03E007I

Project Number: JMW-ST99 - 46

The Impact of SAT Scores on College Admissions

An Interactive Qualifying Project Report
Submitted to the faculty of
Worcester Polytechnic Institute
in partial fulfillment of the requirements for the degree of
Bachelor of Science
By

Matthew James Marino
June 2,2003

Approved By:

Professor John Wilkes, Project Advisor

Table of Contents

Introduction

Beginning in 1993-94 WPI Alumnus Keith McCormick raised the question of how MBTI learning type preferences related to SAT scores. The result was an IQP team advised by Professor John Wilkes (Kingsland et al.) that collected MBTI and GCSI data from approximately three hundred Worcester Public School and Nashoba Regional High School students to begin answering the original question raised by Keith McCormick. The more important legacy left by the original question and the IQP which followed, has been an ongoing relationship for the past ten years between Professor Wilkes, a series of IQP teams, the Deputy Superintendent Caradonio (later to become Superintendent) and his Institutional Researcher Dr. Patricia Mostue.

In this study Dr Mostue provided a new resource, which was the result of a Senior Placement Survey for graduating seniors and what plans they had upon graduation. I requested the data for the class year of 1999 as MBTI data and SAT data had been collected from this group beginning when they were freshmen and would be the first class for which data from four years of high school and the beginning of college was available. My goal was to analyze how high school performance in the class room, on the SAT, and through MBTI coding could be used to predict placement in college and subsequent performance once accepted into a college program.

Previous studies have compared SAT scores against MBTI personality types and have found that there is a statistically significant difference between SAT scores for similar students when course difficulty and variables based on transcript data are controlled. Certain MBTI personalities have performed significantly better on standardized tests than other MBTI types even when they share a similar academic background. Further studies have been done under the guidance of Professor Wilkes, which have replicated this finding in both other class years as well as at other school systems.

Additional studies, branching from the initial pilot, have begun exploring the impact of socio-economic backgrounds as well as the opportunity to take the test multiple times (test-retest data) to determine what policies can be put into place to ensure the "even" playing field for all students taking the SAT implicitly promised by the College Board. Showing a statistically significant difference between MBTI types and average scores is important, but determining a way to level the playing field for all students would help to open the doors of higher education to all deserving students regardless of MBTI type learning styles, which is a factor outside of a students individual control.

My contribution to the earlier effort is to gain a better understanding of how important SAT scores really are in the college admissions process. The assumption has been made in earlier studies that the lower performance of certain MBTI types on the SATs has had a negative impact on the accessibility of higher education to these students. I will be analyzing transcript data and course difficulty data and comparing the results to where the students ultimately went, or what else they did, following the completion of their high school educations.

Furthermore, a pilot study will be outlined which is designed to examine the importance of the SAT in predicting the success of students in their college experience. Initially, this was to be the main focus of my project, but time constraints and logistical issues arose, which prevented this "outcome" study from happening. The question which I later turned to was, so what? What does the SAT really mean when applying for college? Most importantly, what should the admissions offices at various colleges do with SAT scores? These questions will be briefly examined and a questionnaire will be presented which can be used in the future to collect additional data.

In summary, the original plan was to see how the students fared at the various colleges they attended, and incidentally validate the WPS Placement Survey. The fallback plan became explaining the out come of the placement variable to determine if the SAT scores for the city, which are low on average, really held back the students, especially the students whose MBTI type has been known to score lower on average.

Overview

As mentioned in the introductory pages, this project is a continuation of ongoing work to understand the SAT performance of the WPS classes of 1996-1999 and it's consequences for those students. Numerous students have worked under the guidance of Professor John Wilkes of WPI since the pilot study began in 1993 gathering, organizing and analyzing the data. When I arrived the SES data was being added to the data set and I initiated the effort to obtain the first College Placement data to be added to the data set. That being said, much of the literature used to gain background knowledge of the various components of such an effort will rely extensively on the work of the earlier project teams. Much of the background information has been obtained through discussions with Professor Wilkes as well as through the reading of earlier project presentations written by other WPI students. All efforts will be made to give credit to those individuals wherever possible. The work of Professor John Wilkes, Keith McCormick, Gerald Noble, Bai Lan Zhu, Ben Dean-Kawamura, Sara Jeffers and Brian Mentz have been used as reference materials used to prepare this background section.

Keith McCormick's analysis of John Pieper's data set first revealed the "intuitive advantage" on the SAT for students having taken roughly comparable high school programs. Gerald Noble did a follow-up on the cases John Pieper missed and began the analysis of the SES data from 2 of the 4 high schools. Unfortunately his analysis required Keith's HS program data and SES data, and Keith had focused on the class of 1997 data set, the first group to take the PSAT in any number at WPS. Gerald had “fixed” many incomplete cases, unbeknownst to Keith who had dropped incomplete cases from his analysis, and not looked up their HS programs. Ben, Bai Lan, and myself fixed the SES data set lapses and Ben added in all of the follow-up data gathered by Gerald, and redid the class of 1997 analysis with real SAT data, replicated it with the class of 1998 and 1999 data and then looked into the test-retest issue and the gains associated through multiple tests with each learning style.

Bai Lan took the SES data that we were able to find in the data set of some 2500 cases covering the classes of 1996-1999 and found about 950 cases Gerry, She, Ben and I had been able to code occupational prestige scores for. She was at last able to do what Gerry had tried to do and proved him right, that SES has its main impact on SAT scores through course the high school program taken by a student. However, the MBTI distribution is also a bit different at the higher and lower SES levels, which proved to be partly due to ethnicity and MBTI distribution being related in Worcester. Black and Hispanic students in Worcester are about two thirds sensing to one third intuitive as one would expect from the national averages. However, white students are 50% sensing and 50% intuitive, a most unusual distribution, and a significant finding where N’s are known to outperform S’s on the SAT (when high school program is controlled) and they are more likely to be in more difficult courses.

So, as you can see, the stage was set for me to look at the outcome data and to examine the consequences for access to higher education based on the SAT score patterns explored by the others who looked at social class, race, gender, and learning style—and had placed high school program at the center of the debate by tying it to the other variables.

I was surprised to find that Sara Jeffers and Brian Mentz had “borrowed” my class of 1999 placement data when their original “outcome” based study of the WPS students who had gone on to Worcester State college was deemed infeasible. They added this placement data to Ben Dean’s data set and ignored the high school course difficulty variable. They focused on grades and SAT not accounting for the fact that a grade of 85 in an AP course was considerably different than a grade of 85 in an honors course. This was not consistent with the way a college admission board would examine a transcript. In the course of their project Sara and Brian collected the data from the classes of 1998 and 2000, which they were able to provide to me to bolster my number of cases so a replication of their study could be made. After thinking about it for a bit, I decided to not replicate their study with the larger data set, but to reanalyze the class of 1999 in a manner different from theirs’.

I decided that it was more important to get one study right, even if it was with a smaller number of cases, than to replicate findings not consistent with the actual admissions process. In theory, if my analysis adds anything to their findings a subsequent replication can still be made with the larger data set but it will be more accurate. There were a couple of differences in how my study differed from theirs, course difficulty which had been ignored earlier was to be considered as a predictor variable, and more importantly, I considered placement to be a variable which was based on the underlying factors, while their study looked at placement as a ranked outcome to predict whether or not students were over or under achieving.

Myers-Briggs Type Indicator (MBTI)

The Myers-Briggs Type Indicator, also known as the MBTI, is a personality test, which has been used for over fifty years in the study of learning styles. Based on the psychological studies of Carl Jung, Isabel Myers along with Katherine C Briggs developed this test, which classifies personalities into sixteen categories. Four areas of focus are examined, with two possible outcomes for each, the total possible combinations being the sixteen types. For the use of this project as well as those done in the WPI/WPS collaboration these sixteen groupings are looked at as being absolute. The test does allow for the measurement of degree to which an individual is classified though. For example, one pair of traits measured is Extraversion/Introversion. In this data set, as is standard procedure in this test, regardless to the extent one favors one of the two possible categories they are considered either an Extravert or an Introvert. The test does however have the capability of determining how clearly an individual favors one of the preferences.

As mentioned above, the MBTI test attempts to measure an individual's preference between four pairs of opposite personality traits. When combined these traits make up sixteen potential personality types, which define how an individual tends to think and function mentally as well as emotionally. The traits examined are defined as follows:

Extraversion (E): oriented to the outside environment, active, confident in the use of trial and error. The opposite of Extraversion is Introversion (I): oriented to the inner world, reflective, often consider deeply before acting.

Sensing Perception (S): Detail oriented, pays attention to small individual steps in a process, perceives things through the use of all five sensory inputs. The opposite of Sensing is Intuitive (N) Perception: an intuitive personality type looks for the big picture, focuses on patterns and meanings with out much attention initially to the small details, works off of "hunches" but not sure where these instincts came from. As we will see in the analysis intuitive thinkers tend to perform better on standardized tests, particularly when they are stretched beyond their comfort level of knowledge.

Thinking (T): uses logical analysis for decision making purposes, tries to be objective, uses impersonal criteria in making decisions, tends think in "Black and White", often is skeptical. The opposite of Thinking, is Feeling (F): applies empathetic and subjective criteria in decision making, values relationships, weighs motives and values when coming to a decision.

The final pair of traits is Judgment (J): goal oriented, needs structure, seeks closure, organized, controlling and regulating. The emphasis is one getting things done and moving on. The opposite of Judgment is Perception (P): those who favor perception take in information and view decision making as an open-ended process. They are often considered to be curious interested, open minded, better at adapting and changing, but really they are just more resistant in drawing conclusions until all possible data is at hand.[1]

These four pairs of preferences, when combined together, are used to define a person's cognitive style, and therefore logically impact the way an individual is likely to approach as well as perform on a test such as the SAT. The reason why this is so important is that the SAT is designed to be a "level playing field" which fairly compares students across the country, as well as from various school systems. If MBTI type impacts performance then the field is not quite so level after all.

The SAT

The SAT, or Scholastic Assessment Test, is a standardized test taken annually by most students in the country who plan on attending a four year college program. The test attempts to "level the playing field" between competing students from various backgrounds, and educational systems so that college admission boards can evaluate students on a fair basis, rather then relying on highly variable standards such as grading systems. In theory, the students taking the SAT exam take the same exact test, under very similar conditions in a controlled environment. The test is conducted by the ETS, or

[1] Descriptions of the Sixteen Types by Gordon Lawrence 1993

Educational Testing Service, multiple times throughout the school year and is generally taken by both junior (PSAT) as well as senior (SAT) students in high school looking to gain admission into college.

The SAT tests knowledge in the areas of Math and Verbal Reasoning. The math section has three separate sections two of which take thirty minutes and one, which takes fifteen minutes. The questions are arranged in order of difficulty from least to most difficult and cover basic algebra and geometry. No knowledge of calculus or trigonometry is expected or needed to perform well.

The verbal section is also three sections long and again, the questions are in order of difficulty. The verbal section contains questions, which require "sentence completion", critical reading, and analogies in the present format. Again two of the three sections tallow thirty minutes for completion and the third allows for fifteen minutes.

A seventh section known as the "Experimental" section may be either math or verbal and is not used for scoring purposes. The experimental section is used by ETS to test questions to determine their accuracy and difficulty so that they may be used in future exams. The students do not know what section is experimental when they are taking the exam.

The two areas are scored individually in Math and Verbal on a range from 200-800 in each area. The test is graded on a bell curve with the center point of 500 for each type. The "average" student should be scoring a combined 1000 in this setup. Points are earned for questions answered correctly, points are lost for questions answered incorrectly, and no point change is noted if a question is left blank. In terms of "raw" unadjusted points a student receives one point for a correct answer and loses a quarter of a point for each incorrect answer.

Despite there being considerable differences in the level of difficulty between questions, there is no difference in the amount each question counts in the exam. A question of the greatest difficulty counts no more or less than a question of the lowest difficulty. Despite evidence to the contrary, ETS denies that test preparatory programs run by companies such as Kaplan and Princeton Review will help increase a student's score. I have taught for The Princeton Review for the past three years and can attest to the fact that these programs certainly can help increase a student's scores. The cost of these programs however, is often outside the reach of many less wealthy families and this contributes to the socio-economic gap between test scores considerably.

SAT scores are used for various purposes by the college admission boards. Many highly selective schools that receive large volumes of applications will use the SAT score as a screening tool to determine whether or not the rest of the application packet will be considered. The SAT score is an easy to quantify measurement, which requires little time to examine in a busy environment. Schools which have less taxed resources in the admissions office will often place less emphasis on these test scores and will generally use the scores to compare two similar students with other factors such as transcript and recommendations counting for much more.

Recently, there has been a large turn around in the way the SAT is viewed by college admission boards. Driven largely by the demands of the public colleges in the state of California, the SAT is undergoing massive changes to its format. The state education system of California is the largest "customer' of ETS and carries considerable leverage when making such demands. The changes being called for will certainly make the test more expensive for ETS to administer and they have been resistant to change because of this.

The new exam, when it arrives will be more of an achievement test and will include more open-ended questions as well as a writing section. Many colleges are placing less emphasis on the test scores and some have dropped using them all together. Questions regarding, gender, ethnic, and other socio-economic biases (based on variances within the SAT scores) have led to widespread calls for this revision of the exam. In addition to these issues, the test material itself has come under scrutiny for being based below that of what should reasonably be expected out of a student planning to attend college.

The Relationship Between MBTI Types and SAT Scores

In earlier studies of the WPS data set, a statistically significant relationship was found between MBTI type and SAT scores. Specifically, students who were coded as exhibiting the preferences associated with "intuitive" learning, consistently outperformed students who were coded as "sensing" learners on the S-N dimension. Differences in average scores associated with judging versus perceiving preferences were also found but later replication efforts demonstrated that these relationships were not as strong in regards to these differences. Because of the replication efforts, which have shown consistent findings, my research will focus on the sensing/intuitive relationship and their relationship to SAT scores.

Methodology

As mentioned in the introduction, this project and its focus have evolved overtime. The initial goal was to look more closely at the graduating class of 1999 than had been done with the existing data set previously. The class of 1999 was, at the time this project was initiated, the first class for which we had a complete picture within the data set. By saying complete, it would be the class that was in 9th grade when the MBTI data was collected, would have taken the SAT, would have transcript data for all of their time in the WPS and would have graduated and been at college or what ever they had chosen to do after graduation for two years when this project was initiated now for 4 years.

The WPS class of 1999 was at a turning point in the collection of MBTI data. The first four classes worth of data were collected over a two-day period in 1995. At this time the class of 1999 were freshmen. After this collection WPS took over the responsibility of collecting this data when the each class 2000-2003 were in their sophomore year. However, the data collection effort was not very successful until the year 2000 when the class of 2002 data was collected. The data for the class of 2002 was the first class since the class of 1999 that really got a large potion of the MBTI data for the students in a given class year. As this data set was not available at the time I began my project I choose to work with the best available class at the time which was that of the class of 1999.

For the class of 1999, the data available included MBTI type, SAT scores (often for multiple attempts), and transcript data, which had course name, difficulty level and the grade received. I requested, received, and integrated the college placement data for this class year in order to have the variables I needed for my analysis. I made the decision that I would only consider cases for which all of these variables were known. While this caused my data set to lose a considerable number of cases I felt that it was justified by the improvement in the analysis it would provide. Essentially, students who transferred into the WPS system after their freshmen year had no MBTI data so they were eliminated, students who left before graduation had no placement data and were eliminated as well. What this left was a collection of students who had been in the WPS system for the full four years of high school and therefore the results were truly attributed to the environment which was being examined.

A criticism I made in examining Sara and Brian's analysis was that their analysis looked at many different sample sizes and it was not always clear how the number of cases could be so different from chart to chart. By eliminating incomplete cases, any statements of correlation which I made were representative of the whole group not just certain parts of it. In some instances as many as three or four hundred cases were dropped in Sara and Brian's analyses and would then pop back in at later points. My data set after removing incomplete cases left me with 348 cases with a breakdown of 2/3 female to 1/3 male.

The original goal with this project was to essentially step back and look at the "big" picture. A questionnaire was proposed which was designed to detail what happened to these students after they left the WPS. It would be interesting to further examine what the students were doing. Did they go to the college which they told WPS they were planning on attending? If not, where did they go? If they went to college how did they perform? Why they went to the college they were at? Did they transfer? Were financial concerns more of a factor in these decisions than aspirations or ability?

These questions would allow significant analysis to be performed on a variety of important issues. Predictors of collegiate success would be better understood, did the top SAT scorers perform better, worse, or the same as lower scorers. Did certain MBTI types have a better transition from high school to college? Did financial issues limit access to the more selective colleges? To be able to answer these questions in a complete data set looking at the students complete four year journey through high school and see where they ended up would be important both for WPS to better serve their students as well as for college admission boards looking to improve the chance for success in its new student base.

A brief questionnaire was developed in 2000-2001, which was to be sent to the homes of students in our database requesting an update on those who told WPS where they had planned to attend college at. Due the large number of students in the data set it was believed that even a small return rate, as low as ten percent, would provide a significant starting point for these kinds of analysis. It was more of a methodological study, to determine if the parents could and would answer these basic questions. The colleges would not be able to release this personal data, and the addresses of the students at college were not available. If the analysis showed this approach to be feasible—and especially if there were any surprising results, further data could be attained by these means. Otherwise, students would have to sign a release before leaving WPS so that the colleges could be our source of this data. The Worcester State college system would be able to provide data for a significant number of cases if the survey was not feasible. In the appendices, explanations of how analysis was to be performed on the questionnaires has been detailed.

Due to time constraints the questionnaires were never sent out. The questionnaire was developed by myself and approved for distribution by Professor Wilkes. The questionnaire was then sent to Dr Mostue who wished to have some modifications made before it could be sent out. Based on the time constraints of the project I put the process on hold, never imagining that I would still be involved with the project this far out in the future, and turned my focus to the analysis which I could perform on the existing data set. The questionnaire is attached as an appendix item at the end of this report. Future IQP or MQP projects may go forward with the execution of this pilot study in some form or other. I still think the question is interesting and worth carrying out, possibly for the class of 2002 if it were to be performed now.

While the original analysis plan could not be performed with the existing data set, it was determined that analysis could be carried out by looking at where the student records indicated the students went following high school and comparing where they went to where they would be expected to go based upon how they looked on paper based on SAT scores and transcript data. In short I used the placement data as my outcome variable and attempted to use SAT scores and transcript data to draw some conclusions. Would the SAT scores play a significant factor in the admissions process and could transcript data and course difficulty over come the weak SAT scores. If the importance of SAT was secondary to transcript data during the admissions process, than the biases of the SAT related to the MBTI would become less important than what had been indicated by the earlier research.

While transcript data had been examined in the past there were questions raised as to whether or not the use of such data was done in a manner consistent with adjustments for course type as well as course difficulty. This would allow for new data to be created from the raw transcript data set, which should allow for better analysis of the relationship between MBTI types and SAT scores when transcript data is controlled for. This new way of considering transcript data is a major difference from what had been done in earlier projects.

The Data Set

The data set used in this analysis has been combined between raw data received from Dr Patricia Mostue and MBTI data collected and coded through the work of earlier IQP teams. In order for certain regression analysis to be performed additional data types were made from existing data points. An example of this would be the recoding of placement data as well as the manipulation of data used in determining average grades and average level of course difficulty. Through the processes described below, a final data completed data set for the class of 1999 containing 348 cases was obtained.

In this data set I decided that only "complete" cases would be examined. In order for the case to be considered; transcript data, SAT scores from the first attempt, MBTI type, and placement data all needed to be available. This was done so that any data analysis, which was later performed, would be look at the same exact number of cases. By doing this, one can obtain a clearer picture of regression variables and not skew the data set with cases whose relevance was not known.

The next decision involving the data set was related to the course transcript data and course difficulty data. In an attempt to control for transcript data and its relevance to the SAT, only transcript data related to math or English courses was considered. This was done for a variety purposes. By eliminating from the data set courses not directly relevant to the SAT, an average grade variable could be compared to SAT scores that should accurately predict SAT performance. The removal of courses not related to math or English would allow for the most accurate picture of a students performance in the courses the SAT intends to measure performance for. All non-core class data was excluded from analysis.

The additional benefit of removing various courses from the data set was that the measurement for average course difficulty would also become more relevant to the course looked at by the SAT. Course difficulty would have been skewed towards a less difficult level if all courses were considered, as many "specialty" courses were only available at an "average" level of difficulty. For the purposes of this study, by only considering math and English courses, the average difficulty variable would become much more meaningful.

By keeping course difficulty and average grade data separate, regression analysis would be able to be performed individually as well jointly through multiple regression analysis. Measurements which would be looked at in the analysis of the data would include average SAT and Average Placement related to average grades, average difficulty and would be examined by total group, as well as by the male verse female population separately. In working with the data set and noticing certain patterns much of the analysis will look at the students who went to the schools which are more difficult to be accepted at. It became obvious through the collection procedure that as students became less likely to go to the best or better schools that other factors began to come into play that the data set was not prepared to handle.

Data Analysis/Results

After putting together the new data set, an initial regression analysis was performed using MBTI variable (specifically the S-N factor), SAT scores, Average Grades and Average Course Difficulty to estimate College Placement data which is the dependent variable in my model. When this was done there were statistically significant conditional findings for SAT scores, Average Grades and Course difficulty. MBTI type (S/N variable) was very close to being statistically significant as well. Using the correlations function in the SPSS software package the following Spearman's rho (non-parameteric-rank order) correlations were found (Appendix A):

Spearman's Correlation

Average Core Course Grades: correlation coefficient of .686 with Placement

Average Core Course Difficulty: correlation of .674 with Placement

SAT Combined score: correlation of .554 with Placement

These were all statistically significant correlations at the .01 level in a two-tailed analysis.

S/N(Sensing/Intuitive): correlation of .101 with Placement.

As shown above when examining the strongest MBTI link to SAT performance, S/N, was not a statistically significant predictor of placement. Pearson correlations were also performed using SPSS and the results from the Spearman rho analysis were compared together. Using the Pearson analysis Course Grades, Course Difficulty, and SAT combined scores were statistically significant while S/N was not (Appendix B).

Pearson Correlation

AVG Grade: displayed a .644 correlation with Placement

AVG Course Difficulty: displayed a .626 correlation with Placement

AVG Combined SAT Score: displayed a .569 correlation with Placement

Again these were all statistically significant correlations at the .01 level in a two-tailed analysis when using the Pearson correlation analysis method.

S/N(Sensing/Intuitive): correlation of .087 with Placement.

As shown above when examining the strongest MBTI link to SAT performance, S/N, again, was not a statistically significant predictor of placement when using the Pearson correlation as well.

When looked at individually both methods of analysis confirmed the stated hypothesis that course difficulty is a relevant and important variable which was overlooked in the earlier study of Jeffes and Mentz. In fact, Core Cousre Difficulty is the second strongest factor in predicting college placement and is stronger than SAT scores. The next step in the analysis process was to compare them using multi-linear regression. By using multi-linear it would be possible to determine how much each individual factor contributed to the best statistical model when examined together, and to also determine what the addition of the course difficulty variable would add to prior analysis.

Throughout the analysis process is was determined that the Spearman's rho methodod of measureing correlation was most applicable to what I was attempting to accomplish. Spearman's technique stack ranks the variables and determines if there is a pattern between the variables regardless of the magnitude of difference. Pearson's makes the assumption that there is a significant difference between levels of rank and in the case of my study was not as strong of a tool. The two tests were both run however, in an attempt to further validate the findings of each technique individually.

Using the multi-linear regression analysis tool in SPSS, Placement was modeled based on SAT Combined Scores, Average Grades, and Average Level. The first time the multi-linear regression analysis was performed the computer's default setting determined the order of how variables would be added into the equation.

The results from the first multi-linear model were statistically significant with an Adjusted R Square value of .513, meaning that over half of the variance in the dependent variable (College Placement) could be explained by just these three variables. When looking at the regression model resultsit was clear that the course grades were the most highly correlated with placement and would be enetered into the model first. The following Standardized Coefficients Beta were found within the model (Appendix C):

Course Grade= .407

Course Difficulty= .336

SAT Scores= .080

When looked at independently SAT scores had been considered a strong predictor of placement, however, when examined in a multi-variable model the significance of SAT scores on placement was negligible compared to the other variables in the model and the little influence the SAT variable did have was closely tied to the grades and difficulty variable as well.

Based on the multi-linear regression the next question which was raised was what happened to the SAT Score's effect in the combined model? The answer seemed to be that the SAT scores were so closely correlated with course difficulty and course grades that when looked at together the effect was cancelled out. This hypothesis was tested using both correlation as well as multi-linear regression. The correlation results (Appendix D) shown below confirmed the hypothesis.

Using the Spearman' rho calculation the results from above question were answered

The Spearman's values were as follows:

Average Level: displayed a strong correlation of .745 with SAT scores

Average Grade: displayed a correlation of .606

S/N: displayed a correlation of .328 (confirming earlier studies relation MBTI to SAT Scores)

These results were all statistically significant at the .01 level using two-tailed analysis. Interestingly the SAT advantage of Ns over Ss is off set by the S's performance in the classroom as SAT Scores in the multi-linear model had little impact on placement. The strong correlation between SAT scores and Average Level also was very significant in that it explains how the earlier work of the Mentz/Jeffers team remained accurate despite ignoring the second strongest variable in the model.

Following the correlation analysis, multiple regression analysis was performed modeling SAT combined scores with Average Level, Average Grade, and N/S. Forcing the system to step through the addition of variables to the model allowed the models to show how each variable impacted the total accuracy of the model (Appendix E).

The first model looked at just Average Level as it was the most powerful indicator according to the correlation analysis. This model returned an R Square value of .513, Standardized Coefficient Beta of .717. This model was statistically significant.

The second model added the S/N variable to model one. The Adjusted R Square value rose to .548. This was not a drastic change but was still an improvement overall. The Standardized Coefficient Beta for Average Level was .680 and for S/N it was .192.

The third model added in the factor of Average Grades and the results once again were an improvement. The model with all three variables had an Adjusted R Square value of .587. The Standardized Coefficient Beta was .545 for Average Level, .203 for S/N, and .233 for the Average Grades.

At this point in the analysis two major goals were accomplished. A potent variable, course difficulty, was statistically validated as the best single predictor of SAT cores and a strong predictor of Placement as well. The second major accomplishment was being able to provide statistical evidence explaining how the earlier work of Jeffers/Mentz could be almost as accurate as my revised analysis despite the absence of this powerful new variable. SAT scores are very highly related to the missing variable so in the absence of the difficulty variable the SAT variable helps fill the missing gap. Prior to moving on to the results and conclusions, various cross-tabulations and correlations were run in SPSS to examine the data set further some of the more interesting findings have been described below in detail.

As is shown in appendix F, when using linear regression to relate Placement with the variable of SAT scores, Grades, Difficulty, S/N, and J/P each subsequent additional variable decreased the Standardized Coefficient Beta for SAT Scores further displaying the commingled relationship which had misled earlier analysis resulting in inaccurate and inflated conclusions about the significance of SAT scores in college placement. Appendix F also introduces J/P as a potential variable of importance in the model. Following the analysis however J/P did not make any significant improvement to the model and was excluded by the system defaults due to its lack of influence.

Appendix G provides Pearson and Spearman correlation analysis for SAT Combined Scores, Average Level, Average Grade, N/S and Sex. The only significant correlation including sex was with Average level (.121) for Pearson using .05 level confidence in a two-tailed analysis. Spearman's showed a correlation of .114 for Average Level and .110 with Average Grade both were only significant when considered at the .05 level.

Appendices H and I provide cross tabulation frequencies and brief statistical analysis for the significant factors as related to sex. While it seems that the females did not perform significantly different in regards to placement it does appear that they worked harder in the classroom as indicated by both grades as well as in terms of average course difficulty. SAT scores were slightly higher on average for the males but the difference between genders was less than the nationally observed average gender difference in SAT scores. The closer SAT scores seems to have occurred as a result of the increased effort put in by the girls in the WPS classroom.

Wilkes reports, based on the work of Ben Dean and Keith McCormick, that the women in WPS take harder classes, get higher grades, are less often absent, and take the SAT more times, thereby closing the SAT gender gap. If they did not do this then the males would be outscoring the females by an average of fifty points.

Results and Conclusions

Based upon the data analysis it has been statistically proven that Course grades and Course Difficulty are clearly the two most important factors in being admitted into college. By controlling for difficulty, SAT scores and the MBTI biases they carry, have minimal impact on admittance. Course difficulty was previously not considered now has been shown to be the second most powerful predictor of placement. Course Difficulty's correlation to SAT scores was able to explain the results from the earlier study which did not include difficulty as a factor.

The proposed pilot study and questionnaire (Appendix J), would seek to provide better documentation of what other factors are not in the existing data set which play a large factor in placement. The fundamental assumption through this project was that students wanted to go to the best college they could. This assumption may be flawed, and may explain the surprise cases where a top student went to a low ranking school, and why middle ranked students either went to a school below there capability or not at all. Many students make decisions based on which college they attend based on proximity to home, cost, extracurricular activities, and field of study. None of these factors are presently being taken into account based on the existing dataset.

The proposed pilot study would also allow for a complete follow up to analyze what indicators from high school are the best predictors of college success. The correlation of course difficulty and average grades to college performance could be used by the WPS to determine how well they are preparing their students for the college environment. Based on the SAT scores, which are considerably below the national average, and the high grades in what are considered to be honors courses the question that needs to be asked next is why is there such a discrepancy in what the students grades and difficulty of program indicate a student to be capable of and why they fall short on the SAT exam. It seems that a potential argument could be made that grade inflation would explain the difference, but if that was the case than the pilot study would be able to show that be poor college performance in a more competitive college environment.

The second issue to be raised, which would require more detailed analysis and additional data collection is when does MBTI bias begin and why? It appears that the SAT bias related to MBTI type can be explained by the grades and course difficulty also tied to MBTI types. What is it that has certain students in the tougher courses? Why do the students in the tougher courses still seem to perform better? Are certain MBTI types smarter than others?

As has been the case with earlier projects the need for additional answers is obvious. Each question that has been asked and answered seems to raise five more questions in the process. As this report is being completed additional studies are underway using Socio-Economic data which Ben Dean-Kawamura, Bai Lan, and myself decoded in an effort to add to the ever expanding data set which began ten years ago.

Bibliography

Bately, Danielle, Brezniak, Paula, and Purohit, Ashwin. Cognitive Bias in the SAT. Unpublished Interactive Qualifying Project, Worcester Polytechnic Institute, 1995.

Jeffers, Sara and Mentz, Brian. Worcester State Follow-Up. Unpublished Interactive Qualifying Project, Worcester Polytechnic Institute, 2003.

Lawrence, Gordon. Descriptions of the Sixteen Types. Center for Applications of Psychological Types, Inc. 1993

Noble, Gerald. How Much Does Social Class Affect PSAT Performance? Unpublished Interactive Qualifying Project, Worcester Polytechnic Institute, 2000.

Pieper, John. Cognitive and Learning Style Biases in the SAT/PSAT. Unpublished Interactive Qualifying Project, Worcester Polytechnic Institute, 1996.

Wilkes, John. The Worcester Area High School SAT Studies 1993-1999. Unpublished chapter material from upcoming book "The Intuitive Advantage and the Message of the SAT". Worcester Polytechnic Institute, 2000.

Prepared by Matthew Marino

Sample Questionnaire:

Thank you for taking the time to fill out this brief questionnaire. As you may recall during the time you spent in the Worcester Public School system, you participated in an experimental study in which MBTI personality data along with various indicators of high school performance were collected and later analyzed. I am hoping to conduct further analysis and need your help by filling out the questions below. The results of this study will allow the Worcester School District to improve access to higher education through policy changes resulting from this work. Once Again, I thank you in advance for your support.

1.)What college did you attend following your graduation from high school?(If you did not attend college please see 1a.) ______________________________

1a.)What factors influenced your decision to not attend college(ex. Financial aid, career choice, etc.)? ______________________________________

2.) Have you remained at the college you went to? Y/N

2a. If no, what did you later do?_____________________

3.) How would you rate your performance in college? (on a scale of 1 being excellent- 5 being not well)___________________________________

4) What was your average grade while in college? (ex. A, B, C, etc.)___________

App A

Correlations

			AVG Level	AVG Grade	Placement	SAT COM	N/S
Spearman's rho	AVG Level	Correlation Coefficient	1.000	-.647**	.674**	-.745**	.190**
		Sig. (2-tailed)	.	.000	.000	.000	.000
		N	348	348	348	348	348
	AVG Grade	Correlation Coefficient	-.647**	1.000	-.686**	.606**	-.100
		Sig. (2-tailed)	.000	.	.000	.000	.061
		N	348	348	348	348	348
	Placement	Correlation Coefficient	.674**	-.686**	1.000	-.554**	.101
		Sig. (2-tailed)	.000	.000	.	.000	.060
		N	348	348	348	348	348
	SAT COM	Correlation Coefficient	-.745**	.606**	-.554**	1.000	-.328**
		Sig. (2-tailed)	.000	.000	.000	.	.000
		N	348	348	348	348	348
	N/S	Correlation Coefficient	.190**	-.100	.101	-.328**	1.000
		Sig. (2-tailed)	.000	.061	.060	.000	.
		N	348	348	348	348	348

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

Intuition works through
SAT score
and
H.S Program Challenge
Ave Grade Not
Higher,
Placements not better

App A

Correlations

Correlations

		AVG Level	AVG Grade	Placement	SAT COM	N/S
AVG Level	Pearson Correlation	1	-.571**	.626**	-.717**	.193**
	Sig. (2-tailed)	.	.000	.000	.000	.000
	N	348	348	348	348	348
AVG Grade	Pearson Correlation	-.571**	1	-.644**	.558**	-.067
	Sig. (2-tailed)	.000	.	.000	.000	.211
	N	348	348	348	348	348
Placement	Pearson Correlation	.626**	-.644**	1	-.549**	.087
	Sig. (2-tailed)	.000	.000	.	.000	.106
	N	348	348	348	348	348
SAT COM	Pearson Correlation	-.717**	.558**	-.549**	1	-.324**
	Sig. (2-tailed)	.000	.000	.000	.	.000
	N	348	348	348	348	348
N/S	Pearson Correlation	.193**	-.067	.087	-.324**	1
	Sig. (2-tailed)	.000	.211	.106	.000	.
	N	348	348	348	348	348

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

App B

Nonparametric Correlations

App B

Regression

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	SAT COM, AVG Grade, AVG Level[a]	.	Enter

a. All requested variables entered.

b. Dependent Variable: Placement

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.719[a]	.517	.513	.927

a. Predictors: (Constant), SAT COM, AVG Grade, AVG Level

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	316.326	3	105.442	122.781	.000[a]
	Residual	295.421	344	.859		
	Total	611.747	347			

a. Predictors: (Constant), SAT COM, AVG Grade, AVG Level

b. Dependent Variable: Placement

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	6.720	.808		8.320	.000
	AVG Level	.912	.153	.336	5.972	.000
	AVG Grade	-.056	.007	-.407	-8.621	.000
	SAT COM	-.001	.000	-.080	-1.440	.151

a. Dependent Variable: Placement

Correlations

App. D

Correlations

		SAT COM	AVG Level	AVG Grade	N/S
SAT COM	Pearson Correlation	1	-.717**	.558**	-.324**
	Sig. (2-tailed)	.	.000	.000	.000
	N	348	348	348	348
AVG Level	Pearson Correlation	-.717**	1	-.571**	.193**
	Sig. (2-tailed)	.000	.	.000	.000
	N	348	348	348	348
AVG Grade	Pearson Correlation	.558**	-.571**	1	-.067
	Sig. (2-tailed)	.000	.000	.	.211
	N	348	348	348	348
N/S	Pearson Correlation	-.324**	.193**	-.067	1
	Sig. (2-tailed)	.000	.000	.211	.
	N	348	348	348	348

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

Nonparametric Correlations

Correlations

			SAT COM	AVG Level	AVG Grade	N/S
Spearman's rho	SAT COM	Correlation Coefficient	1.000	-.745**	.606**	-.328**
		Sig. (2-tailed)	.	.000	.000	.000
		N	348	348	348	348
	AVG Level	Correlation Coefficient	-.745**	1.000	-.647**	.190**
		Sig. (2-tailed)	.000	.	.000	.000
		N	348	348	348	348
	AVG Grade	Correlation Coefficient	.606**	-.647**	1.000	-.100
		Sig. (2-tailed)	.000	.000	.	.061
		N	348	348	348	348
	N/S	Correlation Coefficient	-.328**	.190**	-.100	1.000
		Sig. (2-tailed)	.000	.000	.061	.
		N	348	348	348	348

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

Regression

App E

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	AVG Level	.	Forward (Criterion: Probability-of-F-to-enter <= .050)
2	N/S	.	Forward (Criterion: Probability-of-F-to-enter <= .050)
3	AVG Grade	.	Forward (Criterion: Probability-of-F-to-enter <= .050)

a. Dependent Variable: SAT COM

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.717[a]	.514	.513	136.378
2	.742[b]	.550	.548	131.463
3	.766[c]	.587	.583	126.213

a. Predictors: (Constant), AVG Level

b. Predictors: (Constant), AVG Level, N/S

c. Predictors: (Constant), AVG Level, N/S, AVG Grade

App E

ANOVA[d]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6819096.2	1	6819096.166	366.641	.000[a]
	Residual	6435202.7	346	18598.852		
	Total	13254299	347			
2	Regression	7291843.4	2	3645921.717	210.961	.000[b]
	Residual	5962455.4	345	17282.479		
	Total	13254299	347			
3	Regression	7774511.0	3	2591503.679	162.685	.000[c]
	Residual	5479787.8	344	15929.616		
	Total	13254299	347			

a. Predictors: (Constant), AVG Level

b. Predictors: (Constant), AVG Level, N/S

c. Predictors: (Constant), AVG Level, N/S, AVG Grade

d. Dependent Variable: SAT COM

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1503.080	36.668		40.991	.000
	AVG Level	-286.563	14.966	-.717	-19.148	.000
2	(Constant)	1583.319	38.533		41.090	.000
	AVG Level	-271.746	14.702	-.680	-18.484	.000
	N/S	-75.333	14.404	-.192	-5.230	.000
3	(Constant)	1091.114	96.768		11.276	.000
	AVG Level	-217.812	17.182	-.545	-12.677	.000
	N/S	-79.393	13.848	-.203	-5.733	.000
	AVG Grade	4.716	.857	.233	5.505	.000

a. Dependent Variable: SAT COM

App E

Excluded Variables[c]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	AVG Grade	.220[a]	4.982	.000	.259	.674
	N/S	-.192[a]	-5.230	.000	-.271	.963
2	AVG Grade	.233[b]	5.505	.000	.285	.672

a. Predictors in the Model: (Constant), AVG Level

b. Predictors in the Model: (Constant), AVG Level, N/S

c. Dependent Variable: SAT COM

Regression

Variables Entered/Removed[b]

Model	Variables Entered	Variables Removed	Method
1	SAT COM	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
2	AVG Grade[a]	.	Enter
3	AVG Level	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	N/S[a]	.	Enter
5	J/P[a]	.	Enter

a. All requested variables entered.

b. Dependent Variable: Placement

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.549[a]	.301	.299	1.112
2	.683[b]	.467	.464	.972
3	.719[c]	.517	.513	.927
4	.720[d]	.518	.513	.927
5	.722[e]	.522	.515	.925

a. Predictors: (Constant), SAT COM

b. Predictors: (Constant), SAT COM, AVG Grade

c. Predictors: (Constant), SAT COM, AVG Grade, AVG Level

d. Predictors: (Constant), SAT COM, AVG Grade, AVG Level, N/S

e. Predictors: (Constant), SAT COM, AVG Grade, AVG Level, N/S, J/P

App F

ANOVA[f]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	184.130	1	184.130	148.986	.000[a]
	Residual	427.617	346	1.236		
	Total	611.747	347			
2	Regression	285.696	2	142.848	151.149	.000[b]
	Residual	326.052	345	.945		
	Total	611.747	347			
3	Regression	316.326	3	105.442	122.781	.000[c]
	Residual	295.421	344	.859		
	Total	611.747	347			
4	Regression	317.012	4	79.253	92.231	.000[d]
	Residual	294.735	343	.859		
	Total	611.747	347			
5	Regression	319.038	5	63.808	74.552	.000[e]
	Residual	292.709	342	.856		
	Total	611.747	347			

a. Predictors: (Constant), SAT COM

b. Predictors: (Constant), SAT COM, AVG Grade

c. Predictors: (Constant), SAT COM, AVG Grade, AVG Level

d. Predictors: (Constant), SAT COM, AVG Grade, AVG Level, N/S

e. Predictors: (Constant), SAT COM, AVG Grade, AVG Level, N/S, J/P

f. Dependent Variable: Placement

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	7.118	.256		27.815	.000
	SAT COM	-.004	.000	-.549	-12.206	.000
2	(Constant)	10.887	.427		25.502	.000
	SAT COM	-.002	.000	-.275	-5.801	.000
	AVG Grade	-.068	.007	-.491	-10.367	.000
3	(Constant)	6.720	.808		8.320	.000
	SAT COM	-.001	.000	-.080	-1.440	.151
	AVG Grade	-.056	.007	-.407	-8.621	.000
	AVG Level	.912	.153	.336	5.972	.000
4	(Constant)	6.897	.832		8.292	.000
	SAT COM	-.001	.000	-.096	-1.639	.102
	AVG Grade	-.055	.007	-.402	-8.424	.000
	AVG Level	.910	.153	.335	5.953	.000
	N/S	-.095	.106	-.036	-.894	.372
5	(Constant)	6.603	.852		7.752	.000
	SAT COM	-.001	.000	-.111	-1.876	.062
	AVG Grade	-.054	.007	-.391	-8.143	.000
	AVG Level	.883	.154	.325	5.753	.000
	N/S	-.059	.109	-.022	-.543	.588
	J/P	.168	.109	.061	1.538	.125

a. Dependent Variable: Placement

Excluded Variables[e]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
1	AVG Grade	-.491[a]	-10.367	.000	-.487	.689
	AVG Level	.480[a]	8.103	.000	.400	.486
	N/S	-.101[a]	-2.145	.033	-.115	.895
	J/P	.171[a]	3.865	.000	.204	.988
2	AVG Level	.336[b]	5.972	.000	.307	.443
	N/S	-.040[b]	-.954	.341	-.051	.877
	J/P	.091[b]	2.266	.024	.121	.946
3	N/S	-.036[c]	-.894	.372	-.048	.876
	J/P	.066[c]	1.697	.091	.091	.934
4	J/P	.061[d]	1.538	.125	.083	.890

a. Predictors in the Model: (Constant), SAT COM

b. Predictors in the Model: (Constant), SAT COM, AVG Grade

c. Predictors in the Model: (Constant), SAT COM, AVG Grade, AVG Level

d. Predictors in the Model: (Constant), SAT COM, AVG Grade, AVG Level, N/S

e. Dependent Variable: Placement

A.PP C

Correlations

		SAT COM	AVG Level	AVG Grade	N/S	Sex Num
SAT COM	Pearson Correlation	1	-.717**	.558**	-.324**	.055
	Sig. (2-tailed)	.	.000	.000	.000	.310
	N	348	348	348	348	348
AVG Level	Pearson Correlation	-.717**	1	-.571**	.193**	.121*
	Sig. (2-tailed)	.000	.	.000	.000	.024
	N	348	348	348	348	348
AVG Grade	Pearson Correlation	.558**	-.571**	1	-.067	-.078
	Sig. (2-tailed)	.000	.000	.	.211	.145
	N	348	348	348	348	348
N/S	Pearson Correlation	-.324**	.193**	-.067	1	-.055
	Sig. (2-tailed)	.000	.000	.211	.	.304
	N	348	348	348	348	348
Sex Num	Pearson Correlation	.055	.121*	-.078	-.055	1
	Sig. (2-tailed)	.310	.024	.145	.304	.
	N	348	348	348	348	348

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

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

App 6

Nonparametric Correlations

App 6

Correlations

			SAT COM	AVG Level	AVG Grade	N/S	Sex Num
Spearman's rho	SAT COM	Correlation Coefficient	1.000	-.745**	.606**	-.328**	.045
		Sig. (2-tailed)	.	.000	.000	.000	.400
		N	348	348	348	348	348
	AVG Level	Correlation Coefficient	-.745**	1.000	-.647**	.190**	.114*
		Sig. (2-tailed)	.000	.	.000	.000	.033
		N	348	348	348	348	348
	AVG Grade	Correlation Coefficient	.606**	-.647**	1.000	-.100	-.110*
		Sig. (2-tailed)	.000	.000	.	.061	.041
		N	348	348	348	348	348
	N/S	Correlation Coefficient	-.328**	.190**	-.100	1.000	-.055
		Sig. (2-tailed)	.000	.000	.061	.	.304
		N	348	348	348	348	348
	Sex Num	Correlation Coefficient	.045	.114*	-.110*	-.055	1.000
		Sig. (2-tailed)	.400	.033	.041	.304	.
		N	348	348	348	348	348

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

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

App H

Crosstabs

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
theort order * Placement	348	100.0%	0	.0%	348	100.0%

theort order * Placement Crosstabulation

			Placement							Total
			4 year highly selective	4 year very selective	4 year select state	Less selective 4 year	community college/ 2year	Work	Miliatary	
theort order	1	Count	0	5	15	28	35	12	2	97
		% within theort order	.0%	5.2%	15.5%	28.9%	36.1%	12.4%	2.1%	100.0%
		% within Placement	.0%	14.7%	18.3%	31.1%	39.3%	35.3%	15.4%	27.9%
	2	Count	1	10	26	19	26	6	2	90
		% within theort order	1.1%	11.1%	28.9%	21.1%	28.9%	6.7%	2.2%	100.0%
		% within Placement	16.7%	29.4%	31.7%	21.1%	29.2%	17.6%	15.4%	25.9%
	3	Count	4	12	32	33	23	13	7	124
		% within theort order	3.2%	9.7%	25.8%	26.6%	18.5%	10.5%	5.6%	100.0%
		% within Placement	66.7%	35.3%	39.0%	36.7%	25.8%	38.2%	53.8%	35.6%
	4	Count	1	7	9	10	5	3	2	37
		% within theort order	2.7%	18.9%	24.3%	27.0%	13.5%	8.1%	5.4%	100.0%
		% within Placement	16.7%	20.6%	11.0%	11.1%	5.6%	8.8%	15.4%	10.6%
Total		Count	6	34	82	90	89	34	13	348
		% within theort order	1.7%	9.8%	23.6%	25.9%	25.6%	9.8%	3.7%	100.0%
		% within Placement	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	27.942[a]	18	.063
Likelihood Ratio	29.668	18	.041
Linear-by-Linear Association	6.867	1	.009
N of Valid Cases	348		

a. 10 cells (35.7%) have expected count less than 5. The minimum expected count is .64.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	-.168	.057	-2.935	.003
N of Valid Cases		348			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

App. H

Crosstabs

App I

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
SEX * Placement	348	100.0%	0	.0%	348	100.0%
SEX * Difficulty of Program	348	100.0%	0	.0%	348	100.0%
SEX * Adjusted GradeforSPSS	348	100.0%	0	.0%	348	100.0%
SEX * SAT into5 groups	348	100.0%	0	.0%	348	100.0%

SEX * Placement

Crosstab

			Placement							
			4 year highly selective	4 year very selective	4 year select state	Less selective 4 year	community college/ 2year	Work	Miliatary	Total
SEX	f	Count	4	24	53	57	52	18	1	209
		% within SEX	1.9%	11.5%	25.4%	27.3%	24.9%	8.6%	.5%	100.0%
		% within Placement	66.7%	70.6%	64.6%	63.3%	58.4%	52.9%	7.7%	60.1%
	m	Count	2	10	29	33	37	16	12	139
		% within SEX	1.4%	7.2%	20.9%	23.7%	26.6%	11.5%	8.6%	100.0%
		% within Placement	33.3%	29.4%	35.4%	36.7%	41.6%	47.1%	92.3%	39.9%
Total		Count	6	34	82	90	89	34	13	348
		% within SEX	1.7%	9.8%	23.6%	25.9%	25.6%	9.8%	3.7%	100.0%
		% within Placement	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

App I

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	18.476[a]	6	.005
Likelihood Ratio	19.678	6	.003
N of Valid Cases	348		

a. 2 cells (14.3%) have expected count less than 5. The minimum expected count is 2.40.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	.223	.076	2.903	.004
N of Valid Cases		348			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

SEX * Difficulty of Program

Crosstab

			Difficulty of Program					
			Most Difficult	Difficult AllHonors	Mostly Honors	Lower 40-20%	Bottom 20th Percentile	Total
SEX	f	Count	42	41	51	39	36	209
		% within SEX	20.1%	19.6%	24.4%	18.7%	17.2%	100.0%
		% within Difficulty of Program	65.6%	66.1%	61.4%	54.9%	52.9%	60.1%
	m	Count	22	21	32	32	32	139
		% within SEX	15.8%	15.1%	23.0%	23.0%	23.0%	100.0%
		% within Difficulty of Program	34.4%	33.9%	38.6%	45.1%	47.1%	39.9%
Total		Count	64	62	83	71	68	348
		% within SEX	18.4%	17.8%	23.9%	20.4%	19.5%	100.0%
		% within Difficulty of Program	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

App. I

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4.060[a]	4	.398
Likelihood Ratio	4.062	4	.398
N of Valid Cases	348		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 24.76.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	.150	.076	1.952	.051
N of Valid Cases		348			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

SEX * Adjusted GradeforSPSS

Crosstab

			Adjusted GradeforSPSS					
			1.00	2.00	3.00	4.00	5.00	Total
SEX	f	Count	26	83	63	32	5	209
		% within SEX	12.4%	39.7%	30.1%	15.3%	2.4%	100.0%
		% within Adjusted GradeforSPSS	68.4%	62.4%	54.3%	60.4%	62.5%	60.1%
	m	Count	12	50	53	21	3	139
		% within SEX	8.6%	36.0%	38.1%	15.1%	2.2%	100.0%
		% within Adjusted GradeforSPSS	31.6%	37.6%	45.7%	39.6%	37.5%	39.9%
Total		Count	38	133	116	53	8	348
		% within SEX	10.9%	38.2%	33.3%	15.2%	2.3%	100.0%
		% within Adjusted GradeforSPSS	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Apt

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.033[a]	4	.552
Likelihood Ratio	3.047	4	.550
N of Valid Cases	348		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is 3.20.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	.099	.083	1.184	.237
N of Valid Cases		348			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

SEX * SAT into5 groups

Crosstab

			SAT into5 groups					
			Over 1100	1000-1100	900-999	800-899	less than 799	Total
SEX	f	Count	16	23	28	36	106	209
		% within SEX	7.7%	11.0%	13.4%	17.2%	50.7%	100.0%
		% within SAT into5 groups	48.5%	67.6%	60.9%	53.7%	63.1%	60.1%
	m	Count	17	11	18	31	62	139
		% within SEX	12.2%	7.9%	12.9%	22.3%	44.6%	100.0%
		% within SAT into5 groups	51.5%	32.4%	39.1%	46.3%	36.9%	39.9%
Total		Count	33	34	46	67	168	348
		% within SEX	9.5%	9.8%	13.2%	19.3%	48.3%	100.0%
		% within SAT into5 groups	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

App. I

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4.435[a]	4	.350
Likelihood Ratio	4.405	4	.354
N of Valid Cases	348		

a. 0 cells (.0%) have expected count less than 5. The minimum expected count is 13.18.

Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	-.081	.084	-.961	.337
N of Valid Cases		348			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.