COMPARISONS OF SPATIAL REASONING ABILITIES OF STRING AND NON-STRING PROFESSIONAL MUSICIANS

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Abstract

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This study provides evidence to support the transferable benefits of musical training to enhance performance on cognitive tasks involving spatial reasoning abilities. Spatial reasoning is an important skill that is essential for success in science, technology, engineering, and mathematics (STEM) achievement. Previous research indicates that students involved with musical instrument training score higher on measures of spatial temporal abilities than students with no musical training. We hypothesized that the greatest development of spatial visualization will be found in string instrument musicians when compared to non-string musicians, because of the visualization required due to the design of these instruments. Two studies compared scores on measures of spatial reasoning between string and non-string instrumentalists. Participants were administered the Visualization and Picture Recognition sub-tests of the 2014 revised Woodcock-Johnson Tests of Cognitive Abilities IV by psychology master's students who were blind to the experiment's hypothesis. In addition, participants a self-report survey of musical aptitude that included measures of proficiency for each instrument that they played. The results from these studies do not suggest that string players have stronger spatial reasoning skills when compared to other instrumentalists. However, the results do

replicate previous research by demonstrating that individuals that play an instrument perform better on spatial reasoning tasks when compared to non-musicians.

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Introduction

The theory of relativity, the invention of the light bulb, and so many other innovations that have changed the world are the products of a creative process that may be strongly related to having strong spatial reasoning skills. Spatial reasoning is a type of intelligence that typically emerges in children 18 to 24 months of age, about when children begin to understand that objects continue to exist even when they are presently unseen (Piaget, 1955). Spatial reasoning is the ability to generate, retain, retrieve, and transform well-structured visual images in the absence of a physical model and is involved when we think ahead several moves developing and evaluating patterns in space and time. Spatial reasoning is linked to positive educational outcomes in science, technology, engineering, and mathematics (STEM), and is a strong predictor of success in the visual arts, vocational manufacturing, and technical careers (Wai & Uttal, 2018). A better understanding of how and why spatial reasoning develops could be useful in educating our children to think, reason, and create.

Similarities between spatial reasoning and musical thinking have been reported for decades (Rauscher & Hinton, 2011). For example, the part-whole-schema is an important construct seen in musical and spatial thinking. This schema requires an understanding of a part in relation to its whole, something exemplified when exploring fractions, decimals, and percentages. The same is seen within musical practice involving tempo, pitch, and rhythmic patterns. Musicians are constantly required to subdivide a whole note of time into halves, quarters, eighths, and further. In addition, musicians are required to know where they are playing within a piece of music. Since sections of a composition are often repeated, musicians need to maintain an overall awareness of where the section is in the context of the whole piece of music. Though the context of both musical and spatial tasks is different, the process of working on a musical task or a spatial task both require similar patterns of thinking.

Transfer of learning is the capacity to apply acquired knowledge and skills to new situations (Hallam, 2015). Learning can be transferred from one domain to another depending on the parallels of the cognitive processes involved. There are two components to transfer of learning, near and far transfer. Near transfer involves a transfer of learning that is more automatic, where far transfer is a more complex process that involves reflection and conscious processing. Fine motor skills, processing of sounds, and memorization of text through music are all examples of near transfer and are more likely to be seen in individuals who practice music. Far transfer can be exemplified in relation to improvements in spatial reasoning skills through musical instrument practice.

The Trion Model serves as a mathematical representation of a neuroscientific framework which demonstrates the relationship between music and spatial cognition. This model is based on Mountcastles (1957) Columnar Organization Principle, which is a widely adopted theory that explains the cortical processing of information. The Trion Model of the cortex provides neurophysiological insights on the transfer of skills. It explains that the same neural firing patterns, which are arranged in code across large regions of the cortex, are used during both musical and spatial reasoning tasks (Leng & Shaw, 1991). According to this model the structured cortex, which is present at birth, has an inherent collection of spatial temporal firing patterns which can be excited and strengthened by changes in connectivity via Hebbian learning rule (Hebb, 1949). The shared firing patterns, used during both spatial and musical tasks, strengthen during repeated practice of either skill. So, practice of one may generalize or transfer to improvement of the other. Over time, these firing patterns evolve to form the common neural language of the cortex.

As such, there is strong evidence that spatial reasoning can be improved by musical training (Holmes & Hallam, 2017). Throughout many empirical studies individuals involved with musical instrument training have improved scores on measures of spatial reasoning when compared to individuals with no musical training (e.g. Bilhartz, Bruhn, & Olson, 1999; Costa-Giomi, 1999; Hurwitz et al., 1975; Rauscher & Zupan, 2000; Sanders, 2012). For example, Portowitz and colleagues (2009) compared 45 at-risk elementary school students enrolled in a musical training after school program to their 35 counterparts in similar programs with no musical components. The 45 students who participated in the program, which consisted of two to three hours of musical instruction every week for two years, had greater improvements on a measure of spatial reasoning (Raven Complex Figures Tests) when compared to their 35 counterparts.

Also, Holmes and Hallam (2017) compared spatial reasoning scores of 90 children aged four to seven who took part in two years of musical instruction to 88 students who followed their usual school schedule. There was no significant difference between groups' spatial reasoning scores before implementation of the music programs. After implementation, the students in the music program achieved greater results on measures of spatial reasoning (picture and puzzle tests), than their peers on one or both measures of spatial reasoning. It is clear that musical instrument training and practice have a positive effect on spatial reasoning skills.

Another study assessed whether the type of musical instrument involvement would impact the level of spatial reasoning enhancements (Tai, 2010). Students involved in comparable singing, piano, and violin training were compared to their non-music group counterparts. There were no differences between the four groups' spatial reasoning pretest scores as measured by the block design and object assembly subsets of the WPPSI-III (Wechsler, 2002) before musical instruction began. However, the violin and piano students showed significantly greater improvement of spatial reasoning skills than the singing and non-music groups over a four-week period. These results highlight the need to explore differences in spatial reasoning skills with different types of instrumentalists.

String instruments (chordophones) are functionally different from woodwind and brass instruments (aerophones) in the way that they produce sound (Hornbostel & Sachs, 1914), because they require different skills to gain proficiency. The increased and arguably more complex involvement of the hands while playing a chordophone may provide cognitive benefits that exceed those gained by playing an aerophone. There are several significant differences not only in design of these instruments but in practicing habits of the instrumentalists who play them. The differences in practice strategies and duration of different instrumentalists were examined among 3,325 individuals who ranged in expertise from beginner to advanced (Hallam et al., 2019). They found no statistically significant differences in practice strategies, except woodwind players were adapting less effective strategies than other musicians. Hallam and colleagues found keyboard instrumentalists spent the most time practicing followed by string, brass, then woodwind musicians.

The current study intends to provide insight on the potential differences in spatial reasoning abilities based on different types of instrument played. There are several reasons this information is worth gathering. First, there is strong supporting evidence that links success on these tasks of spatial reasoning competence with success in mathematics (Casey et al., 2015). A 50-year longitudinal study including 400,000 participants found that individuals with relatively strong spatial abilities tended to gravitate towards and excel in science, technology, engineering, and mathematics (STEM) fields (Wai, Lubinski, & Benbow, 2009). In addition, spatial skills can have a profound impact on children's development of numerical knowledge by aiding in understanding linear spatial relationships of numbers (Gunderson et al., 2012). Spatial reasoning skills are positively correlated with adaptive arithmetic strategies (Geary & Burlingham-Dubree, 1989), measuring fractions, number sense, measurement, geometry, data representation (Casey, Nuttall, & Pezaris, 2001) and overall scores on the math portion of the Scholastic Aptitude Test (SAT-M; Casey et al., 1995). It is clear that spatial reasoning is an important skill that is essential for success in STEM achievement (Stieff & Utall, 2015).

Musical activity has been shown to have a substantial influence on spatial reasoning that is observable through changes in behavior, activation, and structural differences (Hallam, Cross, & Thaut, 2016). Thus, it appears to be beneficial for those who want to excel in STEM fields to practice an instrument. The question of which musical instrument to practice to foster the greatest development in spatial reasoning skills is another area that has not been well researched. This information could be valuable to educators and parents who are interested in developing STEM skills along with musical skills in children. Development and identification of spatial reasoning skills in k-12 students is a missing factor in education policy that should be addressed to help students develop to their full capacity. This kind of knowledge could help to influence pedagogical decisions regarding where to make learning related investments (Rauscher & Zupan, 2000).

A large portion of research looking at enhancements in spatial reasoning skills due to musical practice involves young children and research involving professional musicians is lacking. Engagement of professional musicians provides an opportunity to study the potential long-term effects related to acquiring and sustaining musical performance skills. One study compared 10 professional musicians who played string instruments to 10 medicine and science faculty members who were matched for age (mean age = 42.2 years), handedness, and verbal intelligence (Sluming et al., 2007). The evidence found orchestral musicians showed enhanced performance on complex visuospatial tasks corresponding with increased activation in Broca's area of the brain (involved in sight reading and visuospatial analysis), when compared to non-musical counterparts. This study is one of the few that involve professional musicians and provides support for the concept of increased spatial visualization skills as a result of years of professional orchestral playing. The present study includes professional musicians with long term experience playing a variety of string, woodwind, and brass musical instruments.

We expect that there will be differences in spatial reasoning skills among different types of professional instrumentalists (woodwind, brass, and string). As such, we predict that string musicians will have significantly improved spatial reasoning scores when compared to their brass and woodwind musician counterparts. Because of the unique skills required to play different musical instruments, we expect to see a variance in scores for different types of musicians on a measure of spatial reasoning and expect that string musicians will score higher compared to their musical counterparts. This could be attributed to the more complex nature of string instrument design, or the additional practice time required to play such an instrument at a professional level.

Method

Data from Study 1 were originally collected as part of a faculty research project that is grant funded. Results of study 1 function as pilot data to inform methodological changes for study 2.

Study 1

Participants. Participants included 32 males and 24 females (N = 56) professional musicians, who were members of the Mendocino Music Festival Orchestra aged 18 to 85 years (M = 55). The Mendocino Music Festival is an annual event that has brought musicians together from around the world since 1996. The festival takes place at the Mendocino Headlands state park, in Mendocino California, where a symphony sized tent is erected in the park that overlooks the Pacific Ocean. The orchestra was comprised of professional musicians from the San Francisco Symphony, San Francisco Opera, San Francisco Ballet Orchestra, Symphony of the Redwoods, and other Bay Area orchestras. Participants who identify as a percussion instrumentalist (n = 3) were excluded from the study because of the extreme diversity in the design of these instruments. The sample consisted of 72% Caucasian, 11% Asian, and 17% other ethnicities individuals. 57% of the participants held a master's degree, 21% bachelors, 8% some collage, 3% high school graduates, and 3% doctoral degrees. There were 23 males and 30 females, zero participants identified as non-binary.

Variables. The independent variable is the type of primary instrument (string/ non-string) that musicians play. We also looked at the secondary instrument(s), string/non-string/both, played by the musicians in order to make a comparison of instrumentalists who only play string or non-string instruments, not both. The dependent variables are the participants' scores on two measures of spatial reasoning: block design (123test.com, n.d.) and configuration (jobtestprep.co.uk, n.d.).

Measures. These tests were chosen for this study because of their likeness to measures cited in academic research. Humphrey et al. (1993) was monumental with their construction of the Project Talent 2D and 3D tests. The major function of these two tests was as a pure measurement of spatial abilities by way of mental rotation and block design. Project Talent 2D test involved the accurate prediction of rotating two-dimensional pictures (mental rotation). Alternatively, the Project Talent 3D test was the accurate prediction of a two-dimensional pattern transformed into a three dimensional object (block design). The no cost publicly available measures cited above fit Humphrey's test at face value while cutting costs for the current researcher. The survey used in the study included 10 measures of block design and 5 measures for configuration. To ensure the tests usefulness this study as well as construct validity, descriptive psychometric tests were computed. Reliability of these measures were tested via a Cronbach alpha with a threshold .70 for any given item. This threshold is established by way of the seemingly unidimensional of the measure as suggested by Taber (2017).

Procedures. Members of the Mendocino Music Festival Orchestra were asked to volunteer for this study after a rehearsal. A faculty member working on this study was a member of the orchestra and reached out to musicians prior to the festival to let them know we would be there to conduct research. At the beginning of their first rehearsal a student working on this study addressed the orchestra to explain that we were looking for volunteers to participate, and that anyone who was interested could meet a research proctor at a picnic table outside of the rehearsal tent. For three days of rehearsals, proctors were present to administer the surveys to volunteers who sat at one of the ten picnic tables located nearby in the park. Participants completed a formal consent to participate form. They then completed a twenty to thirty minute spatial reasoning measure that included a series of block design and mental rotation tasks. In addition to this measure of spatial reasoning, participants completed a self-report survey of musical aptitude that included questions regarding the participant's level of proficiency for each instrument that they play. Participants marked the statement that best reflects their skills with their primary instruments, for example "I can do nothing to very little on the piano" or "I can play Bach Fugues or repertoire of comparable difficulty today". Last, participants were rewarded $10.00 to compensate them for their involvement.

Analysis. This study used a between subject's quasi experimental design because we could not assign participants to instrument expertise. Data from this pilot study was analyzed using R software version 1.1.463. The participants were organized into two groups: Individuals who primarily play a string instrument and individuals whose primarily play a brass or woodwind instrument. A Welch's t-test was conducted to assess mean differences between the string and non-string musician's scores on the spatial reasoning tasks. Although a Welch's t-test is typically used only in times of assumption violation, it was chosen for its conservative estimation as a way to reduce the chances of a type I error. To compare spatial reasoning among musicians with varied proficiency, an Analysis of Variance test (ANOVA) was conducted.

Results

It was predicted that string musicians would have significantly improved spatial reasoning scores when compared to their brass and woodwind musician counterparts. The data was first tested for its adherence to the ANOVA assumptions. Normality was tested via skew and kurtosis estimates paired along graphical representations of the data via Q-Q plots. Non-normal data was transformed. If violations persisted with normality issues, the data underwent a bootstrapped ANOVA because bootstrapped approaches are trimmed mean approaches that do not make any assumptions.

The data was first loaded in and filtered to only the variables of interest. The data's demographic information was then recorded. Two participants had a high school education, seven had some college, 12 had bachelors, 31 had masters, and one doctorate. Given that so many statistical tests require normality in the data, variables to be used were tested via Skew and Kurtosis estimates. Variables that were non-normal were transformed as per standard practice.

The spatial reasoning measurement had a negative skew and required a reflective transformation. The scores were reflected by subtracting the highest reached score from each data point. This transformation notably changes result interpretation and this was taken into account when presenting the results below. Proficiency required a non-reflective transformation. Spatial reasoning was fixed best by a square root transformation. Unfortunately, no transformation directly corrected proficiency, however the best fit of a square root transformation was used (see Appendix A).

To begin, differences between instrument types on their levels of proficiency was tested by an independent t-test. Homogeneity of variance was first evaluated at a 4:1 variance and 2:1 sample size threshold. Homogeneity of variance was found to be violated as per the sample size threshold. With this, Welch's correction for unequal variances was assumed to reduce chances of a type I error. There were no significant differences in proficiency per instrumental-type group: $t(26.15) = 0.48$, $p = .632$, $d = 0.14$.

To evaluate differences between spatial reasoning between string and non-string players, an independent samples t-test was computed. Homogeneity of variance was evaluated with the 4:1 variance and 2:1 sample size threshold. Although variance was within a reasonable distance, the assumption sample size equality exceeded the threshold at 39 for string musicians and 15 for non-string musicians. A Welch's correction was implemented assuming unequal variances in the sample. No significant differences were observed on scores of spatial reasoning between string and non-string musicians: $t(25.86) = -1.37$, $p = .183$, $d = 0.41$.

To investigate the relationship between musical proficiency and spatial reasoning scores, a linear regression was computed. The regression assumptions were evaluated as shown in the graphs below. As per the Q-Q plot, the regression model's residuals were adequately normally distributed. However, the Residuals vs. Fitted plot exhibited heteroscedastic as per the distribution of data points, and non-linearity as per a curved loess line. Given the present violations of the regression assumptions, a robust regression was computed, which makes no assumptions. The relationship was found to be non-significant: *b**=.16, p = .264.

Finally, to elucidate the interaction of proficiency and instrument type on the musicians' spatial reasoning scores, a moderated regression was computed. Given the previous regression's residuals, a robust regression model was utilized, which lowers the chances of a type I error. Proficiency (b = 0.07, p = .236) and instrument type (b = -0.83, p = .251) were unrelated to spatial reasoning. These variables were not qualified by an interaction: b = -0.06, p = .600.

The spatial reasoning measurements were then tested for their psychometric strength. Cronbach alphas were computed for each tool and both tests were correlated together as a validity check. A positive relationship between the two would resemble a construct similarity, ergo construct validity. The two tests were found to be unrelated to each other as per a non-significant relationship: r = .21, p = .122, R^2 = .04. This may have to with the respective reliability estimates of each measure. The first test, from 123test.com.yielded a moderately low Cronbach alpha of .68, but test 2, from jobtestprep.co.uk, reported a much lower alpha of .28. Because of the low reliability of the spatial reasoning measures in study 1, we chose to use the Woodcock-Johnson IV Tests of Cognitive Abilities for study 2.

Method

Study 2

Participants. We reached out via email to conductors of local professional music groups: Eureka Symphony, Humboldt Symphony, and an all brass community band. The conductors forwarded a virtual flyer to group members. Interested musicians contacted the lead research to schedule individual appointments for assessment on the Humboldt State University campus in a lab setting. Participants consisted of professional and student musicians located in Humboldt County. There were 24 participants that included a range of ages from 18 to 70 years (*mean age* = 39.2). There were seven females, 14 males, and one non-binary participant. In the sample 4.4% had a high school degree, 43.5% some college, 26.1% bachelor's, 17.4% master's, and 8.7% of participants had a doctorate. The sample consisted of 70.8% Caucasian, 8.3% Latin, 8.3% Multi, 4.2% Asian, 4.2% Mexican, 4.2% Puerto Rican individuals.

Variables. The independent variable was the type of primary instrument (string/ non-string) that musicians play. We also looked at the secondary instruments (string/ non-string/ both) played by the musician. Skill levels, as measured by a self-report survey of musical aptitude, for both primary and secondary instruments were also analyzed. The DV was the spatial reasoning scores from the 2014 revised Woodcock-Johnson Tests of Cognitive Abilities IV (WJ-IV COG). This measure was chosen after analysis of the measure from study 1 demonstrated poor validity and reliability.

Measures. The 2014 revised *Woodcock-Johnson Tests of Cognitive Abilities IV* (WJ IV COG) (WJ-IV; Schrank, Mather, & McGrew, 2014a) was used to assess spatial reasoning skills. This study used the visualization and picture recognition subtests of the WJ-IV COG that measure spatial reasoning ability.

The WJ IV COG was chosen as our measure of spatial reasoning because it has been thoroughly tested for validity and reliability. To the best of our knowledge, this is the first time the WJ IV COG has been used to test spatial reasoning ability of musicians. The WJ IV COG is a collection of tests included in the *Woodcock-Johnson IV Tests of Academic Achievements* (WJ IV ACH) which assess basic skills, application, and fluency in reading, mathematics, written language, and academic knowledge. The authors of the WJ IV ACH recommend that those who administer the WJ IV ACH receive graduate-level training in administration of the examination as well as exact scoring procedures. The test can be administered in whole or in part to anyone aged from 2 to over 90. To assess participant's skills related to spatial reasoning, the visualization and picture recognition subsets of the WJ IV COG were administered by graduate students who were trained in administration and scoring of this measure. These subsets contribute in part or in whole to scores of general intellectual ability, visual processing, and mathematics. They consist of a series of tests of spatial relations, block rotation, and picture recognition figural-visual tasks.

Reliability and validity for the WJ IV COG have been extensively examined by the authors of the measure, and it has been found to be reliable both by them, various universities, and in published journal articles. Reliability for the visualization subset was analyzed for each age group using the weighted composite method (Mosier, 1943). Individual ages were assessed from 2-19, and subsequent age groups were divided into decades (e.g. 20-29, 30-39, etc.). Reliability, calculated as R_{11}, ranged from .79 to .90 with a median score of .85 for visualization, and ranged from .61 to .84 with a median of .74 for the picture recognition subset. Validity was measured in a three-stage approach to establish a relationship between the WJ IV and the Cattell-Horn-Carroll (CHC) broad factors for cognitive abilities (for details, see McGrew, K. S., et al., 2014). Validity for the visualization subset of the WJ IV COG ranged among different age groups from .69 to .86 with a median score of .82 for CHC broad factors.

Visual Processing, as defined by the CHC theory of cognitive abilities, is a broad factor that encompasses the ability to use simulated mental imagery to solve problems. During this proces the eyes transmit visual information to the visual system of the brain, where many low-level computations take place (color differentiation, edge detection, motion detection, etc.). These low-level computations are used by other areas of the brain for higher-order processing to make more complex inferences about the visual image (object recognition, motion prediction, spatial configuration, etc.). Visualization is a narrow factor within the domain of visual processing. Visualization is the ability to perceive how an object may appear if manipulated and/or transformed.

A self-report survey of musical involvement and aptitude was used to assess musicianship. Questions inquired about the amount of time the musicians spend with their instruments and assess levels of other musical skills including sight reading. The survey included questions about type of music education, amount of private lessons taken, and group ensemble involvement (Appendix A). The survey also included questions involving the primary and secondary instruments played by the participants relating to the amount of time spent practicing and skill level with each of their instruments.

Procedures. Participants completed a formal consent to participate form. The participants were then paired with a proctor that was trained to administer the WJ IV COG. The proctor administered the visualization and picture recognition subtests of the WJ IV COG. Students from the School Psychology master's program at Humboldt State University were hired to administer the WJ-IV COG, and were compensated $10 per administration. Each participant was surveyed in a private room with the proctor. After completion of the WJ-IV, participants completed the self-report survey of musical aptitude. Participants were thanked for their time and given a $10.00 honorarium as compensation for their involvement in the study.

Analysis. Data were analyzed using R software version 1.1.463. A Welch's T-test was conducted to assess the differences between the string and non-string musician group mean scores on the measure of spatial reasoning. To compare string musicians, non-string musicians, and individuals who play both, an independent ANOVA was conducted. The assumptions of normality and homogeneity of variance were tested and found to be normal. Then a two-way factorial ANOVA was conducted to test for differences in means among groups, and effect size was assessed using a partial eta squared. Interactions were further analyzed by a test of simple effects.

Results

The data were first entered, cleaned, and factored respectively. There were seven females, 14 males, and one non-binary participant. Seven played string instruments and 16 played non-string. Participants were asked whether they played string, non-string, or both kinds of instruments. There were 17 playing both with only three playing either string or non-string. Given the normality violation, no non-adjusted statistical analysis could be used. Variables were tested for skew and kurtosis. All variables with exception of visualization, required transformation. No skew was negative therefore none required a reflected transformation. The procedure and results of this procedure are shown in Appendix A. The transformations were as follows: proficiency was fixed by a log transformation, starting age was fixed with an inverse transformation, hours per week by a log transformation, and years of training with square root transformation. All variables used were also centered to reduce unlawful error in our moderated regressions.

There were a number of observations missing on a number of dependent variables due to test administration errors. Due to the low number of participants 20 multiple imputations were used for missing test scores. Diagnostics of the convergence showed complete and normal convergence. The default test of imputed data in Zelig is robust testing. Therefore, tests involving the picture recognition and visual processing tests were computed using the robust method. Appendix A displays the imputation process.

To test the differences of visualization by instrument type, an independent samples t-test was computed. Given the differences in sample size, a Welch's correction was computed which assumes unequal variances. There were no significant differences observed between the two groups: $t(13.01) = 0.50$, $p = .622$, $d = 0.22$. To see if proficiency could predict visualization scores, a simple linear regression was computed. Adherence to regression assumptions, this model's residuals were plotted below. As shown by the Q-Q plot, the residuals were normally distributed. However, the Residuals vs. Fitted graph indicates severe heteroscedasticity and non-linearity per the loess line. Due to the presented violations, robust methods were used as they make no assumptions of normality. Every statistic following used a robust method. There was no significant relationship presented between proficiency and visualization: $b^* = -0.28$, $p = .236$. This was also tested on the imputed data with visual processing and picture recognition using robust linear regressions. There was no significant relationship observed between visual processing ($b = -4.37$, $p = .660$) or picture recognition ($b = 8.53$, $p = .400$) on musician proficiency.

A linear regression was calculated to evaluate mean differences between instrument type on visualization, visual processing, and picture recognition respectively. Given the assumption violations and imputed data, a robust linear regression was needed. There was no significant difference between instrument type on visualization ($b^* = -0.12$, $p = .629$), visual processing ($b = -8.96$, $p = .310$), or picture recognition ($b = -9.27$, $p = .260$).

Finally, the interaction between instrument type and musician proficiency on visualization, visual processing, and picture recognition was computed by three robust moderated regressions. Instrument type ($b = -9.38$, $p = .260$) and proficiency ($b = -2.37$, $p = .230$) were not related to visual processing. These findings are not qualified by a significant interaction: *b* = 1.18, *p* = .280. Similar results were found with picture recognition. Instrument type (*b* = -8.55, *p* - .330) and proficiency (*b* = 0.78, *p* = .700) did not predict picture recognition. These findings were not qualified by a significant interaction: *b* = -0.24, *p* = .830.

Contrarily, instrument proficiency (*b* = -2.34, *p* = .006), but not instrument type (*b* = -5.87, *p* = .320), predicted visualization scores. This trend was qualified by a significant interaction: *b* = 2.23, *p* = .017. A test of simple slopes further explained this interaction. For non-string players, there is no relationship between proficiency and visualization (*b* = -2.51, *p* = .766). For string players, however, visualization decreased as their proficiency increased (*b* = -47.59, *p* = .005). Ergo increased proficiency is related to decreased scores in visualization among string players only.

To further explain this relationship, participant age was added in an exploratory robust moderated regression. It would stand to reason that those with more musical proficiency may be older, and spatial reasoning capacities are known to decline with age. However, in the model age (*b* = 0.18, *p* = .196) and proficiency (*b* = -0.28, *p* = .536) were unrelated to visualization. Additionally, these findings were not qualified by a significant interaction: (*b* = 0.03, *p* = .277).

To test the visualization capacity of the sample in relation to national averages, a single subject t-test was computed using the standardized percentiles of the visualization subtest of the WJ IV COG. Because percentiles are being used, mu was set at 50 thus being the average. The sample was shown to be significantly higher than the national average (*t* (22) = 2.12, *p* = .045, *d* = 0.44) with a mean percentile ranking of 61.56.

When testing spatial reasoning differences between male and female participants, there was no significant difference observed on visualization, visual processing, and picture recognition ($p > .05$) using a Welch's t-test. However, a gender difference was observed on levels of proficiency. Female musicians in this sample had significantly higher musical proficiency than their male counterparts (t (12.24) = 2.31, p = .043).

Discussion

The primary purpose of this study is to demonstrate the spatial temporal reasoning skills of different types of instrumentalists. A number of researchers have displayed that students involved with musical instrument training score higher on spatial temporal ability tasks than students with no musical training (e.g. Rauscher & Zupan, 2000). This study is one of few that examine adult musicians who perform on a professional level and compare differences in the primary instrument played by those musicians. The results of this study do not display significant support for our hypothesis that instrumentalists that play string instruments would perform better on a measure of spatial reasoning ability when compared to instrumentalists who played non-string instruments. Due to the shelter-in-place order put into effect recently, data collection was halted during study 2. The resulting small sample size (n = 20) was restricting, and no statistically significant information regarding the relationship between musicians' primary instrument of practice and Visualization/Picture Recognition scores was found. However, a post-hoc analysis of participant’s spatial reasoning scores showed that the musicians in our study performed significantly higher on the Visualization subtest of the *Woodcock-Johnson Tests of Cognitive Abilities* (WJ IV COG) when compared with national averages. These results are consistent with previous research that has found spatial reasoning ability to be enhanced in musicians. An additional post-hoc analysis of participant’s spatial reasoning scores showed that there was no significant difference between male and female participants. Previous research on spatial reasoning has found evidence that males, compared to females, typically perform better on mental rotation tasks due to differences in brain structure (Newman, 2016). Specifically, notable differences were observed in the band of white matter that connects the corpus callosum. The differences appear to be related to viseo-spatial processing and gender. This finding of the preset study suggests that musical training may offset the disparity between genders that some research has found.

A limitation in study one was the measure of spatial reasoning that was used. Reliability for the measure was established via Cronbach alpha, and it was found not reliable and listwise alpha's indicated problem areas. This shortcoming led to the decision to use the WJ IV COG Visualization and Picture Recognition subtests for study two. It is also important to note that for study 1 this survey was administered after rehearsals, in which the musicians had been working for a few hours, this may have impacted the cognitive performance.

Another unexpected finding in study one was that many of the professional musicians had a background in formal piano training. This made finding musicians who had specialized experience with only one type of instrument very difficult. Many school-based musical-training programs, especially at the higher education level, involve instruction on the piano regardless of the primary instrument of the student. We believe this was a confounding variable in the first study, which we aimed to address with a larger sample in the second study. While the sample in our second study did have a more diverse musical background, only three participants in study two played either a string or non-string instrument and not both. The remaining 17 participants had experience with both types of instruments. Therefore, we were unable to establish an experimental or control group for proper comparison. We ultimately compared individuals whose primary instrument was string or non-string regardless of whether or not they played a secondary instrument of the comparison group. This did not yield any significant results.

Another limitation of this study was the musical aptitude survey that was used. After the first study, a few adjustments were made to inquire about practice habits and training experience with each instrument played. The intent behind the aptitude test was to see if there was an ability threshold or specific skill that could predict spatial reasoning ability of the musicians. In other words, is there a certain level of string instrument proficiency that translates into an increased ability in spatial reasoning? In addition, is there a specific skill, such as sight-reading or improvisation, that likewise translates into an increased ability in spatial reasoning? In previous research, sight-reading ability was predicted by scores on measures of aural pattern discrimination and spatial-temporal reasoning (Hayward & Gromko, 2009). Every musician we surveyed indicated that they could sight-read, and we were unable to explore this further. Future research involving spatial reasoning skills and musicians could benefit from examining the role of sight-reading abilities. Increased ability in sight-reading has been linked to increased gray-matter of Brocca's area, the same area which is required for complex visuospatial analysis (Sluming et al., 2007). Understanding the link between this musical training and the previously demonstrated increase in spatial reasoning abilities could lead researchers to better understand how cognitive processes can be enhanced through use of non-traditional training methods.

Music programs are often among the first to lose funding when school budgets are tight. This research and similar research into the enhancement of nonmusical abilities through musical training can influence pedagogical decisions made by policy makers. Previous research has already provided support for non-musical benefits, such as spatial reasoning, of instrumental music training. Future research could benefit from further analysis of professional adult musicians, as well as examining a large variety of instrumentalists. The enhancement of nonmusical abilities, specifically those related to spatial reasoning, through the study of music may be appealing to those who wish to excel in STEM fields. Moreover, if training on specific instruments can provide a greater enhancement in these areas, then further research may provide insight into what cognitive processes involved in playing these instruments produce a greater increase in spatial reasoning abilities. If string instrumentalists have stronger spatial reasoning skills than other instrumentalists, educators who are interested in developing STEM skills along with musical skills will encourage students to choose these instruments. Members of a professional symphony orchestra provide an excellent opportunity to study the potential long-term effects associated with acquiring and sustaining expert musical performance skills (Sluming et al., 2007). This line of research has real world applications that warrant further exploration. Implications include support and advocacy for musical curriculums and practice throughout adulthood, due to the cognitive benefits of instrument practice.

In conclusion, the results of this study demonstrate the spatial abilities of professional orchestral musicians. This study contributes a unique feature to the field of music cognition in that it is one of few studies that involve professional adult musicians and compare such a large variety of instrumentalists. This research aids in understanding what aspects of music involvement lends to improvements of extra musical learning, such as spatial temporal reasoning.

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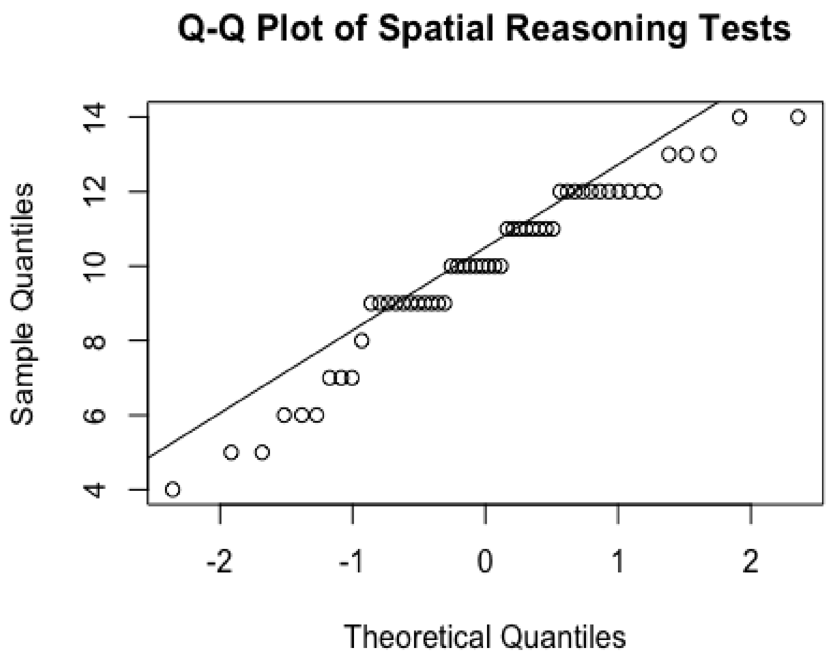
Appendix

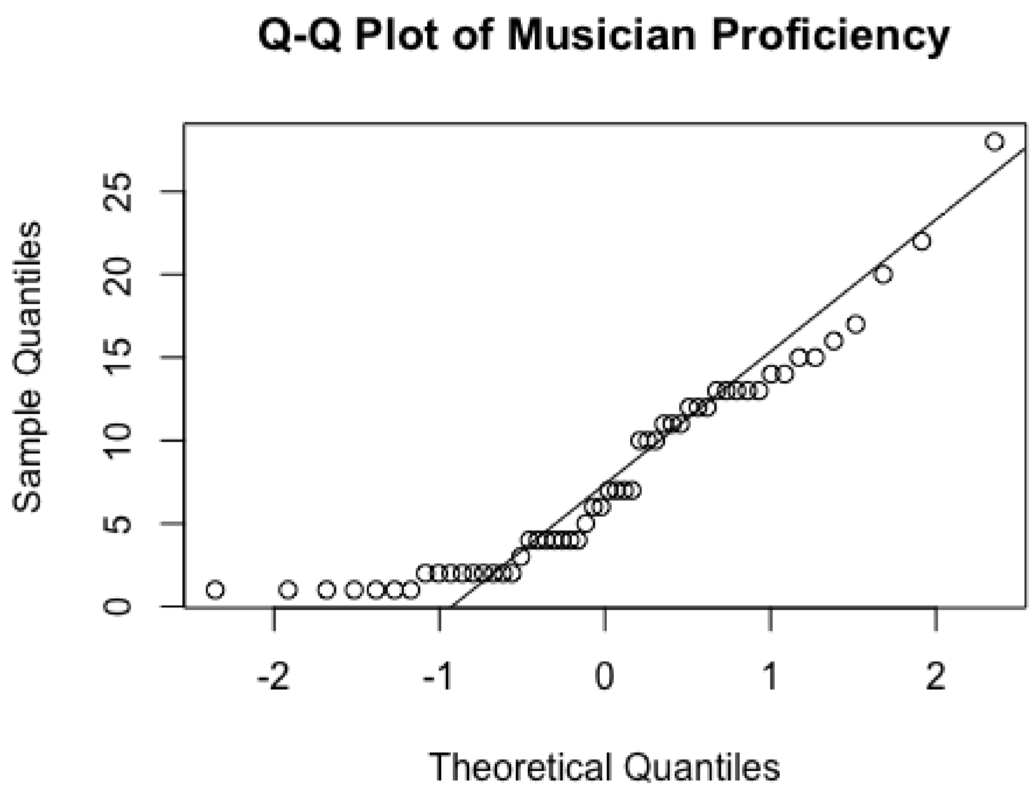
Study 1

```
stu1<-data.frame(study1$total1,study1$total2, study1$totalall, st
udy1$Prim_String_1Non_2Per_3, study1$combined.proficiency, study1
$gender, study1$age, study1$education)

stu1$study1.Prim_String_1Non_2Per_3<-factor(stu1$study1.Prim_Stri
ng_1Non_2Per_3, levels = c(1:3))
levels(stu1$study1.Prim_String_1Non_2Per_3)[1]<-"String"
levels(stu1$study1.Prim_String_1Non_2Per_3)[2]<-"non"

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

stu1<-filter(stu1, study1.Prim_String_1Non_2Per_3=="String" | stu
dy1.Prim_String_1Non_2Per_3=="non")
stu1$inst<-droplevels(stu1$study1.Prim_String_1Non_2Per_3)

stu1$study1.gender<-factor(stu1$study1.gender, levels = c(1:2))
levels(stu1$study1.gender)[1]<-"male"
levels(stu1$study1.gender)[2]<-"female"

stu1$study1.education<-factor(stu1$study1.education, levels = c(1
:8))
levels(stu1$study1.education)[1]<-"none"
levels(stu1$study1.education)[2]<-"some hs"
levels(stu1$study1.education)[3]<-"high school"
levels(stu1$study1.education)[4]<-"trade"
levels(stu1$study1.education)[5]<-"some col"
```

```
levels(stu1$study1.education)[6]<-"College"
levels(stu1$study1.education)[7]<-"Masters"
levels(stu1$study1.education)[8]<-"Doctor"

table(stu1$study1.education)

##
##         none      some hs high school       trade     some col
College
##            0            0            2            0            7
12
##      Masters       Doctor
##           31            1

table(stu1$study1.gender)

##
##   male female
##     23     30

DescTools::Skew(stu1$study1.totalall, method=2, conf.level = .99)

##         skew      lwr.ci      upr.ci
## -0.63057606 -1.21128791 -0.09123593

DescTools::Kurt(stu1$study1.totalall, method = 2, conf.level = .9
9)

##         kurt      lwr.ci      upr.ci
##  0.01667471 -0.98978152  2.09667605

qqnorm(stu1$study1.totalall, main = "Q-Q Plot of Spatial Reasonin
g Tests");qqline(stu1$study1.totalall)
```

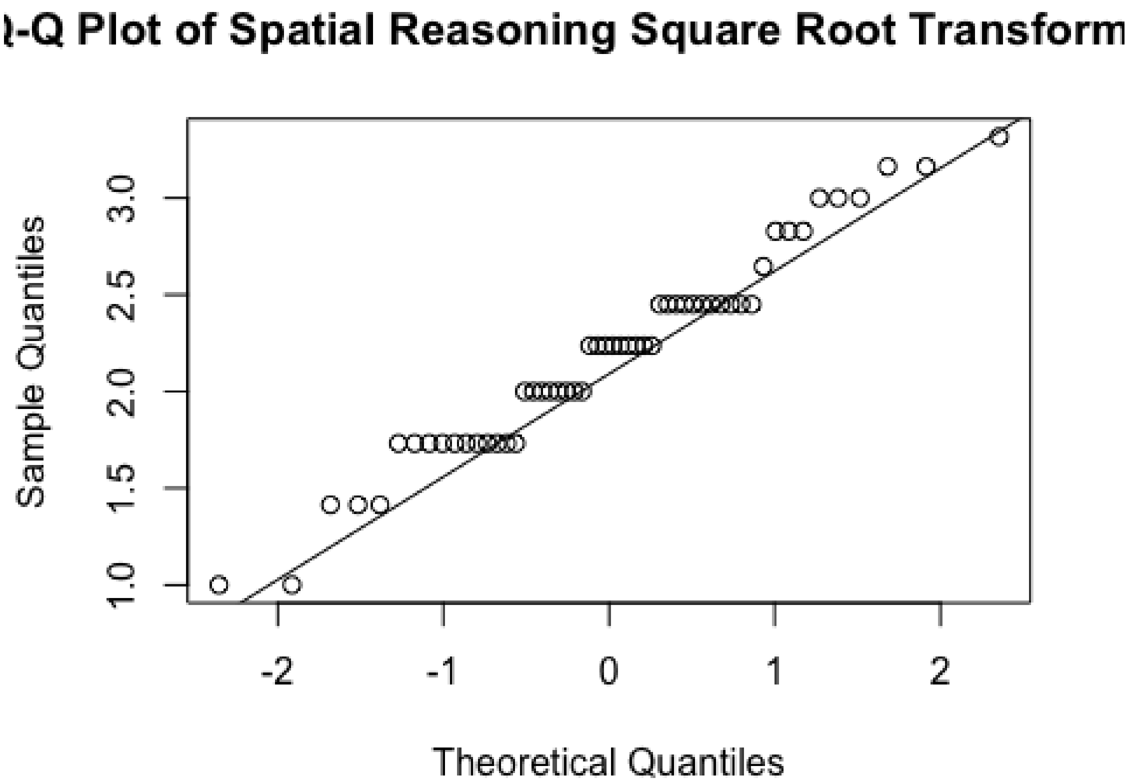



```
DescTools::Skew(stu1$study1.combined.proficiency, method = 2, con
f.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##      skew    lwr.ci    upr.ci
## 0.9078863 0.1745459 1.8756896

DescTools::Kurt(stu1$study1.combined.proficiency, method = 2, con
f.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
##  0.5862048 -1.2114591  3.9320155

qqnorm(stu1$study1.combined.proficiency, main = "Q-Q Plot of Musi
cian Proficiency");qqline(stu1$study1.combined.proficiency)
```




```
summary(stu1$study1.totalall)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   4.000   9.000  10.000   9.944  12.000  14.000

stu1$totalsq<-(14-stu1$study1.totalall+1)^.5
stu1$totallog<-log10(14-stu1$study1.totalall+1)
stu1$totalin<-1/((14-stu1$study1.totalall)+1)

stu1$profsq<-(stu1$study1.combined.proficiency+1)^.5
stu1$proflog<-log10(stu1$study1.combined.proficiency+1)
stu1$profin<-1/(stu1$study1.combined.proficiency+1)

DescTools::Skew(stu1$study1.totalall, method=2, conf.level = .99)

##        skew      lwr.ci      upr.ci
## -0.63057606 -1.36194685 -0.02930425
```

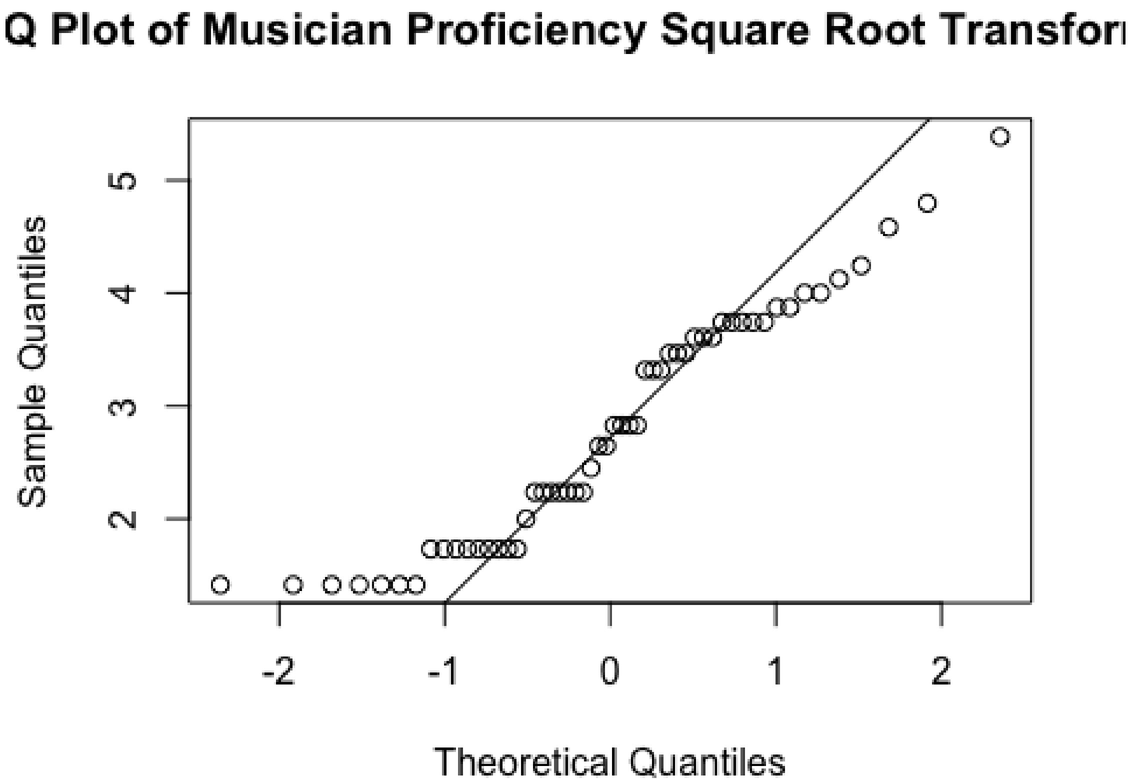
```
DescTools::Kurt(stu1$study1.totalall, method = 2, conf.level = .9
9)

##        kurt      lwr.ci      upr.ci
##  0.01667471 -1.05015948  2.49713878

DescTools::Skew(stu1$totalsq, method=2, conf.level = .99)

##        skew      lwr.ci      upr.ci
##  0.02022902 -0.69119078  0.67474222

DescTools::Kurt(stu1$totalsq, method=2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.1296319 -1.0577086  1.4230555

DescTools::Skew(stu1$totallog, method=2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       skew     lwr.ci     upr.ci
## -0.7821804 -1.5862857  0.1834779

DescTools::Kurt(stu1$totallog, method=2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
##  1.1093514 -0.8742403  3.6508331

DescTools::Skew(stu1$totalin, method=2, conf.level = .99)

##      skew    lwr.ci    upr.ci
## 2.8796292 0.7312527 4.2878906

DescTools::Kurt(stu1$totalin, method=2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
## 10.0422865  0.1115757 26.8904323

qqnorm(stu1$totalsq, main = "Q-Q Plot of Spatial Reasoning Square
Root Transformation"); qqline(stu1$totalsq)
```



a

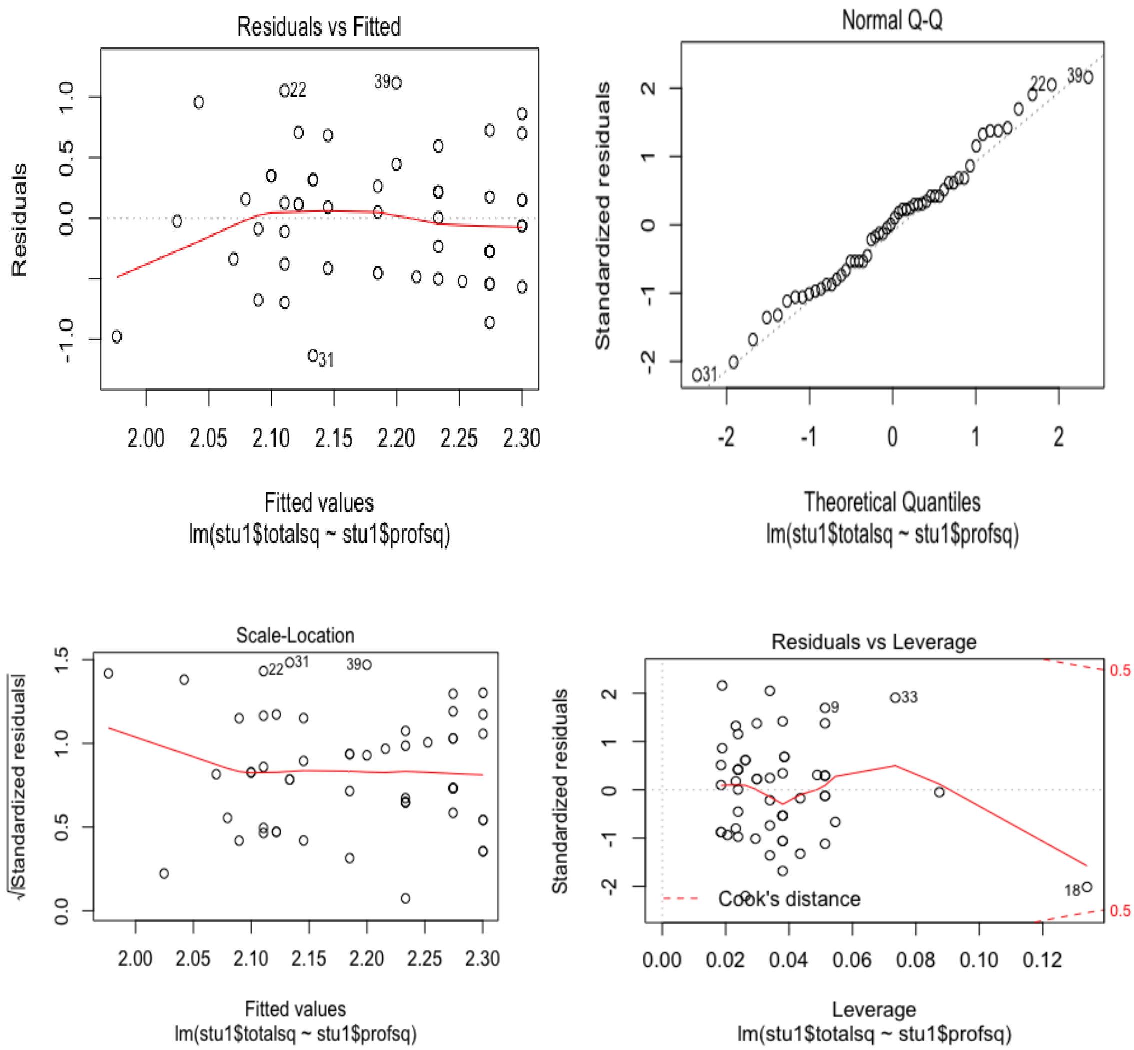
```
DescTools::Skew(stu1$study1.combined.proficiency, method = 2, con
f.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##      skew    lwr.ci    upr.ci
## 0.9078863 0.1432621 1.8319292

DescTools::Kurt(stu1$study1.combined.proficiency, method = 2, con
f.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
##  0.5862048 -1.3538902  5.0115634
```

```
DescTools::Skew(stu1$profsq, method=2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.3176352 -0.2856222  1.0288211

DescTools::Kurt(stu1$profsq, method=2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
## -0.8955123 -1.5578588  1.4859774

DescTools::Skew(stu1$proflog, method=2, conf.level = .99)

##       skew     lwr.ci     upr.ci
## -0.1493946 -0.7587856  0.4494831

DescTools::Kurt(stu1$proflog, method=2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -1.2718070 -1.6775582 -0.7010882

DescTools::Skew(stu1$profin, method=2, conf.level = .99)

##      skew    lwr.ci    upr.ci
## 0.9117810 0.3044958 1.7284240

DescTools::Kurt(stu1$profin, method=2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.4559195 -1.4705001  2.1161032

qqnorm(stu1$profsq, main = "Q-Q Plot of Musician Proficiency Squa
re Root Transformation");qqline(stu1$profsq)
```




```
tapply(stu1$study1.combined.proficiency, stu1$inst, var)

##   String      non
## 41.34413 36.45714

table(stu1$inst)

##
## String    non
##     39     15

t.test(stu1$profsq~stu1$inst, var.equal=FALSE)

##
##  Welch Two Sample t-test
##
## data:  stu1$profsq by stu1$inst
## t = 0.48523, df = 26.147, p-value = 0.6316
## alternative hypothesis: true difference in means is not equal
```

```
to 0
## 95 percent confidence interval:
##  -0.4964034  0.8032961
## sample estimates:
## mean in group String    mean in group non
##             2.837764             2.684317

lsr::cohensD(stu1$profsq~stu1$inst)

## [1] 0.1454768

tapply(stu1$totalsq, stu1$inst, var)

##    String       non
## 0.2727667 0.2634804

table(stu1$inst)

##
## String    non
##     39     15

t.test(stu1$totalsq~stu1$inst, var.equal = FALSE)

##
##  Welch Two Sample t-test
##
## data:  stu1$totalsq by stu1$inst
## t = -1.3678, df = 25.858, p-value = 0.1831
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##  -0.5365729  0.1078611
## sample estimates:
## mean in group String    mean in group non
##             2.128168             2.342524

lsr::cohensD(stu1$totalsq~stu1$inst)

## [1] 0.4123247

reg<-lm(stu1$totalsq~stu1$profsq)
plot(reg)
```




```
library(MASS)

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

rob<-rlm(stu1$study1.totalall~stu1$study1.combined.proficiency)
summary(rob)
```

```
##
## Call: rlm(formula = stu1$study1.totalall ~ stu1$study1.combine
d.proficiency)
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.04871 -1.28110 -0.04254  1.67533  3.66080
##
## Coefficients:
##                                  Value   Std. Error t value
## (Intercept)                       9.7001  0.5133    18.8993
## stu1$study1.combined.proficiency  0.0581  0.0511     1.1374
##
## Residual standard error: 2.115 on 52 degrees of freedom
```

```
2*pt(-1.13, df=52)
```

```
## [1] 0.2636617
```

```
QuantPsyc::lm.beta(rob)
```

```
## stu1$study1.combined.proficiency
##                        0.1568766
```

```
stu1$profcen<-as.numeric(scale(stu1$study1.combined.proficiency,
scale = FALSE))

library(MASS)
robust<-rlm(study1.totalall~inst*profcen, stu1)
summary(robust)
```

```
##
## Call: rlm(formula = study1.totalall ~ inst * profcen, data = s
tu1)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.2362 -1.2539  0.1224  1.4505  3.4103
##
## Coefficients:
##                 Value   Std. Error t value
## (Intercept)     10.3697  0.3748    27.6676
## instnon         -0.8260  0.7142    -1.1564
## profcen          0.0707  0.0590     1.1981
## instnon:profcen -0.0638  0.1191    -0.5353
```

```
##
## Residual standard error: 2.105 on 50 degrees of freedom
```

```
2*pt(-1.16, df=50)
```

```
## [1] 0.251558
```

```
2*pt(-1.20, df=50)
```

```
## [1] 0.2357945
```

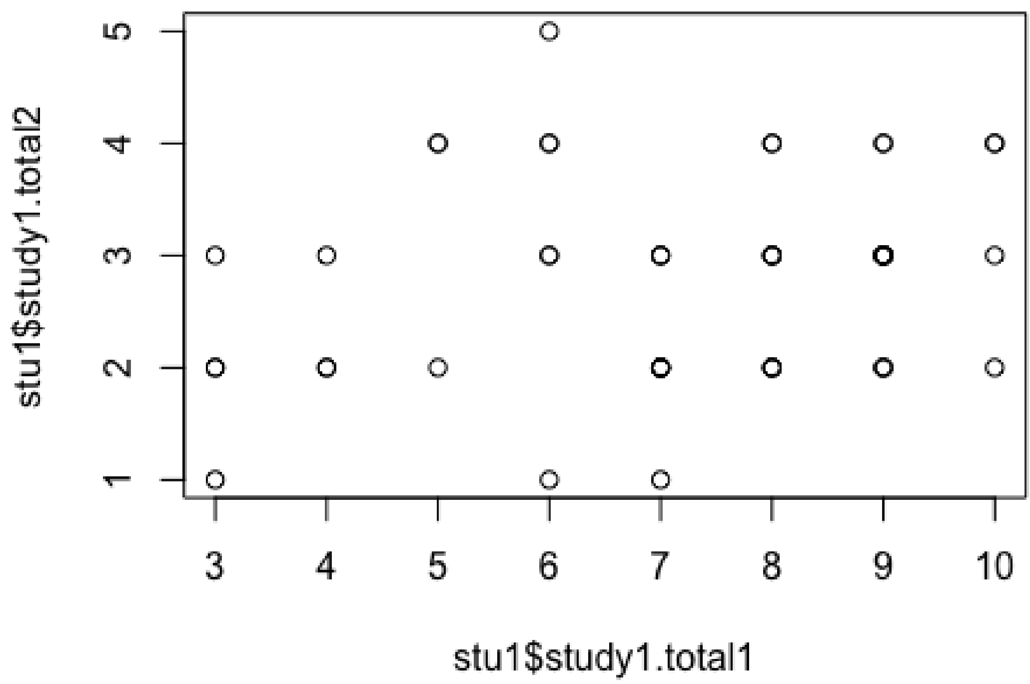
```
2*pt(-0.53, df=50)
```

```
## [1] 0.5984578
```

```
cor.test(stu1$study1.total1, stu1$study1.total2)
```

```
##
##  Pearson's product-moment correlation
##
## data:  stu1$study1.total1 and stu1$study1.total2
## t = 1.5731, df = 52, p-value = 0.1218
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.05793507  0.45493021
## sample estimates:
##       cor
## 0.2131317
```

```
plot(stu1$study1.total1, stu1$study1.total2)
```




```
test1<-data.frame(study1$X.1, study1$X.2, study1$X.3, study1$X.4,
study1$X.5, study1$X.6, study1$X.7, study1$X.8, study1$X.9, study
1$X.10)
psych::alpha(test1,check.keys=TRUE)

## Warning in psych::alpha(test1, check.keys = TRUE): Item = stud
y1.X.2 had no
## variance and was deleted

## Warning in psych::alpha(test1, check.keys = TRUE): Some items
were negatively correlated with total scale and were automaticall
y reversed.
##  This is indicated by a negative sign for the variable name.

##
## Reliability analysis
## Call: psych::alpha(x = test1, check.keys = TRUE)
##
```

```
##   raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd me
dian_r
##       0.68       0.7    0.72       0.2 2.3 0.062  0.7 0.23
0.2
##
##  lower alpha upper     95% confidence boundaries
## 0.56 0.68 0.8
##
##  Reliability if an item is dropped:
##              raw_alpha std.alpha G6(smc) average_r S/N alpha s
e var.r
## study1.X.1        0.66      0.66    0.67      0.19 1.9    0.06
7 0.017
## study1.X.3        0.60      0.62    0.64      0.17 1.7    0.07
9 0.013
## study1.X.4        0.65      0.67    0.68      0.20 2.0    0.06
7 0.015
## study1.X.5        0.66      0.68    0.69      0.21 2.1    0.06
6 0.015
## study1.X.6        0.66      0.68    0.69      0.21 2.1    0.06
5 0.017
## study1.X.7        0.63      0.66    0.68      0.20 1.9    0.07
2 0.018
## study1.X.8        0.68      0.70    0.71      0.23 2.3    0.06
2 0.017
## study1.X.9        0.64      0.66    0.69      0.20 2.0    0.07
1 0.019
## study1.X.10-      0.70      0.72    0.73      0.24 2.5    0.05
7 0.015
##              med.r
## study1.X.1    0.19
## study1.X.3    0.18
## study1.X.4    0.19
## study1.X.5    0.20
## study1.X.6    0.18
## study1.X.7    0.19
## study1.X.8    0.22
## study1.X.9    0.19
## study1.X.10-  0.23
##
##  Item statistics
##               n raw.r std.r r.cor r.drop mean   sd
```

```
## study1.X.1   57  0.53  0.61  0.56   0.45 0.95 0.23
## study1.X.3   57  0.74  0.74  0.73   0.60 0.65 0.48
## study1.X.4   57  0.53  0.56  0.49   0.36 0.77 0.42
## study1.X.5   57  0.47  0.51  0.43   0.34 0.89 0.31
## study1.X.6   57  0.53  0.53  0.44   0.33 0.67 0.48
## study1.X.7   57  0.63  0.59  0.52   0.45 0.42 0.50
## study1.X.8   57  0.41  0.42  0.30   0.23 0.79 0.41
## study1.X.9   57  0.61  0.58  0.49   0.43 0.63 0.49
## study1.X.10- 57  0.38  0.35  0.18   0.15 0.54 0.50
##
## Non missing response frequency for each item
##                 0    1 miss
## study1.X.1  0.05 0.95    0
## study1.X.3  0.35 0.65    0
## study1.X.4  0.23 0.77    0
## study1.X.5  0.11 0.89    0
## study1.X.6  0.33 0.67    0
## study1.X.7  0.58 0.42    0
## study1.X.8  0.21 0.79    0
## study1.X.9  0.37 0.63    0
## study1.X.10 0.54 0.46    0
```

```
test2<-data.frame(study1$X.11, study1$X.12, study1$X.13, study1$X
.14, study1$X.14, study1$X.15)
psych::alpha(test2,check.keys=TRUE)
```

```
## The determinant of the smoothed correlation was zero.
## This means the objective function is not defined.
## Chi square is based upon observed residuals.

## In factor.stats, the correlation matrix is singular, an approx
imation is used

## Warning in psych::alpha(test2, check.keys = TRUE): Some items
were negatively correlated with total scale and were automaticall
y reversed.
##  This is indicated by a negative sign for the variable name.

## In smc, smcs < 0 were set to .0

## Warning in cor.smooth(R): Matrix was not positive definite, sm
oothing was
## done
```

```
## In smc, smcs < 0 were set to .0

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## In smc, smcs < 0 were set to .0

## Warning in cor.smooth(R): Matrix was not positive definite, sm
oothing was
## done

## In smc, smcs < 0 were set to .0
## In smc, smcs < 0 were set to .0

##
Reliability analysis

Call: psych::alpha(x = test2, check.keys = TRUE)


  raw_alpha std.alpha G6(smc) average_r  S/N   ase mean   sd medi
an_r

      0.28      0.27    0.29      0.07 0.38 0.036 0.31 0.22    0.
028


 lower alpha upper     95% confidence boundaries

0.21 0.28 0.35


 Reliability if an item is dropped:

             raw_alpha std.alpha G6(smc) average_r  S/N alpha se
var.r  med.r

study1.X.11       0.21      0.21    0.21     0.064 0.27    0.041
0.016  0.015

study1.X.12       0.16      0.16    0.16     0.045 0.19    0.044
0.016  0.028

study1.X.13       0.32      0.31    0.29     0.101 0.45    0.035
0.014  0.078
```
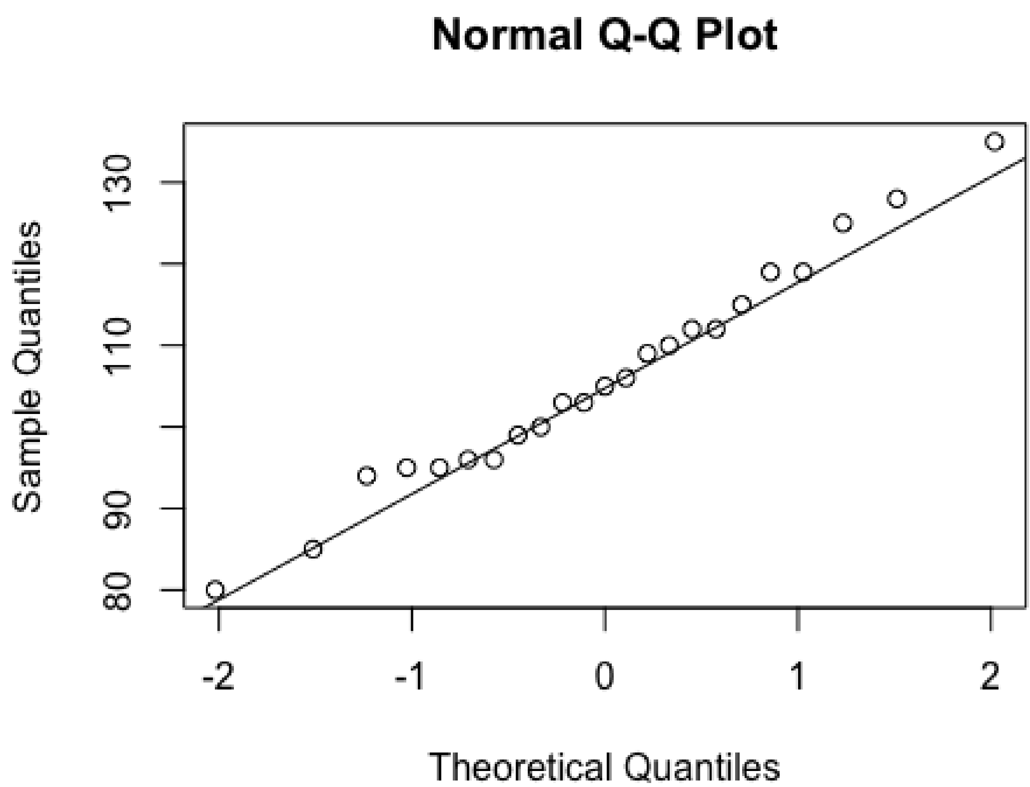

```
study1.X.14-       0.15       0.13     0.15      0.036 0.15     0.043
0.021 -0.019

study1.X.15-       0.32       0.31     0.31      0.103 0.46     0.035
0.026  0.085


 Item statistics

              n raw.r std.r r.cor r.drop mean   sd

study1.X.11   57  0.54  0.52 0.314  0.158 0.25 0.43

study1.X.12   57  0.60  0.56 0.405  0.205 0.68 0.47

study1.X.13   57  0.41  0.43 0.128  0.035 0.21 0.41

study1.X.14- 57  0.57  0.59 0.432  0.227 0.21 0.41

study1.X.15- 57  0.41  0.43 0.075  0.035 0.21 0.41


Non missing response frequency for each item

               0    1 miss

study1.X.11 0.75 0.25 0.94

study1.X.12 0.32 0.68 0.94

study1.X.13 0.79 0.21 0.94

study1.X.14 0.21 0.79 0.94

study1.X.15 0.21 0.79 0.94
```

Study 2

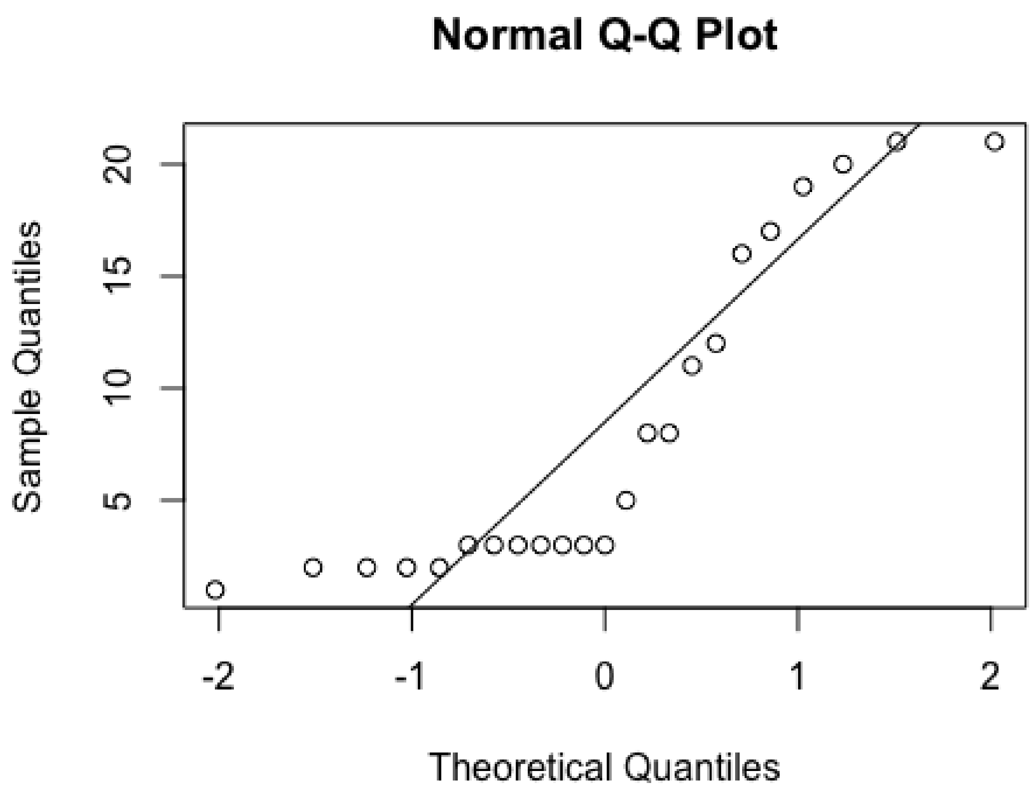
```
study2<-read.csv(file = "/Users/Desktop/Study 2.CSV", header = TR
UE, sep = ",")

study2$visualpro<-study2$VISUAL.PROCESSING..Gv..SS..95..Band.
study2$visualization<-study2$VISUALIZATION.SS..95...Band
study2$pic<-study2$PICTURE.RECOGNITION.SS..95...BAND
```

```
new<-data.frame(study2$Age, study2$Sex, study2$Education, study2$
visualpro, study2$visualization, study2$pic, study2$Combined.Prof
iciency, study2$Primary.inst.Key, study2$Overall.Instruments, stu
dy2$Years.of.Training, study2$Hours.per.Week, study2$Starting.Age
)

new$study2.Primary.inst.Key<-factor(new$study2.Primary.inst.Key,
levels = c(1:2))
levels(new$study2.Primary.inst.Key)[1]<-"String"
levels(new$study2.Primary.inst.Key)[2]<-"non"

new$study2.Overall.Instruments<-factor(new$study2.Overall.Instrum
ents, levels = c(1:3))
levels(new$study2.Overall.Instruments)[1]<-"String"
levels(new$study2.Overall.Instruments)[2]<-"non"
levels(new$study2.Overall.Instruments)[3]<-"both"

new$study2.Education<-factor(new$study2.Education, levels = c(1:8
))
levels(new$study2.Education)[1]<-"none"
levels(new$study2.Education)[2]<-"some hs"
levels(new$study2.Education)[3]<-"high school"
levels(new$study2.Education)[4]<-"trade"
levels(new$study2.Education)[5]<-"some col"
levels(new$study2.Education)[6]<-"College"
levels(new$study2.Education)[7]<-"Masters"
levels(new$study2.Education)[8]<-"Doctor"

table(new$study2.Sex)

##
##     f  m nb
##  1  7 14  1

table(new$study2.Primary.inst.Key)

##
## String    non
##      7     16

table(new$study2.Overall.Instruments)
```

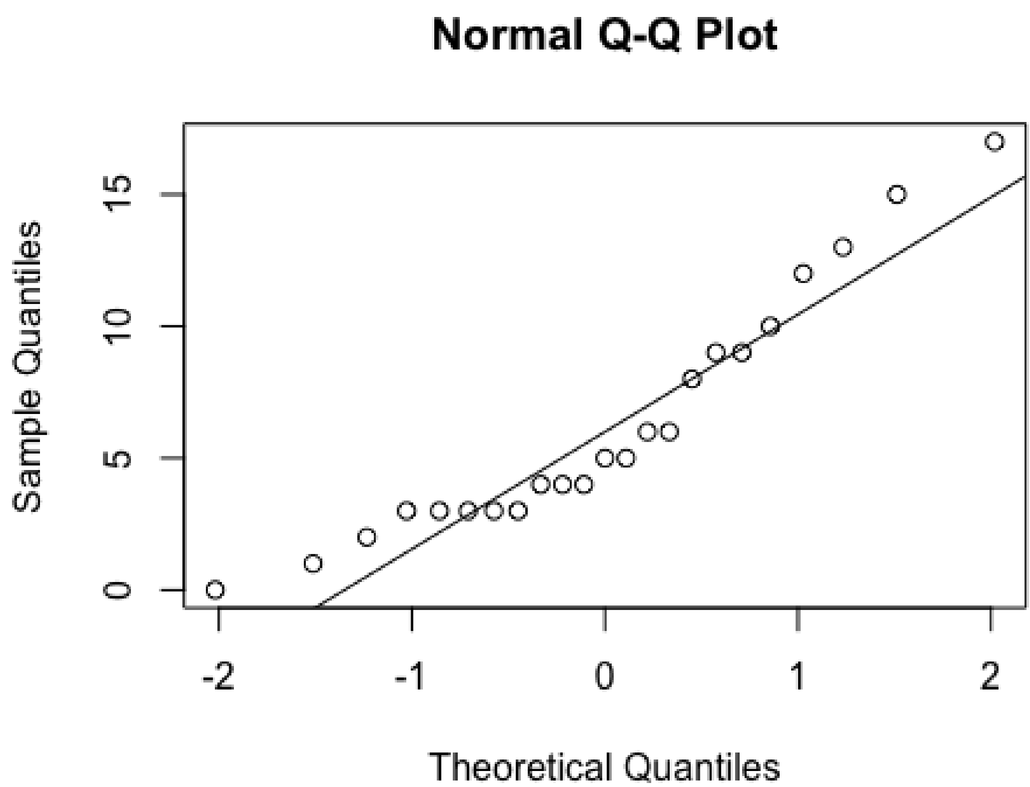
```
##
## String    non   both
##      3      3     17

table(new$study2.Education)

##
##        none      some hs high school       trade    some col
College
##           0           1           0           0          11
5
##     Masters      Doctor
##           4           2

##Visualization requires no transformation
DescTools::Skew(new$study2.visualization, method = 2, conf.level
= .99)

##       skew     lwr.ci     upr.ci
##  0.2455697 -0.7272091  1.3966739

DescTools::Kurt(new$study2.visualization, method = 2, conf.level
= .99)

##       kurt     lwr.ci     upr.ci
## -0.1155584 -1.3718625  3.6755105

qqnorm(new$study2.visualization);qqline(new$study2.visualization)
```




```
##Music proficiency requires a transformation
DescTools::Skew(new$study2.Combined.Proficiency, method = 2, conf
.level = .99)

##       skew     lwr.ci     upr.ci
##  0.8011288 -0.3356069  2.4146795

DescTools::Kurt(new$study2.Combined.Proficiency, method = 2, conf
.level = .99)

##      kurt    lwr.ci    upr.ci
## -1.025217 -2.013283  4.922571

qqnorm(new$study2.Combined.Proficiency);qqline(new$study2.Combine
d.Proficiency)
```

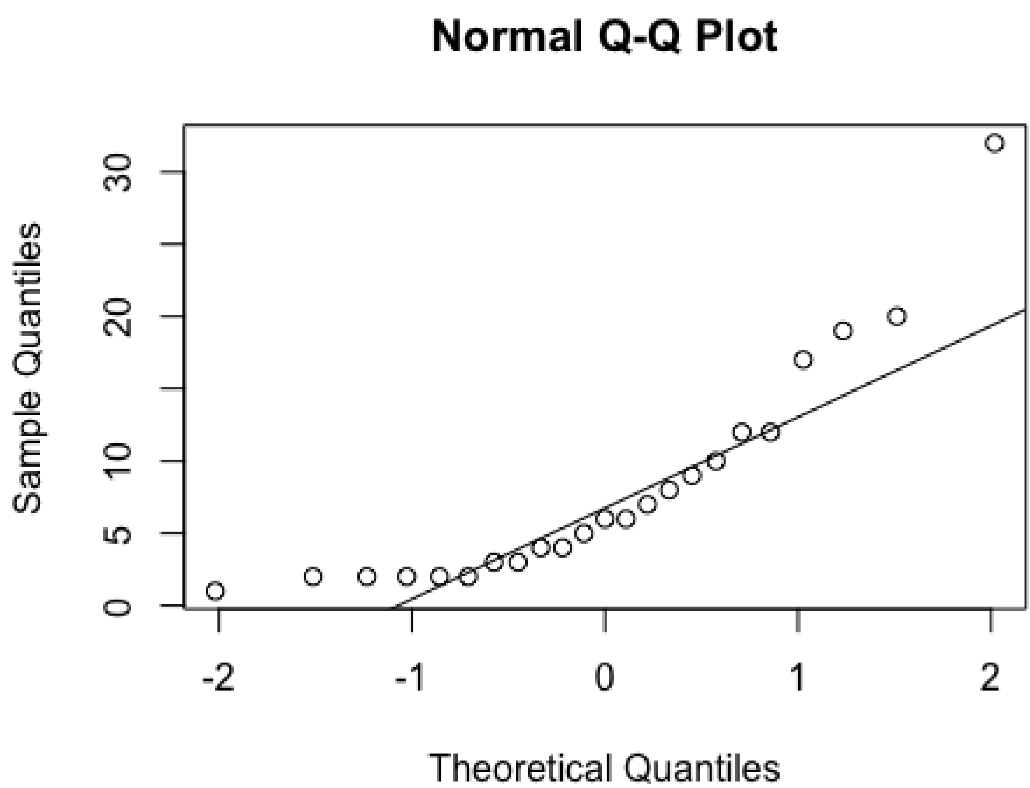



```
##Years of traning requires a transformation
DescTools::Skew(new$study2.Years.of.Training, method = 2, conf.le
vel = .99)

##        skew      lwr.ci      upr.ci
##  0.91948908 -0.06805277  2.43585853

DescTools::Kurt(new$study2.Years.of.Training, method = 2, conf.le
vel = .99)

##       kurt     lwr.ci     upr.ci
##  0.0538453 -1.4726912  7.0584440

qqnorm(new$study2.Years.of.Training);qqline(new$study2.Years.of.T
raining)
```



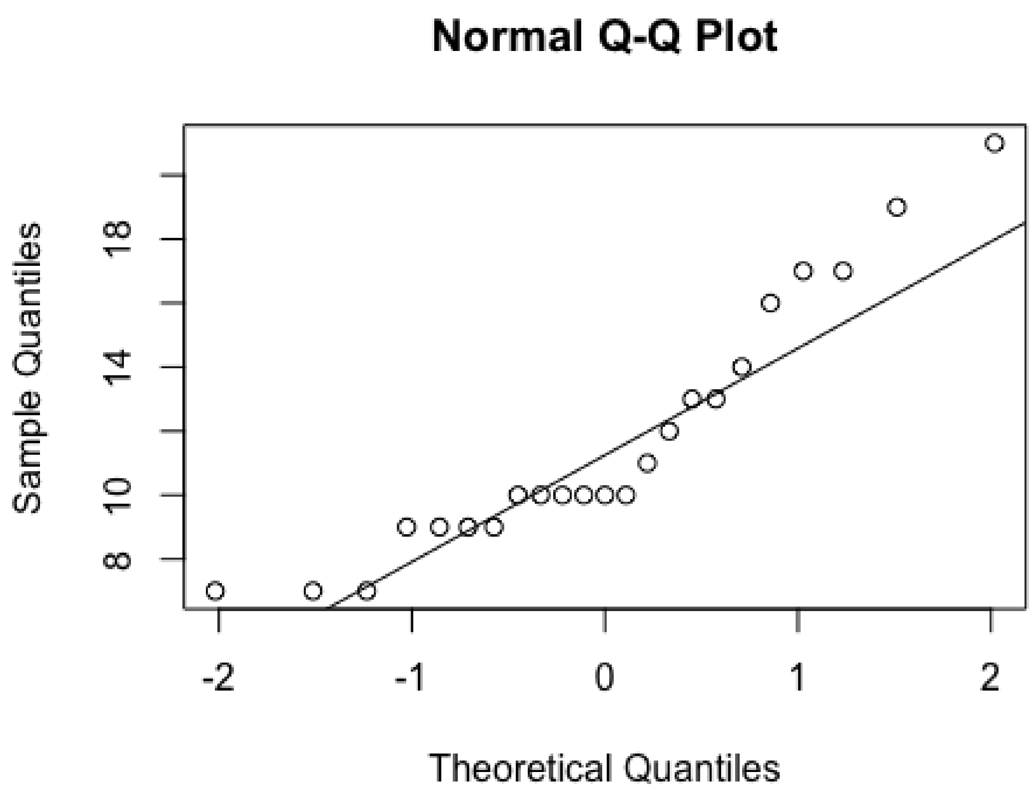

```
##Hours per week requires a transformation
DescTools::Skew(new$study2.Hours.per.Week, method = 2, conf.level
= .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##      skew    lwr.ci    upr.ci
## 1.6941890 0.6160819 3.5952596

DescTools::Kurt(new$study2.Hours.per.Week, method = 2, conf.level
= .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints
```

```
##       kurt     lwr.ci     upr.ci
##  3.0714410 -0.7270857 14.1313076

qqnorm(new$study2.Hours.per.Week);qqline(new$study2.Hours.per.Wee
k)
```




```
##Starting age requires a transformation
DescTools::Skew(new$study2.Starting.Age,method = 2, conf.level =
.99)

##       skew     lwr.ci     upr.ci
## 0.93878057 0.06101243 2.35902367

DescTools::Kurt(new$study2.Starting.Age, method = 2, conf.level =
.99)

##        kurt      lwr.ci      upr.ci
##  0.07353612 -1.58509653  6.22813122
```

```
qqnorm(new$study2.Starting.Age);qqline(new$study2.Starting.Age)
```




```
new$profsqrt<-(new$study2.Combined.Proficiency+1)^.5
new$proflog<-log10(new$study2.Combined.Proficiency+1)
new$profin<-1/(new$study2.Combined.Proficiency+1)

new$sagesqrt<-(new$study2.Starting.Age+1)^.5
new$sagelog<-log10(new$study2.Starting.Age+1)
new$sagein<-1/(new$study2.Starting.Age+1)

new$hoursqrt<-(new$study2.Hours.per.Week+1)^.5
new$hourlog<-log10(new$study2.Hours.per.Week+1)
new$hourin<-1/(new$study2.Hours.per.Week+1)

new$yearsqrt<-(new$study2.Years.of.Training+1)^.5
new$yearlog<-log10(new$study2.Years.of.Training+1)
new$yearin<-1/(new$study2.Years.of.Training+1)
```

```
##Music Proficiency
DescTools::Skew(new$study2.Combined.Proficiency, method = 2, conf
.level = .99)

##       skew     lwr.ci     upr.ci
##  0.8011288 -0.4028665  2.3339193

DescTools::Kurt(new$study2.Combined.Proficiency, method = 2, conf
.level = .99)

##      kurt    lwr.ci    upr.ci
## -1.025217 -1.986733  3.928132

DescTools::Skew(new$profsqrt, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.5806577 -0.4148044  1.9660302

DescTools::Kurt(new$profsqrt, method = 2, conf.level = .99)

##      kurt    lwr.ci    upr.ci
## -1.341563 -2.041432  3.266199

DescTools::Skew(new$proflog, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.3179793 -0.6546094  1.4164938

DescTools::Kurt(new$proflog, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -1.5033568 -2.0025104  0.4444281

DescTools::Skew(new$profin, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       skew     lwr.ci     upr.ci
##  0.4813950 -0.5081339  1.5364651

DescTools::Kurt(new$profin, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints
```

```
##       kurt     lwr.ci     upr.ci
## -0.4167065 -1.7656796  3.5607391

##Starting Age
DescTools::Skew(new$study2.Starting.Age, method = 2, conf.level =
.99)

##         skew       lwr.ci       upr.ci
##  0.938780573 -0.008106922  2.253072993

DescTools::Kurt(new$study2.Starting.Age, method = 2, conf.level =
.99)

##        kurt      lwr.ci      upr.ci
##  0.07353612 -1.48245298  6.09189698

DescTools::Skew(new$sagesqrt, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.7024458 -0.1211546  1.9446743

DescTools::Kurt(new$sagesqrt, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.3151611 -1.5972583  3.8240067

DescTools::Skew(new$sagelog, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.4527775 -0.5404076  1.2842117

DescTools::Kurt(new$sagelog, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.5598676 -1.5106215  2.8189171

DescTools::Skew(new$sagein, method = 2, conf.level = .99)

##        skew      lwr.ci      upr.ci
##  0.08070448 -0.95483779  0.88502333

DescTools::Kurt(new$sagein, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.5954729 -1.6048669  1.4754204
```

```
##Hours Practicing per Week
DescTools::Skew(new$study2.Hours.per.Week, method = 2, conf.level
= .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##      skew    lwr.ci    upr.ci
## 1.6941890 0.6756044 3.5831503

DescTools::Kurt(new$study2.Hours.per.Week, method = 2, conf.level
= .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
##  3.0714410 -0.9251522 13.3049672

DescTools::Skew(new$hoursqrt, method = 2, conf.level = .99)

##      skew    lwr.ci    upr.ci
## 0.9720986 0.1057971 2.1655495

DescTools::Kurt(new$hoursqrt, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       kurt     lwr.ci     upr.ci
##  0.4551476 -1.3254763  7.8074068

DescTools::Skew(new$hourlog, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.3190395 -0.5760904  1.3686227

DescTools::Kurt(new$hourlog, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.8112427 -1.6155817  2.9292103

DescTools::Skew(new$hourin, method = 2, conf.level = .99)
```

```
##       skew     lwr.ci     upr.ci
##  0.7790430 -0.2195329  2.0454621

DescTools::Kurt(new$hourin, method = 2, conf.level = .99)

##        kurt      lwr.ci      upr.ci
## -0.08663917 -1.76048139  4.54252740

##Years of Training
DescTools::Skew(new$study2.Years.of.Training, method = 2, conf.le
vel = .99)

##       skew     lwr.ci     upr.ci
## 0.91948908 0.03986281 2.22603533

DescTools::Kurt(new$study2.Years.of.Training, method = 2, conf.le
vel = .99)

##       kurt     lwr.ci     upr.ci
##  0.0538453 -1.4640720  7.0017821

DescTools::Skew(new$yearsqrt, method = 2, conf.level = .99)

##       skew     lwr.ci     upr.ci
##  0.3336689 -0.6828066  1.2992092

DescTools::Kurt(new$yearsqrt, method = 2, conf.level = .99)

##       kurt     lwr.ci     upr.ci
## -0.4121099 -1.5142531  3.4279793

DescTools::Skew(new$yearlog, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##       skew     lwr.ci     upr.ci
## -0.5665588 -1.9587759  0.5973125

DescTools::Skew(new$yearlog, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints
```

```
##        skew      lwr.ci      upr.ci
## -0.5665588 -1.5754057  0.6868155

DescTools::Skew(new$yearin, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##      skew   lwr.ci   upr.ci
## 3.051200 1.237495 4.170073

DescTools::Kurt(new$yearin, method = 2, conf.level = .99)

## Warning in norm.inter(t, adj.alpha): extreme order statistics
used as
## endpoints

##        kurt      lwr.ci      upr.ci
## 11.1849394 -0.1409884 19.3167352

##Centering of Transformed Variables
new$profcen<-as.numeric(scale(new$study2.Combined.Proficiency, sc
ale = FALSE))
new$agecen<-as.numeric(scale(new$study2.Starting.Age, scale = FAL
SE))
new$hourcen<-as.numeric(scale(new$study2.Hours.per.Week, scale =
FALSE))
new$yearscen<-as.numeric(scale(new$study2.Years.of.Training, scal
e = FALSE))

##Centering of Untransformed Variables
new$proflogcen<-as.numeric(scale(new$proflog, scale = FALSE))
new$sageincen<-as.numeric(scale(new$sagein, scale = FALSE))
new$hourlogcen<-as.numeric(scale(new$hourlog, scale = FALSE))
new$yearsqrtcen<-as.numeric(scale(new$yearsqrt, scale = FALSE))

new$inst<-as.numeric(new$study2.Primary.inst.Key)

summary(new$study2.visualpro)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    78.0   103.0   109.0   109.2   117.5   127.0       4

summary(new$study2.pic)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    76.0   103.0   108.0   108.3   115.5   137.0       4
```

```
new$inst<-as.numeric(new$study2.Primary.inst.Key)
xx<-data.frame(new$study2.visualpro, new$study2.pic, new$agecen,
new$hourcen, new$profcen, new$yearscen, new$inst, new$proflog)
```

```
library(Amelia)
```

```
## Loading required package: Rcpp
```

```
## ##
## ## Amelia II: Multiple Imputation
## ## (Version 1.7.5, built: 2018-05-07)
## ## Copyright (C) 2005-2020 James Honaker, Gary King and Matthe
w Blackwell
## ## Refer to http://gking.harvard.edu/amelia/ for more informat
ion
## ##
```

```
library(Zelig)
```

```
## Loading required package: survival
```

```
mi<-amelia(xx, m=20)
```

```
## Warning in amelia.prep(x = x, m = m, idvars = idvars, empri =
empri, ts =
## ts, : You have a small number of observations, relative to the
number, of
## variables in the imputation model. Consider removing some vari
ables, or
## reducing the order of time polynomials to reduce the number of
parameters.
```

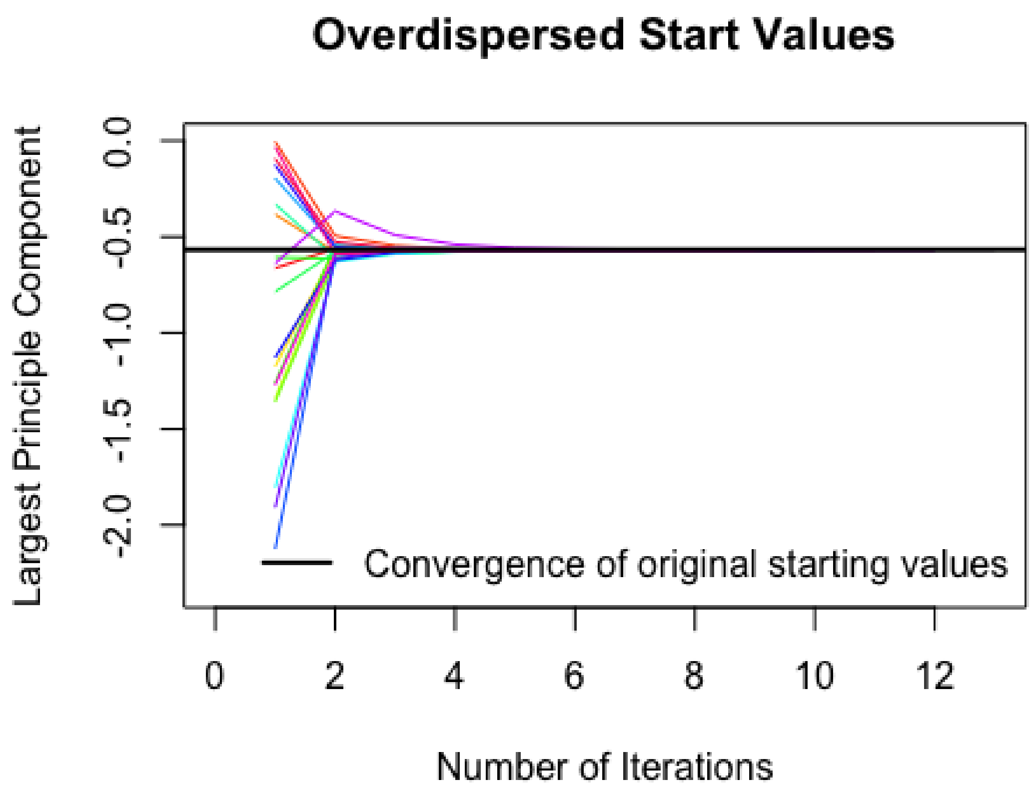
```
## -- Imputation 1 --
##
##   1  2  3  4
##
## -- Imputation 2 --
##
##   1  2  3  4  5
##
## -- Imputation 3 --
```

```
##
##   1  2  3  4  5
##
## -- Imputation 4 --
##
##   1  2  3  4
##
## -- Imputation 5 --
##
##   1  2  3  4
##
## -- Imputation 6 --
##
##   1  2  3  4
##
## -- Imputation 7 --
##
##   1  2  3  4  5  6  7
##
## -- Imputation 8 --
##
##   1  2  3
##
## -- Imputation 9 --
##
##   1  2  3  4  5
##
## -- Imputation 10 --
##
##   1  2  3  4  5
##
## -- Imputation 11 --
##
##   1  2  3  4  5
##
## -- Imputation 12 --
##
##   1  2  3  4  5
##
## -- Imputation 13 --
##
##   1  2  3  4  5
```

```
##
## -- Imputation 14 --
##
##   1  2  3  4
##
## -- Imputation 15 --
##
##   1  2  3  4
##
## -- Imputation 16 --
##
##   1  2  3  4  5
##
## -- Imputation 17 --
##
##   1  2  3  4
##
## -- Imputation 18 --
##
##   1  2  3  4  5
##
## -- Imputation 19 --
##
##   1  2  3  4  5  6
##
## -- Imputation 20 --
##
##   1  2  3  4
```

```
disperse(mi, dims = 1, m = 20)
```

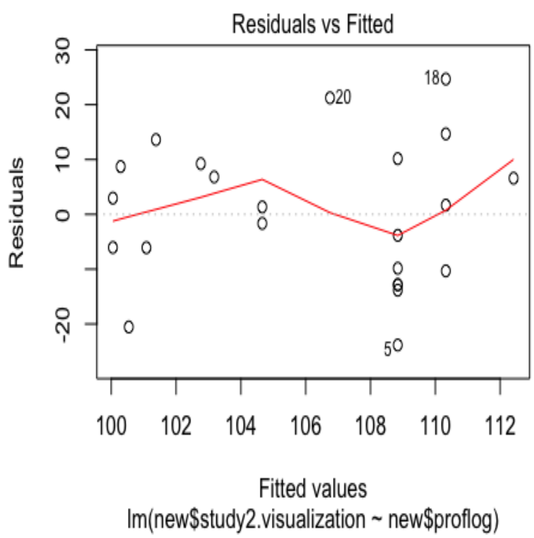
```
## Warning in amelia.prep(x = data, arglist = output$arguments):
You have a
## small number of observations, relative to the number, of varia
bles in the
## imputation model. Consider removing some variables, or reducin
g the order
## of time polynomials to reduce the number of parameters.
```

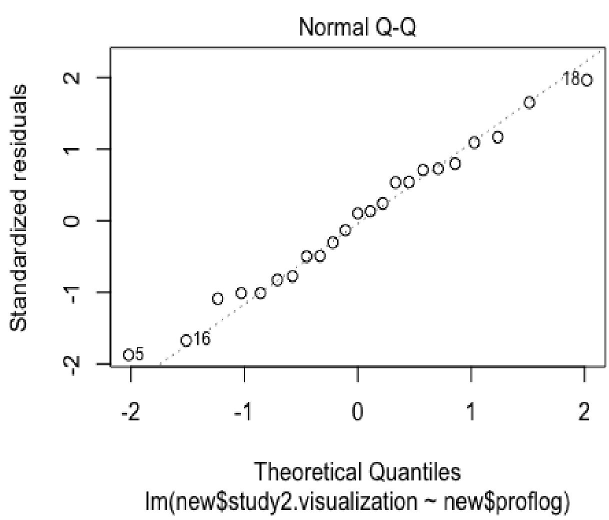


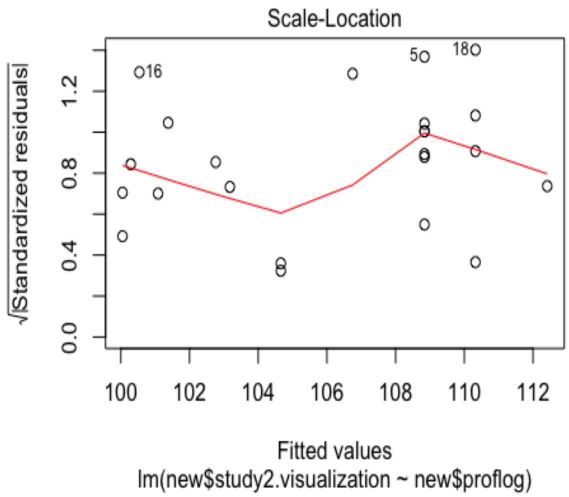

```
t.test(new$study2.Combined.Proficiency~new$study2.Primary.inst.Ke
y, var.equal=FALSE)
```

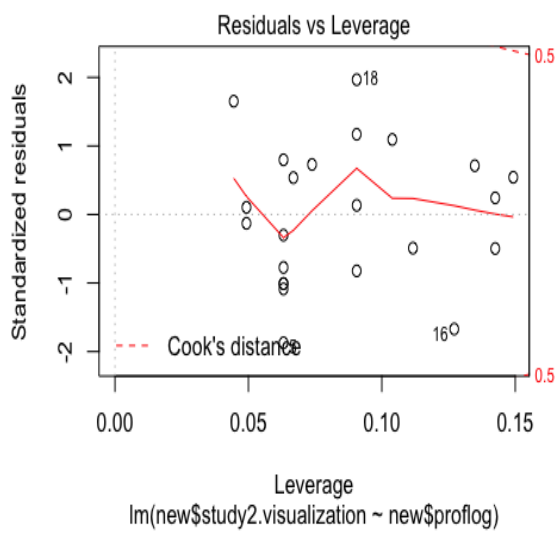
```
##
##  Welch Two Sample t-test
##
## data:  new$study2.Combined.Proficiency by new$study2.Primary.i
nst.Key
## t = 0.50466, df = 13.013, p-value = 0.6222
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##  -5.242757  8.439186
## sample estimates:
## mean in group String    mean in group non
##             9.285714             7.687500
```

```
lsr::cohensD(new$study2.Combined.Proficiency~new$study2.Primary.i
nst.Key)

## [1] 0.2172151

reg1<-lm(new$study2.visualization~new$proflog)
plot(reg1)
```










```
library(MASS)
rbreg1<-rlm(new$study2.visualization~new$proflog)
summary(rbreg1)

##
## Call: rlm(formula = new$study2.visualization ~ new$proflog)
## Residuals:
##      Min       1Q  Median       3Q      Max
## -23.582  -9.777   1.336   8.771  25.028
##
```

```
## Coefficients:
##             Value    Std. Error t value
## (Intercept) 115.2792   8.1614    14.1249
## new$proflog -11.1238   9.0987    -1.2226
##
## Residual standard error: 14.21 on 21 degrees of freedom
```

```
2*pt(-1.22, df=21)
```

```
## [1] 0.2359892
```

```
QuantPsyc::lm.beta(rbreg1)
```

```
## new$proflog
##  -0.2859225
```

```
z.out13<-zelig(new.study2.visualpro~new.proflog, model = "ls", da
ta = mi)
```

```
## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/
```

```
summary(z.out13)
```

```
## Model: Combined Imputations
##
##             Estimate Std.Error z value Pr(>|z|)
## (Intercept)   113.75      8.64   13.16   <2e-16
## new.proflog    -4.60      9.64   -0.48     0.63
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method
```

```
z.out14<-zelig(new.study2.pic~new.proflog, model = "ls", data = m
i)
```

```
## How to cite this model in Zelig:
##   R Core Team. 2007.
```

```
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/
```

```
summary(z.out14)
```

```
## Model: Combined Imputations
##
##               Estimate Std.Error z value Pr(>|z|)
## (Intercept)   101.91      8.43   12.09   <2e-16
## new.proflog     9.00      9.39    0.96     0.34
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method
```

```
rbreg5<-rlm(new$study2.visualization~new$inst)
summary(rbreg5)
```

```
##
## Call: rlm(formula = new$study2.visualization ~ new$inst)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -28.557  -9.143  -2.143   8.357  26.443
##
## Coefficients:
##             Value    Std. Error t value
## (Intercept) 111.9710  12.3094     9.0964
## new$inst     -3.4141   7.0060    -0.4873
##
## Residual standard error: 13.56 on 21 degrees of freedom
```

```
2*pt(-0.49, df=21)
```

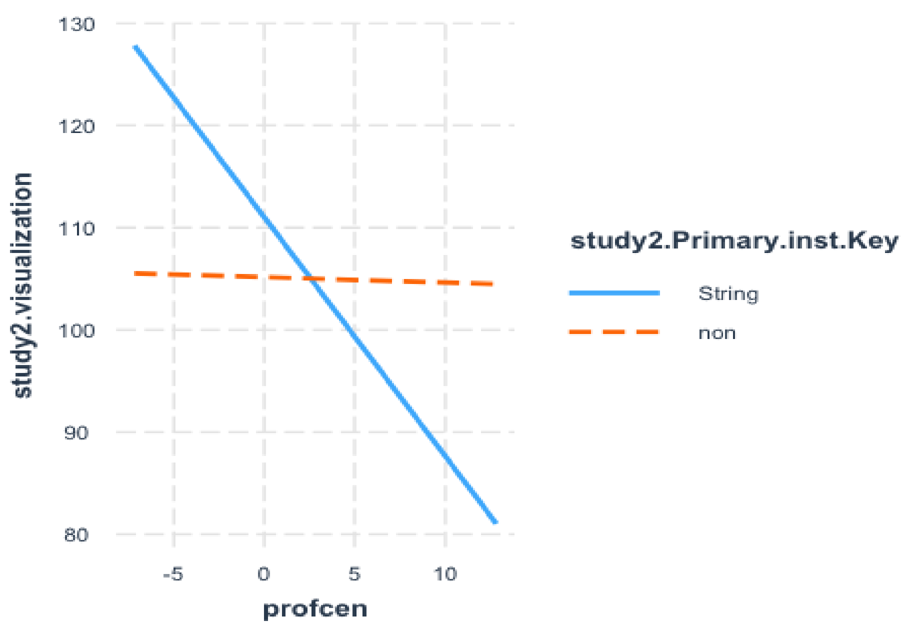
```
## [1] 0.629214
```

```
QuantPsyc::lm.beta(rbreg5)
```

```
##   new$inst
## -0.1189931
```

```
library(Zelig)
z.out1<-zelig(new.study2.visualpro~new.inst, model = "ls", data =
mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out1)

## Model: Combined Imputations
##
##             Estimate Std.Error z value Pr(>|z|)
## (Intercept)   126.85     13.29    9.54   <2e-16
## new.inst       -9.98      7.37   -1.35     0.18
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method

z.out6<-zelig(new.study2.pic~new.inst, model = "ls", data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out6)

## Model: Combined Imputations
##
##             Estimate Std.Error z value Pr(>|z|)
## (Intercept)   126.17     13.14    9.60   <2e-16
## new.inst       -9.90      7.32   -1.35     0.18
##
```

```
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method
```




```
#bootstrapped moderated regression of proficiency*inst on visualp
rocessing
z.out2<-zelig(new.study2.visualpro~new.inst*new.profcen, model =
"ls", data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out2)

## Model: Combined Imputations
##
##                        Estimate Std.Error z value Pr(>|z|)
## (Intercept)              130.06     13.62    9.55   <2e-16
## new.inst                 -11.57      7.48   -1.55     0.12
```

```
## new.profcen                 -2.94      1.98   -1.48     0.14
## new.inst:new.profcen     1.48      1.10    1.35     0.18
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method

#bootstrapped moderated regression of proficiency by instrument o
n picture recognition
z.out7<-zelig(new.study2.pic~new.inst*new.profcen, model = "ls",
data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out7)

## Model: Combined Imputations
##
##                         Estimate Std.Error z value Pr(>|z|)
## (Intercept)             125.1186   13.9767    8.95   <2e-16
## new.inst                 -9.2895    7.7431   -1.20     0.23
## new.profcen               0.4409    1.9413    0.23     0.82
## new.inst:new.profcen    -0.0453    1.0640   -0.04     0.97
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method

#robust moderated regression of proficiency*inst on visualization
library(MASS)
new$inst<-as.numeric(new$study2.Primary.inst.Key)
rbreg3<-rlm(study2.visualization~study2.Primary.inst.Key*profcen,
new)
summary(rbreg3)

##
## Call: rlm(formula = study2.visualization ~ study2.Primary.inst
```

```
.Key *
##     profcen, data = new)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -20.430  -7.930  -1.477   8.293  19.517
##
## Coefficients:
##                                     Value    Std. Error t value
## (Intercept)                         111.0277   4.7983    23.138
8
## study2.Primary.inst.Keynon           -5.8714   5.7294    -1.024
8
## profcen                              -2.3378   0.7613    -3.070
8
## study2.Primary.inst.Keynon:profcen    2.2848   0.8715     2.621
5
##
## Residual standard error: 13.98 on 19 degrees of freedom
```

```
2*pt(-1.02, df=19)
```

```
## [1] 0.3205414
```

```
2*pt(-3.07, df=19)
```

```
## [1] 0.006302394
```

```
2*pt(-2.62, df=19)
```

```
## [1] 0.01684972
```

```
weird<-lm(study2.visualization~study2.Primary.inst.Key*proflogcen
, new)
summary(weird)
```

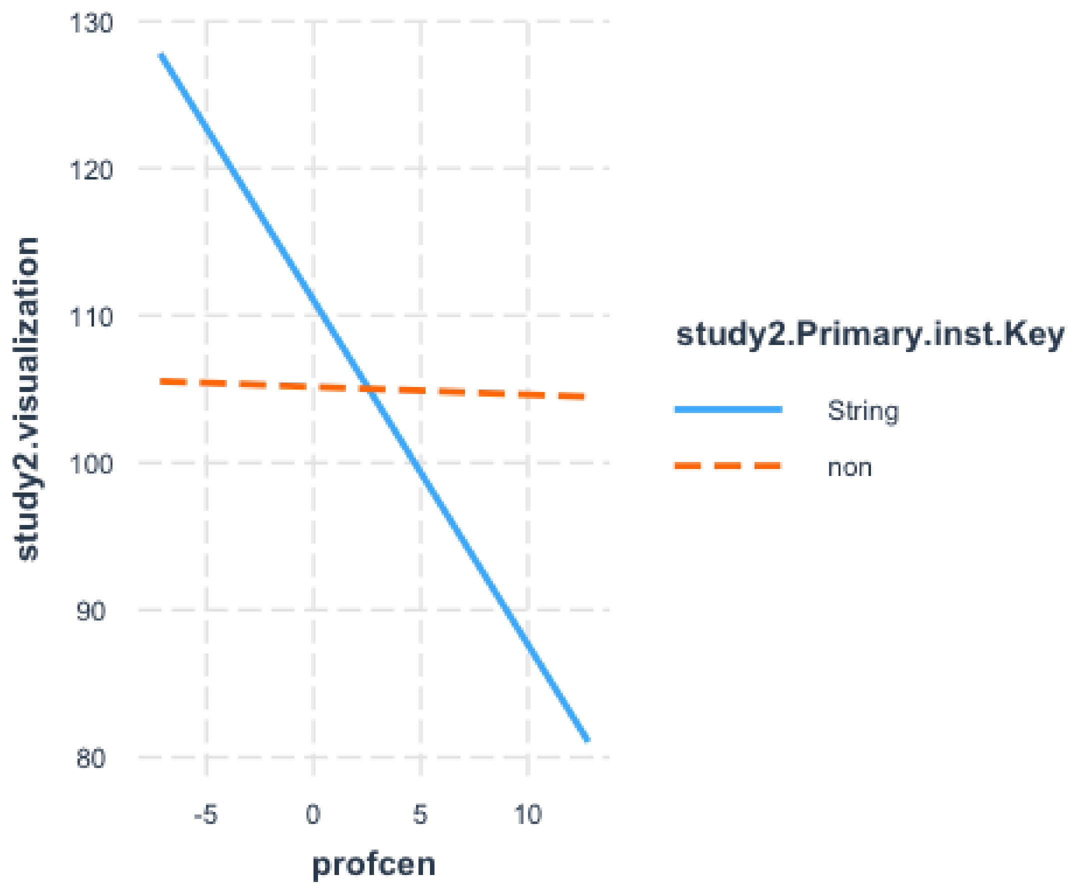
```
##
## Call:
## lm(formula = study2.visualization ~ study2.Primary.inst.Key *
##     proflogcen, data = new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.5976  -9.5976  -0.7425   8.3918  19.0894
```

```
##
## Coefficients:
##                                         Estimate Std. Error t va
lue Pr(>|t|)
## (Intercept)                               112.744      4.611  24.
449 8.03e-16
## study2.Primary.inst.Keynon                 -7.718      5.465  -1.
412  0.17401
## proflogcen                                -47.588     15.029  -3.
166  0.00508
## study2.Primary.inst.Keynon:proflogcen      45.082     17.176   2.
625  0.01668
##
## (Intercept)                           ***
## study2.Primary.inst.Keynon
## proflogcen                            **
## study2.Primary.inst.Keynon:proflogcen *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.66 on 19 degrees of freedom
## Multiple R-squared:  0.3561, Adjusted R-squared:  0.2544
## F-statistic: 3.503 on 3 and 19 DF,  p-value: 0.03556
```

```
interactions::sim_slopes(weird, pred = proflogcen, modx = study2.
Primary.inst.Key, johnson_neyman = FALSE, cond.int = TRUE, digits
= 3)
```

```
## SIMPLE SLOPES ANALYSIS
##
## When study2.Primary.inst.Key = non:
##
##                                  Est.    S.E.   t val.       p
## -------------------------- --------- ------- -------- -------
## Slope of proflogcen           -2.506   8.316   -0.301   0.766
## Conditional intercept        105.026   2.932   35.815   0.000
##
## When study2.Primary.inst.Key = String:
##
##                                  Est.     S.E.   t val.
p
## -------------------------- --------- -------- -------- ------
-
```

```
## Slope of proflogcen            -47.588    15.029    -3.166    0.00
5
## Conditional intercept          112.744     4.611    24.449    0.00
0

interactions::interact_plot(rbreg3, pred = profcen, modx = study2
.Primary.inst.Key)
```




```
#Is age a covariate?
new$demagecen<-as.numeric(scale(new$study2.Age, scale = FALSE))
rebreg7<-rlm(study2.visualization~profcen*demagecen, new)
summary(rebreg7)

##
## Call: rlm(formula = study2.visualization ~ profcen * demagecen
, data = new)
## Residuals:
##       Min        1Q    Median        3Q       Max
```

```
## -22.4346  -9.2843  -0.2011   9.7472  27.0932
##
## Coefficients:
##                    Value    Std. Error t value
## (Intercept)        106.3664   2.8314    37.5665
## profcen             -0.2797   0.4398    -0.6358
## demagecen            0.1840   0.1374     1.3387
## profcen:demagecen    0.0277   0.0247     1.1213
##
## Residual standard error: 14.92 on 19 degrees of freedom
```

```
2*pt(-0.63, df=19)
```

```
## [1] 0.5361983
```

```
2*pt(-1.34, df=19)
```

```
## [1] 0.1960519
```

```
2*pt(-1.12, df=19)
```

```
## [1] 0.2766724
```

```
#robust moderated regression of years of training*inst on visuali
zation
rbreg4<-rlm(study2.visualization~yearscen*study2.Primary.inst.Key
, new)
summary(rbreg4)
```

```
##
## Call: rlm(formula = study2.visualization ~ yearscen * study2.P
rimary.inst.Key,
##     data = new)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.373  -9.945  -1.357   9.355  29.721
##
## Coefficients:
##                                      Value    Std. Error t valu
e
## (Intercept)                          106.2042   4.8757    21.78
24
## yearscen                               3.0390   1.5180     2.00
19
```

```
## study2.Primary.inst.Keynon           -1.1092   5.8401    -0.18
99
## yearscen:study2.Primary.inst.Keynon  -3.2961   1.6529    -1.99
42
##
## Residual standard error: 14.74 on 19 degrees of freedom

2*pt(-0.19, df=19)

## [1] 0.8513243

2*pt(-2, df=19)

## [1] 0.06000204

2*pt(-1.99, df=19)

## [1] 0.06117765

#moderated regression of hours per week*inst on visualization
rbreg5<-rlm(study2.visualization~study2.Primary.inst.Key*hourcen,
new)
summary(rbreg5)

##
## Call: rlm(formula = study2.visualization ~ study2.Primary.inst
.Key *
##     hourcen, data = new)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -28.366  -8.510  -1.510   8.404  26.618
##
## Coefficients:
##                                       Value    Std. Error t value
## (Intercept)                           108.3140   9.4675    11.440
6
## study2.Primary.inst.Keynon            -3.5205  10.3298    -0.340
8
## hourcen                               -0.0163   1.7956    -0.009
1
## study2.Primary.inst.Keynon:hourcen    0.1465   1.8639     0.078
6
##
## Residual standard error: 13 on 19 degrees of freedom
```

```
2*pt(-0.34, df=19)

## [1] 0.7375865

2*pt(-0.02, df=19)

## [1] 0.9842519

2*pt(-0.08, df=19)

## [1] 0.9370739

#moderated regression of starting age*int on visualization
rbreg6<-rlm(study2.visualization~study2.Primary.inst.Key*agecen,
new)
summary(rbreg6)

##
## Call: rlm(formula = study2.visualization ~ study2.Primary.inst
.Key *
##     agecen, data = new)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -29.243  -8.666  -2.219   8.834  24.732
##
## Coefficients:
##                                     Value    Std. Error t value
## (Intercept)                         109.0280   5.8536    18.6257
## study2.Primary.inst.Keynon           -3.9386   7.0176    -0.5613
## agecen                                0.1707   1.0675     0.1599
## study2.Primary.inst.Keynon:agecen   -0.5066   1.7443    -0.2904
##
## Residual standard error: 14.84 on 19 degrees of freedom

2*pt(-0.56, df=19)

## [1] 0.5820225

2*pt(-0.16, df=19)

## [1] 0.8745698

2*pt(-0.29, df=19)

## [1] 0.7749575
```

```
#bootstrapped moderated regression of years of training*inst on v
isual pro
z.out3<-zelig(new.study2.visualpro~new.inst*new.yearscen, model =
"ls", data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out3)

## Model: Combined Imputations
##
##                          Estimate Std.Error z value Pr(>|z|)
## (Intercept)                126.15     13.50    9.35   <2e-16
## new.inst                    -9.66      7.44   -1.30     0.19
## new.yearscen                 3.54      4.35    0.81     0.42
## new.inst:new.yearscen       -2.09      2.25   -0.93     0.35
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method

#bootstrapped moderated regression of hours per week*inst on visu
al pro
z.out4<-zelig(new.study2.visualpro~new.inst*new.hourcen, model =
"ls", data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out4)
```

```
## Model: Combined Imputations
##
##                          Estimate Std.Error z value Pr(>|z|)
## (Intercept)                112.05     16.61    6.75  1.5e-11
## new.inst                    -2.76      8.94   -0.31     0.76
## new.hourcen                 -3.97      3.38   -1.18     0.24
## new.inst:new.hourcen         2.09      1.73    1.21     0.23
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Statistical Warning: The GIM test suggests this model is missp
ecified
##  (based on comparisons between classical and robust SE's; see
http://j.mp/GIMtest).
##  We suggest you run diagnostics to ascertain the cause, respec
ify the model
##  and run it again.
##
## Next step: Use 'setx' method

#bootstrapped moderated regression of starting age*int on visual
pro
z.out5<-zelig(new.study2.visualpro~new.inst*new.agecen, model = "
ls", data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out5)

## Model: Combined Imputations
##
##                         Estimate Std.Error z value Pr(>|z|)
## (Intercept)               126.81     13.19    9.62   <2e-16
## new.inst                  -10.01      7.34   -1.36     0.17
## new.agecen                  1.64      2.94    0.56     0.58
## new.inst:new.agecen        -1.34      1.81   -0.74     0.46
```

```
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Statistical Warning: The GIM test suggests this model is missp
ecified
##  (based on comparisons between classical and robust SE's; see
http://j.mp/GIMtest).
##  We suggest you run diagnostics to ascertain the cause, respec
ify the model
##  and run it again.
##
## Next step: Use 'setx' method
```

```
#bootstrapped moderated regression of proficiency*inst on pic
z.out8<-zelig(new.study2.pic~new.inst*new.profcen, model = "ls",
data = mi)
```

```
## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/
```

```
summary(z.out8)
```

```
## Model: Combined Imputations
##
##                      Estimate Std.Error z value Pr(>|z|)
## (Intercept)          125.1186   13.9767    8.95   <2e-16
## new.inst              -9.2895    7.7431   -1.20     0.23
## new.profcen            0.4409    1.9413    0.23     0.82
## new.inst:new.profcen  -0.0453    1.0640   -0.04     0.97
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method
```

```
#bootstrapped moderated regression of years of training*inst on p
ic
z.out9<-zelig(new.study2.pic~new.inst*new.yearscen, model = "ls",
data = mi)
```

```
## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/

summary(z.out9)

## Model: Combined Imputations
##
##                         Estimate Std.Error z value Pr(>|z|)
## (Intercept)               125.96     13.31    9.46   <2e-16
## new.inst                   -9.85      7.38   -1.33     0.18
## new.yearscen                2.02      4.01    0.50     0.61
## new.inst:new.yearscen      -1.44      2.09   -0.69     0.49
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method

#bootstrapped moderated regression of hours per week*inst on pic
z.out10<-zelig(new.study2.pic~new.inst*new.hourcen, model = "ls",
data = mi)

## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
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t.org/

summary(z.out10)

## Model: Combined Imputations
##
##                        Estimate Std.Error z value Pr(>|z|)
## (Intercept)              109.02     15.99    6.82  9.3e-12
## new.inst                  -1.53      8.62   -0.18     0.86
## new.hourcen               -4.58      3.26   -1.40     0.16
```

```
## new.inst:new.hourcen     2.41      1.67    1.44     0.15
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Statistical Warning: The GIM test suggests this model is missp
ecified
##  (based on comparisons between classical and robust SE's; see
http://j.mp/GIMtest).
##  We suggest you run diagnostics to ascertain the cause, respec
ify the model
##  and run it again.
##
## Next step: Use 'setx' method
```

```
#bootstrapped moderated regression of starting age*int on pic
z.out11<-zelig(new.study2.pic~new.inst*new.agecen, model = "ls",
data = mi)
```

```
## How to cite this model in Zelig:
##   R Core Team. 2007.
##   ls: Least Squares Regression for Continuous Dependent Variab
les
##   in Christine Choirat, Christopher Gandrud, James Honaker, Ko
suke Imai, Gary King, and Olivia Lau,
##   "Zelig: Everyone's Statistical Software," http://zeligprojec
t.org/
```

```
summary(z.out11)
```

```
## Model: Combined Imputations
##
##                      Estimate Std.Error z value Pr(>|z|)
## (Intercept)          126.5530   13.0885    9.67   <2e-16
## new.inst             -10.1500    7.3134   -1.39     0.17
## new.agecen            -0.0102    2.7799    0.00     1.00
## new.inst:new.agecen   -0.5041    1.7651   -0.29     0.78
##
## For results from individual imputed datasets, use summary(x, s
ubset = i:j)
## Next step: Use 'setx' method
```

```
#Proficiency mediates relationship between instrument type and vi
sualization scores
library(lavaan)
```

```
## This is lavaan 0.6-5

## lavaan is BETA software! Please report any bugs.

set.seed(1234)
med<-'
study2.visualization~cp*inst
proflog~a*inst
study2.visualization~b*proflog
ab := a*b
total := cp + (a*b)
'
fitm<-sem(med, data = new, se="bootstrap")

## Warning in lav_data_full(data = data, group = group, cluster =
cluster, :
## lavaan WARNING: some observed variances are (at least) a facto
r 1000 times
## larger than others; use varTable(fit) to investigate

summary(fitm, ci=TRUE)

## lavaan 0.6-5 ended normally after 33 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                          5
##
##   Number of observations                            23
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws             1000
##   Number of successful bootstrap draws            1000
##
## Regressions:
##                             Estimate  Std.Err  z-value  P(>|z|) c
i.lower
```

```
##    study2.visualization ~
##      inst       (cp)         -5.008    6.797   -0.737    0.461
-18.505
##    proflog ~
##      inst        (a)         -0.130    0.147   -0.886    0.376
-0.420
##    study2.visualization ~
##      proflog     (b)        -13.074    8.162   -1.602    0.109
-28.301
##   ci.upper
##
##      8.349
##
##      0.167
##
##      3.455
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##     .study2.vislztn  152.910   31.838    4.803    0.000   73.03
2  197.726
##     .proflog           0.112    0.019    5.827    0.000    0.06
2    0.139
##
## Defined Parameters:
##                     Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##      ab               1.704    2.665    0.640    0.522   -1.64
2    8.706
##      total           -3.304    7.471   -0.442    0.658  -17.74
3   11.601

#Proficiency mediates the relationship bewteen starting age and v
isualization
set.seed(1234)
med<-'
study2.visualization~cp*sagein
proflog~a*sagein
study2.visualization~b*proflog
ab := a*b
total := cp + (a*b)
```

```
'
fitm<-sem(med, data = new, se="bootstrap")

## Warning in lav_data_full(data = data, group = group, cluster =
cluster, :
## lavaan WARNING: some observed variances are (at least) a facto
r 1000 times
## larger than others; use varTable(fit) to investigate

## Warning in lav_model_estimate(lavmodel = lavmodel, lavpartable
=
## lavpartable, : lavaan WARNING: the optimizer warns that a solu
tion has NOT
## been found!

## Warning in bootstrap.internal(object = NULL, lavmodel. = lavmo
del,
## lavsamplestats. = lavsamplestats, : lavaan WARNING: only 998 b
ootstrap
## draws were successful

summary(fitm, ci=TRUE)

## lavaan 0.6-5 ended normally after 48 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                          5
##
##   Number of observations                            23
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws             1000
##   Number of successful bootstrap draws             998
##
## Regressions:
##                          Estimate  Std.Err  z-value  P(>|z|) c
```

```
i.lower
##   study2.visualization ~
##     sagein    (cp)         68.515  133.216    0.514    0.607 -
191.836
##   proflog ~
##     sagein     (a)          1.706    2.569    0.664    0.507
-4.445
##   study2.visualization ~
##     proflog    (b)        -12.398    7.554   -1.641    0.101
-27.144
##  ci.upper
##
##   334.060
##
##     6.202
##
##     2.647
##
## Variances:
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##    .study2.vislztn  155.658   35.926    4.333    0.000   68.74
8  209.150
##    .proflog           0.114    0.019    6.005    0.000    0.06
7    0.144
##
## Defined Parameters:
##                      Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##     ab              -21.147   39.093   -0.541    0.589 -117.50
5   53.093
##     total            47.368  138.209    0.343    0.732 -219.74
8  319.222
```

```
#Hours practicing per week mediates the relationship between star
ting age and visualization
set.seed(1234)
med<-'
study2.visualization~cp*sagein
hourlog~a*sagein
study2.visualization~b*hourlog
ab := a*b
```

```
total := cp + (a*b)
'
fitm<-sem(med, data = new, se="bootstrap")

## Warning in lav_data_full(data = data, group = group, cluster =
cluster, :
## lavaan WARNING: some observed variances are (at least) a facto
r 1000 times
## larger than others; use varTable(fit) to investigate

summary(fitm, ci=TRUE)

## lavaan 0.6-5 ended normally after 48 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of free parameters                          5
##
##   Number of observations                            23
##
## Model Test User Model:
##
##   Test statistic                                 0.000
##   Degrees of freedom                                 0
##
## Parameter Estimates:
##
##   Standard errors                            Bootstrap
##   Number of requested bootstrap draws             1000
##   Number of successful bootstrap draws            1000
##
## Regressions:
##                          Estimate  Std.Err  z-value  P(>|z|) c
i.lower
##   study2.visualization ~
##     sagein    (cp)         48.953  142.590    0.343    0.731 -
234.359
##   hourlog ~
##     sagein     (a)          0.601    3.026    0.199    0.842
-5.111
##   study2.visualization ~
##     hourlog    (b)         -2.636    8.464   -0.311    0.755
-16.544
```

```
##  ci.upper
##
##   319.595
##
##     7.013
##
##    16.376
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##    .study2.vislztn  172.399   43.860    3.931    0.000   71.15
2  243.745
##    .hourlog           0.105    0.023    4.504    0.000    0.05
5    0.143
##
## Defined Parameters:
##                    Estimate  Std.Err  z-value  P(>|z|) ci.lowe
r ci.upper
##     ab               -1.585   27.997   -0.057    0.955  -50.77
4   72.160
##     total            47.368  138.113    0.343    0.732 -219.67
7  318.978
```

```
study2$visualpro<-study2$VISUAL.PROCESSING..Gv..SS..95..Band.
study2$visualization<-study2$VISUALIZATION.SS..95...Band
study2$pic<-study2$PICTURE.RECOGNITION.SS..95...BAND
new<-data.frame(study2$Age, study2$Sex, study2$Education, study2$
visualpro, study2$visualization, study2$pic, study2$Combined.Prof
iciency, study2$Primary.inst.Key, study2$Overall.Instruments, stu
dy2$Years.of.Training, study2$Hours.per.Week, study2$Starting.Age
, study2$VISUALIZATION.PR)
```

```
t.test(new$study2.VISUALIZATION.PR, mu = 50)
```

```
##
##  One Sample t-test
##
## data:  new$study2.VISUALIZATION.PR
## t = 2.1202, df = 22, p-value = 0.0455
## alternative hypothesis: true mean is not equal to 50
```

```
## 95 percent confidence interval:
##  50.25277 72.87767
## sample estimates:
## mean of x
##  61.56522
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
new<-filter(new, study2.Sex=="m" | study2.Sex=="f")
droplevels(new$study2.Sex)
```

```
##  [1] m f m m m m m m f m f m m m f m m f f m f
## Levels: f m
```

```
t.test(new$study2.visualization~new$study2.Sex)
```

```
##
##  Welch Two Sample t-test
##
## data:  new$study2.visualization by new$study2.Sex
## t = -0.74216, df = 11.07, p-value = 0.4734
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##  -19.816843   9.816843
## sample estimates:
## mean in group f mean in group m
##             103             108
```

```
t.test(new$study2.visualpro~new$study2.Sex)
```

```
##
##  Welch Two Sample t-test
##
```

```
## data:  new$study2.visualpro by new$study2.Sex
## t = -0.085259, df = 10.062, p-value = 0.9337
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##  -16.84232  15.59990
## sample estimates:
## mean in group f mean in group m
##        108.8333        109.4545
```

```
t.test(new$study2.pic~new$study2.Sex)
```

```
##
##  Welch Two Sample t-test
##
## data:  new$study2.pic by new$study2.Sex
## t = 0.82525, df = 8.1061, p-value = 0.4328
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##  -11.18830  23.70345
## sample estimates:
## mean in group f mean in group m
##        112.1667        105.9091
```

```
t.test(new$study2.Combined.Proficiency~new$study2.Sex)
```

```
##
##  Welch Two Sample t-test
##
## data:  new$study2.Combined.Proficiency by new$study2.Sex
## t = 2.3128, df = 10.236, p-value = 0.04274
## alternative hypothesis: true difference in means is not equal
to 0
## 95 percent confidence interval:
##   0.297124 14.702876
## sample estimates:
## mean in group f mean in group m
##       13.714286        6.214286
```