Spring 2024

Predicting Academic Performance of High School Students in College Level Classes Based on Intelligence and Time on Task

Michael Ryan
Shawnee State University

SHAWNEE STATE UNIVERSITY

Predicting Academic Performance of High School Students in College Level Classes Based on Intelligence and Time on Task

A Thesis

By

Michael Ryan

Department of Mathematical Sciences

Submitted in partial fulfillment of the requirements

For the degree of

Master of Science, Mathematics

July 24, 2024

Accepted by the Graduate Department

7/28/2024

Graduate Director, Date

The thesis entitled '**Predicting Academic Performance of High School Students in College Level Classes Based on Intelligence and Time on Task**' presented by **Michael Ryan**, a candidate for the degree of **Master of Science in Mathematics**, has been approved and is worthy of acceptance.

7/28/2024
Date

Graduate Director

7/28/2024
Date

Student

ABSTRACT

This study examined the academic performance of high school students who were taking college level courses sought to understand whether intelligence and time on task are significant predictors of student final grade in the course. The findings indicate that student intelligence and amount of time spent on practice tasks by a student both significantly predict a student's final grade in a college course, with both variables having a positive effect. Additionally, this study compared the mean grade for students in college math courses to the mean grade for students in college social studies courses while controlling for student math ability. No difference in mean course grade was found to be significant. These findings support previous literature on the relationship between intelligence and academic performance and provide some clarity on the equivocal relationship between time on task and academic performance. The study provides insight into understanding student differences as they stand at the interchange between high school and college and contributes to the overall picture of understanding how student characteristics contribute to their academic performance.

ACKNOWLEDGMENTS

Thank you to Jesus who helps guide me in life, helped guide me to pursuing a Master of Science degree in Mathematics, and has helped me to understand the mysteries of the universe that He created, especially those of mathematics, statistics, research, and measurement.

Thank you to Dr. Darbro who has spent years creating a research curriculum that is fine tuned so that students like me can learn research methodology step by step and write a thesis step by step. I am especially thankful for Dr. Darbro’s guidance in selecting a thesis topic and in providing many excellent examples that I could follow in writing this thesis.

Thank you to my friend, colleague, and administrator, Christopher Mays, for helping me in finalizing my data set and helping to prepare it for analysis.

Thank you to my wife, Jen, for being so supportive throughout my studies and my writing and for selflessly encouraging me to do well in spite of all the time it took on evenings and weekends.

Thank you to my research peer reviewer, Justin Beal, who always brought me back to my tasks by sending me messages just when I was feeling complacent in making progress on this thesis.

Thank you to all of my brothers and sisters in Christ who have prayed for me every time I asked as I have worked on this thesis and all that led up to it. He who has called me is faithful and he has done it.

Thank you to all of my friends and family members who have encouraged me continually.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Introduction

It is trite to say that all stakeholders in education want desperately to understand the manifold variables that culminate in a student's final grade in a class. Students ask continually, "What can I do to improve my grade?" Parents, instructors, and administrators continually ask, "Is there anything I can do to help?" The global private tutoring market is a multi-billion dollar industry and there seems to be no end to the availability of free learning resources online. Over a century of research examining what determines academic performance in schools has not resulted in parents, teachers, and students having common knowledge of exactly what determines student success in school. It follows, then, that either we do not know at all, do not agree on what factors, or are facing a circumstance where there are an unmanageable number of factors that determine student success.

But the stakeholders of education do desire that students be successful. Few might suppose there are many teachers who are glad when students fail to succeed in their courses and surely the students and their families prefer success over failure. So, as a research community, we explore undiscovered factors, flesh out those showing promise, and continue to examine well-established factors in an ever-changing landscape of education and fields of research.

Background of the Problem

Probably the most established predictor of student academic performance is degree of intelligence, but verbal tests of intelligence show stronger effects than non-verbal tests of intelligence (Roth et al., 2015). Unfortunately, verbal tests of intelligence are founded upon familiarity with common language and shared ideas. Ford (2004) recommends that non-verbal tests of intelligence may be more appropriate for measuring intelligence in circumstances characterized by greater demographic diversity. This presents an opportunity for furthering our understanding of intelligence on academic performance.

Dual enrollment has become a popular means of providing opportunities for high schoolers to get an early start on college, dip their toe in the pool of higher education with less risk, or offer a broader range of deeper academic learning than what has been offered by Advanced Placement (AP) courses. It is an arena that creates an intersection of students who are simultaneously high schoolers and college students. This presents another opportunity for broadening the scope in a field of research that usually has to choose between either high schoolers or college students.

Before the introduction of online learning management systems (LMS) like Blackboard, Canvas, and eCollege, gathering data on how much time students spend practicing their learning in a specific subject was more difficult and may have required more invasive methods. But these LMS platforms generally record exactly how much time students have spent on any digitally accessed assignment. This presents an opportunity to collect more accurate data on the time a student spends on task practicing.

Statement of the Problem

There is much research clearly showing the link between general intelligence, *g*, and academic performance and also linking time on task to learning. If both of these constructs are important for academic performance, then examining both of them simultaneously may provide a link that is less examined in the literature. Also, examining both of these student characteristics across two academic subjects and bridging the separate research settings of high school and college may provide additional external validity to the current knowledge base.

Some may say that these connections have been studied so exhaustively that there is no longer need to examine it further. On the contrary. The landscape of education is ever-changing. The rapid adoption of teaching methods during the COVID pandemic and the behavioral changes in young people who have never lived without smart phones creates an almost brand new education world. Additionally, research methods are ever evolving. It is all the more necessary to continually revisit well researched questions in education to keep us from settling in ignorance on conclusions of decades past.

Significance of the Study

The findings of this study could encourage future studies to include multiple subjects and multiple predictive effects. This study may lend support to studies examining both innate ability and motivational elements in students simultaneously to better understand student learning and performance. It would be encouraging to see other well established education research questions applied to the dual enrollment environment to connect findings on high schoolers to results focused on college students.

Purpose of the Study

The purpose of this study is to apply what is already understood about the connections between (a) general intelligence, *g*, and academic performance and (b) time on task and academic performance to the case of high schoolers enrolled in college-level classes. This study aims to fill a gap between studies focused only on high schoolers and those focused only on college-level students. In this study, we will have high school students performing in college-level classes and examining the role of general intelligence. Additionally, this study plans to cross subject area bounds by examining some of the respondents in math courses and other respondents in economics courses and examining whether there is a difference in outcomes.

Primary Research Questions

The research questions are directly based on this overarching question: Are intelligence and time on task significant predictors of final grades in a college level math or social studies course? However, there is no question directed at the comparison of high school student performance to college student performance. That aspect of the study is a setting consideration and not taken as a variable of the study (though that may be considered for future research). This study will investigate the following questions:

1. Are general intelligence and time spent on practice tasks significant predictors of a final grade in a college level course for a high schooler?
2. Is there a significant mean difference in final grade across course (social studies or math) when controlling for math ability?

Hypotheses

The hypotheses reflecting the research questions above are as follows:

1. Both a high school student's measure of general intelligence and amount of time spent on practice assignments have significant positive relationships on the student's final grade in the course for both math and social studies courses.
2. There is a significant mean difference in final grade between a college math course and a college social studies course when controlling for math ability.

Literature Review

Demetriou, et al. (2023) is the basis for the theoretical frameworks regarding intellectual ability on academic performance. The Raven (2008) chapter gives the foundational psychometric purpose and validity of the Raven Progressive Matrix that will be used to measure intelligence in my study. Roth, et al. (2015) will support the theoretical framework and give theoretical background for showing a relationship between intelligence and academic performance. Guillaume & Khachikian (2011) will support the theoretical framework and give theoretical background for showing a relationship between time on task and academic performance. Adesope et al. (2017) and Ukpong & George (2013) will provide the basis for making comparison of the effects of intelligence and time on task between academic performance in a math class versus academic performance in an economics class.

Research Design

The main focus of the research will be a correlational study while the comparison between math and social studies will be more descriptive in nature. None of the quantitative variables will be manipulated, just recorded as they occur based on student behavior. As such, there can be no causation inferred among the variables.

Data Collection Overview

Four quantitative variables and one qualitative variable will be collected. Qualitatively, each student will be coded for whether they were in a math dual enrollment course (an introductory statistics course) or a social studies dual enrollment course (a course in principles of economics). Each student's 7^{th} grade state math test score will be collected to be used as a covariate. General intelligence, *g*, will be measured by administering the Raven's Standard Progressive Matrices. Time on task will be measured by accumulating all time spent (in hours) by each student on all ungraded practice assignments in the course's LMS software. Final grade will be the overall raw accumulated score on all graded assignments for the semester out of 1,000 points.

There will be two sections of statistics and two sections of economics included. Expected sample size is about $n = 40$ from each course, for a total sample size of about $n = 80$.

The 7th grade state math test score will be collected last after all other data has been collected. The database will be given to an administrator in the school system who will retrieve the scores and put them in the database and then remove the names of the students so that they cannot be identified with the protected information. The database will then be returned to the researcher for analysis.

The Raven's Standard Progressive Matrices (RSPM) is a non-verbal intelligence test, using shapes and patterns instead of words an effort to reduce the effects of culture on test performance. It is a survey of 60 items in which, for each item, a larger image is presented that shows some kind of visual pattern with a missing section in the bottom right of the pattern. The respondent is given a choice of 6 to 8 possible pieces to fill in the missing section of the larger pattern. The respondent chooses the piece that they believe best completes the pattern. It is a test of general intelligence, *g*, which is a well-known construct in psychology research. Pind, et al. (2003) concisely summarize the reasons for the popularity of RSPM in research. Each student will arrange time to meet with the researcher to complete the RSPM and receive a score.

The researcher will gather data from the LMS throughout the semester on how much time each student spent on each practice assignment. Note that practice assignments can be attempted multiple times. Time spent on multiple attempts will be accumulated in the total.

Final grade as a raw score out of 1,000 will be taken from the instructor's gradebook after the conclusion of the course.

Data Analysis Overview

Since score on the intelligence measure, time on task, and final grade are all quantitative, regression analysis and correlation analysis will be used. Final grade will be used as the response variable in the regression analysis with intelligence and time on task as the explanatory variables.

ANCOVA will be used to examine the mean difference in final grade between students in the Statistics class and the students in the Microeconomics class with the covariate, 7th grade state math test score. All analysis will be conducted using the R statistical software.

Ethical Considerations

Participant data will be protected. It is already the responsibility of instructors under FERPA to not share educational and attendance information of dual enrollment students. The usual efforts of the researcher will continue to be applied in the case of this study's participants. Additionally, as mentioned previously regarding the collection of the 7th grade state math test scores, student names will be removed from the database before it is returned to the researcher for use in data analysis.

Theoretical Framework

This study will be positioned in the body of knowledge within a "mental architecture" framework developed by Demetriou et al. (2023) which models school performance outcomes as being predicted by cognitive and personality factors. The overall theoretical framework is a comprehensive and ambitious "overarching model" of learning and academic performance. However, this study zooms in on a portion of the mental architecture model.

Two elements of the Demetriou et al. (2023) model are appropriate for the current research. First, the mental architecture model proposes a direct, unmediated link between intelligence and academic performance. Similarly, there is a direct link in its framework between a construct that includes self-evaluation (which this study will connect with practice time) and academic performance. So, the mental architecture framework and this study are both predicting academic performance with measures of intelligence and self-reflecting practice.

Secondly, Demitriou et al. (2023) propose that the development of the mind throughout the years of preschool, primary school, and secondary school. The research explains different results across different studies as revealing that different cognitive processes play different roles in academic performance as a child progresses through each of these stages of schooling. Since this study is focusing on the link between high school and college learning and performance, it fits into the multiple stages aspect of the mental architecture framework. Additionally, the research summarized in Demetriou et al. (2023) suggests that intelligence has its strongest effect on academic performance during development in the secondary school years.

The mental architecture model proposes that general intelligence, *g*, is a function of three categories of mental processes called executive functions, *Ge*, fluid intelligence, *Gf*, and cognizance, *Gcogn*. Each of these is a function of more detailed mental processes. Executive functions, *Ge*, is a function of attention control (at), cognitive flexibility (fl), and working memory (WM). Fluid intelligence, *Gf*, is a function of relational integration (RI) and reasoning rules reflecting inductive, analogical, and deductive reasoning ($\text{Reas}_{I,A,D}$). Cognizance, *Gcogn*, is a function of awareness of mental processes (Am), self-evaluation (Se), and self-concept (Sc).

All of these have been examined in other research. It is not the purpose of this study to examine any of these architectural elements of general intelligence, *g*, but it will be interesting to emphasize some of these elements that are being tapped by the Raven's Standard Progressive Matrices when it is being administered. Also, there will be emphasis that the hypothesis regarding time on task's effects on final grade is connected to cognizance through self-evaluation as the practice tasks the students in this study will be performing offer timely feedback that allows them to self-evaluate as they are practicing.

Demetriou et al. (2023) emphasize that the mental architecture model includes only cognitive and personality factors and would benefit from future research that expands the prediction of academic performance by including elements of motivation. It can be argued that time on task practicing what is learned has a motivation element to it. In this way, the current study offers an exploration into extension of the mental architecture framework.

Assumptions, Limitations, and Scope

Assumptions. The researcher will assume that each participant will be doing the best they can when completing graded course assignments contributing to the final grade. Dual enrollment courses are voluntary, so the participants are presumably not being coerced to take part in these courses. Likewise, the researcher will assume participants will be honest and do their best when completing the RSPM test of intelligence. Participants have been offered 1% extra credit on their final grade for taking part in the study but it is the consensus of the Institutional Review Board that this amount is not too coercive.

Data Collection Limitations. Some validity problems may arise in data collection. The students being studied were in 9th grade during the COVID pandemic and some of them may not have a 9th grade state math score. That is why 7th grade state test score is being used. Time spent practicing recorded in the LMS software may be skewed if a student fails to submit the assignment and the timer continues counting for hours. Though impossible to mitigate, students may lack motivation while completing the RSPM and hurry through the administration.

The Scope of the Study. The participants of this study are drawn from the population of dual credit enrollment high school students in the eastern Atlanta, GA metropolitan area. I'm not sure if my sample will adequately represent the whole population of east Atlanta dual enrollment students. Since my sample will include mostly 12th grade students, it may not adequately represent the 11th grade dual enrollment students. Also, most dual enrollment students never take a dual enrollment math class, like Intro to Statistics, nor do most of them take a Microeconomics class. It will be a challenge to generalize the results to all east Atlanta dual enrollment students. This study will be cautious to generalize only to those who are likely to take math-oriented or business/consumer-oriented courses.

Definitions of Terms

Dual Enrollment Course. Also called "concurrent enrollment" or "dual credit enrollment," is a course section administered by a college or university but attended by a student who has not yet graduated high school. The course grants both college credit and high school credit upon successful completion. Dual enrollment is not a characteristic of the course section itself but rather a designation of the circumstance of the high school student being enrolled in the college course for high school credit.

Summary

It is a worthwhile endeavor to develop a better understanding of how young people develop as learners and eventually as productive members of society. This study seeks to contribute to that understanding by comparing student intelligence as measured by the Raven's Standard Progressive Matrices and student time spent on practice tasks to their final grade in their course. This study hypothesizes those will both be significant positive relationships. If that is the case, then education stakeholders may be encouraged to put resources toward specifically developing general intelligence and providing plenty of practice time for academic tasks. This study also hypothesizes that there will be a significant difference in mean final grade between math and social studies college courses. If this hypothesis receives support, it may assist in how to allocate resources for students taking dual enrollment courses.

Chapter 2: Literature Review

In 1994, many in the scientific community associated with the American Psychological Association (APA) became embroiled in a large debate regarding the idea of intelligence, its measurement, and how intelligence and its measurement is understood (Neisser et al., 1996). This debate revealed that there was much disagreement among researchers about what was known and scientifically supported within the area of intelligence measurement. It was the opinion of many that political implications had become a part of the interpretations and conclusions rather than strictly on science. The APA commissioned a diverse task force to compile a report on what is known by the community and try to establish some degree of agreement regarding the body of knowledge on the subject of individual intelligence. The report by Neisser et al. (1996) was the published result of that task force.

Since intelligence is a main variable in this study, this literature review includes an attempt to summarize and synthesize some of the research from that body of knowledge that has grown since 1996. This study itself hopes to contribute to that body of knowledge.

Appropriateness and Validation of Raven's Standard Progressive Matrices

John Raven (2008) clarified the purpose of the Raven's Progressive Matrices and seemed to indicate that it was not specifically designed as a measure of intelligence. However, the strong results of tests of construct validity that have compared the RSPM to instruments that are known to measure intelligence (Mills et al., 1993: O'Leary et al., 1991; Pind et al., 2003) indicates that the RSPM appears to be a valid measure of intelligence in spite of Raven's original design. In fact, O'Leary et al. (1991) found evidence that the RSPM can be used as an estimate of the verbal intelligence test WAIS-R FSIQ (Wechsler Adult Intelligence Scale-Revised Full Scale IQs). Mills et al. (1993) note furthermore that many studies have examined the internal reliability of the RSPM which have always found it to be moderate to high. The Raven Standard Progressive Matrices (RSPM) is generally regarded as a nonverbal test of intelligence (Lohman et al., 2008; Raven, 2003).

A cursory search of academic literature will quickly reveal that researchers around the world are interested in the measurement of student intelligence. Ford (2004) cautions researchers that the methods and instruments used for tapping this abstract construct are sensitive to differences across cultures. In areas with a more homogeneous culture (i.e., not much diversity), comparisons among individual scores is not as much of a problem, but in places with great cultural diversity, like the United States, the use of instruments that measure intelligence often favor one cultural group over others (McCallum, 2017; Razani et al., 2007). For example, the Wechsler Abbreviated Scale of Intelligence (WASI) is shown to favor monolingual English-speaking Anglo-Americans over individuals of Hispanic, Asian, and Middle Eastern descent (Razani et al, 2007).

Additionally, there is evidence that students who are economically disadvantaged struggle more with language arts skills (Beiswinger, 2009) which may negatively affect their performance on verbal tests of intelligence. School systems often measure proportion of economically disadvantaged students using the percentage of their students that qualify for Free and Reduced Lunch. Interestingly, Beiswinger (2009) found no significant effect on math scores between students who are economically disadvantaged and those who are not.

Culturally, the setting for this study is highly diverse. Based on the 2020 census, the ethnic composition of the county is 57% Black or African American, 26% White, 10% Hispanic, 2% Asian, 4% mixed race, and 1% other races. Additionally, the average percentage of students that qualify for free and reduced lunch across schools is 73.4%. For the purposes of this study, that means the participants may be limited in their performance on verbal tests of intelligence but may not be affected in their performance in math.

This problem of individual differences causing great variability in the validity of verbal tests of intelligence makes nonverbal tests of intelligence all the more useful when facing circumstances of high cultural diversity and limited language arts skills (Bracken & Naglieri, 2003). However, Ford (2004) cautions that nonverbal tests of intelligence are not free of cultural influence in their construction, but that they are “culture-reduced or less culturally-loaded tests.” Owen (1992) agrees with Ford (2004) on this warning. With this warning in mind, given the circumstances of this study, it makes sense to use a nonverbal test of intelligence, in particular, the RSPM.

Intelligence as a Determinant of Academic Performance

Intelligence is defined, described, and measured by researchers in varying ways. But the results of studies correlating intelligence with academic performance do not vary. This indicates that all of the measures of intelligence must have something in common within the minds of research subjects. For one thing, it has been shown that intelligence as a research variable is normally distributed in the population (Plomin & Dreary, 2015). The following review of research connecting intelligence to academic performance will provide more detail.

Bilalic et al. (2023), Rosander et al. (2011), and Soares et al. (2015) each examined the link between intelligence and academic performance by collecting primary data. Each used previously validated intelligence tests to measure intelligence including the Reasoning Test Battery (Sores et al., 2015), the Wonderlic Personnel Test (Rosander et al., 2011), and the Raven Advanced Progressive Matrices, the Verbal General Ability Test, and the Numerical General Ability Test (Bilalic et al., 2023). To measure academic performance, each of these studies used individual final subject grades of multiple subjects in school including exam grades in Statistics and Introduction to Psychology (Bilalic et al., 2023), final grades in math, social studies, language, practical skills, and sports (Rosander et al., 2011), and a longitudinal study including 7th grade and 9th grade scores in math, science, language, and foreign language (Soares et al., 2015). All three studies examined a direct model between intelligence and academic performance while two of them also examined models where the link between intelligence and academic performance is mediated by previous knowledge and practice time (Bilalic et al., 2023) or previous academic performance from two years prior (Soares et al., 2015). With the exception of the Introduction to Psychology group, all direct relationships were found to be moderate to strong and significant. With the exception of the Statistics group, all mediated relationships were found to be moderate to strong and significant. So, in general, the literature shows that studies that gather primary data using validated intelligence measures tend to show significant effects of intelligence on academic performance in both direct and mediated models.

Garg & Sharma (2016) as well as Leidra et al. (2007) both conducted studies of intelligence on academic performance by measuring intelligence with Raven's Standard Progressive Matrices and collecting GPA data as academic performance. Both studies balanced the number of male and female participants. Leidra et al. (2007) collected data on students from 2nd grade up to 12th grade while Garg & Sharma (2016) examined undergraduate college students. In both studies, intelligence was the strongest predictor of academic performance among all significant predictive variables examined. This study crosses the boundary in that the subjects are both secondary students and in college with the exception that this study will measure academic performance as a primary data source. We expect to find similar results.

What about studies that used custom measures of intelligence instead of measures with widespread validation and usage? Are the results different? Prins et al. (2006) measured intellectual ability using "a series of paper-and-pencil ability tests, representing five primary intelligence factors" including tests of arithmetic, verbal skills, and sequential reasoning. Heaven & Ciarrochi (2012) measured intellectual ability using a local/state standardized numerical and verbal ability test. McCrickard et al. (2018) measured intelligence with the Aplia math assessment test from Cengage Learning. In all three of these studies, the measure of intelligence was found to be significantly correlated to the measure of academic performance.

What about studies that have employed secondary measures of intelligence? Two studies that used either student SAT score (Plant et al., 2005) or ACT score (Johnson & Kuennen, 2006) as measures of intelligence were reviewed. Plant et al. (2005) found that SAT score is significantly correlated with both high school GPA (past) and college GPA (current). Johnson & Kuennen (2006) found that only ACT Scientific Reasoning score significantly predicted academic performance in an undergraduate freshman statistics course. Composite ACT score was not used in the study. McCrickard et al. (2018) used ACT as a secondary measure of intelligence in addition to the Aplia test primary measure. Just as with the Aplia test, ACT score predicted academic performance at the .01 level. So, studies using secondary measures of intelligence seem to provide similar results.

Additionally, three meta-analyses were reviewed regarding the link between intelligence and academic performance. Richardson et al. (2012) chose studies that included individual ACT and SAT scores as measures of intelligence and undergraduate college GPA as the measure of academic performance and found that ACT and SAT were included in the group of variables with the strongest significant correlations with college GPA. Roth et al. (2015) chose studies that included primary measurement of intelligence by verbal, nonverbal, or a mix of verbal and nonverbal instruments with academic performance measured by either school GPA or similar. Meta-analysis results found that intelligence (regardless of verbal, nonverbal, or mixed) is significant and moderately correlated with academic performance. Schneider & Preckel (2017) actually conducted a meta-analysis of meta-analyses of predictors of academic performance in higher education only. This shows how extensively predictors of academic performance have been researched. Each meta-analysis included in their study had some measure of intelligence and some measure of academic performance. Their meta-analysis supported the conclusion that intelligence correlates with medium to large effect sizes with academic performance. So, even secondary compilation studies of original research, which employ varying measures of intelligence and academic performance, find moderate to strong support on this link.

The studies discussed here are just a sample of the numerous research projects that have been conducted over several decades in many countries around the world. Intelligence has been measured using varying verbal, nonverbal, and mixed-method instruments, including the RSPM and other instruments highly correlated with the RSPM. Measures on intelligence have been gathered as primary, secondary, and meta-analysis data. Academic performance has been measured in varying ways, both generally like cumulative GPA and specifically as in course grade. Some studies examined direct relationships between intelligence and academic performance. Some examine mediated relationships. While some examined moderated relationships with other variables like personality or self-efficacy. Regardless of these varying ways that the link between intelligence and academic performance has been analyzed, the result is always a significant, and at least moderately strong, correlation between intelligence and academic performance. In most cases where other predictors are examined alongside intelligence, the strongest predictor is intelligence. It is not surprising, then, that even the APA task force that compiled the state of research on the topic of intelligence in 1995 also concluded unanimously that intelligence definitely correlates moderately well with academic performance (Neisser et al., 1996). This study suggests the same as a hypothesis.

Time On Task as a Determinant of Academic Performance

A brief search and scan of the abstracts of many studies examining time on task for students can reveal that, like intelligence, there are varying paradigms and definitions of what the variable “time on task” means. In particular, some researchers have examined it strictly looking at time *in the classroom* spent practicing on a task while others have examined it as time *outside of the classroom* practicing on a task. This study considers both paradigms in the literature review and will measure practice time on task both during class time and outside of class time.

It may seem redundant to scientifically examine whether a student who spends more time studying will exhibit higher academic performance. However, the review of research that follows will show that the results are not as clear as one might expect. Many professionals in education may assume students that study more will achieve greater performance. But this is exactly the kind of assumption that leads to superstitions, debates among researchers, and poor academic policies in classrooms and school systems. We cannot assume any correlations that have not been backed by statistical evidence. So, we examine the literature connecting amount of study time (time on task) to academic performance and then investigate the relation in this study.

The research reviewed here shows mixed results. Studies conducted by Bilalic et al. (2023), Godwin et al. (2021), Ukpong & George (2013), and Romero & Barbera (2011) on the subject of time spent practicing generally for a significant and positive relationship on academic performance. To the contrary, studies by Guillaume & Khachikian (2011), Johnson & Kuennen

(2006), and Plant et al. (2005) found non-significant direct correlation between practice time and academic performance. Some light is shed on this discrepancy by meta-analyses by Adesope et al. (2017) and Kim & Seo (2015).

There are some qualifying descriptors that come into play in examining how spending time practicing and studying may positively influence academic performance. For example, Bilalic et al. (2023) are found that "deliberate" practice that "avoids distractions" results in time on task significantly predicting higher academic performance in both Introduction to Psychology and Statistics courses at the undergraduate level. Ukpong & George (2013) did not examine time as a quantitative variable but divided time on task categorically into "longer" versus "shorter" study time and found that longer study time resulted in higher academic performance in social studies courses. Romero & Barbera (2011) even looked at time on task based on day of the week and time of day. They found that students who primarily completed study and assignments during "morning hours" achieved greater performance than those who worked on assignments in the "afternoon or evening hours." Overall, they found a moderate and significant correlation between time on task and academic performance. Godwin et al. (2021) found a generally weak but significant relationship. Their study employed a single measure of time on task that resulted in great variance in the strength of effect sizes. So, the idea that differing measures may account for the differing results in studies was not supported by their research.

Contrary to these results, Guillaume & Khachikian (2011) found that, though students believe that time on task is a significant predictor of their grade in a course, the data does not show a significant relationship between practice time and academic performance. This study was conducted over three years examining the same students over 8 courses in an engineering program. The longitudinal nature of this study is compelling for the results but the fact that only engineering students were examined limits the broader application of the results. Johnson & Kuennen (2006) found that students in an undergraduate introductory statistics class did show some relationship between the number of hours spent studying weekly and their final grade in the course, but the result was not statistically significant at even the .05 level. Plant et al. (2005) also found no significant relationship between study time and academic performance. The regression model included other variables. One interpretation they gave of their overall model involves the quality of the study environment. They suggest that environments conducive to productive study require less study for high performance while distracting or disruptive study environments require more study time, confounding the correlation between time on task and academic performance (Plant et al., 2005).

Adesope et al. (2017) conducted a meta-analysis examining the effects of students spending time taking practice tests in preparation for graded tests. Called the "testing effect," the improvements in learning from taking practice tests has shown positive and significant correlation with grades. The time spent on practice tests is another type of time on task since time is spent on the practice tests with the purpose of learning and preparing for assessment. The meta-analysis found a significant large effect size for primary, secondary, and post-secondary school students (Adesope et al., 2017).

Though Kim & Seo (2015) did not directly examine time on task and academic performance, they did examine what may be considered time "off" task, that is, procrastination. The results of their meta-analysis suggests a significant negative relationship between procrastination and academic performance. That is to say that the more students avoid spending time studying, the lower their grade.

It appears as though prior research is not as conclusive on the connection between time on task and academic performance as with intelligence. Indeed, Godwin et al. (2021), in their summary, state "the relationship between time and learning is still poorly understood" in spite of over 40 years of examining the link. They emphasize the need for continued research into this relationship. This may be explained by the idea that quality of time may be more important than quantity of time in study and practice. It also seems that the varying ways to measure time on task and the errors inherent in measurement could also play a role (though Godwin et al. (2021) seems to refute this). But it seems that most of the research examined here suggests that there is a positive relation between quantity of time on task and academic performance, though qualified. That is the hypothesis of this study.

Academic Performance in Math Versus Social Studies

In many ways, social studies subjects and math subjects in school have been perceived differently by students. To start with, there is no social studies portion of the ACT, SAT, or GRE exams. Evidence indicates that elementary school teachers spend more time on math in class than on social studies (Wexler, 2020). Research even reveals that students have differing attitudes toward social studies than they do toward math (Schug, 1982; Stodolsky et al., 1991).

This study aims to examine whether there is any difference in mean academic performance between math classes and social studies classes. More specifically, it proposes that students score very differently in math classes than in social studies classes.

The math course that some of the subjects in this study will complete is a dual enrollment introductory statistics course and the social studies course is a dual enrollment principles of microeconomics course. Some research indicates that math skills are positively correlated to performance in economics courses (Ballard & Johnson, 2004; Arnold & Straten, 2012). Due to this connection, a measure of student math skill level will be collected as a covariate (this will be discussed later).

In general, it could be that high school students have higher performance in math than in social studies regardless of intelligence level. One study found that student performance on the high school state tests was higher for math than for social studies (Duncan et al., 2011). A larger proportion of the students scored in the highest group (pass plus) in Math than they did in Social Studies while a larger proportion of those students scored in the lowest group (fail) in Social Studies than in Math. So, in general, they found that high schoolers exhibit higher academic performance in math than in social studies. However, this was not the case in a similar study that examined middle schoolers. For these younger students, one group performed higher in social studies while the other group performed comparably on both math and social studies (Hicks, 2014). This could indicate an effect difference in stage of life and learning. Similar to the Duncan study, however, another research project found that the mean increases in performance on the annual academic performance state tests for 3rd through 8th graders were greater in math than they were in social studies, though the variance on the gain measures were the same for both math and social studies in each grade level (Paul et al., 1997).

Beyond just over performance of math and social studies, there is also statistical evidence to suggest that the intelligence effect sizes are indeed larger for math learning than for social studies learning. As mentioned earlier, Bilalic et al. (2023), examined the effects of intelligence on academic performance in a Statistics course versus in an Introduction to Psychology course and found that intelligence predicted performance in the Statistics course more strongly than in the Introduction to Psychology course. In fact, performance in the psychology course had no significant direct effect from intelligence. Instead, the effect of intelligence was mediated through student previous knowledge on the subject (Bilalic et al., 2023).

Similarly, in the Rosander et al. (2011) study, intelligence showed a significant and positive correlation with academic performance. But that correlation was stronger for performance in math and weaker for performance in social studies. The Roth et al. (2015) meta-analysis showed similar results. Verbal, nonverbal, and mixed measures of intelligence were all correlated significantly with academic performance, though the math and science performance groups had the strongest effects while the social studies groups had the smallest effects. Though Soares et al. (2015) did not include performance in social studies as an outcome in their study, their results did show that 7^{th} and 9^{th} grade math performance were most strongly affected by the measure of intelligence compared to the other subjects examined.

In light of these limited studies comparing student performance in math versus social studies, we find support in the literature for investigating the hypothesis that academic performance will be significantly different in math than in social studies. Admittedly, aside from seeing that state math scores seem to be generally higher than state social studies scores, our connection between time on task effect size for math over social studies is weak at best. Perhaps this study itself may lend to future investigations on that question.

The Changing Roles of Intelligence and Time On Task as Students Mature

The transition from the final year of high school and the first year of college is important for students and their families in many ways. The dual enrollment environment allows students and their families to experience that transition in portions instead of all at once. For example, the role of the Family Educational Rights and Privacy Act (FERPA) changes as students become the bearer of those rights apart from their parents. For dual enrollment students, the transfer of the

FERPA rights occurs a year or two before they leave for college (though only pertaining to their dual enrollment courses). This can have quite an effect on the dynamics of student academic performance as parents and instructors cannot communicate with one another regarding the student's scholastic activities. The student is truly taking full responsibility during high school as they would when they go off to college. So, that transitional time is an important one for researchers to study.

Research shows that the effects of a person's intelligence on their thinking and behavior changes as they age (Demetriou et al., 2023). Makris et al. (2017) found that "intelligence expresses itself differently" during different age ranges as a person grows and develops intellectual capacities. Also, we know that the degree to which intelligence that is inherited from parents genetically manifests itself more and more in a person's thinking and intellectual activity as they age (Neisser et al., 1996; Plomin & Deary, 2015). That is, a primary school child's intelligence has more to do with their environment and upbringing than with their genes. But as they get older and older, even into their seventies, the effect of their genetics on their intellectual ability becomes more and more prominent. According to Plomin & Deary (2015), this increase in hereditary intelligence is linear. So, for example, adopted children are likely to exhibit more of the intelligence they developed from their adoptive parents during primary and secondary school and then in adulthood will begin to exhibit more the hereditary intelligence from their biological parents.

Relevant to this study, however, is whether intelligence has a stronger effect on academic performance for college students than for high school students or perhaps there is no significant difference at all. This study cannot empirically examine that question given that all of the participants are both high school students and college students simultaneously (though they are of high school age and environment). Nevertheless, it is beneficial to examine existing research on this question as a “frontier” to the scope of this study.

Demetriou et al. (2019) found that intelligence had a greater effect on academic performance among primary school students than among high school students. This would support a hypothesis for intelligence being more predictive before a student goes to college.

On the other hand, Farsides & Woodfield (2003) found in a longitudinal study over three years of undergraduate academic performance that intelligence did not significantly predict academic performance for freshman though it was partially significant for college sophomores. However, the effect if intelligence for college Juniors was significant for all performance measures, indicating that intelligence has a stronger effect as the college student progresses. Consistent with this, Richardson et al. (2012) found that ACT and SAT score had a higher correlation with college GPA than high school GPA and Laidra et al. (2007) found that the Raven’s Standard Progressive Matrices were more highly correlated with student GPA in high school than in elementary school.

This literature review has shown that research has repeatedly found a strong link between intelligence and academic performance. The empirical portion of this study expects the same result. But the mixed support in the literature for the question of effect size of intelligence on academic performance as a student transitions from high school to college indicates that there is still opportunity for contribution to what we know about intelligence and academic performance.

Chapter 3: Methodology

This research aims to provide better understanding of some predictors of student academic performance in the time of transition between high school and college. This chapter will provide an overview of the research setting, the participants involved, and the variables of interest as well as how each will be measured. It will further explain the proposed procedures for gathering data and analyzing the data in addressing the research questions and hypotheses.

Settings and Participants

To attempt to fill the gap in knowledge about predictors of student academic performance between high school and college, this study will make use of the dual enrollment setting in which high school students are taking college courses. The population of high school students in college courses is much smaller compared to that of high schoolers in high school classes and college students in college classes, so access to this kind of setting is somewhat unusual. In this case, the researcher is the instructor of all four included courses.

Participants in this study were high school students in a demographically diverse suburb of the Atlanta, GA metropolitan area. These students were enrolled in one of two college courses, Principles of Microeconomics or Introduction to Statistics, during a Spring semester. The study included students from two sections of Principles of Microeconomics and two sections of Introduction to Statistics. All four of the courses were taught by the researcher of this study. The class sessions for these courses were face to face courses that met in the high school "College and Career Academy" and not on a college campus. That is, the students attended these classes in the same building where they attended other high school classes that were not for dual credit enrollment. Most of the participants were high school seniors (perhaps more than 90%) and the rest were high school juniors, though this information was neither collected nor readily available but was informally encountered in conversations with the students throughout the course of the semester.

The population to which this study can be generalized is very narrow in scope. The sample may not adequately represent the whole population of east Atlanta dual enrollment students. Since the sample will include mostly high school seniors, it may not represent the high school junior dual enrollment students. Also, most dual enrollment students never take a dual enrollment math class, like Introduction to Statistics, nor do most of them take a college level Microeconomics class in high school. Thus, it will be a challenge to generalize the results to all east Atlanta dual enrollment students. We should be cautious to generalize only to those who are likely to take math-oriented dual enrollment courses. This is likely a very small population within the overall population of high school students.

The priori power analysis indicates that the minimum sample size is 68 for a medium effect size (partial R-squared = .13) to achieve a power of .80 with $\alpha = .05$ in multiple regression. For ANCOVA, however, the priori power analysis indicates that the minimum sample size is 125 for a medium effect size (partial eta-squared = .06) to achieve a power of .80 with $\alpha = .05$. G*Power 3.1 software was used to perform power analysis. This study has a sample size of 68 across all four dual enrollment sections: 23 from one section of statistics, 12 from the other section of statistics, 15 from one section of microeconomics, and 18 from the other section of microeconomics.

Instrumentation

This study includes three quantitative variables and one categorical variable. Only one measurement instrument will be given to the participants. All other variables will be measured based on normal and incidental activities of students in the normal course of academic study.

Measuring Academic Performance

During the course of the college semester, each student in both statistics and microeconomics will be graded on 12 quizzes (40 points each), 3 unit exams (130 points each), and a final exam (130 points). This gives a total of 1000 points which will be divided by 10 to yield a final grade between 0 and 100. The final grade will be used as this study's measure of research participant's academic performance.

Measuring Intelligence

Participant intelligence will be measured using a free-of-charge, online version of the Raven Standard Progressive Matrix (RSPM), a nonverbal measure of intelligence (See Appendix A for information on accessing the online version of RSPM utilized in this study). The RSPM is a 60-item inventory. For each item, respondents are shown a large rectangular image with some kind of pattern. A smaller portion in the bottom right of the image is excluded, showing only an outline of the excluded portion. Below the given image is a group of either six or eight possible patterns in the shape of the excluded portion. The respondent selects one of the given possible patterns for each of the 60 items and receives a score.

A meta-analysis of 56 studies that made use of the Raven's Progressive Matrices (RPM) examined the reliability of the RPM using internal consistency coefficients (Cronbach's alpha), test-retest coefficients (Pearson's *r*), and standard error of measurement (SEM) (Alhinai et al., 2019). The results of the meta-analysis indicated good reliability for the RPM with test-retest reliability of $r = 0.76$, internal consistency reliability of 0.85 and SEM of 2.51 for internal consistency and 3.43 for test-retest. These results are consistent with the Burke (1972) results of the reliability of RPM.

The validity of Raven's Standard Progressive Matrices (RSPM) as a measure of intelligence is supported by O'Leary et al. (1991) which correlated the Wechsler Adult Intelligence Scale-Revised Full Scale IQ (WAIS-R FSIQ) with the RSPM stratified by age bands. In all groups between age 16 up to age 64, the RSPM was significantly correlated with the WAIS-R FSIQ at the $p < .001$ level with a strong positive correlation (O'Leary et al., 1991). These results are consistent with the Burke (1972) results of the validity of RPM with an older version of the WAIS.

Measuring Time On Task

Participants will be given the opportunity to spend time practicing for each of the quizzes and for each of the exams by completing practice versions of those assignments in each course's learning management system (LMS). The LMS records details on time spent by a student working on the practice assignments. Time On Task (TimeHrs) for this study will be measured by summing the total number of minutes spent working on all of the practice assignments and then dividing by 60 rounded to two digits for an approximate number of hours spent practicing the course content over the entire semester.

Group Membership

Each participant will be coded according to whether they were a student in the statistics (math) course or a student in the microeconomics (social studies) course. Statistics students will be coded as 1 = Yes as Math Student. Microeconomics students will be coded as 0 = No as Math Student. This study included 35 students in statistics and 33 students in microeconomics.

Math Ability as a Covariate

To control for math ability in comparing performance in math to social studies, we will use each participant's seventh grade state math test score. This information is available in the school systems records for each student who finished seventh grade in the school system of this study's setting. Unfortunately, any student who completed seventh grade in a different system may not have available a seventh grade state test score.

Procedure

Since the participants are eleventh and twelfth grade students in high school, more than half of them are adults and the rest are 17 year old minors. The risk to these minors was minimal. The RSPM is not much different than any typical educational assessment that a teacher might administer to a student. The RSPM is also very similar to the types of nonverbal assessments that school systems throughout the United States administer regularly to students in determining whether they will be classified as gifted, such as the CogAT (Cognitive Abilities Test). Parents give permission for CogAT screening. Similarly, participants in this study who are minors will require parent permission as well. See Appendix B for copies of the assent and consent forms as well as the IRB approval. All data gathered from participants will be kept strictly confidential at all times and identification of participants will not be available throughout and after the study.

Academic performance as measured by a raw sum final grade of all quizzes and exams in the course will be recorded from the gradebook spreadsheet before any grading curves or extra credit is applied. This score will be equal to the sum of all raw points earned before curves and extra credit, out of 1,000 points, then divided by 10 for a rational value between 0 and 100.

To collect data on participant intelligence, each participant will visit the researcher's classroom at a time when there is no class in session and access the free version of the Raven Standard Progressive Matrices as previously described (see Appendix A). There will be no time limit imposed aside from the normal public school time limitations and the participants will be encouraged to simply choose the option that they think is best for each item. Participants will be discouraged from discussing the experience with one another and, though they will be permitted to listen to music during the task, they will be discouraged from doing anything else during the assessment until completion. After completing the intelligence assessment and receiving a score, the researcher will record the score confidentially.

To gather participant data for time spent on practice tasks, the researcher will access the records of each instance of each participant's attempts on a practice quiz or practice exam in each course's learning management system. For each participant, the researcher will sum up the total number of minutes spent by that participant across every attempt on a practice quiz and practice exam. The number of minutes will be then converted into the total number of hours that the student spent on practice tasks. This variable will be a rational decimal value.

As mentioned previously, a participant's enrollment in the statistics course will be used to code them a 1 = Yes for Math Student and enrollment in the microeconomics course will be used to code them as 0 = No for Math Student. The seventh grade state math score data will be provided by administration in the school system and added to the researcher's completed data set. All identifying information about participants will then be removed from the data set before it is returned to the researcher to protect the educational records of the participants.

Data Processing and Analysis

In this section, we give details on how the data will be analyzed to address the two research questions and hypotheses. All data analysis will be conducted using the R statistics software (R Core Team, 2023). For the four quantitative variables (including the covariate), descriptive statistics will be reported, including mean and standard deviation for the overall data set and then also for each of the two subject groups. Since the main question of this study is a correlational analysis, correlations among the four variables will be conducted and reported as well as correlations for the two subject groups. Quartiles will be reported as well as boxplots both for the whole sample and also for each of the two subject groups. The purpose here is to provide more information for future researchers.

To address the first and main question of this study, multiple regression will be employed with final grade as the response variable and intelligence and time spent on practice task as the predictor variables. Regression analysis appears to reasonably common in the literature for examining the link between intelligence and academic performance (Marjoribanks, 1979; Chamorro-Premuzic & Furnham, 2006; Heaven & Ciarrochi, 2012). Though a selection of references is given, a large number of studies use regression analysis for understanding the relationship between intelligence and academic performance. Regression analysis has also been used to examine the link between time on task and academic performance (Bilalic et al., 2023; Godwin et al., 2021; Johnson & Kuennen, 2006; Ukpong & George, 2013). We will examine a single multiple regression model that includes both intelligence and time on task to predict academic performance.

Tests will be conducted to determine whether there appear to be any threats to independence, normality, equal variance, or multicollinearity and charts will be included to support these assumptions. The five number summary and boxplot for the residuals to determine whether there are any influential cases in the data. In the event that there appear to be threats to independence, normality, equal variance, or multicollinearity, additional statistical techniques will be examined.

The full model will be tested against the intercept only model using ANOVA to determine whether the full model is significantly different due to the inclusion of the research variables. The multiple regression coefficients will be reported and analyzed as significant or not significant based on the *p*-value. The adjusted R-squared will be reported as well. The *t* value for each predictive variable will be reported along with the 95% confidence interval for the *t* values.

To address the second research question, the comparison of academic performance between high school students in a college math course versus those in a social studies course, we will use one-way between groups analysis of covariance (ANCOVA). Since a student's performance in a math class is likely to be the result of their math ability, then math ability may confound the comparison of academic performance between math students and social studies students. So, math ability as indicated by each student's 7^{th} grade state math exam score will be used as a covariate to isolate the comparison to subject difference only. Gjana & Kosova (2021) used ANCOVA to compare the academic performance of two groups, one in a traditional classroom setting and the other in an online classroom setting (with score on a pre-test as the covariate). The present study is similar but one group is in a math course while the other group is in a social studies course.

Tests will be conducted to determine whether there appear to be any threats to independence, normality, or equal variance assumptions and charts will be included to support these assumptions. We will also check for interaction effect of 7^{th} grade state math test score and final grade to check for violations of the homogeneity of regression slopes assumption.

Results will be reported to determine whether there is a significant difference in final course grade between math and social studies students. The F-statistic and p-value and eta-squared effect size will be reported. Additionally, the F-statistic, p-value, and eta-squared will be reported for the relationship between the covariate and final grade in the course. G*Power will be used to determine and report observed power. Since there are only two groups in this analysis,, there will be no need for Tukey post-hoc analysis.

Summary

We have discussed in detail the setting, participants, and variables of this study, as well as the importance of confidentiality of the data collected given the sensitive nature of the variables, especially because some of the participants are minors. The methods for measuring each variable was presented with an attempt to justify the instrumentation. The data collection procedure as well as the processing and analysis of the data was presented in detail so that future researchers may practically replicate the study.

Chapter 4: Results

Results from the multiple regression model reveal that both intelligence and time on task are statistically significant predictors of final grade in a course. Results from the ANCOVA analysis reveal that there is no significant difference in student final grade between math course and social studies course after controlling for 7th grade state math test score. All data analysis was conducted using the R statistics software (R Core Team, 2023).

Descriptive Statistics

Descriptive statistics are reported for all respondents (Table 1), for the group of respondents who were enrolled in a math college course (Table 2), and for the group of respondents who were enrolled in a social studies college course (Table 3). Though a larger sample size was initially expected, we collected data on $n = 68$ respondents, though some of them did not have a 7th grade state math test score since they moved into the school system after grade 7. So, the sample size for the covariate is $n = 59$.

Table 1. Descriptive statistics of all participants across both subject groups (math and social studies).

All Students ($n = 68$)	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Final Grade (Performance)	73.83	17.37	17.14	65.8	76.23	86.89	96.96
RSPM Intelligence	101.07	12.01	76	94	100	110	130
Time On Task (Hours)	18.64	8.75	5.78	12.64	17.77	23.33	43.77
Grade 7 State Math ($n = 59$)	547.12	44.74	461	510	546	574	652

Statistics for Grade 7 State Math Test based on participants who had this data available.

Table 2. Descriptive statistics of participants in college math course.

Math Students ($n = 35$)	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Final Grade (Performance)	72.27	16.15	17.14	64.74	74.87	84.22	92.43
RSPM Intelligence	102.31	12.86	76	94.5	100	114	124
Time On Task (Hours)	21.93	8.65	7.08	16.20	20.43	24.46	43.77
Grade 7 State Math ($n = 30$)	545.33	38.24	494	509	548	567	652

Statistics for Grade 7 State Math Test based on participants who had this data available.

Table 3. Descriptive statistics of participants in college social studies course.

Soc. St. Students (n = 33)	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Final Grade (Performance)	75.48	18.69	18.64	68.25	79.60	91.65	96.96
RSPM Intelligence	99.76	11.08	76	94	99	104	130
Time On Task (Hours)	15.15	7.52	5.78	8.30	14.18	22.17	29.93
Grade 7 State Math (n = 29)	549.28	51.2	461	510	543	590	638

Statistics for Grade 7 State Math Test based on participants who had this data available.

There were no issues with collecting data for the Raven Standard Progressive Matrices (RSPM) as a measure of intelligence nor for calculating the raw Final Grade for each participant as a measure for Academic Performance. However, summing the number of hours spent on practice tasks as a measure for Time on Task was very chaotic in practice. Some of the assignments had no time limit, so there were several instances where students began a practice task for a short time and then returned three days later to continue. This gave the impression that a student may have spent more than one hundred hours on the assignment. The LMS kept rough track of actual time stamps on activity but there was no way of knowing for sure that the participant was actually working on the task. Thus, in calculating Time on Task, there was a lot of approximating. The approximation method was consistent across all participants and the process was completed within a few days to minimize variance in the approximation. Additionally, calculations were done in the order of “per assignment” and not “per student” so that any variance in approximation would be distributed across participants. More information on this difficulty will be discussed in Chapter 5.

Correlations among the four quantitative variables are shown for all respondents (Table 1), for the group of respondents who were enrolled in a math college course (Table 2), and for the group of respondents who were enrolled in a social studies college course (Table 3). In the whole group, both intelligence and 7th grade math score were significantly correlated with one another and each with final grade in the course. In the math course group, the only significant correlation was intelligence with 7th grade math score. Like the whole group, the social studies group also showed both intelligence and 7th grade math score as significantly correlated with one another and each with final grade in the course.

Table 4. Pearson Correlations among the four continuous variables for all respondents.

All Students (n = 68)	Final Grade	RSPM (Intelligence)	Time on Task
RSPM Intelligence	.2899*		
Time On Task (Hours)	.2212	–.1719	
Grade 7 State Math (n = 59)	.5604***	.5274***	–.1679

Note: *$p < .05$, **$p < .01$, and ***$p < .001$

Table 5. Pearson Correlations among the four continuous variables for the Math group.

Math Students (n = 35)	Final Grade	RSPM (Intelligence)	Time on Task
RSPM Intelligence	.2706		
Time On Task (Hours)	.2624	–.2794	
Grade 7 State Math (n = 30)	.3513	.4415*	–.2819

Note: *$p < .05$, **$p < .01$, and ***$p < .001$

Table 6. Pearson Correlations among the four continuous variables for the Social Studies group.

Social Studies Students (n = 33)	Final Grade	RSPM (Intelligence)	Time on Task
RSPM Intelligence	.3442*		
Time On Task (Hours)	.3063	–.1682	
Grade 7 State Math (n = 29)	.7056***	.6594***	–.0647

Note: *$p < .05$, **$p < .01$, and ***$p < .001$

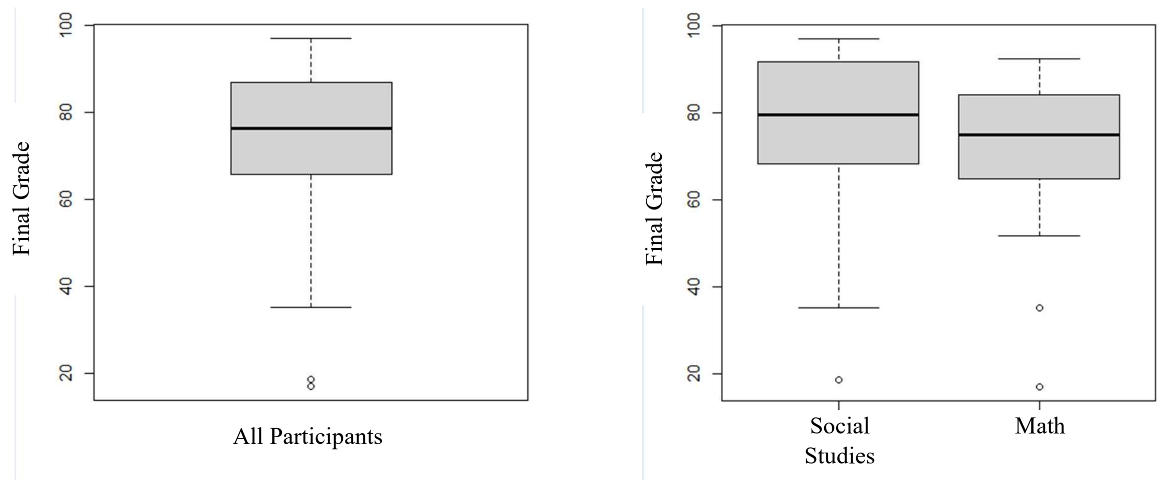

Figure 1. Box and whiskers plots for distribution of Final Grade. The left plot includes all participants. The right shows separate plots for the social studies course group and the math course group.

The distribution of Final Grade across participants is shown in Figure 1. The plot that includes all participants reveals the presence of two outliers. The plots that separate the math course participants from the social studies course participants shows that one of those outliers is a case in the math group while the other is in the social studies group. Separating the plots reveals that there is a third outlier in the math group.

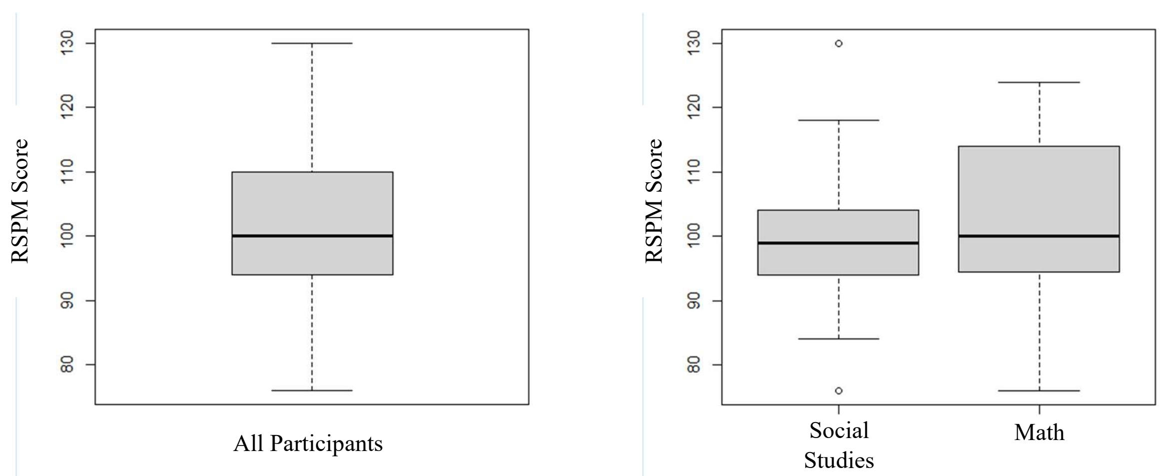

Figure 2. Box and whiskers plots for distribution of Raven's Standard Progressive Matrices. The left plot includes all participants. The right shows separate plots for the social studies course group and the math course group.

The distribution of the intelligence measure, RSPM score, is shown in Figure 2. In the whole group, there does not appear to be outliers but the separated groups indicate that there may be two outliers in the social studies group, one exceptionally high and another exceptionally low.

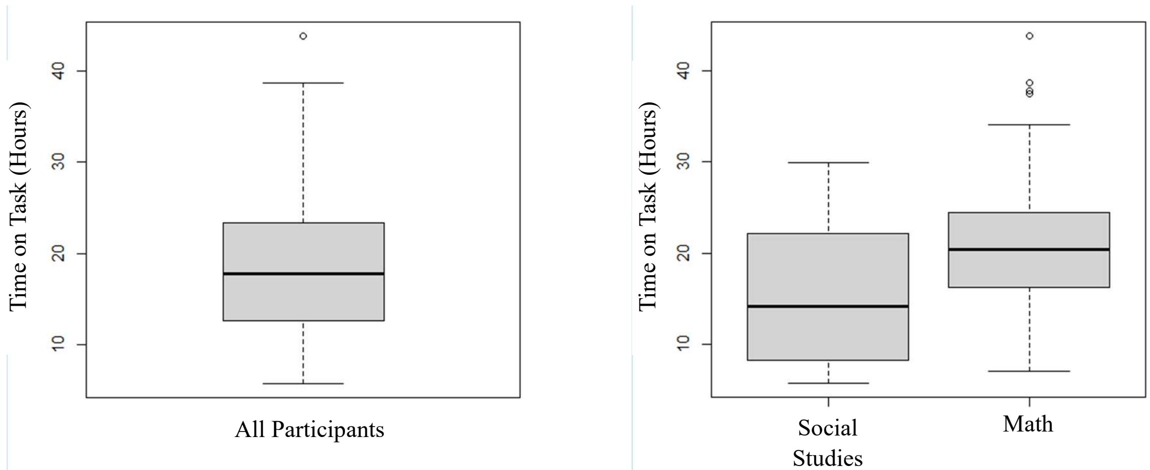

Figure 3. Box and whiskers plots for distribution of Time on Task in hours. The left plot includes all participants. The right shows separate plots for the social studies course group and the math course group.

The distribution of Time on Task in hours is shown in Figure 3. Observing the whole group plot and the separated plots indicate one outlier to the whole group, none in the social studies group, and possibly three outliers in the math group. Figure 4 shows no outliers in the distribution of the Grade 7 State Math scores.

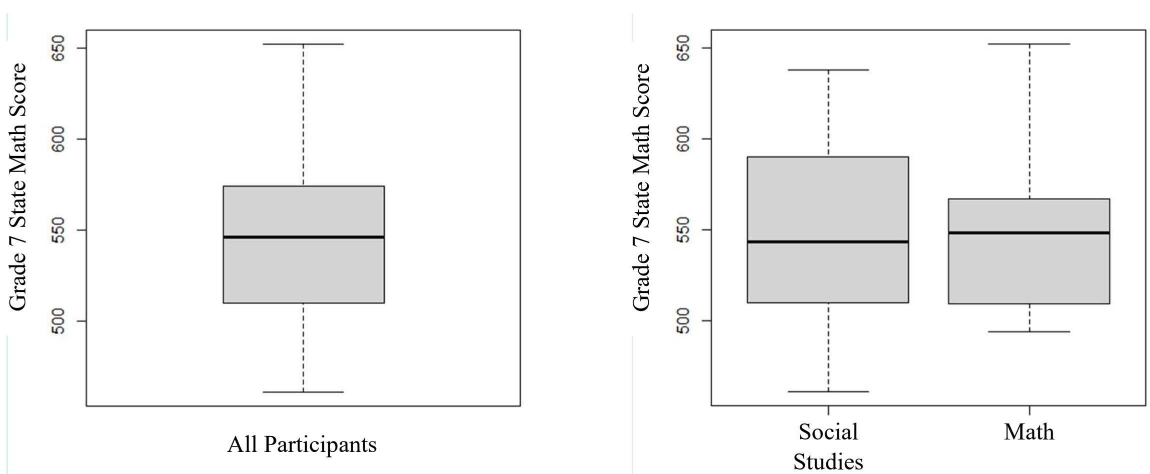

Figure 4. Box and whiskers plots for distribution of Grade 7 State Test Score. The left plot includes all participants. The right shows separate plots for the social studies course group and the math course group.

Intelligence and Time on Task Predicting Academic Performance

A standard multiple regression was performed between Final Grade as the dependent variable and score on the Raven's Standard Progressive Matrices and Time on Task (in hours) as the independent variables. Results were calculated on the complete set of participants, $n = 68$ as there was no missing data for any of the participants. Regression analysis was not conducted on the separate groups (math and social studies course) as this was not relevant to the first research question.

Tests for the assumptions of multiple regression were conducted and there were no concerns with equal variance (see Figure 5), independence, or multicollinearity. Figure 6 and the Shapiro-Wilk normality test (W = 0.94; $p < .01$) indicated that the data violate the normality of residuals assumption, though multiple regression is robust to violations of the normality of residuals assumption. The Durbin-Watson test (D-W statistic = 2.09; $p = .76$) verified the independence assumption. The Variance Inflation Factors confirmed no multicollinearity with both RSPM and Time on Task at 1.03.

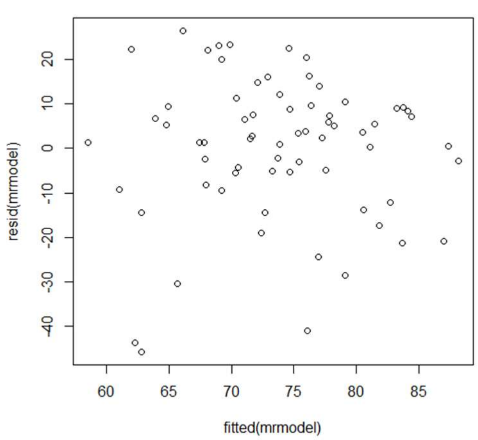

Figure 5. Plot for equal variance assumption.

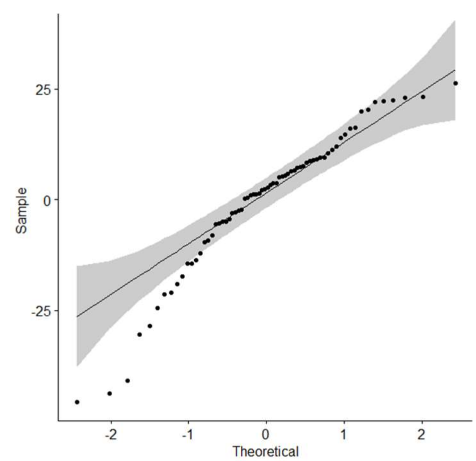

Figure 6. Plot for normality of residuals.

Table 7 displays the correlations between the variables, unstandardized regression coefficients, and the adjusted R^2. A test of the full model against the intercept only model was significant: $F(2, 65) = 6.178$, $p < .01$. Results indicate 13.4% of the variance in Final Grade was explained by the regression on Intelligence and Time on Task. Both regression coefficients included in the model emerged significant. Test-statistic values and confidence intervals are presented for each: RSPM (t = 2.93, (0.16,0.82)) and Time on Task (t = 2.42, (0.10,1.01)). Examination of outlier cases, high standardized residuals, and influential cases led to the deletion of no cases. Observed power, which was calculated using G*Power, was high, .845.

Table 7. Multiple regression analysis results.

Variable	**RSPM**	**Time (Hrs)**	**B**	**SE**	**Mean**	**St. Dev.**
Final Grade	.2899*	.2212			73.83	17.37
RSPM	–	–.1719	0.49**	0.167	101.07	12.01
Time (Hours)	–.1719	–	0.55*	0.229	18.64	8.75
Intercept			14.10	18.208		
Adjusted R^2 = 13.4%						
Power (1 – β) = .845				F (2, 65) = 6.178, *p* < .01		

Note: * *p* < .05, ** *p* < .01, *** *p* < .001 significance level.

Course Difference on Academic Performance

One-way between-groups analysis of covariance (ANCOVA) techniques were used to examine the difference in mean final grade across course subject (math or social studies) while controlling for student math ability (7th grade state math score). All analyses were conducted using R (R Core Team, 2023). Means (standard deviations in parentheses) and frequencies are presented in Table 8.

Table 8. ANCOVA groups descriptive statistics.

	Frequency	Final Grade Mean (SD)	7th Grade Math Mean (SD)
Math	30 (50.8%)	70.98(16.52)	545.03(38.24)
Social Studies	29 (49.2%)	74.56(18.56)	549.28(51.20)

Preliminary checks were conducted to examine possible violations of assumptions for conducting ANOVA. Equal variances may be assumed (Figure 7) as supported by Levene's Test of Homogeneity of Variance, F(1,57) = 0.47, p = .497. As seen above in the multiple regression, the normality assumption is violated (Figure 8) evidenced by results from Shapiro-Wilk Test, W = 0.89, p < .001.

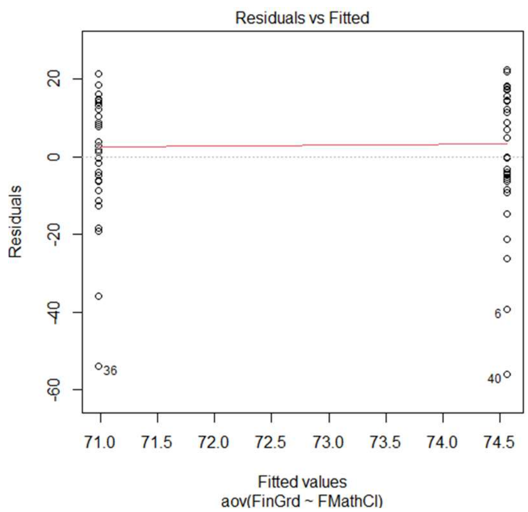

Figure 7. Plot for equal variance assumption.

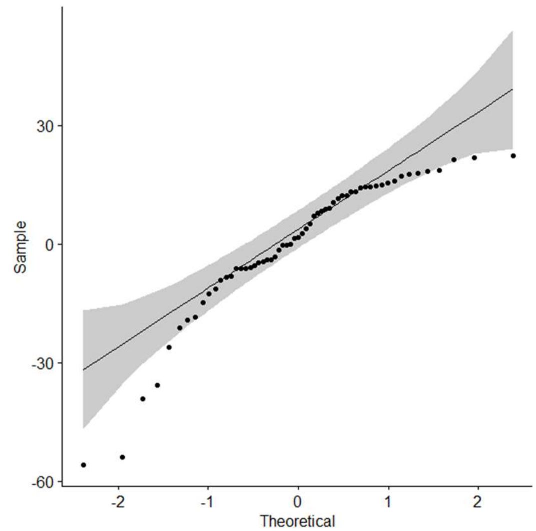

Figure 8. Plot for normality of residuals.

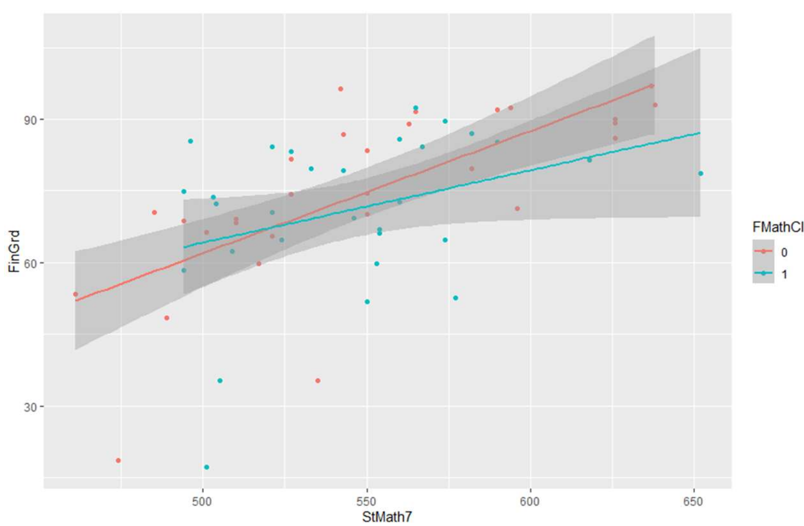

Figure 9. Plot for normality of residuals.

Assumptions specific to the application of ANCOVA techniques were not a concern. The interaction effect of 7th grade state math score and course group (Figure 9) was not statistically significant, $F(1,55) = 1.36$, $p = .249$, which indicates no concern for violation of the homogeneity of regression slopes assumption. Independence between the covariate 7th grade state math score and course group can also be assumed, $F(1,57) = 0.13$, $p = 0.719$.

After adjusting for the covariate, 7th grade state math score, there was no significant difference between the math and social studies courses on final grade, $F(1,56) = 0.878$, $p = .353$, partial-$\eta^2 = .015$, indicating a small effect size. There was a strong relationship between 7th grade state math score and final grade, $F(1,56) = 25.47$, $p < .001$, partial-$\eta^2 = .313$, indicating a large effect for the covariate. Observed power, which was calculated using G*Power, was extremely low, .157. Since there were only two comparison groups, no Tukey post hoc analysis was conducted.

The results of the descriptive statistics, the multiple regression, and the ANCOVA analysis give an interesting picture of this study and the two-group sample. Though there were no outliers on the covariate, all three variables in the multiple regression had multiple outliers. The covariate was significantly and positively correlated with both final grade and with the measure of intelligence but not time on task. Furthermore, time on task correlated negatively but not significantly with both intelligence and the covariate. However, when analyzed with multiple regression, both intelligence and time on task emerged positively-related and significant to final grade. Additionally, though the covariate exhibited a strong effect size in relation to final grade, the ANCOVA analysis showed no significant difference in final grade across course subject groups with both a small effect size and very low power. Finally, in all analyses, the normality assumption of the residuals was not supported.

Chapter 5: Summary

The purpose of this study was to examine the academic performance of high schoolers taking college courses with respect to the roles of student intelligence and time spent practicing in predicting that performance. This research was interested in determining whether intelligence and time on task are significant predictors of final grade in a college course. This study also aimed to examine whether different subjects for college courses would exhibit significant differences in mean final grade.

This chapter will discuss the findings of the previous chapter in relation to the literature review from Chapter 2 and the framework that was presented in Chapter 1. The discussion will be followed by some implications for policy in education, an examination of some of the limitations of this study, and recommendations for future research in the area of academic performance and individual differences.

Findings and Implications

This section presents a discussion of the results of the study that were presented in Chapter 4, beginning with the descriptive statistics and then research questions and hypotheses. This discussion will emphasize themes relevant to the problem and questions presented in Chapter 1. Some practical applications for stakeholders in education will be presented that are focused on the success of students in dual enrollment courses and college courses in general based on the findings of this study.

Discussion of Findings

Descriptive Statistics. Looking at the descriptive statistics in Table 2 and Table 3, the mean final grade for students in the math courses, 72.27, was lower than the mean final grade for students in the social studies courses, 75.48. This is inconsistent with the research reviewed on this comparison in Chapter 2. The reverse was expected. However, this could be a phenomenon of the transition into college level courses given that the research examined was taken from middle school and high school students. Furthermore, there were three low outliers that may have been influential in bringing down the mean, but both the math group and social studies group included low outliers as seen in Figure 1.

Another explanation for this result is specific to the sample in this study. The school system where this study was conducted has a gifted program for high schoolers that selects students based on an academic test and GPA. These students are encouraged to take social studies dual enrollment but forbidden from taking math dual enrollment courses. Thus, the participants in the math group included none of these gifted students in the school system while the social studies courses included several of them. This could have confounded the final grade measure. However, the use of the covariate in the second hypothesis will mitigate this concern.

Though no literature was reviewed on the subject, the mean hours spent by students doing online practice was 18.64 hours for the semester. Since a semester is typically 16 weeks, it appears that a student typically spent an average of a little more than an hour per week on practice activities. Separated by group, math students spent an average of 21.93 hours over the semester doing online practice while social studies students spent 15.15 hours, indicating that the math students spent a larger amount of time practicing, on average, with the result of a lower average final grade.

If the Raven's Standard Progressive Matrices intelligence measure is valid, the mean and standard deviation would be expected to be comparable across both groups, and that's exactly what is seen in Tables 1 through 3. That is, any random group that is representative of students in high school should result in a comparable mean intelligence. These descriptive statistics indicate that, not only is the whole group likely to be representative of the population, but each group seems to be representative of the population. Unfortunately, as will be seen below in limitations, that population is very unique so these results are not very generalizable. Furthermore, this information makes suspect the possibility that the gifted students made any special difference in the mean final grade of the social studies group.

In spite of there being two outliers (low) for the independent variable (Figure 1) and one outlier (high) for time on task (Figure 3) for the whole group of respondents, these data points were included in the analysis. The two low outliers on final grade were kept because it is common for college courses to have students that essentially give up on doing the coursework and miss the withdrawal deadline. This information is still relevant. The one high outlier for time on task may have been an over-approximation for a student that regularly started a practice assignment and then left the timer running.

The only thing notable for the focus of this study in the correlations from Tables 4 through 6 is that there is a significant positive correlation of moderate strength between intelligence and 7^{th} grade state math test score for whole group, math group, and social studies group. This is additional support for the well-established relationship between intelligence and academic performance. A first glance at the non-significant correlation between time on task and final grade in the whole group and in the two sub-groups seems to support the studies that found no significance for time on task predicting academic performance.

Research Question 1 and Hypothesis 1. The first research question inquired whether high school student intelligence and time on task will significantly predict final grade in a college course. This study hypothesized that these predictors would both be significant predictors with positive relation to final grade. As seen in Table 7, the results of multiple regression support this hypothesis in full. As expected and consistent with the majority of previous research on the subject, intelligence was found to be a significant predictor of academic performance. Like all prior research examined in this study, including all meta-analyses, the relationship between intelligence and academic performance is a positive one. That is, it is reinforced that students that measure higher in intelligence will tend to achieve a higher final grade in an undergraduate college course. This explains why tests like the SAT and ACT are often utilized for college acceptance and why, in spite of the temporary pause in requiring ACT or SAT scores for college application during COVID years, colleges are beginning to once again require scores for these tests of intelligence.

The regression coefficient for intelligence, 0.49, means that, holding time on task constant, for every one point increase in intelligence measure, a high school student will have a final grade in a college course that is about 0.5 higher. Since the standard deviation on the intelligence measure in this study is about 12, it can be interpreted that every one standard deviation increase in intelligence gives a student a final grade that is about 6 points higher, which can move a student up a whole letter grade in some cases.

In spite of mixed results from some previous research, but as expected, time on task was also found to be a significant and positive predictor of academic performance. Plant et al. (2005) proposed that the reason time on task is not a significant predictor of academic performance in some studies is because the quality of time practicing must be considered. However, Plant et al. (2005) did not conduct a multiple regression analysis that included student intelligence as a predictor, though they did find significance for time on task when they considered previous success in academic performance in the analysis with time on task. Bilalic et al. (2023) and Johnson & Kuennen (2006) included measures of intelligence along with measures of time on task in their models predicting academic performance and, like this study, found both to be significant positive predictors. Guillaume & Khachikian (2011) found no significant link between time on task and final grade but did not include intelligence or any other student quality in a multiple predictor model.

It was previously noted that the literature indicates that the link between time on task and academic performance is poorly understood. This study adds to overall understanding of this by suggesting that time on task might not be understood as a predictor on its own but is better understood alongside other predictors in some kind of multiple predictor model like the multiple regression utilized in this study.

The regression coefficient for time on task, 0.55, means that, holding intelligence constant, for every additional hour of time spent by a high school student on practice activities, the raw final grade in a college course will be 0.55 points higher. In a typical 16 week college course, just one additional hour each week in studying and practice could result in a final grade that is 8.8 points higher.

The adjusted R^2 for the multiple regression model was 0.134, indicating that 13.4% of the variance in final grade was explained by the regression on intelligence and time on task. The framework for this study, the "mental architecture" framework developed by Demetriou et al. (2023), details several processes that are included in general intelligence and it is likely that the 60-item RSPM does not fully tap all of them. It could be that the untapped elements of the mental architecture framework account for a larger proportion of the variance in final grade. This concern will be addressed below in recommendations for future research.

Research Question 2 and Hypothesis 2. The second research question inquired whether final grade in a college course would be significantly different for high schoolers taking a math course as compared to those taking a social studies course. This study hypothesized that there would be a significant difference between groups on final grade when controlling for the covariate, math ability as measured by student 7th grade state math test score.

The results of the ANCOVA analysis did not support Hypothesis 2, suggesting that high school student academic performance is not influenced by whether they are enrolled in a math college course or a social studies college course. However, it is possible that since all the courses included in this study were taught by the same instructor that this result may have more to do with the instructor and not so much the subject of the course. This may be worth investigating in the future.

Applications

In the case of this study, a high school student with an intelligence measure that is 1.7 standard deviations higher than another could score a full letter grade higher in a college course. This has implications for GPA requirements for scholarship retention (such as the HOPE scholarship in Georgia) as well as acceptance into programs and universities. Ritchie, Bates, & Plomin (2014) found, in an experiment comparing results in identical twins, that development of reading skills in students between 7 and 16 years old resulted in higher intelligence. This highlights that strong reading skills are important for achieving greater academic performance in college and it is worthwhile for school systems to put resources into ensuring students have strong reading skills.

Similarly, time on task findings indicate that a few additional hours of study and practice during a college semester can increase final grade. Some college math professors encourage their students to spend twice as much time outside of class practicing math as they spend in the scheduled class time. This seems like a good recommendation as every two hours of study time has the potential for increasing a student's final grade by 1 point. As for school policy, there has been some debate for a little while about the effectiveness of homework with many proposing that homework does not improve learning. The results of this study suggest that homework study assignments can indeed improve academic performance.

The results from research question 2, though not significant, do raise the question of whether high school counselors, administrators, or parents should be concerned about discouraging students from taking certain subjects for dual enrollment due to difficulty and endangering the student's GPA. The results of this study seem to indicate that any concerns of this sort are unmerited so long as the student would perform well on a measure of intelligence, like the ACT, and is committed to spending the study and practice time necessary for success in any undergraduate college course.

Recommendations

This section details several limitations in methodology and generalizability and proposes recommended directions for future related studies as well as improvements on this study. These are not exhaustive in scope but intend to focus on the spirit of the main problem and questions of the study as described in Chapter 1.

Limitations

Some of the limitations described here were anticipated before data collection and analysis were undertaken and others were encountered along the way. This is not an exhaustive list of the problematic issues encountered during the course of this study. Though there are likely limitations beyond those of generalizability, measurement, and analysis, the examination of the threats to scientific inquiry conducted here represents what are believed to be the most relevant issues given the nature of the problem and questions stated.

Limitations on Generalizability. This study examined the academic performance of high school students in a dual enrollment environment. Therefore, the results can neither be generalized to college courses with college students nor to high school courses with college students. Furthermore, the highly diverse student population of the school system makes it difficult to generalize the results even to other dual enrollment environments in other states or regions. Nonetheless, the main finding of this study is consistent with the results of similar studies that have been conducted at the primary, secondary, and undergraduate levels. Therefore, though the specific results of this study are not generalizable to any dual enrollment, high school, or college situation, the general results that support the positive and significant link between intelligence and academic performance are generalizable when taken with the numerous similar studies like it.

Limitations of Measurement. As noted earlier, though there were no real difficulties in measuring academic performance by final grade, there were some respondents who did not complete every assignment and received a zero for one or more assignments. Though a zero is the just grade for a student who does not complete an assignment, a zero is actually missing data because it represents a lack of information regarding the student's knowledge and learning. But since zeros are a normal part of calculating a student's academic performance, it was necessary from a practical point of view and valid with respect to the interpretation of the results.

Measuring intelligence with Raven's Standard Progressive Matrices did not appear to present any problems. However, it was assumed that all participants tried their best and achieved a score for intelligence that is accurate to their actual intelligence. In reality, it is possible that some students may have raced through the test hastily given that they volunteered to participate during their own free time. Additionally, the participants did not all complete the test at the same time or on the same day, so there may have been threats to validity if a student who completed the test shared information with another student who had not yet taken it. It could make for an interesting study to examine the item analysis of the RSPM across all participants.

The greatest measurement issue was with time on task. Since students were not required to submit a practice assignment after starting it and were given unlimited opportunities on each practice activity, many judgment calls needed to be made while summing the times regarding which time stamps in the LMS indicated actual practice as opposed to the student starting the assignment, leaving to do something else, and returning to continue the assignment. Shorter intervals were generally considered accurate while intervals exceeding five hours seemed unlikely as single study sessions. Thankfully, the LMS did keep track of when a student answered a specific question and when the activity seemed dormant. Though the issue with measuring time on task from the LMS time stamps is a limitation, it does evade the problems associated with respondents self-reporting the time they spent practicing. The meta-analysis by Kim & Seo (2015) calls attention to the fact that some studies collect time on task data by self report and others by more objective measures like in this study.

Limitations of Analysis. For both the multiple regression analysis and the ANCOVA analysis, the normality of residuals assumption was violated for final grade. It is expected that final grade distribution is skewed since the maximum score is 100 and the lowest passing grade is often 70. Since the mean of final grade is 73.83, any cases with a significantly low final grade will contribute to a skewed distribution of the residuals, which clearly happened in this study. As noted earlier in the discussion of descriptive statistics, these cases were not excluded from the analysis purposely. Ideally, a study would have no students scoring so low that the distribution of residuals is not skewed, but that is beyond the control of the instructor or researcher.

For multiple regression, priori power analysis was conducted for a medium effect of adjusted R^2 = .13 indicated a recommended sample size of 68 to achieve a power of 0.80. The observed power for this study almost precisely matched the priori power analysis. However, for hypothesis 2, the ANCOVA analysis required a much larger sample size to achieve adequate power for such a small effect size. The observed power was 0.157, which means there is a .843 probability of incorrectly not rejecting the null hypothesis. Since the ANCOVA analysis was not significant, the null hypothesis was not rejected but the observed power indicates that there is a high probability that this result may be false. To have greater confidence in our conclusions, there needs to be a larger sample.

Future Research

The descriptive statistics separated by math and social studies groups indicated that math students had a lower final grade but a higher amount of practice time than social studies students. It could be that math learning requires a larger amount of out-of-class-time practice in order for a student to score higher on final grade in college courses. This seems like a worthwhile study which would almost replicate this present study but include an intelligence measure as a covariate or control variable rather than a co-predictor.

The question was brought up previously whether the social studies group had a higher mean final grade than the math group because the math group included no students from the system-wide gifted program. A future study could examine whether high school gifted status makes a difference in college-level academic performance. The present study could not examine that question due to the very limited number of gifted students in the sample and because none of the gifted students were present in the math group. But this question could be examined in a college environment with a much larger sample.

This study generally examined and found support for intelligence and time on task as predicting academic performance without separating the math course and social studies course groups. A clearer picture of this phenomenon can be achieved by conducting separate analyses on each subject group. This may show if the results found in this study hold independently for different college courses as seen in Bilalic et al. (2023).

Given that it is unlikely that the RSPM measure of intelligence did not cover the entire breadth of general intelligence in the mental architecture framework (Demetriou et al., 2023), future studies could seek to examine more of the components of this framework with additional measures of general intelligence combined with the RSPM. This study proposed that RSPM is a measure of “fluid intelligence” and that time on task is a component of “cognizance”, but the “executive functions” portion of general intelligence was not included. Perhaps a future study could include a measure of this portion as well as additional components of cognizance.

For future replications of this study, it is recommended that a larger sample size be used for the final grade comparison by group to increase power. Special attention should be given to the collection of time on task data and the administration of the RSPM. If possible, arrange to get individual item data on the 60 items of the RSPM so that item analysis can be conducted.

Conclusion

This summary does not claim to provide an exhaustive discussion of the findings, implications, limitations, and possibilities for future research but only a relevant discussion of the primary points regarding the research questions raised in Chapter 1. This thesis contains research that provides progress into understanding the roles of intelligence and time spent studying for students at the very beginning of their undergraduate college career. Perhaps this study will both inspire more research and provide support for good education policy.

References

Adesope, O. O., Trevisan, D. A., & Sundararajan, N. (2017). Rethinking the Use of Tests: A Meta-Analysis of Practice Testing. *Review of Educational Research*, 87(3), 659-701.

Alhinai, S. S. A., Al Kharusi, H. A. T., & Ibrahim, M. M. (2019). Meta-Analysis Reliability Of Raven's Progressive Matrices Tests. Perdana. *International Journal of Academic Research*, 6(1), 51-68.

Arnold, I. J., & Straten, J. T. (2012). Motivation and Math Skills as Determinants of First-Year Performance in Economics. *The Journal of Economic Education*, 43(1), 33-47.

Ballard, C. L., & Johnson, M. F. (2004). Basic Math Skills and Performance in an Introductory Economics Class. *The Journal of Economic Education*, 35(1), 3-23.

Beiswinger, J. S. (2009). Improving Academic Achievement at a Greater Rate with Increased Instructional Time for Students Who Qualify for Free and Reduced Lunch.

Bilalić, M., Đokić, R., Koso-Drljević, M., Đapo, N., & Pollet, T. (2023). When (Deliberate) Practice is Not Enough–The Role of Intelligence, Practice, and Knowledge in Academic Performance. *Current Psychology*, 42(27), 23147-23165.

Bracken, B. A., & Naglieri, J. A. (2003). Assessing Diverse Populations with Nonverbal Tests of General Intelligence. *Handbook of Psychological and Educational Assessment of Children*, 2, 243-274.

Burke, H. R. (1972). Raven's Progressive Matrices: Validity, reliability, and norms. *The Journal of Psychology*, 82(2), 253-257.

Chamorro-Premuzic, T., & Furnham, A. (2006). Self-Assessed Intelligence and Academic Performance. *Educational Psychology*, 26(6), 769-779.

Demetriou, A., Kazi, S., Spanoudis, G., & Makris, N. (2019). Predicting School Performance from Cognitive Ability, Self-Representation, and Personality from Primary School to Senior High School. *Intelligence*, 76, 101381.

Demetriou, A., Spanoudis, G., Christou, C., Greiff, S., Makris, N., Vainikainen, M. P., ... & Gonida, E. (2023). Cognitive and Personality Predictors of School Performance from Preschool to Secondary School: An Overarching Model. *Psychological Review*, 130(2), 480.

Duncan, D. W., Ricketts, J. C., & Shultz, T. (2011). Science, Math, Social Studies, and Language Arts Achievement of High School Students in Complete Programs of Agriscience Education. *Online Journal for Workforce Education and Development*, 5(3), 4.

Farsides, T., & Woodfield, R. (2003). Individual Differences and Undergraduate Academic Success: The Roles of Personality, Intelligence, and Application. *Personality and Individual Differences*, 34(7), 1225-1243.

Ford, D. Y. (2004). Intelligence testing and cultural diversity: Concerns, cautions, and considerations. National Research Center on the Gifted and Talented.

Garg, A., & Sharma, R. (2016). Intelligence and Affect as Predictors of Academic Performance Among Undergraduate Students. *International Journal of Education and Management Studies*, 6(1), 11.

Gjana, A., & Kosova, R. (2021). Traditional Class, and Online Class Teaching. Comparing the Students Performance Using ANCOVA. *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, 14806-14811.

Godwin, K. E., Seltman, H., Almeda, M., Davis Skerbetz, M., Kai, S., Baker, R. S., & Fisher, A. V. (2021). The Elusive Relationship Between Time On-Task and Learning: Not Simply an Issue of Measurement. *Educational Psychology*, 41(4), 502-519.

Guillaume, D. W., & Khachikian, C. S. (2011). The Effect of Time-On-Task on Student Grades and Grade Expectations. *Assessment & Evaluation in Higher Education*, 36(3), 251-261.

Heaven, P. C., & Ciarrochi, J. (2012). When IQ is Not Everything: Intelligence, Personality and Academic Performance at School. *Personality and Individual Differences*, 53(4), 518-522.

Hicks, S. B. (2014). *Examining Differences in Middle School Student Achievement on the Math, Science, and Social Studies Criterion-Referenced Competency Test (CRCT)* [Doctoral Dissertation, The University of Georgia]. http://getd.libs.uga.edu/pdfs/hicks_sarah_b_201408_edd.pdf

Johnson, M., & Kuennen, E. (2006). Basic Math Skills and Performance in an Introductory Statistics Course. *Journal of Statistics Education*, 14(2).

Kim, K. R., & Seo, E. H. (2015). The Relationship Between Procrastination and Academic Performance: A Meta-Analysis. *Personality and Individual Differences*, 82, 26-33.

Laidra, K., Pullmann, H., & Allik, J. (2007). Personality and Intelligence as Predictors of Academic Achievement: A Cross-Sectional Study from Elementary to Secondary School. *Personality and Individual Differences*, 42(3), 441-451.

Lohman, D. F., Korb, K. A., & Lakin, J. M. (2008). Identifying Academically Gifted English-Language Learners Using Nonverbal Tests: A Comparison of the Raven, NNAT, and CogAT. *Gifted Child Quarterly*, 52(4), 275-296.

Makris, N., Tachmatzidis, D., Demetriou, A., & Spanoudis, G. (2017). Mapping the Evolving Core of Intelligence: Changing Relations Between Executive Control, Reasoning, Language, and Awareness. *Intelligence*, 62, 12-30.

Marjoribanks, K. (1979). Intelligence, Social Environment, and Academic Achievement: A Regression Surface Analysis. *The Journal of Experimental Education*, 47(4), 346-351.

McCallum, R. S. (2017). Context for Nonverbal Assessment of Intelligence and Related Abilities. *Handbook of Nonverbal Assessment*, 3-19.

McCrickard, M., Raymond, A., Raymond, F., & Song, H. (2018). The APLIA Math Assessment Scores and Introductory Economics Courses: An Analysis. *Journal of Business & Educational Leadership*, 8(1), 4-18.

Mills, C. J., Ablard, K. E., & Brady, L. E. (1993). The Raven's Progressive Matrices: Its Usefulness for Identifying Gifted/Talented Students. *Roeper Review*, 15(3), 183-186.

Neisser, U., Boodoo, G., Bouchard Jr, T. J., Boykin, A. W., Brody, N., Ceci, S. J., Halpern, D. F., Loehlin, J. C., Perloff, R., Sternberg, R. J., & Urbina, S. (1996). Intelligence: Knowns and Unknowns. *American Psychologist*, 51(2), 77.

O'Leary, U. M., Rusch, K. M., & Guastello, S. J. (1991). Estimating, Age-Stratified WAIS-R IQS from Scores on the Raven's Standard Progressive Matrices. *Journal of Clinical Psychology*, 47(2), 277-284.

Owen, K. (1992). The Suitability of Raven's Standard Progressive Matrices for Various Groups in South Africa. *Personality and Individual Differences*, 13(2), 149-159.

Paul, T., Swanson, S., Zhang, W., & Hehenberger, L. (1997). *Learning Information System Effects on Reading, Language Arts, Math, Scien ce, and Social Studies*. The Institute for Academic Excellence.

Pind, J., Gunnarsdóttir, E. K., & Jóhannesson, H. S. (2003). Raven's Standard Progressive Matrices: new school age norms and a study of the test's validity. *Personality and Individual Differences*, 34(3), 375-386.

Plant, E. A., Ericsson, K. A., Hill, L., & Asberg, K. (2005). Why Study Time Does Not Predict Grade Point Average Across College Students: Implications of Deliberate Practice for Academic Performance. *Contemporary Educational Psychology*, 30(1), 96-116.

Plomin, R., & Deary, I. J. (2015). Genetics and Intelligence Differences: Five Special Findings. *Molecular Psychiatry*, 20(1), 98-108.

Prins, F. J., Veenman, M. V., & Elshout, J. J. (2006). The Impact of Intellectual Ability and Metacognition on Learning: New Support for the Threshold of Problematicity Theory. *Learning and Instruction*, 16(4), 374-387.

R Core Team (2023). _R: A Language and Environment for Statistical Computing_. R Foundation for Statistical Computing, Vienna, Austria. <https://www.R-project.org/>.

Raven, J. (2003). Raven Progressive Matrices. *Handbook of Nonverbal Assessment* (pp. 223-237). Boston, MA: Springer US.

Raven, J. (2008). The Raven Progressive Matrices Tests: Their Theoretical Basis and Measurement Model. Uses and Abuses of Intelligence. *Studies Advancing Spearman and Raven's Quest for Non-Arbitrary Metrics*, 17-68.

Razani, J., Murcia, G., Tabares, J., & Wong, J. (2007). The Effects of Culture on WASI Test Performance in Ethnically Diverse Individuals. *The Clinical Neuropsychologist*, 21(5), 776-788.

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological Correlates of University Students' Academic Performance: A Systematic Review and Meta-Analysis. *Psychological Bulletin*, 138(2), 353.

Ritchie, S. J., Bates, T. C., & Plomin, R. (2015). Does Learning to Read Improve Intelligence? A Longitudinal Multivariate Analysis in Identical Twins from Age 7 to 16. *Child Development*, 86(1), 23-36.

Romero, M., & Barbera, E. (2011). Quality of E-learners' Time and Learning Performance Beyond Quantitative Time-On-Task. *The International Review of Research in Open and Distributed Learning*, 12(5), 125-137.

Rosander, P., Bäckström, M., & Stenberg, G. (2011). Personality Traits and General Intelligence as Predictors of Academic Performance: A Structural Equation Modelling Approach. *Learning and Individual Differences*, 21(5), 590-596.

Roth, B., Becker, N., Romeyke, S., Schäfer, S., Domnick, F., & Spinath, F. M. (2015). Intelligence and School Grades: A Meta-Analysis. *Intelligence*, 53, 118-137.

Schneider, M., & Preckel, F. (2017). Variables Associated with Achievement in Higher Education: A Systematic Review of Meta-Analyses. *Psychological Bulletin*, 143(6), 565.

Schug, M. C. (1982). Why kids don't like social studies.

Soares, D. L., Lemos, G. C., Primi, R., & Almeida, L. S. (2015). The Relationship Between Intelligence and Academic Achievement Throughout Middle School: The Role of Students' Prior Academic Performance. *Learning and Individual Differences*, 41, 73-78.

Stodolsky, S. S., Salk, S., & Glaessner, B. (1991). Student Views About Learning Math and Social Studies. *American Educational Research Journal*, 28(1), 89-116.

Ukpong, D. E., & George, I. N. (2013). Length of Study-Time Behaviour and Academic Achievement of Social Studies Education Students in the University of Uyo. *International Education Studies*, 6(3), 172-178.

Wexler, N. (202, January 13). Teachers Think Kids Need Science And Social Studies—But Still Focus On Reading And Math. *Forbes*. https://www.forbes.com/sites/nataliewexler/2020/01/13/teachers-think-kids-need-science-and-social-studies-but-still-focus-on-reading-and-math/?sh=5f61fdb6318f

Appendix A

Free Online Version of Raven Standard Progressive Matrices

Access at: https://psycho-tests.com/test/raven-matrixes-test

Appendix B

Assent Form, Consent Form, and IRB Approval

DocuSign Envelope ID: 9B93A996-C047-4AF1-A534-08D212800059

SSU IRB Approved GR 12/9/2023 | 10:14

Shawnee State University

Study # 2023-59

Expedited Review Application

Based on the "Type of Review Flow Chart", I believe that my research project only requires an Expedited Review. *Yes* X *No*

Title of Research Project:
What Can Help A Student To Perform Well In Class?

Name of Principal Investigator	Email Address	Phone Number
Douglas Darbro	DDarbro@shawnee.edu	(740) 351-3441

Department(s)/Division/Agency: Mathematics

Name(s) of Co-Investigators:	Email address:	Faculty	Student	Other
Michael Ryan	RyanM2@mymail.shawnee.edu	☐	☒	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐
		☐	☐	☐

*Please place an asterisk by the investigator name(s) whose Training certificate(s) is/are already on file with the IRB, if the certificate is less than 3 years old.

1. Describe the key demographics (age, SES, ethnicity, geographic locations, gender, etc.) of the sample that you wish to obtain.
Participants will be grade 11 or grade 12 high school students ages 16 to 18 (key demographics of the study) of varying ethnicities, SES's, and genders (these are not key demographics of the study).

1a. What is the greatest number of participants that will be recruited? 150

1b. How will participants be recruited?
Participants will be the students enrolled in the courses where the researcher is the instructor. These students will be recruited by being asked to voluntarily participate in the study.

1c. Check the type of populations listed below that will be included in the study.

__X__ Children (under the age of 18)
_____ Prisoners
_____ Participants with diminished cognitive ability (unable to provide consent)
_____ Pregnant women and/or fetuses
_____ No vulnerable populations will be included

Rev. 9/3/2013;1/24/22 1

Shawnee State University

Study # 2023-59

2. Will participants be remunerated for their participation? Yes X No

2a. If so, how will participants be remunerated? Please indicate the type of remuneration and the amount. For instance, the participants will be given a $10 Amazon Gift Card for participation or the participants will receive 3% of their final grade in extra credit in their Introduction course.
Participants will be given 10 points on their final grade (out of 1,000 possible points which is a 1% increase on their final grade).

2b. If participants do not complete the study, will partial or full remuneration be given? Please describe how that will be determined
Students who do not complete the study will be given an alternative opportunity to receive an extra 10 points on their final grade.

3. What direct benefits (other than remuneration) exist for the participants who participate?
None.

4. What direct risks could the participants potentially face? Check all that apply.

__X__ Risk of breach of confidentiality or privacy

_____ Risk of coercion by researcher(s)

_____ Risk of psychological harm

_____ Risk of physical harm

_____ Other potential risk: ____

4a. Please describe the specific risk(s).
Specific risk includes breach of confidentiality in the form of public knowledge of their 9th grade state math test result. Also, there is the risk of the accidental release of the results of answers to the questions on the online IQ test form that is collected.

4b. What measures will be taken to limit or minimize the risks?
To minimize this risk, after all data has been collected in the classroom, the data will be given to a building-level administrator who will fill in the information on the state math score and then remove all student identifying information from the data set before returning it to the researcher.

5. What are the expected benefits of the research to the scientific community or the common good?
This study will contribute to the body of knowledge on understanding how intellectual ability and time spent learning affects student performance in dual enrollment classes.

6. Does the methodology require that participants be deceived about any aspect of the study?

Yes No X

6a. If so, please justify the use of deception and describe the debriefing procedures that will be used (Please attach the debriefing form and/or a script of the debriefing information).
N/A

7. How will the participants be informed of the risks and benefits of the study?
Students will be informed of the 10 point extra credit benefit and the risks face-to-face, by e-mail, and by announcement through the educational institution's learning management system (Blackboard, Canvas, etc.). Risks will also be communicated on the Consent and Assent forms.

7a. How will consent be obtained from participants (or their legal guardian)?
A Consent form will be distributed and explained to participants face to face and by e-mail. The form will be signed by the appropriate parties and returned to one of the investigators.

7b. Will participants be involved who cannot give legal consent? Yes X No

7c. If so, how will assent be obtained from the participants?
An Assent form will be distributed and explained to participants face to face and by e-mail. The form will be signed by the appropriate parties and returned to one of the investigators.

SSU IRB Approved ER 12/9/2023 | 10:14

Shawnee State University

Study # 2023-59

In submitting this form and the corresponding documents, I acknowledge that I have completed Human Research Participants training and that I understand and will uphold the rights of human participants. I also verify that all information contained in this form and any other corresponding documentation is correct based on my knowledge. I understand that I may not have contact with any research participants until the Shawnee State University IRB has given me their approval. I also understand that I must file an *Amendment/Modification Form* if my project extends beyond a year from my approval date and I must file a *Final Study Form* with all consent forms once the study is complete.

DocuSigned by: Douglas Darbro
1DFACF8D0794406...

Signature of Principal Investigator 1

DocuSigned by: Michael Ryan
1D73D6735428437...

Signature of Co-Investigator 2

Signature of Co-Investigator 3

Signature of Co-Investigator 4

Signature of Co-Investigator 5

Signature of Co-Investigator 6

Date of Submission: 12/3/2023 | 2:38 PM EST

Please compile attachments into one document for each category. If any forms below are not applicable, please attach reasons why.

Human Research Training Certificates:

Data Collection Questions and Forms:

Research Summary:

Consent Forms:

Assent Forms:

Advertisements:

Revisions Requested Yes No X IRB Chair Signature

Date sent for revision (if applicable): ________________

Please attach revisions requested with changes clearly marked

Changes marked

Final copy

DDD

Assent Form for Participation in a Research Study
Shawnee State University

1. **Study Title**: What Can Help A Student To Perform Well In Class?

2. **Where and when will I go to be a part of the study?** Rockdale Career Academy in Mr. Ryan's classroom during your normal class period on a Friday.

3. **Who can I talk to about the study?** Your teacher, Mr. Ryan. You can meet with him, or you can call him at RCA at 770-388-5677 ext 31427, or e-mail him as usual at mryan@rockdale.k12.ga.us .

4. **Why is Mr. Ryan doing this study?** To find out if study habits and abilities affect how good someone's grades will be in a class. Also to see if students do better in math or better in economics.

5. **What kinds of people would be participating with me?** Other high school students, like you, taking Introduction to Statistics or Principles of Microeconomics with Mr. Ryan.

6. **How many people are going to be participating with me?** About 60 to 100 students along with you.

7. **What will I have to do?** You will be asked to complete two groups of questions, like online tests that ask a variety of questions.

8. **Can anything good happen to me?** You will be given 1% extra credit in the class for being part of the study. But even if you do not take part, you will be given another chance to get the 1% extra credit anyways.

9. **Can anything bad happen to me?** The only kind of bad thing that can happen is other people accidentally seeing your final score on the survey questions or seeing your score from your 9th grade Coordinate Algebra milestone. However, we will be taking special care to keep all that secret by taking your name off of all the scores.

10. **What if I do not want to do this?** Then you don't have to! You are free to choose to be a part or not. You can even tell Mr. Ryan that you have changed your mind after you have said yes. Mr. Ryan wants you to do it only if you want to. At any time, you can choose to say no. You will still have a chance for the 1% extra credit.

The results of this project may be published, but your name and information will NOT be published. It will only be shared if a court of law demands any of the personal information from the study. All documents will be stored in a file cabinet in Mr. Ryan's classroom for about 3 years, then they will be destroyed.

I've had a chance to hear about this study and ask questions. If I think of any more questions about anything, I'll ask Mr. Ryan. I've been told I can call or e-mail the Associate Provost or Dr. Richards at Shawnee State University if I don't feel comfortable asking Mr. Ryan. The Associate Provost can be reached at (740) 351-3299 and Dr. Richard's e-mail is brichards2@shawnee.edu.

I agree to participate in Mr. Ryan's study described above. I know that Mr. Ryan said he would give me a signed copy of this form.

Signature of Minor____ Date_________________

Print Your Name______________________________________

SSU IRB Approved ER 12/9/2023 | 10:14

Study # 2023-59

Consent Form for Participation in a Research Study
Shawnee State University

1. Study Title: What Can Help A Student To Perform Well In Class?

2. Location of Study: Rockdale Career Academy

3. Investigators: Mr. Michael Ryan, 770-388-5677 ext 31427, mryan@rockdale.k12.ga.us or ryanm2@mymail.shawnee.edu, any time by e-mail, M-F 7:30 AM to 3:30 PM by phone.

4. Purpose of the Study: The purpose of this study is to find out if students' study habits and abilities affect how good their final grades are. Also to see if grades in math are different than grades in economics.

5. Population to be Studied: High school students taking Introduction to Statistics or Principles of Microeconomics in Spring 2024.

6. Number of subjects: 60 to 100

7. Study Procedures: You will be asked to complete two online forms asking questions about patterns.

8. Benefits: You will receive 10 extra credit points for your overall grade in the course. Your final grade will go up by 1%. Students who do not complete the study will be given an alternative opportunity to receive an extra 10 points on their final grade.

9. Risks: The only risk to you in this study is the accidental release of the results of your answers to the questions on the online form that we collect. There is also the risk of accidental release of your 9th grade state math milestone score. However, this study is anonymous and your information will be labeled with a code that is not linked to your personal information.

10. Right to Refuse: Subjects may choose not to participate or to withdraw from the study at any time without penalty or loss of any benefit to which they might otherwise be entitled. Students who do not complete the study will be given an alternative opportunity to receive an extra 10 points on their final grade.

11. Privacy: Results of the study may be published, but no names or identifying information will be included in the publication. Participant identity will remain confidential unless disclosure is required by law. All documents will be stored in a file cabinet in classroom/office of Michael Ryan for a period of 3 years, at which point the documents will be destroyed.

12. Signatures: I verify that I am 18 years of age or older. The study has been discussed with me and all my questions have been answered. I may direct additional questions regarding study specifics to the investigators listed above. If I have questions about subjects' rights or other concerns, I can contact the Associate Provost, Institutional Review Board, (740) 351-3299. I agree to participate in the study described above and acknowledge the investigator's obligation to provide me with a signed copy of this consent form.

Signature of Participant (if age 18 or older) ______________________________

Signature of Participant's Legal Guardian (if age is under 18) ______________________________

Date ____________________

BIBLIOGRAPHY

Michael Ryan

Candidate for the Degree of

Master of Science, Mathematics

Thesis: PREDICTING ACADEMIC PERFORMANCE OF HIGH SCHOOL STUDENTS IN COLLEGE LEVEL CLASSES BASED ON INTELLIGENCE AND TIME ON TASK

Major Field: Mathematics

Education: Bachelor of Science in Business Management; Master of Science in Economics

Completed the requirements for the Master of Science in Mathematics, Portsmouth, Ohio in July 2024.

7/28/2024

ADVISOR'S APPROVAL: Dr. Douglas Darbro