA 305 1.88 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYHOMLIT	HomeLiRe_None (0) HomeLitRe_One (1) HomeLiRe_two (2) HomeLiRe_50+ (3)	BY home literacy resources Category Label Frequency Unweighted Percent Unweighted ------------------ -- ------------------- 0 Family has none of these resources 703 4.34 1 Family has one of these resources 2,077 12.82 2 Family has two of these resources 3,981 24.58 3 50+ books, daily paper, regular magazine 6,461 39.89 -9 Missing 2,022 12.48 -8 Survey component legitimate skip/NA 305 1.88 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYSTEXP	StEdGoal_HighS	How far in school student thinks will get-composite

	(1, 2) StEdGoal_2Y_Col (3) StEdGoal_4Y_Col (4, 5) StEdGoal_MA (6) StEdGoal_PhD (7)	Category / Label / Frequency Unweighted / Percent Unweighted ------------------ -------------------------------------- ------------------- 1 Less than high school graduation 128 0.79 2 High school graduation or GED only 983 6.07 3 Attend or complete 2-year college/school 880 5.43 4 Attend college, 4-year degree incomplete 563 3.48 5 Graduate from college 5,419 33.46 6 Obtain Master's degree or equivalent 3,153 19.47 7 Obtain PhD, MD, or other advanced degree 2,668 16.47 -8 Survey component legitimate skip/NA 305 1.88 -4 Nonrespondent 648 4.00 -1 Don't know 1,450 8.95 TOTAL 16,197 100.00
BYPARASP	PaExp_HighS (1, 2) PaExp_2Y_Col (3) PaExp_4Y_Col (4, 5) PaExp_MA (6) PaExp_PhD (7)	How far in school parent wants 10th-grader to go-composite Category / Label / Frequency Unweighted / Percent Unweighted ------------------ -------------------------------------- ------------------- 1 Less than high school graduation 16 0.10 2 High school graduation or GED only 575 3.55 3 Attend or complete 2-year college/school 1,241 7.66 4 Attend college, 4-year degree incomplete 156 0.96 5 Graduate from college 7,069 43.64 6 Obtain Master's degree or equivalent 3,332 20.57 7 Obtain PhD, MD, or other advanced degree 3,630 22.41 -4 Nonrespondent 178 1.10 TOTAL 16,197 100.00
BYTXMIRR		Math IRT estimated number right Category / Min / Max / Mean Unweighted / Std Deviation Unweighted ------------------ ------------------ ------------------ ------------------- - Continuous 12.523 69.719 38.059 11.878
BYTXMSTD	MathStdScore	Math test standardized score Category / Min / Max / Mean Unweighted / Std Deviation Unweighted ------------------ ------------------ ------------------ ------------------- Continuous 19.38 86.68 50.71 9.91
BYTXRSTD	ReadingStdScore	Reading test standardized score Category / Min / Max / Mean Unweighted / Std Deviation Unweighted ------------------ ------------------ ------------------ ------------------- - Continuous 22.57 78.76 50.53 9.89
BYTEHDEG	EngTeachEd_BA (1, 2, 3)	Highest degree earned by the English teacher Frequency Percent

	EngTeachEd_Dip&MA (4, 5)) EngTeachEd_PhD (6, 7)	Category Label Unweighted Unweighted ------------------- -- -------------------- 1 No Degree 15 0.09 2 Associate degree (A.A., A.S., etc.) 3 0.02 3 Bachelor's degree (B.A., B.S., etc.) 6,091 37.61 4 Education specialist/prof. diploma 419 2.59 5 Master's (M.A., M.S., M.B.A., etc.) 5,619 34.69 6 Doctorate (Ph.D., Ed.D., D.P.H., etc.) 182 1.12 7 1st Professional (MD, DDS, JD/LLB, etc.) 60 0.37 -9 Missing 2,981 18.40 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
BYTMHDEG	MathTeachEd_BA (1, 2, 3) MathTeachEd_Dip&MA (4, 5)) MathTeachEd_PhD (6, 7)	Highest degree earned by math teacher Frequency Percent Category Label Unweighted Unweighted ------------------- -- -------------------- 1 No Degree 49 0.30 2 Associate degree (A.A., A.S., etc.) 7 0.04 3 Bachelor's degree (B.A., B.S., etc.) 6,279 38.77 4 Education specialist/prof. diploma 438 2.70 5 Master's (M.A., M.S., M.B.A., etc.) 6,066 37.45 6 Doctorate (Ph.D., Ed.D., D.P.H., etc.) 97 0.60 7 1st Professional (MD, DDS, JD/LLB, etc.) 36 0.22 -9 Missing 2,398 14.81 -8 Survey component legitimate skip/NA 179 1.11 -4 Nonrespondent 648 4.00 TOTAL 16,197 100.00
F1FCOMP	FComp_MO&FA (1) FComp_MO&MG (2) FComp_FA&FG (3) FComp_2_Guard (4) FComp_MOorFA (5, 6) FComp_FGorMG (7, 8)	F1 family composition Category Label Unweighted Unweighted Frequency Percent ------------------- -- -------------------- 1 Mother and father 9,625 59.42 2 Mother and male guardian 1,961 12.11 3 Father and female guardian 517 3.19 4 Two guardians 284 1.75 5 Mother only 2,888 17.83 6 Father only 482 2.98 7 Female guardian only 218 1.35 8 Male guardian only 57 0.35 9 Lives with student less than half-time 165 1.02 TOTAL 16,197 100.00
F3EVERDO	Dropout_N Dropout_Yes	F3 ever dropped out of high school (updated version of Frequency Percent Category Label Unweighted Unweighted ------------------- -- --------------------

		0 No evidence of a high school dropout 14,288 88.21 1 Evidence of a high school dropout 1,909 11.79 TOTAL 16,197 100.00
BYA32	HSDiplomatest_No HSDiplomatest_Yes	Students must pass a test for high school diploma Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------ 0 No 5,945 36.70 1 Yes 7,960 49.14 -9 Missing 118 0.73 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA27B	TchEvalTch_N TchEvalTch_Yes	Teachers evaluate teachers Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------ 0 No 11,005 67.94 1 Yes 2,556 15.78 -9 Missing 225 1.39 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 -3 Item legitimate skip/NA 237 1.46 TOTAL 16,197 100.00
BYA27C	StuEvalTch_N StuEvalTch_Yes	Students evaluate teachers Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------ 0 No 11,874 73.31 1 Yes 1,715 10.59 -9 Missing 197 1.22 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 -3 Item legitimate skip/NA 237 1.46 TOTAL 16,197 100.00
BYA41D	TchVideoCam_No TchVideoCam _Yes	Teachers have access to a video camera Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------ 0 No 798 4.93 1 Yes 13,092 80.83

		-9 Missing 133 0.82 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41E	TchVideoPrdStdio_No TchVideoPrdStdio _Yes	Teachers have access to video production studio Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 0 No 7,741 47.79 1 Yes 6,105 37.69 -9 Missing 177 1.09 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
F1A40K	Bulling_daily (1) Bulling_weekly (2) Bulling_monthly (3, 4) Bulling_never (5)	How often student bullying a problem at school Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 1 Daily 254 1.57 2 At least once a week 1,040 6.42 3 At least once a month 2,210 13.64 4 On occasion 7,027 43.38 5 Never 355 2.19 -9 Missing 929 5.74 -8 Survey component legitimate skip/NA 3,819 23.58 -6 Multiple response 1 0.01 -4 Nonrespondent 562 3.47 TOTAL 16,197 100.00
F1A40L	TchVAbuse_daily (1) TchVAbuse_weekly (2) TchVAbuse_monthly (3, 4) TchVAbuse_never (5)	How often verbal abuse of teachers a problem at school Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 1 Daily 207 1.28 2 At least once a week 893 5.51 3 At least once a month 1,854 11.45 4 On occasion 5,997 37.03 5 Never 1,888 11.66 -9 Missing 977 6.03 -8 Survey component legitimate skip 3,819 23.58 -4 Nonrespondent 562 3.47 TOTAL 16,197 100.00
F1A40M	ClassDisorder_weekly	How often disorder in classrooms a problem at school

	(2) ClassDisorder_monthly (3, 4) ClassDisorder_never (5)	Frequency Percent Category Label Unweighted Unweighted ------------------ --------------------------------------- ------------------ 2 At least once a week 136 0.84 3 At least once a month 357 2.20 4 On occasion 3,450 21.30 5 Never 6,989 43.15 -9 Missing 884 5.46 -8 Survey component legitimate skip 3,819 23.58 -4 Nonrespondent 562 3.47 TOTAL 16,197 100.00
F1A07A	EngCo_L_4Y (6) EngCo_4Y (7)	Years of English coursework required to graduate Frequency Percent Category Label Unweighted Unweighted ------------------ --------------------------------------- ------------------ 6 At least 3 years but less than 4 724 4.47 7 4 years 10,947 67.59 -9 Missing 145 0.90 -8 Survey component legitimate skip 3,819 23.58 -4 Nonrespondent 562 3.47 TOTAL 16,197 100.00
F1A07B	MathCo_B_!&2Y (4) MathCo_B_2&3Y (5) MathCo_B_3&4Y (6) MathCo_4Y (7)	Years of mathematics coursework required to graduate Frequency Percent Category Label Unweighted Unweighted ------------------ --------------------------------------- ------------------ 4 At least 1 year but less than 2 73 0.45 5 At least 2 years but less than 3 2,654 16.39 6 At least 3 years but less than 4 7,207 44.50 7 4 years 1,692 10.45 -9 Missing 190 1.17 -8 Survey component legitimate skip 3,819 23.58 -4 Nonrespondent 562 3.47 TOTAL 16,197 100.00
BYA48A	PrinEvalStdTest_No (1) PrinEvalStdTest_Minor (2) PrinEvalStdTest_Great (3)	Principal evaluated on standardized test scores Frequency Percent Category Label Unweighted Unweighted ------------------ --------------------------------------- ------------------ 1 No influence on evaluation 805 4.97 2 Minor influence on evaluation 4,722 29.15 3 Great deal of influence on evaluation 7,655 47.26 -9 Missing 841 5.19 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00

BYA28A	GoodTchAward_No (0) GoodTchAward_Yes (1)	Good teachers given a special award Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------ 0 No 6,754 41.70 1 Yes 6,998 43.21 -9 Missing 271 1.67 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA29	AcaSTDCont_No (0) AcaSTDCont_Yes (1)	Content standards for academic subjects Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------ 0 No 583 3.60 1 Yes 13,353 82.44 -9 Missing 87 0.54 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA31	ContSTD&Perf_No (0) ContSTD&Perf_Yes (1)	Content standards linked with performance standards Category Label Unweighted Frequency Unweighted Percent ------------------ -------------------------------------- ------------------ 0 No 1,903 11.75 1 Yes 11,280 69.64 -9 Missing 257 1.59 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 -3 Item legitimate skip/NA 583 3.60 TOTAL 16,197 100.00
BYA32	HSDiplomatest_No (0) HSDiplomatest_Yes (1)	Students must pass a test for high school diploma Category Label Unweighted Unweighted Frequency Percent ------------------ -------------------------------------- ------------------ 0 No 5,945 36.70 1 Yes 7,960 49.14 -9 Missing 118 0.73 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00

BYA39A	ProcPaDiscPolicy_No (0) ProcPaDiscPolicy_Yes (1)	Process to get parent input on discipline policies Category Label Unweighted Frequency Unweighted Percent ------------------ -------------------------------------- ------------------- 0 No 6,161 38.04 1 Yes 7,764 47.93 -9 Missing 98 0.61 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA39B	TrPaBehProb_No (0) TrPaBehProb _Yes (1)	Training parents to deal with problem behavior Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------- 0 No 8,768 54.13 1 Yes 5,093 31.44 -9 Missing 162 1.00 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA40A	PaidSecSchHrs_No (0) PaidSecSchHrs_Yes (1)	Use paid security at any time during school hours Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------- 0 No 4,951 30.57 1 Yes 9,007 55.61 -9 Missing 65 0.40 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41A	TchAccCableTV_No (0) TchAccCableTV_Yes (1)	Teachers have access to cable TV Category Label Frequency Unweighted Percent Unweighted ------------------ -------------------------------------- ------------------ 0 No 3,386 20.91 1 Yes 10,467 64.62 -9 Missing 170 1.05 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41B	TchAccCCTV_No (0)	Teachers have access to closed-circuit TV Frequency Percent

	TchAccCCTV_Yes (1)	Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 0 No 6,943 42.87 1 Yes 6,787 41.90 -9 Missing 293 1.81 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41C	TchAccDVD_No (0) TchAccDVD _Yes (1)	Teachers have access to videodisc player/VCR/DVD Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 0 No 133 0.82 1 Yes 13,791 85.15 -9 Missing 99 0.61 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41L	TchAccInternet_No (0) TchAccInternet_Yes (1)	Teachers have access to Internet Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------ 0 No 80 0.49 1 Yes 13,868 85.62 -9 Missing 75 0.46 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA41M	TchAccComp_No (0) TchAccComp_Yes (1)	Teachers have access to computer printer Frequency Percent Category Label Unweighted Unweighted ------------------ -------------------------------------- ------------------- 0 No 67 0.41 1 Yes 13,837 85.43 -9 Missing 119 0.73 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA42A	TchCompInstr_No (0) TchCompInstr_Yes	Teachers use computers as instructional tools Frequency Percent Category Label Unweighted Unweighted

	(1)	------------------- --------------------------------------- -------------------- 0 No 885 5.46 1 Yes 13,006 80.30 -9 Missing 132 0.82 -8 Survey component legitimate skip 178 1.10 -7 Not administered 1,823 11.26 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYA46A	PrinInflTchHorF_No PrinInflTchHorF_Some PrinInflTchHorF_Major	Principal's influence on hiring/firing teachers Frequency Percent Category Label Unweighted Unweighted ------------------- --------------------------------------- -------------------- 1 No influence 74 0.46 2 Some influence 1,749 10.80 3 Major influence 11,373 70.22 -9 Missing 803 4.96 -8 Survey component legitimate skip 178 1.10 -7 Not administered; abbreviated interview 1,823 11.26 -6 Multiple response 24 0.15 -4 Nonrespondent 173 1.07 TOTAL 16,197 100.00
BYTXCSTD	Math/ReadStdComp	Standardized test composite score-math/reading Mean Std Deviation Category Min Max Unweighted Unweighted ------------------- ------------------- ------------------- ------------------- - Continuous 20.91 81.04 50.66 9.88
BYTX1MPP	MathBaseY_L1	Mathematics—level 1 Range Weighted mean Weighted standard deviation 0–1 0.92 0.20
BYTX2MPP	MathBaseY_L2	Mathematics—level 2 Range Weighted mean Weighted standard deviation 0–1 0.67 0.42
BYTX3MPP	MathBaseY_L3	Mathematics—level 3 Range Weighted mean Weighted standard deviation 0–1 0.46 0.46
BYTX4MPP	MathBaseY_L4	Mathematics—level 4 Range Weighted mean Weighted standard deviation 0–1 0.21 0.33
BYTX5MPP	MathBaseY_L5	Mathematics—level 5 Range Weighted mean Weighted standard deviation 0–1 0.01 0.07
F1TX1MPP	MathF1Y_L1	Mathematics—level 1 Range Weighted mean Weighted standard deviation

		0–1 0.96 0.12
F1TX2MPP	MathF1Y_L2	Mathematics—level 2 Range Weighted mean Weighted standard deviation 0–1 0.78 0.37
F1TX3MPP	MathF1Y_L3	Mathematics—level 3 Range Weighted mean Weighted standard deviation 0–1 0.62 0.45
F1TX4MPP	MathF1Y_L4	Mathematics—level 4 Range Weighted mean Weighted standard deviation 0–1 0.35 0.41
F1TX5MPP	MathF1Y_L5	Mathematics—level 5 Range Weighted mean Weighted standard deviation 0–1 0.04 0.14
F1BYMTGN	MathgainF1Y	IRT math estimated number right gain: BY to F1 Min Max Mean Unweighted Std Deviation Unweighted 0 46.69 7.14 4.97
BYTXRIRR	ReadIRT_R	Reading IRT estimated number right Min Max Mean Unweighted Std Deviation Unweighted 10.199 49.085 29.922 9.692
BYTXRSTD	ReadSTDScore	Reading test standardized score Min Max Mean Unweighted Std Deviation Unweighted 22.57 78.76 50.53 9.89
BYTX1RPP	ReadProf_L1	Reading proficiency probability at level 1 Min Max Mean Unweighted Std Deviation Unweighted 0.001 1.000 0.905 0.241
BYTX2RPP	ReadProf_L2	Reading proficiency probability at level 2 Min Max Mean Unweighted Std Deviation Unweighted 0 1.000 0.477 0.396
BYTX3RPP	ReadProf_L3	Reading proficiency probability at level 3 Min Max Mean Unweighted Std Deviation Unweighted 0 0.999 0.087 0.217
BYMATHSE	MathSelfEffi_BaseY	Student self-efficacy in math in the base year Min Max Mean Unweighted Std Deviation Unweighted 0.026 1.772 0.918 0.594
BYENGLSE	EngSelfEffi_BaseY	Student self-efficacy in Eng in the base year Min Max Mean Unweighted Std Deviation Unweighted 0.001 1.596 0.831 0.564
BYCONEXP	StuExp_BaseY	Control expectation scale

		Min / Max / Mean Unweighted / Std Deviation Unweighted 0.021 / 1.580 / 0.842 / 0.515
BYINSTMO	StuUInterest_BaseY	Instrumental motivation (utility interest) scale Min / Max / Mean Unweighted / Std Deviation Unweighted 0.011 / 1.579 / 0.821 / 0.560
BYACTCTL	ActionEffort	General effort and persistence scale Min / Max / Mean Unweighted / Std Deviation Unweighted 0.002 / 1.702 / 0.790 / 0.571
BYSTPREP	ClassPrep	Class preparation scale Min / Max / Mean Unweighted / Std Deviation Unweighted 0.076 / 1.034 / 0.650 / 0.306
BYWRTNGA	StuWrAbility	Student writing ability Min / Max / Mean Unweighted / Std Deviation Unweighted 0.017 / 1.951 / 0.762 / 0.617
F1SES2	SES_F1	F1 socio-economic status composite Min / Max / Mean Unweighted / Std Deviation Unweighted 0 / 1.97 / 0.66 / 0.47

Note: the following categories (-9, -8, -7, -4):

- Missing
- Survey component legitimate skip
- Not administered; abbreviated interview/NA
- Nonrespondent

In my data analysis, I have considered all the above categories as missing values. By this approach, I was able to save most of the relevant data.

VITA

Tarek Gad
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Career Summary

Result oriented and valuable electrical/software engineer consultant with sound knowledge in data and economic analysis. Expertise in handling complex problems and ability to give consistent solutions to increase production.

Summary of Skills

- Ability to do efficient project tracking and handling month-end process management
- Capable of preparing accurate weekly performance criteria tracking reports
- Solid quantitative and qualitative data analysis including high-dimensional data analysis
- Sound knowledge in economic analysis (micro and macroeconomics)
- Strong decision-making power and can perform crisis management in unprecedented situations
- In-depth knowledge in software engineering, software development, and testing
- Expert in education, training, and human development
- Excellent problem solving, organizational, and communication skills

EDUCATION

- Ph.D. in Education Psychology: The University of Illinois at Chicago (Measurement, Evaluation, Statistics, and Assessment)
  Dissertation title: Elasticity Theory of Learning Growth in the 21st Century.
  High-dimensional graphs and variable selection with the LASSO model analysis.
  Advisor: Dr. George Karabatsos. 2018
- Masters of Economics and Econometrics: The University of Illinois at Chicago 2007
- University of Chicago: Financial Statement Analysis and Advanced Microeconomics courses 2004
- Master of Science in System and Software Engineering: Southern Methodist University, Dallas, TX 1999
- B.Sc. in Electrical Engineering: Alexandria University, Egypt 1983

Quantitative SKILLS

- Exploratory data analysis (EDA) using probabilistic graphical model (Bayesian networks & high-dimensional graph), cluster, principal component analysis, factor analysis, and structural equation modeling
- Statistical analysis & modeling: includes non-parametric and parametric data analysis
- Experience in statistical software (SAS, SPSS & R), and programming language (C++)
- Survey development
- Data preparation and cleaning

Qualitative data skills

- Case study, ethnography, grounded theory, and narrative
- Quantitative analysis software (ATLAS.ti)

Research Interest

- Knowledge extraction
- Cognitive psychology
- High-dimensional data analysis and robust statistics
- Organization culture and productivity, training and human development, hidden skills recognition and job analysis, classroom culture and achievement.

Languages

English, French, Arabic, and German

- **PROFESSIONAL EXPERIENCE**

The University of Illinois at Chicago: Jan 2016 – PhD 2018

DeVry University: Jan 2013 – Jan 2015 Adjunct Professor
Instructed college algebra

Independent Economic Consultant Egypt: August 2009-January 2012

University of Illinois 2006 - 2007: Graduate Student Instructor
Instructed Business Statistics I & II

DeVry University and Westwood College: 2004 – 2006 Adjunct Professor Information Systems Technology, Math, and Physics (Wide Area Network with TCP/IP, LAN design, Principles of Data Communication, Microsoft Server 2003, Internet Security, Statistics, Calculus I & II, Linear Regression, and Physics)

BAYTECH SERVICES *2002-2004 (USA)* Product marketing consultant.

CISCO SYSTEMS *2000 – 2002 (USA)*
Senior Product Manager & Training Specialist

NORTEL NETWORKS *1995 – 2000 (Canada & USA)*
Senior Software Project Manager, Quality Assurance, Training Specialist

SNC-LAVALIN (HIBERNIA PROJECT) *1992 – 1994 (Montreal, Canada)*
Senior weight Engineer (platform weight control)

PHILIPS PETROLEUM/WEPCO *1986 – 1992 (Egypt, France, Germany)*
Senior Project Manager

Siemens, Cairo, Egypt **(**1983 -1986**)**
Electrical Engineer