Spatial Ability Degradation in Undergraduate Mechanical Engineering Students During the Winter Semester Break

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SPATIAL ABILITY DEGRADATION IN UNDERGRADUATE MECHANICAL ENGINEERING STUDENTS DURING THE WINTER SEMESTER BREAK

by

Benjamin J. Call

A dissertation submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

Engineering Education

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2018
ABSTRACT

Spatial Ability Degradation in Undergraduate Mechanical Engineering Students
During the Winter Semester Break
by
Benjamin J. Call, Doctor of Philosophy
Utah State University, 2018

Major Professor: Dr. Wade H. Goodridge
Department: Engineering Education

While spatial ability has a well-researched correlation with success in engineering, both academically and professionally, the vast majority of research is limited to short-term effects. Researchers have statistically shown that most interventions have a positive impact on spatial ability and claim that the impact is enduring. However, quantifying the duration of impact generally suffers from two limitations: 1) there is not a sufficient gap to determine if the impact endures, i.e., most research fails to follow up with participants more than a week later; and 2) no allowance is made for the influence of non-deliberate factors that may be increasing the spatial ability of participants. The non-deliberate factor of particular concern in this paper is undergraduate engineering coursework (Engineering Graphics and Statics) which have been correlated with increases in spatial ability – thus rendering them a type of indirect intervention even if they are not generally recognized as such.

The research presented herein tracked changes in undergraduate engineering students’ spatial ability during the winter academic break following three courses
(Engineering Graphics, Statics, and Advanced Dynamics) that represent a progression in the mechanical engineering curriculum at Utah State University. This approach removed engineering coursework as an active influence on engineering students’ spatial ability during data collection. The Mental Cutting Test was used to measure spatial ability. Changes in spatial ability were found to be statistically significant when measuring performance in terms of the time 32 participants spent taking the test, and similar, though not statistically significant, trends were seen in the test scores. It was initially observed that newer students tend to *improve* over the winter academic break while students more advanced in their engineering coursework do not exhibit a significant change in spatial ability. Multiple linear regression techniques identified academic performance, the sex of the students, playing music over the break, and prior life experiences as the driving factors in the differences in spatial ability malleability over the break, rather than simply progression through the engineering curriculum.

(258 pages)
Spatial ability represents our ability to mentally arrange, rotate, and explore objects in multiple dimensions. This ability has been found to be important for engineers and engineering students. Past research has shown that many interventions can be created to boost an individual’s spatial ability. In fact, past research has indicated that engineering students significantly increase in spatial ability without an intervention while they are enrolled in certain engineering courses. Some researchers have claimed that the spatial ability boosts are permanent after an intervention. However, most researchers do not check the validity of that claim with continued assessment after more than a week past the end of an intervention. Additionally, if engineering education researchers are trying to measure the impact of their separate spatial ability intervention while the participating engineering students are actively enrolled in engineering courses, a confounding variable is introduced as the courses can impact students’ spatial ability. To resolve this, the work presented in this paper reflects research on engineering students’ spatial ability maintenance during the winter break between semesters. It was found that newer students exhibit spatial ability improvement during the break, while older students maintain their spatial ability at the same level. A deeper statistical analysis revealed that there are other factors that play a role in spatial ability changes over the break that are more significant than how far students had progressed in their studies. Those factors include with academic performance, the sex of the students, playing music during the break, and prior life experiences.
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CHAPTER I
INTRODUCTION

Given the economic need for more engineering graduates (President’s Council of Advisors on Science and Technology, 2012), engineering education has been receiving increased attention. Efforts to improve instruction for engineering students have been going on for quite some time (Borrego, 2007). As engineering educators have sought to hone their craft, engineering students’ ability to visualize objects, their spatial relations, and the directions and magnitudes of forces acting on those objects has been identified as an important asset for many fields of engineering. This topic of spatial ability has inspired cognitive studies, has informed the terminology for concepts, and has been theorized to impact student motivation. This research has resulted in the practice of providing engineering students with spatial ability interventions. Unfortunately, spatial ability gains from these interventions are often implicitly treated like they are permanent since they do not call for follow-up interventions. Explicitly, publications claim that spatial ability can be improved, and the gains are maintained (Uttal et al., 2013).

Research publications that look at the long-term maintenance of spatial ability are extremely rare and have not provided sufficient data to support the hypothesis that spatial ability is maintained over the long term (i.e., multiple months or longer) to the benefit of the students in a meta-analysis on the topic (Uttal et al., 2013).

**Background of the Problem**

Spatial ability is defined herein as a measurement of spatial aptitude, which reflects an individual’s skill in using spatial thinking, a psychological construct (Hegarty, 2010). Spatial ability has long been recognized for its ability to predict success in college,
as evidenced by the inclusion of the Mental Cutting Test (MCT) in college entrance exams in the 1930’s (CEEB, 1939). Spatial thinking, which involves thinking about the arrangement of objects or shapes in space as well as thinking in a way that provides spatial representations for items that are not by definition spatial (e.g., a graph of expenditures) (Hegarty, 2010, p. 266), and spatial ability have been an area of research in the psychology community that has led to efforts in the engineering education community in the present day. Spatial ability is utilized herein as the measurement of a construct of thought, and thus a tool for diagnosis, and spatial aptitude is viewed as a prerequisite for promoting certain types of learning, just as language and mathematic skills are treated as prerequisite for academic achievement. The general motivation within the community of those who research spatial ability and its influence on academic and professional success seems to be that the correlation between spatial ability and academic or professional performance is strong enough to be causal. In other words, the hope is that by improving spatial ability, students will perform better in class. Given the correlations with engineering careers, promoting spatial ability is viewed as a way to improve students’ performance as professional engineers as well (Wai, Lubinski, & Benbow, 2009). The typical engineering education application of spatial ability interventions (Sorby, 2011; Sorby & Baartmans, 2000) revolves around Engineering Graphics courses where spatial ability measurements have been correlated with course performance, and interventions have been developed to increase the scores of those students who exhibit low spatial ability. Reports on those studies indicate that such effects will have a long-term benefit; however, the results have been questioned due to the lack of random assignment in the original research. Additionally, long-term studies on the topic that confirm the effects
over time are lacking, with follow-up typically occurring within one week of any spatial ability intervention. A meta-analysis of spatial ability studies suggests that spatial ability is malleable (i.e., it can be improved via interventions) and that the improvements can be maintained at a consistent level (Uttal et al., 2013).

The spatial ability classroom interventions that have been developed range from explicit instruction that teaches students how to solve spatial problems, to instruction that aids students with interpreting figure visualizations, to indirect techniques that are similar to Engineering Graphics instruction. The final category is referred to herein as indirect spatial ability instruction by means of engineering content instruction. It may be of particular interest for engineering educators given the efficiency of potentially increasing students’ spatial ability simply through course instruction. There is preliminary research into such indirect spatial ability instruction (Wood, Goodridge, Call, & Sweeten, 2016) that has identified the MCT, an instrument that measures a facet of spatial aptitude that is implicit and dynamic, as appropriate for engineering education spatial ability research. The research indicates that demographic and experiential factors play a role in the level of spatial ability that students have upon arrival at the university, and in the amount of growth they experience in spatial ability while enrolled in engineering courses (Sorby & Baartmans, 2000; Wood et al., 2016). There has been a call to better prepare engineering students and better understand how their instruction may be improved. Understanding the role of spatial ability in each engineering course may provide a critical piece of the solution.

**Statement of the Problem**

Establishing the permanence of changes in spatial ability after an intervention has
not been sufficiently proven. The vast majority of studies have not conducted any sort of longitudinal research regarding the maintenance of spatial ability improvements. Most studies conduct their post-assessments within one week of the intervention, and 98% complete their assessments within one month (Uttal et al., 2013). The meta-analysis did not include the results of the remaining studies that had a more longitudinal design, wherein the improvement of spatial ability intervention-participating students relative to their peers tends to diminish over time. Additionally, there is a question of whether exposure to spatial ability interventions has truly stopped if coursework is ongoing during the assessment period – particularly for engineering students. Short-term assessments of less than seven days after instruction offer little in the way of predicting the lasting effects of instruction. If the interim for mid-term assessments (i.e., 7-31 days post-intervention) is not free of indirect spatial ability instruction, then their results may not represent an improvement in predictive capability over short-term results. And if longer-term (i.e. 32+ days post-intervention) results have been left out of the analysis, then it is hard to say if spatial ability gains and their assumed impact on engineering performance will be influential in the long run. If the goal is to improve student preparation for the professional workforce, then long-term results need to be understood. Research is needed that identifies if a degradation of spatial ability, wherein students return to lower levels of spatial ability, is occurring after a period of spatial growth has been observed.

A review of research regarding the degradation of knowledge or ability in students led to literature in K-12 educational research where the study of students’ maintenance of learning during breaks within the academic calendar has been tracked. Given that the knowledge tracked in these studies is the focus of teaching in the
classroom, the degradation of that knowledge that was learned, or at least assessed, in the classroom is also called “learning loss”. Learning loss has been studied extensively for math and language skills in the younger, K-12 arena, typically as the result of the summer academic break. The research that has been done generally focuses on the impact of socio-economic status differences and programs that strive to reduce math and language skill learning loss during the summer (Alexander, Entwisle, & Olson, 2007; Blazer & Miami-Dade County Public Schools, 2011; Cooper, Nye, Charlton, Lindsay, & Greathouse, 1996). Little has been researched regarding learning loss in college students (Dills, Hernández-Julián, & Rothoff, 2016), and no learning loss research has tracked spatial ability. Given that minimal effort is explicitly made in the classroom for students to learn spatial ability and spatial ability is a quantitative measure, the term “degradation” is used for potential spatial ability loss in this study rather than the term “learning loss”.

**Purpose of the Study**

The purpose of this study is to learn about the degradation or maintenance of spatial ability by engineering students during a period of time when they are not receiving spatial training either explicitly or through academically-embedded, indirect spatial interventions. If engineering students are receiving indirect spatial ability instruction through their engineering courses, then the degradation of spatial ability can only accurately be tracked during academic breaks. This study looks at the impact of the removal of indirect spatial ability instruction over a mid-sized break. Engineering courses that have been researched at this institution in the past include Engineering Graphics, Statics, and Advanced Dynamics, and this study includes those courses again, in order to build on that existing research. The focus of research on the effect of removing those
indirect curricular interventions (engineering coursework) and their impact on the retention of spatial ability within those courses, required this research be conducted over the winter break between academic semesters, as Advanced Dynamics is only offered in the fall semester.

If failure to maintain spatial ability levels over the break is observed, then the present understanding of spatial ability’s “malleability”, i.e., an understanding that it only improves (Uttal et al., 2013), would be called into question. This marks the introduction of spatial ability degradation as a research topic, and it is also the first study of a learning loss-type of topic for college students over the winter break.

**Research Hypotheses**

The goal of this research is to determine whether spatial ability is maintained, or if it degrades in the absence of engineering coursework, an intervention that has been correlated with its increase. Insight into other factors that play a role is also of interest. Thus the null hypothesis and hypotheses to be tested in this work are given below:

H0: The null hypothesis for the fundamental research hypothesis is that there will be no difference between the pre-test and post-test scores bracketing the winter academic break.

This is the current belief implied by the community and expressed in Uttal et al. (2013) as malleability only being represented by improvement, and the improvements being durable. There is a current lack of research in this area, and as such this null hypothesis may not be true, thus necessitating this work.

H1: Engineering students will show a decrease in spatial ability, as measured by the MCT, during the winter academic break.
The expectation that skill degradation, as expressed in H1, will occur is based on past experience with engineering, primarily mechanical and aerospace engineering (MAE) courses, coursework, the inability to separate those courses from other academic content, the evidence of learning loss in the absence of instruction in the fields of mathematics and reading, and the established utility of the MCT in detecting changes in the engineering-student population’s spatial ability.

H2: There are demographic and experiential factors during breaks in engineering coursework that moderate the degradation of spatial ability.

If degradation is exhibited by some or all of the participants, then this secondary hypothesis arises. Given the impact that student’s socio-economic status and experiences have on reading learning loss during academic breaks, questions begin to arise about mitigating spatial ability degradation. Additionally, given evidence of demographics and experiential factors’ impacts on students’ spatial ability and its increase, it is anticipated that demographics and experiential factors would impact students’ spatial ability maintenance or degradation.

It is expected that those with more spatially relevant experience would exhibit less of a decline during the break. It is specifically hypothesized that spatial degradation for those with limited past spatial experience would be impacted by activities during the academic break. A survey given to each participant captured demographic and experiential factors that may influence spatial ability and its retention based on initial findings in Wood et al. (2016). In that study, it was found that students who had low experience in drafting, LEGO® brick play, woodworking, and/or welding exhibited significant improvement on the MCT during the semester in which they were enrolled in
Statics, whereas those with high experience in those categories did not exhibit significant improvement. These activities, as well as other experiential factors, are included in the survey twice – once for prior experience levels and once for experience levels over the break.

**Research Design**

In spite of spatial ability’s importance being recognized within the engineering education community, and the focus of engineering education on professional preparation, very little has been done to look at the longitudinal effects of spatial ability instruction. Given the lack of a learning loss approach – where academic instruction is absent – in mid-duration spatial ability maintenance research, the present study intends to start filling that gap. Evidence of decline during the winter break is sought in a sample of MAE students from Utah State University (USU) that covers three separate class topics and three separate classes of academic years (i.e. freshman, sophomore, junior). A pre-test, post-test quasi-experimental design, using the MCT as the spatial ability instrument, was utilized to identify loss or maintenance of spatial ability. A demographic and experiential survey helped to identify factors that may moderate learning loss over the winter break.

In the succeeding chapter, a literature review of spatial ability research and learning loss is presented. In the third chapter, the research methodology is given greater detail. In the final chapters, the results of the research and the conclusions are presented.

**Significance of the Study**

If spatial ability degradation is identified in this study, then it contradicts the accepted belief that the malleability of spatial ability is unidirectional (i.e. improvement
only). This will open new avenues of research in spatial ability. Questions and new hypotheses may arise about the utility of spatial ability interventions in general, the impact of specific intervention types, or methods that may be developed and/or implemented to encourage spatial ability maintenance. The benefits that spatial ability gains bring to engineering education may also be pursued in a new light.

Assumptions and Limitations

Assumptions

MAE students – particularly as freshmen and sophomores – are sufficiently representative of other engineering students such that findings related to MAE students may be applied to other engineering student groups and vice versa, although it is recognized that different courses may have different impacts in terms of indirect spatial ability instruction and its associated retention or development. Additionally, engineering students at the single institution where research is conducted (i.e., USU) are sufficiently representative of other engineering students to provide initial insight into the topic at hand.

The categorical subset of spatial activities that are intrinsic and dynamic (Utall et al., 2013), as defined in the Definitions section, capture the measures of spatial ability that correspond best to engineering performance. This aligns with the regular practice of using such measures in engineering education studies.

Measuring spatial ability with the MCT covers similar tests that are in the same category (i.e., intrinsic and dynamic), which are an appropriate measure of the facet of spatial ability emphasized in engineering education. The MCT in particular is appropriate due to the reduced impact of ceiling effect on its results.
It is not necessary for this study to validate engineering coursework as a cause of spatial ability increase due to the timeframe, participant population, and nature of the data collected.

**Limitations**

1. This study is researching whether spatial ability degradation happens during the winter academic break, not the best course of action to remedy it.

2. This study looks at students across the grade levels of coursework, providing a form of longitudinal insight, but does not track individual students through the three grade levels, thus precluding a fully longitudinal design.

3. This study reports on activities and demographic factors that are correlated with spatial ability. Due to a lack of random assignment (which is impossible for past life experiences), it cannot be determined if the activities influence spatial ability levels or if spatial ability levels influenced participants to choose those activities.

4. This study is limited to researching engineering students, which have been shown to have above-average spatial ability when they arrive on campus. Thus, they do not represent the general population. Reasons for the differences in engineering students’ growth in spatial ability compared to the general populations’ have not been documented and are not identified in this study.

5. This study is conducted at a single institution, thus limiting the generalizability of the findings unless confirmed by similar findings at institutions with different faculty and student demographics.

6. While this study is looking at a prolonged period of more than one week, it was limited by the length of the winter academic break. Thus, while its insights may motivate
research into longer periods of time, it does not represent them.

7. This study is not researching the relationship between spatial ability gains and engineering performance. Nor is it looking at the durability of any gains in engineering performance that may be based on spatial ability gains.

8. This study is limited by the number of students involved, and the impacts of mortality in a longer-term study that includes an academic break. Statistical significance is achieved in many measures, but larger numbers would provide more definitive results.

Definition of Terms

Spatial ability: A measure of spatial aptitude, to be used as a tool in diagnosing learning and educational interventions.

Spatial aptitude: Individual skill in performing spatial thinking.

Spatial thinking: Mental activities that require a spatial component, including: navigation; 2-D spatial arrangements, orientation, and rotation; 3-D spatial arrangement, orientation, and rotation; 3-D perspective taking; and spatially representing non-spatial items (e.g., conceptual overlap or rates of expenditure represented graphically).

Spatial ability malleability: Changes in spatial ability.

Spatial ability degradation: Decreases in spatial ability.

Intrinsic: A label for spatial activities that involve the comparison of an object’s features within itself (Utall et al., 2013).

Dynamic: A label for spatial activities that involve motion that can include translation, rotation, and bending (Utall et al., 2013).

Intrinsic and dynamic: This defines a category of spatial activities. This category includes spatial activities of spatial visualization and mental rotation (Utall et al., 2013).
Mental Cutting Test (MCT): A spatial ability test that is intrinsic and dynamic (CEEB, 1939).

K-12: A reference to pre-collegiate education, kindergarten through 12th grade (or the senior year of high school).

Learning loss: When students forget facts, experience regression in their skill-set, or otherwise show the opposite of the improvement they previously exhibited as a result of instruction.

Indirect intervention: An activity that does not have the primary intent of increasing spatial ability, but, as a side effect, serves as a spatial ability-promoting intervention due to characteristics embedded in the activity.
CHAPTER II
LITERATURE REVIEW

Calls from the federal government have established a need to train more science, technology, engineering, and mathematics (STEM) graduates, and to make the academic instruction better, i.e., more relevant and effective at preparing them for the professional world after graduation. The basis for the need is to improve the financial outlook of the nation (President’s Council of Advisors on Science and Technology, 2012; U.S. Department of Commerce, 2013). In an effort to make those improvements, various foci have been developed to improve the recruitment, retention, and preparation of STEM students. Out of existing research, it has been found that spatial ability is a quantitative measure of a particular construct of spatial thinking, and it has been correlated to success in STEM fields (Wai, Lubinski, & Benbow, 2009). Many have similar findings, and more research, experimental and otherwise, has been executed to better understand the connection between spatial ability and STEM (Miller & Halpern, 2013; Stieff & Uttal, 2015; Wai et al., 2009), and how to leverage that connection to improve STEM instruction (Miller & Halpern, 2013; Sorby & Baartmans, 2000; Sorby, Casey, Veurink, & Dulaney, 2013). As part of an engineering education research dissertation, this chapter reviews the literature on spatial ability, its relation to engineering education, and the expected long-term impact of instruction that enhances spatial ability.

Spatial Ability

Spatial ability is a measurement of an individual’s spatial intelligence, which Hegarty (2010) defines as “adaptive spatial thinking”. She states that we are presented with increasingly more visual information that include spatial components that are easily
manipulated and can bring increased understanding or may require increased spatial understanding. Herein “adaptive spatial thinking” is considered to refer to solving problems with spatial thinking. This type of problem solving relies on the individual to consider the spatial relation of objects to themselves (with regard to internal features) or to other objects, and may include consideration of relative position and orientation, manipulations of the shape (e.g. along folding lines), or perspective. This has been found to be a significant predictor of success and enrollment in STEM disciplines (Hegarty, 2010; Kozhevnikov, Motes, & Hegarty, 2007; Sorby et al., 2013; Wai et al., 2009).

Of particular note for this paper are the linkages and influences between spatial ability and professional and academic engineering skills (Sorby, Casey, Veurink, & Dulaney, 2013; Prieto, & Velasco, 2010; Sorby, 2009). The work of Sheryl Sorby (Sorby, 2011; Sorby & Baartmans, 2000; Sorby & Veurink, 2012) has been particularly foundational in providing inspiration for replication within the academic community (Miller & Halpern, 2013). Overall, the impact of spatial ability holds promise to improve retention of many engineering students as we can identify those students who would be well-served by spatially-enhanced interventions and to improve enrollment as we work to identify students with high spatial ability as potential candidates for academia (Shea, Lubinski, & Benbow, 2001; Webb, Lubinski, & Bendbow, 2007).

The findings of Wai et al. (2009) demonstrate that spatial ability is a better predictor of academic success for engineering students than math SAT scores, which are generally treated as the best predictor. The inclusion of spatial ability in academia’s strategy, particularly as we heed the call to connect students’ education to their professions (National Research Council, 2012b) and to identify field- and course-specific
spatial ability content (National Research Council, 2012a).

The recognition of spatial ability’s correlation to success in academia has a long history, as evidenced by its inclusion in college entrance exams in the 1930s (CEEB, 1939), and analysis of the tests that attempt to identify its various facets has been ongoing for decades as well (Adané & Velasco, 2002; Ekstrom, French, Harman, & Dermen, 1976). Uttal, Newcombe, Halpern, and Hegarty are four of the primary psychologists leading in spatial ability today. All four contribute to spatial ability broadly (Halpern & Collaer, 2005; Hegarty, 2010; Newcombe, Uttal, & Sauter, 2013). However, each shows tendencies toward certain lenses into spatial ability with Uttal referring to geospatial skills (Baker et al., 2015; Jee et al., 2014); Hegarty to spatial ability and representational competence’s links to the sciences like chemistry (Padalkar & Hegarty, 2015; Stull, Gainer, Padalkar, & Hegarty, 2016); and Halpern and Newcombe show special interest in sex differences (Baenninger & Newcombe, 1989; Halpern, 2013; Halpern et al., 2007; Newcombe, Mathason, & Terlecki, 2002). It should be stated that Newcombe argues that while sex differences are “scientifically interesting,” the focus should be on methods of improving spatial ability (Newcombe et al., 2002). Of particular note for this dissertation, Newcombe and Uttal have been involved in meta-analyses of spatial ability interventions that provide a sense of validity to the community’s reports of interventions that permanently increase spatial ability (Baenninger & Newcombe, 1989; Uttal et al., 2013), which claim this study is investigating.

**Spatial Interventions**

Numerous interventions have been implemented to study spatial ability in various age groups. Sundberg, et al. (1994) provided instruction using physical models to 5th
grade geometry students that resulted in an increase in spatial ability. Toptas et al. (2012) identified increased spatial ability gains through using 3D modeling software instead of just creating 2D drawings on paper in 8th grade students. Similarly, Onyancha, Derov, and Kinsey (2009) recognized increased spatial ability gains when more in-depth 3D modeling tools were provided rather than the standard CAD instruction for undergraduate mechanical engineering students, keeping in mind that the intervention, consistent with Sorby’s early work (Sorby & Baartmans, 2000), was not fully experimental since the participant population consisted of pre-screened, low-scoring volunteers while those in the control group were simply those who did not volunteer. Adanez and Velasco (2002) also looked at engineering students and found a correlation between spatial ability and engineering student performance. Sorby’s intervention for undergraduate engineering students is similarly based on descriptive geometry instruction, motivated by a correlation between spatial ability and course performance, and has resulted in statistically significant increases in spatial ability scores (Sorby, 2011; Sorby & Baartmans, 2000). This research is generally well-received but it utilized a self-selecting population of low-spatial ability students and lacked experimental application of the intervention.

Score improvement is being found in areas other than in explicit interventions. Using the Purdue Spatial Visualization Test Visualization of Rotations (PSVT:R) (Guay, 1976) and MCT, enrollment in engineering courses, such as Statics (Wood et al., 2016) and Engineering Graphics (Bell, Goodridge, Call, Devitry-Smith, 2016), has been found to be correlated with an increase in spatial ability. It should also be noted that other STEM courses, such as Anatomy, have had their course performance correlated with spatial ability, but enrollment in those courses does not necessarily correlate with a
spatial ability increase (Wood et al., 2016). In other words, even though STEM courses may all exhibit a correlation between spatial ability and course performance, spatial ability gains can be measured when students are enrolled in only certain engineering courses (which do not provide an explicit spatial ability intervention), while other STEM courses may not provide the same indirect benefit.

Interest in such indirect interventions (i.e., standard engineering coursework) is piqued due to the inherent efficiencies to be found in such an approach, but more so because the growth in spatial ability may be mapped to specific course features that can provide insight into how spatial ability connects to that specific course’s work and demographic and experiential factors in the student population. Such features may be leveraged for application into similar courses later. For example, it has been found that providing physical manipulatives to students as they solved Statics truss problems enabled them to physically investigate the force interactions in a very spatial form that ultimately enabled students to better visualize the problem space (Mejia, Goodridge, Call, & Wood, 2016).

Factors Influencing Spatial Ability

Wood et al. (2016) found evidence of some influential experiential factors as exhibited by the PSVT:R and MCT. Specifically, those who reported low experience in drafting, LEGO brick play, woodworking, and/or welding exhibited statistically significant gains while enrolled in a Statics course in the MCT and PSVT:R (note: gains based on low woodworking experience were only found on the MCT). Sorby and Baartmans (2000) found that experience with construction toys and design-related courses were significant predictors of performance on the PSVT:R, but were gender-
biased because males tended to participate more often than females in these activities that predict higher spatial ability. Most studies in spatial ability find differences by gender, with males typically outperforming females in spatial rotation tasks, but the effects appear to be tied to previous experiences and the gender differences generally do not exhibit any difference in the abilities of participants to improve in spatial ability (Newcombe et al., 2002). They also considered experience with industrial arts, video games, work experience, and sports. Other studies have found that experience with 2D and 3D video games have a positive impact on spatial ability (Lee & Peng, 2006).

**Instruments to Measure Spatial Ability**

Uttal et al. (2013) have categorized spatial skills and processes into a typology that they illustrated well with a 2x2 matrix, as shown in Table 1 below. In this matrix, the first axis differentiates between intrinsic versus extrinsic information as the basis of the spatial task, and the other axis differentiates between static versus dynamic spatial tasks. Using such an approach, the intrinsic-and-dynamic cell of this matrix would contain any task that involves consideration of internal or external features of one object at a time (i.e. not extrinsically comparing one object to other objects) and requires consideration of a different orientation of the object in order to identify the correct answer. This category contains the assessments that are typically used in studies correlating STEM subjects to spatial ability. It covers the mental rotation category identified by (Linn & Petersen, 1985) and part of the spatial visualization category they identified as well. Specific measures found in this category include the Purdue Spatial Visualization Test: Visualization of Rotations (PSVT:R) (Guay, 1976) and the Mental Cutting Test (MCT) (CEEB, 1939). Sorby in particular utilizes the PSVT:R a great deal (Sorby & Baartmans, 2013).
Table 1. A 2x2 Classification of Spatial Skills with Descriptions from Uttal et al. (2013)

<table>
<thead>
<tr>
<th></th>
<th>Intrinsic (Within Object)</th>
<th>Extrinsic (Between Objects)</th>
</tr>
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<tbody>
<tr>
<td>Static</td>
<td>Perceiving objects, paths, or spatial configurations amid distracting background information</td>
<td>Understanding abstract spatial principles, such as horizontal invariance or verticality</td>
</tr>
<tr>
<td>Dynamic</td>
<td>Piecing together objects into more complex configurations, visualizing and mentally transforming objects, often from 2D to 3D, or vice versa. Rotating 2D or 3D objects</td>
<td>Visualizing an environment in its entirety from a different position</td>
</tr>
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Numerous measures have also been used to measure spatial ability. A more complete listing may be found in Halpern and Collaer (2005). The following provide a short overview of some studies that have correlated spatial ability to STEM topics, and the measures they used.

Kozhevnikov et al. (2007) researched undergraduate college students and the relationship between spatial ability and kinematic physics performance using the Paper Folding Test, the Form Board Test, the Card Rotation Test, and the Cube Comparison Test. Sundberg et al. (1994) used the Middle Grades Mathematics Project-Spatial Visualization Test. Toptas et al. (2012) used the the Mental Rotation Test, Differential Aptitude Test-Spatial Relations, and Spatial Visualization Test. Onyancha et al (2009) used an online version of the Purdue Spatial Visualization Test: Visualization of Rotations (PSVT:R) test (Guay, 1976). Sorby primarily uses the PSVT:R, and has also used the Mental Cutting Test (MCT) (CEEB, 1939) and the Differential Aptitude Test: Space Relations (Sorby & Baartmans, 2000). Adanez and Velasco (2002) went into great depth proving the psychometric qualities of the MCT as a valid instrument for use in engineering education research, and it has been found that the MCT is less likely to impose a ceiling effect than the PSVT:R (Call, Goodridge, & Sweeten, 2016). That said,
the causality of spatial ability increasing engineering performance, or transferability of expertise, has not been generally proven or disproven (Stieff & Uttal, 2015).

The primary method of quantifying performance on a spatial ability instrument is through looking at scores. However, Linn and Petersen (1985) also report on the use of measuring the time required to obtain a solution as a quantitative measure in spatial ability studies. Their findings indicate that when scores are extremely high, mental rotation items are used to measure the time required for solution rather than accuracy. They found that speed differences apply to spatial ability sex differences, but are less likely apply to math and science performance. They noted that “…variability in response times for females was greater than for males because of a bimodal distribution of scores for females” and posit that “…speed of rotation is probably less critical in spatial visualization than in mental rotation.... [or] may reflect caution on the part of females."

Need for Spatial Ability Research

While studies have shown that spatial ability can be improved through interventions (Uttal et al., 2013), and some have demonstrated indications of transferability to a number of transfer topics (Miller & Halpern, 2013; Sorby et al., 2013; Stieff & Uttal, 2015), the research has generally been limited to periods of time that are concurrent with instruction in or assessment of the spatial ability and/or transfer topics. This study aims to identify how durable spatial ability gains are after a period of no instruction on spatial ability or science, technology, engineering, or math (STEM) transfer topics. It is interesting to note in Miller and Halpern (2013) that after short, 12 hours cumulative, spatial ability instruction, there was a significant improvement in spatial ability and physics performance for participants assigned to an intervention
compared to the control group, but eight months later, no relative improvement was detectable.

While publications on the topic of spatial ability improvement are present in research literature, it is more difficult to find publications on the topic of spatial ability degradation or decline. This may be influenced by the fact that spatial ability research typically times its assessments to occur during instruction in transfer topics, which may be providing an indirect spatial ability intervention effect, and shortly after the conclusion of spatial ability interventions. Thus, a broader search for degradation research regarding learned skills is required.

**Skill Degradation and Learning Loss**

When cognitive skills that were learned in the classroom degrade, the term “learning loss” is commonly used in educational research literature. Learning loss during school breaks is a commonly studied as a topic in K-12 educational research, and the learning loss research literature is generally focused on mathematical and language abilities, not spatial ability (Alexander et al., 2007; Blazer & Miami-Dade County Public Schools, 2011; Cooper et al., 1996; Dills et al., 2016; Graves, 2011; McMullen & Rouse, 2012). Learning loss research rarely occurs with healthy adult learners such as would be found in a collegiate engineering classroom (Dills et al., 2016). As such, the learning loss research has focused on the long summer break, and not shorter breaks that are on the order of ~1 week like winter or spring break for K-12. However, data from year-round schooling indicates that learning loss – at least cumulatively – for the 3-week breaks that are part of the year-round schedule is significant and does not differ much from the summer learning loss found in the traditional schedule (Graves, 2011; McMullen &
Rouse, 2012). This indicates that studying a break like the collegiate winter break, which is typically on the order of 3-4 weeks, could provide a deeper understanding of learning loss or skill degradation.

Most spatial ability studies perform post-test measurements within a week of the end of the study’s intervention, and all but a small percentage (~2%) perform post-tests within one month of the end of the intervention (Uttal, Meadow, Tipton, Hand, Alden, Warren, & Newcombe, 2013). As such, most post-test measurements are performed during a period of academic instruction, which may be a confounding influence, particularly for engineering students. The spatial ability research literature for studies with less than one month separation for post-tests indicates that learning loss (i.e. spatial ability degradation) has not occurred in post-test measures (Utall et al., 2013). This research fills a gap in adult educational research as well as engineering education research, and may be the first to include a look at adult learning loss in a specific skill (spatial ability) over a winter break between academic semesters.
CHAPTER III
RESEARCH METHODOLOGY

In order to develop a methodology for this research, a methodological framework was established within which the selected methods are demonstrated as valid. The framework described in this chapter is defined in an order proceeding from the general to the specific. The order of topics treated is: Approaches to engineering Educational research, Statistical methods, Theoretical paradigms implied by statistical methods, Correlation of spatial ability with engineering performance, Measurement of spatial ability, Limitation of confounding factors, Collection of data, and Approach to analysis.

Quantitative Research

In response to the call for more trained engineering professionals, engineering education policy is often informed by quantitative data and the conclusions that can be drawn therefrom as it is aimed at impacting a large group. Quantitative research itself is generally founded on statistical methods and the underlying assertion that groups are represented by their mean. Thus, if the mean performance of a group is improved, then it is assumed to be an improvement for the group in general. There are numerous inherent assumptions regarding the behavior of quantitative data (e.g. normalcy, constant variance) that were checked as part of a quantitative analysis, keeping in mind that some statistical benchmarks consistent in engineering research differ than those in behavioral research. For example, the question of acceptable correlation ($R^2$) values differs between the sciences such as engineering, and behavioral sciences such as engineering education. An $R^2$ of 0.7 is often viewed as a lower limit in engineering. However, as reviewed in Ruesch et al. (2017), $R^2$ between 0.04 and 0.6 are sought for behavioral research – where
anything higher may indicate a Type II (i.e., false negative) statistical error (Cohen, 1992). The traditional standard for identifying statistical significance is to find a p-value < 0.05. However, given the wide variability that occurs in educational research it is appropriate to increase that number. For exploratory educational research studies, p<0.1 may be used (Gall, Gall, & Borg, 2007, pp. 138-142). This increases the chance of a Type I (i.e., false positive) error, but it decreases the chance of committing a Type II error.

Exploratory research is often limited by its sample size, which is true in this study, which decreases the tendency to find significant results; and exploratory research is typically viewed as casting a wider net to identify directions for future research, which is also true of this study. Due to these characteristics, it is deemed that reducing Type II error should be prioritized and that p<0.1 should be utilized in place of p<0.05. Multiple effect sizes can be calculated and used to establish acceptance of statistical results, and many of them are more appropriate when mean differences do not aid interpretation (Cohen, Cohen, West, & Aiken, 2003, p. 5). However, given that this study is looking for general trends of the participant population, it was primarily based on mean differences. P-value significance and Cohen’s d, calculated via an R script (Arun, 2013), for effect size were used as the criteria for mean differences; for the regression models, the effect size was the multiple correlation coefficient squared, R², (Cohen, 1992; Ferguson, 2009; Sullivan & Feinn, 2012). Additionally, nonparametric statistics are calculated, wherein the reliance is on the median rather than the mean, and thus assumptions of normal distribution and constant variance are not required. These have their own estimates of the correlation coefficient, r or r² values calculated via an R script (Logos, 2009; Marshall & Marquier), for effect size (Tomczak & Tomczak, 2014), which may be interpreted on the same scale.
as $R^2$ (Ferguson, 2009). Consistent effect sizes across the different types of effect sizes are found in Ferguson (2009), wherein the recommended minimum for a practical effect size via Cohen’s $d$ is 0.41, while 1.15 indicates a moderate effect size, and 2.70 indicates a strong effect size; via $r^2$ and $R^2$, 0.04 is the recommended minimum for a practical effect size, with 0.25 indicating a moderate effect, and 0.64 indicating a strong effect size; via $r$, the three levels are 0.2, 0.5, and 0.8.

It is recognized that a positionality statement is typically provided for to educational research, when qualitative methods are used, in order to make biases more explicit in publications. Positionality for the quantitative approach used in this study is given in Appendix A.

**Research Design**

When performing a spatial ability study, whether it implements an experimental intervention to increase spatial ability or only seeks to measure spatial ability, most researchers use established spatial ability measurement instruments. This provides a means for consistent measures, avoids many of the issues with reliability and validity, and allows for convenient comparisons to other studies. In the study of changing (or malleable) spatial ability, the most analytically useful studies in spatial ability are those that have a pre-test and a post-test, also known as "mixed" studies (Uttal et al., 2013). Thus, this study followed that standard pre-test, post-test pattern, with the tests bracketing the winter academic break between semesters.

In past research, it has been found that in engineering classes – specifically Engineering Graphics (Bell, Goodridge, Call, & DeVitry, 2016) and Statics (Wood et al., 2016) – there are increases in engineering students’ spatial ability in spite of there being
no explicit spatial ability intervention. Students enrolled in Anatomy courses do not demonstrate in increase in spatial ability while enrolled in the class (Wood et al., 2016). It was posited that the same is true for Advanced Dynamics due to so much of the coursework being based on coordinate system and vector rotation. Thus, for this study, the intervention of interest is attendance in engineering coursework, rather than STEM coursework in general. Specifically, the engineering courses of interest are Engineering Graphics, Statics, and Advanced Dynamics, as in earlier research (Bell, Goodridge, Call, & DeVitry, 2016; Wood et al., 2016). By focusing on these courses again, the trends of improvement during the semester in Engineering Graphics and Statics were already identified. Looking at these courses also enabled a longitudinal view of spatial ability as they are intended for enrollment by freshman, sophomore, and junior students, respectively.

Spatial ability-specific confounding factors that need to be considered include the past activities of students. In this study, there is particular concern about activities during school breaks. Activities such as video games (which are often spatially oriented) have been shown to improve spatial ability. Other hobbies such as woodworking have also been found (via t-test) to correspond with the absence of spatial ability improvement (Wood et al., 2016). Survey questions asking about these confounding factors were used to control for them.

**Threats to Research Validity**

A number of threats to validity are presented in Gall et al. (2007, pp. 379-394). Each one is discussed within the context of this study. The threats are categorized as threats to internal validity or external validity.
Internal validity takes into account how well the researcher has controlled for extraneous variables. Twelve such threats are discussed with the applied precautions taken herein. 1) History, wherein the experiences of participants differentiate them and impact the treatment within the study, is the primary focus of the second research hypothesis, and differences in experience were thus treated directly in this research. 2) Maturation, wherein participants improve as a natural result of the progression of time, is assumed to be limited due to the short duration of the study, but is discussed in the results section as a threat that may have unique impact on research in spatial ability done engineering student populations. 3) Testing, wherein participants improve their performance on the instrument through repetition, is assumed to be handled by waiting the recommended month between iterations (Stangor, 2003). There is an additional consideration of testing as a threat to this research because some of the Advanced Dynamics may have taken the MCT prior to this study as one of the two sections of Statics offered when they were sophomores (even more than a month previous) had provided students the opportunity to take the MCT and PSVT:R (Wood et al., 2016). To track the impact of past experience with spatial ability instruments, data were collected on the topic as part of the survey. 4) Instrumentation, wherein the nature of the measuring instrument changes during the study, is not considered to be a threat to this research. 5) Statistical regression, wherein participants would regress to a common mean over repeated measures, are treated by having a pre-test and a post-test in this study, and the comparisons of means and standard deviations between pre-test and post-test scores via t tests analysis also controled for this threat. 6) Differential selection is not a threat to this study as no control group is involved. 7) Experimental mortality, wherein some research
participants may cease participating in this study, is a real threat to this study and of concern due to a perceived likelihood that students may not respond to the invitation to complete the post-test and survey phase of the study while enjoying time off from school during an academic break. In order to limit this, students are being invited to provide text message or email as their preferred means of contact during the break. 8) Selection-maturation interaction, just as differential selection, is not a threat to this study due to the lack of a control group. 9) Experimental treatment diffusion, wherein participants seek the treatment applied to other groups due to a perceived benefit, is not a concern in this study due to the lack of an experimental treatment. Additionally, although the potential for differences between the differing, previous indirect influences of coursework exists, students are not believed to be seeking insight from each other about different courses’ materials over the academic break. 10) Compensatory rivalry by the control group is not a threat to this research due to a lack of a control group. 11) Compensatory equalization of treatments, wherein treatment administrators seek to give the similar benefits across the participants, is not a threat to this study in the traditional sense. However, differences in instruction provided in the courses (viewed as indirect interventions) may provide a threat – this was further treated as a threat to external validity. 12) Resentful demoralization of the control group is also not a threat to this research due to the absence of a control group in this study.

Threats to external validity may limit the applicability of the study to other populations or settings. External validity is divided into ecological validity, which represents the environmental conditions of a study, and population validity, which represents the applicability of results to other populations. Ecological validity concerns
are treated herein through an attempt to be thorough in providing details regarding the research design, rationale for selection, and demographic and background details regarding the participants. Given that this study is conducted with a relatively small sample size and the population is drawn from a university with a fairly uniform demographic, the population validity is considered to be fairly low, i.e., the threats may be high and/or realized. There are two population threats discussed by Gall et al. (2007, pp. 379-394), and they are included herein. 1) *The extent to which one can generalize from the experimental sample to a defined population* is essentially a realized threat to this study due to the relatively uniform demographic found in the accessible population at USU. The source and participant populations are predominantly white, middle-class, and male. Thus the applicability of this research to student populations from other demographics is unknown and unproven. Fortunately, there is some variation in the past experiences of the participant population, which should provide some insight, even in populations with different demographics. 2) *The extent to which personological variables interact with treatment effects*, just as the *history* internal threat, is the primary focus of the second research hypothesis, and was thus accounted for in this research.

Control for internal threats and external threats to validity are described above. Threats to population validity are of the highest concern, and both limit the general applicability of this study and align with its hypothetical foci.

**Research Hypotheses**

As mentioned in the first chapter, the primary hypothesis is “Engineering students will show a decrease in spatial ability, as measured by the MCT, during academic breaks.” There is no evidence of such degradation in the literature. However, based on
the literature reviewed, this area has not been thoroughly researched. And if the correlation between engineering course performance and spatial ability is bi-directional, then the decrease in course performance observed over academic breaks should indicate a decrease in spatial ability as well.

The secondary research hypothesis, which is dependent on at least part of the participant population decreasing in spatial ability is: “There are demographic and experiential factors during breaks in engineering coursework that moderate the degradation of spatial ability.” Based on the influence of experiential factors seen in the literature, it is expected that those with more spatially relevant experience would exhibit less of a decline during the break. It is also hypothesized that experiences with those activities during the break, at least for those with limited past experience, would also impact the potential for decline during the break.

**Population, Demographics, and Sample**

The selected sampling technique is convenience sampling based on class enrollment. Access to engineering classrooms in past research has primarily involved MAE courses – Engineering Graphics and Advanced Dynamics – or courses that include MAE students as well as civil, environmental, and biological engineering students – Statics (Call, Goodridge, & Sweeten, 2016; Wood et al., 2016). Continuing to access this pool of classes makes sense in light of comparing with previous results, having observed growth in spatial ability. It also is insightful as the courses provide a natural progression of MAE students through their academic careers, with Engineering Graphics being offered to freshmen, Statics being offered to sophomores, and Advanced Dynamics being offered to juniors. Three sections of Engineering Graphics (~120 students), one section of
Statics (~220 students), and one section of Advanced Dynamics (~110 students) were contacted for recruitment. Based on past experience, it was estimated that 10% of the students would volunteer, leaving the study with 45 participants. Reporting student academic year (freshman, sophomore, junior, senior) is considered to be problematic due to the high number of credits earned by many incoming college students and its inability to provide an accurate picture of how far students are in their engineering curriculum. This is especially true of engineering students. Additionally, at USU there are many students who defer their admission or pursue a leave of absence for more than a year during the early part of the collegiate education. This also creates ambiguity regarding the use of age as an appropriate marker for progress through the engineering curriculum as well. Due to the plan of study promoted by the engineering departments at USU, enrollment in Engineering Graphics, Statics, or Advanced Dynamics is the best indicator of progress through the engineering curriculum available in this study. While there are some exceptions, most engineering students take Engineering Graphics during their freshman year, take Statics during their sophomore year, and most mechanical engineering students take Advanced Dynamics during their junior year. For these reasons, analysis comparing spatial ability attainment to progress through the engineering curriculum was linked to the class from which each participant was recruited (i.e., course enrollment acted a surrogate for experience in engineering curriculum).

It is considered particularly important to look at data from the freshman and sophomore classes as those are viewed as “the most critical to the retention and recruitment of STEM majors.” (President’s Council of Advisors on Science and Technology, 2012). Participants from those classes offer the most opportunity for insight
that may begin to inform how spatial ability may play a role in student retention, based on differences between degradation in the junior year and degradation during the first two years in undergraduate engineering.

**Instrumentation**

As mentioned above, the intrinsic-and-dynamic category of spatial ability instruments is commonly used in studies correlating participants’ learning of STEM subjects to spatial ability. See Table 1 for the categorization of spatial skills. An example from the MCT is shown in Figure 1 below, wherein it can be seen that only one object is used (thus it is an intrinsic problem), but in order to visualize the correct answer, the object must be mentally rotated so that the cut surface is normal to the participant’s line of sight (thus it is dynamic).

Look at Sample Problem 1.

These figures show that D is the correct answer choice for Sample Problem 1.

Figure 1. Sample Problem 1 from the MCT (CEEB, 1939), Copyright Expired

Limitations of the instruments may prove to be problematic as participants with high spatial performance introduce ceiling effects to the data where current instruments
cannot identify spatial ability improvement, retention, or learning loss. Past research has shown that some instruments are more susceptible to ceiling effects than others. Specifically, Call, Goodridge, and Sweeten (2016) demonstrated that for sophomore engineering student populations, the PSVT:R has a more limiting ceiling effect than the MCT. Due to this limitation of the PSVT:R, which prevents identifying change in high-spatial-ability participants, this study used the MCT.

To account for the confounding and moderating factors, a survey instrument was given to all participants to identify the activities that they participated in during the school break and to cover other demographic factors. The MCT pre-test and post-test were delivered online via Qualtrics, as was the demographics and activity survey. The survey questions were written to align with the Wood et al. (2016) study in order to ensure that the same factors may be compared in the results. Two-dimensional spatial activities were also tracked in the question set. The instruments can be found in Appendix B.

**Quantifying Performance**

As an instrument, performance on the MCT is typically represented quantitatively by the raw score, where higher scores represent better performance. When participants score approximately equally on the MCT, the time spent on the MCT can be used to differentiate participants in terms of performance, with shorter times representing better performance. It has been seen that such differentiation may be needed with engineering students who hit the ceiling of what is measurable by spatial ability instruments (Call, Goodridge, & Sweeten, 2016). Conference session discussions after the presentation of the Call, Goodridge, and Sweeten (2016) paper included the proposal
to use duration as a means of differentiating performance between individuals who achieved similar scores on spatial ability exams. This approach aligns with the Linn and Petersen (1985) finding that the time spent on mental rotation items are helpful when scores are high, as they are expected to be with engineering students. By delivering the spatial ability assessment in an online format, the MCT duration data are easily available from the survey-reporting software for comparisons between participants. The timing data were used to represent the total duration of time spent by each participant on each full application of the instrument.

**Survey Details**

The survey used is largely intended to match, where possible, and build on a survey used in previous work (Wood, Goodridge, & Call, 2016). The new survey reflected the previous one in both question topics as well as response formats. The survey asked about a number of aspects regarding their scholastic experiences, prior experiences, experiences during the break. The topics covered are Repetition of the same course from which they were recruited, employment during the school semester, previous spatial exams, classification of hometown size, drafting classes, playing with blocks as a child, model construction and puzzles, radio controlled toys, FIRST robotics, JETS, Future City, TechXplore, VEX robotics, Think Quest, LEGO Engineering®, INSPIRE!, Botball, Odyssey of the Mind, Minecraft, Erector sets, LEGO brick play, Tetris, first-person video games, other 3-D video games, 2-D puzzle video games, 2-D strategy games, woodworking, welding, fabrication, electronics, mechanics, cabinetry, building computers, gardening, artistic painting, artistic drawing, residential/commercial painting, construction, sewing, embroidery, cooking, dancing, sports, and playing music. The
survey also covers demographic factors like self-identified biological sex, race, age, and college major. The survey questions are included in Appendix B.

**Data Collection**

Stangor (2003) recommends at least one month separation between pre- and post-tests to limit repeated practice artifacts (or having participants learn the tests) in the data. In order to maximize the amount of time participants spend outside of STEM classrooms, the post-test was given at the end of the school break. For the winter school break, which lasts less than one month, this means that the pre-test had to be given before the end of the fall semester in order to have one month between the pre-test and the post-test. Willing participants who were slow to participate the study would have been allowed to take the pre-test during the week of finals and were allowed to take the post-test during the first day or two of the semester before they have engaged in their engineering coursework.

The recruitment process is represented graphically in Figure 2. To recruit participants, visits were made to classes that have been studied in the past for their links to spatial ability: Engineering Graphics, Statics, and Advanced Dynamics. During the fall semester, there were 3 Engineering Graphics sections with approximately 40 students each, one Statics section with approximately 220 students, and one Advanced Dynamics section with approximately 110 students. In total, 450 students were invited to participate. With an estimated participation rate of 10%, it was anticipated that close to 45 students to participate in the study over the winter break. This sample size should be sufficient for a statistical analysis.

In each class where recruiting was done, a link to the study’s pre-test was given in
Canvas, and, alternatively, students were invited to reach out to express interest in participating via email and/or text message. The graduate student’s usu.edu email address was used for email correspondence, and a Google Voice number set up for this research was used for text message correspondence. Further correspondence with participants was done via the course's Canvas page (a link to the study in the Announcements), email, and/or text.

<table>
<thead>
<tr>
<th>Courses for Recruiting</th>
<th>Class Sections</th>
<th>Course Enrollment</th>
<th>Anticipated Study Participation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering Graphics</td>
<td></td>
<td>~120 students</td>
<td></td>
</tr>
<tr>
<td>Statics</td>
<td></td>
<td>~220 students</td>
<td>Participation ~45 students</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td></td>
<td>~110 students</td>
<td></td>
</tr>
</tbody>
</table>

Figure 2. Recruitment Process and Anticipated Participation

The MCT pre-test included the Internal Review Board (IRB)-approved Informed Consent document and required that potential participants both verify that they are 18 or older and that they accept the Informed Consent before proceeding with participation. The Informed Consent document is included in Appendix B. The pre-test also included a request for each participant’s preference between email or text message correspondence, and then requested the participant’s email address or phone number depending on their answer. This contact information was only used to follow up for the post-test.

Participants were asked to complete the pre-test by the end of the week before finals. A link to the online post-test and activity & demographic survey was sent via email or text message just prior to the start of the next semester. Participants were asked to complete
the post-test before completing their first day of classes during the succeeding semester.

A relative timeline for data collection is shown in Figure 1 below. The last day of finals week was December 15, and the first day of classes after the break was January 7, providing a 3-week gap in instruction or greater depending on what day participants completed finals and whether they showed up to classes on the first day of school or not. Pre-test data collection started on December 4, and post-test data collection ended on January 8 with 31 days enforced as a minimum gap between pre-test and post-test for each individual participant.

<table>
<thead>
<tr>
<th>Recruit</th>
<th>Pre-test</th>
<th>minimum 31 Days</th>
<th>Post-test &amp; survey</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last week of class</td>
<td>Finals</td>
<td>Winter Break</td>
<td>First week spring semester</td>
</tr>
</tbody>
</table>

Figure 3. Relative Timeline for Data Collection

Data Analysis

At best, a quasi-experimental statistical approach may be used due to the lack of an experimental intervention (i.e. the engineering coursework that participants have taken was not experimentally applied, nor were the participants’ activities before the study or during the academic break) and the treatment of each participant as an individual. In such an approach, the number of participants may be used as the sample size in linear single and multiple regression/correlation (MRC) analyses. Defining sample size in this manner follows the standard, quasi-experimental statistical approach typically used in educational research defines. MRC analyses are useful for hypothesis testing in place of t-tests (which could also be used to determine a mean change in score between the pre-test and the post-test). They are also useful for identifying the strength of other factors, such as the nominal demographic data and interval experiential data collected in the survey, on the
dependent variable of interest (Cohen et al., 2003, pp. 3-10). The targeted dependent variable is the change in MCT performance, represented by change in score and change in duration, in this study. Statistically speaking, the null hypothesis for the primary research hypothesis (essentially, that decrease should occur between the pre-test before the break and the post-test after the break) is that there is no difference between the pre-test and post-test scores. If differences occurred, then p<.1 significance testing, as mentioned above, was utilized as the criterion for significance.

For a truly experimental approach, given five sections, it would be argued that the sample size is only five – because that is how many applications of the treatment (engineering coursework) were delivered – but only if those interventions were delivered experimentally. In spite of the non-experimental application of the treatment that this study must apply, it is still desirable to compare the results of the classes (and academic years) included in the research. Each class/year may have a different mean structure, and thus an ANOVA approach is appropriate to determine how the impact of the various courses on spatial ability retention differs between classes (Oehlert, 2000, pp. 44-52). Additionally, the data collected for non-mechanical engineering students in the Statics class may also be investigated, if there are enough non-mechanical engineering participants, to determine if students from different majors represent separate mean structure groups in spatial ability as determined by the MCT. MRC analysis was also applied to determine the significance of these nominal factors, class and major.

While the issues of quasi-experimental research are rarely discussed in educational research publications, the practice is widely accepted in educational research publications. That said, the nature and number of survey questions, which revealed the
unique qualities of every student, should make it obvious that no two students have received the same treatment over the course of their lifetime, and thus their treatment as individual samples may be appropriate. Perhaps there is an implied acceptance of this different-treatment-over-lifetime for each student; however, it is likely that the community simply recognizes the prohibitive costs and difficulty of collecting data that can be used for experimental statistics instead of quasi-experimental statistics. This study used the quasi-experimental approach due to the difficulties in fully implementing a fully experimental approach with the population, venue, and intervention to be studied.

Given that there is no guarantee that the assumptions of normalcy or constant variance are obtained with the data collected, and given the limitations of the small sample size obtained, nonparametric statistics were also investigated for further insight into the data collected. Spearman’s rho calculations and Siegel nonparametric linear regression (Siegel, 1982) provide nonparametric approaches to correlation and linear regression statistics. Unfortunately, although nonparametric multivariate models can be analyzed, they require a large sample size (Cohen et al., 2003, p. 253) and thus were not be included in this analysis.

**Data Description**

The means and standard deviations for the data collected were provided in order to describe the data. Simple t-tests were used to compare data from different groups and paired t-tests were used to track changes in individual performance. The Mann-Whitney U Test was used to provide a nonparametric alternative to the t-test, and the Wilcoxon Signed Rank Test provided a nonparametric alternative to the paired t-test.
Data Diagnostics

In general, due to the exploratory nature of this study, it is desirable to leave as many participants in the study as possible. It is recognized that the small sample size may mean that statistical analysis presented in results were heavily impacted by individuals – both in terms of the trends seen in the data as well as the statistical significance of the results. However, in order to gain insight into the participant population and the impact of their experiences on spatial ability, outliers may be left in if their results appear to be accurate. Results from participants who do not complete the survey and both instances of the MCT were excluded from the study.

Before running regression analyses, diagnostics were performed on the data for each potential independent variable. Homoscedasticity and normal distribution were graphically checked. Other than identifying data that should not be used for regression, no measures were taken to improve the variance or distributions of the data, given the small data size. Per Bohrnstedt and Carter (1971), only marked heterogeneity in variance impacts linear regression results, and violating the normal distribution assumption does not impact linear regression results. Similarly, violations of the normal distribution assumption do not preclude ANOVA either (Schmider, Ziegler, Danay, Beyer, & Bühner, 2010). Thus, the variables that exhibit the worst variance were excluded from direct MRC analyses. Checks for a normal distribution were performed graphically, but exclusion of data was unlikely given that the distribution does not impact results. Leverage, DFFIT, and DFBETA outliers were reviewed, given that they impact regression parameters. However, as mentioned above, outliers were not excluded as a matter of course. Outlier data may be used to identify participants with particularly
notable trends in the data. If those trends appeared to be unlikely to be accurate, the participant were removed from the analysis.

Given how robust the linear regression methods are to violations of the normal distribution and constant variance assumptions, nonparametric results are discussed together with linear regression results, rather than replacing them. Loess (or Lowess) data fits (Cohen et al., 2003, p. 252; Fox, 2000) were viewed during the diagnostic process (the span parameter used for Loess fits is .85) and parameters from Spearman’s rho calculations and Siegel nonparametric linear regression were compared with least-squares-based statistics. Specifically, Spearman’s rho was compared with least-squares correlation, Siegel linear parameters (i.e., slopes) (Siegel, 1982) were compared with least-squares linear regression results, and the p-values for both of those methods provided diagnostic insight into the least-squares results obtained.

**Principal Component Analysis**

While the diagnostics discussed above consider the relationship between dependent variables and independent variables, it is also possible to find insight by reviewing the independent variables together. Using principal component analysis (PCA), data distributions are represented using the primary eigenvectors and eigenvalues that describe the variation of the data. The principal components that account for the most variance within the data set were selected, and the loadings of their eigenvectors were analyzed to determine which of the original variables represent the most variance within the group. Multiple references were used in formulating the PCA strategy described below (Analytics Vidhya Content Team, 2016; Dason, 2013; Marc in the box, 2013).

Given that principal components, being based on the eigenvalues representing...
unique axes (eigenvectors) within the data, match the minimum size of the data provided (either the sample size or the number of variables fed into the algorithm), they provide so many components as to pose interpretability problems, and often have no direct interpretation. Thus, an effort needs to be made to identify the primary principal components and gain insight into which of the input variables were driving the variance in those primary principal components. Two approaches can be used to identify the primary principal components based on the variance of the dataset that they each account for. First, the cumulative variance is plotted for the principal components (in order of eigenvalue size). Those that account for a majority of the variance are selected as the primary components. Alternatively, those components with eigenvalues > 1.0 may also be selected. In order to distinguish the variables most associated with the primary components, a matrix of those principal components was multiplied by a matrix containing the variable loadings for those principal components to effectively reduce the number of components in a PCA to those selected as primary components. The resulting matrix then has a column for each of the original variables, now scaled by the loadings of the primary components. Taking the absolute value of those scaled values, the mean of each column may then provide a sense for the influence of each variable on the variance of the dataset. Doing this requires that the variables have scaled and centered values before performing the principal component analysis.

These results were compared with the results of the MRC to see if the influential variables identified as influential within the independent variables align with the independent variables identified as most influential on the dependent variables.
Tool Details

The survey and instruments were delivered using Qualtrics (Qualtrics, 2018). The statistical analyses were performed in R (R Core Team, 2017), version 3.4.3 (2017-11-30). Several packages were used as well, including MASS (Venables & Ripley, 2002), for the stepAIC() function used for the stepwise algorithm; car (Fox & Weisberg, 2011), for the qqPlot() function used for diagnostics; mblm (Komsta, 2013), for the mblm() function used for nonparametric regression; stringr (Wickham, 2017), for the str_count() function used in processing data from the source spreadsheet; doBy (Højsgaard & Halekoh, 2016), for the summaryBy() function used to generate some of the tables; and apaTables (Stanley, 2017), for the apa.aov.table() and apa.reg.table() functions used to generate ANOVA and regression results tables.

Implementation and Review

Internal Review Board (IRB) approval was required before beginning data collection. IRB protocol #8944 relates to this study, and approval with the approved Informed Consent document was received November 3, 2017.

Implementation Timeline

The anticipated steps required for the study are presented with the final schedule in the table below. The actual timeline required much more time spent analyzing the data behavior, conducting the statistical analyses, summarizing the results, and developing the conclusions.

Conclusion

In order to identify degradation in spatial ability, a quantitative look was applied to differences between pre-test and post-test MCT scores. The participant population was
primarily MAE students, and the recruitment pools provided a look through the first three years of their academic careers.

Table 2. Implementation Steps and Schedule

<table>
<thead>
<tr>
<th>Step</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obtain instructor authorization to recruit in classes</td>
<td>10/30/2017</td>
</tr>
<tr>
<td>Develop instruments in Qualtrics</td>
<td>11/01/2017</td>
</tr>
<tr>
<td>Obtain IRB approval</td>
<td>11/03/2017</td>
</tr>
<tr>
<td>Recruit participants in classes</td>
<td>11/29/17 - 12/06/17</td>
</tr>
<tr>
<td>Send out links to pre-test (Canvas, email, text)</td>
<td>11/29/17 - 12/06/17</td>
</tr>
<tr>
<td>Collect pre-test responses</td>
<td>11/29/17 - 12/15/17</td>
</tr>
<tr>
<td>Review pre-test responses, Collect follow-up information</td>
<td>12/16/17 - 12/31/17</td>
</tr>
<tr>
<td>Send out links to post-test (email, text)</td>
<td>01/01/18 - 01/06/18</td>
</tr>
<tr>
<td>Collect post-test responses</td>
<td>01/01/18 - 01/08/18</td>
</tr>
<tr>
<td>Review post-test responses, Check/Control for data behavior, variance</td>
<td>01/01/18 - 01/15/18</td>
</tr>
<tr>
<td>Analyze results using MRC and ANOVA in R</td>
<td>01/16/18 - 01/31/18</td>
</tr>
<tr>
<td>Summarize results</td>
<td>01/23/18 - 02/10/18</td>
</tr>
<tr>
<td>Develop conclusions</td>
<td>02/05/18 - 02/23/18</td>
</tr>
</tbody>
</table>
CHAPTER IV
RESULTS

Introduction

This chapter reports on the quantitative findings with respect to the research questions asked earlier and to the separation of subgroups within the participant population. The research hypotheses to be tested in this work are:

1) Engineering students will show a decrease in spatial ability, as measured by the MCT, during academic breaks.

2) There are demographic and experiential factors during breaks in engineering coursework that moderate the degradation of spatial ability.

The independent variables for this study derive from the survey responses and include the specific course from which each participant was recruited (which generally identifies their progress through the curriculum) as well as activity information regarding their experiences prior to enrolling in that course and their experiences over the academic break. The dependent variables are associated with participant performance on the MCT and include scores on the pre-test and the post-test scores, change in score between the pre- and post-tests, length of time spent on the MCT in the pre- and post-test, and change in duration between the pre- and post-tests. Descriptive statistics for the independent variables are presented below. Principle component analysis (PCA) has been used to distill insight from the independent variables, and were presented as part of the dependent variable results. Descriptive statistics and basic trends seen in the dependent variables are then presented, followed by more complex statistical analysis to identify the impact of the independent variables on the dependent variables. Linear regression and ANOVA
techniques have been employed to identify statistically significant predictors of performance.

**Analysis and Principal Components of Survey Responses**

Due to the appearance of trends based on course enrollment, and also due to the lack of statistical significance at this stage, it is desirable to refine our understanding of the potential dependent variables. This section reviews the insights gained from participants’ responses to the survey questions regarding their past experiences as well as their activities during the academic break. As a first step toward simplifying any future models to be developed from the data, the survey questions are split into three primary categories: individual characteristics, experiences before the study began, and experiences during the study. Descriptive statistics are provided regarding participants’ responses to these questions, with results presented separately for each course. Then the results of principle component analyses performed on the two categories of data are presented in order to identify the primary features revealed within the collected data.

**Individual Characteristics**

The work looked to categorize participant responses into different experience category timeframes, namely pre-study experiences and experiences during the academic break. Certain survey responses do not fit well within the pre-study experience category or the academic break category, as their impact was ongoing. These included participants’ biological sex, age, race and ethnicity, marriage and parental status, performance in school as measured by GPA, and progression through the curriculum. As mentioned previously, the course in which participants were enrolled when recruited for this study is used to represent progression through the curriculum. These characteristics
may influence the impact of pre-study experiences as well as the impact of experiences during the break. The descriptive statistics of these characteristics are provided for each course in the table below.

Table 3. Individual Characteristic Descriptive Statistics

<table>
<thead>
<tr>
<th>Course</th>
<th>Biological Sex</th>
<th>Age in years</th>
<th>Race</th>
<th>Married Ratio</th>
<th>Number of Children</th>
<th>GPA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M (SD)</td>
<td>Race</td>
<td>M (SD)</td>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>7 male 2 female</td>
<td>22.78 (2.11)</td>
<td>9 white</td>
<td>56%</td>
<td>0.33 (0.50)</td>
<td>3.47 (0.24)</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>9 male 4 female</td>
<td>22.85 (4.08)</td>
<td>11 white 2 other</td>
<td>31%</td>
<td>0.08 (0.28)</td>
<td>3.46 (0.80)</td>
</tr>
<tr>
<td>Statics</td>
<td>8 male 3 female</td>
<td>20.64 (1.50)</td>
<td>11 white</td>
<td>18%</td>
<td>0.00 (0.00)</td>
<td>3.72 (0.25)</td>
</tr>
</tbody>
</table>

The participant population exhibits a lack of racial diversity. Thus, the impact of race were not investigated in this study. Additionally, the number of female participants is low, which generally precluded finding statistically significant results in the predictive analysis below. It is interesting to note that the freshman-level course, Engineering Graphics, had a higher average age for this participant population than the junior-level course, Advanced Dynamics. Appropriately, Engineering Graphics also had the highest standard deviation on age.

Pre-Study Experiences

The experiences assigned to the pre-study experiences category are those where participants were asked to select their level of activity prior to the semester. The survey questions vary from very specific experience (e.g., VEX Robotics) to more generic experiences (e.g., 2-D puzzle video games). As a result, the specific-experience participation rates are much lower. In the results from this survey, none of the participants reported having any experience with Future City, TechXplore, INSPIRE!, or
Botball, and data for those experiences are not included below.

In the survey used in previous work (Wood et al., 2016) as well as the new survey, many questions regarding the amount of experience participants had with a given topic utilized a 6 point (values 0 to 5) slider-control Likert scale with the spaced labels “very little to none”, “some experience”, “moderate experience”, “considerable experience”, “immersed experience”. Others utilized radio buttons with similar labels to create a 5-point Likert scale. The applicable range for the applied Likert scales are indicated in Table 4 below. Other questions needed more unique scales, and the responses to those questions are provided in Table 5. In data collected from this survey, none of the participants reported having any experience with Future City, TechXplore, INSPIRE!, or Botball, and data for those experiences are not included below.

Table 4. Activity levels within Pre-Study Experiences by Course

<table>
<thead>
<tr>
<th>Experience/Activity (Likert Range)</th>
<th>Engineering Graphics M (SD)</th>
<th>Statics M (SD)</th>
<th>Advanced Dynamics M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Block Play (1-5)</td>
<td>2.31 (0.95)</td>
<td>2.64 (0.81)</td>
<td>2.67 (0.50)</td>
</tr>
<tr>
<td>Models &amp; Puzzles (1-5)</td>
<td>2.62 (1.19)</td>
<td>2.82 (1.17)</td>
<td>2.00 (1.00)</td>
</tr>
<tr>
<td>Radio-Controlled Toys (1-5)</td>
<td>1.69 (0.63)</td>
<td>1.82 (0.87)</td>
<td>2.00 (0.87)</td>
</tr>
<tr>
<td>FIRST Robotics (0-5)</td>
<td>0.77 (1.69)</td>
<td>0.55 (1.51)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>JETS (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.09 (0.30)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>VEX Robotics (0-5)</td>
<td>0.38 (0.77)</td>
<td>0.27 (0.65)</td>
<td>0.33 (0.71)</td>
</tr>
<tr>
<td>ThinkQuest (0-5)</td>
<td>0.08 (0.28)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>LEGO Engineering (0-5)</td>
<td>1.00 (1.87)</td>
<td>0.36 (0.92)</td>
<td>0.89 (1.54)</td>
</tr>
<tr>
<td>Odyssey of the Mind (0-5)</td>
<td>0.23 (0.83)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Minecraft (0-5)</td>
<td>1.62 (1.80)</td>
<td>0.91 (1.04)</td>
<td>1.56 (1.42)</td>
</tr>
<tr>
<td>Erector Sets (0-5)</td>
<td>1.31 (1.60)</td>
<td>0.09 (0.30)</td>
<td>1.00 (1.50)</td>
</tr>
<tr>
<td>LEGO Brick Play (0-5)</td>
<td>3.15 (2.23)</td>
<td>2.45 (1.92)</td>
<td>2.78 (1.20)</td>
</tr>
<tr>
<td>Tetris (0-5)</td>
<td>2.23 (2.05)</td>
<td>1.64 (1.57)</td>
<td>2.67 (1.41)</td>
</tr>
<tr>
<td>1st-Person Video Games (0-5)</td>
<td>2.62 (2.10)</td>
<td>0.64 (0.67)</td>
<td>1.78 (1.64)</td>
</tr>
<tr>
<td>Experience/Activity (Likert Range)</td>
<td>Engineering Graphics</td>
<td>Statics</td>
<td>Advanced Dynamics</td>
</tr>
<tr>
<td>----------------------------------</td>
<td>----------------------</td>
<td>---------</td>
<td>-------------------</td>
</tr>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Other 3D Video Games (0-5)</td>
<td>3.00 (2.20)</td>
<td>1.55 (1.57)</td>
<td>2.44 (1.94)</td>
</tr>
<tr>
<td>2D Puzzle Video Game (0-5)</td>
<td>2.31 (2.14)</td>
<td>1.36 (1.29)</td>
<td>1.78 (1.30)</td>
</tr>
<tr>
<td>2D Strategy Games (0-5)</td>
<td>2.85 (2.27)</td>
<td>1.18 (1.33)</td>
<td>2.33 (2.18)</td>
</tr>
<tr>
<td>Woodworking (0-5)</td>
<td>2.00 (1.58)</td>
<td>1.82 (1.66)</td>
<td>2.44 (1.59)</td>
</tr>
<tr>
<td>Welding (0-5)</td>
<td>0.85 (1.34)</td>
<td>0.82 (1.47)</td>
<td>1.44 (1.67)</td>
</tr>
<tr>
<td>Fabrication (0-5)</td>
<td>0.46 (1.39)</td>
<td>0.91 (1.58)</td>
<td>0.56 (1.13)</td>
</tr>
<tr>
<td>Electronics (0-5)</td>
<td>1.00 (1.15)</td>
<td>0.73 (0.65)</td>
<td>1.22 (0.97)</td>
</tr>
<tr>
<td>Mechanics (0-5)</td>
<td>1.69 (1.75)</td>
<td>1.27 (1.56)</td>
<td>1.78 (1.30)</td>
</tr>
<tr>
<td>Cabinetry (0-5)</td>
<td>0.77 (1.48)</td>
<td>0.64 (1.21)</td>
<td>1.00 (1.66)</td>
</tr>
<tr>
<td>Building Computers (0-5)</td>
<td>0.92 (1.71)</td>
<td>0.55 (0.93)</td>
<td>0.89 (1.27)</td>
</tr>
<tr>
<td>Gardening (0-5)</td>
<td>2.08 (1.38)</td>
<td>2.00 (1.61)</td>
<td>1.78 (1.48)</td>
</tr>
<tr>
<td>Artistic Painting (0-5)</td>
<td>0.38 (1.12)</td>
<td>0.18 (0.60)</td>
<td>0.78 (1.39)</td>
</tr>
<tr>
<td>Artistic Drawing (0-5)</td>
<td>0.77 (1.48)</td>
<td>0.27 (0.47)</td>
<td>0.78 (0.97)</td>
</tr>
<tr>
<td>Residential/Commercial Painting (0-5)</td>
<td>0.77 (1.48)</td>
<td>0.36 (0.92)</td>
<td>0.67 (0.87)</td>
</tr>
<tr>
<td>Construction (0-5)</td>
<td>1.31 (1.49)</td>
<td>0.73 (1.10)</td>
<td>1.33 (1.50)</td>
</tr>
<tr>
<td>Sewing (0-5)</td>
<td>1.08 (1.26)</td>
<td>0.73 (0.79)</td>
<td>1.11 (1.69)</td>
</tr>
<tr>
<td>Embroidery (0-5)</td>
<td>0.62 (1.12)</td>
<td>0.18 (0.60)</td>
<td>0.33 (0.71)</td>
</tr>
<tr>
<td>Cooking (0-5)</td>
<td>2.77 (1.42)</td>
<td>2.45 (1.75)</td>
<td>2.33 (1.87)</td>
</tr>
<tr>
<td>Dancing (0-5)</td>
<td>1.46 (1.71)</td>
<td>2.00 (1.79)</td>
<td>0.78 (1.72)</td>
</tr>
<tr>
<td>Sports (0-5)</td>
<td>2.77 (1.83)</td>
<td>2.55 (1.57)</td>
<td>2.44 (1.94)</td>
</tr>
<tr>
<td>Music (0-5)</td>
<td>3.77 (1.83)</td>
<td>3.18 (1.94)</td>
<td>2.33 (1.94)</td>
</tr>
</tbody>
</table>

Other pre-course variables (that were not characterized with the Likert-style questions as shown in Table 4) cover repetition of the course, employment during the school semester, previous spatial exams, classification of hometown size, and prior graphics or drafting classes. The questions asking students about previous graphics or drafting classes differentiated between drafting and solid modeling, and it allowed for high school, collegiate, or self-taught instruction. Descriptive statistics regarding how many forms of previous graphics or drafting instruction are given below. It was found
that viewing home-town classification by factors (shown in Table 7 below) provided more insight than asking students to estimate the population of their hometown.

Table 5. Counts for Number of Participants with Specific Pre-Study Experience Types

<table>
<thead>
<tr>
<th>Course</th>
<th>Repeating Course</th>
<th>Employed During School</th>
<th>Previous Spatial Exam</th>
<th>Prior Graphics/Drafting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>8</td>
<td>8</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>5</td>
<td>6</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>Statics</td>
<td>5</td>
<td>8</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 6. Descriptive Statistics for Amount of Previous Spatial Exam and Graphics/Drafting Experience

<table>
<thead>
<tr>
<th>Course</th>
<th>Previous Spatial Exam Count</th>
<th>Prior Graphics/Drafting Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M (SD)</td>
<td>M (SD)</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>1.67 (1.32)</td>
<td>2.00 (0.87)</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>0.15 (0.38)</td>
<td>0.62 (0.51)</td>
</tr>
<tr>
<td>Statics</td>
<td>0.00 (0.00)</td>
<td>0.80 (0.42)</td>
</tr>
</tbody>
</table>

Table 7. Counts for Home-Town Classification by Course

<table>
<thead>
<tr>
<th>Course</th>
<th>Home-Town Classification</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>Rural</td>
<td>4</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>Sub-urban</td>
<td>5</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>Urban</td>
<td>0</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>Rural</td>
<td>4</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>Sub-urban</td>
<td>7</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>Urban</td>
<td>2</td>
</tr>
<tr>
<td>Statics</td>
<td>Rural</td>
<td>5</td>
</tr>
<tr>
<td>Statics</td>
<td>Sub-urban</td>
<td>5</td>
</tr>
<tr>
<td>Statics</td>
<td>Urban</td>
<td>1</td>
</tr>
</tbody>
</table>

It is interesting to note that two of the participants from the Statics course responded “No” to the question asking if they had taken a prior graphics or drafting course. However, those two students did list Engineering Graphics as a course that they
had completed previously, so it appeared that there may have been confusion regarding that question. Further investigation revealed that these two students were enrolled in Engineering Graphics during the same semester that they took Statics (note: Engineering Graphics is not a prerequisite for Statics). Since the Prior Graphics/Drafting question asked if a graphics or drafting course had been taken before the previous semester, these responses are believed to be accurate.

**Experiences during the break**

Participants were asked to provide insight into their activities over the academic break, and were given the same Likert-style interfaces for the same categories of activities as were investigated in the pre-study experiences, with the exception of playing with blocks, as this question was directed toward their activity level as younger children. In this survey, none of the participants reported having any experience with FIRST Robotics, JETS, Future City, TechXplore, ThinkQuest, LEGO Engineering, INSPIRE!, Botball, Odyssey of the Mind, Erector sets, residential/commercial painting, or embroidery during the break, and data for those experiences are not included below. The descriptive statistics for the remaining experience types are included in the table below.

Additionally, participants were asked questions to identify other activities that they potentially experienced over the break. These include employment status, weekly employment hours, whether participants were enrolled in coursework, weekly study hours, weekly exercise hours, the number of hobby- and interest-type activities in which they participated, and the monthly number of hours spent on those activities. These data are provided in

Table 9 and Table 10 below.
Table 8. Activity levels within Academic Break Experiences by Course

<table>
<thead>
<tr>
<th>Experience/Activity (Likert Range)</th>
<th>Engineering Graphics M (SD)</th>
<th>Statics M (SD)</th>
<th>Advanced Dynamics M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Models &amp; Puzzles (1-5)</td>
<td>2.31 (1.44)</td>
<td>1.82 (0.75)</td>
<td>1.44 (0.53)</td>
</tr>
<tr>
<td>Radio-Controlled Toys (1-5)</td>
<td>1.31 (0.63)</td>
<td>1.36 (0.67)</td>
<td>1.44 (1.01)</td>
</tr>
<tr>
<td>VEX Robotics (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.11 (0.33)</td>
</tr>
<tr>
<td>Minecraft (0-5)</td>
<td>0.62 (1.45)</td>
<td>0.27 (0.90)</td>
<td>0.89 (1.27)</td>
</tr>
<tr>
<td>LEGO Brick Play (0-5)</td>
<td>0.38 (0.65)</td>
<td>1.00 (1.61)</td>
<td>0.33 (0.71)</td>
</tr>
<tr>
<td>Tetris (0-5)</td>
<td>0.23 (0.83)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>1st-Person Video Games (0-5)</td>
<td>1.69 (2.14)</td>
<td>0.45 (0.69)</td>
<td>1.33 (1.66)</td>
</tr>
<tr>
<td>Other 3D Video Games (0-5)</td>
<td>1.69 (1.89)</td>
<td>0.73 (1.01)</td>
<td>2.33 (1.94)</td>
</tr>
<tr>
<td>2D Puzzle Video Game (0-5)</td>
<td>1.08 (1.80)</td>
<td>0.73 (1.27)</td>
<td>0.67 (1.32)</td>
</tr>
<tr>
<td>2D Strategy Games (0-5)</td>
<td>1.85 (2.30)</td>
<td>0.91 (1.30)</td>
<td>1.44 (1.81)</td>
</tr>
<tr>
<td>Woodworking (0-5)</td>
<td>0.31 (1.11)</td>
<td>0.82 (1.40)</td>
<td>0.56 (0.88)</td>
</tr>
<tr>
<td>Welding (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.09 (0.30)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Fabrication (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.27 (0.90)</td>
<td>0.44 (1.33)</td>
</tr>
<tr>
<td>Electronics (0-5)</td>
<td>0.15 (0.55)</td>
<td>0.27 (0.47)</td>
<td>0.22 (0.44)</td>
</tr>
<tr>
<td>Mechanics (0-5)</td>
<td>0.38 (1.39)</td>
<td>0.82 (1.25)</td>
<td>0.67 (1.00)</td>
</tr>
<tr>
<td>Cabinetry (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.09 (0.30)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Building Computers (0-5)</td>
<td>0.15 (0.55)</td>
<td>0.18 (0.40)</td>
<td>0.11 (0.33)</td>
</tr>
<tr>
<td>Gardening (0-5)</td>
<td>0.31 (1.11)</td>
<td>0.18 (0.60)</td>
<td>0.11 (0.33)</td>
</tr>
<tr>
<td>Artistic Painting (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.18 (0.60)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Artistic Drawing (0-5)</td>
<td>0.31 (0.63)</td>
<td>0.18 (0.40)</td>
<td>0.44 (0.73)</td>
</tr>
<tr>
<td>Construction (0-5)</td>
<td>0.46 (1.39)</td>
<td>0.00 (0.00)</td>
<td>0.11 (0.33)</td>
</tr>
<tr>
<td>Sewing (0-5)</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
<td>0.56 (1.33)</td>
</tr>
<tr>
<td>Cooking (0-5)</td>
<td>1.85 (1.63)</td>
<td>1.73 (1.85)</td>
<td>1.11 (1.36)</td>
</tr>
<tr>
<td>Dancing (0-5)</td>
<td>1.00 (1.78)</td>
<td>1.18 (1.54)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Sports (0-5)</td>
<td>1.62 (2.10)</td>
<td>1.82 (1.99)</td>
<td>1.11 (1.36)</td>
</tr>
<tr>
<td>Music (0-5)</td>
<td>2.00 (2.24)</td>
<td>2.27 (1.85)</td>
<td>0.56 (0.88)</td>
</tr>
</tbody>
</table>

One participant reported being enrolled in multiple courses over the winter break,
including an advanced technical class. This seems doubtful, and it may be that the student mistakenly reported their course schedule for the following semester. Given that only one student reported taking any classes over the break, this was not further considered in the analysis.

Table 9. Counts for Number of Participants with Specific Academic Break Experience Types

<table>
<thead>
<tr>
<th>Course</th>
<th>Employed During Break</th>
<th>Enrolled in Coursework</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>6</td>
<td>0</td>
</tr>
<tr>
<td>Statics</td>
<td>9</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 10. Descriptive Statics for Activity Levels During the Academic Break

<table>
<thead>
<tr>
<th>Course</th>
<th>Employment Hours During Break M (SD)</th>
<th>Study Hours During Break M (SD)</th>
<th>Exercise Hours During Break M (SD)</th>
<th>Activity Count During Break M (SD)</th>
<th>Activity Hours During Break M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>18.71 (10.58)</td>
<td>1.44 (1.01)</td>
<td>4.33 (4.50)</td>
<td>4.44 (2.46)</td>
<td>11.63 (3.93)</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>27.17 (10.21)</td>
<td>1.92 (1.50)</td>
<td>4.08 (4.42)</td>
<td>5.46 (2.50)</td>
<td>12.92 (3.50)</td>
</tr>
<tr>
<td>Statics</td>
<td>25.22 (7.95)</td>
<td>2.09 (1.58)</td>
<td>4.82 (3.12)</td>
<td>4.82 (1.17)</td>
<td>11.00 (4.07)</td>
</tr>
</tbody>
</table>

It was noted that four students marked “11 or more” weekly exercise hours during the break, which was assigned a value of 11. It was also noted that fifteen students marked “15 or more” monthly activity hours during the break, which was assigned a value of 15.

Principle Component Analyses (PCA)

Due to the large number of survey questions, it can become difficult to identify the most influential dependent variables. It may also be expected that responses to some survey questions may be highly correlated with responses to other survey questions, although this covariance has not been previously identified and thus must be treated during analysis. These problems are exacerbated when the number of participants is
limited, such as in this study. In order to account for the covariance between variables, and to simplify the number of dependent variables in the model, principle component analyses were performed.

**PCA of Pre-Study Experience**

The first PCA is based on the Likert-style questions regarding pre-study experience topics listed above in Table 4 with the addition of biological sex. Biological sex is included as it may vary with some of these survey questions due to literatures reported correlation of gender-typed activities and biological sex. Ultimately four experiences were left out due to the low participation rates mentioned above. This reduced the list of prior experiences within the PCA to biological sex, playing with blocks as a child, model construction and puzzles, radio controlled toys, FIRST robotics, LEGO Engineering, Minecraft, Erector sets, LEGO brick play, Tetris, first-person video games, other 3-D video games, 2-D puzzle video games, 2-D strategy games, woodworking, welding, fabrication, electronics, mechanics, cabinetry, building computers, gardening, artistic painting, artistic drawing, residential/commercial painting, construction, sewing, cooking, dancing, sports, and playing music. The numeric values for each of these variables were each scaled by subtracting their respective mean value and dividing by their respective standard deviation.

Two approaches were used to identify the primary principal components based on the variance of the dataset that they each accounted for. First, the cumulative variance was plotted for the principal components (in order of eigenvalue size), as shown in Figure 4 below. Based on the observation that they accounted for ~80% of the variance, the first nine principal components were selected as the primary components. For an alternative
means of identifying the primary principal components, those components with eigenvalues > 1.0 were selected. This approach resulted in identifying the same nine principal components. Again, these nine components do not necessarily represent anything with an obvious interpretation.

Figure 4. Plot of Cumulative Explained Variance of the Pre-Study Principal Components

Given that the nine primary components do not necessarily represent anything with an obvious interpretation, it was determined that the variables most associated with the components needed to be identified. In order to distinguish the variables most associated with the nine primary components, a matrix of those principal components was multiplied by a matrix containing the variable loadings for those principal components. Taking the absolute value of those resulting scaled values, the mean of each
column was plotted to provide a sense for the influence of each variable on the variance of the dataset. The data are plotted in Figure 5 below.

![Mean Loading-Scaled Magnitude of Pre-Study Experience Variables in Primary Principal Components](image)

Figure 5. Loading-Scaled Magnitudes of the Pre-Study Experience Variables, per Loadings of the Nine Primary Principal Components

There are some visible groupings within the data. The highest data point corresponds to experience with 2D strategy games. The whole list of variables, sorted from largest to smallest, is given in Table 11 below. The gaps in the chart shown above are marked with dashed lines in the table.
Table 11. Primary PCA Magnitude-Sorted List of Pre-Study Experience Variables

<table>
<thead>
<tr>
<th>Pre-Study Experience Variable</th>
<th>Rank</th>
<th>Pre-Study Experience Variable</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-D strategy games</td>
<td>1</td>
<td>welding</td>
<td>22</td>
</tr>
<tr>
<td>gardening</td>
<td>2</td>
<td>playing music</td>
<td>23</td>
</tr>
<tr>
<td>dancing</td>
<td>3</td>
<td>Minecraft</td>
<td>24</td>
</tr>
<tr>
<td>sports</td>
<td>4</td>
<td>fabrication</td>
<td>25</td>
</tr>
<tr>
<td>biological sex</td>
<td>5</td>
<td>model construction and puzzles</td>
<td>26</td>
</tr>
<tr>
<td>other 3-D video games</td>
<td>6</td>
<td>LEGO Engineering</td>
<td>27</td>
</tr>
<tr>
<td>2-D puzzle video games</td>
<td>7</td>
<td>artistic painting</td>
<td>28</td>
</tr>
<tr>
<td>Tetris</td>
<td>8</td>
<td>FIRST robotics</td>
<td>29</td>
</tr>
<tr>
<td>cooking</td>
<td>9</td>
<td>artistic drawing</td>
<td>30</td>
</tr>
<tr>
<td>sewing</td>
<td>10</td>
<td>mechanics</td>
<td>31</td>
</tr>
<tr>
<td>woodworking</td>
<td>11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cabinetry</td>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LEGO brick play</td>
<td>13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>radio controlled toys</td>
<td>14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>playing with blocks as a child</td>
<td>15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>electronics</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>building computers</td>
<td>17</td>
<td></td>
<td></td>
</tr>
<tr>
<td>first-person video games</td>
<td>18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>construction</td>
<td>19</td>
<td></td>
<td></td>
</tr>
<tr>
<td>residential/commercial painting</td>
<td>20</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Erector sets</td>
<td>21</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**PCA of Experiences During the Break**

The second PCA is based on the Likert-style questions regarding the experience topics during the break listed above in Table 8, and also includes the addition of biological sex just as the pre-study experiences PCA. Again, a number of experiences were left out due to low participation rates. This reduced the list of prior experiences within the PCA to biological sex, model construction and puzzles, radio controlled toys, Minecraft, LEGO brick play, first-person video games, other 3-D video games, 2-D puzzle video games, 2-D strategy games, woodworking, mechanics, cooking, dancing, sports, and playing music. The numeric values for each of these variables were each scaled by removing subtracting their respective mean value and dividing by their
respective standard deviation.

As was presented above, two approaches were used to identify the primary principal components based on the variance of the dataset that they each accounted for. First, the cumulative variance was plotted for the principal components (in order of eigenvalue size), as shown in Figure 6 below. This time, the first eight principal components accounted for ~80% of the variance, and were selected as the primary principal components. The alternative criterion of eigenvalues > 1.0 identifies the first seven principal components.

![Cumulative Explained Variance of Break Principal Components]

Figure 6. Plot of Cumulative Explained Variance of the Academic Break Principal Components

To gain insight into the variables most associated with the eight primary components, a matrix of those principal components was multiplied by a matrix
containing the variable loadings for those principal components. The resulting matrix then has a column for each of the original variables, now scaled by the loadings. Insight can then be gained by taking the absolute value of those scaled values, the mean of each column may then provide a sense for the influence of each variable on the variance of the dataset. Doing so provided the data plotted in Figure 7 below.

![Mean Loading-Scaled Magnitude of Break Experience Variables in Primary Principal Components](image)

**Figure 7.** Loading-Scaled Magnitudes of the Pre-Study Experience Variables, per Loadings of the Nine Primary Principal Components

As with the pre-study data, there are some visible groupings within the data. The highest data point corresponds with biological sex. The whole list of variables, sorted from largest to smallest, is given in Table 12 below. The gaps in the chart shown above are marked with dashed lines in the table.
Table 12. Primary PCA Magnitude-Sorted List of Academic Break Experience Variables

<table>
<thead>
<tr>
<th>Academic Break Experience Variable</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>biological sex</td>
<td>1</td>
</tr>
<tr>
<td>model construction and puzzles</td>
<td>2</td>
</tr>
<tr>
<td>woodworking</td>
<td>3</td>
</tr>
<tr>
<td>cooking</td>
<td>4</td>
</tr>
<tr>
<td>radio controlled toys</td>
<td>5</td>
</tr>
<tr>
<td>first-person video games</td>
<td>6</td>
</tr>
<tr>
<td>mechanics</td>
<td>7</td>
</tr>
<tr>
<td>Minecraft</td>
<td>8</td>
</tr>
<tr>
<td>2-D puzzle video games</td>
<td>9</td>
</tr>
<tr>
<td>playing music</td>
<td>10</td>
</tr>
<tr>
<td>LEGO brick play</td>
<td>11</td>
</tr>
<tr>
<td>other 3-D video games</td>
<td>12</td>
</tr>
<tr>
<td>dancing</td>
<td>13</td>
</tr>
<tr>
<td>sports</td>
<td>14</td>
</tr>
<tr>
<td>2-D strategy games</td>
<td>15</td>
</tr>
</tbody>
</table>

Analysis of Pre-Test and Post-Test Performance

As shown in Figure 8 below, histogram plots of the pre-Test MCT scores, post-Test MCT scores, pre-Test MCT durations, and post-Test MCT durations do not grossly violate normality, and therefore the analysis may continue without transformation of key independent variables. It is noted that there appears to be a ceiling effect spike in the pre-MCT durations where participants are clustering around the 20-minute time limit, but statistical methods of dealing with this phenomenon are limited. This work therefore maintains the original form of the data so the data analysis results had a more straightforward interpretation.
Two of the participants who completed the pre-test and post-test were removed for not finishing the survey and/or not completing one of the MCT tests. Diagnostic analysis of the data conducted with predictor independent variables revealed another participant who was an outlier in nearly every measure. Closer examination revealed that this participant had spent 90% less time on the post-test MCT than on the pre-test, making this participant the fastest to complete the post-test, and had scored 44% less on the post-test than the pre-test, earning this participant the lowest score on the post-test.
and the largest percent decrease in duration and score amongst all participants. The decrease in time spent on the post-test may indicate a lack of effort, and the score appears to confirm this. Thus, this participant was removed from the analysis below for any measure that includes post-test performance, including investigations into change in performance.

**Comparing Pre-Test MCT Performance**

There were 33 total participants over the winter break who completed the study. Early in the analysis, it was apparent that general trends were different based on the course from which participants were recruited. The breakdown of participation counts in each of the courses is shown in Figure 9 below. As mentioned previously, the course in which students were enrolled when they were recruited for this study acts as an indicator for progress through the engineering curriculum. The initial trends in performance discussed below are differentiated based on course enrollment.

![Figure 9. Participant Count by Course](image)
Confounding Factors

If progress through the engineering curriculum is linked to spatial ability improvement, then re-taking a class represents a case where confounding influences may be present in the data. To account for this, the survey included a question about whether the student was repeating the course, and this was included in the predictive analysis below.

Score Comparisons

Given that previously-obtained empirical data indicates that students’ spatial ability improves while the students are enrolled in engineering courses (at least for Engineering Graphics and Statics), it is expected that the students participating in this study who are farther along in their coursework would show an increase in spatial ability. A comparison of mean scores by course type is provided below.

Table 13. Pre-Test MCT Score Comparisons by Course

<table>
<thead>
<tr>
<th>Course Recruited from</th>
<th>Pre-Test MCT Score M (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering Graphics</td>
<td>16.62 (4.46)</td>
</tr>
<tr>
<td>Statics</td>
<td>15.09 (4.21)</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>18.22 (4.47)</td>
</tr>
</tbody>
</table>

As shown in Table 13, students from the Advanced Dynamics course do exhibit the highest mean score of the three courses, as would be expected if progression in spatial ability is occurring as students advance through the curriculum. However, the mean score for Statics students is lower than that for Engineering Graphics students, which represents a departure from the expected trend. A t-tests and Mann-Whitney U tests both reveal that the differences between the course types are not significant, and this can be described visually via a boxplot, as shown in Figure 10 below.
With the number of participants from each course and the spread of the scores observed in the participant population, the null hypothesis (that students have the same score, regardless of their progression through the engineering curriculum) cannot be rejected at this time.

**Duration Comparisons**

Based on the data given above for MCT scores, a similar trend in the time spent completing the MCT test would be apparent if there is a decrease as students progressed through the curriculum, i.e., if they truly are continuing to increase in their spatial abilities. The mean durations for MCT exams do, in fact, indicate that such a trend is taking place, as shown in Table 14 below.
Table 14. Pre-Test MCT Duration Comparisons by Course

<table>
<thead>
<tr>
<th>Course Recruited from</th>
<th>Pre-Test Duration in seconds</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering Graphics</td>
<td>813.23 (266.98)</td>
</tr>
<tr>
<td>Statics</td>
<td>628.14 (269.38)</td>
</tr>
<tr>
<td>Advanced Dynamics</td>
<td>476.42 (168.30)</td>
</tr>
</tbody>
</table>

As shown in Table 14, students from the Advanced Dynamics course do exhibit the shortest mean duration (i.e., best performance) of the three courses. The mean duration for Statics students is longer than for Advanced Dynamics, but is shorter than that for Engineering Graphics students. In order to verify the significance of the differences between these different experience groups simple t-tests were performed, which reveal that the difference between the Engineering Graphics and Advanced Dynamics courses is significant, whereas the other two pairings are not significant as shown in Table 15. The effect sizes are also provided, and it is noted that according to Cohen’s criteria (Cohen, 1992; Sullivan & Feinn, 2012), the effect sizes for the insignificant pairings are medium, and the effect size for the difference between Engineering Graphics and Advanced Dynamics is considered very large. According to Ferguson (2009), the insignificant (by p-value) pairings would be considered greater than the recommended minimum for a significant effect size, and the effect size between Engineering Graphics and Advanced Dynamics would be considered moderate. For a visual description of MCT duration differences between courses, see the box plot in Figure 11.

Another quantitative view can also be obtained via a simple ANOVA based on pre-test MCT duration and course type, see Table 16 below. The coefficients in Table 17 also show that the difference between Advanced Dynamics and Engineering Graphics is significant, while the difference between Advanced Dynamics and Statics is not
Table 15. P-Values and Cohen’s d from Welch Two Sample t-test and Mann-Whitney U (MWU) Test Comparisons of Pre-Test MCT Duration by Course

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>df</th>
<th>p-value</th>
<th>d</th>
<th>MWU p</th>
<th>MWU $\eta^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adv Dyn vs Statics</td>
<td>1.54</td>
<td>16.99</td>
<td>.14</td>
<td>0.66a</td>
<td>.11</td>
<td>0.19a</td>
</tr>
<tr>
<td>Engr Graphics vs Statics</td>
<td>-1.68</td>
<td>21.28</td>
<td>.11</td>
<td>0.69a</td>
<td>.09†</td>
<td>0.17a</td>
</tr>
<tr>
<td>Adv Dyn vs Engr Graphics</td>
<td>3.63</td>
<td>19.90</td>
<td>.0017**</td>
<td>1.45b</td>
<td>.004**</td>
<td>0.50b</td>
</tr>
</tbody>
</table>

†p < .1. **p < .01. a minimum practical effect, b moderate effect.

Table 16. Fixed-Effects ANOVA Results Using Pre-Test MCT Duration as the Criterion and Course Enrollment as the Independent Variable

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>partial $\eta^2$</th>
<th>90% CI [LL, UL]</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>2042767.95</td>
<td>1</td>
<td>2042767.95</td>
<td>33.90</td>
<td>.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course</td>
<td>619696.53</td>
<td>2</td>
<td>309848.27</td>
<td>5.14</td>
<td>.012*</td>
<td>.26</td>
<td>[.04, .41]</td>
</tr>
<tr>
<td>Error</td>
<td>1807622.22</td>
<td>30</td>
<td>60254.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. * indicates p < .05. LL and UL represent the lower-limit and upper-limit of the partial $\eta^2$ confidence interval, respectively.

Table 17. Regression Results Using Pre-Test MCT Duration as the Criterion and Course Enrollment as the Predictor

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI [LL, UL]</th>
<th>$sr^2$</th>
<th>95% CI [LL, UL]</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>476.42**</td>
<td>[309.31, 643.52]</td>
<td>.25</td>
<td>[-.01, .50]</td>
<td></td>
</tr>
<tr>
<td>Adv Dyn vs Engr Graphics</td>
<td>336.81**</td>
<td>[119.43, 554.19]</td>
<td>[.05</td>
<td>[-.08, .17]</td>
<td></td>
</tr>
<tr>
<td>Adv Dyn vs Statics</td>
<td>151.73</td>
<td>[-73.60, 377.05]</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .255*$
95% CI[.01,.45] F(2,30) = 5.142
p = .012**

Note. * indicates p < .05; ** indicates p < .01. A significant $b$-weight indicates the semi-partial correlation is also significant. $b$ represents unstandardized regression weights; $sr^2$ represents the semi-partial correlation squared. LL and UL indicate the lower and upper limits of a confidence interval, respectively.
Figure 11. Boxplot of Pre-Test MCT Duration by Course

Comparing the Change in Performance

Since this study is focused on the possibility of spatial ability degradation in the absence of engineering coursework, rather than reviewing the trends in post-test MCT scores and duration, the data were represented as the change in score (i.e., pre-test score subtracted from post-test score). The overall trends for changes in MCT score are shown in the Figure 12 below.
Looking at the mean change in score between the courses reveals some unexpected trends, as shown in Table 18 below. The trends indicate that students in Advanced Dynamics scores decrease, while Statics students score increase and Engineering Graphics students’ scores increase more.

Table 18. MCT Score Improvement over Course Break

<table>
<thead>
<tr>
<th>Course</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>-0.56</td>
<td>2.92</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>1.58</td>
<td>3.20</td>
</tr>
<tr>
<td>Statics</td>
<td>0.91</td>
<td>2.77</td>
</tr>
</tbody>
</table>

When considering the standard deviation for these improvements, it becomes apparent that the changes in score, and any perceived differences between course type,
are not significant. This is apparent when looking at simple t-tests comparing pre-test MCT scores and post-test MCT scores for each course type separately. None of the courses exhibit post-test MCT scores that are significantly different than the pre-test MCT scores. This is also supported via t-tests and ANOVAs that compare the difference course types on the basis of MCT score change. The Wilcoxon signed rank nonparametric statistic does not return significant values either. Given the difference in sign in MCT score change between the Advanced Dynamics course and the other two courses, a binomial regression was run comparing Advanced Dynamics to the other courses, which was still not significant ($F(1,30) = 2.456$, $p=0.13$).

Similar trends, wherein Advanced Dynamics students do not appear to improve while Engineering Graphics and Statics students do appear to improve, are visible when looking at the mean change in duration. However, while similar to the case above where a significant difference exists between Advanced Dynamics and Engineering Graphics for the pre-test MCT durations, the difference in change in duration is also significant between Advanced Dynamics and Engineering Graphics, as shown below. A histogram of the changes in performance as measured by duration (or differences in time in taking the MCT) is given in Figure 13 below. The mean and standard deviation for changes, separated by course enrollment, are shown in Table 19.

As mentioned above, the difference in change in duration between Advanced Dynamics and Engineering Graphics is statistically significant, as shown in the t-test (Table 20), ANOVA (Table 21) and regression (Table 22) summaries below. To demonstrate it visually, a boxplot representation of the changes in duration is provided in Figure 14.
Figure 13. Histogram of Change in MCT Duration

Table 19. MCT Duration Change over Course Break

<table>
<thead>
<tr>
<th>Course</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>14.91</td>
<td>196.93</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>-144.73</td>
<td>202.97</td>
</tr>
<tr>
<td>Statics</td>
<td>-121.38</td>
<td>112.67</td>
</tr>
</tbody>
</table>

Table 20. P-Values and Cohen’s d from Welch Two Sample t-test and Mann-Whitney U (MWU) Test Comparisons of Change in MCT Duration

<table>
<thead>
<tr>
<th></th>
<th>t</th>
<th>df</th>
<th>p-value</th>
<th>d</th>
<th>MWU p</th>
<th>MWU r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adv Dyn vs Statics</td>
<td>-1.84</td>
<td>12.161</td>
<td>.090†</td>
<td>0.87a</td>
<td>.095†</td>
<td>.21a</td>
</tr>
<tr>
<td>Engr Graphics vs Statics</td>
<td>0.34</td>
<td>17.47</td>
<td>.73</td>
<td>0.14</td>
<td>.83</td>
<td>.004</td>
</tr>
<tr>
<td>Adv Dyn vs Engr Graphics</td>
<td>-1.81</td>
<td>17.67</td>
<td>.087†</td>
<td>0.80a</td>
<td>.17</td>
<td>.14a</td>
</tr>
</tbody>
</table>

† indicates p < .1. a minimum practical effect, b moderate effect.
Table 21. Fixed-Effects ANOVA Results Using Change in MCT Duration as the Criterion and Course Enrollment as the Independent Variable

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>partial $\eta^2$</th>
<th>90% CI [LL, UL]</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>2000.00</td>
<td>1</td>
<td>2000.00</td>
<td>0.07</td>
<td>.800</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course</td>
<td>145729.37</td>
<td>2</td>
<td>72864.68</td>
<td>2.37</td>
<td>.111</td>
<td>.14</td>
<td>[.00, .30]</td>
</tr>
<tr>
<td>Error</td>
<td>890392.24</td>
<td>29</td>
<td>30703.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. LL and UL represent the lower-limit and upper-limit of the partial $\eta^2$ confidence interval, respectively.

Table 22. Regression Results Using Change in MCT Duration as the Criterion with Course as the Predictor

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI [LL, UL]</th>
<th>$sr^2$</th>
<th>95% CI [LL, UL]</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>14.91</td>
<td>[-104.55, 134.36]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adv Dyn vs Engr Graphics</td>
<td>-159.64*</td>
<td>[-317.67, -1.61]</td>
<td>.13</td>
<td>[-.09, .34]</td>
<td></td>
</tr>
<tr>
<td>Adv Dyn vs Statics</td>
<td>-136.29†</td>
<td>[-297.37, 24.79]</td>
<td>.09</td>
<td>[-.09, .27]</td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .141$
95% CI [.00, .34]
F(2, 29) = 2.373
p = 0.11

Note. † indicates p < .1; * indicates p < .05; ** indicates p < .01. A significant $b$-weight indicates the semi-partial correlation is also significant. $b$ represents unstandardized regression weights; $sr^2$ represents the semi-partial correlation squared. LL and UL indicate the lower and upper limits of a confidence interval, respectively.
These differences in change in duration between course types are supported by t-test statistics that compare pre-test MCT duration measurements with post-test MCT duration measurements. Paired t-tests results for each of the courses are shown in Table 23 below comparing pre-test MCT duration and post-test MCT duration.

Table 23. Paired t-test Results Comparing Pre-Test MCT Duration with Post-Test MCT Duration by Course

<table>
<thead>
<tr>
<th>Course</th>
<th>df</th>
<th>t</th>
<th>p</th>
<th>d</th>
<th>Wilcoxon p</th>
<th>Wilcoxon r²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced Dynamics</td>
<td>8</td>
<td>-0.227</td>
<td>.826</td>
<td>0.06</td>
<td>.820</td>
<td>.005</td>
</tr>
<tr>
<td>Engineering Graphics</td>
<td>11</td>
<td>2.470</td>
<td>.031*</td>
<td>0.52a</td>
<td>.042*</td>
<td>.34b</td>
</tr>
<tr>
<td>Statics</td>
<td>10</td>
<td>3.573</td>
<td>.005**</td>
<td>0.50a</td>
<td>.007**</td>
<td>.67c</td>
</tr>
</tbody>
</table>

*p < .05. **p < 0.01. aminimum practical effect, bmoderate effect, cstrong effect.
Predictive Models of Change in MCT Performance

In order to identify which experiences impact the change in MCT performance, regression models were utilized to quantify the impact of experiential variables as well as their significance in the model. First, some basic bivariate models (i.e., the dependent variable as a function of one independent variable) were reviewed, and then multivariate models were presented. Only models for change in MCT performance as measured by change in duration are presented, as no significant models were identified for change in MCT score.

Diagnostic checks revealed that homoscedasticity is a concern for many of the variables due to lack of data. For some variables, the spread of data is fairly consistent at the minimum and maximum values, and this was deemed sufficient for an exploratory study. Since dependent variable is the change of a quantitative value, it is possible that the results of the model may be misread. By way of explanation, when the b (or slope) term of a regression model is positive, it means that as the independent variable increases, so does the dependent variable. Since the dependent variable herein represents the difference in duration between a pre-test and post-test, a positive b term means that as the independent variable increases so does the growth of the gap between the pre-test and the post-test. The sign of the b term never indicates if one group took longer (or less) time than another group, it only represents how much more (or less) the difference in the pre-test and post-test durations are. Note that the results presented below are for centered variables (i.e., the mean has been subtracted from each variable) so that the intercept of the regression models represents the mean dependent variable value at the mean(s) of the predictor variable(s). Since the predictor variables are not scaled by their standard
deviations, this improves the interpretability of the b terms’ magnitudes.

**Significant bivariate regression models**

As shown above, the course from which participants were recruited – taken to signify their progression through the curriculum – has a significant impact on the trends seen in the change in MCT performance over the course of the academic break. Additionally, a few other independent variables individually combined with change in MCT duration to reveal significant bivariate regression models. These significant predictors are pre-test MCT duration, prior experience with LEGO brick play, and the prior Building Toys Group. Only significant predictors were presented.

**Change in MCT Duration as a Function of Pre-Test MCT Duration**

For the pre-test MCT Duration regression model, shown below in Table 24, given that the pre-test score is used to determine something based on the post-test, this is a lagged regression model where past performance is used as a predictor for subsequent performance. The b term for the intercept is significant, and since the pre-test MCT duration data is centered, the b term for the intercept represents the average change in MCT duration based on average performance on the pre-MCT. The b term for the predictor variable is also significant, and indicates that, on average, for every 1.0 seconds longer a participant took on the pre-test, their time was reduced by 0.25 seconds on the post-test. The $R^2$ term is greater than the practical significant-effect threshold in Ferguson (2009) and indicates that the model covers 13.1% of the variance seen in the change in MCT duration.

The nonparametric analysis of this model provided a Loess fit that indicates a linear fit is possible for the relationship between change in MCT duration and pre-test
MCT duration. The Spearman's rho rank correlation is significant ($r_s(32) = -0.43, p = 0.016$). The Siegel regression slope estimate (-0.34) is significant ($df = 30, p < 0.001$) and larger in magnitude than seen in the table above. A nonparametric investigation into the individual courses reveals that the Advanced Dynamics dataset does not have a linear fit, nor is the rank correlation significant. The Engineering Graphics fit looks potentially linear, and while the Siegel regression slope estimate (-0.39) is significant ($df = 10, p = 0.025$), $r_s$ is not. The Statics fit also looks reasonably linear, and its rank correlation ($r_s(11) = -0.68, p = 0.025$) and Siegel regression slope estimate ($-0.37, df = 9, p = 0.003$) are significant.

Table 24. Regression Results Using Change in MCT Duration as the Criterion and Pre-Test MCT Duration as the Predictor

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI [LL, UL]</th>
<th>beta</th>
<th>95% CI [LL, UL]</th>
<th>$sr^2$</th>
<th>95% CI [LL, UL]</th>
<th>$r$</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-91.81**</td>
<td>[-154.34, -29.28]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.36*</td>
<td></td>
</tr>
<tr>
<td>Centered Pre-test Duration</td>
<td>-0.25*</td>
<td>[-0.48, -0.01]</td>
<td>-0.36</td>
<td>[-0.71, -0.01]</td>
<td>.13</td>
<td>[.00, .35]</td>
<td>-.36*</td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .131* 
95\% CI [.00, .35] 
F(1,30) = 4.54 
p = 0.04*$

*Note. * indicates $p < .05; ** indicates $p < .01$. A significant $b$-weight indicates the beta-weight and semi-partial correlation are also significant. $b$ represents unstandardized regression weights; beta indicates the standardized regression weights; $sr^2$ represents the semi-partial correlation squared; $r$ represents the zero-order correlation. LL and UL indicate the lower and upper limits of a confidence interval, respectively.

Change in MCT duration as a function of prior LEGO brick play experience

For the model based on prior experience with LEGO brick play (as measured in a Likert scale), shown in Table 25, the $b$ term for the intercept is significant, and since the data is centered, the $b$ term for the intercept represents the average change in MCT duration based on average prior experience with LEGO brick play. The $b$ term for the predictor variable is also significant, and indicates that, on average, for every point higher
a participant rated themselves on the Likert scale for prior LEGO brick play experience, their time was reduced by 43.38 seconds on the post-test. The $R^2$ term is greater than the practical significant-effect threshold in Ferguson (2009) and indicates that the model covers 18.7% of the variance seen in the change in MCT duration.

Table 25. Regression Results Using Change in MCT Duration as the Criterion and Prior Experience with LEGO Brick Play as the Predictor

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI [LL, UL]</th>
<th>$beta$</th>
<th>95% CI [LL, UL]</th>
<th>$sr^2$</th>
<th>95% CI [LL, UL]</th>
<th>$r$</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-91.81**</td>
<td>[-152.32, -31.30]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Centered Prior LEGO brick play Experience</td>
<td>-43.38*</td>
<td>[-77.15, -9.60]</td>
<td>-0.43</td>
<td>[-0.77, -0.10]</td>
<td>.19</td>
<td>[.01, .41]</td>
<td>-.43*</td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .187^*$  
95% CI [.01, .41]  
F(1,30) = 6.88  
p = 0.014*

* indicates $p < .05$; ** indicates $p < .01$. A significant $b$-weight indicates the beta-weight and semi-partial correlation are also significant. $b$ represents unstandardized regression weights; $beta$ indicates the standardized regression weights; $sr^2$ represents the semi-partial correlation squared; $r$ represents the zero-order correlation. LL and UL indicate the lower and upper limits of a confidence interval, respectively.

The nonparametric analysis of this model provided a Loess fit that indicates a linear fit is possible for the relationship between change in MCT duration and prior experience with LEGO brick play. The Spearman's rho rank correlation is significant ($r_s(32) = -.41, p = .019$). The Siegel regression slope estimate (-64.20) is significant (df = 30, $p < .0001$) and larger in magnitude than the parameter in the table above. A nonparametric investigation into the individual courses reveals that the Advanced Dynamics dataset does not have a linear fit, but the rank correlation ($r_s(9) = -.66, p = 0.055$) is significant. The Engineering Graphics fit is approximately linear, and while the Siegel regression slope estimate (-.39) is significant (df = 10, $p = .025$), $r_s$ is not. The Statics fit looks potentially linear, and while the Siegel regression slope estimate (-48.94)
is significant \( (df = 9, p = .010) \), \( r_s \) is not.

**Change in MCT duration as a function of Building Toys Group experience**

For the model based on prior experience with the Building Toys Group (a sum of two Likert scale responses), shown in Table 26 below, the \( b \) term for the intercept is significant, and since the data is centered, the \( b \) term for the intercept represents the average change in MCT duration based on average prior experience with the Building Toys Group. The \( b \) term for the predictor variable is also significant, and indicates that, on average, for every point higher a participant rated themselves on the Likert scales summed for prior Building Toy Group experience, their time was reduced by 24.30 seconds on the post-test. The \( R^2 \) term is greater than the practical significant-effect threshold in Ferguson (2009) and indicates that the model covers 13.0% of the variance seen in the change in MCT duration.

Table 26. Regression Results Using Change in MCT Duration as the Criterion and Prior Experience with the Building Toys Group as the Predictor

<table>
<thead>
<tr>
<th>Predictor</th>
<th>( b )</th>
<th>95% CI [LL, UL]</th>
<th>( beta ) 95% CI [LL, UL]</th>
<th>( sr^2 ) 95% CI [LL, UL]</th>
<th>( r )</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-91.81**</td>
<td>[-154.39, -29.23]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Centered Prior Building Toys Group Experience</td>
<td>-24.30*</td>
<td>[-47.75, -0.86]</td>
<td>-0.36 [-0.71, -0.01]</td>
<td>0.13 [0.00, 0.35]</td>
<td>-0.36*</td>
<td></td>
</tr>
</tbody>
</table>

\( R^2 = .130^* \)
95% CI[0.00, 0.35]
\( F(1,30) = 4.48 \)
\( p = 0.043^* \)

*Note. * indicates \( p < .05 \); ** indicates \( p < .01 \). A significant \( b \)-weight indicates the beta-weight and semi-partial correlation are also significant. \( b \) represents unstandardized regression weights; \( beta \) indicates the standardized regression weights; \( sr^2 \) represents the semi-partial correlation squared; \( r \) represents the zero-order correlation. \( LL \) and \( UL \) indicate the lower and upper limits of a confidence interval, respectively.

The nonparametric analysis of this model provided a Loess fit that indicates a linear fit is possible for the relationship between change in MCT duration and prior
experience with the Building Toys Group’s activities. The Spearman’s rho rank correlation is barely significant ($r_s(32) = -.31, p = .09$). The Siegel regression slope estimate (-34.13) is significant (df = 30, $p < .0001$) and larger in magnitude than the parameter in the table above. A nonparametric investigation into the individual courses reveals that none of the courses have data that can be approximated by a linear fit, nor is $r_s$ significant for their data.

**Significant bivariate models summary**

Given that the LEGO brick play regression model has a greater effect size than the prior Building Toys Group model, which contains LEGO brick play as a component, it is unlikely that both would be included in the final multivariate model. However, both are considered in the development of the multivariate model in the next section.

No experiences over the break, on their own, were shown to be statistically significant. The closest were experiences with mechanics and cabinetry; however, as indicated above, both had very poor variance. Thus, these are poor candidates for inclusion in regression models; however, the equivalent variables for prior experience (i.e., in mechanics and cabinetry) were considered in the development of multivariate models. The other single, significant predictors discussed in this section are the first to be considered in the multivariate model developed below.

**Multiple linear regression**

Given that progression through the curriculum has a significant impact on the change in MCT performance, it is analyzed with a multivariate model. Going through the combinations of multiple variables in search of an optimum model was performed using a stepwise approach that considered the significant predictors initially, and then was re-
executed with more of the independent variables included. Given that the stepwise algorithm, combined with the sample size, limits the number of practical variables that can be included, some investigation was required, wherein the results of the stepwise algorithm were reviewed and insignificant predictors were removed and replaced by other candidates. Ultimately, the variables provided to the stepwise algorithm were limited to

- prior experience with sports,
- prior experience with first-person video games,
- GPA,
- prior experience with RC toys,
- prior experience in construction,
- prior experience in mechanics,
- break experience with playing music,
- biological sex,
- course from which students were recruited,
- prior experience with 2D puzzle video games,
- marriage status,
- prior experience with playing music,
- and prior experience with other 3D video games.

As a linear multivariate model, each b term is properly interpreted as the slope when all other variables are held constant. The resulting model is described in Table 27 below.
Table 27. Multivariate Regression Results Using Change in MCT Duration as the Criterion

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI</th>
<th>beta</th>
<th>95% CI</th>
<th>$sr^2$</th>
<th>95% CI</th>
<th>$r$</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-247.00**</td>
<td>[-383.97, -110.04]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prior LEGO brick play Experience</td>
<td>-30.47†</td>
<td>[-65.32, 4.38]</td>
<td>-0.30</td>
<td>[-0.65, 0.04]</td>
<td>0.06</td>
<td>[-0.04, 0.15]</td>
<td>-0.43*</td>
<td></td>
</tr>
<tr>
<td>Prior Sports Experience</td>
<td>87.78**</td>
<td>[35.43, 140.13]</td>
<td>0.83</td>
<td>[0.33, 1.32]</td>
<td>0.20</td>
<td>[0.01, 0.39]</td>
<td>-0.27</td>
<td></td>
</tr>
<tr>
<td>Prior FP Video Game Experience</td>
<td>-83.21**</td>
<td>[-131.08, -35.34]</td>
<td>-0.81</td>
<td>[-1.28, -0.35]</td>
<td>0.22</td>
<td>[0.02, 0.41]</td>
<td>-0.26</td>
<td></td>
</tr>
<tr>
<td>GPA</td>
<td>-417.28**</td>
<td>[-628.07, -206.49]</td>
<td>-0.74</td>
<td>[-1.11, -0.37]</td>
<td>0.28</td>
<td>[0.06, 0.50]</td>
<td>-0.26</td>
<td></td>
</tr>
<tr>
<td>Prior RC Toy Experience</td>
<td>-152.28**</td>
<td>[-236.00, -68.56]</td>
<td>-0.63</td>
<td>[-0.97, -0.28]</td>
<td>0.24</td>
<td>[0.03, 0.44]</td>
<td>-0.31</td>
<td></td>
</tr>
<tr>
<td>Prior Construction Experience</td>
<td>65.77*</td>
<td>[9.71, 121.84]</td>
<td>0.49</td>
<td>[0.07, 0.91]</td>
<td>0.10</td>
<td>[-0.03, 0.23]</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>Prior Mechanics Experience</td>
<td>-55.66*</td>
<td>[-103.26, -8.06]</td>
<td>-0.48</td>
<td>[-0.88, -0.07]</td>
<td>0.10</td>
<td>[-0.03, 0.23]</td>
<td>-0.03</td>
<td></td>
</tr>
<tr>
<td>Break Music Experience</td>
<td>-52.12**</td>
<td>[-87.37, -16.86]</td>
<td>-0.52</td>
<td>[-0.88, -0.17]</td>
<td>0.16</td>
<td>[-0.01, 0.32]</td>
<td>-0.24</td>
<td></td>
</tr>
<tr>
<td>Biological Sex</td>
<td>206.54*</td>
<td>[34.15, 378.93]</td>
<td>0.49</td>
<td>[0.08, 0.91]</td>
<td>0.10</td>
<td>[-0.03, 0.24]</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>Prior 2D Puzzle Video Game Experience</td>
<td>28.26</td>
<td>[-18.57, 75.10]</td>
<td>0.26</td>
<td>[-0.17, 0.69]</td>
<td>0.03</td>
<td>[-0.04, 0.09]</td>
<td>-0.23</td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .669**$

95% CI[.14,.70]

F(10,20) = 4.04

$p = .004**$

Note. † indicates $p < .1$; * indicates $p < .05$; ** indicates $p < .01$. A significant $b$-weight indicates the beta-weight and semi-partial correlation are also significant. $b$ represents unstandardized regression weights; $beta$ indicates the standardized regression weights; $sr^2$ represents the semi-partial correlation squared; $r$ represents the zero-order correlation. LL and UL indicate the lower and upper limits of a confidence interval, respectively. All predictors are centered.

It was found that a nearly-identical model to the one in Table 27 above replaced prior 2D puzzle video games experience with the number of prior graphics courses. It is noted that the independent variable for prior experience with 2D puzzle video games is not significant as a predictor, although the stepwise algorithm left it in the model. The
same is true for the prior graphics courses count in the alternate equivalent model. If the 2D puzzle video games variable (or the prior graphics courses count variable) is removed from the model, then prior experience with LEGO brick play ceases to be significant as a predictor. If the prior experience with LEGO brick play variable is removed from the model, this still results in a model with an $R^2$ near the Ferguson (2009) threshold of 0.64 for a strong effect size, and the multivariate model described in Table 28 below results.

Table 28. Multivariate Regression Results Using Change in MCT Duration as the Criterion without Prior LEGO Brick Play or 2D Puzzle Video Game Experiences

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$b$</th>
<th>95% CI</th>
<th>$beta$</th>
<th>95% CI</th>
<th>$sr^2$</th>
<th>95% CI</th>
<th>$r$</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-216.07**</td>
<td>[-334.50, -97.63]</td>
<td>1.00</td>
<td>[0.22, 1.18]</td>
<td>.16</td>
<td>[-.02, .35]</td>
<td>-.27</td>
<td></td>
</tr>
<tr>
<td>Prior Sports Experience</td>
<td>74.54**</td>
<td>[23.51, 125.56]</td>
<td>.70</td>
<td>[0.22, 1.18]</td>
<td>.29</td>
<td>[.06, .52]</td>
<td>-.26</td>
<td></td>
</tr>
<tr>
<td>Prior FP Video Game Experience</td>
<td>-76.46**</td>
<td>[-115.86, -37.06]</td>
<td>-.75</td>
<td>[-1.13, -0.36]</td>
<td>.29</td>
<td>[.06, .52]</td>
<td>-.26</td>
<td></td>
</tr>
<tr>
<td>GPA</td>
<td>-420.79**</td>
<td>[-638.56, -203.01]</td>
<td>-.74</td>
<td>[-1.13, -0.36]</td>
<td>.29</td>
<td>[.06, .52]</td>
<td>-.26</td>
<td></td>
</tr>
<tr>
<td>Prior RC Toy Experience</td>
<td>-154.73**</td>
<td>[-238.94, -70.52]</td>
<td>-.64</td>
<td>[-0.98, -0.29]</td>
<td>.26</td>
<td>[.04, .48]</td>
<td>-.31</td>
<td></td>
</tr>
<tr>
<td>Prior Construction Experience</td>
<td>58.79*</td>
<td>[1.58, 115.99]</td>
<td>.44</td>
<td>[0.01, 0.87]</td>
<td>.08</td>
<td>[-.05, .21]</td>
<td>.07</td>
<td></td>
</tr>
<tr>
<td>Prior Mechanics Experience</td>
<td>-59.63*</td>
<td>[-108.43, -10.83]</td>
<td>-.51</td>
<td>[-0.93, -0.09]</td>
<td>.11</td>
<td>[-.04, .27]</td>
<td>-.03</td>
<td></td>
</tr>
<tr>
<td>Break Music Experience</td>
<td>-51.64**</td>
<td>[-85.43, -17.84]</td>
<td>-.52</td>
<td>[-0.86, -0.18]</td>
<td>.18</td>
<td>[-.01, .37]</td>
<td>-.24</td>
<td></td>
</tr>
<tr>
<td>Biological Sex</td>
<td>162.52*</td>
<td>[18.61, 306.42]</td>
<td>.39</td>
<td>[0.04, 0.73]</td>
<td>.10</td>
<td>[-.04, .24]</td>
<td>.10</td>
<td></td>
</tr>
</tbody>
</table>

$R^2 = .606**$
95% CI [.12, .67]
F(8,22) = 4.23
p = .003**

Note. * indicates $p < .05$; ** indicates $p < .01$. A significant $b$-weight indicates the beta-weight and semi-partial correlation are also significant. $b$ represents unstandardized regression weights; $beta$ indicates the standardized regression weights; $sr^2$ represents the semi-partial correlation squared; $r$ represents the zero-order correlation. LL and UL indicate the lower and upper limits of a confidence interval, respectively.

It is noted that, among others, pre-test MCT duration and course enrollment are
dropped from the model by the stepwise algorithm. This was deemed an appropriate action by the algorithm when multicollinearity was checked as the course enrollment variable generally had a variance inflation factor (VIF) greater than 10 in different multivariate combinations.

**Principal component regression**

The primary principal components for pre-study experiences and for experiences during the break were separately checked in multi-variate regression models to determine if they could significantly predict change MCT performance. The same stepwise function was used to reduce the model, and no significant results were found. The course from which students were recruited was added to the models for pre-study experiences and experiences during the break, but this did not produce significant results either.

**Summary**

This chapter presented the results of the data collected from the pre-test, post-test, and survey taken by the participants in the form of charts and descriptive statistics tables. The results of regression models based on that data have also been presented. Basic linear regression models identified the course from which students were recruited, pre-test MCT duration, prior experience with LEGO brick play, and prior experience with building toys (which includes LEGO brick play) as significant bivariate regression model predictor variables, and those models’ statistics are provided in tabular form above. A stepwise approach was used to explore the multivariate model space, and the final results were presented, which included the independent variables for prior sports experience, prior first-person video game experience, GPA, prior RC toy experience, prior construction experience, prior mechanics experience, playing music during the academic break, and
self-identified biological sex. This model has a moderately strong effect size.
CHAPTER V

CONCLUSIONS, IMPLICATIONS, AND RECOMMENDATIONS

Conclusions and Discussion

It has been discussed in the literature that for long-term studies (i.e., approximately 1 year in duration, which were left out of the statistical calculations of the meta-analysis), there may not be much improvement in spatial ability (Uttal et al., 2013). Furthermore, this discussion proceeds to leave the long-term studies out of its calculations for change in spatial ability. Most studies compare pre-test and post-test scores that compare students before and after interventions, rather than through a series of successive interventions. No spatial ability intervention studies recognize or attempt to control for the influence that engineering courses have as cotemporal, indirect interventions of potential spatial ability improvement. Recognizing this unique missing perspective for understanding spatial ability, this work seeks to establish an initial foundation of knowledge leading to better understanding of spatial ability from a longitudinal view, a view where students’ spatial ability is subject to improvement or degradation as they move through intense engineering coursework and interspersed academic break periods. Specifically, this work focuses on understanding spatial ability degradation over a winter holiday. Such a look may be beneficial in determining the long-term impacts of interventions, and that long-term impact may be limited as discussed by Uttal et al. (2013) in the meta-analysis. This study validates that there needs to be continuing investigation measuring student spatial ability repeatedly after an intervention has taken place. Indeed it has been noticed that continued improvement appears to be a possibility for some student groups after the intervention has ended. This
study found no specific evidence of a degradation in spatial ability after indirect interventions (i.e., engineering courses) within the winter academic break, but it is noted that this finding is limited, again, by the duration and number of participants in the present study.

**Primary Research Hypothesis**

The first research hypothesis proposed was:

1) Engineering students will show a decrease in spatial ability, as measured by the MCT, during academic breaks.

Findings from this study reject this hypothesis, but there are some interesting insights revealed through an in-depth look at the data. This is particularly true as some groups of students actually increased in spatial ability over the winter academic break while others maintained their spatial ability.

**Discussion on Intra-Study Changes in Performance**

In comparing the change in score between the pre- and the post-test MCT attempts, no significant difference was found. Thus the null hypothesis – that students maintain the same proficiency over time – was confirmed. However, the mean scores, when separated by course from which students were recruited, indicate an *increase* for Engineering Graphics and Statics students (with the mean increase in score for Engineering Graphics students being greater than for Statics students) while there is a very slight decrease in mean for Advanced Dynamics students (see Table 18). Although not absolute, there is an indication that the change in performance by the students in lower levels of coursework runs counter to the primary hypothesis, and a significantly deeper statistical analysis was performed to increase knowledge about the results.
To gain further insight into performance on the MCT, the durations (i.e., the times students spent taking the MCT) were analyzed for similar results, with increased speed representing increased performance. When inspecting differences between pre- and post-test MCT durations, i.e., the amount of time each group took to take the MCT test, the same trend in duration was shown as was seen with the MCT mean scores: Engineering Graphics students showed the greatest improvement, taking less time on the post-test than on their pre-test, followed by Statics students who show some improvement of post-test time over pre-test, followed by Advanced Dynamics students who show slight decrease in duration times or rather taking a greater amount of time on the post-test (see Table 19). As opposed to the data for the similar MCT mean score trends, the improvements seen in Statics and Engineering Graphics were statistically significant (see Table 23). The degradation seen in Advanced Dynamics students, though, was still not significant. Therefore, this work has revealed a significant improvement in the times required to take the MCT by Engineering Graphics and Statics students. The MCT is very graphical in nature, and thus an amplified impact from Engineering Graphics may be seen as appropriate. It is strongly encouraged that this work continue with a larger study population to verify the trends.

Evidence of Long-Term Spatial Ability Trends

A fundamental co-hypothesis that arose is that if students are improving in spatial ability as they take engineering courses, as demonstrated in (Bell et al., 2016) and (Wood et al., 2016), then participants in this study should exhibit improvement dependent on their progress through the curriculum. This would be observable in scores starting with Engineering Graphics, followed by Statics, and then Advanced Dynamics and would
allow us to understand if such a trend holds. The mean score data confirm this trend (see Table 13), but the differences in pre-test scores by course type were not statistically significant. However, the trend in mean duration of times to take the MCT also indicates that there is improvement as students progress through the curriculum (see Table 14), and the difference between Engineering Graphics and Advanced Dynamics students is significant. It was noted that, while the t-test statistics for differences between Statics and Advanced Dynamics and between Engineering Graphics and Statics are not significant in terms of p-value, they do have effect sizes worth noting per Cohen (1992) and Ferguson (2009). Findings therefore indicate that spatial ability does improve as students progress in their coursework, and further work is highly recommended to confirm this finding with larger participant populations. Given the significance of the trends in pre-test duration, there is evidence that long-term improvement in spatial ability is occurring between the freshman- and junior-level students.

**Secondary Research Hypothesis**

The second research hypothesis proposed was:

2) There are demographic and experiential factors during breaks in engineering coursework that moderate the degradation of spatial ability.

Individual factors were identified that predicted the change in MCT duration in bivariate models; however, none of them were based on experiences occurring over the academic break. The significant predictors for bivariate models were course enrollment, pre-test MCT duration and prior experience with LEGO brick play or with building toys. Course enrollment was the first factor to be identified that seemed to predict the duration. Changes in duration were significantly different between Engineering Graphics and
Advanced Dynamics (although less significant than what was seen in pre-test MCT duration differences between classes) as well as between Statics and Advanced Dynamics (which is a trend not see in the pre-test MCT duration comparisons). These differences are statistically significant to the $p < .1$ level, and they have effect sizes that are well above the minimum reportable threshold. The difference between Statics and Engineering Graphics in terms of duration improvement, however, does not exhibit a statistically significant $p$-value, nor does it have a “practically” significant effect size by Cohen’s or Ferguson’s standards (Cohen, 1992; Ferguson, 2009).

Ultimately, a multivariate model was created and analyzed, and it included one experience factor that occurred during the academic break. The significant predictors include prior sports experience, prior first-person video game experience, GPA, prior RC toy experience, prior construction experience, prior mechanics experience, playing music during the academic break, biological sex, and prior 2D puzzle video game experience. This model has a strong effect size. A nearly identical model was also found that replaced prior 2D puzzle video game experience with the previous graphics and drafting courses count. Not all of those variables are significant within the model, however, and when prior experience with LEGO brick play and 2D puzzle video games (or the previous graphics and drafting courses count) are removed from the model, then all remaining predictors are significant and, though reduced, the effect size for the multivariate model is still substantial. It is worth noting for interpretation that the remaining variables are significant when the others are held constant. Which says that the impact of GPA is significant if all other variables are held constant (and the same goes for every other variable).
With that in mind, reviewing the results of the multivariate model in Table 28 reveals that an increase in GPA by one point corresponds to an improvement between tests of 420 seconds. Admittedly, GPA is an interesting predictor variable for spatial ability, given that higher spatial ability should provide a benefit in engineering coursework, and may thus provide a boost in GPA. This intertwined relationship between GPA and spatial ability could not be analyzed with the sample size and methods implemented in this study. An increase in prior sports experience makes the difference between tests worse by 75 seconds for every point higher on the Likert scale. Prior experience with first-person video games, on the other hand, shows an improvement of 76 seconds for every point higher on the Likert scale. A one point increase in the Likert scale response for radio-controlled toy experience corresponds to a 155 second improvement between tests. Prior construction experience corresponds with getting worse by 59 seconds while prior mechanics experience corresponds with improving by 60 seconds per Likert-scale point. Playing music over the break corresponds with a 51-second improvement for every point higher on the Likert scale. And finally, it shows that female participants improve 163 seconds more than men during the break, on average, when all of the other variables in this model are held constant (note that for the biological sex variable, men are coded with a 1 and women are coded with a 0). For the most part, these results indicate that the more prior experience participants had with spatially-related activities, or the better they performed academically as indicated by GPA, the more they improved in spatial ability over the academic break. This runs counter to the results that were identified in Wood et al. (2016) and may indicate that prior experience impacts the growth of spatial ability differently for participants when they are actively enrolled in a
spatially-intensive course as opposed to when they are experiencing residual effects of that course. This may even call into question whether the preceding course has any impact, since most of the driving factors existed before registration for the preceding semester. However, the interactions with the other variables in the model prevent any definite conclusions. Further research, ideally with a larger sample size, is needed to characterize the interactions between the terms.

Given that only one break-concurrent experience was ultimately identified in the multivariate model that predicted any change in spatial ability performance, as measured by the change in MCT duration, the null hypothesis is confirmed, although in a limited fashion. However, there are additional factors in the multivariate model based on prior experiences that also predict the change in MCT duration over the break.

In reviewing the PCA results, no useful correlation with the multilinear regression results are found. The prior experience variables and their PCA magnitude-sorted rankings are given in the table below. The only break-concurrent experience, playing music, was ranked 10th of 15 experiences in the PCA magnitude-sorted rankings for experiences during the break.

Table 29. Multilinear Regression Variables' PCA Magnitude-Sorted Ranks

<table>
<thead>
<tr>
<th>Pre-Study Experience Variable</th>
<th>PCA Magnitude-Sorted Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sports</td>
<td>4</td>
</tr>
<tr>
<td>2-D puzzle video games</td>
<td>7</td>
</tr>
<tr>
<td>LEGO brick play</td>
<td>13</td>
</tr>
<tr>
<td>radio controlled toys</td>
<td>14</td>
</tr>
<tr>
<td>first-person video games</td>
<td>18</td>
</tr>
<tr>
<td>Construction</td>
<td>19</td>
</tr>
<tr>
<td>Mechanics</td>
<td>31</td>
</tr>
</tbody>
</table>

The PCA in this study provided no insight, as evidenced by the lack of insight for regression from the magnitude-sorted ranks and from the multiple linear regression
performed with the principal components.

**Implications**

From this work, it appears unlikely that students would experience spatial ability degradation over a short-term break. There is little that can initially be recommended to students over a small break to help them develop or maintain their spatial ability, with the exception of playing music over the break. Playing music may be linked directly to spatial ability, or it may be representative of a factor that is not as easily observable. There is evidence from electroencephalographic research on spatial ability that experience playing music or even just listening music notably affects how participants’ brains perform during spatial ability exercises (Bhattacharya, Petsche, Feldmann, & Rescher, 2001; Rideout & Laubach, 1996), so identifying music as a factor in spatial aptitude research is not unique. The impact of music on performance may be profitably studied in the future. Insight may also be gained by continuing to look at the factors from prior (i.e., before the break and before the study) experiences that also appear to promote continued spatial ability gain during the break.

It appears that students are not progressing in spatial ability after Advanced Dynamics during their junior year, as shown by a lack of significant change in either scores or durations over the winter break. This could be interpreted in a number of ways: 1) as an indication that students have generally reached a plateau in their spatial ability that will allow them to function in future mechanical engineering activities, 2) as an indication that the Advanced Dynamics course does not promote spatial ability growth, 3) that students who had lower spatial ability levels, and thus room to grow, in lower-level courses have been “weeded out” and have not been allowed entry into Advanced Dynamics. The data in this study are insufficient to identify which, if any, of these
interpretations apply. However, the high VIF representing multicollinearity between
course enrollment and other experience variables may be an indicator that students
without a certain set of previous experiences are being weeded out of mechanical
engineering before their junior year. The third interpretation is also supported by the high
average age and higher average pre-Test MCT score observed in the Engineering
Graphics participant population. The distribution of change in performance seen in the
Engineering Graphics students is very different than that seen for Statics students, and
while this results in a failure of nonparametric statistics to detect a difference between
Engineering Graphics and Advanced Dynamics students (see
Table 20), it is indicative that there is likely a filtering of the population successfully
transitioning from Engineering Graphics to Statics.

Alternatively, there is evidence that with increased expertise, there is decreased
usage of spatial ability (Uttal & Cohen, 2012). The participants’ lack of improvement
during the break following Advanced Dynamics may simply be the result of their
achieving a level of expertise sufficient that they no longer leverage spatial ability as
much as a more novice student, and thus they cease to develop their spatial aptitude
which results in a lack of change in their spatial ability.

The evidence that pre-test MCT duration is a significant predictor of change in
MCT duration has a couple of implications for research into spatial ability. First, this
implies that not only is spatial ability malleable as Uttal et al. (2013) identified, but that a
lower score does not preclude improvement. Second, this implies that the approach of
offering spatial ability interventions only to those who score below a current threshold
(Sorby & Baartmans, 2000) has an impact on the measured effect. In doing so, the
likelihood of seeing a significant effect in the participant population is increased. Those who implement such an approach could argue that in doing so they are maximizing their effect and minimizing the impact on students’ time—for those who achieve a higher score and are not recommended to take the intervention.

**Implications of Limitations and Threats**

It is possible that engineering students are increasing in spatial ability on their own, potentially as part of some segment of the population that does so without interventions. There is evidence, represented by the high multicollinearity of progress through the curriculum with other factors, that this ongoing increase may be based more on previous experiences than the coursework in which they are enrolled. Engineering students may simply represent a population of individuals who progress in spatial ability regardless of any interventions, and that may be connected to traits that draw them to engineering. Year-to-year improvement exhibited by students progressing through the engineering curriculum (not significantly represented by score, but significantly represented by duration, or time taken to complete the MCT) lends support for the postulation that long-term spatial ability improvement is occurring as a result of participation in engineering curriculum. There is also evidence that similarly-aged students in a different STEM course, Anatomy, do not exhibit spatial ability progress (Wood et al., 2016).

The Engineering Graphics (Bell et al., 2016) and Statics (Wood et al., 2016) courses at USU have not been statistically proven to sit solely as spatial ability interventions that causes students to increase in spatial ability. However, research has identified those classes as being correlated with an increase in spatial ability observed to
occur at the same time. Unpublished data from a previous study indicates that Advanced Dynamics students at USU do not significantly increase in spatial ability from the beginning of the semester to the end of the semester, as do students in Statics and Engineering Graphics. It is possible that a different approach to teaching Advanced Dynamics may have impacted spatial ability differently than the approach used in the course that preceded this study. The question remains unanswered as to whether the curricular approach used for Advanced Dynamics represents a spatial intervention that becomes un-quantifiable because junior-level students are reaching a peak required spatial ability for engineering curriculum or experiencing a ceiling effect with the given instruments, or if a different approach to teaching the course could continue to promote spatial ability improvement in junior-level students.

Participant Population Notes

Give the small sample size for a study like this, it is not unexpected that achieving statistical significance was difficult. Having duration data that significantly confirmed the insignificant results seen in the score data was a fortuitous by-product of delivering the instrument in an online format. An online format was chosen to accommodate students who had busy schedules during the pre-test phase and who were off-campus during the post-test phase. It is recommended that collecting timing data be used as a best practice for gaining insight into spatial ability trends.

Significant changes in models can be driven by small numbers of participants when dealing with such small sample sizes. The outlier who was ultimately removed from the model due to suspect post-test performance were happened to be a minority in many experiential and demographic factors. When they are included in the model, then
race and hometown appear as significant predictors in bivariate models. The multivariate model also exhibited differences, including course as a significant predictor, for example. Although p<0.1 may be acceptable for exploratory research studies, the conclusion should not be that the relationships discussed above are truly there, but it should be that replication is needed. Given that educational research sampling is not truly random (i.e., the experiences and demographic factors used as independent variables cannot be randomly assigned), the need for replication at other institutions is particularly encouraged.

The insight into the impact of student employment during the semester is limited because the instrument did not record the number of hours students were employed during the semester when the survey was issued. However, this is believed to have limited impact on the results of the study given the lack of significance seen in the employment status of student during the semester.

Participant mortality (i.e., dropping out of the study) played a role in the final sample size. Of the 450 students who were invited to participate, 54 students accepted the invitation, took the pre-test MCT, and gave their informed consent (first phase participation rate of 12.0%), only 36 participated in the post-test MCT and survey portion of the study (study completion participation rate of 8.0%). As covered previously, of those 36 there were two participants who did not complete enough of the pre-test MCT, post-test MCT, and survey to be included in the analysis; and there was an additional outlier who was not included in most of the analysis, resulting in a sample size of 33 (complete participation rate of 7.3%). In terms of investigating long-term spatial ability trends, if students are being weeded out, given that enrollment decreases from freshman
to junior year, then that can impact research endeavors as a type of mortality in the participant population as well.

The Statics course had four participants who were non-mechanical engineering students: three majoring in biological engineering and one majoring in environmental engineering students. Given the small sample size, particularly when looking at the three course types individually, the mechanical engineering students and the non-mechanical engineering students were grouped together for this study.

Nonparametric statistics were used due to the small sample sizes to confirm the parametric statistics, and they generally reflect the same results as seen with the parametric statistics. Exceptions include identifying a significant difference in the pre-test MCT durations by course and not identifying the difference between the change in MCT duration for Advanced Dynamics and Engineering Graphics as being significant. In the case of the latter discrepancy with parametric statistics, this is understandable as those two datasets do not appear to be normally distributed as the Statics dataset appears to be. Most of the data checked with parametric t-tests are normally distributed, and thus it would be expected that the parametric statistics appear to be similar to the nonparametric statistics. It does not appear that the limitations of sample size and normal distribution impacted the least-squares regression statistics significantly, given that the nonparametric statistics tell a similar story. The fact that linear regression (parametric or nonparametric) is significant for the bivariate models discussed is only to be expected given the generally linear Loess plots obtained during diagnostic checking. Nonparametric regression was not used for multiple regression given the need for a large dataset (Cohen et al., 2003, p. 253).
Other Confounding Variables and Threats

This is a difficult population to study. Some of the variation in performance (by score and/or by time spent taking the MCT) may be attributed to participants’ lackadaisical attitude toward the study. Stress may also have been a factor during the timeframe for the pre-test (just before finals), and distractions incumbent to the academic break may have prevented students from focusing on the study and caused lower scores achieved and/or longer times spent completing the instrument. Alternatively, the reduction of stress after completing the semester may have boosted performance during the post-test.

Upon reflection, it is felt that the survey should have asked students for the number of hours spent on activities over the break on a weekly basis and not a monthly basis. This way the time-period would better align with the responses given, since many of the participants selected “15 or more”. The monthly option was developed from previous literature and a similar survey where students were expected to have less time than is available during an academic break. Additionally, this change would align the time period for the activities question with the time period used by the questions regarding employment and study.

Seasonal effects – both the impact of the fall semester and the impact of the holiday season during the academic break – may have influenced the study. It is not known if similar results would be seen from spring semester students over the duration of the summer academic break.

The testing threat stemming from some Advanced Dynamics students having taken spatial ability tests previously is still present. However, given the fact that
experience with previous spatial ability instruments was collected in the data and not found to be significant in the regression analyses, it is believed that this threat has not been realized.

**Potential New Research Questions**

There are a number of potential new research questions arising from this work. Given the long-term increase seen in students progressing through the curriculum, one such question may treat the maintenance of participants’ spatial ability after they leave university studies.

Additionally, questions arise regarding the explanation of the increase that students exhibit after the end of the semester. Perhaps Engineering Graphics and Statics students are exhibiting improvement because they are learning to see the world around them differently. Or maybe engineering students are progressing on their own, independent of the interventions (coursework or otherwise) provided to them. Associated research questions are probably best answered via qualitative research.

Given the questions raised above about the approach utilized for teaching Advanced Dynamics, it would be of interest to examine the impact of different teaching approaches in courses that can be viewed as indirect spatial interventions. Bell et al. (2016) indicated that teaching approaches – even delivered by the same instructor – had statistically significant impacts on the growth in spatial ability in an Engineering Graphics course. Similarly, the impact of an instructor’s personal spatial ability may have on their teaching approach is worth questioning and researching.

**Recommendations for Future Work**

Due to the small sample size involved in this study the statistics should be used as
a starting point for investigations and not as findings one which to base policy or practice. The small sample size limitations are particularly underscored by the differing behavior seen in the data collected from different courses and the limited amount of participation in many of the experiences included in the survey. Given larger sample sizes, statistical analyses of the relationship between GPA and spatial ability are recommended.

The immediate recommendation is to replicate this study over a longer academic break to see if the same results are found. The summer break is long enough to look at spatial ability changes across a number of different timeframes while controlling for seasonal effects.

Additional replications of this winter break study, particularly at more diverse institutions are recommended. This would provide the benefits of A) increasing the sample size, and B) providing insight into different student populations with different instructors. Particularly, it may be worth investigating if the indication that junior-level students cease to improve is consistent across different student populations and different approaches to teaching Advanced Dynamics. Additionally, further research is needed to separate the impacts of students’ improvement in spatial ability as they progress through curriculum and students who may have lower spatial scores dropping out instead of progressing through the curriculum.

Independent studies on stress and its impact on spatial ability instrument performance are also recommended. The influence of taking assessments during an academic break may be significant, and insight into the topic may provide insight into the relationship between instrument scores and duration times. Additionally, the neural efficiency hypothesis is recommended as an avenue of neuroscientific research into the
relationship between instrument scores and duration times (Call, Goodridge, Villanueva, Wan, & Jordan, 2016; Ruesch et al., 2017).

It is recommended that all future studies collect and analyze duration data as a measure of performance.
REFERENCES


CEEB. (1939). CEEB Special aptitude test in spatial rotations. USA.

doi: [http://dx.doi.org/10.1037/0033-2909.112.1.155](http://dx.doi.org/10.1037/0033-2909.112.1.155)


doi:10.1037/a0015808

doi:10.4135/9781412985307.n1

http://socserv.socsci.mcmaster.ca/jfox/Books/Companion


Contrasts, Utilities (Version R package version 4.5-15). Retrieved from
https://CRAN.R-project.org/package=doBy

Education, 44(6), 859-883.

Komsta, L. (2013). mblm: Median-Based Linear Models (Version R package version
0.12). Retrieved from https://CRAN.R-project.org/package=mblm

doi:10.1080/15326900701399897

Effects of Computer Games? A Comprehensive Review of the Current Literature
Playing video games: Motives, responses, and consequences. (pp. 327-345).

Differences in Spatial Ability: A Meta--Analysis. Child Development, 56(6),
1479. doi:10.1111/1467-8624.ep7252392

from https://www.r-bloggers.com/wilcoxon-mann-whitney-rank-sum-test-or-test-u/


doi:10.1007/s10648-015-9304-8


APPENDICES
APPENDIX A: Positionality
Positionality

Quantitative research approaches generally imply certain belief systems about the nature of truth and our ability to measure it. In fact, *post-positivism* appears to be the most appropriate. With both positivism and post-positivism, a belief is present that truth exists – or a single answer exists. Post-positivism, however, recognizes difficulty in measuring or identifying the truth and assumes a probabilistic nature within the laws of cause and effect (Creswell, 2013)p.23-24, which fits with most approaches to quantitative, statistically-based science. A theory is applied, an effect is expected from a given cause, data is collected and reduced, and implications are found in the final analysis. This research utilized such a scientific approach. That said, *pragmatism* – wherein researchers use what works for their purposes and focus on the intended outcome without too much conviction or existential turmoil regarding the nature of truth (Creswell, 2013)p.28 – more accurately identifies the practical foundation of this methodology, and perhaps the practice of engineering in general. In the interest of making more biases explicit, the author of this research is a cisgender, male, Caucasian, mechanical engineer, which implies multiple things about his experience with engineering education – such as not being subject to stereotype threat during baccalaureate and postgraduate education – which is not otherwise discussed in this research.

The theoretical framework for this methodology is based on the assumption that positive spatial ability malleability is correlated with increases in engineering performance, although such correlations still need to be better researched, proven, and understood. With a foundation for statistical methods presented above, and a review establishing the practice of spatial ability measurement and correlation as accepted within
the engineering education research community, the details of the methods used in this research are presented in the CHAPTER III – RESEARCH METHODOLOGY.
APPENDIX B: Informed Consent and Survey / MCT Instruments
Informed Consent

The Informed Consent document was presented to participants during the pre-survey. It was also made available for download during the post-survey.
We will collect your information primarily through Qualtrics. We may collect your contact information through email or text message if you choose contact us directly to volunteer to participate. This information will be securely stored in a restricted-access folder on Box.com, an encrypted, cloud-based storage system. After data collection, it will be downloaded from Qualtrics and consolidated, after which your personal identifiers will be separated from the data, destroyed, and replaced with randomly-generated identifiers before proceeding with data analysis and publication. This removal of your personal identifiers will occur within 90 days of the completion of data collection. Your identity will be kept confidential so that no instructors will know which students have participated in the study. The data will not be shown to Dr. Goodridge until the personal identifiers have been removed and random identifiers have been put in place so that he will not know which students are participating. The record of your approval of this form will be kept for three years, and then it will be destroyed.

It is unlikely, but possible, that others (Utah State University, or state or federal officials) may require us to share the information you give us from the study to ensure that the research was conducted safely and appropriately. We will only share your information if law or policy requires us to do so.

The research team works to ensure confidentiality to the degree permitted by technology. It is possible, although unlikely, that unauthorized individuals could gain access to your responses because you are responding online. However, your participation in this online survey involves risks similar to a person’s everyday use of the Internet.

Voluntary Participation & Withdrawal

Your participation in this research is completely voluntary. If you agree to participate now and change your mind later, you may withdraw at any time by contacting Dr. Goodridge or his graduate research assistant, Benjamin Call, via email, phone (including text or voice-mail to 435-915-6586), or in-person request. If you choose to withdraw after we have already collected information about you, we will remove your data from the complete dataset if it is still possible to identify which data are associated with your identity (i.e., once your personal identifiers have been placed by randomly-generated identifiers, it will not be possible to remove your data from the complete dataset). The researchers may choose to terminate your participation in this research study if you do not participate in the data collection activities (i.e., in Qualtrics) during the windows made available for the study (i.e., the week before finals for the pre-test, and again at least 30 days later, but before the following semester starts). The researchers are also not allowed to collect data from you if you are under the age of 18.

IRB Review

The Institutional Review Board (IRB) for the protection of human research participants at Utah State University has reviewed and approved this study. If you have questions about the research study itself, please contact the Principal Investigator at 435-797-3051 or wade.goodridge@usu.edu. If you have questions about your rights or would simply like to speak with someone other than the research team about questions or concerns, please contact the IRB Director at (435) 797-0567 or irb@usu.edu.

Wade Goodridge
Principal Investigator
(435) 797-3051; wade.goodridge@usu.edu

Benjamin Call
Graduate Student Investigator
ben.call@usu.edu

Informed Consent

By selecting “YES, I am over 18 and agree to participate in this research study” in Qualtrics, you agree to participate in this study. You indicate that you understand the risks and benefits of participation, and that you know what you will be asked to do. You also agree that you have asked any questions you might have, and are clear on how to stop your participation in the study if you choose to do so. Please be sure to retain a copy of this form for your records.

Engineering Education Department | (435) 797-2758 | 4160 Old Main Hill | Logan, UT 84322
Pre-Survey

Informed Consent and MCT Pre-Test for Spatial Degradation Study

Survey Flow

Standard: Informed Consent Example (7 Questions)
Standard: MCT Intro & Questions Block - Timed - Scored (28 Questions)
Standard: Display Score (1 Question)

Page Break

Start of Block: Informed Consent Example

Please fully review this Informed Consent document before deciding whether to proceed with this study.

☐ YES, I am over 18 and agree to participate in this research study. (1)

☐ NO, I am not over 18 and/or do not wish to participate in this research study. (2)

Skip To: End of Survey If Please fully review this Informed Consent document before deciding whether to proceed with this s...

Please provide your signature:

Please provide your full name, A#, and today's date:

☐ Please provide your full name: (1)

☐ Please provide your A#: (2)

☐ Please indicate today's date: (3)
How would you like to be contacted for follow-up for the final phase of the study?

- Email (1)
- Text Message (2)

Display This Question:
If How would you like to be contacted for follow-up for the final phase of the study? = Email

Please enter the email address where you want to receive email correspondence for the next phase of the study.

________________________________________________________________

Display This Question:
If How would you like to be contacted for follow-up for the final phase of the study? = Text Message

Please enter the phone number where you want to receive text message correspondence for the next phase of the study.

________________________________________________________________

Page Break

Thank you for agreeing to participate in the study. You will now be presented with the Mental Cutting Test, which has a 20-minute time limit. Please ensure that you will be able to work on the task at hand for 20 minutes without interruption.

Click to continue...

[see Mental Cutting Test Questions below]
Mental Cutting Test Questions

MCT Intro & Questions Block - Timed - Scored

This is the Mental Cutting Test originally developed as part of a college entrance examination close to 1930. You have 5 minutes to review the directions and understand how to accomplish the problems. You then have 20 minutes to complete the 25 questions. Do the best you can in that time and then the computer will time you out of the test. Remember while you will receive a score showing how you did on the test, this is only for your information. Your spatial ability measured with this instrument will not factor into your course grade. Please work alone on this test.

In this test each problem consists of a picture of a block enclosed in a solid line which shows where a cut is to be made. The answer is the shape of the surface which would be made by cutting along the solid line. Look at Sample Problem 1.

The figures below show that D is the correct answer choice for Sample Problem 1.

In these pictures you see the block cut in two and the front part of the block removed. Then the block is turned so that the cut side is facing directly toward you. The answer is the shape of the cut side only, shown shaded in the last picture.

Now try Sample Problem 2.

The figures below show that C is the correct answer choice for Sample Problem 2.

Question 1

[Images of different shapes and options]

Question 2

[Images of different shapes and options]
Your score was [fills in score]
Post-Survey

MCT Post-Test and Survey for Spatial Degradation Study

Survey Flow

<table>
<thead>
<tr>
<th>Standard: Personal Identifiers Introductory Questions - Blank Informed Consent (3 Questions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard: MCT Intro &amp; Questions Block - Timed - Scored (28 Questions)</td>
</tr>
<tr>
<td>Standard: Display Score (1 Question)</td>
</tr>
<tr>
<td>Standard: Academic Break Demographic and Activity Questions (43 Questions)</td>
</tr>
</tbody>
</table>

Page Break

Start of Block: Personal Identifiers Introductory Questions - Blank Informed Consent

Please enter your personal identifiers (full name and A#).

- Full Name (1) ________________________________
- A# (2) ______________________________________

Review Informed Consent, if desired.

Thank you for agreeing to participate in the study. You will now be presented with the Mental Cutting Test, which has a 20-minute time limit. It will then be followed by a demographic and interest survey. Please ensure that you will be able to work on the task at hand for 20 minutes without interruption.

Click to continue...

[see Mental Cutting Test Questions above]

Start of Block: Academic Break Demographic and Activity Questions

And now for the Demographic and Activity Questions:

Click to continue...
What is your biological sex?

- Male (1)
- Female (2)

What is your age?

________________________________________________________________

What is your racial or ethnic identity?

- White or Caucasian (1)
- Hispanic or Latino (2)
- Black or African American (3)
- Native American or American Indian (4)
- Asian (5)
- Pacific Islander (6)
- Other (7) ________________________________________________

Are you married?

- Yes (1)
- No (2)
Do you currently care for any children while continuing your education? (outside of a job responsibility)

- Yes (1)
- No (2)

If you currently care for children while continuing your education then please report the number. (outside of care for a job responsibility)

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 or more (11)

What is your Major while participating in the study?

________________________________________________________________________________________
How many years of college/university experience have you received at the time of your participation in the study?

- (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 (11)
- 11 (12)
- 12 or more (13)
What is your year of status in your major?

- Freshman (1)
- Sophomore (2)
- Junior (3)
- Senior (4)

Had you previously taken, or completed, the class where you were recruited to participate in this survey?

- Yes (1)
- No (2)

Have you completed any of the following classes before? Please mark all that apply.

- Statics (1)
- Advanced Dynamics (2)
- Engineering Graphics (3)
- Interior Design (4)
- Anatomy (college-level) (5)
- Dynamics (6)
- Strength of Materials (7)
- Fundamentals of Electronics (8)
What classes did you take in the semester when you were recruited to participate in this study?

________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________

Did you take any classes during the break between fall and spring semesters?

○ Yes  (5)
○ No  (6)

Display This Question:
If Did you take any classes during the break between fall and spring semesters? = Yes

What classes did you take during the break between fall and spring semesters?

________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________
________________________________________________________________

What is your University GPA?

________________________________________________________________
Do you work a job while taking coursework in your major?

- Yes (3)
- No (4)

Display This Question:
If Do you work a job while taking coursework in your major? =

How many hours a week do you work at this job while pursuing your education?

- 0 (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- 31-35 (8)
- 36-40 (9)
- 40 or more (10)

Did you work a job during the break between semesters?

- Yes (1)
- No (2)
Display This Question:

If Did you work a job during the break between semesters? = Yes

How many hours a week did you work at this job during the break?

- 0 (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- 31-35 (8)
- 36-40 (9)
- 40 or more (10)
How many activities did you participate in during the break? (hobbies, interests, etc.)

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)

Display This Question:

If How many activities did you participate in during the break? (hobbies, interests, etc.) \( \neq 0 \)

On average, how many hours a month do you feel you spent on these activities, hobbies, or
interests during the break?

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)
- 6 (11)
- 7 (12)
- 8 (13)
- 9 (14)
- 10 (15)
- 11 (16)
- 12 (17)
- 13 (18)
- 14 (19)
- 15 or more (20)

On average, how many hours a week do you feel you put into studying and doing homework for
engineering classes over the break?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 (11)
- 11 (12)
- 12 (13)
- 13 (14)
- 14 (15)
- 15 (16)
- 16 (17)
- 17 (18)
- 18 (19)
How many hours a week did you exercise during the break?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 (8)
- 8 (9)
- 9 (10)
- 10 (11)
- 11 or more (12)
Discounting your experience in this study, have you ever taken any of the following spatial ability exams? Check those you have taken before.

- [ ] Purdue spatial visualization test of rotations (1)
- [ ] Mental cutting test (2)
- [ ] Mental rotation test (3)
- [ ] Paper folding test (4)
- [ ] Minnesota Paper Form Board Test (5)
- [ ] None (6)
- [ ] Other (7) ________________________________
What is your estimate of the population of your home town?

- 0-1000 (1)
- 1001-2000 (2)
- 2001-4000 (3)
- 4001-6000 (4)
- 6001-8000 (5)
- 8001-10,000 (6)
- 10,001-15,000 (7)
- 15,001-30,000 (8)
- 30,001-50,000 (9)
- 50,001-75,000 (10)
- 75,001-100,000 (11)
- 100,001-200,000 (12)
- 200,001-400,000 (13)
- 400,001-600,000 (14)
- 600,001-1,000,000 (15)
- >1,000,000 (16)
How would you classify your hometown?

- Rural (1)
- Sub-urban (2)
- Urban (3)

Have you had prior graphics or drafting course experience (before the previous semester)?

- Yes (1)
- No (2)

Display This Question:

If Have you had prior graphics or drafting course experience (before the previous semester)? = Yes
What previous graphics and drafting course experience do you have? Choose all that apply.

- High school board drafting (1)
- High school solid modeling (Inventor, Solid Works, Solid Edge, Katia, etc.) (2)
- High School Architectural Drafting (hand, Chief Architect, Autodesk Architectural Desktop, Revit, etc.) (3)
- Trade school board drafting (4)
- Trade school solid modeling (Inventor, Solid Works, Solid Edge, Katia, etc.) (5)
- Trade School Architectural Drafting (hand, Chief Architect, Autodesk Architectural Desktop, Revit, etc.) (6)
- High School Basic Computer Aided Drafting (7)
- Trade School Basic Computer Aided Drafting (8)
- College/University board drafting (9)
- College/University solid modeling (Inventor, Solid Works, Solid Edge, Katia, etc.) (10)
- College/University Architectural Drafting (Hand, Chief Architect, Autodesk Architectural Desktop, Revit, etc.) (11)
- College/University Basic Computer Aided Drafting (12)
- Self taught (13)
- None (14)

Display This Question:

If Have you had prior graphics or drafting course experience (before the previous semester)? = Yes
How many graphics or drafting courses did you take prior to the last semester?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (6)
- 6 (7)
- 7 or more (8)

How much did you play with blocks (of any kind) as a child?

- Never (21)
- Very seldom (22)
- Once in a while (23)
- Most of the time (24)
- All the time (25)

What craft-type of hobbies did you pursue over the break? (scrapbooking, graphic arts, sculpture, etc.)

________________________________________________________________
________________________________________________________________
________________________________________________________________

________________________________________________________________
On average, how many hours a month do you feel you spend on these craft-type hobbies?

- 0 (1)
- 1 (2)
- 2 (3)
- 3 (4)
- 4 (5)
- 5 (11)
- 6 (12)
- 7 (13)
- 8 (14)
- 9 (15)
- 10 (16)
- 11 (17)
- 12 (18)
- 13 (19)
- 14 (20)
- 15 or more (21)
How much experience did you have before last semester with model construction or puzzles? (rockets, planes, cars, trains, puzzles, etc.)

- very little to none (1)
- some, I play (or have played) around with them a little, but average less than a few hours a month (2)
- moderate, I play (or have played) around with them for several hours a month on average (3)
- considerable, I play (or have played) with them for several hours a week on average (4)
- immersed, I play (or have played) with them on a daily basis (5)

How much time did you spend during the break with model construction or puzzles? (rockets, planes, cars, trains, puzzles, etc.)

- very little to none (1)
- some, I played around with them a little, but average less than a few hours a month (2)
- moderate, I played around with them for several hours a month on average (3)
- considerable, I played with them for several hours a week on average (4)
- immersed, I played with them on a daily basis (5)
How much prior experience did you have before last semester with radio controlled toys?

- very little to none (1)
- some, I play (or have played) around with it a little, but average less than a few hours a month (2)
- moderate, I play (or have played) around with it for several hours a month on average (3)
- considerable, I play (or have played) with it for several hours a week on average (4)
- immersed, I play (or have played) with it on a daily basis (5)

How much time did you spend during the break with radio controlled toys?

- very little to none (1)
- some, I played around with them a little, but average less than a few hours a month (2)
- moderate, I played around with them for several hours a month on average (3)
- considerable, I played with them for several hours a week on average (4)
- immersed, I played with them on a daily basis (5)

How much experience did you have with these extracurricular activities before last semester? (if you do not recognize an item then please do not select it)

<table>
<thead>
<tr>
<th>very little to none</th>
<th>some experience</th>
<th>moderate experience</th>
<th>considerable experience</th>
<th>immersed experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>5</td>
</tr>
<tr>
<td>Activity</td>
<td>Experience</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------------------------------</td>
<td>-------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FIRST robotics ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JETS ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Future city ()</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>TechXplore ()</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>VEX robotics ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Think Quest ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lego Engineering ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INSPIRE! ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Botball ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Odyssey of the Mind ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minecraft ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Erector sets ()</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Legos ()</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Tetris ()</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>First-person video games (Portal, Halo, Call of Duty, Myst, etc.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other 3D video games (Legend of Zelda, Super Mario Odyssey, flight simulators, etc.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2D puzzle video games (Candy Crush Saga, Bejeweled, Rush Hour, etc.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2D strategy video or board games (League of Legends, Risk, StarCraft, etc.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

How much experience did you spend during the break with these extracurricular activities? (if
<table>
<thead>
<tr>
<th>Activity</th>
<th>Experience Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIRST robotics ()</td>
<td>3</td>
</tr>
<tr>
<td>JETS ()</td>
<td>3</td>
</tr>
<tr>
<td>Future city ()</td>
<td>3</td>
</tr>
<tr>
<td>TechXplore ()</td>
<td>3</td>
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<tr>
<td>VEX robotics ()</td>
<td>3</td>
</tr>
<tr>
<td>Think Quest ()</td>
<td>3</td>
</tr>
<tr>
<td>Lego Engineering ()</td>
<td>3</td>
</tr>
<tr>
<td>INSPIRE! ()</td>
<td>3</td>
</tr>
<tr>
<td>Botball ()</td>
<td>3</td>
</tr>
<tr>
<td>Odyssey of the Mind ()</td>
<td>3</td>
</tr>
<tr>
<td>Minecraft ()</td>
<td>3</td>
</tr>
<tr>
<td>Erector sets ()</td>
<td>3</td>
</tr>
<tr>
<td>Legos ()</td>
<td>3</td>
</tr>
<tr>
<td>Tetris ()</td>
<td>3</td>
</tr>
<tr>
<td>First-person video games</td>
<td>3</td>
</tr>
<tr>
<td>Other 3D video games</td>
<td>3</td>
</tr>
<tr>
<td>2D puzzle video games</td>
<td>3</td>
</tr>
<tr>
<td>2D strategy video or board</td>
<td>3</td>
</tr>
</tbody>
</table>

Note: If you do not recognize an item, please do not select it.
<table>
<thead>
<tr>
<th>Activity</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woodworking ()</td>
<td>4</td>
</tr>
<tr>
<td>Welding ()</td>
<td>3</td>
</tr>
<tr>
<td>Fabrication ()</td>
<td>4</td>
</tr>
<tr>
<td>Electronics ()</td>
<td>4</td>
</tr>
<tr>
<td>Mechanics (automobile, etc.) ()</td>
<td>4</td>
</tr>
<tr>
<td>Cabinetry ()</td>
<td>3</td>
</tr>
<tr>
<td>Building computers ()</td>
<td>4</td>
</tr>
<tr>
<td>Gardening ()</td>
<td>5</td>
</tr>
<tr>
<td>Artistic painting ()</td>
<td>5</td>
</tr>
<tr>
<td>Artistic drawing ()</td>
<td>4</td>
</tr>
<tr>
<td>Residential/Commercial painting ()</td>
<td>5</td>
</tr>
<tr>
<td>Construction ()</td>
<td>4</td>
</tr>
<tr>
<td>Sewing ()</td>
<td>4</td>
</tr>
<tr>
<td>Embroidery ()</td>
<td>4</td>
</tr>
<tr>
<td>Cooking ()</td>
<td>4</td>
</tr>
<tr>
<td>Dancing ()</td>
<td>4</td>
</tr>
<tr>
<td>Sports (skiing, basketball, shooting, team roping, etc.) ()</td>
<td>4</td>
</tr>
<tr>
<td>Playing music ()</td>
<td>4</td>
</tr>
</tbody>
</table>
How much time did you spend during the break doing following activities?

<table>
<thead>
<tr>
<th>Very little to none</th>
<th>Little</th>
<th>Some</th>
<th>Moderate</th>
<th>Considerable</th>
<th>Immersed</th>
<th>Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Activity</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woodworking ()</td>
<td></td>
</tr>
<tr>
<td>Welding ()</td>
<td></td>
</tr>
<tr>
<td>Fabrication ()</td>
<td></td>
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<tr>
<td>Electronics ()</td>
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</tr>
<tr>
<td>Mechanics (automobile, etc.) ()</td>
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</tr>
<tr>
<td>Cabinetry ()</td>
<td></td>
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<td>Residential/Commercial painting ()</td>
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<td>Cooking ()</td>
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<tr>
<td>Dancing ()</td>
<td></td>
</tr>
<tr>
<td>Sports (skiing, basketball, shooting, team roping, etc.) ()</td>
<td></td>
</tr>
<tr>
<td>Playing music ()</td>
<td></td>
</tr>
</tbody>
</table>

How honest were you while filling out this survey?

<table>
<thead>
<tr>
<th>How honest</th>
<th>Not honest</th>
<th>Neutral</th>
<th>Completely Honest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scale</td>
<td>0 1 2 3 4 5 6 7 8 9 10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Honesty Scale ()

Is there any feedback you would like to provide us regarding this survey or the study in general? (Questions you have, confusion experienced, etc.)

__________________________________________________________________________
__________________________________________________________________________
__________________________________________________________________________
__________________________________________________________________________
__________________________________________________________________________

End of Block: Academic Break Demographic and Activity Questions
APPENDIX C: R Scripts for Data Analysis
Script Explanation

The code provided below includes both the scripts run as well as a number of comments providing insight into the data analysis process. Some parts of the code have been commented out even though they were part of the analysis. This happened because either A) the results of the code were not significant, or B) the results of the code had been documented and the code was commented out to clean up the output so further interpretation would be more straightforward. Comments are marked by lines starting with #.

The code is presented in two subsections. The first, titled Spatial Degradation Analysis Scripts, consists of the code that ran the analysis and holds the comments for analysis. This code was run in a piece-meal fashion, and while the first lines down to the definition of the cohens_d(), wilcoxPValue_r(), and mannWhitneyU_r() functions need to be run in order, the rest of the scripting was run in small blocks in various orders as questions arose and returned during the analysis. The other subsection, titled simpleDiagnostics.r, was an external R file that contained the functions singleIvDiagnostics() and singleIvNonParamDiagnosticsWith3LevelCatVar().

For improved printing, the script code is marked with Courier New font, single spaced, in a smaller font size.

Spatial Degradation Analysis Scripts

```r
#setwd("C:\Users\A00309880\Box Sync\Dissertation\Data and Recruiting\data")
setwd("C:\Users\A00309880\Box\Dissertation\Data and Recruiting\data")
directory.data = getwd()
initial.consolidatedSpaDataW18_TDF = read.delim("consolidatedSpaDataW18_TDF.txt", header = TRUE, sep = "\t", dec = ",", na.strings = c("","NA"))
#setwd("C:\Users\A00309880\Box Sync\Dissertation\Data and Recruiting\data analysis")
setwd("C:\Users\A00309880\Box\Dissertation\Data and Recruiting\data analysis")
```
directory.dataAnalysis = getwd()
# setwd("C:\\Users\\A00309880\\Box Sync\\Dissertation\\Data and Recruiting\\data analysis\\diagnostics")
setwd("C:\\Users\\A00309880\\Box\\Dissertation\\Data and Recruiting\\data analysis\\diagnostics")
directory.diagnostics = getwd()

setwd(directory.dataAnalysis)

#nrow(initial.consolidatedSpaDataW18_TDF)

## Remove participants who did not provide good response data
# SDW1876 did not answer a lot of the survey, and seems to have not tried very hard on the MCT either.
# SDW1870 did not answer all of the pre-MCT and got a low score (but proceeded to finish and get a really high score on post-MCT - an interesting case since it looks like they have more background in art than stereotypical engineering-type hobbies)
consolidatedSpaDataW18_TDF = subset(initial.consolidatedSpaDataW18_TDF, Random_ID != "SDW1876" & Random_ID != "SDW1870")
#nrow(consolidatedSpaDataW18_TDF)

#capabilities("libcurl") # needs to be TRUE
#options(download.file.method = "libcurl") # setting needed on some machines (requires URL to be input to install.packages())

#should not need to run this again
#install.packages("doBy")
#load the library so the doBy functions can be used
library(doBy) # needed for summaryBy

#install.packages("apaTables")
# load the apaTables library for nicely-formatted output (package was installed in another cell)
library(apaTables)

### May not need to install this one by hand###install.packages("stringr")
library(stringr)

#Get the mass package for the stepwise regression function, stepAIC
### Shouldn't need to run install.packages for MASS - something else has already installed it. Just load the library###install.packages("MASS")
library(MASS) ### needed for stepAIC

### Did not need to do ###install.packages("car") either
library(car) ### needed for qqPlot()

#load the mblm library so the mblm function can be used
#install.packages("mblm", repos='http://cran.case.edu/')
#install.packages("mblm")
library(mblm)

#install.packages("rcompanion", repos='http://cran.case.edu/') #For plotPredy() function
#install.packages("rcompanion")
#library(rcompanion)

R.Version()
citation()
citation(package = "MASS")
citation(package = "car")
citation(package = "stringr")
citation(package = "doBy")
citation(package = "apaTables")
citation(package = "mblm")

# Create new columns of data
consolidatedSpaDataW18_TDF$BlockPlay_Child_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$BlockPlay_Child_Text, levels=c("Very seldom", "Once in a while", "Most of the time", "All the time")))
levels(consolidatedSpaDataW18_TDF$BlockPlay_Child_Text)
hist(consolidatedSpaDataW18_TDF$BlockPlay_Child_Numeric)

consolidatedSpaDataW18_TDF$priorXP_MdlPzzl_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$priorXP_MdlPzzl_Text, levels=c("very little to none", "some, I play (or have played) around with them a little, but average less than a few hours a month", "moderate, I play (or have played) around with them for several hours a month on average", "considerable, I play (or have played) with them for several hours a week on average", "immersed, I play (or have played) with them on a daily basis")))
levels(consolidatedSpaDataW18_TDF$priorXP_MdlPzzl_Text)
hist(consolidatedSpaDataW18_TDF$priorXP_MdlPzzl_Numeric)

consolidatedSpaDataW18_TDF$priorXP_RCToys_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$priorXP_RCToys_Text, levels=c("very little to none", "some, I play (or have played) around with it a little, but average less than a few hours a month", "moderate, I play (or have played) around with it for several hours a month on average", "considerable, I play (or have played) with it for several hours a week on average", "immersed, I play (or have played) with it on a daily basis")))
levels(consolidatedSpaDataW18_TDF$priorXP_RCToys_Text)
hist(consolidatedSpaDataW18_TDF$priorXP_RCToys_Numeric)

consolidatedSpaDataW18_TDF$breakTime_MdlPzzl_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$breakTime_MdlPzzl_Text, levels=c("very little to none", "some, I played around with them a little, but average less than a few hours a month", "moderate, I played around with them for several hours a month on average", "considerable, I played with them for several hours a week on average", "immersed, I played with them on a daily basis")))
levels(consolidatedSpaDataW18_TDF$breakTime_MdlPzzl_Text)
hist(consolidatedSpaDataW18_TDF$breakTime_MdlPzzl_Numeric)

consolidatedSpaDataW18_TDF$breakTime_RCToys_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$breakTime_RCToys_Text, levels=c("very little to none", "some, I played around with them a little, but average less than a few hours a month", "moderate, I played around with them for several hours a month on average", "considerable, I played with them for several hours a week on average", "immersed, I played with them on a daily basis")))
levels(consolidatedSpaDataW18_TDF$breakTime_RCToys_Text)
hist(consolidatedSpaDataW18_TDF$breakTime_RCToys_Numeric)

consolidatedSpaDataW18_TDF$BioSex_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$BioSex, levels=c("Female", "Male"))) - 1
levels(consolidatedSpaDataW18_TDF$BioSex)
hist(consolidatedSpaDataW18_TDF$BioSex_Numeric)

consolidatedSpaDataW18_TDF$isMarried_Numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$isMarried, levels=c("No", "Yes"))) - 1
levels(consolidatedSpaDataW18_TDF$isMarried)
hist(consolidatedSpaDataW18_TDF$isMarried_Numeric)

consolidatedSpaDataW18_TDF$numberOfChildren_Numeric = consolidatedSpaDataW18_TDF$numberOfChildren
consolidatedSpaDataW18_TDF$numberOfChildren_Numeric[is.na(consolidatedSpaDataW18_TDF$numberOfChildren)] <- 0
levels(consolidatedSpaDataW18_TDF$numberOfChildren)
hist(consolidatedSpaDataW18_TDF$numberOfChildren_Numeric)
# consolidatedSpaDataW18_TDF$numberOfChildren_Numeric
# hist(consolidatedSpaDataW18_TDF$numberOfChildren_Numeric)

# hist(consolidatedSpaDataW18_TDF$RaceEthnicityWhite_Numeric)
c = ifelse(consolidatedSpaDataW18_TDF$RaceEthnicity == "White or Caucasian", 1, 0)
# hist(consolidatedSpaDataW18_TDF$RaceEthnicityWhite_Numeric)

# Excel wrongly replaced "6-10" with "10-Jun", and "11-15" with "15-Nov". Need to re-replace those.
## These data.frame(lapply...) functions somehow transform Pre_mctScore into a factor instead of a numeric
# consolidatedSpaDataW18_TDF <- data.frame(lapply(consolidatedSpaDataW18_TDF, function(x) {gsub("10-Jun", "06-10", x)})) # need to use "06" instead of just "6" so the order will be appropriate if plotted
# consolidatedSpaDataW18_TDF <- data.frame(lapply(consolidatedSpaDataW18_TDF, function(x) {gsub("15-Nov", "11-15", x)}))

#plot(consolidatedSpaDataW18_TDF$hoursWeekly_Employed_Break), main="Number of Hours Worked During the Break\n(for those employed)"
# consolidatedSpaDataW18_TDF$hoursWeekly_Employed_Break <- factor(consolidatedSpaDataW18_TDF$hoursWeekly_Employed_Break, levels=c("0-5", "6-10", "11-15", "16-20", "21-25", "26-30", "31-35", "36-40", "40 or more"))

# consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break.numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break, levels=c("1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "11", "12", "13", "14", "15 or more")))
# consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break.numeric[is.na(consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break)] <- 0
# levels(consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break) <- 0

# levels(consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break)
#hist(consolidatedSpaDataW18_TDF$hoursMonthly_Activities_Break)

# consolidatedSpaDataW18_TDF$hoursWeekly_Exercise_Break.numeric = as.numeric(factor(consolidatedSpaDataW18_TDF$hoursWeekly_Exercise_Break, levels=c("0", "1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "11 or more")))-1
# levels(consolidatedSpaDataW18_TDF$hoursWeekly_Exercise_Break)
#hist(consolidatedSpaDataW18_TDF$hoursWeekly_Exercise_Break)

# consolidatedSpaDataW18_TDF$RepeatClass_dummy = as.numeric(consolidatedSpaDataW18_TDF$RepeatClass)-1
# consolidatedSpaDataW18_TDF$isEmployed_School_dummy = as.numeric(consolidatedSpaDataW18_TDF$isEmployed_School)-1

# consolidatedSpaDataW18_TDF$previousSpatialExams_dummy = ifelse((consolidatedSpaDataW18_TDF$previousSpatialExams == "None") | is.na(consolidatedSpaDataW18_TDF$previousSpatialExams), 0, 1)
# consolidatedSpaDataW18_TDF$priorGraphicsDrafting_dummy = as.numeric(consolidatedSpaDataW18_TDF$hadPriorGraphicsDrafting)-1

# consolidatedSpaDataW18_TDF$previousSpatialExams_count = ifelse(consolidatedSpaDataW18_TDF$previousSpatialExams_dummy == 0, 0, str_count(consolidatedSpaDataW18_TDF$previousSpatialExams, ',')+1)
# consolidatedSpaDataW18_TDF$priorGraphicsDraftingTypes_count = ifelse(consolidatedSpaDataW18_TDF$priorGraphicsDrafting_dummy == 0, 0, str_count(consolidatedSpaDataW18_TDF$priorGraphicsDrafting, ',')+1)
consolidatedSpaDataW18_TDF$basic_count <- 1

consolidatedSpaDataW18_TDF$isEmployed_Break_dummy =
as.numeric(consolidatedSpaDataW18_TDF$isEmployed_Break)-1

consolidatedSpaDataW18_TDF$hasCoursework_Break_dummy =
as.numeric(consolidatedSpaDataW18_TDF$enrolledInCourseDuringBreak)-1

consolidatedSpaDataW18_TDF$CourseShortName <-
consolidatedSpaDataW18_TDF$CourseRecruitedFrom
levels(consolidatedSpaDataW18_TDF$CourseShortName)[levels(consolidatedSpaDataW18_TDF$CourseShortName) == "Engineering Graphics"] <- "E.G."
levels(consolidatedSpaDataW18_TDF$CourseShortName)[levels(consolidatedSpaDataW18_TDF$CourseShortName) == "Advanced Dynamics"] <- "A.D."
levels(consolidatedSpaDataW18_TDF$CourseShortName)[levels(consolidatedSpaDataW18_TDF$CourseShortName) == "Statics"] <- "S."

consolidatedSpaDataW18_TDF$CourseNotAdvDynamics =
ifelse(consolidatedSpaDataW18_TDF$CourseRecruitedFrom == "Advanced Dynamics", 0,1)

consolidatedSpaDataW18_TDF$CourseIsAdvDynamics =
ifelse(consolidatedSpaDataW18_TDF$CourseRecruitedFrom == "Advanced Dynamics", 1,0)

consolidatedSpaDataW18_TDF$CourseIsEngrGraphics =
ifelse(consolidatedSpaDataW18_TDF$CourseRecruitedFrom == "Engineering Graphics", 1,0)

consolidatedSpaDataW18_TDF$CourseIsStatics =
ifelse(consolidatedSpaDataW18_TDF$CourseRecruitedFrom == "Statics", 1,0)

consolidatedSpaDataW18_TDF$mctScoreImprovement =
consolidatedSpaDataW18_TDF$Post_mctScore -
consolidatedSpaDataW18_TDF$Pre_mctScore

consolidatedSpaDataW18_TDF$mctDuration =
consolidatedSpaDataW18_TDF$Post_prelimLastClick -
consolidatedSpaDataW18_TDF$Post_FirstClick

##Create new columns for consolidated data
#VideoGames.3D.Group = 1stPersonVideoGames, Other3DVideGames, Minecraft

consolidatedSpaDataW18_TDF$priorXP.VideoGames.3D.Group =
consolidatedSpaDataW18_TDF$priorXP_Minecraft_Scale +
consolidatedSpaDataW18_TDF$priorXP_1stPersonVideoGame_Scale +
consolidatedSpaDataW18_TDF$priorXP_Other3DVideoGame_Scale

consolidatedSpaDataW18_TDF$breakXP.VideoGames.3D.Group =
consolidatedSpaDataW18_TDF$breakXP_Minecraft_Scale +
consolidatedSpaDataW18_TDF$breakXP_1stPersonVideoGame_Scale +
consolidatedSpaDataW18_TDF$breakXP_Other3DVideoGame_Scale

#VideoGames.2D.Group = Tetris, 2DPuzzleVideoGame

consolidatedSpaDataW18_TDF$priorXP.VideoGames.2D.Group =
consolidatedSpaDataW18_TDF$priorXP_Tetris_Scale +
consolidatedSpaDataW18_TDF$priorXP_2DPuzzleVideoGame_Scale

consolidatedSpaDataW18_TDF$breakXP.VideoGames.2D.Group =
consolidatedSpaDataW18_TDF$breakXP_Tetris_Scale +
consolidatedSpaDataW18_TDF$breakXP_2DPuzzleVideoGame_Scale

#BuildingToys.Group = Legos, Erector sets
consolidatedSpaDataW18_TDF$priorXP.BuildingToys.Group = consolidatedSpaDataW18_TDF$priorXP_ErectorSets_Scale + consolidatedSpaDataW18_TDF$priorXP_Legos_Scale
consolidatedSpaDataW18_TDF$breakXP.BuildingToys.Group = consolidatedSpaDataW18_TDF$breakXP_ErectorSets_Scale + consolidatedSpaDataW18_TDF$breakXP_Legos_Scale

#ExtraCurricularSTEM.Group = FIRST, JETS, VEX, ThinkQuest, LegoEngineering, OdysseyOfTheMind, Future City, TechXplore, INSPIRE!, or Botball
consolidatedSpaDataW18_TDF$priorXP.ExtraCurricularSTEM.Group = consolidatedSpaDataW18_TDF$priorXP_FIRST_Scale + consolidatedSpaDataW18_TDF$priorXP_JETS_Scale + consolidatedSpaDataW18_TDF$priorXP_FutureCity_Scale + consolidatedSpaDataW18_TDF$priorXP_TechXplore_Scale + consolidatedSpaDataW18_TDF$priorXP_VEX_Scale + consolidatedSpaDataW18_TDF$priorXP_ThinkQuest_Scale + consolidatedSpaDataW18_TDF$priorXP_LegoEngr_Scale + consolidatedSpaDataW18_TDF$priorXP_INSPIRE_Scale + consolidatedSpaDataW18_TDF$priorXP_Botball_Scale + consolidatedSpaDataW18_TDF$priorXP_OdysseyOfMind_Scale
consolidatedSpaDataW18_TDF$breakXP.ExtraCurricularSTEM.Group = consolidatedSpaDataW18_TDF$breakXP_FIRST_Scale + consolidatedSpaDataW18_TDF$breakXP_JETS_Scale + consolidatedSpaDataW18_TDF$breakXP_FutureCity_Scale + consolidatedSpaDataW18_TDF$breakXP_TechXplore_Scale + consolidatedSpaDataW18_TDF$breakXP_VEX_Scale + consolidatedSpaDataW18_TDF$breakXP_ThinkQuest_Scale + consolidatedSpaDataW18_TDF$breakXP_LegoEngr_Scale + consolidatedSpaDataW18_TDF$breakXP_INSPIRE_Scale + consolidatedSpaDataW18_TDF$breakXP_Botball_Scale + consolidatedSpaDataW18_TDF$breakXP_OdysseyOfMind_Scale

#Fabrication.Group = woodworking, fabrication, cabinetry, construction
consolidatedSpaDataW18_TDF$priorXP.Fabrication.Group = consolidatedSpaDataW18_TDF$priorXP_Woodwork_Scale + consolidatedSpaDataW18_TDF$priorXP_Fabrication_Scale + consolidatedSpaDataW18_TDF$priorXP_Cabinetry_Scale + consolidatedSpaDataW18_TDF$priorXP_Construction_Scale
consolidatedSpaDataW18_TDF$breakXP.Fabrication.Group = consolidatedSpaDataW18_TDF$breakXP_Woodwork_Scale + consolidatedSpaDataW18_TDF$breakXP_Fabrication_Scale + consolidatedSpaDataW18_TDF$breakXP_Cabinetry_Scale + consolidatedSpaDataW18_TDF$breakXP_Construction_Scale

#Electronics.Group = electronics, building computers
consolidatedSpaDataW18_TDF$priorXP.Electronics.Group = consolidatedSpaDataW18_TDF$priorXP_Electronics_Scale + consolidatedSpaDataW18_TDF$priorXP_BuildComputers_Scale
consolidatedSpaDataW18_TDF$breakXP.Electronics.Group = consolidatedSpaDataW18_TDF$breakXP_Electronics_Scale + consolidatedSpaDataW18_TDF$breakXP_BuildComputers_Scale

#Mechanics.Group = mechanics, welding
consolidatedSpaDataW18_TDF$priorXP.Mechanics.Group = consolidatedSpaDataW18_TDF$priorXP_Mechanics_Scale + consolidatedSpaDataW18_TDF$priorXP_Weld_Scale
consolidatedSpaDataW18_TDF$breakXP.Mechanics.Group = consolidatedSpaDataW18_TDF$breakXP_Mechanics_Scale + consolidatedSpaDataW18_TDF$breakXP_Weld_Scale

#VisualArts.Group = ArtisticDrawing, ArtisticPainting
consolidatedSpaDataW18_TDF$priorXP.VisualArts.Group = consolidatedSpaDataW18_TDF$priorXP_ArtPaint_Scale +
consolidatedSpaDataW18_TDF$priorXP_ArtDraw_Scale
consolidatedSpaDataW18_TDF$breakXP.VisualArts.Group =
consolidatedSpaDataW18_TDF$breakXP_ArtPaint_Scale +
consolidatedSpaDataW18_TDF$breakXP_ArtDraw_Scale

#FiberArts.Group = Sewing, Embroidery
consolidatedSpaDataW18_TDF$priorXP.FiberArts.Group =
consolidatedSpaDataW18_TDF$priorXP_Sew_Scale +
consolidatedSpaDataW18_TDF$priorXP_Embroidery_Scale
consolidatedSpaDataW18_TDF$breakXP.FiberArts.Group =
consolidatedSpaDataW18_TDF$breakXP_Sew_Scale +
consolidatedSpaDataW18_TDF$breakXP_Embroidery_Scale

#PhysicalActivity.Group = Dancing, Sports
consolidatedSpaDataW18_TDF$priorXP.PhysicalActivity.Group =
consolidatedSpaDataW18_TDF$priorXP_Dance_Scale +
consolidatedSpaDataW18_TDF$priorXP_Sports_Scale
consolidatedSpaDataW18_TDF$breakXP.PhysicalActivity.Group =
consolidatedSpaDataW18_TDF$breakXP_Dance_Scale +
consolidatedSpaDataW18_TDF$breakXP_Sports_Scale

# SDW1823 showed up as an outlier for nearly every IV diagnostic check, so will
# be removed.
inclSDW1823.DF = consolidatedSpaDataW18_TDF
removedSDW1823.DF = subset(consolidatedSpaDataW18_TDF, Random_ID != "SDW1823")

# IVs by type of data
ivColumnNames.quantitative = c("BlockPlay_Child_Numeric",
"priorXP_MdlPzzl_Numeric", "priorXP_RCToys_Numeric",
"numberOfChildren_Numeric", "hoursWeekly_Employed_Break_Numeric",
"hoursMonthly_Activities_Break.numeric", "hoursWeekly_Exercise_Break.numeric",
"previousSpatialExams_count", "priorGraphicsDraftingTypes_count", "Age", "GPA",
"priorXP_FIRST_Scale", "priorXP_JETS_Scale", "priorXP_VEX_Scale",
"priorXP_ThinkQuest_Scale", "priorXP_LegoEngr_Scale",
"priorXP_OdysseyOfMind_Scale", "priorXP_Minecraft_Scale",
"priorXP_ErectorSets_Scale", "priorXP_Legos_Scale", "priorXP_Tetris_Scale",
"priorXP_1stPersonVideoGame_Scale", "priorXP.Other3DVideoGame_Scale",
"priorXP_2DPuzzleVideoGame_Scale", "priorXP_2DStrategyGames_Scale",
"priorXP_Woodwork_Scale", "priorXP_Weld_Scale", "priorXP_Fabrication_Scale",
"priorXP_Electronics_Scale", "priorXP_Mechanics_Scale",
"priorXP_Cabinetry_Scale", "priorXP_BuildComputers_Scale",
"priorXP_Garden_Scale", "priorXP_ArtPaint_Scale", "priorXP_ArtDraw_Scale",
"priorXP_ResCommPaint_Scale", "priorXP_Constructio_Scale", "priorXP_Sew_Scale",
"priorXP_Electronics_Scale", "priorXP_Mechanics_Scale",
"priorXP_Cabinetry_Scale", "priorXP_BuildComputers_Scale",
"priorXP_Garden_Scale", "priorXP_ArtPaint_Scale", "priorXP_ArtDraw_Scale",
"priorXP_Constructio_Scale", "priorXP_Sew_Scale", "priorXP_Cook_Scale",
"priorXP_Dance_Scale", "priorXP_ExtracurricularActivities_Scale",
"priorXP_Sports_Scale", "priorXP_PlayMusic_Scale", "breakTime_MdlPzzl_Numeric",
"breakTime_Week_Scale", "breakTime_Week_Scale", "breakTime_MdlPzzl_Numeric",
"breakXP_Legos_Scale", "breakXP_Tetris_Scale",
"breakXP_1stPersonVideoGame_Scale", "breakXP.Other3DVideoGame_Scale",
"breakXP_2DPuzzleVideoGame_Scale", "breakXP_2DStrategyGames_Scale",
"breakXP_Woodwork_Scale", "breakXP_Weld_Scale", "breakXP_Fabrication_Scale",
"breakXP_Electronics_Scale", "breakXP_Mechanics_Scale",
"breakXP_Cabinetry_Scale", "breakXP_BuildComputers_Scale",
"breakXP_Garden_Scale", "breakXP_ArtPaint_Scale", "breakXP_ArtDraw_Scale",
"breakXP_Constructio_Scale", "breakXP_Sew_Scale", "breakXP_Cook_Scale",
"breakXP_Dance_Scale", "breakXP_ExtracurricularActivities_Scale",
"hoursWeekly_Study_Break", "count_Activities_Break", "Pre_mctScore",
"Pre_mctDuration", "priorXP.VideoGames.3D_Group",
"breakXP.VideoGames.3D_Group", "priorXP.VideoGames.2D_Group",
"breakXP.VideoGames.2D_Group", "priorXP.BuildingToys_Group",
"breakXP.BuildingToys_Group", "priorXP.ExtracurricularSTEM_Group",
"breakXP.ExtracurricularSTEM_Group", "priorXP.Fabrication_Group",
"breakXP.Fabrication.Group", "priorXP.Electronics_Group",
"breakXP.Electronics.Group", "priorXP.Mechanics_Group",}
"breakXP.FiberArts.Group", "priorXP.PhysicalActivity.Group",
"breakXP.PhysicalActivity.Group"

ivColumnNames.binomial = c("BioSex_Numeric", "isMarried_Numeric",
"RaceEthnicityWhite_Numeric", "RepeatClass_dummy", "isEmployed_School_dummy",
"previousSpatialExams_dummy", "priorGraphicsDrafting_dummy",
"isEmployed_Break_dummy", "hasCoursework_Break_dummy", "CourseNotAdvDynamics",
"CourseIsAdvDynamics", "CourseIsEngrGraphics", "CourseIsStatics")

ivColumnNames.factor = c("CourseRecruitedFrom", "classificationHomeTown")

# Need to center the quantitative data - at least for the independent variables
# that will be used in bivariate regression models
ivColumnNames.centered = paste(ivColumnNames.quantitative, ".ctrd", sep="")
consolidatedSpaDataW18_TDF[ivColumnNames.centered] =
scale(consolidatedSpaDataW18_TDF[ivColumnNames.quantitative], center=TRUE, scale=FALSE)
removedSDW1823.DF[ivColumnNames.centered] =
scale(removedSDW1823.DF[ivColumnNames.quantitative], center=TRUE, scale=FALSE)
iclSDw1823.DF[ivColumnNames.centered] =
scale(inclSDw1823.DF[ivColumnNames.quantitative], center=TRUE, scale=FALSE)

# Need to scale (center and divide by std dev) the quantitative data - at least
# for the independent variables
ivColumnNames.scaled = paste(ivColumnNames.quantitative, ".scaled", sep="")
consolidatedSpaDataW18_TDF[ivColumnNames.scaled] =
scale(consolidatedSpaDataW18_TDF[ivColumnNames.quantitative], center=TRUE, scale=TRUE)
removedSDW1823.DF[ivColumnNames.scaled] =
scale(removedSDW1823.DF[ivColumnNames.quantitative], center=TRUE, scale=TRUE)
iclSDw1823.DF[ivColumnNames.scaled] =
scale(inclSDw1823.DF[ivColumnNames.quantitative], center=TRUE, scale=TRUE)

# Subsets for each course
engrGraphicsDataSet = subset(consolidatedSpaDataW18_TDF,
CourseRecruitedFrom=="Engineering Graphics")
engrGraphicsDataSet.no1823 = subset(removedSDW1823.DF,
CourseRecruitedFrom=="Engineering Graphics")

staticsDataSet = subset(consolidatedSpaDataW18_TDF,
CourseRecruitedFrom=="Statics")
staticsDataSet.no1823 = subset(removedSDW1823.DF,
CourseRecruitedFrom=="Statics")

advDynDataSet = subset(consolidatedSpaDataW18_TDF,
CourseRecruitedFrom=="Advanced Dynamics")
advDynDataSet.no1823 = subset(removedSDW1823.DF, CourseRecruitedFrom=="Advanced Dynamics")

# Quick implementation from
https://stackoverflow.com/questions/15436702/estimate-cohens-d-for-effect-size
cohens_d <- function(x, y) {
  lx <- length(x) - 1
  ly <- length(y) - 1
  md <- abs(mean(x) - mean(y))        ## mean difference (numerator)
  csd <- lx * var(x) + ly * var(y)
  csd <- csd/(lx + ly)
  cd <- md/csd                        ## cohen's d
  return(cd)
}
#Quick implementation based on https://www.sheffield.ac.uk/polopoly_fs/1.714576!/file/stcp-marquier-WilcoxonR.pdf

```r
wilcoxPValue_r <- function(pValue, n) {
    # Calculate the standardised z statistic Z and call it Zstat
    Zstat <- qnorm(pValue/2)

    # Calculate the effect size using
    r.WilcoxonSignedRank <- abs(Zstat)/sqrt(n)
}
```


```r
mannWhitneyU_r <- function(vector.group1, vector.group2) {
    # sizes of samples
    n.group1 = length(vector.group1)
    n.group2 = length(vector.group2)

    # sum of rank
    combinedVectors = c(vector.group1, vector.group2)
    sum.rank.group1 = sum(rank(combinedVectors)[1:n.group1])
    sum.rank.group2 = sum(rank(combinedVectors)[(n.group1+1):(n.group1+n.group2)])

    # find mean rank
    mean.rank.group1 = sum.rank.group1/n.group1
    mean.rank.group2 = sum.rank.group2/n.group2

    r.MannWhitU <- 2*(mean.rank.group1 - mean.rank.group2)/(n.group1 + n.group2)
}
```

```r
head(consolidatedSpaDataW18_TDF)
```

```r
columnNames <- colnames(consolidatedSpaDataW18_TDF)
length(columnNames)
```

```r
plot(consolidatedSpaDataW18_TDF$CourseRecruitedFrom)
nrow(consolidatedSpaDataW18_TDF)
```

```r
hist(consolidatedSpaDataW18_TDF$Pre_mctScore, breaks=4)
```

```r
preMct_fnCourseLm <- lm(Pre_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
summary(preMct_fnCourseLm)
```

```r
# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
preMct_fnCourseLm <- lm(Pre_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
summary(preMct_fnCourseLm)
```

```r
# test the apaTables function for ANOVA
#apa.aov.table(preMct_fnCourseLm, filename = "TestAnovaTable_APA.doc", table.number = 1)
```
```r
# Boxplots
boxplot(Pre_mctScore~CourseRecruitedFrom, main="Pre-Test MCT Score Data by Course", ylab="MCT Score", data = consolidatedSpaDataW18_TDF)

hist(consolidatedSpaDataW18_TDF$Pre_mctScore)

# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
postMct_fnCourseLm <- lm(Post_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
summary(postMct_fnCourseLm)

hist(consolidatedSpaDataW18_TDF$mctScoreImprovement, main="Histogram of Changes in MCT Scores with SDW1823", xlab="Change in MCT Score")
hist(removedSDW1823.DF$mctScoreImprovement, main="Histogram of Changes in MCT Scores", xlab="Change in MCT Score")

# Look at Post_mctDuration
hist(consolidatedSpaDataW18_TDF$Post_mctDuration, main="Histogram of Post-Test MCT Duration with SDW1823", xlab="MCT Duration (sec)")
hist(removedSDW1823.DF$Post_mctDuration, main="Histogram of Post-Test MCT Duration", xlab="MCT Duration (sec)")

# Look at changes in duration
hist(consolidatedSpaDataW18_TDF$mctDurationGrowth, main="Histogram of Changes in MCT Duration with SDW1823", xlab="Change in MCT Duration (sec)")
hist(removedSDW1823.DF$mctDurationGrowth, main="Histogram of Changes in MCT Duration", xlab="Change in MCT Duration (sec)")

summaryBy(mctScoreImprovement ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)
summaryBy(mctScoreImprovement ~ CourseRecruitedFrom, data = removedSDW1823.DF, FUN=c(mean, sd), na.rm=TRUE)

# The trends in Pre MCT duration are interesting - definitely make it look like Advanced Dynamics students are more advanced (their pre-test scores are higher, but they get worse over the break), followed by Engineering Graphics, and then Statics
summaryBy(Pre_mctDuration+Pre_mctScore+Post_mctScore~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

# Are the differences between the scores significant for each course type?
Nope.

# Are the differences between the durations significant for each course type?
Yep.

t.test(consolidatedSpaDataW18_TDF$Pre_mctScore,consolidatedSpaDataW18_TDF$Post_mctScore, paired=TRUE)
t.test(engrGraphicsDataSet$Pre_mctScore,engrGraphicsDataSet$Post_mctScore, paired=TRUE)
t.test(engrGraphicsDataSet$Pre_mctDuration,engrGraphicsDataSet$Post_mctDuration, paired=TRUE)
t.test(engrGraphicsDataSet.no1823$Pre_mctDuration,engrGraphicsDataSet.no1823$Post_mctDuration, paired=TRUE)
d.mctDurGrwth.engrgrphcs.no1823 = cohens_d(engrGraphicsDataSet.no1823$Pre_mctDuration,engrGraphicsDataSet.no1823$Post_mctDuration, paired=TRUE)
```

---

# Histograms

```r
#hist(consolidatedSpaDataW18_TDF$Post_mctScore)
hist(consolidatedSpaDataW18_TDF$Post_mctScore, main="Histogram of Post-Test MCT Scores", xlab="MCT Score")

# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
postMct_fnCourseLm <- lm(Post_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
summary(postMct_fnCourseLm)
```

---

# Summary tables

```r
# Look at Post_mctDuration
hist(consolidatedSpaDataW18_TDF$Post_mctDuration, main="Histogram of Post-Test MCT Duration with SDW1823", xlab="MCT Duration (sec)")
hist(removedSDW1823.DF$Post_mctDuration, main="Histogram of Post-Test MCT Duration", xlab="MCT Duration (sec)")

# Look at changes in duration
hist(consolidatedSpaDataW18_TDF$mctDurationGrowth, main="Histogram of Changes in MCT Duration with SDW1823", xlab="Change in MCT Duration (sec)")
hist(removedSDW1823.DF$mctDurationGrowth, main="Histogram of Changes in MCT Duration", xlab="Change in MCT Duration (sec)")

summaryBy(mctScoreImprovement ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)
summaryBy(mctScoreImprovement ~ CourseRecruitedFrom, data = removedSDW1823.DF, FUN=c(mean, sd), na.rm=TRUE)
```

---

# T-tests

```r
# The trends in Pre MCT duration are interesting - definitely make it look like Advanced Dynamics students are more advanced (their pre-test scores are higher, but they get worse over the break), followed by Engineering Graphics, and then Statics
summaryBy(Pre_mctDuration+Pre_mctScore+Post_mctScore~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

# Are the differences between the scores significant for each course type?
Nope.

# Are the differences between the durations significant for each course type?
Yep.

t.test(consolidatedSpaDataW18_TDF$Pre_mctScore,consolidatedSpaDataW18_TDF$Post_mctScore, paired=TRUE)
t.test(engrGraphicsDataSet$Pre_mctScore,engrGraphicsDataSet$Post_mctScore, paired=TRUE)
t.test(engrGraphicsDataSet$Pre_mctDuration,engrGraphicsDataSet$Post_mctDuration, paired=TRUE)
t.test(engrGraphicsDataSet.no1823$Pre_mctDuration,engrGraphicsDataSet.no1823$Post_mctDuration, paired=TRUE)
d.mctDurGrwth.engrgrphcs.no1823 = cohens_d(engrGraphicsDataSet.no1823$Pre_mctDuration,engrGraphicsDataSet.no1823$Post_mctDuration, paired=TRUE)
```
Post_mctDuration)
d.mctDurGrwth.engrgrphcs.no1823

#t.test(staticsDataSet$Pre_mctScore,staticsDataSet$Post_mctScore, paired=TRUE)
#t.test(staticsDataSet$Pre_mctDuration,staticsDataSet$Post_mctDuration, paired=TRUE)
t.test(staticsDataSet.no1823$Pre_mctDuration,staticsDataSet.no1823$Post_mctDuration, paired=TRUE)
d.mctDurGrwth.statics.no1823 = cohens_d(staticsDataSet.no1823$Pre_mctDuration,staticsDataSet.no1823$Post_mctDuration)
d.mctDurGrwth.statics.no1823

#t.test(advDynDataSet$Pre_mctScore,advDynDataSet$Post_mctScore, paired=TRUE)
#t.test(advDynDataSet$Pre_mctDuration,advDynDataSet$Post_mctDuration, paired=TRUE)
t.test(advDynDataSet.no1823$Pre_mctDuration,advDynDataSet.no1823$Post_mctDuration, paired=TRUE)
d.mctDurGrwth.advDyn.no1823 = cohens_d(advDynDataSet.no1823$Pre_mctDuration,advDynDataSet.no1823$Post_mctDuration)
d.mctDurGrwth.advDyn.no1823

# Check nonparametric statistics for differences between pre- and post- durations
## # dependent 2-group Wilcoxon Signed Rank Test
## wilcox.test(y1,y2,paired=TRUE) # where y1 and y2 are numeric
#exact=TRUE for small samle sizes, per
https://www.sheffield.ac.uk/polopoly_fs/1.714576!/file/stcp-marquier-WilcoxonR.pdf

# If I use this, need to choose an effect size for Wilcox tests.
# For r based on Z, see
# And for calculating r based on output p-value, see
https://www.sheffield.ac.uk/polopoly_fs/1.714576!/file/stcp-marquier-WilcoxonR.pdf

## Are the differences between the scores significant for each course type?
Nope. Just like for above
#wilcox.test(consolidatedSpaDataW18_TDF$Pre_mctScore,consolidatedSpaDataW18_TDF$Post_mctScore, paired=TRUE)
#wilcox.test(engrGraphicsDataSet$Pre_mctScore,engrGraphicsDataSet$Post_mctScore, paired=TRUE)
#wilcox.test(staticsDataSet$Pre_mctScore,staticsDataSet$Post_mctScore, paired=TRUE)
#wilcox.test(advDynDataSet$Pre_mctScore,advDynDataSet$Post_mctScore, paired=TRUE)

wilcox.AdvDyn = wilcox.test(advDynDataSet.no1823$Pre_mctDuration,advDynDataSet.no1823$Post_mctDuration, paired=TRUE, exact=TRUE)
wilcox.AdvDyn

# Find n
n.AdvDyn = nrow(advDynDataSet.no1823)

# Find r
print(paste0("r = ", r.wilcox.AdvDyn))
print(paste0("r^2 = ", r.wilcox.AdvDyn^2))
## Are the differences between the durations significant for each course type?

Yep. Not surprisingly, these values are just slightly higher than for the parametric t-test comparisons above.

```r
wilcox.EngrGraph = wilcox.test(engrGraphicsDataSet.no1823$Pre_mctDuration, engrGraphicsDataSet.no1823$Post_mctDuration, paired=TRUE, exact=TRUE)
wilcox.EngrGraph
```

# Find n
n.EngrGraph = nrow(engrGraphicsDataSet.no1823)

# Find r
r.wilcox.EngrGraph = wilcoxPValue_r(wilcox.EngrGraph$p.value, n.EngrGraph)
print(paste0("r = ", r.wilcox.EngrGraph))
print(paste0("r^2 = ", r.wilcox.EngrGraph^2))

```r
wilcox.Statics = wilcox.test(staticsDataSet.no1823$Pre_mctDuration, staticsDataSet.no1823$Post_mctDuration, paired=TRUE, exact=TRUE)
wilcox.Statics
```

# Find n
n.Statics = nrow(staticsDataSet.no1823)

# Find r
r.wilcox.Statics = wilcoxPValue_r(wilcox.Statics$p.value, n.Statics)
print(paste0("r = ", r.wilcox.Statics))
print(paste0("r^2 = ", r.wilcox.Statics^2))

# Are the differences between course type in pre-scores significant? Nope.

# T-TESTS:
```
t.test(staticsDataSet$Pre_mctScore, engrGraphicsDataSet$Pre_mctScore)
t.test(staticsDataSet$Pre_mctScore, advDynDataSet$Pre_mctScore)
t.test(engrGraphicsDataSet$Pre_mctScore, advDynDataSet$Pre_mctScore)
```

# Are the differences in pre-MCT time duration significant? Definitely between Engr Graphics and Adv Dynamics

# Using data including SDW1823, since the SDW1823 problem is with post-data (and this is only pre-data)
```
t.test(staticsDataSet$Pre_mctDuration, engrGraphicsDataSet$Pre_mctDuration)
d.preMct.statsVsEngrgrphcs = cohens_d(staticsDataSet$Pre_mctDuration, engrGraphicsDataSet$Pre_mctDuration)
d.preMct.statsVsEngrgrphcs
t.test(staticsDataSet$Pre_mctDuration, advDynDataSet$Pre_mctDuration)
d.preMct.statsVsAdvdyn = cohens_d(staticsDataSet$Pre_mctDuration, advDynDataSet$Pre_mctDuration)
d.preMct.statsVsAdvdyn
t.test(engrGraphicsDataSet$Pre_mctDuration, advDynDataSet$Pre_mctDuration) # the only significant one!
d.preMct.EngrgrphcsVsAdvdyn = cohens_d(engrGraphicsDataSet$Pre_mctDuration, advDynDataSet$Pre_mctDuration)
d.preMct.EngrgrphcsVsAdvdyn
```

# alternatively, I probably should have just done:
```
pairwise.t.test(consolidatedSpaDataW18_TDF$Pre_mctDuration, consolidatedSpaDataW18_TDF$CourseRecruitedFrom, p.adjust="bonferroni")
```

# Using data including SDW1823, since the problem is with post-data
```
boxplot(Pre_mctDuration~CourseRecruitedFrom, main="Pre-Test MCT Duration Data by Course", ylab="MCT Duration", data = consolidatedSpaDataW18_TDF)
```

# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
```
preMctDur_inCourseLm <- lm(Pre_mctDuration ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
```
# Look at coefficient results
apa.reg.table(preMctDur_fnCourseLm, filename = "preMctDuration_fnCourseLMTable.doc", table.number = 1)

# Look at ANOVA results
apa.aov.table(preMctDur_fnCourseLm, filename = "preMctDuration_fnCourseANOVAtable.doc", table.number = 1)

# Check out the same things with nonparametric statistics
## independent 2-group Mann-Whitney U Test
wilcox.test(y,x) # where y and x are numeric
# Note: for a binomial factor, A, use wilcox.test(y~A) to conduct an
# independent 2-group Mann-Whitney U Test

# Are the differences in pre-MCT time duration significant? Definitely between
# Engr Graphics and Adv Dynamics
# Using data including SDW1823, since the SDW1823 problem is with post-data
# (and this is only pre-data)
wilcox.test(staticsDataSet$Pre_mctDuration,engrGraphicsDataSet$Pre_mctDuration)
# this is significant to p<0.1, as opposed to the parametric measure above
# Calculate effect size
r.MannWhitU.StatEngrGrph = mannWhitneyU_r(staticsDataSet$Pre_mctDuration,engrGraphicsDataSet$Pre_mctDuration)
print(paste0("r = ", r.MannWhitU.StatEngrGrph))
print(paste0("r^2 = ", r.MannWhitU.StatEngrGrph^2))

wilcox.test(staticsDataSet$Pre_mctDuration,advDynDataSet$Pre_mctDuration) #Not
# significant - just like the parametric measure above
# Calculate effect size
r.MannWhitU.StatAdvDyn = mannWhitneyU_r(staticsDataSet$Pre_mctDuration,advDynDataSet$Pre_mctDuration)
print(paste0("r = ", r.MannWhitU.StatAdvDyn))
print(paste0("r^2 = ", r.MannWhitU.StatAdvDyn^2))

wilcox.test(engrGraphicsDataSet$Pre_mctDuration,advDynDataSet$Pre_mctDuration)
# this is still significant, though not quite to the same level as the
# parametric measure above
# Calculate effect size
r.MannWhitU.EngrGrphAdvDyn = mannWhitneyU_r(engrGraphicsDataSet$Pre_mctDuration,advDynDataSet$Pre_mctDuration)
print(paste0("r = ", r.MannWhitU.EngrGrphAdvDyn))
print(paste0("r^2 = ", r.MannWhitU.EngrGrphAdvDyn^2))

#preDuration_Tukey <- TukeyHSD(preDuration_ANOVA)
#plot(preDuration_Tukey, las=0)

# Pre-MCT ANOVA by course type is not significant
#preMct_ANOVA <- aov(Pre_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
#summary(preMct_ANOVA)

# Post-MCT ANOVA by course type is not significant
#postMct_ANOVA <- aov(Post_mctScore ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
#summary(postMct_ANOVA)

preDuration_ANOVA <- aov(Pre_mctDuration ~ CourseShortName, data=consolidatedSpaDataW18_TDF)
summary(preDuration_ANOVA)
# May want to run an ANOVA here
# note: aov uses lm and lm can handle multinomial factors just fine
improvement_fnCourseLm <- lm(mctScoreImprovement ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
#summary(improvement_fnCourseLm) #not significant

improvement_fnCourseLm.no1823 <- lm(mctScoreImprovement ~ CourseRecruitedFrom, data=removedSDW1823.DF)
#summary(improvement_fnCourseLm.no1823) #not significant

## Take a look at the improvement data by class
#staticsData = subset(consolidatedSpaDataW18_TDF, CourseRecruitedFrom == "Statics")
#hist(staticsData$mctScoreImprovement)
#engrGraphicsData = subset(consolidatedSpaDataW18_TDF, CourseRecruitedFrom == "Engineering Graphics")
#hist(engrGraphicsData$mctScoreImprovement)
#advDynamicsData = subset(consolidatedSpaDataW18_TDF, CourseRecruitedFrom == "Advanced Dynamics")
#hist(advDynamicsData$mctScoreImprovement)

# Check if there is a difference between Advanced Dynamics and the other classes (since other data has shown that Advanced Dynamics students do not improve much during the semester)
improvement_fnCourseNotAdvDynLm <- lm(mctScoreImprovement ~ CourseNotAdvDynamics, data=consolidatedSpaDataW18_TDF)
#summary(improvement_fnCourseNotAdvDynLm)

improvement_fnCourseNotAdvDynLm.no1823 <- lm(mctScoreImprovement ~ CourseNotAdvDynamics, data=removedSDW1823.DF)
summary(improvement_fnCourseNotAdvDynLm.no1823)

improvement_fnCourseIsAdvDynLm <- lm(mctScoreImprovement ~ CourseIsAdvDynamics, data=consolidatedSpaDataW18_TDF)
#summary(improvement_fnCourseIsAdvDynLm)

improvement_fnCourseIsAdvDynLm.no1823 <- lm(mctScoreImprovement ~ CourseIsAdvDynamics, data=removedSDW1823.DF)
summary(improvement_fnCourseIsAdvDynLm.no1823)

# Check if there is a difference between Engineering Graphics and the other classes
improvement_fnCourseIsEngrGraphicsLm <- lm(mctScoreImprovement ~ CourseIsEngrGraphics, data=consolidatedSpaDataW18_TDF)
improvement_fnCourseIsEngrGraphicsLm.no1823 <- lm(mctScoreImprovement ~ CourseIsEngrGraphics, data=removedSDW1823.DF)
#summary(improvement_fnCourseIsEngrGraphicsLm) #Not significant
#summary(improvement_fnCourseIsEngrGraphicsLm.no1823) #Not significant

# Check if there is a difference between Statics and the other classes
improvement_fnCourseIsStaticsLm <- lm(mctScoreImprovement ~ CourseIsStatics, data=consolidatedSpaDataW18_TDF)
#summary(improvement_fnCourseIsStaticsLm) #Not significant

# Does it help if I control for the initial score?
improve_fnCourseIsEngrGraphics_InclPreMCTLm <- lm(mctScoreImprovement ~ CourseIsEngrGraphics + Pre_mctScore, data=consolidatedSpaDataW18_TDF)
#summary(improve_fnCourseIsEngrGraphics_InclPreMCTLm) #not significant
improve_fnCourseIsStatics_InclPreMCTLm <- lm(mctScoreImprovement ~ CourseIsStatics + Pre_mctScore, data=consolidatedSpaDataW18_TDF)
#summary(improve_fnCourseIsStatics_InclPreMCTLm) #not significant
# What about just the initial score as a predictor of improvement?
improve_fnPreMCTLm <- lm(mctScoreImprovement ~ Pre_mctScore,
data=consolidatedSpaDataW18_TDF)
improve_fnPreMCTLm.no1823 <- lm(mctScoreImprovement ~ Pre_mctScore,
data=removedSDW1823.DF)

#summary(improve_fnPreMCTLm) #not significant
#summary(improve_fnPreMCTLm.no1823) #not significant

#summaryBy(Post_mctDuration+Post_mctScore ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)
#summaryBy(Post_mctDuration+Post_mctScore ~ CourseRecruitedFrom, data = removedSDW1823.DF, FUN=c(mean, sd), na.rm=TRUE)

#summaryBy(mctDurationGrowth+mctScoreImprovement ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)
#summaryBy(mctDurationGrowth+mctScoreImprovement ~ CourseRecruitedFrom, data = removedSDW1823.DF, FUN=c(mean, sd), na.rm=TRUE)

#Boxplots & ANOVA for MCT Score Change
boxplot(mctScoreImprovement~CourseRecruitedFrom, main="MCT Score Improvement Data by Course", ylab="MCT Score Change", data = consolidatedSpaDataW18_TDF)

boxplot(mctScoreImprovement~CourseRecruitedFrom, main="MCT Score Change Data by Course no SDW1823", ylab="MCT Score Change", data = removedSDW1823.DF)

# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
mctImprove_fnCourseLm <- lm(mctScoreImprovement ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)

summary(mctImprove_fnCourseLm)
mctImprove_fnCourseLm.no1823 <- lm(mctScoreImprovement ~ CourseRecruitedFrom, data=removedSDW1823.DF)

summary(mctImprove_fnCourseLm.no1823)

# t-tests for MCT Duration Change
t.test(staticsDataSet.no1823$mctDurationGrowth,engrGraphicsDataSet.no1823$mctDurationGrowth) # not significant
d.mctDurGrowth.statsVsEnggrphcs.no1823 = cohens_d(staticsDataSet.no1823$mctDurationGrowth,engrGraphicsDataSet.no1823$mctDurationGrowth)
d.mctDurGrowth.statsVsEnggrphcs.no1823
t.test(staticsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth) # significant to p<0.1
d.mctDurGrowth.statsVsAdvdyn.no1823 = cohens_d(staticsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth)
d.mctDurGrowth.statsVsAdvdyn.no1823
t.test(engrGraphicsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth) # significant to p<0.1
d.mctDurGrowth.EnggrgrphcsVsAdvdyn.no1823 = cohens_d(engrGraphicsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth)
d.mctDurGrowth.EnggrgrphcsVsAdvdyn.no1823

# Excluding SDW1823, since the change in duration depends on the suspect post-data

#Boxplots & ANOVA for MCT Duration Change
boxplot(mctDurationGrowth~CourseRecruitedFrom, main="MCT Duration Change Data by Course with SDW1823", ylab="MCT Duration Change (sec)", data = consolidatedSpaDataW18_TDF)

boxplot(mctDurationGrowth~CourseRecruitedFrom, main="MCT Duration Change Data by Course", ylab="MCT Duration Change (sec)", data = removedSDW1823.DF)
# Do a quick ANOVA to compare class type (Advanced Dynamics is used as baseline for comparison)
mctDurationGrowth_fnCourseLm <- lm(mctDurationGrowth ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
summary(mctDurationGrowth_fnCourseLm) #Engr Graphics difference is significant
mctDurationGrowth_fnCourseLm.no1823 <- lm(mctDurationGrowth ~ CourseRecruitedFrom, data=removedSDW1823.DF)
summary(mctDurationGrowth_fnCourseLm.no1823) # Engr Graphics difference is significant (less so), and Statics is <0.1 now

# Look at coefficient results
apa.reg.table(mctDurationGrowth_fnCourseLm, filename = "mctDurationGrowth_fnCourseLmTable.doc", table.number = 1)
apa.reg.table(mctDurationGrowth_fnCourseLm.no1823, filename = "mctDurGrth_fnCourseLmTable_no1823.doc", table.number = 2)

# Look at ANOVA results
apa.aov.table(mctDurationGrowth_fnCourseLm, filename = "mctDurationGrowth_fnCourseANOVATable.doc", table.number = 1)
apa.aov.table(mctDurationGrowth_fnCourseLm.no1823, filename = "mctDurGrth_fnCourseANOVATable_no1823.doc", table.number = 2)

# Run nonparametric tests for MCT duration change
hist(engrGraphicsDataSet.no1823$mctDurationGrowth)
hist(staticsDataSet.no1823$mctDurationGrowth)
hist(advDynDataSet.no1823$mctDurationGrowth)

t.test(staticsDataSet.no1823$mctDurationGrowth, engrGraphicsDataSet.no1823$mctDurationGrowth) # not significant, just like for parametric t-test
wilcox.test(staticsDataSet.no1823$mctDurationGrowth, engrGraphicsDataSet.no1823$mctDurationGrowth)
# Calculate effect size
r.MannWhitU.StatEngrGraph.DurrGrowth = mannWhitneyU_r(staticsDataSet.no1823$mctDurationGrowth,engrGraphicsDataSet.no1823$mctDurationGrowth)
print(paste0("r = ", r.MannWhitU.StatEngrGraph.DurrGrowth))
print(paste0("r^2 = ", r.MannWhitU.StatEngrGraph.DurrGrowth^2))

t.test(staticsDataSet.no1823$mctDurationGrowth, advDynDataSet.no1823$mctDurationGrowth)
wilcox.test(staticsDataSet.no1823$mctDurationGrowth, advDynDataSet.no1823$mctDurationGrowth) # significant to p<0.1, just like for parametric t-test
# Calculate effect size
r.MannWhitU.StatAdvDyn.DurrGrowth = mannWhitneyU_r(staticsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth)
print(paste0("r = ", r.MannWhitU.StatAdvDyn.DurrGrowth))
print(paste0("r^2 = ", r.MannWhitU.StatAdvDyn.DurrGrowth^2))

t.test(engrGraphicsDataSet.no1823$mctDurationGrowth, advDynDataSet.no1823$mctDurationGrowth) # not significant to p<0.1, as it was for parametric t-test
wilcox.test(engrGraphicsDataSet.no1823$mctDurationGrowth, advDynDataSet.no1823$mctDurationGrowth) # the only significant one!
# Excluding SDW1823, since the change in duration depends on the suspect post-data
# Calculate effect size
r.MannWhitU.EngrGrphAdvDyn.DurrGrowth = mannWhitneyU_r(engrGraphicsDataSet.no1823$mctDurationGrowth,advDynDataSet.no1823$mctDurationGrowth)
print(paste0("r = ", r.MannWhitU.EngrGrphAdvDyn.DurrGrowth))
print(paste0("r^2 = ", r.MannWhitU.EngrGrphAdvDyn.DurrGrowth^2))

# Look at the survey results
#summaryBy(BioSex_Numeric ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

#Note: The number under BioSex_Numeric.mean represents the ratio of male students to the total number of students
summaryBy(BioSex_Numeric + Age + RaceEthnicityWhite_Numeric + isMarried_Numeric + numberOfChildren_Numeric + GPA ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(RepeatClass_dummy + isEmployed_School_dummy + previousSpatialExams_dummy + priorGraphicsDrafting_dummy ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

plot(consolidatedSpaDataW18_TDF$RepeatClass)

summaryBy(RepeatClass_dummy ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(sum), na.rm=TRUE)

#courseRepetition.byEmployment.lm = lm(RepeatClass_dummy ~ isEmployed_School_dummy, data = consolidatedSpaDataW18_TDF)
#summary(courseRepetition.byEmployment.lm) # not significant (nor is R^2 high)

summaryBy(basic_count ~ CourseRecruitedFrom + classificationHomeTown, data = consolidatedSpaDataW18_TDF, FUN=c(sum), na.rm=TRUE)

#Prior to the semester
summaryBy(BlockPlay_Child_Numeric+priorXP_MdlPzzl_Numeric+priorXP_RCToys_Numeric+priorXP_FIRST_Scale+priorXP_JETS_Scale+priorXP_VEX_Scale+priorXP_ThinkQuest_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(priorXP_LegoEngr_Scale+priorXP_OdysseyOfMind_Scale+priorXP_Minecraft_Scale+priorXP_ErectorSets_Scale+priorXP_Legos_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(priorXP_Tetris_Scale+priorXP_1stPersonVideoGame_Scale+priorXP_Other3DVideoGame_Scale+priorXP_2DPuzzleVideoGame_Scale+priorXP_2DStrategyGames_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(priorXP_Woodwork_Scale+priorXP_Weld_Scale+priorXP_Fabrication_Scale+priorXP_Electronics_Scale+priorXP_Mechanics_Scale+priorXP_Cabinetry_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(priorXP_BuildComputers_Scale+priorXP_Garden_Scale+priorXP_ArtPaint_Scale+priorXP_ArtDraw_Scale+priorXP_ResCommPaint_Scale+priorXP_Constuction_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

#During-the-break
summaryBy(breakTime_MdlPzzl_Numeric+breakTime_RCToys_Numeric+breakXP_VEX_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(breakXP_Minecraft_Scale+breakXP_Legos_Scale+breakXP_Tetris_Scale+breakXP_1stPersonVideoGame_Scale+breakXP_Other3DVideoGame_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(breakXP_2DPuzzleVideoGame_Scale+breakXP_2DStrategyGames_Scale+breakXP_Woodwork_Scale+breakXP_Weld_Scale+breakXP_Fabrication_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(breakXP_Electronics_Scale+breakXP_Mechanics_Scale+breakXP_Cabinetry_Scale+breakXP_BuildComputers_Scale+breakXP_Garden_Scale+breakXP_ArtPaint_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

summaryBy(breakXP_ArtDraw_Scale+breakXP_Constuction_Scale+breakXP_Sew_Scale+breakXP_Cook_Scale ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)
```
e ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

# Non-Likert data: Employment, hours weekly, activity hours monthly, exercise hours weekly
summaryBy(isEmployed_Break_dummy + hasCoursework_Break_dummy ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(sum), na.rm=TRUE)

summaryBy(hoursWeekly_Employed_Break.Numeric+hoursWeekly_Study_Break+hoursWeekly_Exercise_Break.numeric+count_Activities_Break+hoursMonthly_Activities_Break.numeric ~ CourseRecruitedFrom, data = consolidatedSpaDataW18_TDF, FUN=c(mean, sd), na.rm=TRUE)

# Run a PCA on prior experience variables I like this explanation: https://www.analyticsvidhya.com/blog/2016/03/practical-guide-principal-component-analysis-python/
# Limit the dataframe to only numeric data for prior experience
# Select the column names that have the numeric data I want: myvars <- c("v1", "v2", "v3")
# Decided to add in BioSex.Numeric as it may vary with some of these survey questions (due to our social views of gender and activities traditionally being tied to biological sex)
priorXpVars <- c("BioSex_Numeric", "BlockPlay_Child_Numeric", "priorXP_MdlPzzl_Numeric", "priorXP_RCToys_Numeric", "priorXP_FIRST_Scale", "priorXP_JETS_Scale", "priorXP_VEX_Scale", "priorXP_ThinkQuest_Scale", "priorXP_LegoEngr_Scale", "priorXP_OdysseyOfMind_Scale", "priorXP_Minecraft_Scale", "priorXP_ErectorSets_Scale", "priorXP_Legos_Scale", "priorXP_Tetris_Scale", "priorXP_1stPersonVideoGame_Scale", "priorXP_Other3DVideoGame_Scale", "priorXP_2DStrategyGames_Scale", "priorXP_Woodwork_Scale", "priorXP_Weld_Scale", "priorXP_Fabrication_Scale", "priorXP_Electronics_Scale", "priorXP_Cabinetry_Scale", "priorXP_Botball_Scale", "priorXP_ResCommPaint_Scale", "priorXP_Construction_Scale", "priorXP_Sew_Scale", "priorXP_Embroidery_Scale", "priorXP_Cook_Scale", "priorXP_Dance_Scale", "priorXP_Sports_Scale", "priorXP_PlayMusic_Scale")
# Note: These columns had no variation, so they were left out:
"priorXP_FutureCity_Scale", "priorXP_TechXplore_Scale", "priorXP_INSPIRE_Scale", "priorXP_BuildComputers_Scale", "priorXP_Garden_Scale", "priorXP_ArtPaint_Scale", "priorXP_ArtDraw_Scale", "priorXP_ResCommPaint_Scale", "priorXP_Construct_Scale", "priorXP_Sew_Scale", "priorXP_Embroidery_Scale", "priorXP_Cook_Scale", "priorXP_Dance_Scale", "priorXP_Sports_Scale", "priorXP_PlayMusic_Scale")
# Also considering leaving out (for low participation): "priorXP_JETS_Scale", "priorXP_ThinkQuest_Scale", "priorXP_VEX_Scale", "priorXP_OdysseyOfMind_Scale", priorXpVars.short <- c("BioSex_Numeric", "BlockPlay_Child_Numeric", "priorXP_MdlPzzl_Numeric", "priorXP_RCToys_Numeric", "priorXP_FIRST_Scale", "priorXP_LegoEngr_Scale", "priorXP_Minecraft_Scale", "priorXP_ErectorSets_Scale", "priorXP_Legos_Scale", "priorXP_Tetris_Scale", "priorXP_1stPersonVideoGame_Scale", "priorXP_Other3DVideoGame_Scale", "priorXP_2DStrategyGames_Scale", "priorXP_Woodwork_Scale", "priorXP_Weld_Scale", "priorXP_Fabrication_Scale", "priorXP_Electronics_Scale", "priorXP_Cabinetry_Scale", "priorXP_Botball_Scale", "priorXP_ResCommPaint_Scale", "priorXP_Construct_Scale", "priorXP_Sew_Scale", "priorXP_Embroidery_Scale", "priorXP_Cook_Scale", "priorXP_Dance_Scale", "priorXP_Sports_Scale", "priorXP_PlayMusic_Scale")
# Maybe also consider leaving out (for low participation): "priorXP_Embroidery_Scale"(?), priorXpVars.shorter <- c("BioSex_Numeric", "BlockPlay_Child_Numeric", "priorXP_MdlPzzl_Numeric", "priorXP_RCToys_Numeric", "priorXP_FIRST_Scale", "priorXP_LegoEngr_Scale", "priorXP_Minecraft_Scale", "priorXP_ErectorSets_Scale", "priorXP_Legos_Scale", "priorXP_Tetris_Scale", "priorXP_1stPersonVideoGame_Scale", "priorXP_Other3DVideoGame_Scale", "priorXP_2DStrategyGames_Scale", "priorXP_Woodwork_Scale", "priorXP_Weld_Scale", "priorXP_Fabrication_Scale", "priorXP_Electronics_Scale", "priorXP_Cabinetry_Scale", "priorXP_Botball_Scale", "priorXP_ResCommPaint_Scale", "priorXP_Construct_Scale", "priorXP_Sew_Scale", "priorXP_Embroidery_Scale", "priorXP_Cook_Scale", "priorXP_Dance_Scale", "priorXP_Sports_Scale", "priorXP_PlayMusic_Scale")
```
"priorXP_Woodwork_Scale", "priorXP_Weld_Scale", "priorXP_Fabrication_Scale",
"priorXP_Electronics_Scale", "priorXP_Mechanics_Scale",
"priorXP_Cabinetry_Scale", "priorXP_BuildComputers_Scale",
"priorXP_Garden_Scale", "priorXP_ArtPaint_Scale", "priorXP_ArtDraw_Scale",
"priorXP_ResCommPaint_Scale", "priorXP_Construction_Scale", "priorXP_Sew_Scale",
"priorXP_Cook_Scale", "priorXP_Dance_Scale", "priorXP_Sports_Scale",
"priorXP_PlayMusic_Scale")

# Create a new dataframe using those column names: newdata <- mydata[myvars]
priorXpData <- consolidatedSpaDataW18_TDF[priorXpVars]
priorXpData.short <- consolidatedSpaDataW18_TDF[priorXpVars.short]
priorXpData.shorter <- consolidatedSpaDataW18_TDF[priorXpVars.shorter]

# head(priorXpData)
# nrow(priorXpData)
# is.na(priorXpData)

# Find the principle components of the data (tell it to normalize the data with
# center=TRUE and scale.=TRUE, have it handle constant columns (i.e., where
everybody entered 0 in their response) by setting tol =
# sqrt(.Machine$double.eps))
priorXpPCs = prcomp(priorXpData, center = TRUE, scale. = TRUE, tol =
# sqrt(.Machine$double.eps))
priorXpPCs.short = prcomp(priorXpData.short, center = TRUE, scale. = TRUE, tol
# = sqrt(.Machine$double.eps))
priorXpPCs.shorter = prcomp(priorXpData.shorter, center = TRUE, scale. = TRUE,
# tol = sqrt(.Machine$double.eps))

columnNames.prior <- colnames(priorXpData)
length(columnNames.prior)
columnNames.prior.short <- colnames(priorXpData.short)
length(columnNames.prior.short)
columnNames.prior.shorter <- colnames(priorXpData.shorter)
length(columnNames.prior.shorter)

### Thanks to help from: https://stats.stackexchange.com/questions/57467/how
to-perform-dimensionality-reduction-with-pca-in-r

### looking at the results
# head(priorXpPCs)
# priorXpPCs$sdev # The square roots of the eigenvalues (standard deviations)
priorXpPCs.shorter$sdev # The square roots of the eigenvalues (standard
deviations)
# length(priorXpPCs$sdev)
# priorXpPCs$rotation # The loadings
# priorXpPCs.short$rotation # The loadings
# priorXpPCs.shorter$rotation # The loadings
# priorXpPCs.shorter$rotation[,10:22] # The loadings
# length(priorXpPCs$rotation)
# priorXpPCs.shorter$x # The Principal Components (PCs)
# length(priorXpPCs$x)

# By squaring the eigenvalues, you get the variance explained by each PC:
# plot(cumsum(priorXpPCs$sdev^2/sum(priorXpPCs$sdev^2))) # cumulative explained
# variance - 11 of the 32 cover ~80% of the variance
# plot(cumsum(priorXpPCs.short$sdev^2/sum(priorXpPCs.short$sdev^2))) # cumulative
# explained variance - 10 of the 32 cover ~80% of the variance
# plot(cumsum(priorXpPCs.shorter$sdev^2/sum(priorXpPCs.shorter$sdev^2)),
# main="Cumulative Explained Variance of Pre-Study Principal Components",
xlab="Principal Component Index", ylab="Cumulative Variance") # cumulative
# explained variance - 9 of the 31 cover ~80% of the variance
priorPC.use.shorter = 9 # Note: this happens to match the number of PCs with
# Eigenvalue>1

# Take the leading (most important) PCs
# priorXpPCs.trunc.shorter <- priorXpPCs.shorter$x[,1:priorPC.use.shorter] %*
# t(priorXpPCs.shorter$rotation[,1:priorPC.use.shorter])
priorXpPCs.trunc.shorter <- priorXpPCs.shorter$x[,1:9] %*
# t(priorXpPCs.shorter$rotation[,1:9])
priorXpPCs.trunc.shorter.unscaled = priorXpPCs.trunc.shorter

# TO FIND THE HIGHEST LOADINGS, I THINK I NEED TO TAKE THE ABSOLUTE VALUE OR SQUARE THE VALUES SO NEGATIVE VALUES DO NOT CANCEL OUT POSITIVE VALUES (LEAVING ME WITH VERY SMALL VALUES)
sort(colMeans(abs(priorXpPCs.trunc.shorter.unscaled)))
plot(sort(colMeans(abs(priorXpPCs.trunc.shorter.unscaled))), main="Mean Loading-Scaled Magnitude of Pre-Study Experience Variables\n in Primary Principal Components", ylab="Mean Loading-Scaled Magnitude", xlab="Magnitude-Sorted Index of Pre-Study Experience Variables")

columnNames.prior.trunc.shorter <- colnames(priorXpPCs.trunc.shorter)
# and add the center (and re-scale) back to data [this should approximate the original data]
priorXpPCs.trunc.shorter <- scale(priorXpPCs.trunc.shorter, center = FALSE , scale=1/priorXpPCs.shorter$scale)
priorXpPCs.trunc.shorter <- scale(priorXpPCs.trunc.shorter, center = -1 * priorXpPCs.shorter$center, scale=FALSE)

#head(priorXpPCs.shorter$x)
#head(priorXpPCs.trunc.shorter)
dim(priorXpPCs.trunc.shorter)
dim(priorXpData.shorter)

#dim(priorXpPCs.shorter$x[,1:9])
#dim(t(priorXpPCs.shorter$rotation[,1:9]))

# below, run a linear regression with the data: lm(y ~ pcData$x[,1] + pcData$x[,2] + ...)

# Run a PCA on break experience variables.
# I like this explanation:
# Limit the dataframe to only numeric data for prior experience
# Select the column names that have the numeric data I want: myvars <- c("v1", "v2", "v3")
# Decided to add in BioSex_Numeric as it may vary with some of these survey questions (due to our social views of gender and activities traditionally being tied to biological sex)
# Select the column names that have the numeric data I want: myvars <- c("v1", "v2", "v3")
# Note: These columns had no variation, so they were left out:
# Also considering leaving out (for low participation): "breakXP_VEX_Scale", "breakXP_Tetris_Scale", "breakXP_Weld_Scale", "breakXP_Cabinetry_Scale", "breakXP_BuildComputers_Scale", "breakXP_Garden_Scale",
"breakXP_ArtPaint_Scale", "breakXP_ArtDraw_Scale", "breakXP_Sew_Scale",
breakXpVars.short <- c("BioSex_Numeric","breakTime_MdlPzz1_Numeric",
"breakTime_RCToys_Numeric", "breakXP_Minecraft_Scale", "breakXP_Legos_Scale",
"breakXP_1stPersonVideoGame_Scale", "breakXP_Other3DVideoGame_Scale",
"breakXP_2DPuzzleVideoGame_Scale", "breakXP_2DStrategyGames_Scale",
"breakXP_Woodwork_Scale", "breakXP_Fabrication_Scale",
"breakXP_Electronics_Scale", "breakXP_Mechanics_Scale",
"breakXP_Construction_Scale", "breakXP_Cook_Scale", "breakXP_Dance_Scale",
"breakXP_Sports_Scale", "breakXP_PlayMusic_Scale")
#Maybe also consider leaving out (for low participation):
"breakXP_Electronics_Scale"(?), "breakXP_Fabrication_Scale"(?),
"breakXP_Construction_Scale"(?),
breakXpVars.shorter <- c("BioSex_Numeric","breakTime_MdlPzz1_Numeric",
"breakTime_RCToys_Numeric", "breakXP_Minecraft_Scale", "breakXP_Legos_Scale",
"breakXP_1stPersonVideoGame_Scale", "breakXP_Other3DVideoGame_Scale",
"breakXP_2DPuzzleVideoGame_Scale", "breakXP_2DStrategyGames_Scale",
"breakXP_Woodwork_Scale", "breakXP_Mechanics_Scale", "breakXP_Cook_Scale",
"breakXP_Dance_Scale", "breakXP_Sports_Scale", "breakXP_PlayMusic_Scale")
#Create a new dataframe using those column names: newdata <- mydata[myvars]
breakXpData <- consolidatedSpaDataW18_TDF[breakXpVars]
breakXpData.short <- consolidatedSpaDataW18_TDF[breakXpVars.short]
breakXpData.shorter <- consolidatedSpaDataW18_TDF[breakXpVars.shorter]
#Find the principle components of the data (tell it to normalize the data with
center=TRUE and scale.=TRUE, have it handle constant columns (i.e., where
everybody entered 0 in their response) by setting tol =
sqrt(.Machine$double.eps))
breakXpPCs = prcomp(breakXpData, center = TRUE, scale. = TRUE, tol =
sqrt(.Machine$double.eps))
breakXpPCs.short = prcomp(breakXpData.short, center = TRUE, scale. = TRUE, tol =
sqrt(.Machine$double.eps))
breakXpPCs.shorter = prcomp(breakXpData.shorter, center = TRUE, scale. = TRUE, tol =
sqrt(.Machine$double.eps))

breakXpPCs.short$rotation #The loadings
### Thanks to help from: https://stats.stackexchange.com/questions/57467/how-to-perform-dimensionality-reduction-with-pca-in-r
###looking at the results
#head(breakXpPCs)
#breakXpPCs$sdev #The square root of the eigenvalues (standard deviations)

# Which Eigenvalues are greater than 17
breakXpPCs.short$sdev #The square roots of the eigenvalues (standard deviations)

#length(breakXpPCs$sdev) #The square roots of the eigenvalues (standard deviations)
#length(breakXpPCs$rotation #The loadings
#length(breakXpPCs.short$rotation #The loadings
#length(breakXpPCs.shorter$rotation #The loadings
#length(breakXpPCs$rotation)
#breakXpPCs$x # The Principal Components (PCs)
#length(breakXpPCs$x)

##By squaring the eigenvalues, you get the variance explained by each PC:
#plot(cumsum(breakXpPCs$sdev^2/sum(breakXpPCs$sdev^2))) #cumulative explained variance - 10 of the 27 cover ~80% of the variance
plot(cumsum(breakXpPCs.short$sdev^2/sum(breakXpPCs.short$sdev^2)),
main="Cumulative Explained Variance of Break Principal Components",
xlab="Principal Component Index", ylab="Cumulative Variance") #cumulative explained variance - 9 of the 31 cover ~80% of the variance
plot(cumsum(breakXpPCs.shorter$sdev^2/sum(breakXpPCs.shorter$sdev^2)))
#cumulative explained variance - 7 of the 14 cover ~80% of the variance

breakXpPCs.trunc.short <- breakXpPCs.short$x[,1:8] %*%
t(breakXpPCs.shorter$rotation[,1:8])
breakXpPCs.trunc.short.unscaled = breakXpPCs.trunc.short

#breakXpPCs.trunc.shorter <- breakXpPCs.shorter$x[,1:7] %*% t(breakXpPCs.shorter$rotation[,1:7])
#breakXpPCs.trunc.shorter.unscaled = breakXpPCs.trunc.shorter

#TO FIND THE HIGHEST LOADINGS, I THINK I NEED TO TAKE THE ABSOLUTE VALUE OR SQUARE THE VALUES SO NEGATIVE VALUES DO NOT CANCEL OUT POSITIVE VALUES (LEAVING ME WITH VERY SMALL VALUES)
sort(colMeans(abs(breakXpPCs.trunc.short.unscaled)))
plot(sort(colMeans(abs(breakXpPCs.trunc.short.unscaled))), main="Mean Loading-Scaled Magnitude of Break Experience Variables\n\n in Primary Principal Components", ylab="Mean Loading-Scaled Magnitude", xlab="Magnitude-Sorted Index of Break Experience Variables")

#sort(colMeans(abs(breakXpPCs.trunc.shorter.unscaled)))
#plot(sort(colMeans(abs(breakXpPCs.trunc.shorter.unscaled))), main="Mean Loading-Scaled Magnitude of Academic Break Experience Variables\n\n in Primary Principal Components", ylab="Mean Loading-Scaled Magnitude", xlab="Magnitude-Sorted Index of Academic Break Experience Variables")

#run a linear regression with the data: lm(y ~ pcData$x[,1] + pcData$x[,2] + ...

# Which Eigenvalues are greater than 1?
break.corMatx = cor(breakXpData)
break.corMatx # Display the correlation matrix (note: This is so big, it may need to be exported to a file first)

#breakXpPCs$center

## Run diagnostics. For those that have significant, or near-significant, linear models, check those remaining in a multivariate model
setwd(directory.diagnostics)
source("simpleDiagnostics.r")
courseIndex = grep("CourseRecruitedFrom", colnames(removedSDW1823.DF))
dvIndex = grep("mctDurationGrowth", colnames(removedSDW1823.DF))
dvNo1823ShortName = "Change in Duration"
idIndex = grep("Random_ID", colnames(removedSDW1823.DF))

## Check MCT performance predictors (pre-score and pre-duration)
setwd(directory.diagnostics)
source("simpleDiagnostics.r")
#run diagnostics on during-the-break stuff. Does any of it look good enough to include?
varIndex = grep("Pre_mctScore.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Pre-MCT Score"
# decent residuals, mostly normal, 9+ leverage outliers, 2 DFFIT outliers (SDW1846, SDW1857), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
#TemporaryComment#augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$Pre_mctScore.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
mctDurGrwth_fnPreMctScoreCtrd.no1823 <- lm(mctDurationGrowth ~ Pre_mctScore.ctrd, data=removedSDW1823.DF)
summary(mctDurGrwth_fnPreMctScoreCtrd.no1823)

varIndex = grep("Pre_mctDuration.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Pre-MCT Duration"
# decent residuals, normal-ish, 7 leverage outliers, 4 DFFIT outliers (SDW1824, SDW1827, SDW1832, SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is SIGNIFICANT p=0.04151
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$Pre_mctDuration.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
# get model results
mctDurGrwth_fnPreDurationCtrd.no1823 <- lm(mctDurationGrowth ~ Pre_mctDuration.ctrd, data=removedSDW1823.DF)
summary(mctDurGrwth_fnPreDurationCtrd.no1823)

# Temporary Comment
apa.reg.table(mctDurGrwth_fnPreDurationCtrd.no1823, filename = "mctDurationGrowth_fnPreMctDurationCtrd.doc", table.number = 1)

postMctDvIndex = grep("Post_mctDuration", colnames(removedSDW1823.DF))
postMctDNo1823ShortName = "Post-MCT Duration"
# Decent residuals, normal-ish, 7 leverage outliers, 4 DFFIT outliers, (SDW1824, SDW1827, SDW1832, SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is VERY SIGNIFICANT p=3.018e-07
# Temporary Comment
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$Pre_mctDuration.scaled)], postMctDvIndex, postMctDNo1823ShortName, varIndex, varShortName, idIndex)
# Why do the line above and below not agree? The line above is Post-MCT Duration ~ Scaled Pre-MCT Duration, while the line below is MCT Duration Growth ~ Centered Post-MCT Duration
# DUMB CHECK. Why is Centered Post-MCT Duration a predictor variable?
mctDurGrwth_fnPostDurationCtrd.no1823 <- lm(mctDurationGrowth ~ Post_mctDuration.ctrd, data=removedSDW1823.DF)
# DUMB CHECK: summary(mctDurGrwth_fnPostDurationCtrd.no1823)

## Check Nonparametric MCT performance predictors (pre-score and pre-duration)
# Note: This uses Pre_mctScore.ctrd and Pre_mctDuration.ctrd rather than the .scaled versions

setwd(directory.diagnostics)
source("simpleDiagnostics.r")
# run diagnostics on during-the-break stuff. Does any of it look good enough to include?
varIndex = grep("Pre_mctScore.ctrd", colnames(removedSDW1823.DF))
varShortName = "Centered Pre-MCT Score"
# decent residuals, mostly normal, 9+ leverage outliers, 2 DFFIT outliers (SDW1846, SDW1857), DFBETA slope and intercept bands are narrow and most are outliers
# Linear Regression is not significant
augmentedSpaData <- singleIVNonParamDiagnosticsWith3LevelCatVar(removedSDW1823.DF[!is.na(removedSDW1823.DF$Pre_mctScore.ctrd)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex, courseIndex)
# Nonparametric Regression is not significant (for the whole model nor for the individual courses)
# Loess does not look great for any of them
varIndex = grep("Pre_mctDuration.ctrd", colnames(removedSDW1823.DF))
varShortName = "Centered Pre-MCT Duration"
# decent residuals, normal-ish, 7 leverage outliers, 4 DFFIT outliers (SDW1824, SDW1827, SDW1832, SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Linear Regression is SIGNIFICANT p=0.04151
# Loess fit looks linear-ish
# Nonparametric Spearman's rho rank correlation is significant (p-value = 0.01559), rho = -0.4266862, rho^2: 0.182061227785279
# Siegel Regression slope: -0.341 (p-value = 0.000113)
# Advanced Dynamics loess fit is not linear (kind of U-shaped)
# Nonparametric Spearman's rho is not significant
# Siegel regression slope is not significant (DF=7)
# Engineering Graphics loess fit looks decent (span=0.85)
# But the Siegel regression slope is -0.3924 (p-value = 0.02526) (DF=10)
# Statics loess fit looks decent (span=0.85)
# Nonparametric Spearman's rho is significant (p-value = 0.02548), rho = -0.6818182, rho^2: 0.464876033057851
# Siegel regression slope is -0.3694 (p-value = 0.002930) (DF=9)

postMctDvIndex = grep("Post_mctDuration", colnames(removedSDW1823.DF))
postMctDNo1823ShortName = "Post-MCT Duration"
# Decent residuals, normal-ish, 7 leverage outliers, 4 DFFIT outliers, (SDW1824, SDW1827, SDW1832, SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Linear Regression is VERY SIGNIFICANT p=3.018e-07
# Loess fit looks linear
# Nonparametric Spearman's rho rank correlation is very significant (p-value = 2.749e-06), rho = 0.7448868, rho^2: 0.554828389848729
# Siegel Regression slope: 0.659 (p-value = 1.34e-06) (DF=30)
# Advanced Dynamics loess fit is not very linear, but has strong right endpoint
# Nonparametric Spearman's rho is not significant (although rho^2: 0.2178)
# But the Siegel regression slope is 1.185 (p-value = 0.01953) (DF=7)
# Engineering Graphics loess fit looks linear (span=0.85)
# Nonparametric Spearman's rho is significant (p-value = 0.01), rho = 0.7272727, rho^2: 0.528925619834711
# Siegel regression slope is 0.6076 (p-value = 0.00324) (DF=10)
# Statics loess fit looks linear (span=0.85)
# Nonparametric Spearman's rho is significant (p-value = 0.01048), rho = 0.7545455, rho^2: 0.569338842975207
# Siegel regression slope is 0.6306 (p-value = 0.002930) (DF=9)

attributes(corrDurrGrowth_preScore)
corrDurrGrowth_preScore
corrDurrGrowth_preScore$estimate
177

SDW1898?), 2 DFFIT outliers (SDW1846 (just barely), SDW1898?), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakTime_MdlPzz_1_Numeric.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakTime_RCToys_Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break RC Toys"
# Residuals are not great, not very normal, 3 leverage outliers (SDW1805, SDW1827, SDW1848), 3 DFFIT outliers (SDW18273, SDW1846, SDW1848), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakTime_RCToys_Numeric.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_VEX_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break VEX"
# Bad residuals (only one participant over the break), not normal data, leverage outlier(SDW1830), SDW1823 is DFFIT outlier, DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_VEX_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Minecraft_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Minecraft"
# Residuals not great, not very normal, 4 leverage outliers, 3 DFFIT outliers (SDW1827, SDW1846, SDW1857), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.43484
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Minecraft_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Legos_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Legos"
# Residuals not great, almost normal-ish, 2 leverage outliers (SDW1840, SDW1883), 2 DFFIT outliers (SDW1827, SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.33019
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Legos_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Tetris_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Tetris"
### Bad residuals (only one participant over the break), 1 leverage outlier (SDW1893?), 1 DFFIT outlier (SDW1823), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.21475
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Tetris_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_1stPersonVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 1st Person VG"
# Residuals almost good, almost normal-ish, 5 leverage outliers, 3 DFFIT
outliers (SDW1832, SDW1846, SDW1857), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_1stPersonVideoGame_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Other3DVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 3D VG"
# Half-decent residuals (given sample size), pretty darn close to normal, 4 leverage outliers (SDW1800, SDW1827, SDW1848, SDW1873), 3 DFFIT outliers (SDW1827, SDW1846 barely, SDW1848), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Other3DVideoGame_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_2DPuzzleVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 2D Puzzle VG"
# Residuals are maybe okay, not very normal, 5 leverage outliers, 2 DFFIT outliers (SDW1846, SDW1893), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_2DPuzzleVideoGame_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_2DStrategyGames_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 2D Strategy Games"
# Half-decent residuals (given sample size), pretty darn close to normal, 4 leverage outliers, 4 DFFIT outliers, DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_2DStrategyGames_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Woodwork_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Woodwork"
### Not great residuals, not very normal, 3 leverage outliers (SDW1840, SDW1883, SDW1884), 1 DFFIT outlier (SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Woodwork_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Weld_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Welding"
### Bad residuals (only one participant over the break), 1 leverage outlier (SDW1890), 1 DFFIT outlier (SDW1823), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Weld_Sca
le.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Fabrication_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Fabrication"
# Residuals are okay-ish, normal distributions is not great, 4 leverage outliers, 2 DFFIT outliers (SDW1846, SDW1898?), DBeta slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Fabrication_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Electronics_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Electronics"
# Not good residuals, not really normal, 6 leverage outliers, 3 DFFIT outliers (SDW1823, SDW1846, SDW1848), DBeta slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Electronics_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Mechanics_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Mechanics"
# Residual plot looks poor, not very normal, leverage shows 3 outliers (SDW1840, SDW1873, and SDW1898?), 2 DFFIT outliers (SDW1823 & SDW1840), DBeta slope and intercept bands are narrow and most are outliers
# Regression is ALMOST SIGNIFICANT 0.12061
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Mechanics_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Cabinetry_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Cabinetry"
# Bad residuals (only one participant over the break), 1 leverage outlier (SDW1840), 1 DFFIT outlier (SDW1846, barely), DBeta slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Cabinetry_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_BuildComputers_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Build PCs"
# Residuals are poor (only 4 participants over the break), 4 leverage outliers, 2 DFFIT outliers (SDW1846, SDW1848), DBeta slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_BuildComputers_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Garden_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Gardening"
# Residuals are poor (only 3 participants over the break), 2 leverage outliers (SDW1840, SDW1898?), 3 DFFIT outliers (SDW1823, SDW1840, SDW1898?), DBeta slope and intercept bands are narrow and most are outliers
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Garden_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_ArtPaint_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Artistic Painting"
# Bad residuals (only one participant over the break), 1 leverage outlier (SDW1822), 1 DFFIT outlier (SDW1846), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_ArtPaint_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_ArtDraw_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Artistic Drawing"
# Poor residuals, not really normal, 2 leverage outliers (SDW1800, SDW1873), 1 DFFIT outlier (SDW1846), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_ArtDraw_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Construction_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Construction"
# Residuals are poor (only 3 participants over the break), 1 leverage outliers (SDW1898), 3 DFFIT outliers (SDW1823, SDW1898), DBETA slope and intercept bands are narrow and most are outliers
# Regression is ALMOST SIGNIFICANT p=0.13032
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Construction_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Sew_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Sewing"
# Residuals are poor (only 2 participants over the break), 1 leverage outliers (SDW1803), 3 DFFIT outliers (SDW1803, SDW1823, SDW1846), DBETA slope and intercept bands are super narrow and most are outliers
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Sew_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Cook_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Cooking"
# Decent residuals, pretty normal, 5 leverage outliers, 3 DFFIT outliers (SDW1846, SDW1881, SDW1898), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Cook_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Dance_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Dance"
# Residual plot looks poor, not normal, leverage has 5 outliers, 3 DFFIT outliers (SDW1823, SDW1805, SDW1832), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
# augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Dance_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_Sports_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Sports"
# Residuals are probably okay, is fairly normal, several leverage outliers, 2 DFFIT outliers (SDW1832, SDW1846), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_Sports_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP_PlayMusic_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Music"
# Residual plot is pretty good, data looks fairly normal, 2 Leverage (SDW1800, SDW1898?), 3 DFFIT outliers (SDW1827, SDW1846, SDW1881), DBETA slope and intercept bands are narrow and most are outliers
# Regression is NEARLY ALMOST SIGNIFICANT 0.19799
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP_PlayMusic_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("hoursWeekly_Study_Break.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Weekly Study Time"
# Residual plot is poor, not very normal, 1 leverage outliers (SDW1840), 2 DFFIT outliers (SDW1840, SDW1846), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$hoursWeekly_Study_Break.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("count_Activities_Break.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Activity Count"
# Kind of okay residuals, kind of normal, 6 leverage outliers, 4 DFFIT outliers (SDW1827, SDW1846, SDW1881, SDW1898?), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$count_Activities_Break.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

setwd(directory.diagnostics)
# run diagnostics on other quantitative stuff. Does any of it look good enough to include?
varIndex = grep("BlockPlay_Child_Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Childhood Block Play"
# maybe passable residual variance, 5 leverage outliers, 2 DFFIT outliers (SDW1846, SDW1893?), DBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.73487
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$BlockPlay_Child_Numeric.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_MdlPzzl_Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Model Puzzle"
# Regression is not great, normal distribution is ok-ish, 1 leverage outlier, 3 DFFIT outliers
# Regression is not significant p=0.95919
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_MdlPzzl_Numeric.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_RCToys_Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior RC Toys"
# Regression is alright (1 outlier), normal curve is not great, 4? leverage outliers, 2 DFFIT outliers
# Regression is ALMOST SIGNIFICANT p=0.12010
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_RCToys_Numeric.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("numberOfChildren_Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Children Count"
# Decent residual variance (but on 4 participants), 4 leverage outliers, 3 DFFIT outliers (SDW1827, SDW1846, SDW1872), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.22243
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$numberOfChildren_Numeric.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("hoursWeekly_Employed_Break.Numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Weekly Employment"
# Decent residuals, reasonably normal, 5 leverage outliers, 1 DFFIT outlier (SDW1857), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.3890
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$hoursWeekly_Employed_Break.Numeric)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("hoursMonthly_Activities_Break.numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Monthly Activity"
# Residuals not great, nearly normal, 4 leverage outliers (SDW1846, SDW1858, SDW1881, SDW18987), 3 DFFIT outliers (SDW1827, SDW1846, SDW1881), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.32011
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$hoursMonthly_Activities_Break.numeric)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("hoursWeekly_Exercise_Break.numeric.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Weekly Exercise"
# Residuals not horrible, nearly normal, 5 leverage outliers, 3 DFFIT outliers (SDW1827, SDW1846, SDW1881), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.86914
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$hoursWeekly_Exercise_Break.numeric)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("previousSpatialExams_count.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Previous Spatial Exam Count"
# Regression is not horrible, normal fit is not good, several leverage
outliers, 2 DFFIT outliers (SDW1827, SDW1846)
# Regression is not significant p=0.59906
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$previousSpatialExams_count.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorGraphicsDraftingTypes_count.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Graphics Course Count"
# Residuals are okay, normal curve is not good, 3 leverage outliers (SDW1842, SDW1827, SDW1860), 4 DFFIT outliers (SDW1812 is low, SDW1827, SDW1846, SDW1898? are high)
# Regression is not significant p=0.2926
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorGraphicsDraftingTypes_count.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("Age.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Age"
# Residuals not horrible, nearly normal, 3 leverage outliers (SDW1827, SDW1839, SDW1848), 3 DFFIT outliers (SDW1823, SDW1846, SDW1848), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$Age.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("GPA.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled GPA"
# Residuals are strange, maybe passable [is this a trend in the engineering student population?]; fairly normal; 2 leverage outliers: SDW1823, SDW1856, 2 DFFIT outliers: SDW 1823, SDW1827; the DFBETA slope band is impossibly narrow (so all may be outliers), the DFBETA intercept band is also narrow so all but two are outliers
# Regression is ALMOST SIGNIFICANT p=0.15
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$GPA.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_FIRST_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior FIRST"
# Low participation
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_FIRST_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_JETS_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior JETS"
# Low participation
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_JETS_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_VEX_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior VEX"
# Low participation
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_VEX_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
varIndex = grep("priorXP_Delete_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Delete"
# No participants without SDW1823
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Delete_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_LegoEngr_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Lego Engineering"
# Regression is not significant
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_LegoEngr_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_OdysseyOfMind_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Odyssey of the Mind"
# Only one participant
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_OdysseyOfMind_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Minecraft_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Minecraft"
# Residuals are not horrible, normal is okay-ish, 3 leverage outliers, 2 DFFIT outliers
# Regression is not significant
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Minecraft_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_ErectorSets_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Erector Sets"
# Residuals look okay, normal distribution is violated, several leverage outliers, 2 DFFIT outliers
# Regression is not significant
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_ErectorSets_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Legos_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Legos"
# Residuals look okay, normal distribution is okay, several leverage outliers, 4 DFFIT outliers
# Regression IS SIGNIFICANT p=0.0136
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Legos_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
# get model results
mctDurGrwth_fnPriorLegoXpXpCtd.no1823 <- lm(mctDurationGrowth ~ priorXP_Legos_Scale.ctrd, data=removedSDW1823.DF)
summary(mctDurGrwth_fnPriorLegoXpXpCtd.no1823)
apa.reg.table(mctDurGrwth_fnPriorLegoXpXpCtd.no1823, filename = "mctDurationGrowth_fnPriorLegoXpXpCtd.doc", table.number = 2)

varIndex = grep("priorXP_Tetris_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Tetris"
# Residuals are not horrible, normal distribution is okay-ish, 4 leverage outliers, 4 DFFIT outliers
# Regression is ALMOST SIGNIFICANT p=0.1179
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Tetris_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_1stPersonVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 1st Person VG"
# Residuals look okay, normal distribution is okay-ish, 4 leverage outliers, 4 DFFIT outliers
# Regression is ALMOST SIGNIFICANT p=0.14251
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_1stPersonVideoGame_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Other3DVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 3D VG"
# Residuals look okay-ish, normal distribution is okay-ish, no leverage outliers, 2 DFFIT outliers
# Regression is ALMOST SIGNIFICANT p=0.15656
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Other3DVideoGame_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_2DPuzzleVideoGame_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 2D Puzzle VG"
# Residuals look okay, normal distribution is okay, 3 leverage outliers, 2 DFFIT outliers
# Regression is not significant p=0.2012
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_2DPuzzleVideoGame_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_2DStrategyGames_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 2D Strategy Games"
# Residuals look okay, normal distribution is okay, no leverage outliers, 3 DFFIT outliers
# Regression is not significant
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_2DStrategyGames_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Woodwork_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Woodwork"
# Residuals not amazing
# Regression not significant
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Woodwork_Scale.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Weld_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Welding"
# Residuals not horrible
# Regression is not significant p=0.48793
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Weld_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Fabrication_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Fabrication"
# Residuals not great, normal distribution not great
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Fabrication_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Electronics_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Electronics"
# Residuals are poor
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Electronics_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Mechanics_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Mechanics"
# Residuals are okay-ish
# Regression is not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Mechanics_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Cabinetry_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Cabinetry"
# Residuals are okay-ish, normal curve fit not great
# Regression is not significant p=0.2971
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Cabinetry_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_BuildComputers_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Build PCs"
# Residuals not great
# Regression not significant
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_BuildComputers_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Garden_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Gardening"
# Residuals are okay-ish, Normal curve is okay
# Regression is not significant p=0.33876
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[[!is.na(removedSDW1823.DF$priorXP_Garden_Scale.scaled),]], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_ArtPaint_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Artistic Painting"
# Residuals are poor
# Regression is not significant
#augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_ArtPaint_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_ArtDraw_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Artistic Drawing"
# Residuals are poor
# Regression is not significant p=0.36549
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_ArtDraw_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_ResCommPaint_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Residential Painting"
# Residuals are poor
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_ResCommPaint_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Construction_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Construction"
# Residuals are poor
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Construction_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Sew_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Sewing"
# Residuals not so great
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Sew_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Embroidery_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Embroidery"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Embroidery_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Cook_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Cooking"
# Residuals are not horrible
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Cook_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_Dance_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Dance"
# Residuals are okay-ish
# Regression is not significant p=0.44577
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Dance_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
varIndex = grep("priorXP_Sports_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Sports"
# Residuals are not horrible
# Regression is ALMOST SIGNIFICANT p=0.15384
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Sports_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP_PlayMusic_Scale.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Music"
# Residuals are okay
# Regression is ALMOST SIGNIFICANT p=0.19032
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_PlayMusic_Scale.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

# Nonparametric check on prior legos
varIndex = grep("priorXP_Legos_Scale.ctrd", colnames(removedSDW1823.DF))
varShortName = "Centered Prior Legos"
# Residuals look okay, normal distribution is okay, several leverage outliers, 4 DFFIT outliers
# (least-squares regression p-value=0.0136)
augmentedSpaData <- singleIvNonParamDiagnosticsWith3LevelCatVar(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP_Legos_Scale.ctrd),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex, courseIndex)
# Loess fit looks linear-ish
# Nonparametric Spearman's rho rank correlation is significant (p-value = 0.01938), rho = -0.4112303, rho^2: 0.169110400071576
# Siegel Regression slope: -64.20 (p-value = 1.8e-05) (DF=30)
# Advanced Dynamics loess fit is not linear (more like a V)
# Nonparametric Spearman's rho is barely significant (p-value = 0.05525), rho = -0.6555623, rho^2: 0.429761904761905
# Siegel regression slope is -162.68 (p-value = 0.01172) (DF=7) [ignore because fit is not linear]
# Engineering Graphics loess fit looks mostly linear (span=0.85)
# Nonparametric Spearman's rho is not significant
# But the Siegel regression slope is -67.00 (p-value = 0.04538) (DF=10)
# Statics loess fit looks mostly linear (span=0.85)
# Nonparametric Spearman's rho is not significant
# Siegel regression slope is -48.94 (p-value = 0.009766) (DF=9)

## Check the consolidated groups
setwd(directory.diagnostics)
source("simpleDiagnostics.r")

varIndex = grep("priorXP.Fabrication.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Fabrication Group"
### Residuals maybe are not horrible, normal distribution is okay, 3 leverage outliers (SDW1898? is really high, SDW1873 and SDW1872 are high), 4 DFFIT outliers (SDW1881 is barely low, SDW1846 and SDW1827 are barely high, SDW1898? is really high), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.6090
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.Fabrication.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.Fabrication.Group.scaled",

Residuals are not great, normal is not great, several leverage outliers, 2 DFFIT outliers (SDW1846, SDW1898), DBETA slope and intercept bands are narrow and most are outliers

Regression is not significant p=0.96420

Residuals are not horrible, normal is okay-ish, 3 leverage outliers (SDW1848 is really high, SDW1856 and SDW1873 are a little high), 3 DFFIT outliers (SDW1848 is low, SDW1827 and SDW1846 are a little high), DBETA slope and intercept bands are narrow and most are outliers

Regression is not significant p=0.93778

Residuals are not so great, normal distribution is violated, 3 leverage outliers (SDW1848 is really high, SDW1805 and SDW1890 are a bit high), 2 DFFIT outliers (SDW1846 is a bit high, SDW1848 is really low), DBETA slope and intercept bands are narrow and most are outliers

Regression is not significant p=0.88207

Residuals are pretty good, normal is okay-ish, several leverage outliers, 4 DFFIT outliers (SDW1846 is barely high, SDW1998? is high, SDW1857 and SDW1881 are a bit low), DBETA slope and intercept bands are narrow and most are outliers

Regression is not significant p=0.91999

Residuals are not great, normal distribution is not great, 4 leverage outliers (SDW1840, SDW1873, SDW1890?, SDW1898?), 3 DFFIT outliers (SDW1840, SDW1846, SDW1898?), DBETA slope and intercept bands are narrow and most are outliers

Regression is ALMOST SIGNIFICANT p=0.11171

Residuals are pretty ugly

Regression is not significant p=0.39568
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.VisualArts.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.VisualArts.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Visual Arts Group"
# Residuals are not so good, normal distribution is not awful, 3 leverage outliers (SDW1800, SDW1822, SDW1873), 1 DFFIT outlier (SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.96344
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.VisualArts.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP.FiberArts.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Fiber Arts Group"
# Residuals are not so great, normal distribution is violated, 3 leverage outliers (SDW1803, SDW1839, SDW1893?), 3 DFFIT outliers (SDW1827 barely, SDW1846 a little high, SDW18937 a little low), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.6074
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.FiberArts.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.FiberArts.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Fiber Arts Group"
# Residuals not good (only 2 participants)
# Regression is not significant p=0.59477
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.FiberArts.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP.PhysicalActivity.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Physical Activity Group"
# Residuals look good, normal distribution looks good, several leverage outliers, 3 DFFIT outliers (SDW1827, SDW1846, SDW1881), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is ALMOST SIGNIFICANT p=0.12439
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.PhysicalActivity.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.PhysicalActivity.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break Physical Activity Group"
# Residuals not so great, normal curve looks ok, 4 leverage outliers (SDW1801, SDW1805, SDW1832, SDW1858), 2 DFFIT outliers (SDW1832, SDW1846 just barely), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.83367
augmentedSpaData <- singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.PhysicalActivity.Group.scaled),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP.VideoGames.3D.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 3D Video Games Group"
# Residuals are maybe okay, normal distribution looks good, 3 leverage outliers
(SDW1800 is quite high, SDW1832 and SDW1873 are high), 2 DFFIT outliers (SDW1832 and SDW1846), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.30112
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.VideoGames.3D.Group.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.VideoGames.3D.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 3D Video Games Group"
# Residuals are okay, normal distribution is alright, 3 leverage outliers (SDW1800 is really high, SDW1827 and SDW1857 are a little high), 3 DFFIT outliers (SDW1827 is quite high, SDW1846 is barely high, SDW1857 is low), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.92995
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.VideoGames.3D.Group.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP.VideoGames.2D.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior 2D Video Games Group"
# Residuals are maybe okay, normal distribution is achieved, 3 leverage outliers (SDW1800, + 2 others), 2 DFFIT outliers (SDW1846 a bit high, SDW1881 low), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is ALMOST SIGNIFICANT p=0.10401
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.VideoGames.2D.Group.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

get model results
mctDurGrwth_fnPrior2DVGGrpCtrd.no1823 <- lm(mctDurationGrowth ~ priorXP.VideoGames.2D.Group.ctrd, data=removedSDW1823.DF)
summary(mctDurGrwth_fnPrior2DVGGrpCtrd.no1823)
apa.reg.table(mctDurGrwth_fnPrior2DVGGrpCtrd.no1823, filename = "mctDurationGrowth_fnPrior2DVGGrpCtrd.doc", table.number = 4)

varIndex = grep("breakXP.VideoGames.2D.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Break 2D Video Games Group"
# Residuals are decent, normal distribution is pretty solid, 4 leverage outliers (SDW1800 + 3 more), 3 DFFIT outliers (SDW1846 a bit high, SDW1893? a bit low), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.39592
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.VideoGames.2D.Group.scaled)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorXP.BuildingToys.Group.scaled", colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Building Toys Group"
# Residuals are decent, normal distribution is pretty solid, 4 leverage outliers (SDW1800 + 3 more), 3 DFFIT outliers (SDW1846 and SDW1873 are a little high, SDW1881 is a little low), DFBETA slope and intercept bands are narrow and most are outliers
# Regression IS SIGNIFICANT p=0.04268
augmentedSpaData <- singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.Building
Toys.Group.scaled),\], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
# get model results
mctDurGrwth_fnPriorBldgToyGrpCtrd.no1823 <- lm(mctDurationGrowth ~
priorXP.BuildingToys.Group.ctrd, data=removedSDW1823.DF)
summary(mctDurGrwth_fnPriorBldgToyGrpCtrd.no1823)
apa.reg.table(mctDurGrwth_fnPriorBldgToyGrpCtrd.no1823, filename =
"mctDurationGrowth_fnPriorBldgToyGrpCtrd.doc", table.number = 3)

varIndex = grep("breakXP.BuildingToys.Group.scaled",
colnames(removedSDW1823.DF))
varShortName = "Scaled Break Building Toys Group"
# Residuals mostly alright (two high outliers), normal distribution is
approximate (a few high outliers), 2 leverage outliers (SDW1840, SDW1883), 2
DFFIT outliers (SDW1827, SDW1846), DFBETA slope and intercept bands are narrow
and most are outliers
# Regression is not significant p=0.33019
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.Building
Toys.Group.scaled)],\], dvIndex, dvNo1823ShortName, varIndex, varShortName,
idIndex)

varIndex = grep("priorXP.ExtraCurricularSTEM.Group.scaled",
colnames(removedSDW1823.DF))
varShortName = "Scaled Prior Extra-Curricular STEM Group"
# Residuals are alright, except for one outlier, normal distribution is
basically achieved (one high extreme outlier, 2 low barely outliers), 1
leverage outlier (SDW1800), 2 DFFIT outliers (barely SDW1846, SDW1800 is
extreme), DFBETA slope and intercept bands are narrow and most are outliers
# Regression is not significant p=0.63718
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorXP.ExtraCurricular
STEM.Group.scaled)],\], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("breakXP.ExtraCurricularSTEM.Group.scaled",
colnames(removedSDW1823.DF))
varShortName = "Scaled Break Extra-Curricular STEM Group"
# Residuals reveal this is not great (only one participant)
# Regression is not significant p=0.52870
augmentedSpaData <-
singleIVDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$breakXP.ExtraCurricular
STEM.Group.scaled)],\], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

# Nonparametric check on prior Building Toys Group
varIndex = grep("priorXP.BuildingToys.Group.ctrd", colnames(removedSDW1823.DF))
varShortName = "Centered Prior Building Toys Group"
# Residuals are decent, normal distribution is pretty solid, 4 leverage
outliers (SDW1800 + 3 more), 3 DFFIT outliers (SDW1846 and SDW1873 are a little
high, SDW1881 is a little low), DFBETA slope and intercept bands are narrow and
most are outliers
# (least-squares regression p-value =0.04268)
augmentedSpaData <-
singleIVNonParamDiagnosticsWith3LevelCatVar(removedSDW1823.DF[!is.na(removedSDW
1823.DF$priorXP.BuildingToys.Group.ctrd)],\], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex, courseIndex)
# Loess fit looks linear-ish
# Nonparametric Spearman's rho rank correlation is barely significant (p-
value = 0.08709), rho = -0.3073124 , rho^2: 0.094409325897973
# Siegel Regression slope: -34.13 (p-value = 0.000965) (DF=30)
# Advanced Dynamics loess fit is not linear (more like an L)
# Nonparametric Spearman's rho is not significant
# But the Siegel regression slope is -66.31 (p-value = 0.00781) (DF=7)
[ignore because fit is not linear]
# Engineering Graphics loess fit looks curvy (span=0.85)
# Nonparametric Spearman's rho is not significant
# But the Siegel regression slope is -16.52 (p-value = 0.0167) (DF=10)
[ignore because fit is not linear]
# Statics loess fit looks curvy (span=0.85)
# Nonparametric Spearman's rho is not significant
# Siegel regression slope is -48.94 (p-value = 0.009766) (DF=9) [ignore because fit is not linear]

### Diagnostics on binomial and factor IVs

```r
setwd(directory.diagnostics)

varIndex = grep("BioSex_Numeric", colnames(removedSDW1823.DF))
varShortName = "Biological Sex"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$BioSex_Numeric),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("RepeatClass_dummy", colnames(removedSDW1823.DF))
varShortName = "Class Repetition"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$RepeatClass dummy),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("previousSpatialExams_dummy", colnames(removedSDW1823.DF))
varShortName = "Any Previous Spatial Exam"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$previousSpatialExams_dummy),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("priorGraphicsDrafting_dummy", colnames(removedSDW1823.DF))
varShortName = "Any Previous Graphics or Drafting"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$priorGraphicsDrafting_dummy),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("isMarried_Numeric", colnames(removedSDW1823.DF))
varShortName = "Married"
# Residuals are not great
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$isMarried_Numeric),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("RaceEthnicityWhite_Numeric", colnames(removedSDW1823.DF))
varShortName = "Race - white or not"
# Bad Residuals (only one participant with SDW1823 removed)
# Regression is not significant
augmentedSpaData <-
  singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$RaceEthnicityWhite_Numeric),], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)
```

varIndex = grep("isEmployed_School_dummy", colnames(removedSDW1823.DF))
varShortName = "Employed During Semester"

# Residuals are pretty good
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$isEmployed_School_dummy)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("isEmployed_Break_dummy", colnames(removedSDW1823.DF))
varShortName = "Employed During Break"

# Residuals are okay
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$isEmployed_Break_dummy)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("hasCoursework_Break_dummy", colnames(removedSDW1823.DF))
varShortName = "Coursework During Break"

# Bad Residuals (only one participant, and even that is questionable)
# Regression is very significant p=0.00782
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$hasCoursework_Break_dummy)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("CourseRecruitedFrom", colnames(removedSDW1823.DF))
varShortName = "Class Recruited From"

# Residuals are okay-ish
# Regression is SIGNIFICANT (difference between Advanced Dynamics and EngrGraphics p=0.0479, difference between Advanced Dynamics and EngrGraphics p=0.0942)
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$CourseRecruitedFrom)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

varIndex = grep("classificationHomeTown", colnames(removedSDW1823.DF))
varShortName = "Classification of Hometown"

# Residuals are okay
# Regression is not significant
augmentedSpaData <-
singleIvDiagnostics(removedSDW1823.DF[!is.na(removedSDW1823.DF$classificationHomeTown)], dvIndex, dvNo1823ShortName, varIndex, varShortName, idIndex)

# Develop a multivariate model

## Significant predictors:
# priorXP_Legos_Scale.scaled (priorXP.BuildingToys.Group.scaled is less significant)
# Pre_mctDuration.scaled
# CourseRecruitedFrom

# Near-significant predictors:
# priorXP_VideoGames.2D.Group.scaled
# priorXP_PhysicalActivity.Group.scaled
# breakXP_Mechanics.Group.scaled
# priorXP_PlayMusic_Scale.scaled
# priorXP_Sports_Scale.scaled
# priorXP_1stPersonVideoGame_Scale.scaled
# priorXP_Tetris_Scale.scaled
# GPA.scaled
# priorXP_RCToys_Numeric.scaled
# breakXP_Construstion_Scale.scaled (poor residuals)
# Individual IVs that are not significant, but I may want to include anyway:
# breakXP.BuildingToys.Group.scaled
# priorXP_2DPuzzleVideoGame_Scale.scaled
# priorGraphicsDraftingTypes_count.scaled
# breakXP_PlayMusic_Scale.scaled
# numberOfChildren_Numeric.scaled (I am guessing this will fall out)
# priorXP_Constructs𝙎𝙚𝙡𝙞𝙘𝙩𝙞𝙤𝙣_Scale.scaled

## WHAT ABOUT OTHER DUMMY-TYPE VARIABLES (none of which are significant)
# BioSex_Numeric
# RepeatClass_dummy
# previousSpatialExams_dummy
# priorGraphicsDrafting_dummy
# isMarried_Numeric
# RaceEthnicityWhite_Numeric
# isEmployed_School_dummy
# isEmployed_Break_dummy
# hasCoursework_Break_dummy

# Other factor variables:
# classificationHomeTown

setwd(directory.dataAnalysis)

# durGrth.oldMultiIv.Lm = lm(mctDurationGrowth ~ priorXP_Sports_Scale.scaled +
# priorGraphicsDraftingTypes_count.scaled + CourseRecruitedFrom,
data=sub1removedSDW1823.DF)
# summary(durGrth.oldMultiIv.Lm)

durGrth.signMultiIv.Lm = lm(mctDurationGrowth ~ priorXP_Legos_Scale.scaled +
Pre_mctDuration.scaled + CourseRecruitedFrom,
data=removedSDW1823.DF)
# summary(durGrth.signMultiIv.Lm)

sub1RemovedSDW1823.DF = subset(removedSDW1823.DF, !is.na(GPA.scaled))
sub2RemovedSDW1823.DF = subset(removedSDW1823.DF, !is.na(GPA.scaled) &
!is.na(priorGraphicsDraftingTypes_count.scaled))

durGrth.nearSigMultiIv.Lm = lm(mctDurationGrowth ~ Pre_mctDuration.scaled +
CourseRecruitedFrom +
  priorXP.VideoGames.2D.Group.scaled +
  priorXP.PhysicalActivity.Group.scaled +
  breakXP.Mechanics_Group.scaled +
  priorXP_PlayMusic_Scale.scaled + priorXP_Sports_Scale.scaled
  + priorXP_1stPersonVideoGame_Scale.scaled
  + priorXP_Tetris_Scale.scaled +
  + breakXP_Constructs觚Scale.scaled +
  + breakXP_Mechanics_Scale.scaled +
  priorXP_Legos_Scale.scaled, data=sub1RemovedSDW1823.DF)
# summary(durGrth.nearSigMultiIv.Lm)
# stepwise.durGrth.nearSigMultiIv.Lm = stepAIC(durGrth.nearSigMultiIv.Lm)
# summary(stepwise.durGrth.nearSigMultiIv.Lm)

# lm(formula = mctDurationGrowth ~ CourseRecruitedFrom + GPA.scaled +
# priorXP_RCToys_Numeric.scaled + breakXP_Constructs觚Scale.scaled +
# priorXP_Legos_Scale.scaled, data = subRemovedSDW1823.DF)

# Residuals:
#       Min       1Q     Median       3Q      Max

195
## Coefficients:

|                                | Estimate | Std. Error | t value | Pr(>|t|) |
|--------------------------------|----------|------------|---------|----------|
| (Intercept)                    | 16.81    | 50.65      | 0.332   | 0.7429   |
| CourseRecruitedFromEngineering | -176.01  | 70.37      | -2.501  | 0.0196   |
| Graphics                       |          |            |         |          |
| CourseRecruitedFromStatics     | -141.11  | 70.14      | -2.012  | 0.0556   |
| GPA.scaled                     | -42.63   | 28.36      | -1.503  | 0.1458   |
| priorXP_RCToys_Numeric.scaled  | -76.09   | 29.73      | -2.560  | 0.0172   |
| breakXP_Construction_Scale.scaled | 51.62  | 29.00      | 1.780   | 0.0877   |
| priorXP_Legos_Scale.scaled     | -42.13   | 29.86      | -1.411  | 0.1711   |

Residual standard error: 144.7 on 24 degrees of freedom
Multiple R-squared: 0.5136, Adjusted R-squared: 0.392
F-statistic: 4.224 on 6 and 24 DF, p-value: 0.004861

Should not have breakXP.Mechanics.Group.scaled and breakXP_Mechanics_Scale.scaled in the same model
Removing either of them produces the exact same result as given above

What if priorXP_Mechanics_Scale.scaled is used in place of breakXP_Mechanics_Scale.scaled?
This results in a better R^2 than using breakXP for Mechanics (group or original IV).

```r
durGrth.nearSigPriorMechMultiIv.Lm = lm(mctDurationGrowth ~ Pre_mctDuration.scaled + CourseRecruitedFrom + priorXP.VideoGames.2D.Group.scaled + priorXP.PhysicalActivity.Group.scaled + priorXP_PlayMusic_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_Tetris_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Legos_Scale.scaled + priorXP_Mechanics_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Legos_Scale.scaled, data=sub1RemovedSDW1823.DF)
```

# Summary

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-238.92</td>
<td>-87.53</td>
<td>-10.94</td>
<td>66.09</td>
<td>259.09</td>
</tr>
</tbody>
</table>

## Coefficients:

|                                | Estimate | Std. Error | t value | Pr(>|t|) |
|--------------------------------|----------|------------|---------|----------|
| (Intercept)                    | -1.075   | 51.975     | -0.021  | 0.98370  |
| Pre_mctDuration.scaled         | -50.829  | 41.246     | -1.232  | 0.23145  |
| CourseRecruitedFromEngineering | -141.766 | 78.609     | -1.803  | 0.08569  |
| Graphics                       |          |            |         |          |
| CourseRecruitedFromStatics     | -121.010 | 68.383     | -1.770  | 0.09132  |
| Graphics                       |          |            |         |          |
# priorXP_Sports_Scale.scaled               76.584 40.489  1.891  0.07244
# GPA.scaled                               -57.597 34.217 -1.683  0.10713
# priorXP_RCToys_Numeric.scaled            -91.458 30.933 -2.957  0.00753
** # breakXP_Construction_Scale.scaled     88.998 34.098  2.610  0.01635
# priorXP_Mechanics_Scale.scaled           -61.264 32.763 -1.870  0.07550
# priorXP_Legos_Scale.scaled               -51.355 30.272 -1.696  0.10457

# Residual standard error: 138.6 on 21 degrees of freedom
# Multiple R-squared:  0.6098,    Adjusted R-squared:  0.4425
# F-statistic: 3.646 on 9 and 21 DF,  p-value: 0.006966

# What if priorXP.Mechanics.Group.scaled is used in place of priorXP_Mechanics_Scale.scaled? R^2 is slightly worse
# durGrth.nearSigPriorMechMultiIv.Lm = lm(mctDurationGrowth ~ Pre_mctDuration.scaled + CourseRecruitedFrom +
#     priorXP.VideoGames.2D.Group.scaled +
#     priorXP.PhysicalActivity.Group.scaled +
#     priorXP.PlayMusic_Scale.scaled +
#     priorXP_Sports_Scale.scaled +
#     priorXP_1stPersonVideoGame_Scale.scaled + priorXP_Tetris_Scale.scaled +
#     GPA.scaled +
#     priorXP_RCToys_Numeric.scaled + breakXP_Construction_Scale.scaled +
#     priorXP.Mechanics.Group.scaled +
#     priorXP_Legos_Scale.scaled, data=sub1RemovedSDW1823.DF)
# summary(durGrth.nearSigNoMechGrpMultiIv.Lm)
# stepwise.durGrth.nearSigPriorMech.Lm = stepAIC(durGrth.nearSigPriorMechMultiIv.Lm)
# summary(stepwise.durGrth.nearSigPriorMech.Lm)

# lm(formula = mctDurationGrowth ~ Pre_mctDuration.scaled + CourseRecruitedFrom +
#     priorXP_Sports_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled +
#     breakXP_Construction_Scale.scaled + priorXP.Mechanics.Group.scaled +
#     priorXP_Legos_Scale.scaled, data = sub1RemovedSDW1823.DF)
# Residuals:                          Min     1Q    Median     3Q    Max
#      -237.49 -88.08     -11.39    75.11   253.38

# Coefficients:
#     Estimate Std. Error   t value     Pr(>|t|)
# (Intercept)     -3.926    52.306   -0.075      0.94088
# Pre_mctDuration.scaled  -51.957    41.674   -1.247      0.22622
# CourseRecruitedFromEngineering Graphics  -138.419     79.081   -1.750      0.09466
# CourseRecruitedFromStatics      -116.385    68.928   -1.688      0.10611
# priorXP_Sports_Scale.scaled       74.712    40.553    1.842      0.07959
# GPA.scaled                      -57.478    34.466   -1.668      0.11023
# priorXP_RCToys_Numeric.scaled    -92.309    31.150   -2.963      0.00742
** # breakXP_Construction_Scale.scaled   85.673    33.679    2.544      0.01890
# priorXP.Mechanics.Group.scaled    -57.906    32.312   -1.792      0.08754
# priorXP_Legos_Scale.scaled        -52.640    30.418   -1.731      0.09820
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 139.4 on 21 degrees of freedom
Multiple R-squared:  0.6052,    Adjusted R-squared:  0.436
F-statistic: 3.577 on 9 and 21 DF,  p-value: 0.007701

## Try adding in things like priorGraphicsDraftingTypes_count.scaled and BioSex_Numeric
# BioSex_Numeric is significant (to p<0.1) and improves R^2
durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm = lm(mctDurationGrowth ~
priorXP_Legos_Scale.scaled + Pre_mctDuration.scaled +
  CourseRecruitedFrom +
priorXP_VideoGames.2D.Group.scaled +
priorXP_PlayMusic_Scale.scaled +
priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RCToys_Numeric.scaled +
priorXP_Mechanics_Scale.scaled +
priorGraphicsDraftingTypes_count.scaled
+ BioSex_Numeric, data=sub2RemovedSDW1823.DF)
# summary(durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm)
# stepwise.durGrth.nearSigPriorMechGraftSex.Lm =
# stepAIC(durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm)
# summary(stepwise.durGrth.nearSigPriorMechGraftSex.Lm)

# lm(formula = mctDurationGrowth ~ priorXP_Legos_Scale.scaled +
# CourseRecruitedFrom + priorXP_Sports_Scale.scaled +
priorXP_1stPersonVideoGame_Scale.scaled +
# GPA.scaled + priorXP_RCToys_Numeric.scaled +
breakXP_Constuction_Scale.scaled +
priorXP_Mechanics_Scale.scaled + BioSex_Numeric, data =
sub2RemovedSDW1823.DF)

# Residuals:
#    Min     1Q   Median     3Q    Max
# -246.082 -56.310    8.525   60.559  197.752

# Coefficients:
#                   Estimate Std. Error t value Pr(>|t|)
# (Intercept)       -91.38      70.39  -1.298  0.20972
# priorXP_Legos_Scale.scaled  -41.72      29.74  -1.403  0.17674
# CourseRecruitedFromEngineering Graphics -141.11      70.48  -2.002  0.05975
# * CourseRecruitedFromStatics -185.51      68.73  -2.699  0.01422
# * priorXP_Sports_Scale.scaled    75.43      35.23   2.141  0.04547
# * priorXP_1stPersonVideoGame_Scale.scaled  -75.84      41.38  -1.833  0.08258
# GPA.scaled       -82.71      32.18  -2.562  0.01905
# * priorXP_RCToys_Numeric.scaled  -116.61      32.18  -3.623  0.00181
# ** breakXP_Constuction_Scale.scaled    62.74      34.81   1.802  0.08737
# * priorXP_Mechanics_Scale.scaled   -57.35      31.10  -1.844  0.08085
# * BioSex_Numeric             146.27      71.36   2.050  0.05445
# duplicate.durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm = lm(mctDurationGrowth ~ priorXP_Legos_Scale.scaled +
# CourseRecruitedFrom + priorXP_Sports_Scale.scaled +
priorXP_1stPersonVideoGame_Scale.scaled +
# GPA.scaled + priorXP_RSToys_Numeric.scaled +
breakXP_Constuction_Scale.scaled +
# priorXP_Mechanics_Scale.scaled + BioSex_Numeric, data =
sub2RemovedSDW1823.DF)
# summary(duplicate.durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm)

#What if I remove Legos - does it make other IVs less significant or does it reduce R^2?
#It reduces R^2 a little bit, and it makes some things more significant (like EngineeringGraphics) and others less (like prior sports)
duplicateNoLegos.durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm = lm(mctDurationGrowth ~
# CourseRecruitedFrom + priorXP_Sports_Scale.scaled +
priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RSToys_Numeric.scaled +
breakXP_Constuction_Scale.scaled +
# priorXP_Mechanics_Scale.scaled + BioSex_Numeric, data =
sub2RemovedSDW1823.DF)
# This looks pretty
good!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
# Why does replacing break Mech & Const with prior XP, and adding in the dummy variables reduce CourseRecruitedFrom significance?
# summary(duplicateNoLegos.durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm)

# Coefficients:
# (Intercept)       Estimate Std. Error   t value Pr(>|t|)
#               -90.61      72.07     -1.257  0.22313
# CourseRecruitedFromEngineering Graphics -158.33      71.06     -2.228  0.03752
# *
# CourseRecruitedFromStatics -185.83      70.37     -2.641  0.01568
# *
# priorXP_Sports_Scale.scaled 68.15 35.68    1.910  0.07061
# .
# priorXP_1stPersonVideoGame_Scale.scaled -86.40 41.66    -2.074  0.05124
# .
# GPA.scaled -77.45 32.83    -2.359  0.02859
# *
# priorXP_RSToys_Numeric.scaled -121.94 32.72    -3.726  0.00133
# **
# breakXP_Constuction_Scale.scaled 73.16 34.82    2.101  0.04852
# *
# priorXP_Mechanics_Scale.scaled -62.14 31.65    -1.963  0.06368
# *
# BioSex_Numeric 155.59 72.75    2.139  0.04499
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 135.3 on 20 degrees of freedom
# Multiple R-squared:  0.6377,  Adjusted R-squared:  0.4747
# F-statistic: 3.912 on 9 and 20 DF,  p-value: 0.005309

#What if breakXP_Constuction_Scale.scaled is replaced with priorXP_Constuction_Scale.scaled (note: breakXP_Constuction_Scale.scaled has poor residuals)?
#It changes the model a fair bit. What if it is just removed?
```r
# duplicateNoLegos.durGrth.nearSigPriorMechConstPriorGrftSexMultiIv.Lm =
# lm(mctDurationGrowth ~
#   CourseRecruitedFrom + priorXP_Sports_Scale.scaled +
#   priorXP_1stPersonVideoGame_Scale.scaled +
#   GPA.scaled + priorXP_RCToys_Numeric.scaled +
#   priorXP_Constuction_Scale.scaled +
#   priorXP_Mechanics_Scale.scaled + BioSex_Numeric, data =
#   sub2RemovedSDW1823.DF)
# summary(duplicateNoLegos.durGrth.nearSigPriorMechConstPriorGrftSexMultiIv.Lm)

# Coefficients:
#                                             Estimate Std. Error t value Pr(>|t|)
# (Intercept)                                  -121.48     75.59  -1.607  0.12371
# CourseRecruitedFromEngineering Graphics      -102.05     71.25  -1.432  0.16754
# CourseRecruitedFromStatics                   -198.68     75.68  -2.625  0.01622
# priorXP_Sports_Scale.scaled                  69.05      41.40   1.668  0.11091
# priorXP_1stPersonVideoGame_Scale.scaled      -134.24     43.04  -3.119  0.00540
# GPA.scaled                                    -70.68      35.20  -2.008  0.05832
# priorXP_RCToys_Numeric.scaled                -118.16     35.26  -3.351  0.00318
# priorXP_Constuction_Scale.scaled             39.83      40.61   0.981  0.33841
# priorXP_Mechanics_Scale.scaled               -52.05      37.92  -1.373  0.18504
# BioSex_Numeric                               178.48      77.50   2.303  0.03215
# ---
# Signif. codes:  0 '**' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 146 on 20 degrees of freedom
# Multiple R-squared:  0.5781, Adjusted R-squared:  0.3882
# F-statistic: 3.045 on 9 and 20 DF,  p-value: 0.01826

# duplicateNoLegos.durGrth.nearSigPriorMechPriorGrftSexMultiIvNoConst.Lm =
# lm(mctDurationGrowth ~
#   CourseRecruitedFrom + priorXP_Sports_Scale.scaled +
#   priorXP_1stPersonVideoGame_Scale.scaled +
#   GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Mechanics_Scale.scaled +
#   BioSex_Numeric, data = sub2RemovedSDW1823.DF)
# summary(duplicateNoLegos.durGrth.nearSigPriorMechPriorGrftSexMultiIvNoConst.Lm)

# Coefficients:
#                                             Estimate Std. Error t value Pr(>|t|)
# (Intercept)                                  -130.81     74.92  -1.746  0.09542
# CourseRecruitedFromEngineering Graphics      -103.07     71.18  -1.448  0.16240
# CourseRecruitedFromStatics                   -207.83     75.03  -2.770  0.01148
# priorXP_Sports_Scale.scaled                  52.10      37.58   1.386  0.18023
# priorXP_1stPersonVideoGame_Scale.scaled      -121.80     41.09  -2.964  0.00740
# GPA.scaled                                    -70.68      35.08  -2.008  0.06502
# priorXP_RCToys_Numeric.scaled                -115.83     35.15  -3.296  0.00344
# priorXP_Mechanics_Scale.scaled               -28.73      29.51  -0.974  0.34137
# BioSex_Numeric                               192.20      76.16   2.523  0.01974
# ---
# Signif. codes:  0 '**' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```
# Residual standard error: 145.9 on 21 degrees of freedom
# Multiple R-squared: 0.5578, Adjusted R-squared: 0.3893
# F-statistic: 3.311 on 8 and 21 DF, p-value: 0.01318

# I am feeling pretty good about replacing the poor residual items
# (breakXP_Constuction_Scale_scaled and 
# breakXP_Mechanics_Scale_scaled) with the prior experience ones and running
# the stepAIC again.

durGrth.nonsigBreakMultiIv.Lm = lm(mctDurationGrowth ~
    priorXP_Legos_Scale_scaled + Pre_mctDuration_scaled + CourseRecruitedFrom +
    priorXP.VideoGames.2D.Group_scaled +
    priorXP.PhysicalActivity.Group_scaled + priorXP_PlayMusic_Scale_scaled +
    priorXP_Sports_Scale_scaled +
    priorXP_1stPersonVideoGame_Scale_scaled + priorXP_Tetris_Scale_scaled +
    GPA_scaled +
    priorXP_RCToys_Numeric_scaled + priorXP_Constuction_Scale_scaled +
    priorXP_Mechanics_Scale_scaled +
    priorGraphsDraftingTypes_count_scaled +
    breakXP_BuildingToys.Group_scaled + breakXP_PlayMusic_Scale_scaled,
    data = sub2RemovedSDW1823.DF)

# stepwise.durGrth.nonsigBreak.Lm = stepAIC(durGrth.nonsigBreakMultiIv.Lm)
# summary(stepwise.durGrth.nonsigBreak.Lm)
# lm(formula = mctDurationGrowth ~
#    priorXP_Legos_Scale_scaled + Pre_mctDuration_scaled + CourseRecruitedFrom +
#    priorXP_Sports_Scale_scaled +
#    priorXP_1stPersonVideoGame_Scale_scaled + GPA_scaled +
#    priorXP_RCToys_Numeric_scaled +
#    priorXP_Constuction_Scale_scaled + priorXP_Mechanics_Scale_scaled +
#    breakXP.BuildingToys.Group_scaled, data = sub2RemovedSDW1823.DF)

# Residuals:
#   Min    1Q  Median    3Q   Max
# -260.41 -71.95   10.81  75.18 205.03

# Coefficients:
#                     Estimate Std. Error t value Pr(>|t|)
# (Intercept)         -19.98     54.75  -0.365 0.71943
# priorXP_Legos_Scale  -96.95     38.01  -2.551 0.02007 *
# Pre_mctDuration_scaled -69.72     44.07  -1.582 0.13108
# CourseRecruitedFromEngineering Graphics -36.61     83.04  -0.441 0.66457
# CourseRecruitedFromStatics -184.58     80.31  -2.298 0.03375 *
# priorXP_Sports_Scale_scaled  120.52     49.83   2.419 0.02640 *
# priorXP_1stPersonVideoGame_Scale_scaled -79.67     39.83  -2.003 0.06042
# GPA_scaled          -58.94     37.57  -1.569 0.13408
# priorXP_RCToys_Numeric_scaled -101.78     34.28  -2.969 0.00822 **
# priorXP_Constuction_Scale_scaled  75.60     40.92   1.848 0.08114 .
# priorXP_Mechanics_Scale_scaled -76.07     41.06  -1.853 0.08036 .
# breakXP.BuildingToys.Group_scaled  41.77     35.82   1.166 0.25882
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# Residual standard error: 145.1 on 18 degrees of freedom
# Multiple R-squared: 0.6247, Adjusted R-squared: 0.3954
# F-statistic: 2.724 on 11 and 18 DF, p-value: 0.02871
# I forgot my dummy variables: BioSex_Numeric, RepeatClass_dummy, priorGraphicsDrafting_dummy

durGrowth.dummyNonsigBreakMultiIv = lm(mctDurationGrowth ~ priorXP_Legos_Scale.scaled + Pre_mctDuration.scaled + CourseRecruitedFrom + priorXP.VideoGames.2D.Group.scaled + priorXP.PhysicalActivity.Group.scaled + priorXP_PlayMusic_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + priorXP_Tetris_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Construction_Scale.scaled + priorXP_Mechanics_Scale.scaled + priorGraphicsDraftingTypes_count.scaled + breakXP.BuildingToys.Group.scaled + breakXP_PlayMusic_Scale.scaled + BioSex_Numeric + RepeatClass_dummy + priorGraphicsDrafting_dummy, data=sub2RemovedSDW1823.DF)

# stepwise.durGrowth.dummyNonsigBreak.Lm = stepAIC(durGrowth.dummyNonsigBreakMultiIv.Lm)
# summary(stepwise.durGrowth.dummyNonsigBreak.Lm)

# This looks pretty good - high R^2, lots of significant IVs (note: playing music is the only thing that appears over the break as significant. This is probably representative of another, hidden factor although I do have that paper on music and spatial ability.)
# Interesting to note: CourseRecruitedFrom goes away when I add in those dummy variables
# THIS IS WORTH NOTING IN THE REPORT!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!

# lm(formula = mctDurationGrowth ~ priorXP_Legos_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Construction_Scale.scaled + priorXP_Mechanics_Scale.scaled + breakXP.BuildingToys.Group.scaled + breakXP_PlayMusic_Scale.scaled + BioSex_Numeric + priorGraphicsDrafting_dummy, data = sub2RemovedSDW1823.DF)

# Residuals:
# Min 1Q Median 3Q Max
# -196.20 -60.32 -14.45 72.69 214.85

# Coefficients:
# (Intercept) Estimate Std. Error t value Pr(>|t|)
# *** -302.66 84.36 -3.588 0.00196
# priorXP_Legos_Scale.scaled -66.33 33.32 -1.991 0.06108
# priorXP_Sports_Scale.scaled 138.24 41.59 3.324 0.00357
# priorXP_1stPersonVideoGame_Scale.scaled -109.39 37.69 -2.902 0.00913
# GPA.scaled -117.92 36.00 -3.275 0.00398
# priorXP_RCToys_Numeric.scaled -108.10 31.88 -3.391 0.00307
# priorXP_Construction_Scale.scaled 88.14 37.67 2.340 0.03035
# priorXP_Mechanics_Scale.scaled -90.06 36.44 -2.471 0.02310
# breakXP_PlayMusic_Scale.scaled -86.38 30.15 -2.866 0.00990
# BioSex_Numeric 154.17 68.68 2.245 0.03689
# priorGraphicsDrafting_dummy 118.42 75.42 1.570 0.13288
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 131.2 on 19 degrees of freedom
# Multiple R-squared:  0.6766,  Adjusted R-squared:  0.5063
# F-statistic: 3.974 on 10 and 19 DF,  p-value: 0.00473

# What if I remove priorGraphicsDrafting_dummy?
duplicate.dummyNonsigBreakMultiIvNoPriorGraph.Lm = lm(mctDurationGrowth ~
priorXP_Legos_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RCToys_Numeric.scaled +
priorXP_Constuction_Scale.scaled + priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
BioSex_Numeric, data = sub2RemovedSDW1823.DF)
# summary(duplicate.dummyNonsigBreakMultiIvNoPriorGraph.Lm)
# Still decent R^2, Legos is no longer significant
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) -203.30  57.79  -3.518  0.00216 **
# priorXP_Legos_Scale.scaled -41.63  30.43  -1.368  0.18644
# priorXP_Sports_Scale.scaled 135.38  43.04   3.145  0.00509 **
# priorXP_1stPersonVideoGame_Scale.scaled -122.46  38.08  -3.216  0.00434 **
# GPA.scaled -135.41  35.46  -3.818  0.00108 **
# priorXP_RCToys_Numeric.scaled -111.86  32.93  -3.397  0.00286 **
# priorXP_Constuction_Scale.scaled  84.14  38.93   2.161  0.04300 *
# priorXP_Mechanics_Scale.scaled -93.80  37.67  -2.490  0.02170 *
# breakXP_PlayMusic_Scale.scaled -84.19  31.20  -2.699  0.01381 *
# BioSex_Numeric 148.01  71.04   2.084  0.05024 .
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 135.9 on 20 degrees of freedom
# Multiple R-squared:  0.6346,  Adjusted R-squared:  0.4701
# F-statistic: 3.859 on 9 and 20 DF,  p-value: 0.005705

#What if I remove Legos? What if I add CourseRecruitedFrom back in?
duplicate.dummyNonsigBreakMultiIvNoPriorGraphLegos.Lm = lm(mctDurationGrowth ~
priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RCToys_Numeric.scaled +
priorXP_Constuction_Scale.scaled + priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
BioSex_Numeric, data = sub2RemovedSDW1823.DF)
# summary(duplicate.dummyNonsigBreakMultiIvNoPriorGraphLegos.Lm)
# R^2 drops a little, but significance improves. THIS MAY BE THE BEST ONE!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
# But note how BioSex_Numeric decreases p-val. Playing with Legos is moderating/mediating the effect of sex. (!!!!!!)
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) -216.02  58.21  -3.711  0.001293 **
# priorXP_Sports_Scale.scaled 131.42  43.83   2.999  0.006842 **
# priorXP_1stPersonVideoGame_Scale.scaled -141.36 36.21 -3.903 0.000818 ***
# GPA.scaled -134.43 36.19 -3.715 0.001281 **
# priorXP_RCToys_Numeric.scaled -117.18 33.37 -3.511 0.002076 **
# priorXP_Constuction_Scale.scaled 84.66 39.73 2.131 0.045104 *
# priorXP_Mechanics_Scale.scaled 96.71 38.39 -2.519 0.019928 *
# breakXP_PlayMusic_Scale.scaled -93.09 31.14 -2.990 0.006985 **
# BioSex_Numeric 166.11 71.23 2.332 0.029741 *

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# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 138.7 on 21 degrees of freedom
# Multiple R-squared:  0.6004,    Adjusted R-squared:  0.4481
# F-statistic: 3.944 on 8 and 21 DF,  p-value: 0.005483

# And if I add in CourseRecruitedFrom?
duplicate.dummyNonsigBreakCourseNoPriorGraphLegos.Lm = lm(mctDurationGrowth ~
  priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Constuction_Scale.scaled +
  priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
  BioSex_Numeric + CourseRecruitedFrom, data = sub2RemovedSDW1823.DF)

# summary(duplicate.dummyNonsigBreakCourseNoPriorGraphLegos.Lm)
# R^2 goes up, but significance gets worse.
# Coefficients:
#               Estimate Std. Error t value Pr(>|t|)
#  (Intercept) -179.74     78.90  -2.278  0.03446 *
# priorXP_Sports_Scale.scaled  117.35     47.77   2.457  0.02381 *
# priorXP_1stPersonVideoGame_Scale.scaled -152.33     42.12  -3.617  0.00184 **
# GPA.scaled -115.31     41.78  -2.760  0.01247 *
# priorXP_RCToys_Numeric.scaled -122.16     33.56  -3.640  0.00174 **
# priorXP_Constuction_Scale.scaled  68.09     41.71   1.633  0.11903
# priorXP_Mechanics_Scale.scaled -85.11     40.52  -2.101  0.04926 *
# breakXP_PlayMusic_Scale.scaled -68.33     38.37  -1.781  0.09096
# BioSex_Numeric 184.26     73.68   2.501  0.02171 *
# CourseRecruitedFromEngineering Graphics -34.38     77.61  -0.443  0.66276
# CourseRecruitedFromStatics -115.66     85.68  -1.350  0.19289

---

# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 138.7 on 19 degrees of freedom
# Multiple R-squared:  0.6384,    Adjusted R-squared:  0.4481
# F-statistic: 3.355 on 10 and 19 DF,  p-value: 0.01121

# What about adding in other 3D video games for prior experience? What about
# prior music instead of break music?
# What about previous spatial? Being married?
dummyNonsigBreakCourseNoPriorGraphLegos.3dVgMarried.Lm = lm(mctDurationGrowth ~
priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RCToys_Numeric.scaled +
priorXP_Constuction_Scale.scaled +
priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
BioSex_Numeric + CourseRecruitedFrom +
priorXP_2DVideoGame_Scale.scaled + isMarried_Numeric + priorXP_PlayMusic_Scale.scaled + priorXP_Other3DVideoGame_Scale.scaled,
data = sub2RemovedSDW1823.DF)
# stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dMrd.Lm =
stepAIC(dummyNonsigBreakCourseNoPriorGraphLegos.3dVgMarried.Lm)
# summary(stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dMrd.Lm)
# Same result as removing Legos
above!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!

# Coefficients:
# (Intercept) -216.02 58.21 -3.711 0.001293 **
# priorXP_Sports_Scale.scaled 131.42 43.83 2.999 0.006842 **
# priorXP_1stPersonVideoGame_Scale.scaled -141.36 36.21 -3.903 0.000818 ***
# GPA.scaled -134.43 36.19 -3.715 0.001281 **
# priorXP_RCToys_Numeric.scaled -117.18 33.37 -3.511 0.002076 **
# priorXP_Constuction_Scale.scaled 84.66 39.73 2.131 0.045104 *
# priorXP_Mechanics_Scale.scaled -96.71 38.39 -2.519 0.019928 *
# breakXP_PlayMusic_Scale.scaled -93.09 31.14 -2.990 0.006985 **
# BioSex_Numeric 166.11 71.23 2.332 0.029741 *
# ---
# Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

# Residual standard error: 138.7 on 21 degrees of freedom
# Multiple R-squared:  0.6004,    Adjusted R-squared:  0.4481
# F-statistic: 3.944 on 8 and 21 DF,  p-value: 0.005483

# what about including pre-MCT duration and Legos again?
dummyNonsigBreakCourseLegosPreDur.3dVgMarried.Lm =
lm(mctDurationGrowth ~
priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled +
GPA.scaled + priorXP_RCToys_Numeric.scaled +
priorXP_Constuction_Scale.scaled +
priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
BioSex_Numeric + CourseRecruitedFrom +
priorXP_2DVideoGame_Scale.scaled + isMarried_Numeric + priorXP_PlayMusic_Scale.scaled + priorXP_Other3DVideoGame_Scale.scaled,
data = sub1RemovedSDW1823.DF)
# first: look at the difference made by adding in the missing participant(s)
left out in sub2
# stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dMrd.sub1.Lm =
stepAIC(dummyNonsigBreakCourseNoPriorGraphLegos.3dVgMarried.Lm)
# summary(stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dMrd.sub1.Lm) #
basically the same results
# adding in pre-MCT duration and Legos
dummyNonsigBreakCourseLegosPreDur.3dVgMarried.Lm = lm(mctDurationGrowth ~
priorXP_Legos_Scale.scaled +
...
Pre_mctDuration.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Constuction_Scale.scaled + priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled + BioSex_Numeric + CourseRecruitedFrom + priorXP_2DPuzzleVideoGame_Scale.scaled + isMarried_Numeric + priorXP_PlayMusic_Scale.scaled + priorXP_Other3DVideoGame_Scale.scaled, data = sub1RemovedSDW1823.DF)

# stepwise.durGrth.dummyNonsigBreakLegosDur.3dMrd.Lm = stepAIC(dummyNonsigBreakCourseLegosPreDur.3dVgMarried.Lm)
# summary(stepwise.durGrth.dummyNonsigBreakLegosDur.3dMrd.Lm) # Legos increases R^2, and makes 2D puzzles significant
# Call:
# lm(formula = mctDurationGrowth ~ priorXP_Legos_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + priorXP_Constuction_Scale.scaled + priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled + BioSex_Numeric + priorXP_2DPuzzleVideoGame_Scale.scaled, data = sub1RemovedSDW1823.DF)

# Residuals:
#     Min  1Q Median     3Q    Max
#-234.531 -55.150  -8.503   56.972  206.751

# Coefficients:
#           Estimate Std. Error t value  Pr(>|t|)
# (Intercept) -247.00      65.66 -3.762     0.00123**
# priorXP_Legos_Scale.scaled -55.47      30.41 -1.824  0.08316.
# priorXP_Sports_Scale.scaled 152.75      43.67  3.498  0.00227**
# priorXP_1stPersonVideoGame_Scale.scaled -149.05      41.11 -3.626  0.00168**
# GPA.scaled -136.95      33.17 -4.129     0.00052***
# priorXP_RCToys_Numeric.scaled -118.82      31.32 -3.794     0.00114**
# priorXP_Constuction_Scale.scaled 90.13      36.83  2.447  0.02376*
# priorXP_Mechanics_Scale.scaled -87.08      35.70 -2.439  0.02415*
# breakXP_PlayMusic_Scale.scaled -96.24      31.21 -3.083     0.00586**
# BioSex_Numeric 206.54      82.64  2.499  0.02127*
# priorXP_2DPuzzleVideoGame_Scale.scaled 47.27      37.55  1.259     0.22260

# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 130.8 on 20 degrees of freedom
# Multiple R-squared:  0.6688, Adjusted R-squared:  0.5031
# F-statistic: 4.038 on 10 and 20 DF, p-value: 0.003834

# What about looking at centered variables instead of scaled variables?
centered.MultiIv.Lm = lm(formula = mctDurationGrowth ~ priorXP_Legos_Scale.ctrd + priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd + GPA.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd + priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd + BioSex_Numeric + priorXP_2DPuzzleVideoGame_Scale.ctrd, data = sub1RemovedSDW1823.DF)

summary(centered.MultiIv.Lm)
apa.reg.table(centered.MultiIv.Lm, filename = "multivariateHighR2CtdLmTable.doc", table.number = 1)

# Residuals:
#     Min  1Q Median     3Q     Max
#-234.531 -55.150  -8.503   56.972  206.751
# Coefficients:

| Term                          | Estimate | Std. Error | t value | Pr(>|t|) |
|-------------------------------|----------|------------|---------|---------|
| (Intercept)                   | -247.00  | 65.66      | -3.762  | 0.00123 ** |
| priorXP_Legos_Scale.ctrd      | -30.47   | 16.71      | -1.824  | 0.08316 .  |
| priorXP_Sports_Scale.ctrd     | 87.70    | 25.10      | 3.498   | 0.00227 ** |
| priorXP_1stPersonVideoGame_Scale.ctrd | -83.21   | 22.95      | -3.626  | 0.00168 ** |
| GPA.ctrd                      | -417.28  | 101.05     | -4.129  | 0.00052 *** |

** ***

| Term                          | Estimate | Std. Error | t value | Pr(>|t|) |
|-------------------------------|----------|------------|---------|---------|
| priorXP_RCToys_Numeric.ctrd   | -152.28  | 40.14      | -3.794  | 0.00114 ** |
| priorXP_Constuction_Scale.ctrd| 65.77    | 26.88      | 2.447   | 0.02376 * |
| priorXP_Mechanics_Scale.ctrd  | -55.66   | 22.82      | -2.439  | 0.02415 * |
| breakXP_PlayMusic_Scale.ctrd  | -52.12   | 16.90      | -3.083  | 0.00586 ** |
| BioSex_Numeric                | 206.54   | 82.64      | 2.499   | 0.02376 * |
| priorXP_2DPuzzleVideoGame_Scale.ctrd | 28.26    | 22.45      | 1.259   | 0.22260 |

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 130.8 on 20 degrees of freedom
Multiple R-squared: 0.6688, Adjusted R-squared: 0.5031
F-statistic: 4.038 on 10 and 20 DF, p-value: 0.003834

centered.No2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Legos_Scale.ctrd + priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd + GPA.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd + priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd +
BioSex_Numeric,
data = sub1RemovedSDW1823.DF)

# summary(centered.No2DPuzVG_MultiIv.Lm)

centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd + GPA.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd + priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd +
BioSex_Numeric,
data = sub1RemovedSDW1823.DF)

summary(centered.NoLegos2DPuzVG_MultiIv.Lm)

apa.reg.table(centered.NoLegos2DPuzVG_MultiIv.Lm, filename = "multivariateAllSignificantNoLego2DPuzzVGctrdLmTable.doc", table.number = 1)

# Residuals:

<table>
<thead>
<tr>
<th>Min</th>
<th>1Q</th>
<th>Median</th>
<th>3Q</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>-271.658</td>
<td>-77.121</td>
<td>2.815</td>
<td>80.668</td>
<td>223.322</td>
</tr>
</tbody>
</table>

# Coefficients:

| Term                          | Estimate | Std. Error | t value | Pr(>|t|) |
|-------------------------------|----------|------------|---------|---------|
| (Intercept)                   | -216.07  | 57.11      | -3.783  | 0.001021 ** |
| priorXP_Sports_Scale.ctrd     | 74.54    | 24.60      | 3.029   | 0.006158 ** |
| priorXP_1stPersonVideoGame_Scale.ctrd | -76.46   | 19.00      | -4.025  | 0.000568 *** |
| GPA.ctrd                      | -420.79  | 105.01     | -4.007  | 0.000593 *** |
| priorXP_RCToys_Numeric.ctrd   | -154.73  | 40.61      | -3.811  | 0.000956 *** |

** ***

| Term                          | Estimate | Std. Error | t value | Pr(>|t|) |
|-------------------------------|----------|------------|---------|---------|
| priorXP_Constuction_Scale.ctrd| 58.79    | 27.59      | 2.131   | 0.044506 * |
| priorXP_Mechanics_Scale.ctrd  | -59.63   | 23.53      | -2.534  | 0.018905 * |
| breakXP_PlayMusic_Scale.ctrd  | -51.64   | 16.30      | -3.169  | 0.004445 ** |
| BioSex_Numeric                | 162.52   | 69.39      | 2.342   | 0.028631 * |

---

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 136.1 on 22 degrees of freedom
Multiple R-squared: 0.606, Adjusted R-squared: 0.4628
F-statistic: 4.23 on 8 and 22 DF, p-value: 0.003391
# Note: Including Building Toys Group results in a model that has multiple
# predictors that are not significant (even though the model is).
# This looks like a poor quality model (admittedly, this may improve if there
# was a larger sample size)

dummyNonsigBreakCourseLegosPreDurBTG.3dVgMarried.Lm = lm(mctDurationGrowth ~
  priorXP_Legos_Scale.scaled + priorXP.BuildingToys.Group.scaled +
  Pre_mctDuration.scaled + priorXP_Sports_Scale.scaled +
  priorXP_1stPersonVideoGame_Scale.scaled +
  GPA.scaled + priorXP двиг.3DNumeric.scaled +
  priorXP_Constuction_Scale.scaled +
  priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
  BioSex Numeric + CourseRecruitedFrom +
  priorXP_2DPuzzleVideoGame_Scale.scaled + isMarried Numeric
  + priorXP_PlayMusic_Scale.scaled + priorXP_3DVideoGame_Scale.scaled,
  data = sub1RemovedSDW1823.DF)
# stepwise.durGrth.dummyNonsigBreakLegosDurBTG.3dMrd.Lm =
# stepAIC(dummyNonsigBreakCourseLegosPreDurBTG.3dVgMarried.Lm)
#summary(stepwise.durGrth.dummyNonsigBreakLegosDurBTG.3dMrd.Lm)
# Call:
# lm(formula = mctDurationGrowth ~ priorXP.BuildingToys.Group.scaled +
#     Pre_mctDuration.scaled + priorXP_Sports_Scale.scaled +
#     priorXP_1stPersonVideoGame_Scale.scaled +
#     GPA.scaled + priorXP двиг.3DNumeric.scaled +
#     priorXP_Constuction_Scale.scaled +
#     priorXP_Mechanics_Scale.scaled + BioSex Numeric + CourseRecruitedFrom,
#     data = sub1RemovedSDW1823.DF)
# Residuals:
#     Min      1Q  Median      3Q     Max
# -205.844 -61.433   4.725  66.453 193.922
# Coefficients:
#                Estimate Std. Error t value Pr(>|t|)
# (Intercept)     -104.94     67.98  -1.544  0.13914
# priorXP.BuildingToys.Group.scaled    -75.43     30.65  -2.461  0.02359  *
# Pre_mctDuration.scaled    -54.99     40.45  -1.359  0.18994
# priorXP_Sports_Scale.scaled    114.29     43.42   2.632  0.01641  *
# priorXP_1stPersonVideoGame_Scale.scaled  -110.17     38.03  -2.897  0.00924  **
# GPA.scaled          -81.97     33.55  -2.443  0.02451  *
# priorXP двиг.3DNumeric.scaled  -115.77     30.43  -3.804  0.00120  **
# priorXP_Constuction_Scale.scaled    58.77     35.53   1.654  0.11459
# priorXP_Mechanics_Scale.scaled    -79.40     34.76  -2.284  0.03403  *
# BioSex Numeric       111.84     73.13   1.529  0.14265
# CourseRecruitedFromEngineering Graphics  -25.98     75.59  -0.344  0.73484
# CourseRecruitedFromStatics  -186.52     67.18  -2.777  0.01202  *
# ---
# Signif. codes:  *** 0.001 *** 0.01 ** 0.05 . 0.1  ' ' 1
# Residual standard error: 129.7 on 19 degrees of freedom
# Multiple R-squared:  0.6909,    Adjusted R-squared:  0.5119
# F-statistic:  3.86 on 11 and 19 DF,  p-value: 0.004868

# What about replacing priorXP_1stPersonVideoGame_Scale.scaled with
# priorXP.VideoGames.3D.Group.scaled?
dummyNonsigBreakCourseNoPriorGrphLegos.3dGrpMarried.Lm =
  lm(mctDurationGrowth ~
  priorXP_Sports_Scale.scaled + priorXP.VideoGames.3D.Group.scaled +
  GPA.scaled + priorXP двиг.3DNumeric.scaled +

priorXP_Construction_Scale.scaled +
  # priorXP_Mechanics_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
  # BioSex_Numeric + CourseRecruitedFrom +
  priorXP_2DPuzzleVideoGame_Scale.scaled + isMarried_Numeric
  # + priorXP_PlayMusic_Scale.scaled, data = sub2RemovedSDW1823.DF)
  # stepAIC(dummyNonsigBreakCourseNoPriorGraphLegos.3dGrpMrd.Lm =
  summary(stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dGrpMrd.Lm)
  # summary(stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dGrpMrd.Lm)
  # Woah. This makes courses significant again, but really drops the R^2. Why
  would the 1st-person Video Games play such a big role?
  # lm(formula = mctDurationGrowth ~ priorXP.VideoGames.3D.Group.scaled +
  #   GPA.scaled + priorXP_RCToys_Numeric.scaled + BioSex_Numeric +
  #   CourseRecruitedFrom, data = sub2RemovedSDW1823.DF)
  # Residuals:
  #  Min 1Q Median 3Q Max
  # -226.50 -96.11 -26.58 66.81 307.45
  # Coefficients:
  #                       Estimate Std. Error t value
  # (Intercept)          -65.83      72.50   -0.908
  # 0.37332
  # priorXP.VideoGames.3D.Group.scaled -68.16      33.19    -2.054
  # 0.05154 .
  # GPA.scaled           -51.26      31.72    -1.616
  # 0.11971
  # priorXP_RCToys_Numeric.scaled -103.94      33.08    -3.142
  # 0.00457 **
  # BioSex_Numeric       108.85      69.64     1.563
  # 0.13172
  # CourseRecruitedFromEngineering Graphics -139.85      72.28    -1.935
  # 0.06540 .
  # CourseRecruitedFromStatics -185.50      77.83    -2.383
  # 0.02580 *
  # ---
  # Signif. codes:      0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  # Residual standard error: 152.9 on 23 degrees of freedom
  # Multiple R-squared:  0.4676,   Adjusted R-squared:  0.3287
  # F-statistic: 3.367 on 6 and 23 DF,  p-value: 0.0157
  # Try adding Legos back in
  # dummyNonsigBreakCourseNoPriorGraph.3dGrpMrd.Lm = lm(mctDurationGrowth ~
  # priorXP_Legos_Scale.scaled +
  #   priorXP_Sports_Scale.scaled + priorXP.VideoGames.3D.Group.scaled +
  #   GPA.scaled + priorXP_RCToys_Numeric.scaled +
  #   priorXP_Construction_Scale.scaled + breakXP_PlayMusic_Scale.scaled +
  #   BioSex_Numeric + CourseRecruitedFrom +
  #   priorXP_2DPuzzleVideoGame_Scale.scaled + isMarried_Numeric
  #   + priorXP_PlayMusic_Scale.scaled, data = sub2RemovedSDW1823.DF)
  # stepAIC(dummyNonsigBreakCourseNoPriorGraph.3dGrpMrd.Lm =
  summary(stepwise.durGrth.dummyNonsigBreakNoPriorGraphLegos.3dGrpMrd.Lm)
  # This increases R^2 and improves significance (including that of Engineering
  # graphics, but not Statics)
  # lm(formula = mctDurationGrowth ~ priorXP_Legos_Scale.scaled +
  #   GPA.scaled + priorXP_RCToys_Numeric.scaled + CourseRecruitedFrom,
  #   data = sub2RemovedSDW1823.DF)
  # Residuals:
  # Min 1Q Median 3Q Max
# Coefficients:

|                     | Estimate | Std. Error | t value | Pr(>|t|) |
|---------------------|----------|------------|---------|----------|
| (Intercept)         | 3.832    | 52.511     | 0.073   | 0.9424   |
| priorXP_Legos_Scale | -66.802  | 29.678     | -2.251  | 0.0338 * |
| GPA_scaled          | -53.651  | 30.593     | -1.754  | 0.0922   |
| priorXP_RCToys_Numeric | -75.868 | 32.268     | -2.351  | 0.0273 * |
| CourseRecruitedFromEngineering | -139.045 | 70.596 | -1.970 | 0.0605 |
| CourseRecruitedFromStatics | -159.483 | 75.181 | -2.121 | 0.0444 * |

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 . ‘ ’ 1

Residual standard error: 151.2 on 24 degrees of freedom  
Multiple R-squared:  0.4567,    Adjusted R-squared:  0.3435  
F-statistic: 4.035 on 5 and 24 DF,  p-value: 0.008465

I should probably check for collinearity between Legos and 1st-person Video Games/3D Video Games group
And 1st-person Video Games and other things
durGrth.nearSigNoLegoMultiIv.Lm = lm(mctDurationGrowth ~ Pre_mctDuration.scaled + CourseRecruitedFrom + priorXP.VideoGames.2D.Group.scaled + priorXP.PhysicalActivity.Group.scaled + breakXP.Mechanics.Group.scaled + priorXP_PlayMusic_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + priorXP_Tetris_Scale.scaled + GPA.scaled + priorXP_RCToys_Numeric.scaled + breakXP_Constuction_Scale.scaled + breakXP_Mechanics_Scale.scaled, data=sub1RemovedSDW1823.DF)
## summary(durGrth.nearSigNoLegoMultiIv.Lm)
## stepwise.durGrth.noLegomultiIv.Lm = stepAIC(durGrth.nearSigNoLegoMultiIv.Lm)
## summary(stepwise.durGrth.noLegomultiIv.Lm)

# Residuals:
## Min 1Q Median 3Q Max
## -301.291 -69.102 8.359 47.780 259.749

# Coefficients:
## Estimate Std. Error t value
Pr(>|t|)
## (Intercept) 4.612 53.203 0.087 0.93163
## CourseRecruitedFromEngineering Graphics -171.162 72.745 -2.353 0.02716 *
## CourseRecruitedFromStatics -114.550 73.139 -1.566
durGrth.nearSigNoLegoPreMultiIv.Lm = lm(mctDurationGrowth ~ priorGraphicsDraftingTypes_count.scaled + CourseRecruitedFrom + priorXP.VideoGames.2D.Group.scaled + priorXP.PhysicalActivity.Group.scaled + priorXP_PlayMusic_Scale.scaled + priorXP_Sports_Scale.scaled + priorXP_1stPersonVideoGame_Scale.scaled + priorXP_Tetris_Scale.scaled + priorXP_RCToys_Numeric.scaled + breakXP_Mechanics_Scale.scaled + GPA.scaled + breakXP_Constuction_Scale.scaled, data = sub2RemovedSDW1823.DF)

# Variables that still look decent:
# priorGraphicsDrafting_dummy
# priorXP_Sports_Scale.scaled
# priorGraphicsDraftingTypes_count.scaled
# GPA.scaled
# Maybe RaceEthnicityWhite_Numeric
# CourseRecruitedFrom (also: CourseNotAdvDynamics CourseIsEngrGraphics)
# This will require different type of diagnostic than singleIVDiagnoses
# function
# classificationHomeTown
# This will require different type of diagnostic than singleIVDiagnoses

# sub1removedSDW1823.DF = subset(removedSDW1823.DF,
!is.na(priorGraphicsDrafting_dummy) & !is.na(priorXP_Sports_Scale.scaled) &
!is.na(priorGraphicsDraftingTypes_count.scaled) & !is.na(GPA.scaled) &
!is.na(RaceEthnicityWhite_Numeric) & !is.na(breakXP_PlayMusic_Scale.scaled) &
!is.na(hoursWeekly_Study_Break.scaled))
# sub1removedSDW1823.DF = subset(sub1removedSDW1823.DF, Random_ID !=
"SDW1823")

# durationSub1.multiIv.Df = lm(mctDurationGrowth ~
priorGraphicsDrafting_dummy + priorXP_Sports_Scale.scaled +
priorGraphicsDraftingTypes_count.scaled + GPA.scaled +
RaceEthnicityWhite_Numeric + CourseRecruitedFrom + classificationHomeTown +
breakXP_PlayMusic_Scale.scaled + hoursWeekly_Study_Break.scaled,
data=sub1removedSDW1823.DF)
# summary(durationSub1.multiIv.Df)
# stepwise.durationSub1.multiIv.Df = stepAIC(durationSub1.multiIv.Df)
# summary(stepwise.durationSub1.multiIv.Df)
# recreate.multiIv.Df = lm(mctDurationGrowth ~ priorGraphicsDrafting_dummy +
priorXP_Sports_Scale.scaled + priorGraphicsDraftingTypes_count.scaled +
GPA.scaled + RaceEthnicityWhite_Numeric + CourseRecruitedFrom,
data=sub1removedSDW1823.DF)
# summary(recreate.multiIv.Df)
# #apa.reg.table(recreate.multiIv.Df, filename =
"mctDurationGrowth_multiVariateLmTable.doc", table.number = 1)

# reducedNoRace.multiIv.Df = lm(mctDurationGrowth ~
priorGraphicsDrafting_dummy + priorXP_Sports_Scale.scaled +
priorGraphicsDraftingTypes_count.scaled + GPA.scaled + CourseRecruitedFrom,
data=sub1removedSDW1823.DF)
# summary(reducedNoRace.multiIv.Df)
# #apa.reg.table(reducedNoRace.multiIv.Df, filename =
"mctDurationGrowth_multiVariateNoRaceLmTable.doc", table.number = 1)

# reducedNoRaceOrCourse.multiIv.Df = lm(mctDurationGrowth ~
priorGraphicsDrafting_dummy + priorXP_Sports_Scale.scaled +
priorGraphicsDraftingTypes_count.scaled + GPA.scaled,
data=sub1removedSDW1823.DF)
# summary(reducedNoRaceOrCourse.multiIv.Df)

# length(ivColumnNames.scaled)
# length(ivColumnNames.binomial)
# length(ivColumnNames.factor)
## FOR EXAMPLE, THE simpleDiagnostics.r function that I wrote could be used to save off the plots
## TO USE IT WOULD REQUIRE DEFINING THE NAME AND THE INDEX OF THE D.V. AS WELL AS ANY I.V.'S OF INTEREST

## Before using the variables in models, should I scale them? (subtract off the center and divide by std dev?)
# see https://stackoverflow.com/questions/15215457/standardize-data-columns-in-r (lower, not-accepted answer)
# dat # a dataframe
# dat2 <- dat %>% mutate_each_(funs(scale(.) %>% as.vector),
#                        vars=c("y","z"))
# this makes the y and z columns in dat2 scaled versions of what is in dat

## WHICH VARIABLES SHOULD BE ANALYZED: ALL POTENTIAL I.V.'S, OR JUST THE ONES NOT CONSIDERED WITHIN THE PCA?
## IT SEEMS LIKE ALL VARIABLES SHOULD BE CONSIDERED
### KEY VARIABLES THAT APPEAR SIGNIFICANT: GPA, CourseRecruitedFrom
### OTHER IMPORTANT VARIABLES TO CONSIDER (BEFORE DECLARING THEY ARE NOT SIGNIFICANT): BioSex, Pre_mctScore (for mctScoreImprovement), Pre_mctDuration (for mctDurationGrowth)

#Analyze moderation a little bit
# what if BioSex.Numeric is left out?
noSex.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd +
GPA.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Construction_Scale.ctrd +
priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd,
  data = sub1RemovedSDW1823.DF)
# summary(noSex.centered.NoLegos2DPuzVG_MultiIv.Lm)
apa.reg.table(noSex.centered.NoLegos2DPuzVG_MultiIv.Lm, filename =
"multivariateAllSignificantButSexNoLego2DPuzzVGCtrdLmTable.doc", table.number = 1)

#Residuals:
#   Min  1Q Median  3Q    Max
# -349.26 -78.73  -16.24 94.74 286.88
# Coefficients:
#                   Estimate Std. Error t value Pr(>|t|)
# (Intercept)     -95.23     26.77   -3.558  0.00168 **
# priorXP_Sports_Scale.ctrd    66.06     26.60    2.483  0.02075 *
# priorXP_1stPersonVideoGame_Scale.ctrd  -61.20    19.51    -3.137  0.00462 **
# GPA.ctrd         -411.38    114.71    -3.586  0.00156 **
# priorXP_RCToys_Numeric.ctrd    -128.08    42.61    -3.006  0.00630 **
# priorXP_Construction_Scale.ctrd      69.68     29.72     2.344  0.02806 *
# priorXP_Mechanics_Scale.ctrd       -54.79     25.62    -2.138  0.04336 *
# breakXP_PlayMusic_Scale.ctrd       -48.08     17.74    -2.711  0.01247 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 148.7 on 23 degrees of freedom
# Multiple R-squared:  0.5078,    Adjusted R-squared:  0.358
# F-statistic:  3.39 on 7 and 23 DF,  p-value: 0.01234

#Analyze moderation a little bit
# what if GPA.ctrd is left out?
nogpa.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd +
priorXP_RCToys_Numeric.ctrd + priorXP_Construction_Scale.ctrd +
priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd +
BioSex_Numeric,
data = sub1RemovedSDW1823.DF)
#summary(noGpa.centered.NoLegos2DPuzVG_MultiIv.Lm)
#apa.reg.table(noGpa.centered.NoLegos2DPuzVG_MultiIv.Lm, filename =
"multivariateAllSignificantButGpaNoLego2DPuzzVGcrtdLmTable.doc", table.number = 1)
# Residuals:
#     Min      1Q  Median 3Q Max
#-361.63 -82.58 -22.78  79.72  398.57
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept)  208.79  73.42  2.844  0.0092 **
# priorXP_Sports_Scale.ctrd  12.59  24.62  0.511  0.6140
# priorXP_1stPersonVideoGame_Scale.ctrd  45.78  22.36  2.047  0.0523 .
# priorXP_RCToys_Numeric.ctrd  93.60  48.41  1.934  0.0656 .
# priorXP_Constuction_Scale.ctrd  31.40  34.38  0.913  0.3705
# priorXP_Mechanics_Scale.ctrd  21.34  27.66  0.772  0.4482
# breakXP_PlayMusic_Scale.ctrd  24.05  19.00  1.266  0.2182
# BioSex_Numeric  151.88  89.19  1.703  0.1021
# ***
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 175 on 23 degrees of freedom
# Multiple R-squared:  0.3185,    Adjusted R-squared:  0.1111
# F-statistic: 1.536 on 7 and 23 DF,  p-value: 0.2051

#Analyze moderation a little bit
# what if BioSex_Numeric and GPA.ctrd are left out?
noSexGpa.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd +
priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd +
priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd,
data = sub1RemovedSDW1823.DF)
#summary(noSexGpa.centered.NoLegos2DPuzVG_MultiIv.Lm)
#apa.reg.table(noSexGpa.centered.NoLegos2DPuzVG_MultiIv.Lm, filename =
"multivariateAllSignificantButSexGpaNoLego2DPuzzVGcrtdLmTable.doc", table.number = 1)
# Residuals:
#     Min      1Q  Median 3Q Max
#-432.38 -108.83  -9.85 68.78  398.13
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) -95.840  32.719 -2.929  0.00734 **
# priorXP_Sports_Scale.ctrd  5.954  25.255  0.236  0.81562
# priorXP_1stPersonVideoGame_Scale.ctrd -32.129  21.689 -1.481  0.15152
# priorXP_RCToys_Numeric.ctrd -69.938  48.169 -1.452  0.15947
# priorXP_Constuction_Scale.ctrd  42.175  35.103  1.201  0.24129
# priorXP_Mechanics_Scale.ctrd -17.613  28.646 -0.615  0.54444
# breakXP_PlayMusic_Scale.ctrd  21.298  19.664  1.083  0.28953
# ***
# Signif. codes:  0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 181.8 on 24 degrees of freedom
# Multiple R-squared:  0.2326,    Adjusted R-squared:  0.04071
# F-statistic: 1.212 on 6 and 24 DF,  p-value: 0.3343

#Analyze moderation a little bit
# What if priorXP_1stPersonVideoGame_Scale.ctrd is removed (it has just as high
#sr^2 as GPA)
no1stpvg.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~
priorXP_Sports_Scale.ctrd + GPA.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd +
priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd +
BioSex_Numeric,
data = sub1RemovedSDW1823.DF)
# summary(nolstpqvg.centered.NoLegos2DPuzVG_MultiIv.Lm)
#apa.reg.table(nolstpqvg.centered.NoLegos2DPuzVG_MultiIv.Lm, filename =
#"multivariateAllSignificantBut1stpvgNoLego2DPuzzVGCtrdLmTable.doc",
#table.number = 1)

#Residuals:
#     Min      1Q  Median 3Q Max
#-346.07  -73.28  -7.66  58.94  385.67
#Coefficients:
#                  Estimate Std. Error t value Pr(>|t|)
#(Intercept)     -147.21    70.22   -2.096   0.0472 *
#priorXP_Sports_Scale.ctrd 14.19     25.14    0.565   0.5778
#GPA.ctrd        -250.42   123.85   -2.026   0.0550 .
#priorXP_RCToys_Numeric.ctrd -99.89    49.30   -2.026   0.0545 .
#priorXP_Constuction_Scale.ctrd 15.68    32.76    0.479   0.6367
#priorXP_Mechanics_Scale.ctrd -22.50    27.90   -0.807   0.4282
#breakXP_PlayMusic_Scale.ctrd -33.09    20.14   -1.643   0.1140
#BioSex_Numeric    66.69     84.00    0.794   0.4353

---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 175.3 on 23 degrees of freedom
# Multiple R-squared: 0.3159, Adjusted R-squared: 0.1077
# F-statistic: 1.518 on 7 and 23 DF, p-value: 0.2109

# Analyze moderation a little bit
# What if priorXP_1stPersonVideoGame_Scale.ctrd and GPA.ctrd are removed (they
# have the highest sr^2 ("semi-partial correlation squared"))
noGpa1stpvg.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth
~ priorXP_Sports_Scale.ctrd + priorXP_RCToys_Numeric.ctrd + priorXP_Constuction_Scale.ctrd +
  priorXP_Mechanics_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd +
  BioSex_Numeric,
  data = sub1RemovedSDW1823.DF)
# summary(noGpa1stpvg.centered.NoLegos2DPuzVG_MultiIv.Lm)
#apa.reg.table(noGpa1stpvg.centered.NoLegos2DPuzVG_MultiIv.Lm, filename =
#"multivariateAllSignificantButGpa1stpvgNoLego2DPuzzVGCtrdLmTable.doc",
#table.number = 1)

#Residuals:
#     Min      1Q  Median 3Q Max
#-388.78  -73.06   3.95  47.55  487.09
#Coefficients:
#                  Estimate Std. Error t value Pr(>|t|)
#(Intercept)     -161.67     74.21   -2.178   0.0394 *
#priorXP_Sports_Scale.ctrd -12.62     22.69   -0.556   0.5834
#priorXP_RCToys_Numeric.ctrd 72.09    50.29    1.433   0.1646
#priorXP_Constuction_Scale.ctrd 8.52     34.60    0.246   0.8076
#priorXP_Mechanics_Scale.ctrd -5.89     28.32   -0.208   0.8372
#breakXP_PlayMusic_Scale.ctrd -18.78    20.03   -0.937   0.3580
#BioSex_Numeric    86.46     88.63    0.976   0.3390

---
# Signif. codes:  0 '****' 0.0001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 186.3 on 24 degrees of freedom
# Multiple R-squared: 0.1943, Adjusted R-squared: -0.007069
# F-statistic: 0.9649 on 6 and 24 DF, p-value: 0.4695

# Just for comparing to something with approximately the same sr^2, what if GPA
# and mechanics are removed (mechanics sr^2: 0.11, biosex sr^2: 0.10 [only
# construction has lower sr^2 at 0.08])
# Analyze moderation a little bit
# what if priorXP_Mechanics_Scale.ctrd and GPA.ctrd are left out? [The multiple
# R^2 (0.3009) is quite a bit higher than for no sex and no GPA (0.2326)]:

# summary(nolstpqvg.centered.NoLegos2DPuzVG_MultiIv.Lm)
noMechGpa.centered.NoLegos2DPuzVG_MultiIv.Lm = lm(formula = mctDurationGrowth ~ priorXP_Sports_Scale.ctrd + priorXP_1stPersonVideoGame_Scale.ctrd + priorXP_RTCtoys_Numeric.ctrd + priorXP_Construction_Scale.ctrd + breakXP_PlayMusic_Scale.ctrd + BioSex_Numeric, data = sub1RemovedSDW1823.DF)
summary(noMechGpa.centered.NoLegos2DPuzVG_MultiIv.Lm)

# Check for multicollinearity
"durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm"

\text{vif}(\text{durGrth.nearSigPriorMechPriorGrftSexMultiIv.Lm}) \ # \ VIF>10 \ (or \ close):
\text{CourseRecruitedFrom} \ 9.381978, \ \text{priorXP.VideoGames.2D.Group}\text{.scaled} \ 11.416989,
\text{priorXP_Tetris_Scale}\text{.scaled} \ 10.724861

"durGrth.nonsigBreakMultiIv.Lm"

\text{vif}(\text{durGrth.nonsigBreakMultiIv.Lm}) \ # \ VIF>10: \ \text{CourseRecruitedFrom} \ 15.59457,
\text{priorXP_Sports_Scale}\text{.scaled} \ 11.240363,

"durGrth.dummyNonsigBreakMultiIv.Lm"

\text{vif}(\text{durGrth.dummyNonsigBreakMultiIv.Lm}) \ # \ lots \ of \ VIF>10: \ \text{CourseRecruitedFrom},
\text{priorXP.VideoGames.2D.Group}\text{.scaled}, \ \text{priorXP_Tetris_Scale}\text{.scaled}, \ \text{priorGraphicsDraftingTypes_count}\text{.scaled}

"dummyNonsigBreakCourseNoPriorGraph.3dGrpMarried.Lm"

\text{vif}(\text{dummyNonsigBreakCourseNoPriorGraph.3dGrpMarried.Lm}) \ # \ no \ VIF>10, \ high \ is
\text{priorXP.VideoGames.3D.Group}\text{.scaled} \ 8.111433

# In the stepAIC runs, I got the impression that BioSex_Numeric and
\text{CourseRecruitedFrom} \ have \ some \ interplay -
# is \ there \ a \ way \ to \ quantify \ that \ relationship \ that \ explains \ why
\text{CourseRecruitedFrom} \ is \ left \ out \ of \ the
# \ multivariate \ model \ (but \ not \ BioSex_Numeric)?

removalSDW1823.DF$\text{BioSex_Numeric}

##Check \ binomial \ and \ factor \ variables \ vs \ mctDurationGrowth
\text{BioSex_Numeric} \ is \ not \ significant \ on \ its \ own, \ but \ it \ is \ kind \ of \ close (0.1561)
\text{durationLm.fnOf.BioSex_Numeric} \ <- \ lm(\text{mctDurationGrowth} ~ \text{BioSex_Numeric},
data=consolidatedSpaDataW18_TDF)
\text{summary(durationLm.fnOf.BioSex_Numeric)}

\text{isMarried_Numeric} \ is \ not \ significant \ on \ its \ own
\text{durationLm.fnOf.isMarried_Numeric} \ <- \ lm(\text{mctDurationGrowth} ~ \text{isMarried_Numeric},
data=consolidatedSpaDataW18_TDF)
\text{summary(durationLm.fnOf.isMarried_Numeric)}

\text{RaceEthnicityWhite_Numeric} \ IS \ SIGNIFICANT \ on \ its \ own (0.0019410)
durationLm.fnOf.RaceEthnicityWhite_Numeric \ <- \ lm(\text{mctDurationGrowth} ~ \text{RaceEthnicityWhite_Numeric},
data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.RaceEthnicityWhite_Numeric.no1823 \ <- \ lm(\text{mctDurationGrowth} ~ \text{RaceEthnicityWhite_Numeric},
data=removedSDW1823.DF)
\text{summary(durationLm.fnOf.RaceEthnicityWhite_Numeric)} \ # \ only \ significant \ if
\text{SDW1823} \ is \ included

#apa.reg.table(durationLm.fnOf.RaceEthnicityWhite_Numeric, \ filename =
"mctDurationGrowth_fnRaceLmTable.doc", \ table.number = 1)
\text{summary(durationLm.fnOf.RaceEthnicityWhite_Numeric.no1823)} \ # \ not \ significant

\text{RepeatClass_dummy} \ is \ not \ significant \ on \ its \ own
\text{durationLm.fnOf.RepeatClass_dummy} \ <- \ lm(\text{mctDurationGrowth} ~ \text{RepeatClass_dummy},
data=consolidatedSpaDataW18_TDF)
\text{summary(durationLm.fnOf.RepeatClass_dummy)}

\text{isEmployed_School_dummy} \ is \ not \ significant \ on \ its \ own
\text{durationLm.fnOf.isEmployed_School_dummy} \ <- \ lm(\text{mctDurationGrowth} ~ \text{isEmployed_School_dummy},
data=consolidatedSpaDataW18_TDF)
\text{summary(durationLm.fnOf.isEmployed_School_dummy)}

\text{previousSpatialExams_dummy} \ is \ not \ significant \ on \ its \ own
\text{durationLm.fnOf.previousSpatialExams_dummy} \ <- \ lm(\text{mctDurationGrowth} ~
\text{previousSpatialExams_dummy}, \ data=\text{consolidatedSpaDataW18_TDF})
priorGraphicsDrafting_dummy IS (KIND OF) SIGNIFICANT on its own (0.09331)

This shows others getting worse (note: this is linked to how much better the engineering graphics students get because they are the only ones who maybe have not had a graphics class before - it emphasizes how much of an impact having that experience before or during ENGR GRAPHICS is)

durationLm.fnOf.priorGraphicsDrafting_dummy <- lm(mctDurationGrowth ~ priorGraphicsDrafting_dummy, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.priorGraphicsDrafting_dummy.no1823 <- lm(mctDurationGrowth ~ priorGraphicsDrafting_dummy, data=removedSDW1823.DF)

#summary(durationLm.fnOf.priorGraphicsDrafting_dummy) #only significant if SDW1823 is included

apa.reg.table(durationLm.fnOf.priorGraphicsDrafting_dummy, filename = "mctDurationGrowth_fnPriorGraphicsLmTable.doc", table.number = 1)

isEmployed_Break_dummy is not significant on its own

durationLm.fnOf.isEmployed_Break_dummy <- lm(mctDurationGrowth ~ isEmployed_Break_dummy, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.isEmployed_Break_dummy)

Don't run this one for winter dataset because the only non-0 datapoint is suspect

durationLm.fnOf.hasCoursework_Break_dummy <- lm(mctDurationGrowth ~ hasCoursework_Break_dummy, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.hasCoursework_Break_dummy)

CourseNotAdvDynamics IS SIGNIFICANT on its own (0.0401)

durationLm.fnOf.CourseNotAdvDynamics <- lm(mctDurationGrowth ~ CourseNotAdvDynamics, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.CourseNotAdvDynamics)

CourseIsAdvDynamics IS SIGNIFICANT on its own (0.040078) [as it should be, based on previous results]

durationLm.fnOf.CourseIsAdvDynamics <- lm(mctDurationGrowth ~ CourseIsAdvDynamics, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.CourseIsAdvDynamics)

CourseIsEngrGraphics IS (KIND OF) SIGNIFICANT on its own (0.0795)

durationLm.fnOf.CourseIsEngrGraphics <- lm(mctDurationGrowth ~ CourseIsEngrGraphics, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.CourseIsEngrGraphics)

CourseIsStatics is not significant on its own

durationLm.fnOf.CourseIsStatics <- lm(mctDurationGrowth ~ CourseIsStatics, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.CourseIsStatics)

Covered earlier in the discussion

durationLm.fnOf.CourseRecruitedFrom <- lm(mctDurationGrowth ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)

#summary(durationLm.fnOf.CourseRecruitedFrom)

classificationHomeTown IS SIGNIFICANT on its own (0.0101) [that is, Urban is significantly different than rural]

durationLm.fnOf.classificationHomeTown <- lm(mctDurationGrowth ~ classificationHomeTown, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.classificationHomeTown.no1823 <- lm(mctDurationGrowth ~ classificationHomeTown, data=removedSDW1823.DF)

#summary(durationLm.fnOf.classificationHomeTown) #only significant if SDW1823 is included

apa.reg.table(durationLm.fnOf.classificationHomeTown, filename = "mctDurationGrowth_fnClassificationLmTable.doc", table.number = 1)
"mctDurationGrowth_fnHometownLmTable.doc", table.number = 1)
#summary(durationLm.fnOf.classificationHomeTown.no1823) # not significant

##Check binomial and factor variables vs mctScoreImprovement
#BioSex_Numeric is not significant on its own
#scoreChangeLm.fnOf.BioSex_Numeric <- lm(mctScoreImprovement ~ BioSex_Numeric, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.BioSex_Numeric)

#isMarried_Numeric is not significant on its own
#scoreChangeLm.fnOf.isMarried_Numeric <- lm(mctScoreImprovement ~ isMarried_Numeric, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.isMarried_Numeric)

# RaceEthnicityWhite_Numeric not significant on its own
#scoreChangeLm.fnOf.RaceEthnicityWhite_Numeric <- lm(mctScoreImprovement ~ RaceEthnicityWhite_Numeric, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.RaceEthnicityWhite_Numeric)

#RepeatClass_dummy is not significant on its own
#scoreChangeLm.fnOf.RepeatClass_dummy <- lm(mctScoreImprovement ~ RepeatClass_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.RepeatClass_dummy)

#isEmployed_School_dummy is not significant on its own
#scoreChangeLm.fnOf.isEmployed_School_dummy <- lm(mctScoreImprovement ~ isEmployed_School_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.isEmployed_School_dummy)

#previousSpatialExams_dummy is not significant on its own
#scoreChangeLm.fnOf.previousSpatialExams_dummy <- lm(mctScoreImprovement ~ previousSpatialExams_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.previousSpatialExams_dummy)

#priorGraphicsDrafting_dummy is not significant on its own
#scoreChangeLm.fnOf.priorGraphicsDrafting_dummy <- lm(mctScoreImprovement ~ priorGraphicsDrafting_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.priorGraphicsDrafting_dummy)

#isEmployed_Break_dummy is not significant on its own
#scoreChangeLm.fnOf.isEmployed_Break_dummy <- lm(mctScoreImprovement ~ isEmployed_Break_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.isEmployed_Break_dummy)

# Don’t run this one for winter dataset because the only non-0 datapoint is suspect
#scoreChangeLm.fnOf.hasCoursework_Break_dummy <- lm(mctScoreImprovement ~ hasCoursework_Break_dummy, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.hasCoursework_Break_dummy)

#CourseNotAdvDynamics is not significant on its own
#scoreChangeLm.fnOf.CourseNotAdvDynamics <- lm(mctScoreImprovement ~ CourseNotAdvDynamics, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.CourseNotAdvDynamics)

#CourseIsAdvDynamics is not significant on its own
#scoreChangeLm.fnOf.CourseIsAdvDynamics <- lm(mctScoreImprovement ~ CourseIsAdvDynamics, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.CourseIsAdvDynamics)

#CourseIsEngrGraphics is not significant on its own
#scoreChangeLm.fnOf.CourseIsEngrGraphics <- lm(mctScoreImprovement ~ CourseIsEngrGraphics, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.CourseIsEngrGraphics)

#CourseIsStatics is not significant on its own
#scoreChangeLm.fnOf.CourseIsStatics <- lm(mctScoreImprovement ~ CourseIsStatics, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.CourseIsStatics)

#CourseRecruitedFrom was covered earlier in the discussion
#scoreChangeLm.fnOf.CourseRecruitedFrom <- lm(mctScoreImprovement ~ CourseRecruitedFrom, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.CourseRecruitedFrom)

#classificationHomeTown is not significant on its own
#scoreChangeLm.fnOf.classificationHomeTown <- lm(mctScoreImprovement ~ classificationHomeTown, data=consolidatedSpaDataW18_TDF)
#summary(scoreChangeLm.fnOf.classificationHomeTown)

##Check scaled quantitative variables vs mctDurationGrowth
#BlockPlay_Child_Numeric.scaled is not significant on its own
#durationLm.fnOf.BlockPlay_Child_Numeric <- lm(mctDurationGrowth ~ BlockPlay_Child_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.BlockPlay_Child_Numeric)

#priorXP_MdlPzzl_Numeric.scaled not significant on its own
#durationLm.fnOf.priorXP_MdlPzzl_Numeric.scaled <- lm(mctDurationGrowth ~ priorXP_MdlPzzl_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_MdlPzzl_Numeric)

#priorXP_RCToys_Numeric.scaled is not significant on its own
#durationLm.fnOf.priorXP_RCToys_Numeric.scaled <- lm(mctDurationGrowth ~ priorXP_RCToys_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_RCToys_Numeric)

#numberOfChildren_Numeric.scaled is not significant on its own
#durationLm.fnOf.numberOfChildren_Numeric.scaled <- lm(mctDurationGrowth ~ numberOfChildren_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.numberOfChildren_Numeric)

#hoursWeekly_Employed_Break.scaled.Numeric is not significant on its own
#durationLm.fnOf.hoursWeekly_Employed_Break.scaled.Numeric <- lm(mctDurationGrowth ~ hoursWeekly_Employed_Break.scaled.Numeric, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.hoursWeekly_Employed_Break)

#hoursMonthly_Activities_Break.scaled.numeric is not significant on its own
#durationLm.fnOf.hoursMonthly_Activities_Break.numeric <- lm(mctDurationGrowth ~ hoursMonthly_Activities_Break.numeric, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.hoursMonthly_Activities_Break.numeric)

#previousSpatialExams_count.scaled is not significant on its own
#durationLm.fnOf.previousSpatialExams_count.scaled <- lm(mctDurationGrowth ~ previousSpatialExams_count.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.previousSpatialExams_count)

#priorGraphicsDraftingTypes_count.scaled is ALMOST significant on its own (0.10562)
durationLm.fnOf.priorGraphicsDraftingTypes_count.scaled <- lm(mctDurationGrowth ~ priorGraphicsDraftingTypes_count.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.priorGraphicsDraftingTypes_count.no1823 <- lm(mctDurationGrowth ~
~ priorGraphicsDraftingTypes_count.scaled, data=removedSDW1823.DF)

#summary(durati
onLm.fnOf.priorGraphicsDraftingTypes_count)
#apa.reg.table(durati
onLm.fnOf.priorGraphicsDraftingTypes_count, filename =
"mctDurationGrowth fnGraphicsCountLmTable.doc", table.number = 1)
#summary(durati
onLm.fnOf.priorGraphicsDraftingTypes_count.no1823) #not significant without SDW1823 (0.2926)

#Age.scaled is not significant on its own
#durationLm.fnOf.Age <- lm(mctDurationGrowth ~ Age.scaled,
data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.Age)

#GPA.scaled IS SIGNIFICANT on its own
durationLm.fnOf.GPA <- lm(mctDurationGrowth ~ GPA.scaled,
data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.GPA.no1823 <- lm(mctDurationGrowth ~ GPA.scaled,
data=removedSDW1823.DF)
#summary(durati
onLm.fnOf.GPA)
#apa.reg.table(durati
onLm.fnOf.GPA, filename =
"mctDurationGrowth fnGpaLmTable.doc", table.number = 1)
#summary(durati
onLm.fnOf.GPA.no1823) # Not quite significant without SDW1823 (0.15254)

#priorXP_FIRST_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_FIRST_Scale <- lm(mctDurationGrowth ~ priorXP_FIRST_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_FIRST_Scale)

#priorXP_JETS_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_JETS_Scale <- lm(mctDurationGrowth ~ priorXP_JETS_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_JETS_Scale)

#priorXP_VEX_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_VEX_Scale <- lm(mctDurationGrowth ~ priorXP_VEX_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_VEX_Scale)

#priorXP_ThinkQuest_Scale.scaled IS SIGNIFICANT on its own (0.000194), but homoscedasticity is a problem
#durationLm.fnOf.priorXP_ThinkQuest_Scale <- lm(mctDurationGrowth ~ priorXP_ThinkQuest_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_ThinkQuest_Scale)

#priorXP_LegoEngr_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_LegoEngr_Scale <- lm(mctDurationGrowth ~ priorXP_LegoEngr_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_LegoEngr_Scale)

#priorXP_OdysseyOfMind_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_OdysseyOfMind_Scale <- lm(mctDurationGrowth ~ priorXP_OdysseyOfMind_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_OdysseyOfMind_Scale)

#priorXP_Minecraft_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Minecraft_Scale <- lm(mctDurationGrowth ~ priorXP_Minecraft_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_Minecraft_Scale)

#priorXP_ErectorSets_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_ErectorSets_Scale <- lm(mctDurationGrowth ~ priorXP_ErectorSets_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durati
onLm.fnOf.priorXP_ErectorSets_Scale)
##priorXP_Legos_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Legos_Scale <- lm(mctDurationGrowth ~
priorXP_Legos_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Legos_Scale)

##priorXP_Tetris_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Tetris_Scale <- lm(mctDurationGrowth ~
priorXP_Tetris_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Tetris_Scale)

##priorXP_1stPersonVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_1stPersonVideoGame_Scale <- lm(mctDurationGrowth ~
priorXP_1stPersonVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_1stPersonVideoGame_Scale)

##priorXP_Other3DVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Other3DVideoGame_Scale <- lm(mctDurationGrowth ~
priorXP_Other3DVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Other3DVideoGame_Scale)

##priorXP_2DPuzzleVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_2DPuzzleVideoGame_Scale <- lm(mctDurationGrowth ~
priorXP_2DPuzzleVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_2DPuzzleVideoGame_Scale)

##priorXP_2DStrategyGames_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_2DStrategyGames_Scale <- lm(mctDurationGrowth ~
priorXP_2DStrategyGames_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_2DStrategyGames_Scale)

##priorXP_Woodwork_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Woodwork_Scale <- lm(mctDurationGrowth ~
priorXP_Woodwork_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Woodwork_Scale)

##priorXP_Weld_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Weld_Scale <- lm(mctDurationGrowth ~
priorXP_Weld_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Weld_Scale)

##priorXP_Fabrication_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Fabrication_Scale <- lm(mctDurationGrowth ~
priorXP_Fabrication_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Fabrication_Scale)

##priorXP_Electronics_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Electronics_Scale <- lm(mctDurationGrowth ~
priorXP_Electronics_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Electronics_Scale)

##priorXP_Mechanics_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Mechanics_Scale <- lm(mctDurationGrowth ~
priorXP_Mechanics_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Mechanics_Scale)

##priorXP_Cabinetry_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Cabinetry_Scale <- lm(mctDurationGrowth ~
priorXP_Cabinetry_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Cabinetry_Scale)

##priorXP_BuildComputers_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_BuildComputers_Scale <- lm(mctDurationGrowth ~
priorXP_BuildComputers_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_BuildComputers_Scale)

#priorXP_Garden_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Garden_Scale <- lm(mctDurationGrowth ~ priorXP_Garden_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Garden_Scale)

#priorXP_ArtPaint_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_ArtPaint_Scale <- lm(mctDurationGrowth ~ priorXP_ArtPaint_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_ArtPaint_Scale)

#priorXP_ArtDraw_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_ArtDraw_Scale <- lm(mctDurationGrowth ~ priorXP_ArtDraw_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_ArtDraw_Scale)

#priorXP_ResCommPaint_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_ResCommPaint_Scale <- lm(mctDurationGrowth ~ priorXP_ResCommPaint_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_ResCommPaint_Scale)

#priorXP_Constuction_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Constuction_Scale <- lm(mctDurationGrowth ~ priorXP_Constuction_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Constuction_Scale)

#priorXP_Sew_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Sew_Scale <- lm(mctDurationGrowth ~ priorXP_Sew_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Sew_Scale)

#priorXP_Embroidery_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Embroidery_Scale <- lm(mctDurationGrowth ~ priorXP_Embroidery_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Embroidery_Scale)

#priorXP_Cook_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Cook_Scale <- lm(mctDurationGrowth ~ priorXP_Cook_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Cook_Scale)

#priorXP_Dance_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_Dance_Scale <- lm(mctDurationGrowth ~ priorXP_Dance_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_Dance_Scale)

#priorXP_Sports_Scale.scaled is ALMOST significant on its own (0.10063)
durationLm.fnOf.priorXP_Sports_Scale <- lm(mctDurationGrowth ~ priorXP_Sports_Scale.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.priorXP_Sports_Scale.no1823 <- lm(mctDurationGrowth ~ priorXP_Sports_Scale.scaled, data=removedSDW1823.DF)
summary(durationLm.fnOf.priorXP_Sports_Scale)
summary(durationLm.fnOf.priorXP_Sports_Scale.no1823) # not quite significant (0.15384) without SDW1823

#priorXP_PlayMusic_Scale.scaled is not significant on its own
#durationLm.fnOf.priorXP_PlayMusic_Scale <- lm(mctDurationGrowth ~ priorXP_PlayMusic_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.priorXP_PlayMusic_Scale)

#breakTime_MdlPzzl_Numeric.scaled is not significant on its own
#durationLm.fnOf.breakTime_MdlPzzl_Numeric <- lm(mctDurationGrowth ~ breakTime_MdlPzzl_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakTime_MdlPzzl_Numeric)

#breakTime_RCToys_Numeric.scaled is not significant on its own
#durationLm.fnOf.breakTime_RCToys_Numeric <- lm(mctDurationGrowth ~ breakTime_RCToys_Numeric.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakTime_RCToys_Numeric)

#breakXP_VEX_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_VEX_Scale <- lm(mctDurationGrowth ~ breakXP_VEX_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_VEX_Scale)

#breakXP_Minecraft_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Minecraft_Scale <- lm(mctDurationGrowth ~ breakXP_Minecraft_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Minecraft_Scale)

#breakXP_Legos_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Legos_Scale <- lm(mctDurationGrowth ~ breakXP_Legos_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Legos_Scale)

#breakXP_Tetris_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Tetris_Scale <- lm(mctDurationGrowth ~ breakXP_Tetris_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Tetris_Scale)

#breakXP_1stPersonVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_1stPersonVideoGame_Scale <- lm(mctDurationGrowth ~ breakXP_1stPersonVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_1stPersonVideoGame_Scale)

#breakXP_Other3DVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Other3DVideoGame_Scale <- lm(mctDurationGrowth ~ breakXP_Other3DVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Other3DVideoGame_Scale)

#breakXP_2DPuzzleVideoGame_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_2DPuzzleVideoGame_Scale <- lm(mctDurationGrowth ~ breakXP_2DPuzzleVideoGame_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_2DPuzzleVideoGame_Scale)

#breakXP_2DStrategyGames_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_2DStrategyGames_Scale <- lm(mctDurationGrowth ~ breakXP_2DStrategyGames_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_2DStrategyGames_Scale)

#breakXP_Woodwork_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Woodwork_Scale <- lm(mctDurationGrowth ~ breakXP_Woodwork_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Woodwork_Scale)

#breakXP_Weld_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Weld_Scale <- lm(mctDurationGrowth ~ breakXP_Weld_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Weld_Scale)

#breakXP_Fabrication_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Fabrication_Scale <- lm(mctDurationGrowth ~ breakXP_Fabrication_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Fabrication_Scale)
#breakXP_Electronics_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Electronics_Scale <- lm(mctDurationGrowth ~ breakXP_Electronics_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Electronics_Scale)

#breakXP_Mechanics_Scale.scaled is ALMOST significant on its own (0.12012)
durationLm.fnOf.breakXP_Mechanics_Scale <- lm(mctDurationGrowth ~ breakXP_Mechanics_Scale.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.breakXP_Mechanics_Scale.no1823 <- lm(mctDurationGrowth ~ breakXP_Mechanics_Scale.scaled, data=removedSDW1823.DF)
summary(durationLm.fnOf.breakXP_Mechanics_Scale)
summary(durationLm.fnOf.breakXP_Mechanics_Scale.no1823) # ALMOST significant (0.12061) without SDW1823

#breakXP_Cabinetry_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Cabinetry_Scale <- lm(mctDurationGrowth ~ breakXP_Cabinetry_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Cabinetry_Scale)

#breakXP_BuildComputers_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_BuildComputers_Scale <- lm(mctDurationGrowth ~ breakXP_BuildComputers_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_BuildComputers_Scale)

#breakXP_Garden_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Garden_Scale <- lm(mctDurationGrowth ~ breakXP_Garden_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Garden_Scale)

#breakXP_ArtPaint_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_ArtPaint_Scale <- lm(mctDurationGrowth ~ breakXP_ArtPaint_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_ArtPaint_Scale)

#breakXP_ArtDraw_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_ArtDraw_Scale <- lm(mctDurationGrowth ~ breakXP_ArtDraw_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_ArtDraw_Scale)

#breakXP_Construction_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Construction_Scale <- lm(mctDurationGrowth ~ breakXP_Construction_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Construction_Scale)

#breakXP_Sew_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Sew_Scale <- lm(mctDurationGrowth ~ breakXP_Sew_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Sew_Scale)

#breakXP_Cook_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Cook_Scale <- lm(mctDurationGrowth ~ breakXP_Cook_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Cook_Scale)

#breakXP_Dance_Scale.scaled IS (KIND OF) SIGNIFICANT on its own (0.09605)
durationLm.fnOf.breakXP_Dance_Scale <- lm(mctDurationGrowth ~ breakXP_Dance_Scale.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.breakXP_Dance_Scale.no1823 <- lm(mctDurationGrowth ~ breakXP_Dance_Scale.scaled, data=removedSDW1823.DF)
#summary(durationLm.fnOf.breakXP_Dance_Scale)
#summary(durationLm.fnOf.breakXP_Dance_Scale.no1823) #IS NOT SIGNIFICANT without SDW1823
#breakXP_Sports_Scale.scaled is not significant on its own
#durationLm.fnOf.breakXP_Sports_Scale <- lm(mctDurationGrowth ~
breakXP_Sports_Scale.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.breakXP_Sports_Scale)

#breakXP_PlayMusic_Scale.scaled is significant on its own (0.03703)
durationLm.fnOf.breakXP_PlayMusic_Scale <- lm(mctDurationGrowth ~
breakXP_PlayMusic_Scale.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.breakXP_PlayMusic_Scale.no1823 <- lm(mctDurationGrowth ~
breakXP_PlayMusic_Scale.scaled, data=removedSDW1823.DF)
#summary(durationLm.fnOf.breakXP_PlayMusic_Scale)
#apa.reg.table(durationLm.fnOf.breakXP_PlayMusic_Scale, filename =
"mctDurationGrowth_fnPlayMusicLmTable.doc", table.number = 1)
#summary(durationLm.fnOf.breakXP_PlayMusic_Scale.no1823) # is not really
significant (0.19799) without SDW1823

#hoursWeekly_Study_Break.scaled is (ALMOST) significant on its own (0.10359)
durationLm.fnOf.hoursWeekly_Study_Break <- lm(mctDurationGrowth ~
hoursWeekly_Study_Break.scaled, data=consolidatedSpaDataW18_TDF)
durationLm.fnOf.hoursWeekly_Study_Break.no1823 <- lm(mctDurationGrowth ~
hoursWeekly_Study_Break.scaled, data=removedSDW1823.DF)
#summary(durationLm.fnOf.hoursWeekly_Study_Break)
#summary(durationLm.fnOf.hoursWeekly_Study_Break.no1823) # is not significant
without SDW1823

#count_Activities_Break.scaled is not significant on its own
#durationLm.fnOf.count_Activities_Break <- lm(mctDurationGrowth ~
count_Activities_Break.scaled, data=consolidatedSpaDataW18_TDF)
#summary(durationLm.fnOf.count_Activities_Break)

simpleDiagnostics.r

#!/------------------------------------------------------------------------
# singleIvDiagnostics()
#    Creates plots of histogram, stacked histogram, leverage, DFFITS, DFBETA,
#    and identifies outliers for leverage, DFFITS, and DFBETAs.
#    Returns the dataframe with new columns for outlier identification added.
#    Does not look at VIF (collinearity).
#    Requires that the car library be loaded for Q-Q Plots.
#
#/////////////////////////////////////////////////////////////////////
#singleIvDiagnostics <- function(dfData, dvIndex, dvShortName, ivIndex,
#ivShortName, idIndex) {
    #make sure that none of the input values have NA values
    if (anyNA(dfData[[dvIndex]])) {
        stop("The D.V. contains an NA value")
    }

    mainDir = getwd()
    dvSubDir = dvShortName
    dir.create(file.path(mainDir, dvSubDir), showWarnings = FALSE)
    setwd(file.path(mainDir, dvSubDir))
    
    if (anyNA(dfData[[ivIndex]])) {
        printFilename =
paste0("DiagnosticNote_for_",dvShortName,"_fnOf_",ivShortName,".txt")
        sink(printFilename, append=FALSE, split=FALSE)
        # model details
        print(paste0("dv = ", dvShortName, ", iv = ", ivShortName))
    }
print(paste0("The I.V., ", ivShortName, ", contains an NA value"))
sink() # end output to a file
setwd(mainDir)
stop(paste0("The I.V., ", ivShortName, ", contains an NA value"))
}

dvMainDir = getwd()
ivSubDir = ivShortName
dir.create(file.path(dvMainDir, ivSubDir), showWarnings = FALSE)
setwd(file.path(dvMainDir, ivSubDir))

# loop through the values in the vector as indices for the I.V.'s
# For each I.V.:
print(ivShortName)
# Create a model of just that I.V. and the D.V.
singleIvLm <- lm(dfData[[dvIndex]] ~ dfData[[ivIndex]])
# Residual plot (resids as a function of I.V.)
residDiagSingleIvLm = resid(singleIvLm)
print(dvShortName)
mainLabel = paste0("Residuals for ",dvShortName,"("",ivShortName,"")")
# save the plot
plotFilename =
paste0("ResidualsFor_",dvShortName,"_fnOf_",ivShortName,".tiff")
tiff(plotFilename)
plot(dfData[[ivIndex]], residDiagSingleIvLm, xlab=ivShortName, ylab="Residual of Bi-Variate Model", main=mainLabel)
dev.off() # end of saving plot

# Mean resids plot (as a function of I.V.)
mainLabel = paste0("Mean Residuals for ",dvShortName,"("",ivShortName,"")")
if (is.numeric(dfData[[ivIndex]])) {
  ivCategories <- as.factor(dfData[[ivIndex]])
  # save the plot
  plotFilename =
paste0("MeanResidualsFor_",dvShortName,"_fnOf_",ivShortName,".tiff")
tiff(plotFilename)
  plot(ivCategories, residDiagSingleIvLm, xlab=ivShortName, ylab="Residual of Bi-Variate Model", main=mainLabel)
dev.off() # end of saving plot
} else {
  # the residual plot above should appear as a box-plot that shows the means already
}

# Histogram & QQ Plots
if (is.numeric(dfData[[ivIndex]])) {
  ivMinValue = min(dfData[[ivIndex]])
  ivMaxValue = max(dfData[[ivIndex]])
  binLimitLow = ivMinValue-0.5
  binLimitHigh = ivMaxValue+0.5
  ivBins = c(binLimitLow:binLimitHigh)
  # save the plot
  mainLabel = paste0("Histogram of ",ivShortName)
  plotFilename = paste0("Histogram_",ivShortName,".tiff")
tiff(plotFilename)
  hist(dfData[[ivIndex]], col="GRAY",main=mainLabel, xlab=ivShortName)
dev.off() # end of saving plot
}

if("package:car" %in% search()){
  ## Q-Q Plot for demonstrating normalcy
  mainLabel = paste0("Q-Q Plot of ",ivShortName)
  xlabel = paste0("Quantile of ",ivShortName)
}
plotFilename = paste0("qqPlot_", ivShortName, ".tiff")
tiff(plotFilename)
qqPlot(dfData[[ivIndex]], main= mainLabel, xlab= xlabel,
ylab="Quantile of Normal Distribution")
dev.off() # end of saving plot
else {
  print("The car library/package is not found, cannot use qqPlot")
}

# Calculated diagnostic parameters
diagnosticSingleIvLm.k <- length(attr(singleIvLm$terms,"term.labels"))
kValueText = paste0("'k' for the linear model: ", diagnosticSingleIvLm.k)
print(kValueText)
diagnosticSingleIvLm.n <- length(dfData[[ivIndex]])
nValueText = paste0("'n' for the linear model: ", diagnosticSingleIvLm.n)
print(nValueText)

# Leverage plot
leverageLabel = paste0("ivHatLeverage_", ivShortName)
leverageOutlierLabel = paste0("outlierLeverage_", ivShortName)
dfData[[leverageLabel]] <- hatvalues(singleIvLm)

### TODO: Figure out how to add columns by index (e.g. find the last index
# for a dataframe, and then add onto it to store new data)
mainLabel = paste0("Leverage for ", dvShortName, " (", ivShortName, ")")
# save the plot
plotFilename = paste0("LeverageFor_", dvShortName, ",_fnOf_", ivShortName, ",.tiff")
tiff(plotFilename)
plot(dfData[[idIndex]], dfData[[leverageLabel]], main=mainLabel)

# calculate Leverage cutoff
leverageCutoff = 3*diagnosticSingleIvLm.k/diagnosticSingleIvLm.n
abline(h=leverageCutoff)

# leverageCutoff = 0.0175
# abline(h=.0175)

# identify data points that exceed the cutoff
dfData[[leverageOutlierLabel]] <- as.numeric(dfData[[leverageLabel]]>leverageCutoff)
outlierLeverageData <- subset(dfData,
  dfData[[leverageLabel]]>leverageCutoff) # leverage is positive, so no need to
# check for below negative cutoff
if (nrow(outlierLeverageData)>0) {
  text(outlierLeverageData[[idIndex]],
  outlierLeverageData[[leverageLabel]], outlierLeverageData[[idIndex]],pos=4)
}
dev.off() # end of saving plot

outlierCountLeverage = paste0("Number of outliers for Leverage ",
  dvShortName, " (", ivShortName, ")": ", nrow(outlierLeverageData)
print(outlierCountLeverage)

leverageCutText = paste0("Leverage cutoff for the linear model (3*k/n): ",
  leverageCutoff)
print(leverageCutText)

# Influence (DFFIT) plot
dffitLabel = paste0("DFFIT_", ivShortName)
dffitOutlierLabel = paste0("outlierDFFIT_", ivShortName)
dfData[[dffitLabel]] <- dffits(singleIvLm)

### TODO: Figure out how to add columns by index (e.g. find the last index
# for a dataframe, and then add onto it to store new data)
mainLabel = paste0("DFFIT for ", dvShortName, " (", ivShortName, ")")
# save the plot
plotFilename = paste0("DffitFor_", dvShortName, ",_fnOf_", ivShortName, ",.tiff")
```r
tiff(plotFilename)
plot(dfData[[idIndex]], dfData[[dffitLabel]], main=mainLabel)
# calculate DFFIT cutoff
largeDataDffitCutoff = 2*sqrt((diagnosticSingleIvLm.k+1)/diagnosticSingleIvLm.n)
smallDataDffitCutoff = 1
selectedDffitcutoff = largeDataDffitCutoff
abline(h=selectedDffitcutoff)
abline(h=-selectedDffitcutoff)
# identify data points that exceed the cutoff
dfData[ [dffitOutlierLabel] ] <- as.numeric(dfData[[dffitLabel]] > selectedDffitcutoff | dfData[[dffitLabel]] < (-selectedDffitcutoff))
outlierDffitData <- subset(dfData, dfData[[dffitLabel]] > selectedDffitcutoff | dfData[[dffitLabel]] < (-selectedDffitcutoff))
if (nrow(outlierDffitData)>0) {
text(outlierDffitData[[idIndex]], outlierDffitData[[dffitLabel]], outlierDffitData[[idIndex]],pos=4)
}
dev.off() # end of saving plot
outlierCountDffit = paste0("Number of outliers for DFFIT ", dvShortName, ", ivShortName, ": ", nrow(outlierDffitData))
print(outlierCountDffit)
dffitCutText = paste0("Influence (DFFIT) cutoff for the large data (2*sqrt((k+1)/n)): ", selectedDffitcutoff)
print(dffitCutText)
```

```r
# Influence (DFBETA) plots
dfData$SingleIvDfbeta <- dbeta(singleIvLm)
### TODO: Figure out how to add columns by index (e.g. find the last index for a dataframe, and then add onto it to store new data)
# calculate DFBETA cutoff
largeDataDfbetaCutoff = 2/sqrt(diagnosticSingleIvLm.n)
# DFBETA intercept plot
mainLabel = paste0("DFBETA for ", dvShortName, "(", ivShortName, ") Intercept")
# save the plot
plotFilename = paste0("DfbetaInterceptFor_",dvShortName,"_fnOf_",ivShortName,".tiff")
tiff(plotFilename)
plot(dfData[[idIndex]], dfData$SingleIvDfbeta[,1], main=mainLabel)
abline(h=largeDataDfbetaCutoff)
abline(h=-largeDataDfbetaCutoff)
# identify DFBETA intercept data points that exceed the cutoff
outlierDfbeta1Data <- subset(dfData, dfData$SingleIvDfbeta[,1] > largeDataDfbetaCutoff | dfData$SingleIvDfbeta[,1] < (-largeDataDfbetaCutoff))
if (nrow(outlierDfbeta1Data)>0) {
text(outlierDfbeta1Data[[idIndex]], outlierDfbeta1Data$SingleIvDfbeta[,1], outlierDfbeta1Data[[idIndex]],pos=4)
}
dev.off() # end of saving plot
outlierCountDfbeta1 = paste0("Number of outliers for DFBETA intercept ", dvShortName, "(", ivShortName, ") Intercept")
print(outlierCountDfbeta1)
```
abline(h=largeDataDfbetaCutoff)
abline(h=-largeDataDfbetaCutoff)

# identify DFBETA slope data points that exceed the cutoff
outlierDfbeta2Data <- subset(dfData, dfData$SingleIvDfbeta[,2] > largeDataDfbetaCutoff | dfData$SingleIvDfbeta[,2] < (-largeDataDfbetaCutoff))

if (nrow(outlierDfbeta2Data)>0) {
  text(outlierDfbeta2Data[[idIndex]],
       outlierDfbeta2Data$SingleIvDfbeta[,2], outlierDfbeta2Data[[idIndex]],pos=4)
}

dev.off() # end of saving plot

outlierCountDfbeta2 = paste0("Number of outliers for DFBETA slope ",

dvShortName, " (", ivShortName, "): ", nrow(outlierDfbeta2Data))

print(outlierCountDfbeta2)

dfbetaCutText = paste0("Influence (DFBETA) cutoff for the large data

(2/sqrt(n)): ", largeDataDfbetaCutoff)

print(dfbetaCutText)

# Output data to file instead of to plot figures

printFilename =
paste0("DescriptionsAndVif_ for ", dvShortName, ", fnOf ", ivShortName, ", .txt")

sink(printFilename, append=FALSE, split=FALSE)

# model details

print(paste0("dv = ", dvShortName, " , iv = ", ivShortName))

print(summary(singleIvLm))

# Outlier counts

print(outlierCountLeverage)

print(leveragCutText)

print(outlierCountDffit)

print(dffitCutText)

print(outlierCountDffit)

print(outlierCountDffit)

print(outlierCountDffit)

sink() # end output to a file

print(ivShortName)

# all done

setwd(mainDir) # return to original directory before proceeding

return(dfData)


#//////////////////////////////////////////////////////////////////////////////
# singleIvNonParamDiagnosticsWith3LevelCatVar()
#    Creates plots of loess, checks Spearman rank correlation, and checks
# Siegel
# nonparametric linear regression forthe DV-IV prediction. These checks are
# done for the DV-IV relationship as a whole and again for every level of the
# catVarIndex.
#  Requires that the mblm and rcompanion library for the mblm() function.
#  
#//////////////////////////////////////////////////////////////////////////////

singleIvNonParamDiagnosticsWith3LevelCatVar <- function(dfData, dvIndex, dvShortName, ivIndex, ivShortName, idIndex, catVarIndex) {

mainDir = getwd()

on.exit(print(paste0(dvShortName, " as a function of ", ivShortName, " with ", colnames(dfData)[[catVarIndex]], " categories.")))

setwd(mainDir)

return(dfData)

}

dvSubDir = dvShortName
dir.create(file.path(mainDir, dvSubDir), showWarnings = FALSE)
setwd(file.path(mainDir, dvSubDir))

# make sure that none of the input values have NA values
if (anyNA(dfData[[dvIndex]])) {
  textFilename =
  paste0("DiagnosticNote_for_", dvShortName,"_fnOf_", ivShortName,".txt")
  sink(textFilename, append=FALSE, split=FALSE)
  print("The D.V. contains an NA value")
  sink() # end output to a file
  stop("The D.V. contains an NA value")
}

if (anyNA(dfData[[ivIndex]])) {
  textFilename =
  paste0("DiagnosticNote_for_", dvShortName,"_fnOf_", ivShortName,".txt")
  sink(textFilename, append=FALSE, split=FALSE)
  # model details
  print(paste0("dv = ", dvShortName,", iv = ", ivShortName))
  print(paste0("The I.V., ", ivShortName,", contains an NA value"))
  sink() # end output to a file
  setwd(mainDir)
  stop(paste0("The I.V., ", ivShortName,", contains an NA value"))
}

if (anyNA(dfData[[catVarIndex]])) {
  textFilename =
  paste0("DiagnosticNote_for_CatVar_of_", dvShortName,"_fnOf_", ivShortName,".txt")
  sink(textFilename, append=FALSE, split=FALSE)
  # model details
  print(paste0("dv = ", dvShortName,", iv = ", ivShortName))
  print(paste0("The Category Variable contains an NA value"))
  sink() # end output to a file
  setwd(mainDir)
  stop(paste0("The Category Variable contains an NA value"))
}

dvMainDir = getwd()
ivSubDir = ivShortName
dir.create(file.path(dvMainDir, ivSubDir), showWarnings = FALSE)
setwd(file.path(dvMainDir, ivSubDir))

# For output of data to file in addition to plot figures
spanParameter <- 0.85

# Look at the whole model
# Perform Loess regressions
tryCatch({
suppressWarnings({
  loess.Gauss = loess(dfData[[dvIndex]] ~ dfData[[ivIndex]],
  data=dfData,
  span = spanParameter, ### higher numbers for smoother fits
  degree=2, ### use polynomials of order 2
  family="gaussian") ### the default, use least squares to fit
}), error = function(e) {
  # message(e)
  sink(textFilename, append=FALSE, split=FALSE)
  print("There has been an error with the Loess Gaussian approximation. Exiting...")
  sink()
  stop("There has been an error with the Loess Gaussian approximation. Exiting...")
})
#summary(loess.Gauss)
#      if (is.na(loess.Gauss$enp)) {
#         sink(textFilename, append=TRUE, split=FALSE)
#            print("The Loess Gaussian results are NA.")
#         sink()
#      } else {
# sink(textFilename, append=FALSE, split=FALSE)
# model details
#       print(paste0("dv = ", dvShortName, ", iv = ", ivShortName))
#       print(paste0("Gaussian Loess for ", dvShortName, ", as a function
of ", ivShortName))
#       print(summary(loess.Gauss))
#      }
#      }
#tryCatch({ suppressWarnings({loess.Symmetric = loess(dfData[[dvIndex]] ~
dfData[[ivIndex]],
    data=dfData,
    span = spanParameter,### higher numbers for
    degree=2,### use
polynomials of order 2
    family="symmetric")### the default, use least squares to
}))}, error = function(e) {
# message(e)
#      sink(textFilename, append=TRUE, split=FALSE)
# print("There has been an error with the Loess Symmetric
approximation. Exiting...")
#      sink()
# stop("There has been an error with the Loess Symmetric approximation.
Exiting..."))
#      }
#summary(loess.Symmetric)
#      if (is.na(loess.Symmetric$enp)) {
#         sink(textFilename, append=TRUE, split=FALSE)
#            print("The Loess Symmetric results are NA.")
#         sink()
#      } else {
# sink(textFilename, append=TRUE, split=FALSE)
# model details
#       print(paste0("Symmetric Loess for ", dvShortName, ", as a function
of ", ivShortName))
#       print(summary(loess.Symmetric))
#      }
#      }
## Loess regression plots
plotFilename = paste0("loessPlots_", ivShortName, ".tiff")
tiff(plotFilename)
plot(dfData[[dvIndex]] ~ dfData[[ivIndex]], dfData,
    xlab = ivShortName,
    ylab = dvShortName,
    main = "Full Dataset Loess Fits")
iv.j <- order(dfData[[ivIndex]])
lines(dfData[[ivIndex]][iv.j], loess.Gauss$fitted[iv.j], col = "blue",
lty="dashed")
lines(dfData[[ivIndex]][iv.j], loess.Symmetric$fitted[iv.j], col = "red",
lty="solid")
legend("topleft",c("Gaussian", "Symmetric"), col=c("blue", "red"),
lty=c("dashed", "solid")
dev.off() #end of saving plot
# Calculate Spearman's rho (rank correlation)
spearmanRho.corr <- cor.test(x=dfData[[ivIndex]], y=dfData[[dvIndex]],
method = 'spearman')

sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Spearman's rho rank correlation for ", dvShortName, " as a function of ", ivShortName, ":")
print(paste0("rho^2: ", spearmanRho.corr$estimate^2))
print(spearmanRho.corr)
sink()

# Perform Siegel nonparametric linear regression
if("package:mblm" %in% search()){
## Siegel nonparametric linear regression
string.biv.relationship = paste0(names(dfData)[[dvIndex]], " ~ ", names(dfData)[[ivIndex]])
bivariate.relationship = eval(parse(text=string.biv.relationship))
siegel.regression = mblm(bivariate.relationship, data=dfData)
#summary(siegel.regression)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Siegel nonparametric linear regression for ", dvShortName, " as a function of ", ivShortName))
print(summary(siegel.regression))
sink()
} else {

sink(textFilename, append=TRUE, split=FALSE)
print("The mblm library/package is not found, cannot use mblm")
sink()
stop(paste0("The mblm library/package is not found, cannot use mblm"))
}

# Look at each of the 3 category levels individually
catLevels = levels(dfData[[catVarIndex]])

# Look at Level 1
# Perform Loess regressions
Cat1.df = subset(dfData, dfData[[catVarIndex]]==catLevels[[1]])
tryCatch({ suppressWarnings({cat1.loess.Gauss = loess(cat1.df[[dvIndex]] ~ cat1.df[[ivIndex]],
          data=cat1.df,
          span = spanParameter, ### higher numbers for smoother fits
          degree=2, ### use polynomials of order 2
          family="gaussian" ### the default, use least squares to fit
        })), error = function(e) {
          # message(e)
          sink(textFilename, append=TRUE, split=FALSE)
          print(paste0("There has been an error with the ", catLevels[[1]], " Loess Gaussian approximation. Exiting..."))
          sink()
          stop(paste0("There has been an error with the ", catLevels[[1]], " Loess Gaussian approximation. Exiting..."))
        })
#summary(cat1.loess.Gauss)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Category = ", catLevels[[1]])
print(paste0("Gaussian Loess for ", dvShortName, ", as a function of ", ivShortName, " for just ", catLevels[[1]]))
print(summary(cat1.loess.Gauss))
sink()
tryCatch({ suppressWarnings({cat1.loess.Symmetric = loess(cat1.df[[dvIndex]] ~ cat1.df[[ivIndex]],
          data=cat1.df,
          span = spanParameter, ### higher numbers for smoother fits
          degree=2, ### use polynomials of order 2
          family="symmetric" ### the default, use least squares to fit
          family="gaussian" ### the default, use least squares to fit
        })), error = function(e) {
          # message(e)
          sink(textFilename, append=TRUE, split=FALSE)
          print(paste0("There has been an error with the ", catLevels[[1]], " Loess Gaussian approximation. Exiting..."))
          sink()
          stop(paste0("There has been an error with the ", catLevels[[1]], " Loess Gaussian approximation. Exiting..."))
        })
#summary(cat1.loess.Symmetric)
degree=2,           ### use polynomials of order 2
family="symmetric")  ### look at symmetric too
})}, error = function(e) {
  # message(e)
  sink(textFilename, append=TRUE, split=FALSE)
  print(paste0("There has been an error with the ", catLevels[[1]], "
Loess Symmetric approximation. Exiting..."))
  sink()
  stop(paste0("There has been an error with the ", catLevels[[1]], "
Loess Symmetric approximation. Exiting..."))
})
#summary(cat1.loess.Symmetric)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Symmetric Loess for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[1]]))
print(summary(cat1.loess.Symmetric))
sink()
## Loess regression plots
plotFilename = paste0("cat1LoessPlots_",ivShortName,".tiff")
tiff(plotFilename)
plot(cat1.df[[dvIndex]] ~ cat1.df[[ivIndex]], cat1.df,
xlab = ivShortName,
 ylab = dvShortName,
main = paste0(catLevels[[1]], " Loess Fits"))
iv.j <- order(cat1.df[[ivIndex]])
lines(cat1.df[[ivIndex]]][iv.j], cat1.loess.Gauss$fitted[iv.j], col = "blue", lty="dashed")
lines(cat1.df[[ivIndex]]][iv.j], cat1.loess.Symmetric$fitted[iv.j], col = "red", lty="solid")
legend("topleft",c("Gaussian", "Symmetric"), col=c("blue", "red"),
lty=c("dashed", "solid"))
dev.off() #end of saving plot

# Calculate Spearman's rho (rank correlation)
cat1.spearmanRho.corr <- cor.test(x=cat1.df[[ivIndex]],
y=cat1.df[[dvIndex]], method = 'spearman')
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Spearman's rho rank correlation for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[1]]))
print(paste0("rho^2: ", cat1.spearmanRho.corr$estimate^2))
print(cat1.spearmanRho.corr)
sink()

# Perform Siegel nonparametric linear regression
## Siegel nonparametric linear regression
cat1.siegel.regression = mblm(bivariate.relationship, data=cat1.df)
#summary(cat1.siegel.regression)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Siegel nonparametric linear regression for ",
dvShortName, ", as a function of ", ivShortName, " for just ", catLevels[[1]]))
print(summary(cat1.siegel.regression))
sink()

# Look at Level 2
# Perform Loess regressions
cat2.df = subset(dfData,dfData[[catVarIndex]]==catLevels[[2]])
tryCatch({ suppressWarnings({cat2.loess.Gauss = loess(cat2.df[[dvIndex]] ~ cat2.df[[ivIndex]]],
data=cat2.df,
span = spanParameter,        ### higher numbers for smoother
fits
  degree=2,           ### use polynomials of order 2
family="gaussian")  ### the default, use least squares to fit
error = function(e) {
  # message(e)
  sink(textFilename, append=TRUE, split=FALSE)
  print(paste0("There has been an error with the ", catLevels[[2]], ", Loess Gaussian approximation. Exiting..."))
  sink()
  stop(paste0("There has been an error with the ", catLevels[[2]], ", Loess Gaussian approximation. Exiting..."))
}
#summary(cat2.loess.Gauss)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Category = ", catLevels[[2]]))
print(paste0("Gaussian Loess for ", ivShortName, ", as a function of ", dvShortName, ", for just ", catLevels[[2]]))
print(summary(cat2.loess.Gauss))
sink()
tryCatch({
  suppressWarnings({
    cat2.loess.Symmetric = loess(cat2.df[[dvIndex]] ~ cat2.df[[ivIndex]],
    data=cat2.df,
    span = spanParameter, ### higher numbers for smoother fits
    degree=2, ### use polynomials of order 2
    family="symmetric" ### look at symmetric too
  })},
  error = function(e) {
    # message(e)
    sink(textFilename, append=TRUE, split=FALSE)
    stop(paste0("There has been an error with the ", catLevels[[2]], ", Loess Symmetric approximation. Exiting..."))
    sink()
    stop(paste0("There has been an error with the ", catLevels[[2]], ", Loess Symmetric approximation. Exiting..."))
  }
  #summary(cat2.loess.Symmetric)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Symmetric Loess for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[2]]))
print(summary(cat2.loess.Symmetric))
sink()
# Loess regression plots
plotFilename = paste0("cat2LoessPlots_", ivShortName, ".tiff")
tiff(plotFilename)
plot(cat2.df[[dvIndex]] ~ cat2.df[[ivIndex]], cat2.df,
  xlab = ivShortName,
  ylab = dvShortName,
  main = paste0(catLevels[[2]], ", Loess Fits"))
iv.j <- order(cat2.df[[ivIndex]])
lines(cat2.df[[ivIndex]][iv.j], cat2.loess.Gauss$fitted[iv.j], col = "blue", lty="dashed")
lines(cat2.df[[ivIndex]][iv.j], cat2.loess.Symmetric$fitted[iv.j], col = "red", lty="solid")
legend("topleft", c("Gaussian", "Symmetric"), col=c("blue", "red"), lty=c("dashed", "solid"))
dev.off() # end of saving plot

# Calculate Spearman's rho (rank correlation)
cat2.spearmanRho.corr <- cor.test(x=cat2.df[[ivIndex]],
y=cat2.df[[dvIndex]], method = 'spearman')
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Spearman's rho rank correlation for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[2]]))
print(paste0("rho^2: ", cat2.spearmanRho.corr$estimate^2))
print(cat2.spearmanRho.corr)
sink()}
# Perform Siegel nonparametric linear regression

## Siegel nonparametric linear regression

cat2.siegel.regression = mblm(bivariate.relationship, data=cat2.df)

#summary(cat2.siegel.regression)

sink(textFilename, append=TRUE, split=FALSE)

print(paste0("Siegel nonparametric linear regression for ",

dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[2]])

print(summary(cat2.siegel.regression))

sink()

# Look at Level 3

# Perform Loess regression

cat3.df = subset(dfData, dfData[[catVarIndex]]==catLevels[[3]])

tryCatch({
suppressWarnings({
cat3.loess.Gauss = loess(cat3.df[[dvIndex]] ~ cat3.df[[ivIndex]],

data=cat3.df,

span = spanParameter,       ### higher numbers for smoother

fits

degree=2,       ### use polynomials of order 2

family="gaussian")       ### the default, use least squares to fit

}), error = function(e) {

# message(e)

sink(textFilename, append=TRUE, split=FALSE)

print(paste0("There has been an error with the ",
catLevels[[3]], ",
Loess Gaussian approximation. Exiting..."))

sink()

stop(paste0("There has been an error with the ",
catLevels[[3]], ",
Loess Gaussian approximation. Exiting..."))

})

#summary(cat3.loess.Gauss)
sink(textFilename, append=TRUE, split=FALSE)

print(paste0("Category = ",
catLevels[[3]]))

print(paste0("Gaussian Loess for ",

dvShortName, ", as a function of ",

ivShortName, ", for just ",
catLevels[[3]])

print(summary(cat3.loess.Gauss))
sink()

tryCatch({
suppressWarnings({
cat3.loess.Symmetric =

loess(cat3.df[[dvIndex]] ~ cat3.df[[ivIndex]],

data=cat3.df,

span = spanParameter,       ### higher numbers for smoother

fits

degree=2,       ### use polynomials of order 2

family="symmetric")       ### look at symmetric too

}), error = function(e) {

# message(e)

sink(textFilename, append=TRUE, split=FALSE)

print(paste0("There has been an error with the ",
catLevels[[3]], ",
Loess Symmetric approximation. Exiting..."))

sink()

stop(paste0("There has been an error with the ",
catLevels[[3]], ",
Loess Symmetric approximation. Exiting..."))

})

#summary(cat3.loess.Symmetric)
sink(textFilename, append=TRUE, split=FALSE)

print(paste0("Symmetric Loess for ",

dvShortName, ", as a function of ",

ivShortName, ", for just ",
catLevels[[3]])

print(summary(cat3.loess.Symmetric))
sink()

## Loess regression plots

plotFilename = paste0("cat3LoessPlots_", ivShortName, ".tiff")

tiff(plotFilename)

plot(cat3.df[[dvIndex]] ~ cat3.df[[ivIndex]], cat3.df,
xlab = ivShortName,
ylab = dvShortName,
main = paste0(catLevels[[3]], " Loess Fits"))
iv.j <- order(cat3.df[[ivIndex]])
lines(cat3.df[[ivIndex]][, iv.j], cat3.loess.Gauss$fitted[iv.j], col = "blue", lty="dashed")
lines(cat3.df[[ivIndex]][, iv.j], cat3.loess.Symmetric$fitted[iv.j], col = "red", lty="solid")
legend("topleft",c("Gaussian", "Symmetric"), col=c("blue", "red"), lty=c("dashed", "solid"))
dev.off() #end of saving plot

# Calculate Spearman's rho (rank correlation)
cat3.spearmanRho.corr <- cor.test(x=cat3.df[[ivIndex]], y=cat3.df[[dvIndex]], method = 'spearman')
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Spearman's rho rank correlation for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[3]]))
print(paste0("rho^2: ", cat3.spearmanRho.corr$estimate^2))
sink()

# Perform Siegel nonparametric linear regression
## Siegel nonparametric linear regression
cat3.siegel.regression = mblm(bivariate.relationship, data=cat3.df)
#summary(cat3.siegel.regression)
sink(textFilename, append=TRUE, split=FALSE)
print(paste0("Siegel nonparametric linear regression for ", dvShortName, ", as a function of ", ivShortName, ", for just ", catLevels[[3]]))
print(summary(cat3.siegel.regression))
sink()
CURRICULUM VITAE

Benjamin Call
(December 2018)

EDUCATION:

PH.D., ENGINEERING EDUCATION – Defense: September 12, 2018, Utah State University, Logan, UT. Advisor: Dr. Wade Goodridge.
Dissertation Title: Spatial Ability Degradation in Undergraduate Mechanical Engineering Students During the Winter Semester Break
Research topics: spatial ability, creativity, self-efficacy, entrepreneurship.
Coursework topics: Foundations of education, learning and course assessment, educational research (quantitative and qualitative), online education, grant and proposal writing.

SYSTEMS ANALYSIS AND OPERATIONS RESEARCH, Coursework. 2012-2013, Naval Postgraduate School online.

DEPARTMENT OF DEFENSE SYSTEMS ENGINEERING CERTIFICATION:
DAWIA Level III, 2012, for Systems Planning, Research, Development and Engineering

M.S. & B.S., MECHANICAL ENGINEERING, (concurrent program) Aerospace Emphasis. 2006, Utah State University, Logan, UT. Graduate Advisor: Dr. Rees Fullmer.
Graduate Research and Project Topic: LADAR Simulation.

EMPLOYMENT HISTORY:

PRESIDENTIAL DOCTORAL RESEARCH FELLOW, September 2014 – Present. Utah State University, Logan, UT. Awarded after working one summer on graduate assistantship in Department of Engineering Education.

SOFTWARE ENGINEER, May 2014 – Present. ASI, Mendon, UT. MATLAB
developer for Agricultural product team and member of Systems & Validation functional group. Developing digital control system models, automated system tests, and embedded code generation for autonomous vehicles. Test planning, test execution, and team coordination within the Agile framework.

MECHANICAL ENGINEER, July 2006 – May 2014. Naval Air Warfare Center, Weapons Division (NAVAIR), China Lake, CA. Served as Division Lead for new analytical capability development and Team Lead for development of existing analytical software suite. Utilized Team Software Process. Planned development and presented to sponsors, management, and user base. Developed and managed a task portfolio totaling $700K+ annually from various sponsors and organizations.


TEST INTERN, May 2003 – August 2003. Orbital Sciences Corporation, Chandler, AZ. Supported tests on rocket fairings, isolators, and small technical components. Primary role was LabVIEW developer.

TECHNICAL TEACHING & MENTORING:

NUMERICAL METHODS FOR ENGINEERS (ENGR 2450), Instructor. Spring 2018.

TEACHING, LEARNING, & ASSESSMENT IN ENGINEERING EDUCATION (EED 6910/7150), Co-Instructor. Fall 2016.

ENGINEERING MECHANICS STATICS (ENGR 2010), Graduate Assistant and

**UNDERGRADUATE RESEARCH TEAM LEAD, Supervising Dr. Wade Goodridge**’s research team of undergraduate and graduate students. Summer 2016 – Present

**RESEARCH EXPERIENCES FOR UNDERGRADUATES (REU), Engineering education research for undergraduates funded by NSF, Graduate Mentor. Summer 2015 & 2016.**

**ENTREPRENEURSHIP CLUB CONSULTANT, September 2014 – May 2015.** Advised Commercialization Office and student businesses (various industries) at Utah State University.

**ENGINEER AND SCIENTIST DEVELOPMENT PROGRAM (NAWCWD), 2007-2014.** Mentored and collaborated with young engineers and physicists on military systems analysis and software development.

**PEER-REVIEWED PUBLICATIONS:**

**JOURNAL ARTICLES:**

http://www.jove.com/video/53327

**CONFERENCE PAPERS:**

Villanueva, I., Goodridge, W.H., **Call, B.J.** An initial exploration of engineering students’ emotive responses to spatial and engineering statics problems, *2018 ASEE*

https://peer.asee.org/29789


Call, B. J., Goodridge, W.H., Scheaffer, M.S. Entrepreneurial Motivations for High-Interest Students, *2017 ASEE Annual Conference & Exposition*, Columbus, OH,


Call, B. J., Goodridge, W. H., Sweeten, T. L. Spatial Ability Instrument Ceiling Effect and Implications, 2016 ASEE Annual Conference & Exposition, New Orleans, LA, June 2016.**

https://peer.asee.org/25849


https://peer.asee.org/25673


https://peer.asee.org/26594


http://www.aera.net/Publications/Online-Paper-Repository/AERA-Online-Paper-Repository/Owner/975026


https://peer.asee.org/24742


*Mentored undergraduate researchers, **Gave the presentation

OTHER PRESENTATIONS / CONFERENCE INVOLVEMENT:


Hansen, J., Goodridge, W.H., **Call, B.J.** Defining Directions for Future Spatial Ability Research: K-12 Math and Physics, *Oral Presentation at Utah State University’s...*
2017 Student Research Symposium, Logan, UT, 13 April 2017.*

Call, B.J., Goodridge, W.H, Green, C. Strategy, Task Performance, and Behavioral Themes from Students Solving 2-D and 3-D Force Equilibrium Problems, Oral Presentation at Utah State University’s 2015 Student Research Symposium, Logan, UT, 9 April 2015. Awarded “Excellent Oral Communicator” rating.**


*Undergraduate mentoring provided, ** Gave presentation(s)

SOCIETY MEMBERSHIP AND SERVICE:

AMERICAN SOCIETY FOR ENGINEERING EDUCATION:

• Published with the Engineering Research Methods, Mechanics, and Engineering Design Graphics Divisions

• Paper reviewer for the Entrepreneurship Division

BOY SCOUTS OF AMERICA:
• Adult Leadership Positions – held 2006-2014, 2017-Present

• Eagle Scout

PAST MEMBERSHIPS

• Directed Energy Professional Society

• American Institute of Aeronautics and Astronautics

• American Society of Mechanical Engineers (student member only)

• Tau Beta Pi

PROFESSIONAL COMPUTER SKILLS:

• MATLAB, Simulink, LabVIEW (simulation, control development, code generation)

• C/C++/C# in Visual Studio, Eclipse, TeamCity, TestComplete (development and automated testing)

• Process Dashboard (Team Software Process) & Jira (Agile/Scrum)

• R/SAS/SPSS Statistical packages

• Canvas learning management system for course development

• Adobe Connect Online / Defense Connect Online for online presentation/collaboration management

• Various specialty analytical tools for System Analysis

FOREIGN LANGUAGES:

ITALIAN