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Trinity College Admissions: The Implementation of Predictors of Success

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Introduction

Think back to when you were applying to college. Did you ever find yourself wondering how the admissions process worked at the institutions to which you applied? As a current undergraduate senior at Trinity College, I have frequently found myself pondering over the question of how the admissions process works at Trinity College. My own desire to learn more about Trinity’s admissions process sparked my interest to uncover what goes on behind the scenes. During my junior year at Trinity, I interviewed Angel Perez, the Vice President of Enrollment and Success at Trinity, in order to learn about Trinity's decision to become a test-optional institution in 2015. The test-optional movement began in 2015 when applicants for Trinity's class of 2020 were given the option to not submit their test scores during the application process. Before 2015, all applicants were mandated to submit their SAT, ACT or similar test scores as a required admissions document. After learning that the implementation of the test-optional movement was just one change that Trinity’s admissions department instituted in order to attract students who demonstrate qualities that the college values, I began to inquire into whether Trinity made any other changes in its admissions process.

When the test-optional movement went into effect, Trinity simultaneously instituted a new way to measure applicants. This new system, which is still in place today, allows Admissions Officers to note whether applicants exhibit any of the 13 characteristics, known as the predictors of success, which Trinity claims to value as an institution. Based on quantitative data obtained from the Trinity Admissions Office, the 13 predictors of success include:

- Comfort in minority of 1
- Creativity
- Critical thinking

- Curiosity
- Delayed gratification
- Empathy
- Grit
- Innovation
- Openness to change
- Optimism
- Overcoming adversity
- Persistence
- Risk taking

According to Angel Perez, admissions counselors use application documents, such as applicant's recommendation letters, interviews, essays, conversations with high school counselors, and advocacy from any other individual in the admissions process in order to determine if student's exhibit any predictors. All applicants, regardless of whether or not they submit their test scores or not, have the opportunity to be assigned with predictors. However, not all students are assigned predictors. Admissions counselors are instructed to assign predictors only if the student's file displays clear evidence of this quality in two or more places. For example, an admissions counselor would assign a student with the "optimism" predictor if it appeared in a teacher's recommendation and an interviewer picked up on it as well (Perez).

In addition to the new list of 13 predictors, Trinity admissions staff continue to assign two numerical scores -- an academic rating and a personal rating -- on a 1 to 9 scale to each applicant. Using two de-identified data sets for students in the enrolled classes of 2020 and 2021, which are abbreviated below as "Year 0" and "Year 1", my study analyzes a new element of Trinity's admissions process, which has pushed away from using test scores as a factor to determine a student's admittance to Trinity and has moved towards looking at certain aspects of character that Trinity values and wants to see in its student body. My study investigates the relationship between Trinity's implementation of the predictors of success and the long-standing process of assigning applicants with numerical evaluations that are based on their personality. Therefore, I am asking the following research question: *What is the relationship, if any, between the predictors of success and the numerical personal ratings assigned to students?*

My statistical analysis produced three key findings. First, the proportion of enrolled students who were assigned at least one predictor declined from 74% in year 0 to 36% in year 1. The reason for this decline is unknown to me and beyond the scope of my study. Second, for both years combined, there is a moderate positive relationship between an applicant's total number of predictors of success and his or her numerical personal rating. In other words, students who were assigned two or more predictors (such as "grit" and "optimism") were more likely to receive a high personal rating (on the 1 to 9 scale) than those who were assigned only one predictor. Third, according to my multivariate analysis of both years combined, only 3 out of 13 predictors -- empathy, optimism, and overcoming adversity -- were significantly associated with an increase in the numerical personal rating. In other words, Trinity Admissions gave higher ratings to enrolled students with characteristics of empathy, optimism, and overcoming adversity than to enrolled students who displayed other characteristics such as creativity, delayed gratification, grit, and persistence, ect. No predictors were statistically associated with a decrease in the numerical personal rating.

Literature Review

The process of rating applicants using numerical evaluations is not unique to Trinity. Mitchell Stevens demonstrates in "Creating A Class" that Hamilton College, a highly competitive New England liberal arts college, participates in the process of assigning applicants with numerical ratings. According to Stevens, "reading and rating" applications was a standard evaluation process for the college's admissions department. Like Trinity, student applicants were each assigned with an "Applicant Rating" on a scale from 0 to 9. There were three individual components that made up the "Applicant Rating" for applicants to Hamilton College. Majority of the "Applicant Rating" was based off applicant's standardized test scores and academic performance, especially their high school grades, yet part of what went into the "Applicant Rating" was the "Personal" score that admissions officers assigned. This "Personal" score was based primarily off of the extracurricular activities in which student applicants participated (Stevens 191-194). As opposed to Hamilton College, which relies mainly on applicant's academic and extracurricular performances to provide numerical evaluations of students, Trinity assigns its own "personal ratings" to students that are based solely on aspects of applicant's character or personality. Trinity's focus on character is also evident through the predictors of success that the school looks for, a process in which Hamilton College does not participate.

Similar to Trinity, many institutions of higher education, as seen with Bates College and Wesleyan University, have pushed back against using grades and test scores as the sole measurement to evaluate their student applicants and have rather adopted more holistic measurements in an attempt to find students who have qualities that the institution values. Adopting "new tools of assessment" in order to measure "noncognitive traits that could predict success in college" is part of this holistic admissions process (Bial and Rodriquez 26). Rebecca Zwick, a researcher and Professor of Education at the University of California, writes "noncognitive measures have been promoted as a means of acquiring a richer and more complete picture of college applicants than can be obtained through test scores and high school grades alone" (Zwick, *Who Gets In* 148). She later articulates that "researchers and college officials alike have expressed the hope that including non-cognitive attributes in admissions decisions can both improve the predictor of college success and boost the admission of underrepresented minorities" (Zwick, *Who Gets In* 156). My own study fails to look at whether Trinity's implementation of the predictors of success has increased the admission of underrepresented minorities and actually predicts college success. However, my study does investigate the relationship between the implementation of non-cognitive attributes in the admissions process and the numerical evaluations that are assigned to enrolled students.

While there are many benefits associated with measuring applicants based on non-cognitive qualities, one drawback is that it can be difficult to ensure that these non-cognitive behaviors are being measured consistently and systematically. Rebecca Zwick acknowledges this drawback as a risk associated with using character as a way to measure student applicants (Zwick, "The Risks" 2). As Zwick points out in her article, the word "grit" can be hard to define because it consists of many characteristics and does not have one set definition (Zwick, "The Risks" 1). While my study does not look into how Trinity admissions' department defines each of the predictors so as to make sure that the predictors are being assigned fairly, my own study takes a new step in analyzing whether these non-cognitive admissions predictors are associated with higher numerical evaluations. I would expect to find the numerical personal ratings that applicants receive to be reflective of the predictors of success that they are assigned, and my study is important because it evaluates the extent to which Trinity's numerical personal ratings are related to the predictors of success assigned. I hope to help Trinity's admissions department realize whether the personal ratings that the admissions officers assign to applicants are reliable and reflective of the predictors of success that they look for and value in student applicants.

Primary Source

Before I could begin my research project, I needed to receive permission from Angel Perez in order to obtain data from the Trinity Admissions Department that I needed to conduct my study. Upon receiving approval from Angel to conduct my study and acquire the necessary data, I emailed Robert Greene, the Admissions Computing Data Specialist at Trinity College, asking for the specific data that I needed. Robert Greene provided me with two de-identified quantitative data sets that include applicant data for the population of enrolled students in Trinity's class of 2020 and 2021. From now on, I will be referring to the population of enrolled students in Trinity's class of 2020 as "Year 0" and the population of enrolled students in Trinity's class of 2021 as "Year 1". A complete list of the eight variables that were included in the data which I received from Robert Greene is found in Table 1 in my appendix. However, for the purpose of my study, I only utilized the data for the final numerical personal rating assigned to each applicant along with predictors of success that both reader 1 and 2 assigned to applicants. A sample of the variables and data that I used for my study can be found below:

Student	**Numerical Personal Rating**	**Predictors of Success**
1	5	Grit

2	6+	Curiosity, innovation
3	7-	Overcoming adversity

While the table above only contains sample data for three students, the data sets that I used contained information for the population of 574 enrolled students in Year 0 and for the population of 585 enrolled students in Year 1.

Ethical Considerations

My study did not require IRB approval because I did not receive individually-identifiable data that can be traced back to specific individuals. As seen in the sample data above, the data that I received from admissions identified students by a chronological list of numbers rather than by their names. In addition, neither Angel Perez nor Robert Greene required that I mask the identity of Trinity College.

Methodology

Data Cleaning

Step 1: In order to be able to run statistical tests on my data so that I could draw conclusions from it, I had to clean-up the data. Dealing with the numerical ratings was the first step in my clean-up process. The pluses and minuses placed next to the numbers for the final personal ratings are for rating purposes. For example, a 6+ is higher rating than a 6 while a 6- is a lower rating than a 6 but still higher than a 5+. For the sake of statistical analysis, I have converted the plus and minus signs into numbers: For example, a 5- became a 4.67 while a 5+ became a 5.33.

Step 2: The next step in my clean-up process involved dividing the predictors so that each predictor was in its own column. I also created a code sheet for each predictor and rewrote each predictor according to my coding scheme, which can be found below:

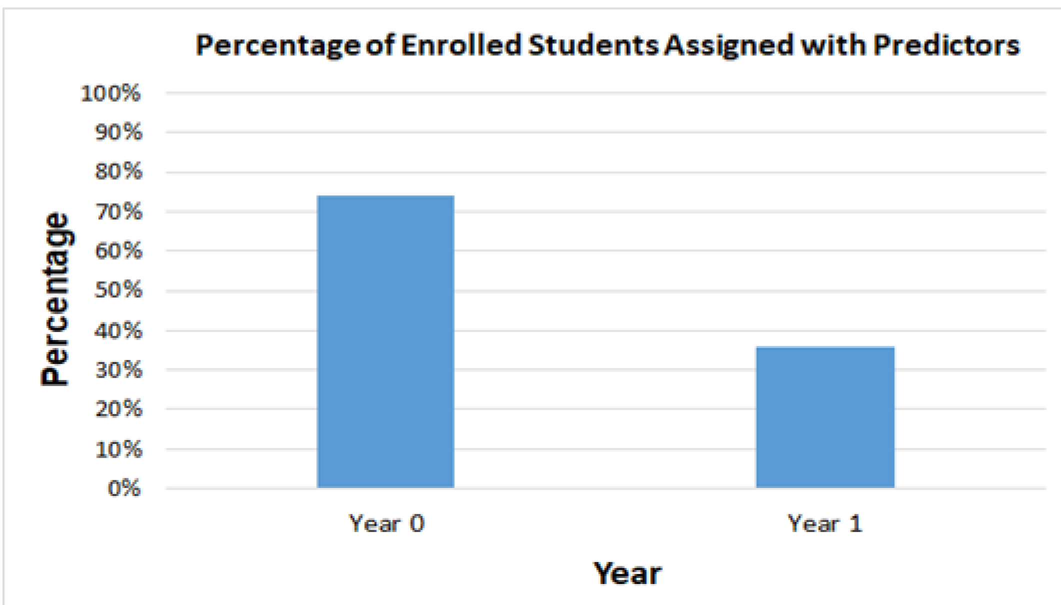
Predictor	**Code letter**
Comfort in minority of 1	comf
Creativity	crea
Critical thinking	crit
Curiosity	curi
Delayed gratification	dela
Empathy	empa
Grit	grit
Innovation	inno
Openness to change	open
Optimism	opti
Overcoming adversity	over
Persistence	pers
Risk taking	risk

Step 3: After dividing up my coded predictors and placing them alongside my personal numerical ratings, I created a frequency chart that showed how often each predictor was assigned

to each student. In my frequency chart, the presence of the predictor is denoted with a 1 and the absence of the predictor is denoted with a 0.

Initial Findings

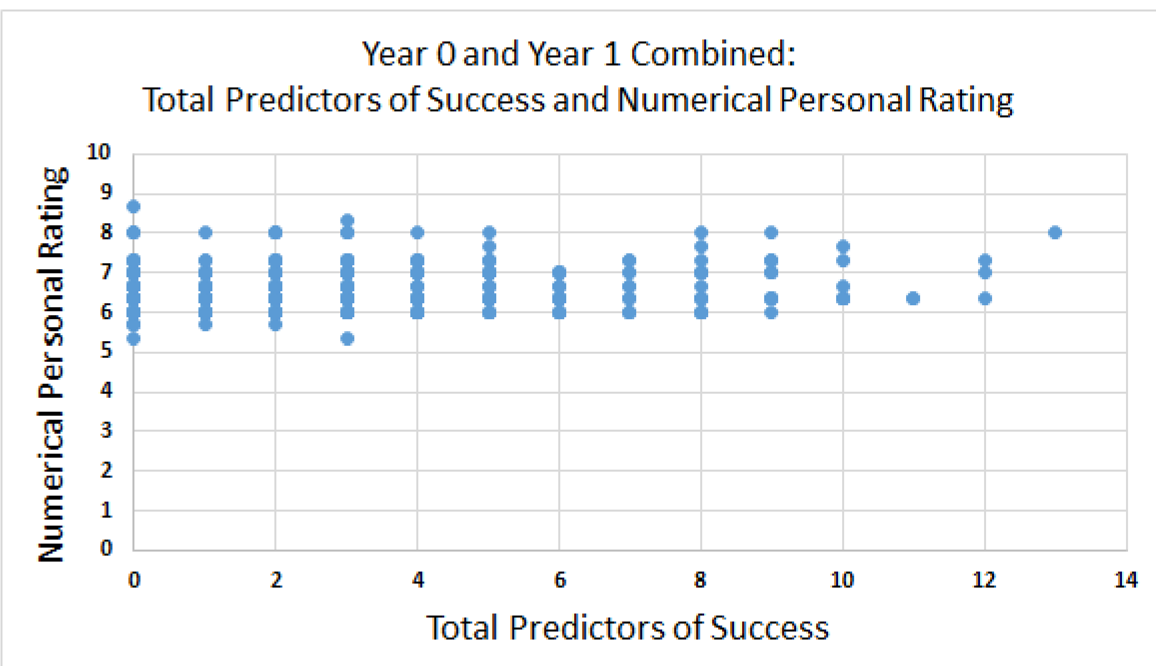
During my initial study of the admissions data that I had received, I was shocked to find that the number of students who were assigned with predictors differs largely from year 0 to year 1. I noticed that the number of students receiving at least one predictor declined from 74% in year 0 to 36% in year 1. I created the following bar graph in order to visually display how the percentage of applicants who were assigned with predictors declined by 38% from year 0 to year 1.



Although my study cannot provide an answer for why so few students were assigned with predictors in year 1 compared with year 0, the question of why this difference exists between the two years is not my main question. I rather decided to use data for enrolled students in year 0 and year 1 in order to look at the relationship between non-cognitive factors and numerical ratings.

Are The Total Number of Predictors Associated with Numerical Ratings?

According to a statistical analysis of the combined data for Year 0 and Year 1, a moderate positive relationship exists between an applicant's total number of predictors of success and his or her numerical personal rating. In order to determine the strength and direction of the relationship as either positive or negative, I had to calculate the correlation, which looks at how likely it is that the personal rating is associated with the total predictors of success assigned. A correlation +0.333 exists between the total number of predictors and the personal rating. According to a common standard correlation chart, a correlation that falls between ±0.3 to ±0.5 is classified as moderate. Classifying a relationship as moderate means that there is a slight but not strong relationship between the number of predictors and the personal rating assigned. In addition, by saying that a positive relationship exists means that on average, the personal rating assigned to students tend to increase when more predictors are assigned. A scatter plot which displays a moderate positive relationship between the personal ratings and total predictors of success for Year 0 and Year 1 is shown below:



As seen from the scatterplot above, the number of predictors assigned is slightly yet not substantially associated with whether a student gets a high or low personal rating. Applicants who received more predictors of success tended to on average, receive higher numerical personal ratings, but this is not always the case. There are multiple instances where applicants display the same number of predictors but receive different numerical personal ratings. For example, many students were assigned with eight predictors but the numerical ratings that they received varied from the numerical rating of 6 to 8. A similar situation is seen with applicants who displayed seven characteristics. While some students who displayed more predictors were assigned with higher scores, as seen with the Being assigned with seven predictors does not guarantee that a student will receive a higher score than a student who is not assigned with any predictors at all.

When I separated the data for Year 0 and Year 1, I found a slight increase in the correlation between the total predictors displayed and the numerical personal rating assigned to each applicant. A correlation of +0.405 exists Year 0, while Year 1 contains a slightly stronger correlation of +0.452. Since the correlations of +0.3 and +0.4 are very similar, there is consistent evidence that a moderate positive relationship exists between the total predictors and the numerical evaluations. See Figure 1 in the appendix to locate a scatterplot displaying the moderate positive relationship between the total predictors and the numerical personal rating for students in Year 0, and see Figure 2 in the appendix to find a similar looking scatterplot for students in Year 1.

Which Predictors are Associated with Higher or Lower Numerical Ratings?

Using a statistical software tool known as Stata allowed me to make the claim that empathy, optimism, and overcoming adversity have a significant relationship with the numerical personal rating that a student receives. Since my data includes multiple instances where students are assigned with more than one predictor that may be associated with the numerical personal rating, I had to run what is known as a multivariate regression on Stata. Multivariate regression analysis allowed me to look at the relationship between each individual predictor allocated to a student and the personal rating that the student received while ignoring all of the other predictors that the student may have also displayed. Before using Stata, I created frequency charts for the data for Year 0 and 1. These frequency charts tallied how often each predictor was assigned or not assigned to each student and also included a column with the numerical personal rating that I student received. I uploaded the frequency chart for year 0 and year 1 combined onto Stata and received the following output, which I will describe below:

```
Linear regression                                        Number of obs = 1,159
                                                            F(13, 1145)= 12.35
                                                           Prob > F = 0.0000
                                                          R-squared = 0.1627
                                                           Root MSE = .39629

------------------------------------------------------------------------------
             |               Robust
finalperso~g |      Coef.   Std. Err.    t    P>|t|    [95% Conf. Interval]
-------------+----------------------------------------------------------------
comfpredic~r |   .0167014   .0556477    0.30   0.764   -.0924814    .1258842
creapredic~r |  -.0484366   .0424567   -1.14   0.254   -.1317382     .034865
critpredic~r |   .1132943   .0452572    2.50   0.012    .0244979    .2020907
curipredic~r |   .0411984   .0408352    1.01   0.313   -.0389219    .1213186
delapredic~r |  -.0293327   .0736726   -0.40   0.691   -.1738811    .1152156
empapredic~r |   .1264819   .0330496    3.83   0.000    .0616373    .1913266
gritpredic~r |   -.022091   .0460209   -0.48   0.631   -.1123857    .0682038
innopredic~r |   .1697908   .0821815    2.07   0.039    .0085476    .3310341
openpredic~r |   .0110786   .0457749    0.24   0.809   -.0787336    .1008908
optipredic~r |    .169511   .0462464    3.67   0.000    .0787738    .2602481
overpredic~r |   .2778982   .0451289    6.16   0.000    .1893537    .3664428
perspredic~r |  -.0310695   .0421441   -0.74   0.461   -.1137579    .0516189
riskpredic~r |   .0239532   .0552762    0.43   0.665   -.0845008    .1324073
       _cons |   6.220441   .0134396  462.84   0.000    6.194072     6.24681
------------------------------------------------------------------------------
```

Correlation Coefficients

In order to understand the table above, first focus on the column referred to as "coef." The abbreviation "coef" stands for correlation coefficient, which measures the strength and direction of the relationship between each individual predictor and the numerical personal rating. For example, the coefficient correlation for overcoming adversity is +0.278, which means that being assigned with the predictor of overcoming adversity is associated with a 0.278 increase in the numerical personal rating assigned holding constant all other predictors. Correlation coefficients can also be negative, as seen with the predictor of creativity. The correlation coefficient for creativity is -0.048, which means that being assigned with the predictor of creativity is associated with a 0.048 decrease in the numerical personal rating while ignoring all other predictors. It is important to note that correlation does not imply causation. In other words, while an association or relationship may exists between the predictor and the numerical personal rating, one cannot draw the conclusion that each of the predictors causes a certain increase or decrease in the numerical personal score. For example, it would be incorrect to say that being assigned with the predictor of creativity causes a student to have a decrease of 0.048 in the numerical personal rating that they receive. There may be other factors other than the predictors which may have an effect on the numerical personal rating.

P-Values and Statistical Significance

Secondly, focus on the "P>|t|" column in the table above. The "P>|t|" column lists what are referred to as p-values, which tell us whether a relationship between each the predictor and the numerical personal rating is likely to occur or not. A p-value that is below the critical value of 0.05 means there is a likely relationship between the predictor and the numerical personal rating, and this likely relationship is referred to as statistically significant. A p-value that falls below 0.05 is statistically significant because this means that one can confidently claim that there is a relationship between the predictor and the numerical personal rating because the probability of observing that a relationship exists does not exist is less than five-percent, which is very small.. For example, the p-value for the predictor of empathy is 0.000, which means that the relationship between being assigned with the predictor of empathy and the numerical personal rating is statistically significant because it is very likely to be true. It is very likely that being assigned with the predictor of empathy is associated with a 0.126 increase in the numerical personal rating holding constant all other predictors.

Positive Statistically Significant Findings

The multivariate regression table above for the combined data for Year 0 and Year 1 demonstrates that of the 13 predictors that Trinity looks for in students, the predictors of empathy, optimism, and overcoming adversity are the ones that are statistically significant and are therefore very likely to be associated with an increase in the numerical personal score that an applicant receives. The predictor of overcoming adversity is associated with the highest statistically significant increase in the numerical personal rating. Based on the p-value of 0.0000, it is reliable to claim that being assigned with the predictor of overcoming adversity is very likely to be associated with a 0.278 increase in an applicant's numerical personal rating holding constant all other predictors.

Negative Statistically Significant Findings

It is important to recognize that none of the 13 predictors are statistically associated with decreases in the numerical personal rating. While four predictors -- creativity, delayed gratification, grit, and persistence-- have negative correlation coefficients neither of these predictors are associated with a statistically significant decrease in the numerical personal rating because their p-values are all greater than 0.05. Therefore, it is not reliable to claim that students who displayed the predictors of creativity, delayed gratification, grit, or persistence received decreases in their numerical personal ratings. For example, it is not reliable to claim that being assigned with the predictor of “delayed gratification” is associated with a statistically significant decrease of 0.029 in the numerical personal rating assigned holding constant all other predictors because the the p-value of 0.691 says that this relationship is not very likely to occur. It makes sense that none of the predictors are statistically associated with decreases in the numerical personal ratings because all of the 13 predictors are classified as positive traits that Trinity’s admissions department values. Applicants should never receive a lower numerical rating because they were assigned with a predictor.

Year 0 and Year 1 Separated

When looking at the data for Year 0 and Year 1 separately, I found similar results. Of the 13 predictors, only empathy, optimism, and overcoming adversity were once again statistically significant for each of the years, which means that they are very likely to be associated with an increase in an applicant’s numerical personal rating. The multivariate regression tables that I created separately though Stata for Year 0 and Year 1 are located in the appendix below as Table 2 and Table 3. As seen with the combined data, a multivariate regression analysis for Year 0 displays that overcoming adversity is once again a statistically significant predictor that is associated with the largest increase in the numerical personal rating. Being assigned with the predictor of overcoming adversity is associated with a 0.223 increase in the numerical personal score for students in Year 0 holding constant all other predictors. Interestingly though, for Year 1, the predictor of optimism, rather than overcoming adversity, is most likely to be associated with the highest increase in the numerical personal score. Being associated with the predictor of optimism is associated with an increase of 0.345 increase in an applicant's numerical personal rating holding constant all other predictors. The predictor of overcoming adversity falls somewhat closely behind for students in Year 1 since overcoming adversity is associated with a 0.248 increase in the numerical personal score while ignoring all other predictors.

Suggestions for Further Research

One suggestion for further research is to look at the extent to which two admissions officers agree on the predictors of success and numerical personal ratings that they assign to applicants, which is referred to as interrater reliability. I initially began my study thinking that I would focus on calculating interrater reliability; however, upon receiving the data, I realized that there was a disproportionate number of predictors that were assigned to student applicants from the two readers that read each application. I therefore decided to not focus my study on interrater reliability but on a topic that would allow me to learn more about the relationship between Trinity's already existing process of assigning applicants with numerical evaluations and the new process of looking for predictors of success. Although I did not decide to focus on interrater reliability, it can still be calculated for the predictors and the numerical evaluations assigned using the data that I received from admissions. In addition, the data that I received may have been incomplete, which may have explained why reader 2 assigned so few predictors for students in year 0 and why reader 1 assigned so few predictors for students in year 1. If the data is incomplete, making sure to receive a complete set would allow a researcher to conduct an even stronger study on interrater reliability. Calculating interrater reliability will help the admissions officers learn about how consistent they are when looking for predictors and rating applicants.

A second suggestion for future research would be to conduct interviews with Angel Perez and admissions officers in order to learn about how the admissions department defines each of the predictors, especially the predictor of "grit". Interviews would add more depth to my research and would also help future researchers to learn more about how reliable to admissions department is when they take note of whether applicants display any predictors.

A third suggestion for future research would be to conduct a study similar to my own on the population of all applicants for the class of 2020 and 2021 not just enrolled students. It would be interesting to compare the numerical personal ratings and predictors of success that were assigned to students who were accepted and denied. It would also be interesting to trace the class of 2020 and the class of 2021 throughout their four years in order to compare whether the number and types of predictors of success that these students displayed when they applied did predict their "success" in college. In order to do so, one would have to learn how Trinity's admissions department defines success, and it would also require the admissions department to study students more closely throughout their years at Trinity.

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Appendix

Table 1: Sample of the Admissions Data Received from Trinity's Admissions Department

Student	**Reader 1 Academic Rating**	**Reader 1 Personal Rating**	**Reader 1 Predictors of Success**	**Reader 2 Academic Rating**	**Reader 2 Personal Rating**	**Reader 2 Predictors of Success**	**Final Academic Rating**	**Final Personal Rating**
1	5	7-	Grit	5	7+	Grit, optimism, critical thinking	5	7
2	6-	6		6+	6	Comfort in minority of 1	6	6
3	7+	6+		7+	6+	Risk taking	7+	6+

Figure 1: Scatterplot for the Relationship Between the Total Predictors Displayed and the Numerical Rating Assigned to Students in Year 0

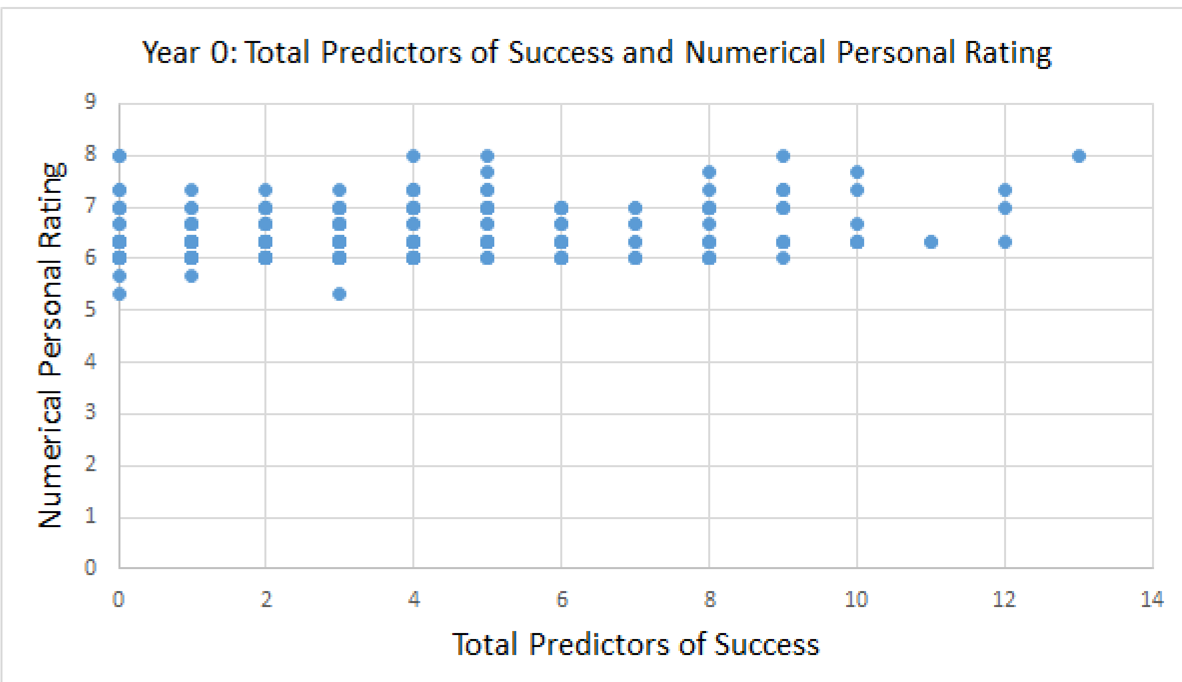

Figure 2: Scatterplot for the Relationship Between the Total Predictors Displayed and the Numerical Rating Assigned to Students in Year 1

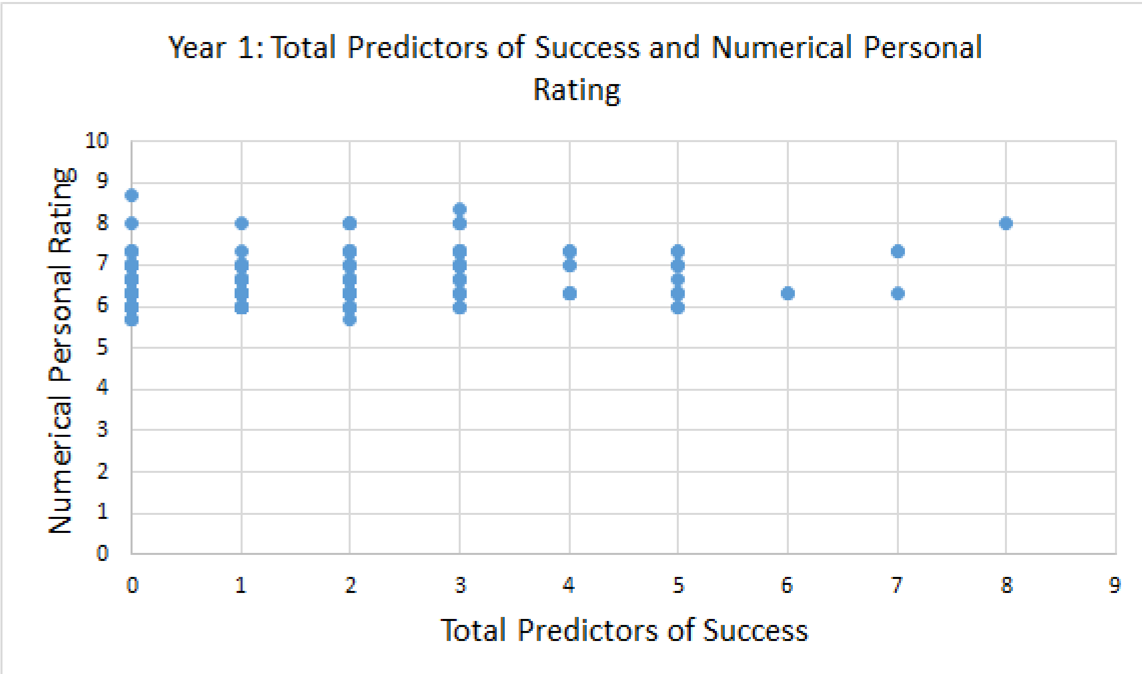

Table 2: Multivariate Regression Table for Year 0

```
Linear regression                                          Number of obs = 574
                                                             F(13, 560)= 7.85
                                                             Prob > F = 0.0000
                                                           R-squared = 0.2074
                                                             Root MSE = .37166
-------------------------------------------------------------------------------
                    |           Robust
finalperson~g |       Coef.    Std. Err.   t       P>|t|      [95% Conf. Interval]
       --------------+----------------------------------------------------------
comfpredictor |   .0510806     .053466    0.96    0.340     -.0539377  .156099
creapredictor |   .0210146     .048876    0.43    0.667      -.074988  .1170172
critpredictor |   .0848572     .048361    1.75    0.080     -.0101339  .1798482
curipredictor |   .0401002    .0420112    0.95    0.340     -.0424186  .1226189
delapredictor |   .0387036    .0818174    0.47    0.636     -.1220028   .19941
empapredictor |   .1385602    .0351122    3.95    0.000      .0695925  .2075278
gritpredictor |   .0219794     .045894    0.48    0.632     -.0681659  .1121248
innopredictor |   .1453066    .0838404    1.73    0.084     -.0193734  .3099867
openpredictor |   .0215378    .0483943    0.45    0.656     -.0735187  .1165943
```

```
optipredictor |   .1404896   .0454566   3.09   0.002     .0512033  .2297759
overpredictor |   .2232648   .0543327   4.11   0.000     .1165441  .3299856
perspredictor |  -.0536997   .0477134   -1.13  0.261    -.1474188  .0400194
riskpredictor |   .0194616   .0557419   0.35   0.727     -.090027  .1289503
        _cons |   6.137341   .0217085  282.72   0.000     6.094701  6.179981
------------------------------------------------------------------------------
```

Table 3: Multivariate Regression Table for Year 1

```
Linear regression                                       Number of obs = 585
                                                          F(13, 571)= 7.72
                                                         Prob > F = 0.0000
                                                        R-squared = 0.2471
                                            ,            Root MSE = .39164

------------------------------------------------------------------------------
             |            Robust
finalperson~g |     Coef.   Std. Err.   t    P>|t|    [95% Conf. Interval]
--------------+---------------------------------------------------------------
comfpredictor |   .2233009   .1560739   1.43   0.153  -.0832481    .5298499
creapredictor |  -.0790101    .074138   -1.07  0.287  -.2246267    .0666064
critpredictor |   .1338886   .0903555   1.48   0.139   -.043581    .3113583
curipredictor |   .0950372   .0911832   1.04   0.298  -.0840582    .2741326
delapredictor |  -.0464539   .1360031  -0.34   0.733  -.3135813    .2206736
empapredictor |   .2445094   .0716451   3.41   0.001   .1037893    .3852295
gritpredictor |    .174546    .142408   1.23   0.221  -.1051616    .4542535
innopredictor |    .305434   .1935731   1.58   0.115  -.0747682    .6856363
openpredictor |   .0176916   .1033937   0.17   0.864  -.1853868    .2207701
optipredictor |   .3246463   .1000818   3.24   0.001   .1280729    .5212197
overpredictor |   .2479621   .0746335   3.32   0.001   .1013724    .3945519
perspredictor |   .0340319   .0719592   0.47   0.636  -.1073051    .1753689
riskpredictor |   .2547341   .1376794   1.85   0.065  -.0156857    .5251539
        _cons |   6.243263   .0167831  372.00  0.000    6.210299    6.276227
------------------------------------------------------------------------------
```