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R.I.T

Statistics Anxiety Towards Learning New
Statistical Software

M.S. Master of Science

in Applied Statistics

College of Science

By

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School of Mathematical Science
Rochester Institute of Technology
Rochester, New York
August 2018

Dedicated to my parents, siblings, grandmother who passed away, and my friends for their support, love, and encouragement throughout my study.

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Abstract

Based on previous research, statistics anxiety towards statistics were discussed. There is a study about anxiety and attitude of graduate students in on-campus vs. online statistics courses, and student attitude toward statistics. To date, no one has seemed to examine anxiety toward statistics with regard to use of coding vs. noncoding software. The purpose of this study was to know the level of anxiety towards learning new statistical software. Responses from seventy-nine graduate students who have or had classes in the Applied Statistics Division were collected. The survey made for this study had a Likert scale that included three categories of interest: Learning Statistical Concepts, Learning Statistical Software, and Learning to Read/Interpret Results. Also, there were demographic characteristics considered as possible effective factors on the Likert scale. A repeated single measure was used for this study. The results showed software type, gender, and major are statistically significant indicating these factors impact the anxiety towards learning new statistical software.

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1. Introduction

The field of statistics is enormous and most studies rely on it. Researchers use statistics by either analyzing or predicting results. In order to analyze or predict results, they use statistical software packages. These software packages typically depend on some type of programming. To be able to analyze the data from any research study or statistics course, researchers and students need to learn how to work with these software packages. In fact, learning these software packages requires time and effort, and can be difficult. These consequences may lead to statistics anxiety. Statistics anxiety can happen when students take any statistics courses or anything related to statistics. (Cruise, Cash, and Bolton, 1985). The aim of this study is to assess the students' anxiety levels based on whether they learned statistics using software that was driven by programming or non-programming-menus. Also, we want to know the relationship to the anxiety of factors like gender, software type, major, etc. Surveys are the best way to know other people's opinions, so we are using a survey in this study. To accomplish the goal of the study, we first need to discuss the idea of a Likert scale that used in the survey. Spector (1992) explained that the scale is commonly used in social science to test attitudes, opinion, emotional states like anxiety and anger, etc. In this study, I created my own survey questions that handled the aim of the study. A Likert scale was used in the survey, and it consists of sixteen statements that was built based on three categories of interest: Learning Statistical Concepts, Learning Statistical Software, and Learning to Read/Interpret Results. Participants were asked to respond on a five-point Likert scale. The survey also asked demographic questions such as major, age, software type, etc. that we used as explanatory variables. Thus, we need to assess whether there is a relationship between a Likert scale response and a categorical input. If we treat the Likert scale as a continuous response, then we can analyze using an ANOVA. This is sometimes done because we are interested in the ordinal nature of the response, similar to what we

usually do with a continuous variable. But, that only works when we have many potential response values. In this case, we are using the 5-point Likert scale. Therefore, in this study we will conduct an ordinal logistic regression.

1.1 Ordinal Logistic Regression (OLR)

Before introducing the idea of OLR, the difference between Anova and Regression analysis need to be explained. Regression and Anova are statistical models usually used when the dependent variable is numerical continuous. However, the difference between the two statistical models are the input variables (predictors). Generally, in Regression analysis the input variables are continuous, and in Anova the predictors are categorical variables. Logistic Regression is a special case of regression analysis where the dependent variable is categorical. Logistic regression is similar to standard regression in that both measure the predictive value of the input variables (independent variables). The difference is in the dependent variable (response): in logistic regression we measure the change in the odds ratio and in the standard regression we measure the change in the quantitative response itself. To apply a Logistic Regression model, we use SAS software. From the type I effects table, we can determine which of the main factors significantly affect the response. The logistic procedure allows the user to specify either continuous or categorical input variables, so any input variable considered as a potential effect (SAS,2008). In addition to evaluating main effect factors, we also need to check the goodness of fit for the model. There are many tests to check the model fit, one of them is Hosmer and Lemeshow test. Hosmer and Lemeshow (2000) introduced a statistic that is distributed as a chi-square when the dependent variable (predictor) is binary. The survey in this study relies on a Likert scale, ordinal type data (Strongly disagree to strongly agree). In this study, we used OLR to retain the information from ordinal responses, and will use an ordinal version of the Hosmer and Lemeshow test.

The OLR is considered to be a special case of multinomial regression (Warner, 2007) and models the relationship between the response and the input variables (factors).

Therefore, since we have sixteen response variables and seven input variables, we will use the ordinal logistic regression for each response, resulting in sixteen repeated OLR. Recognizing the level of multiplicity in this approach, we will first attempt to decrease this multiplicity and potentially reduce the dimensionality inside the three high-level areas in which the questions were based (Learning Statistical Concepts, Learning Statistical Software, and Learning to Read/Interpret Results).

1.2 Cronbach's alpha

There are sixteen responses among the three categories of questions. If the responses were continuous, principal component and/or factor analysis could be used to reduce dimensionality. The data we have in this study is discrete and ordinal, and so Cronbach's alpha is more appropriate than principal component analysis. Cronbach's alpha is used to measure the internal consistency in the Likert scale. According to Gliem and Gliem (2003) "Cronbach's alpha is a test reliability technique that requires only a single test administration to provide a unique estimate of the reliability for a given test. Cronbach's alpha is the average value of the reliability coefficients one would obtain for all possible combinations of items when split into two half-tests.". The score of Cronbach's alpha needs to be high enough (greater than or equal to 0.7) for the scales to be combined and to avoid single-variable analyses. Bland and Altman (1997) mentioned in their paper that the Cronbach's alpha equation is:

$$\alpha = \frac{k}{K-1} \left(1 - \frac{\sum s_i^2}{s_T^2} \right);$$

"where k is the number of items, $\sum s_i^2$ is the variance of the ith item, and s_T^2 is the variance of the total score formed by summing all the items".

The following sections of this paper are: Literature review, Methods, Analysis, Discussion and limitations, Conclusions, and Areas for future research.

2. Literature review

2.1 Anxiety scales

In 1998, Kazelskis conducted a study of mathematics anxiety scales and he suggested that researchers should be aware when they choose their tools for measuring anxiety. Also, Kazelskis recommended that researchers calculate scores in the scale for each factor instead of calculating the sum of scores. Hopko, Mahadevan, Bare, and Hunt (2003) improved the Abbreviated Math Anxiety Scale (AMAS) using a large sample and replicating the sample. The six subscales of the Statistics Anxiety Rating Scale have internal consistency (Hanna, Shevlin, and Dempster, 2008). The six factors are fear of statistics teachers, worth of statistics, interpretation anxiety, fearing of asking for help, test and class anxiety, and computational self-concept.

2.2 Related studies

A great deal of previous research has focused on anxiety towards statistics. Onwuegbuzie and Wilson (2003) claim that students who are required to register in statistics courses record high levels of anxiety towards statistics. They also comment that up to 80% of graduate students face unusual levels of anxiety towards statistics. In fact, statistics requires a lot of work collecting, analyzing and interpreting data. Some studies have shown that this increases anxiety towards statistics. Two articles (Cruise, Cash and Bolton, 1985; Onwuegbuzie, Daros, and Ryan, 1997) claim that working with and interpreting data cause statistics anxiety (cited in Hanna, Mark, and Dempster, 2008). Mills (2004) mentions a study in which the attitudes of students towards statistics were negative. In 2010, Williams questioned the instructor immediacy and statistics anxiety relationship. He found that when the students receive immediacy, they tend to show a low level of anxiety.

In addition, there is research focused on the attitudes and the anxiety of graduate students who took statistics courses on-campus vs. online. It was noted that anxiety decreases, and attitudes are more positive, when online faculty members motivate students. The use of intelligent technologies and resources in online classes help to eliminate anxiety and increase retention (Devaney, 2010). In 2014, Williams studied the relation between preference for numerical information (PNI) and six types of statistics anxiety, and the results showed that four types of statistics anxiety were positively related to PNI. Moreover, statistics anxiety affects students' plans of study. Anxiety about statistics could lead the students to procrastinate taking statistics courses until immediately before graduation (Parney and Ravid, 1990). In 2010, DeVaney compared the level of anxiety and attitude of graduate students in on-campus vs. online statistics courses. He found that the anxiety was reduced for students taking the online version versus the on-campus course. Despite the fact that a variety of studies address statistics anxiety and attitudes towards statistics, statistical anxiety towards learning new statistical software has received less attention. The purpose of this article is to better understand the relationship between statistics anxiety for the three categories (Learning Statistical Concepts, Learning Statistical Software, and Learning to Read/Interpret Results) and learning new statistical software among graduate students.

3. Methods

3.1 Participants

The participants are Applied Statistics and Non Applied Statistics graduate students enrolled in courses in the Division of Applied Statistics at the Rochester Institute of Technology. Students completed a web-based survey about anxiety towards learning new statistical software. It was distributed to current and former students. Eighty-seven students completed the survey: forty-two Applied Statistics students, thirty-three engineering students, two economic students, one biology student, and seven students from other majors. When

looking at the data, there were some missing values, so the observations that had the missing values were deleted. Therefore, the total number of the observations (responses) decreased to seventy-nine.

3.2 Instrumentation

The form of the survey was influenced by Devaney’s Anxiety and Attitude of Graduate Students in On-Campus vs. Online Statistics Courses (2010). The survey, in Appendix A, was constructed with three categories: Learning Statistical Concepts, Learning Statistical Software, and Learning to Read/Interpret Results. The statements in Table 2 were presented in random order rather than organized separately by categories. Each category has many items, so the survey consists of 16 items with a Likert scale ranging from strongly disagree to strongly agree. Table 1 gives a brief description of the Likert scale that has been used in the survey.

Table 1. Brief description of the Likert scale.

<i>Categories (number of statements)</i>	<i>Sample Statements</i>
Learning Statistical Concepts (5)	<ul style="list-style-type: none"> • Statistics lectures are easy to understand. • I am afraid of statistics because I didn't learn it from elementary like other subjects.
Learning Statistical Software (6)	<ul style="list-style-type: none"> • Statistical programming languages are so difficult to understand. • I feel under stress when I write a statistical programming code.
Learning to Read/Interpret Results (5)	<ul style="list-style-type: none"> • Statistical outputs are easy to understand. • I like interpreting the results than working on programming.

The survey also had demographic questions like age, gender, major, etc. These demographic characteristics should be considered as factors that might be affecting responses in the three categories of interest. There were two questions about the major: the first one had many major choices, and the second one was for statistics major regarding whether the student was Applied or Theoretical statistics. Therefore, when the data was collected, these

two questions have been combined to one question: Applied Statistics and Non Applied Statistics. In addition, there was a text question that asked about what software they use regularly, and the answers were software names such as Minitab, R, SAS, Python, Matlab, Excel, etc. To facilitate the analysis, the data for this question have been recorded as coding or non-coding software type.

4. Analysis of Data

4.1 Preliminary analysis

The demographic characteristics of the seventy-nine students who completed the survey are shown in Table 2. In the table, the characteristics are summarized by software type: coding, non-coding, or both. It is clear that there are differences between the three types of software regularly used among the demographic characteristics. There are gender differences within software type where 67.74 % of the students who used noncoding programs are males and 32.26% of the students who used noncoding programs are females. Also, in the major category, there is a considerable difference. 82.35% of the students who regularly use coding are Applied Statistics students where 80.65% of the students who regularly use non-coding software are Non Applied Statistics. For the class type, it seems that there is no significant difference in coding between online and on-campus students. However, there is a difference between online and on-campus in the non-coding type of software where 3.23% of the students who use non-coding software are in the online class type and 67.74% of the students who use non-coding software are in the on-campus class type.

Table 2. Demographic Information.

<i>Demographic</i>	Software Type		
	<i>Coding (n=34)</i>	<i>Noncoding (n=31)</i>	<i>Both (n=14)</i>
<i>Male</i>	18 (52.94%)	21 (67.74 %)	9 (64.29%)
<i>Female</i>	16 (47.06%)	10 (32.26%)	5 (35.71%)
<i>US Citizen</i>	24 (70.59%)	12 (38.71%)	7 (50.00%)
<i>Not US Citizen</i>	10 (29.41%)	19 (61.29%)	7 (50.00%)
<i>Applied Statistics</i>	28 (82.35%)	6 (19.35%)	13 (92.86%)
<i>Not Applied Statistics</i>	6 (17.65%)	25 (80.65%)	1 (7.14%)
<i>Bachelors</i>	4 (11.76%)	1 (3.23%)	1 (7.14%)
<i>Master</i>	27 (79.41%)	29 (93.55%)	12 (85.71%)
<i>Doctorate</i>	2 (5.88%)	0 (0%)	1 (7.14%)
<i>Certificate</i>	-	1 (3.23 %)	-
<i>Other</i>	1 (2.94%)	-	-
<i>Online</i>	11 (32.35%)	1 (3.23 %)	2 (14.29%)
<i>On-Campus</i>	11 (32.35%)	9 (29.03%)	6 (42.86%)
<i>Both</i>	12 (35.29%)	21 (67.74%)	6 (42.86%)
<i>Age</i>	Mean =28.44 SD= 7.31	Mean =24.60 SD=3.12	Mean = 30.00 SD= 9.59

4.2 Cronbach's alpha

Using Minitab software, the set of all questions overall had Cronbach's alpha = 0.5856, which is an unacceptable score and suggested that there was a very large variability in responses. In addition to Minitab, SAS software was also used. The SAS code in Appendix C Part 1 is from Gennarelli and Goodman (2013). The results in tables B1-B3 in Appendix B show the Cronbach's alpha for questions in each category (programming, interpreting, and learning). All three tables show unacceptable alpha scores.

4.3 Ordinal Logistic Regression

Due to the large variability indicated by Cronbach's alpha, the sixteen responses couldn't be combined. For this reason, the responses have been analyzed separately. SAS was used for OLR and the codes are Appendix C Part 2. The results provided a Main Effects table, indicating the significant and non-significant factors for each response, see Tables 3 through 8 for results based on each category of questions. For the factors listed across the header row in the tables, software type is coding or non-coding or both. Class type means whether the class is online or on-campus, major is either Applied Statistics or Non Applied Statistics. Lastly, Degree has five levels: Bachelors, Master, Doctorate, Certificate, Other.

Table 3 lists p-values for the seven factors in each OLR among statements (responses) in the learning category. For the first statement, "*Statistics lectures are easy to understand*," both software type and gender are statistically significant: the p-value for software type is 0.0145 which is less than $\alpha = 0.05$ and the p-value for gender is equal to $0.0045 < \alpha = 0.05$. Major is close to being statistically significant since the p-value is 0.0690. For the second statement, "*Learning new statistical application increases the anxiety towards statistics*", the p-value for the software type is less than $\alpha = 0.05$, so it is statistically significant, and major factor is close to being statistically significant as well. In the third statement, "*Studying new statistical application takes time and effort*", only Degree is significant.

In OLR, each categorical factor (input variable) has a default value. When a value other than the default is used, there is a coefficient associated with it. Table 4 shows the coefficients for the non-default levels of each factor associated for the Learning Statistical Concepts category responses. In the first and last statements, non-coding and female (input values) are associated with less anxiety than coding and male. Non Applied Statistics students tend to face higher levels of anxiety than Applied Statistics students towards understanding the statistics lectures. For all statements, Doctorate students tend to have less anxiety level than Masters students. However, the second and the third statements represent that non-coding, female, and not-applied statistics input variables are associated with higher levels of anxiety than coding, male, and applied statistics factors.

Table 3. Learning Statistical Concepts: p-values of main effects for category responses.

	<i>Software Type</i>	<i>Classes types</i>	<i>Gender</i>	<i>Citizenship</i>	<i>Age</i>	<i>Major</i>	<i>Degree</i>
<i>Statistics lectures are easy to understand</i>	0.0145	0.1446	0.0045	0.3072	0.7212	0.0690	0.2475
<i>Learning new statistical application increases the anxiety towards statistics</i>	0.0008	0.2362	0.1905	0.4370	0.3732	0.0575	0.6203
<i>Studying new statistical application takes time and effort</i>	0.6633	0.9444	0.4384	0.2539	0.7917	0.5525	0.0177
<i>I am afraid of statistics because I didn't learn it from elementary like other subjects</i>	0.1403	0.5272	0.5222	0.3171	0.5894	0.1357	0.5832

Table 4. Learning Statistical Concepts: coefficients table for category responses.

	<i>Both coding and noncoding</i>	<i>Noncoding</i>	<i>Female</i>	<i>Non US-Citizen</i>	<i>Both On-campus and Online</i>	<i>On-Campus</i>	<i>Non-Applied Statistics</i>	<i>Bachelors</i>	<i>Certification</i>	<i>Doctorate</i>	<i>Other</i>
<i>Statistics lectures are easy to understand</i>	0.5068	-1.5123	-1.2056	-0.4036	1.1789	0.8635	1.0608	1.1945	2.2390	-0.0822	2.0853
<i>Studying new statistical software takes time and effort</i>	-0.5272	0.1473	0.4017	-0.7315	0.1284	-0.0290	-0.4997	-1.2369	11.9829	-4.7421	-3.8278

<i>Learning new statistical application increases the anxiety towards statistics</i>	0.7030	2.7547	0.5916	-0.3665	-1.1008	-1.6582	-1.4636	-0.1175	-2.6779	-0.7922	-0.0232
<i>I am afraid of statistics because I didn't learn it from elementary like other subjects</i>	-0.9058	-1.2069	-0.3155	0.5521	0.9847	1.0012	1.0466	-0.0374	3.3064	-15.2893	-0.5423

In Table 5, software type and gender are statistically significant in the first response in Learning Statistical Software category, “*I feel insecure when I do some programming stuff*”, with p-values less than α (software type p-value= 0.0215 < $\alpha = 0.05$ and gender p-value=0.0019 < $\alpha = 0.05$). Gender is the only significant variable in the third response, “*Statistical programming languages are so difficult to understand*”, where the p-value is $0.0246 < \alpha = 0.05$. In the fourth statement, “*I like programming than interpreting the results*”, software type is significant where the p-value is $0.0488 < \alpha = 0.05$.

Table 5. Learning Statistical Software: p-values of main effects for category responses.

	<i>Software Type</i>	<i>Class Type</i>	<i>Gender</i>	<i>Citizenship</i>	<i>Age</i>	<i>Major</i>	<i>Degree</i>
<i>I feel insecure when I do some programming stuff</i>	0.0215	0.9003	0.0019	0.2239	0.6545	0.9998	0.5251
<i>Statistics program are easy to understand</i>	0.2916	0.3286	0.2353	0.7413	0.7840	0.8318	0.4611
<i>Statistical programming languages are so difficult to understand</i>	0.0935	0.7305	0.0246	0.9932	0.3516	0.5575	0.8178
<i>I like programming than interpreting the results</i>	0.0488	0.3100	0.0644	0.6861	0.2149	0.8818	0.8775
<i>I feel under stress when I write a statistical programming code</i>	0.0003	0.5664	0.0028	0.6008	0.0294	0.9541	0.2527
<i>I prefer spending my time on programming than understanding the statistical concept</i>	0.1671	0.0427	0.0178	0.2779	0.2557	0.9650	0.9838

<i>I have less anxiety when working on programming than interpreting the results</i>	0.3110	0.1052	0.0497	0.8800	0.8942	0.7313	0.9368
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Software type, Gender, and Age are the significant factors in the fifth statement, “*I feel under stress when I write a statistical programming code*”, where the p-values are less than $\alpha = 0.05$. In the sixth statement, “*I prefer spending my time on programming than understanding the statistical concept*”, class type and gender are statistically significant, the p-values are equal to 0.0427 and 0.0178 respectively. Gender factor in the last statement, “*I have less anxiety when working on programming than interpreting the results*”, is the only significant factor where the p-value is equal to 0.0497 which is less than $\alpha = 0.05$.

Table 6 represents the coefficients table for Learning Statistical Software category responses. In the first, fifth, sixth and seventh statements the noncoding and female factors indicate less anxiety than coding and male factors. However, in the second, third, and fourth statements both noncoding and female input variables are facing more anxiety than coding and male factors.

Table 6. Learning Statistical Software: coefficients table for category responses.

	<i>Both coding and noncoding</i>	<i>Noncoding</i>	<i>Female</i>	<i>Non-US-Citizen</i>	<i>Both On-campus and Online</i>	<i>On-Campus</i>	<i>Not-Applied Statistics</i>	<i>Bachelors</i>	<i>Certification</i>	<i>Doctorate</i>	<i>Other</i>
<i>I have less anxiety when working on programming than interpreting the results.</i>	-0.8051	-0.7721	-0.9270	-0.1101	1.5966	1.2954	-0.2024	0.7908	0.5833	-0.1134	15.8266
<i>I feel insecure when I do some programming stuff.</i>	0.9123	1.8765	1.5101	-0.6620	0.0140	-0.2493	-0.0784	-0.5029	-1.2600	-1.7567	-1.4373
<i>I feel under stress when I write a statistical programming code.</i>	0.8204	2.9143	1.3810	-0.0103	-0.4606	-1.0661	-0.3936	0.3683	-1.6969	-1.9217	-15.8042
<i>Statistical programming languages are difficult to understand.</i>	-0.1781	1.3949	1.0480	0.1172	-0.5181	-0.8185	-0.5682	-0.4918	-0.4326	-1.0178	-0.7335

<i>I like programming more than interpreting the results.</i>	-0.1002	-1.5821	-0.7828	0.0440	0.9900	1.4406	0.3524	0.4278	1.4668	0.0524	16.2470
<i>I prefer spending my time on programming than understanding the statistical concept.</i>	-0.0333	-1.1285	-1.0816	-0.7335	1.7270	2.2773	0.2715	-0.1205	-12.5181	0.1316	16.9458
<i>Statistics program are easy to understand</i>	0.5716	-0.6237	-0.5776	0.2470	1.1284	0.8769	-0.0840	1.4029	2.1095	1.5181	17.5768

Table 7 shows the p-values for Learning to Read/Interpret Results category responses. Starting with the first statement, “*Statistical outputs are easy to understand*”, the p-value for the software type variable is 0.0547 which is very close to $\alpha = 0.05$. Therefore, it might be considered as statistically significant. Moreover, in the third statement, “*I like interpreting the results than working on programming*”, software type and age have significant p-values where software type = $0.0096 < \alpha = 0.05$ and age = $0.0145 < \alpha = 0.05$.

Table 7. Learning to Read/Interpret Results: p-values of main effects for category responses.

	<i>Software Type</i>	<i>Class Type</i>	<i>Gender</i>	<i>Citizenship</i>	<i>Age</i>	<i>Major</i>	<i>Degree</i>
<i>Statistical outputs are easy to understand</i>	0.0547	0.4016	0.3954	0.6724	0.2275	0.9944	0.799
<i>Seeing statistical symbols in the results increases the anxiety</i>	0.1124	0.4430	0.2006	0.3206	0.4162	0.4832	0.3037
<i>I like interpreting the results than working on programming</i>	0.0096	0.4971	0.1683	0.2905	0.0145	0.9791	0.8571
<i>The results from statistical software are difficult to understand</i>	0.9025	0.1437	0.2666	0.3175	0.9848	0.0911	0.3917
<i>Statistical outputs take time to interpret</i>	0.4219	0.3097	0.4928	0.1938	0.5888	0.7910	0.9874

Table 8 shows the coefficients for Learning to Read/Interpret Results category responses. The second statement shows low levels of anxiety for students who regularly use

noncoding software versus coding software. However, all other statements show higher levels of anxiety for noncoding than (vs.) coding.

Table 8. Learning to Read/Interpret Results: coefficients table for category responses.

	<i>Both coding and noncoding</i>	<i>Noncoding</i>	<i>Female</i>	<i>Non US-Citizen</i>	<i>Both On-campus and Online</i>	<i>On-Campus</i>	<i>Not-Applied Statistics</i>	<i>Bachelors</i>	<i>Certification</i>	<i>Doctorate</i>	<i>Other</i>
<i>I like interpreting the results more than working on programming</i>	0.5163	1.8925	0.5529	0.8669	-0.5944	1.0938	-0.3726	0.1991	13.7896	0.0599	-17.1175
<i>Statistical outputs are easy to understand.</i>	1.0920	-0.7764	-0.2919	0.1336	1.1424	0.9558	0.2372	-0.7138	1.3455	-0.5641	1.5035
<i>Statistical outputs take time to interpret.</i>	-0.7108	0.1248	0.3189	-0.7836	-0.0444	-0.8469	-0.3172	0.3005	-0.6968	0.6682	15.2552
<i>Seeing statistical symbols in the results increases the anxiety.</i>	-0.0226	1.3338	0.5447	0.7197	0.3985	-0.2784	-0.5725	1.0922	-1.8702	-1.6717	0.0925
<i>The results from statistical software are difficult to understand.</i>	0.2630	0.0741	0.5636	-0.6927	-0.7445	-1.5099	1.1215	-0.1570	-2.4941	-0.8836	3.1715

5. Discussion and Limitations

In this paper, we did a study about anxiety towards learning new statistical software. As mentioned in the above sections there are three categories in the study that we want to test. In the results, we found that software type, gender, major and degree are the most effective factors in Learning Statistical Concepts category. The anxiety towards learning new statistical software would be increased by differences in the four effective factors. Also, software type, gender, and age remarkably impact the Learning Statistical Software category. In the Learning to Read/Interpret Results category, software type and age were the most effective variables.

Despite the fact that the OLR for each response produced statistically significant results, not all factors were statistically significant. The potential reason for this could be a design issue. The survey was distributed to numerous students in different classes, but not all

the students replied with responses. The survey was sent only to the students who took classes with one professor. Also, this was an observational study where the software type and the classes could not be controlled. Moreover, Gliem and Gliem (2003) discussed analysis of single-item in Likert-Type scales is not reliable.

6. Conclusions and Areas for future research

The purpose of this study was to discover factors affecting statistical anxiety towards learning new statistical software. The survey consisted of questions in three important categories: Learning Statistical Concepts, Learning Statistical Software and Learning to Read/Interpret Results. Each category has multiple statements that were impacted by various factors. Therefore, it appears that the anxiety towards learning new statistical software would be affected by the software type, whether it is coding or noncoding, gender and major (Applied and Non Applied Statistics).

As mentioned in the discussion and limitations section, there are gaps in this research that might benefit from further research. I would recommend addressing differences in specific software such as R vs. Minitab to represent coding and noncoding, examining majors more specific than “applied statistics” vs. “non applied statistics”.

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Appendices

Appendix A. Additional Material

Copy of the Survey:

Anxiety towards Learning new statistical software

Directions: The statements bellow are created to see your level of anxiety towards learning new statistical software. Each statement has 5 different responses. The responses range from 1 (Strongly Disagree) through 3 (Neither Agree nor Disagree) to 5 (Strongly Agree). If you have no answer or opinion chose 3. Please choose only one answer in each statement that represents your opinion. Please respond to all the statements.

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)
Statistics lectures are easy to understand. (1)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like interpreting the results more than working on programming. (2)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I have less anxiety when working on programming than interpreting the results. (3)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Studying new statistical software takes time and effort. (4)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Statistical outputs are easy to understand. (5)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel insecure when I do some programming stuff. (6)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Statistical outputs take time to interpret. (7)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Learning new statistical software increases the anxiety towards statistics. (8)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel under stress when I write a statistical programming code. (9)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Seeing statistical symbols in the results increases the anxiety. (10)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Statistical programming languages are difficult to	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

understand.
(11)

I am afraid of
statistics
because I
didn't learn it
from
elementary
school like
other subjects.
(12)

I like
programming
more than
interpreting the
results. (13)

I prefer
spending my
time on
programming
than
understanding
the statistical
concept. (14)

Statistics
program are
easy to
understand.
(15)

The results
from statistical
software are
difficult to
understand.
(16)

<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Q3 What software do you constantly use ? if it is more than one please list them all

Q34 When studying statistics, I attended classes:

On-Campus only (1)

Online only (2)

Both (3)

Q4 Gender:

Male (1)

Female (2)

Q5 Citizenship:

US Citizen. (1)

Non US Citizen (2)

Q6 Age (in years):

Q7

Choose your major, and if you are already graduated, choose your most recent major

- Arts/Humanities (1)
 - Biology (2)
 - Chemistry (3)
 - Economics (4)
 - Engineering (5)
 - Statistics (12)
 - Mathematics (6)
 - Medicine/ pre-medicine (7)
 - Psychology (8)
 - Sociology / Social Work (9)
 - Mangement (10)
 - Other (11)
-

Q8 If your major is statistics please specify the area of interest.

- Theoretical Statistics (1)
 - Applied statistics (2)
-

Q9 Degree you are currently seeking, and if you are already graduated, choose your most recent degree

- Associate (1)
- Bachelors (2)
- Master (3)
- Doctorate (4)
- Certification (5)
- Post-bachelor's Licensure (6)
- Specialist (7)
- Other (8)



Q10 Please write any comment that you want us to know

Appendix B. Results Material

Table B1. Analysis of Cronbach's alpha for questions in the learning category.

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.139919
Standardized	0.178826

Table B2. Analysis of Cronbach's alpha for questions in the programming category.

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	0.404969
Standardized	0.407782

Table B3. Analysis of Cronbach's alpha for questions in the interpreting category.

Cronbach Coefficient Alpha	
Variables	Alpha
Raw	-.145976
Standardized	-.161036

Appendix C. Coding Material

Part (1) Codes for Cronbach's alpha:

```
PROC print DATA=WORK.Anxiety2; RUN;

* programming;
proc corr data=WORK.Any2 alpha nomiss;
var Q2_3 Q2_6 Q2_9 Q2_11 Q2_13 Q2_14      ;
run;

*learning;
proc corr data=WORK.Any2 alpha nomiss;
var Q2_1 Q2_4 Q2_8 Q2_12;
run;

*Interpreting;
proc corr data=WORK.Any2 alpha nomiss;
var Q2_2 Q2_5 Q2_7 Q2_10 Q2_15 Q2_16;
run;
```

Part (2) Codes for Ordinal Logistic Regression:

```
PROC print DATA=WORK.Any;run;

data Any2;
set any(drop=AA AB AC AD AE AF AG AH AI AJ AK AL AM AN AO AP
AQ AR AS AT AU AV AW AX AY AZ BA BB BC BD BE BF BG BH BI BJ BK
BL BM BN)
;
run;

proc contents data=Any2;run;

proc print data=any2;run;

* discriptive;

proc sort data=any2;by q3;run;

proc freq data=any2;by q3; run;
*Q1;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_1 = Q3|Q4|Q5|Q34|QQ8|Q9 @2 / clparm=pl lackfit
aggregate rsquare scale=D;
run;
quit;

proc glmselect data=Any2 ;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_1= Q3 Q4 Q5 Q34 QQ8 Q9/ selection =
stepwise(select=AIC);
run;
quit;

*Q2;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_2 = Q3 | Q4 | Q5 | Q34 |QQ8 |Q9 @2 / clparm=pl
lackfit scale=D;
```

```
run;  
quit;
```

```
*Q3;  
proc logistic data=Any2 descending plots=effectplot;  
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5  
(ref="US_Citizen" param=ref)  
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"  
param=ref) Q9(ref="Master" param=ref);  
model Q2_3 = Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;  
run;  
quit;
```

```
*Q4;  
proc logistic data=Any2 descending plots=effectplot;  
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5  
(ref="US_Citizen" param=ref)  
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"  
param=ref) Q9(ref="Master" param=ref);  
model Q2_4 = Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;  
run;  
quit;
```

```
*Q5;  
proc logistic data=Any2 descending plots=effectplot;  
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5  
(ref="US_Citizen" param=ref)  
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"  
param=ref) Q9(ref="Master" param=ref);  
model Q2_5 = Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;  
run;  
quit;
```

```
*Q6;  
proc logistic data=Any2 descending plots=effectplot;  
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5  
(ref="US_Citizen" param=ref)  
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"  
param=ref) Q9(ref="Master" param=ref);  
model Q2_6 = Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;  
run;  
quit;
```

```
*Q7;  
  
proc logistic data=Any2 descending plots=effectplot;  
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5  
(ref="US_Citizen" param=ref)  
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"  
param=ref) Q9(ref="Master" param=ref);  
model Q2_7= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
```

```

run;
quit;

*Q8;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_8= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
run;
quit;

*Q9;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_9= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
run;
quit;

*Q10;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_10= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
run;
quit;

*Q11;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_11= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
run;
quit;

*Q12;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) Q08 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_12= Q3 Q4 Q5 Q34 Q08 Q9/ clparm=pl lackfit scale=D;
run;
quit;

```

```

*Q13;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_13= Q3 Q4 Q5 Q34 QQ8 Q9/ clparm=pl lackfit scale=D;
run;
quit;

```

```

*Q14;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_14= Q3 Q4 Q5 Q34 QQ8 Q9/ clparm=pl lackfit scale=D;
run;
quit;

```

```

*Q15;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_15= Q3 Q4 Q5 Q34 QQ8 Q9/ clparm=pl lackfit scale=D;
run;

```

```

*Q16;
proc logistic data=Any2 descending plots=effectplot;
class Q3 (ref="Coding" param=ref) Q4 (ref="Male" param=ref) Q5
(ref="US_Citizen" param=ref)
Q34(ref="Online" param=ref) QQ8 (ref="Applied_statistics"
param=ref) Q9(ref="Master" param=ref);
model Q2_16= Q3 Q4 Q5 Q34 QQ8 Q9/ clparm=pl lackfit scale=D;
run;
quit;

```