WHAT'S THE DAMAGE? COVID-19 ACADEMIC IMPACT AMONG HIGH SCHOOL STUDENTS

A Thesis
by
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Abstract

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The COVID-19 pandemic has interrupted the learning of millions of American students and forced educators to modify their curriculums to meet the unprecedented challenges. Unfortunately, educators are wholly unprepared for the situation, and have little information about the collective impact of the pandemic. To remedy the situation, existing research on traditional summertime off, absences, and virtual instruction can be used to advise educators on the extent of academic achievement impact caused by the pandemic. The current study measures impact on high school student test scores by comparing differences in forecasted scores to realized student performance in January of 2021. Mean differences of -1.04 and -1.87 in math and reading indicate students are only slightly behind on average, though some students are much further behind. Findings can be used to inform educators of the current learning state of students and advise instructional changes in the following semesters.

Acknowledgments

My thesis committee chair, Dr. Shawn Bergman, has been instrumental in keeping the project moving forward and overcoming the unique challenges of the times. Dr. Jennifer Wilson-Kearse, and all the members of Vela Institute, have also provided an immense amount of support by providing data and funding to assist with the project. Data organized by staff of the study's school district, in addition to the students, have made the project possible. The time and effort of Dr. Kemp Ellington and Dr. Yalcin Acikgoz has also been greatly appreciated. All members sacrificed a great deal of time with their families to assist my goals in finishing the project, and for that I am grateful.

Dedication

My work is dedicated to all the people who have influenced, inspired, and encouraged me to get to where I am today. Your boundless support may have been under-rewarded, but it was surely noticed and appreciated.

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What's the damage? COVID-19 Learning Impact among High School Students

The educational routines of millions of students in the United States have been turned upside-down as a result of the coronavirus disease 2019 (COVID-19) pandemic. School districts across the country have scrambled to address the needs of students, with many schools closing early in the spring or delaying openings in the fall. In attempts to ensure student safety, many districts transitioned to forms of online instruction during the spring of 2020 and continue to utilize them through the 2020-2021 academic year (Education Week, 2020). These changes led to an extension of the summer break for many students, and increased absences during the fall of 2020 as instruction transitioned online (Kurtz, 2020).

Though these changes to schooling are unprecedented, there are many similarities to past situations prior research has examined that may provide insights into the academic achievement influences of the pandemic. Individual days of student absence from in-class instruction, for example, have been shown to contribute losses of up to .05 standard deviations in standardized test score achievement (Goodman, 2014). Absences in excess of ten per year often indicate potential for serious course grade and test score reduction (Liu et al., 2019; Nichols, 2003). Students' time away from school between grades commonly describe learning impacts as "learning loss," "summer slide," or "summer setback" and show losses in student testing achievement due to time away from instruction over the summer (Cooper et al., 1996; Kuhfeld, 2019). The declines, mostly found through comparing late spring and early fall standardized test scores, have been shown to be substantial, causing a reduction in achievement of about a month of learning (Cooper et al., 1996; Kuhfeld, 2019). This "learning lost" requires educators to devote additional time for reviewing material that has already been covered and presumably learned during the previous school year (Lauer et al., 2006; Goodman, 2014; von Hippel & Hamrock, 2019). In tandem, absences and summertime off from school cause difficulties for teachers to provide consistent instruction for students, while students receive less opportunities to learn new material and practice previously gained skills. Student academic achievement may suffer as a result of these issues.

In addition to these factors, the role of instructional method may help to contribute to an understanding of how COVID-19 may influence student academic achievement. Typically, students in the U.S. attend schools in person with their peers, with only 3% of students homeschooled and around 90% of students attending public schools (Riser-Kositsky, 2020; U.S. Department of Education, 2020). Prior to the pandemic, literature comparing online instruction and traditional in-class instruction showed that online learning has the potential to be equally as effective as in-person instruction (Cavanaugh, 2001; Cavanaugh et al., 2004; Means et al., 2009), though other studies investigating high school students attending online charter schools revealed they may perform worse than other students (Ahn & McEachin, 2017; Woodworth et al., 2015). This area of research appears to be particularly applicable because many schools have moved to types of remote or hybrid, a combination of in-person and remote, instruction during the pandemic. Though it is difficult to determine the impact of the shift in instructional method on teachers and students, it is reasonable to assume many teachers were not prepared for a sudden transition to online instruction, and the quality of instruction has suffered. With the decreased quality and shifting instructional methods, teachers and students are prone to react negatively (Davis et al., 2007; Hawkins et al., 2012; Northcote, 2008).

Unfortunately, many educators fear declines far beyond normal trends in student academic achievement due to COVID-19 factors (Di Pietro et al., 2020, Kuhfeld et al., 2020; von Hippel, 2020). Many students spent longer amounts of time out of school over the summer break and have been in classes far less after returning due to increased absences (Kurtz, 2020). In addition, the rapid shift from traditional in-person instruction to hybrid or fully virtual instruction likely decreases the effectiveness of learning. Given the multiple areas of influence the pandemic has played in education, it is appropriate to offer a more concise definition of the issue specific to the aims of the current study. The pandemic's effects on student academics will be collectively regarded as "COVID academic achievement impact" (COVID-AAI). Previous work relevant to COVID-19 is projecting an overall loss in academic performance for students (Di Pietro et al., 2020; Kaffenberger, 2020; Kuhfeld et al., 2020). However, this work has been in the aggregate and the role that individual student-level factors will have on academic achievement due to the COVID-19 pandemic has yet to be examined. The uncertainty of the relationship between student factors and COVID-AAI is the cause of concern for many teachers and forms the basis of the need for the current study.

Understanding potential COVID-AAI is critical for educators to manage short-term and long-term student issues. A key first step to mitigating COVID-AAI is identifying the current learning progress of students. In the short-term, educators will be able to distinguish students who have suffered the greatest COVID-AAI and tailor their instruction to assist them. In the long-term, educators must also deal with compounded COVID-AAI, where students may have fallen behind on their educational goals. With reduced learning, academic achievement suffers and students are less likely to graduate from high school and pursue post-secondary education options (Liu et al., 2019). Educators can use COVID-AAI data to guide policies and curriculum designed to get students back on track, preventing COVID-AAI from acting as an obstacle to greater education. Furthermore, identifying areas of difficulty for students in the short-term allows for specific learning remediation solutions needed for certain students. In summary, understanding the student academic achievement impact of the COVID-19 pandemic will supply educators with the information they need to provide students with better opportunities to regain their footing and stay on track towards educational achievements.

The purpose of this study is to examine how individual student-level factors relate to COVID-AAI among high school students. Previous research was used to identify the student-level characteristics that are thought to relate to COVID-AAI most strongly, and a model was developed using information from previous school years. The model was used to forecast student test score achievement without the influence of the pandemic. Differences in predicted and realized student scores were utilized to identify student characteristics that relate to COVID-AAI.

Review of Relevant Literature

Due to the unprecedented nature of the COVID-19 pandemic, there is little information that is directly applicable to the educational effects of the novel virus. However, there are areas of research that reflect characteristics of the pandemic and can provide information. By reviewing previous literature, the mechanisms driving COVID-AAI can better illuminate the situations that have arisen because of COVID-19 and its predicted effect on student learning and achievement. Three main areas of literature provide evidence on COVID-AAI: 1) seasonal summer breaks, 2) student absences, and 3) shifts to virtual instruction methods. The following summarizes previous findings in these areas and demonstrates how the educational effects of the novel virus are thought to have impacted student academic achievement.

Seasonal Summer Learning

Historically, the investigation of seasonal differences in academic gains and learning achievement have been described using the terms “learning loss”, “summer slide”, or “summer setback” (Kuhfeld, 2019). Regardless of the terminology, seasonal research attempts to describe declines in student achievement between the spring and fall semesters as a result of extended time out of school spanning the summer break. The reasoning for the decline is simple. When students are out of school, they are not engaging with learning materials as often as when in school. Their previously flowing stream of information is suddenly turned off, as Entwisle, Alexander, and Olson liken to a “faucet” (2000). Instead of spending time on schoolwork, they spend time with their families. However, family time may harbor vastly different opportunities for students. An example of the varying family preferences for how students spend their summertime is the difference in the amount of television a child will watch (Gershenson, 2013). Though the ratio of recreational and educational activities may vary between families, nearly all students spend relatively little time on academics. Over the entire summer, with little time spent reviewing previously learned concepts or learning new ones, they tend to forget some of what was learned in the previous school year.

Though summertime off may seem harmless, the learning lost can be extensive. The investigation of summer effects began in the early 1900’s, and has had periods of heightened interest, particularly sparked by Cooper and colleagues’ synthesis of research from studies conducted through the 1990’s (Cooper et al. 1996). The authors found that typical student losses over the summer hovered around one month of learning. Additional investigations have reflected this finding, including recent evidence from modern adaptive testing (Kuhfeld, 2019; Atteberry & McEachin, 2020). Kuhfeld found median summer losses of 1-2 months in reading and 1-3 months of learning in math in elementary and middle school students, while Atteberry and McEachin found losses between 17 and 28% of school year growth in English and Language subjects and losses between 25 and 34% in math. However, some researchers have argued that the extent of summer learning losses may be exaggerated due to the difficulty of obtaining accurate learning loss measurement (Kuhfeld, 2019; von Hipple 2019; von Hipple & Hamrock, 2019).

While previous results were found during "normal," pre-pandemic summers, it is likely that the effects are heightened due to the increased length in time out of school. Many schools closed early in the spring semester and delayed opening in the fall, extending the period of time students were not receiving schooling. Though summer programs and camps may provide students access to learning materials and have the potential to reduce summer learning losses (Augustine et al., 2016; Lenhoff et al., 2020) it is unlikely that programs were held in full scope during the summer of 2020 in order to ensure public health safety practices. Overall, it is expected that the normal trend of summer losses in student achievement are amplified due to the lengthened and disrupted summer brought by COVID-19.

Absences

A second body of literature that can inform COVID-19 learning impact is the role of student absences on student learning achievements. Absences cover time students fail to attend school while school is still in session with chronic absenteeism being defined as missing at least 15 school days (U.S. Department of Education, 2020). This leads to increased time out of school and causes students to miss information that the rest of a class covers, leading to reduced opportunities for learning**.**

Evidence from previous investigations reveal a strong correlation between student absences and student test performance (Roby, 2004). The negative effects of absences can stack up as the occurrences increase because the relationship between absences and achievement is close to linear (Goodman, 2014; Liu, et al., 2019). In Goodman's study investigating the effects of snow day absences, students were found to suffer up to a .05 standard deviation drop in math achievement for each absence (2014). The finding is likely due to the fact that teachers often do not stop to catch-up students with individual absences. While the rest of a class continues their learning, a student who is absent may fall behind after missing material. In addition to the linear effects of absences, high school students with at least ten absences in a school year, marking an approach to chronic absenteeism, have been found to have reduced performance on standardized test scores by an average of 7% of a standard deviation and reduced course grades by 19% of a standard deviation than students with lower amounts of absences (Liu, et al., 2019).

Beyond effects on test and course grades, absences have long-term impact on educational attainment. Students who exceed ten absences are 8% less likely to graduate high school on time, and 7% less likely to enroll in post-secondary education (Liu et al., 2019). When students attend fewer classes, they have less time to learn the material needed to meet expectations for graduation or college enrollment. With less time, it becomes more and more difficult for a student to keep up to date with his or her learning, often causing them to fall behind. This leads to long-term negative consequences. Effects may compound from school year to school year, and students who are chronically absent in one year often continue the pattern throughout high school (Nichols, 2003).

This evidence is particularly concerning given the present circumstances. With the introduction of new health challenges from COVID-19 as well as shifting instructional methods, absence rates have skyrocketed (Lieberman, 2020). A study conducted in October of 2020 sampling 790 K-12 educators indicated absence rates have jumped from 6% prior to the pandemic to 10% in the fall of 2020 (Kurtz, 2020). In districts that report instruction being fully online, absence rates are even higher, at 12% (Kurtz, 2020). With this spike in absences, the average instructional time students receive shrinks. Furthermore, instructors may lack the ability to identify students who may be behind and lack time to provide individual support. These factors make it more difficult for instructors to keep all students on track, causing absent students to fall behind. Even if instructors do manage to identify and assist students who have fallen behind, spillover effects of absences impact other students, who then receive less time learning new material and are forced to slow down to ensure other students are keeping up (Goodman, 2014). Altogether, the presence of COVID-19 has resulted in a greater number of student absences, which in turn will lead to lowered academic achievement.

Instructional Method

The last major body of literature that can help explain COVID-19 impact on student academic achievement is the difference between online and in-person instruction. Typically, students attend schools in person, with opportunities to directly interact with their peers and teachers. However, online education offerings have been on the rise due to COVID-19. Literature comparing online instruction and traditional in-class instruction has shown that online instruction has the potential to be equally or even more effective than in-person instruction in student and adult learners (Cavanaugh, 2001; Cavanaugh et al., 2004; Means et al., 2009). However, studies specifically investigating online charter schools have determined that high school students may perform significantly worse in online environments compared to in-person environments, with 0.2 to 0.4 standard deviation differences across all subjects (Ahn & McEachin, 2017; Woodworth et al., 2015). These effects may be partially explained by the type of students who attend online schools; lower achieving students often attend online schools at higher rates than average or high achieving students (Ahn & McEachin, 2017). However, the extent of lower performance is not fully explained by the type of student.

Due to the mix of evidence for the effectiveness of online schooling, it is important to take a deeper look into the characteristics of online learning which may be applicable to all students during the pandemic. Overall, there are aspects of online instruction that can be detrimental to both teachers and students which may be exacerbated by COVID-19. To start, teachers will be highly unprepared for the sudden change in instructional method. School districts began transitioning to forms of online instruction during the spring of 2020 due to COVID-19 and continued to do so throughout the year, leaving most districts at least partially online (Education Commission, 2020; Education Week, 2020). Given the normal circumstances, most teachers have experience with in-person learning environments and have little experience with online courses. Even those who did teach online prior to the pandemic had minimal experience; 93% had spent five years or less doing so (Rice & Dawley, 2009). This lack of experience likely left teachers uncomfortable in new virtual settings, causing them to struggle to adapt their instruction to the new medium.

Although there are many similarities between teaching in-person and in virtual environments, the role of a teacher may change, causing teachers to feel more distant from their students (Davis et al., 2007; Hawkins et al., 2012). For example, a critical role of a teacher was to act as the facilitator of information in a classroom, actively presenting and engaging with students (Hawkins et al., 2012). In a virtual environment, the importance of facilitation is reduced and replaced with an added emphasis on written student feedback. In addition to the shifted role as facilitator, teachers may experience changes in their role as a monitor of the classroom. Teachers may lack opportunities to monitor student feedback through online learning. In fact, an absence of physical and visual cues in online format removes the ability for teachers to immediately gain student feedback on a concept (Hawkins et al., 2012). These cues also help instructors build rapport with students and create stronger personal relationships that can inspire learning. Combined, the sudden change teachers are facing as a result of COVID-19 have likely led to lower quality of instruction.

Students may also face obstacles in transitioning to online learning environments that have impacted their academic performance. Similar to teachers, the vast majority of students have little to no experience with online education. Online education often requires students to work through a curriculum independently, though students' school experience has typically been more guided (Ahn & McEachin, 2017). This change in the level of explicit guidance will result in negative achievement outcomes for students, as many students lack the ability needed to effectively independently regulate their work (Ahn & McEachin, 2017; Hawkins, et al., 2012). Though self-paced work may suit some high school students, the new increase in independent work will likely cause most high school students to struggle to find their place in an online course (Northcote, 2008). In addition, lack of social interactions due to quarantine and isolation will have ramifications for student learning. Children in isolation have been found more likely to suffer from stress disorders (Sprang & Silman, 2013), and such psychological factors may lead to negative learning effects (Kuban & Steele, 2011). Overall, the consequences of students' lack of experience with online learning will result in suffering academic performance.

Collectively, though online instruction is not always inferior to in-person instruction, the sudden changes of instructional practices have likely caused detrimental effects on student academic achievement. With both teachers and students lacking experience learning in an online environment, both may struggle to fulfill new roles and responsibilities. Teachers are forced to develop new curriculums and operate with less chances to provide feedback to students, and students must regulate their own learning with lessened social opportunities. Due to these novel issues, students have not been learning as effectively in online environments, and their academic achievements will suffer as a result.

Overall COVID-19 Impact and Current Study

The impact of COVID-19 on summertime out of school, absences, and instructional changes are likely to result in unprecedented negative influences on student academic achievement. Students have fallen behind on their learning because of extended time off from school and increased absences upon their return. They also likely remain behind without opportunities to recover due to challenges in transitioning to an online learning environment. In addition to the struggles all students may be facing, the range in student academic performance will likely be far greater than previous years, introducing added difficulty for teachers to provide equal instruction (Di Pietro et al., 2020; Kuhfeld et al., 2020). A previous study of COVID-19 related learning loss projected middle school student test performance from spring to fall of 2020 could be as low as 30% of a normal year's gains (Kuhfeld et al., 2020). This study, however, only examined test performance in aggregate and failed to take into account student-level characteristics and differences that could help explain variations in COVID-AAI among students.

The importance of including these differences ties back to findings from previous research on summer learning. These findings indicated that losses may not be experienced consistently by all students (Atteberry & McEachin, 2020; Kuhfeld, 2019). Kuhfeld (2019) found that 25% of students showed either no losses or actual gains in MAP test scores, while Atteberry and McEachin (2020) found that up to half of students may exhibit gains. These findings are important to consider in estimating COVID-AAI: students may have a wide range of effects, leading to gaps in achievement between students. If some students are months behind, others have jumped ahead, and others remaining "on track", teachers will likely struggle to provide adequate and equal instruction. Collectively, these findings underscore the need to evaluate student-level effects to better understand COVID-AAI.

The current study offers insights into the COVID-AAI on high school students by taking into account student-level factors on testing performance. Using existing background evidence, the study has identified the student-level characteristics that are most likely related to COVID-AAI. Data was collected and a model created that will forecast the extent of achievement impacts due to the COVID-19 pandemic. The model will also examine the role of student characteristics including absences, socioeconomic status (SES), and race-ethnicity to better understand individual differences in impact among students. By including these factors in combination with the role of academic subject, the current study will offer much needed insight into the specific impact of COVID-19 on student academic achievement.

Results will prove useful in crafting policies and procedures for educational systems to follow in order to minimize negative effects of the pandemic. By identifying where COVID-AAI is occurring, educators can take steps to minimize it and focus recovery efforts on students most impacted.

Student Level Characteristics Influencing Academic Achievement

Given that normal summer losses average around a month of learning (Cooper et al. 1996; Kuhfeld 2019), absences add continued academic impact (Goodman, 2014; Kurtz, 2020; Liu, et al., 2019), and shifts to virtual instruction may provide challenges (Ahn & McEachin, 2017; Davis, 2007; Woodworth et al., 2015), the total COVID-AAI is likely to be significant across all students. To better understand this impact, it is important to consider other circumstances that may influence it. Variability in experienced academic impact among students, especially as a result of summer break, is common and could possibly be explained through unmeasured factors (Cooper et al., 1996; Kuhfeld, 2019). Taking into account additional student-level factors may provide better understanding of where this variability is occurring, why it is happening, and how educators can use the information to better mitigate the effects of COVID-19. The following section will provide additional background into factors that may relate to COVID-AAI and explain the rationale for expected findings of the current study.

Academic Subject

An important factor to consider is the effect of COVID-19 on learning in different school subjects. Overall, negative learning impact of summer learning losses has been found to be stronger in math subjects than reading subjects (Cooper et al. 1996; Kuhfeld 2019). A meta-analysis from Cooper and colleagues indicated summer vacation consistently led to a loss in math skills in all students, while reading loss varied (Cooper et al., 1996). Other investigations have also revealed a greater commonality in summer math learning declines, finding more consistent losses in math subjects compared to reading; 70-78% of students lost ground in math compared to only 62-73% in reading (Kuhfeld, 2019).

Greater negative learning impacts found in math are likely due to multiple factors that increase student engagement with reading material at home compared to math material. Firstly, it is thought that math skills are viewed more traditionally as a school lesson than an at home lesson (Cooper et al., 1996). Opportunities for gaining reading and language skills may exist in a student’s home and community, but opportunities for gaining math skills are more scarce. This may sway parents and students away from seeking math knowledge on their own, favoring reading instead. This explains why, in particular, younger students gain reading skills at much quicker rates than math during the summer (Downey et al., 2004). In addition, many families may lack needed materials to teach students math at home, particularly in older students taking more advanced courses. Coley, Kruzik, and Votruba-Drzal's (2019) investigation of summer learning losses by subjects revealed that academic achievement losses in lower SES students were particularly strong compared to higher SES students, indicative of the role of resources in reducing losses.

Secondly, math subjects require greater factual and procedural skills than reading and language, and therefore require more extensive practice (Cooper & Sweller, 1987; Geary, 1995). In school, students are given instruction and assignments that build on each other, providing ample time and experience building both reading and math skills. However, over the summer, students may lack these opportunities, particularly in math. Reading and language materials can be found more easily, such as through vacation brochures, toy instructions, cooking directions, or other mediums that students may naturally be interested in (Lenhoff et al., 2020; Mraz & Rasinski, 2007). Math materials, on the other hand, are scarce- especially for older students beyond simple addition and subtraction. With reduced time for practice, students will lose more of the information previously learned, resulting in lower academic achievement.

Collectively, summer and absence trends provide evidence to suggest that COVID-AAI will be greater in math than in reading subjects as a result of students tending to receive higher amounts and quality of practice with reading and language concepts compared to math. As a result, the current study projects these trends to be replicated.

Hypothesis 1a: Average differences in COVID-AAI will be greater in the subject of math compared to reading

Hypothesis 1b: A larger percentage of students will be in the predicted COVID-AAI range in the subject of math compared to reading.

Student Absences

As previously discussed, student absences have a strong relationship with student academic performance (Goodman, 2014; Liu et al., 2019; Nichols, 2003; Roby, 2004). As the number of absences increases, students lose valuable instructional time, causing grades and test score performance to decline. Previous research has described the strong relationship between student absences and achievement, with each absence explaining up to .05 of a standard deviation in math achievement lost (Goodman, 2014). Similar results were found by Liu, Lee, and Gershenson (2019) indicating a linear relationship between absences and student achievement, which was stronger in middle and high school. Students with ten or more days of absence experience a .07 standard deviation reduction in test score performance and .19 standard deviation drop in course grades. These findings are likely due to the compounding effect of missing class; as students miss more material, they fall further and further behind. By the time they reach ten days of absence, the effects become easily noticeable across many students. Effects on achievement include short-term reduction in course grades and testing performance, but also extend to long term effects of reduced graduation rates and post-secondary school enrollment (Liu et al., 2019).

The effects of absences are likely to be heightened during the times of COVID-19. Absence rates were found to have jumped from 6% prior to the pandemic to 10% in the fall of 2020 (Kurtz, 2020). In districts that report being fully online, absence rates are even higher, at 12% (Kurtz, 2020). These findings are likely a consequence of the shifting challenges students and parents face as they struggle to make it to school due to health concerns or fail to adjust to new online instructional methods (von Hippel, 2020). These findings suggest that the previous impact found from absences will be greatly increased during COVID-19 as students are missing class in greater numbers. All in all, evidence suggests that the previous impact found from absences will be greatly increased during COVID-19 across the board as students are missing class in greater numbers.

The current study predicts the increased number of absences due to COVID-19 will negatively impact the academic achievements of students. Even before the pandemic, more than 20% of high school students in the United States were chronically absent (U.S. Department of Education, 2020), and it is likely that these rates will increase. Students with historically higher rates of absences will likely carry this trend into the 2020-2021 school year, and undoubtedly experience lower academic performance than their peers who are able to attend class more regularly.

Hypothesis 2: Students with historically greater numbers of absences will experience a stronger, negative COVID-AAI in both math and reading.

Socioeconomic Status

The role of SES is critical in understanding COVID-AAI due to its broad relationship with student academic performance. SES relates to the ability of students to have access to resources such as reliable internet and devices, which are crucial for access to virtual learning (Downey et al., 2004; von Hippel, 2020). In addition, the financial situation of parents may prove pivotal in the level of support a student is receiving during both in-person and online learning. Three indicators of student SES, including qualification for free meals, living in a single parent household, and parental education, have been shown to reduce the amount of time students spend on schoolwork compared to their peers amid the COVID-19 pandemic (Bayrakdar & Guveli, 2020). With parents of less advantaged backgrounds, low SES students are not afforded the same enriching after school care or attention provided to students of greater privilege. Overall, there are simply more opportunities for learning among students of higher SES backgrounds, leading to lessened negative effects of out of school time, especially over the summer. These increased opportunities for learning do not necessarily hinder students of disadvantaged backgrounds but allow other students to comparatively pull ahead (Alexander et al., 2007; Cooper et al., 1996; Downey et al., 2004).

Additionally, researchers have noted that students of lower SES backgrounds often have less varied summer experiences, such as summer program opportunities, educational resources, books, or other reading material, compared to students of higher SES backgrounds (Borman et al., 2005; Chin & Phillips, 2004). These findings explain why students of lower SES tend to experience greater learning losses; they do not have as much time to learn or do not have the materials they would need to do so. Students of lower SES report far greater amounts of television watching during the summer (Gershenson, 2013), while students of higher SES enjoy experiences that assist them in using previously learned skills, or even gain new ones (Borman et al., 2005; Chin & Phillips, 2004). Together, these findings indicate a clear connection between student SES and learning impact.

Collectively, COVID-19 has likely heightened the influence of SES on student academic achievement, but the extent of their impact is difficult to estimate. Students will likely face additional stress from multiple uncertainties during the pandemic (Sprang & Silman, 2013). As their classes shift online, they may struggle to adjust to the changes (Northcote, 2008) or struggle to access the technology required to learn. At the same time, parents may face additional financial struggles, requiring them to shift their focus from their student to more pressing needs. Students who are of higher SES, however, will likely be far less impacted by these factors, and comparatively suffer less in their academic achievement. Overall, due to the unprecedented nature of the pandemic, it is clear that SES will play a role in student academic achievement.

Hypothesis 3: COVID-AAI in the subjects of math and reading will be greater in students of low SES backgrounds than high SES backgrounds.

Race and Ethnicity

The role of race and ethnicity in COVID-19 impact is important to understand in order to determine which students may be affected more strongly. Early studies of summer break impact revealed no significant differences based on the race of students once SES was taken into account (Cooper et al., 1996). Additional evidence has shown that differences in learning level for lower elementary students were mostly attributed to differences before school ever began, and that these differences likely do not vary drastically during summer time off (Alexander et al., 2001; Downey et al., 2004; von Hippel & Hamrock, 2019). These results point to overall academic differences between students from different racial and ethnic backgrounds, but do not appear to support that these differences grow over the summer breaks.

Race and ethnicity have been shown to impact student absence rates as well. Using data from 2015-2016, American Indian students were found to have the highest rates of chronic absence in high school (31%), followed by Pacific Islander (27%), Black (26.4%) and Hispanic students (24%). Asian and White students had the lowest rates of chronic absence of 10% and 19%, respectively (U.S. Department of Education, 2020). Given that chronic absenteeism leads to less time spent in class learning and lowered academic performance (Goodman, 2014; Liu et al., 2019; Roby, 2004) it is likely that the increased rate of absences among racial-ethnic groups will lead to differences in academic achievement among students.

Despite differences, when factors such as SES are accounted for, the race-ethnicity of the student has not been shown to have large, or in some cases any, effect on summer gap impact on testing performance. A definitive look into the role of race in test scores following summer gaps by Quinn revealed that different modeling produced differing results between Black and White students' summer learning impact (2015). Researchers using the same data had drawn different conclusions. Collectively, these results suggested that amounts of reading and math growth over summer breaks between Black and White students are no different from each other and can be attributed to additional, often covarying, factors, such as student SES. COVID-AAI will affect groups of students differently, but additional factors will better explain this relationship. Due to the limited sample for the study, differences in race and ethnicity will be investigated holistically.

Hypothesis 4: Differences in COVID-AAI in both math and reading will be observed between students of different racial and ethnic groups.

Methods

Sample

Data was collected from a Midwest high school and middle school in the same district, tracing student academics from the academic year of 2015-2016 to the academic year of 2020-2021. In sum, student test data from 5th to 11th grade was collected to develop the prediction model, including a total of 3,600 math tests and 3,623 reading tests from more than 400 students. Breakdowns of the testing data can be found in Table 1 and Figures 1 and 2.

Measures

Learning Impact

COVID-AAI was primarily measured using data gathered from Northwest Evaluation Association (NWEA) MAP Growth assessments. The test is computer adaptive, which provides increasingly more difficult items as students provide correct answers (Fleming, 2017). MAP tests are untimed and consist of about 50 questions which measure current student knowledge based on what is expected of their grade level. It is designed to measure student growth over time, and administered three times a year (fall, winter, and spring). Test scores are reported using the Rasch unIT (RIT) scale representing current student achievement in given testing subjects. Scores remain on the same scale across grades, making longitudinal student growth comparisons easier (Map Help Center, n.d.; Fleming 2017; Burns & Young, 2019).

Data was collected from student test scores starting the in academic year of 2016-2017 and ending in the winter of the 2020-2021 academic year. The number of tests administered per year varied. Each year two (2017-2018 and 2019-2020 school year) or three (2016-2017 and 2018-2019) tests were administered to students. Totals for pre-COVID-19 tests used can be found in Table 1. In years with two tests given, students complete one during the fall season and during the winter season. In years with three tests administered, students were given an additional test in the spring. These tests were administered to students in grades leading up to 12th grade, though the vast majority of 12th grades do not complete the tests, leading the current study to not project 12th grade scores and instead focus on 9th, 10th, and 11th grade. RIT score results from 2016-2017 to 2019-2020 (i.e., pre-COVID-19 tests) were used to forecast expected test score achievement in students following their past growth trajectories. These trajectories essentially assumed that COVID-19 did not happen and that students would maintain their previous trajectories into the 2020-2021 school year. These trajectories were used to predict scores on the 2020-2021 winter MAP tests. Differences between scores predicted for each student and actual scores students received on tests in the winter of 2021 were used to determine COVID-AAI, using a total of 414 students who took math and reading tests. A summary of this data is reported in the results section and in Table 2.

Absences

Monthly totals for each day a student was absent were included in the sample from all academic years prior to the pandemic, 2015-2016 to 2019-2020. Total absences were determined by adding all student absences, including partial day absences, spanning the academic year. Averages across all years of student data were calculated, with a summary of student absences found in Table 3. The mean number of yearly absences per year per student was 7.23, (SD=5.28). Absences for the 2020-2021 academic year were not included in the current study due to the changes in absence reporting from the school district. These changes negated the use of absence data as a characteristic of current 2021 students, though historical absence averages were examined to determine if students with historically low or high absences were affected by the pandemic. These historical absence counts were used to divide students into quintiles groups and used as a categorical variable in ANCOVA testing. Correlations between absences and COVID-AAI yield similar results when applied categorically and continuously.

Socioeconomic Status

For the purposes of this study, students who qualify for free or reduced lunch, as determined by their household income eligibility, acted as the indicator for a student of low SES. In addition, categorization as homeless was investigated separately as a second indicator of low SES. All student data from academic years 2015-2016 to 2020-2021 was meant to include an indicator for if the student met the requirements for assistance or homelessness, though this was not always the case. If students were indicated to have either indication of low SES in two thirds or more of the years in which data was collected while attending middle school, they were classified as low SES for that category (low income or homeless) in middle school. If students were indicated to have low SES in one third or less of the years in which data was collected, they were classified as not low SES for that category. Students who fell in between these categories were identified as having a fluctuating SES in that category. Lastly, students who only had one year or less of SES data were classified as having missing data in the category, due to the inability to gain additional information about the student. The same process was repeated for high school students. All students were then classified in a final SES category for both low income and homelessness based on their results in both middle and high school if they graduated from middle to high school during the years in which data was collected. Students classified in the same SES category in both middle and high school retained that classification. Students who had any degree of fluctuation were classified as fluctuating SES, and any student with data half present and half missing was categorized based on their existing data category. Final category breakdowns are reported in Table 4.

Race/Ethnicity

Separate flags for student race and ethnicity were included in the dataset to distinguish groups. The sample was composed by a large majority of white students, leading data to be dichotomized based for both race and ethnicity. In the finalized data comparing projected and achieved 2021 test scores, students with a race of anything other than entirely white were classified as non-white, which resulted in a breakdown of the sample including 99% white students and 1% non-white students, as reported in Table 4.

Similar lack of diversity is reported in student ethnicity, which was measured by student classification as Hispanic or non-Hispanic. The final sample used to compare projected and actual test score differences among high school students was 98% non-Hispanic and 2% Hispanic, as seen in Table 4.

Gender

Student gender was included to investigate differences in academic achievement among female and male students. The final sample of data comparing projected and actual winter 2021 test scores included a near even split of male and female students, with 51% female and 49% male, as reported in Table 4.

Grade Point Average

Student course performance data is reported four times per academic year from 2015-2016 to 2019-2020, measured on a traditional four-point scale. The effect of Grade Point Average (GPA) was aggregated by calculating average GPA for a student across all available data. The mean GPA of students in the final sample was 3.18 (SD=0.64), as reported in Table 3. Grade data for the 2020-2021 academic year was not used in the current study due to the changes in the way grades have been reported during the time of the COVID-19 pandemic. These changes would likely negatively impact the pattern of previous student GPA and are why the current study negated the use of 2020-2021 GPA.

Projecting and Measuring COVID-19 Impact

A major goal of the study was to develop the best model of projection to understand the test scores which students would be expected to achieve had it not been for the academic disruption of COVID-19.

Typical test score growth rates for students were estimated separately for reading and math using linear mixed models. A series of models were first fit to independently examine the trajectory of pre-COVID reading and math test scores (i.e., test scores from

2016-2017 to 2019-2020). Tests were conducted using a maximum likelihood estimator and model fit statistics (i.e., AIC, BIC, log likelihood, and deviance, overall pseudo-R^2, pseudo-R^2 for fixed effects, and residual standard deviations for the model's residuals, intercepts, and slopes) were examined to determine the model of best fit for reading and math test scores. Prior to fitting the models, a time variable was created that assessed the number of days between the final pre-COVID disruption test (i.e., winter 2019-2020) and the previous tests back through academic year 2016-2017. This meant that the intercepts in the prediction models represented students' scores on the winter 2019-2020 test. The slope represented the observed change in test scores over time with time being measured as the number of days in between tests.

The first series of models that were fit to math and reading test scores were referred to as the Level One Prediction Models in Table 5 and Table 6. These unconditional means models (i.e., a model that estimated each student's score on the winter 2019-2020 test) (Singer & Willett, 2003). Next, an unconditional change model (i.e., Fixed Time model) was fit that continued to allow each students' intercepts to vary and fit a single slope to all of the student's test scores that examined their aggregated scores change over time (Singer & Willett, 2003). Next, another unconditional means model was fit that continued to allow each students' intercepts to vary and allowed each student to have their own individual slope that assessed that student's change in test scores over time. This model had a diagonal Tau matrix (i.e., Random- Diagonal) and did not estimate the correlation between each students' intercept and slope. The final level one model that was examined had an unstructured Tau matrix (Random – UN) and allowed the students' intercept and slopes to vary but also estimated the correlation between the two.

After Level One Prediction Models with the best fit was determined, several conditional change models with level two predictors were added to the level one model of best fit (Singer & Willett, 2003). All Level Two Prediction Models were examined to determine the best fitting model. These models used students' 2020-2021 grade level, average number of pre-COVID absences, and average pre-COVID GPA as predictors to improve the prediction of students' pre-COVID test scores. These models also examined the interaction between the change in test scores over time (i.e., Time Slope) and these level two predictors. These conditional change models looked to see if the growth seen in student test scores over time were also a product of a students' current grade level, their previous attendance, or classroom academic performance.

Overall Model Trajectories

Forecasted trajectories for student testing achievement among different projected 2021 grade levels between are shown in Figure 3 for math testing and Figure 4 for reading tests. As would be expected, students have a positive growth trend over time, and students expected to be in higher grades in 2021 start with higher test scores. This effect is barely noticeable in reading test score projections, where there is little difference between students expected to be in 11^{th} and 12^{th} grade in 2021. It is important to note, however, the wide variance in student scores, as indicated by the spread of the data point at each test administration.

Complete model fit results for math and reading prediction can be found in Tables 5 and 6, respectively. The level one math model which had the best model fit was the Random – Diagonal model that allowed each student to have their own intercept and slope. This model had the lowest AIC, BIC, and Deviance scores, the lowest residual standard deviation, and the highest overall pseudo-R^2. The level two math model that had the best model fit was the GPA & Grade Level * Interaction model. This model allowed each student to have their own intercept and slope and included students' 2020-2021 grade level and their 2016-2017 to 2019-2020 average GPA as predictors. This model also included the interaction between students' grade level and the change in test scores over time. This model had the lowest overall AIC, BIC, and Deviance scores and had the highest overall and fixed pseudo-R^2 values.

The level one reading model that had the best model fit was also the Random – Diagonal model that allowed each student to have their own intercept and slope. This model had the lowest AIC, BIC, and Deviance scores. The level two math model that had the best model fit was also the GPA & Grade Level * Interaction model. This model allowed each student to have their own intercept and slope and included students' 2020-2021 grade level and their 2016-2017 to 2019-2020 average GPA as predictors. This model also included the interaction between students' grade level and the change in test scores over time. The GPA & Grade Level * Interaction model had the lowest overall AIC, BIC, and Deviance scores and had the highest overall and fixed pseudo-R^2 values of the level two models.

Once the best fitting prediction models were identified for math and reading, these models were used to forecast students' winter 2020-2021 test scores. This was accomplished by multiplying each students' associated score to the corresponding coefficient. A count of 391 days was used as the time constant in these forecast models since the time between the winter 2019-2020 and winter 2020-2021 tests was 391 days. Multiplying 391 days and each students' associated score to the corresponding coefficient in the resulting math and reading model produced test scores that were based on each student's previous pre-COVID performance trajectory and represented each students' forecasted winter 2020-2021 score.

These predicted scores were then compared to mid-pandemic test scores from the winter of the 2020-2021 school year. This comparison was made by first subtracting the forecasted test score from the realized winter 2020-2021 so that negative numbers indicated an actual winter 2020-2021 score was *lower* than their predicted score. Differences in prediction scores were then used to determine the academic effects of COVID-19 on testing scores overall and across student groups, including by academic subject, historical absences, socioeconomic status, student race/ethnicity, gender, and previous average GPA. This was accomplished by using an ANCOVA that had the predicted-realized winter 2020-2021 difference score as the outcome, the predicted winter 2020-2021 difference score as a co-variate, and the grouping variable of interest as the predictor. Eta and d-values were examined along with the *p*-value to determine the extent to which COVID-AAI impact different across student groups.

Results

Projected and Actual Score Differences

Differences between model-predicted student scores and actual scores achieved by students during the mid-pandemic winter 2021 testing can be found in Table 2. As shown, the difference scores in both math and reading subjects was negative, indicating that the models over-projected student achievement. These results indicate the expected COVID-AAI, which resulted in scores dropping below what would have been expected if students had followed their previous trajectories. However, the average differences between the predicted and realized student test scores, indicating COVID-AAI, were higher in reading test compared to math tests, with a mean difference of -1.87 compared to -1.04. In addition, it appears that more students in total had an impact on their reading scores when compared to math: through the 60^{th} percentile of student achievement, students were still behind projections in reading, while by that same mark in math, they had actually surpassed their projections. These results do not support hypothesis 1a and 1b, which expected students to have a larger COVID-AAI in math compared to reading.

Absences

Differences in predicted and realized scores were examined by the average number of individual student absences per year between the pre-COVID academic years from 2015-2016 to 2019-2020. An ANCOVA test controlling for predicted test score was conducted in order to determine if there was a disparity in the resulting differences between projected and actual winter 2021 math and reading test scores among students within different absence achievement quintiles. Quintile groupings of students were used in order to negate the effects of outliers and to represent a summary of expected absences among students in the 2020-2021 year. The results of the ANCOVA tests revealed that the average absences of students overall did not have a significant impact on COVID-AAI in math, $F(4,178) = 1.48$, $\rho = 0.210$, $\eta^2 = 0.032$, $1-\beta = 0.46$. Levene's test of homogeneity of the math test sample was insignificant, $F(4,179) = 0.407$, $\rho = 0.803$, supporting the assumption of homogenous residual variance among student absence groups.

Similar results were found for the effect of absence quintile on reading COVID-AAI, with a non-significant result of the ANCOVA, $F(4,178) = 1.25$, $\rho = 0.292$, $\eta^2 = 0.027$, $1-\beta = 0.39$ and non-significant results for Levene's homogeneity of variance test, $F(4,179) = 1.19$, $\rho = 0.316$).

Given the relatively low power of both ANCOVA tests, exploratory post hoc comparisons were conducted between absence levels. Results indicated a statistically significant difference between predicted and actual winter 2021 math test score difference between students from the 40-60% and 80-100% absence percentile range, $t(178) = 2.19$, $\rho = 0.036$, $d = 0.54$). Other group differences approached significance, but did not meet the threshold of $\rho < 0.05$ as detailed in Table 7.

In reading testing, the post hoc comparison test revealed one statistically significant group difference, between students in the 0-20% absence percentile and those in the 60-80% absence percentile, $t(178) = 2.01$, $\rho = 0.046$, $d = 0.46$. Nearly all difference scores between students in the 0-20% absence quintile and other groups approached significance, indicating a possible relationship between increased absences and lowered reading achievement, as seen in Table 8. Post hoc estimated marginal means can be found in Figure 5 and Figure 6.

The results from group differences among reading test scores provided limited support for hypothesis 2. The hypothesis expected a greater relationship between student absences and COVID-AAI in both subjects. While neither ANCOVA yielded statistically significant overall results, post hoc examinations showed that reading scores trended toward differences in students, with students of historically low absences scoring closer to their predicted scores.

Low Income Categorization

An ANCOVA was run in order to determine differences among income categories of student's COVID-AAI in both reading and math, the results of which can be found in Table 7 and Table 8. It was found that the income category did have a statistically significant impact on the difference between predicted and realized winter 2021 math scores, $F(3,180) = 3.74$,

$\rho = 0.012$, $\eta^2 = 0.056$, $1-\beta = 0.81$, but did not achieve statistical significance for reading scores, though significance was approached, $F(3,179) = 2.07$, $\rho = 0.106$, $\eta^2 = 0.033$, $1-\beta = = 0.52$. In order to check assumptions, Levene's test of homogeneity of variance was run and yielded non-significant results for math $F(3,181) = 0.609$, $\rho = 0.610$ and reading, $F(3,180) = 0.941$, $\rho = 0.422$.

Examinations of post hoc tests were conducted for additional information. Differences between multiple groups, including between students with fluctuating and missing low income data (mean difference of -12.045, $t(180) = -2010$, $\rho = 0.046$, and $d = 2.05$) and students with fluctuating and not low income (mean difference of 2.429, t(180) = 2.371, $\rho = 0.019$, and $d = 0.41$) were observed in math testing. Additionally among math scores, differences in the group with missing data and those who were indicated as not low income (mean difference of 14.475, $t(180) = 2.423$, $\rho = 0.016$, and $d = 2.46$) and between those with missing data and low income (mean difference=12.587, t(180) = 2.110, $\rho = 0.036$, and $d = 2.14$) achieved statistical significance. The test results for math and reading ANOVA's can be found in Table 9 and Table 10.

The post hoc test for reading revealed a statistically significant difference between students designated as not low income and students designated as having low income (mean difference of 2.79, $t(179) = 2.313$, $\rho = 0.022$, $d = 0.43$). Overall, these mixed results provided limited support for hypothesis 3, that COVID-AAI in the subjects of math and reading will be greater in students of low SES backgrounds than high SES backgrounds. Significant differences were not found in both ANCOVA tests, though there were noticeable differences between groups, such as a positive mean difference between students not of low SES and students with low SES, indicating a possible stronger COVID-AAI in students of low SES. Differences between students missing income data and other groups were found likely due to the low sample size of the group. These examinations of estimated marginal means can be found in Figure 7 and Figure 8. Wholly, the evidence does not support hypothesis 3, though the data may trend in the direction of support.

Homeless Categorization

To investigate an additional student SES characteristic that could influence the COVID-19 achievement of students, an ANCOVA was run in order to determine impacts among homelessness categories on student's predicted and actual winter 2021 test score differences. It was found that homeless category did not have a statistically significant impact on the difference between predicted and realized winter 2021 math scores, $F(3,180) = 1.87$, $\rho = 0.136$, $\eta^2 = 0.014$, $1-\beta = 0.49$. Homelessness category, however, did have a significant impact on the difference between predicted and actual winter 2021 reading test score, $F(3,179) = 4.66$, $\rho = 0.004$, $\eta^2 = 0.072$, $1-\beta = 0.89$. In order to check assumptions, Levene's test of homogeneity of variance was run and showed non-significant results in math test differences, $F(3,181) = 0.504$, $\rho = 0.680$) and reading test differences $F(3,180) = 1.17$, $\rho = 0.322$.

Examinations of post hoc tests in math tests, which was not significant, also revealed additional differences between groups. However, these results were centered on the "Missing" data category for students, similar to the results of the low income examination, and are likely explained by the low sample of students in this category. Differences among students with fluctuating and missing low income data (mean difference of -12.811, $t(180) = -2.105$, $\rho = 0.037$, and $d = 2.15$), students with missing data and not homeless (mean difference of 12.979, $t(180) = 2.151$, $\rho = 0.033$, and $d = 2.18$), and students in the group with missing data and those who were categorized as homeless (mean difference of 15.753, $t(180) = 2.359$, $\rho = 0.019$, and $d = 2.64$) achieved statistical significance. These results are shown in Table 11.

Investigation of the post hoc comparison test for reading score differences, on the other hand, revealed a significant difference between students who fluctuated between homelessness and students who were classified as not homeless (mean difference of -2.45, $t(179) = -2.383$, $\rho = 0.018$, and $d = 0.39$), students fluctuating between homeless and students classified as homeless (mean difference of 7.36, $t(179) = 2.238$, $\rho = 0.026$, $d = 1.16$), and students who were classified as not homeless and students classified as homeless (mean difference of 9.8, $t(179) = 3.037$, $\rho = 0.003$, $d = 1.54$). These results are shown in Table 12. Estimated marginal means for both math and reading tests can be found in Figure 9 and Figure 10, respectively.

Overall, the trend in reading test score differences among homeless groups is that students who were homeless scored lower than predicted. Though those results are somewhat supported in the findings from math, the differences were not always statistically significant. These findings provide limited support to hypothesis 3, which notes that students of lower SES may have been more greatly impacted by COVID-19.

Ethnicity

Ethnicity of the student was tested to discover disparities in test score differences between students identified as Hispanic or not Hispanic. The ANCOVA tests showed that the effect of ethnicity on score differences was not significant in math, $F(1,182) = 0.632$, $\rho = 0.428$, $\eta^2 = 0.003$, $1-\beta = 0.67$, as well as reading, $F(1,181) = 1.016$, $\rho = 0.315$, $\eta^2 = 0.006$, $1-\beta = 0.18$. Additional tests were conducted to ensure assumptions were met.

Levene's test for homogeneity of variance was not significant, $F(1{,}183) = 0.058$, $\rho = 0.810$, in the math ANCOVA, while Levene's test for homogeneity of variance was not significant, $F(1{,}182) = 0.021$, $\rho = 0.884$), in the reading ANCOVA.

Again due to the relatively low power of the tests, post hoc test were examined. Firstly, the post hoc comparison showed a mean difference of -2.80, $t(179) = -0.795$, $\rho = 0.428$, $d = 2.8$ in math and a mean difference of 0.382, $t(180) = -0.100$, $\rho = 0.921$, $d = 0.06$ for reading, as displayed in Table 13 and Table 14. An investigation of the estimated marginal means also revealed that the mean difference is greater in Hispanic students, compared to non-Hispanic students. In addition, the group of Hispanic students had a confidence interval spanning nearly double the range of students who were not Hispanic. These results are shown in Figure 11 and Figure 12, and do not support hypothesis 4.

Race

As previously detailed, due to low sample size, student race was dichotomized in order to identify effect differences. An ANCOVA was conducted in order to determine if the race category of a student, White or non-White, had any impacts on the difference score between predicted and actual winter 2021 test scores representing COVID-AAI. The test indicated that there was not a significant difference between groups in math test scores, $F(1{,}182) = 0.06$, $\rho = 0.807$, $\eta^2 = 0.000$, $1-\beta = 0.05$. These results can be found in Table 15. Assumptions to the test were met, as Levene's test for homogeneity of variance was not significant, $F(1{,}181) = 1.47$, $\rho = 0.226$.

In reading test score differences, the ANCOVA revealed that overall, student race did not have a significant impact on the difference between predicted and achieved winter 2021 test scores, $F(1,183) = 0.353$, $\rho = 0.553$, $\eta^2 = 0.002$, $1 - \beta = 0.09$, as can be seen in Table 16. Levene's test for homogeneity of variance was not significant, $F(1,182) = 1.47$, $\rho = 0.226$.

Due to the extremely low power of the ANCOVA tests, post hoc comparisons were also run, resulting in a mean difference in math score differences of -1.05, $t(182) = -0.245$, $\rho = 0.807$, and $d = 0.17$, and reading differences of -2.77, $t(181) = -0.594$, $\rho = 0.553$, and $d = 0.42$. Graphical difference scores can be found in Figure 13 and Figure 14. These results do not support hypothesis 4 and trend toward the opposite notion that students who are not white may have performed better than their predictions, relative to white students.

Gender

Disparities between student gender and predicted and actual winter 2021 test score differences were also investigated through ANCOVA tests, the results of which can be found in Table 17 and Table 18. The impact of gender on COVID-AAI was not significant in math score differences, $F(1,182) = 1.05$, $\rho = 0.308$, $\eta^2 = 0.006$, $1-\beta = 0.18$ and reading score differences, $F(1,181) = 1.01$, $\rho = 0.316$, $\eta^2 = 0.006$, $1-\beta = 0.18$. Assumption checks from Levene's test of homogeneity of variance yielded non-significant results in math, $F(1,183) = 0.686$, $\rho = 0.408$ and reading tests, $F(1,182) = 1.23$, $\rho = 0.269$.

Due to low power of the ANCOVA tests, post hoc comparisons were run. These tests revealed a mean difference between female and male students of 0.91, $t(182) = 1.02$, $\rho = 0.308$, $d = 0.15$ in math, and values of similar strength but opposite direction (mean difference of -0.969, $t(181) = -1.01$, $\rho = 0.316$, $d = 0.15$) for reading. Results of these tests can be found in Figure 15 and Figure 16.

Grade Point Average

Differences in predicted and realized scores were examined by the average GPA of students in years prior to the COVID-19 pandemic. An ANCOVA was conducted in order to understand if there was a difference in the resulting gaps between projected and actual winter 2021 test scores among students from different GPA achievement quintiles in both math and reading, the results of which can be seen in Table 18 and Table 19. The results of the ANCOVAs revealed that the GPA of students overall did not have a significant impact on the difference scores in math, $F(4,179) = 1.16$, $\rho = 0.332$, $\eta^2 = 0.024$, $1 - \beta = 0.37$, or reading, $F(4,178) = 0.413$, $\rho = 0.799$, $\eta^2 = 0.009$, $1 - \beta = 0.14$. Levene's test of homogeneity of the math test sample was not significant, $F(4,180) = 0.192$, $\rho = 0.942$, supporting the assumption of homogenous residual variance among student grade level groups. However, the Levene's test in reading was significant, $F(4,179) = 4.22$, $\rho = 0.003$, which violates the test's assumption.

Again, due to low test power, post hoc comparisons were conducted between grade levels. The comparison yielded a statistically significant difference between predicted and actual winter 2021 math test scores between students from the 20-40% and 60-80% GPA range, $t(179)=2.08$, $\rho = 0.039$, $d = 0.54$. Additional details from post hoc comparisons in math are found in Figure 17, while all non-significant post hoc results from the reading score ANCOVA post hoc testing can be found in Figure 18.

2021 Grade Level

An ANCOVA was conducted in order to determine if there was a difference in COVID-AAI among students from different grade levels in both math and reading. The results of the tests revealed that the grade level of students did not have a significant impact on the difference scores in math $F(2,181) = 1.20$, $\rho = 0.303$, $\eta^2 = 0.016$, $1-\beta = 0.26$, but did in reading testing, $F(2,180) = 4.89$, $\rho = 0.009$, $\eta^2 = 0.051$, $1-\beta = 0.19$. These results are displayed in Table 21 and Table 22. A test of homogeneity of the math test sample was not significant, $F(2,182) = 0.05$, $\rho = 0.955$), supporting the assumption of homogenous residual variance among student grade level groups. The Levene's test for homogeneity of variance in reading score differences also was not significant, $F(2,181) = 0.494$, $\rho = 0.611$.

Finally, post hoc comparisons were conducted between grade levels, and are reported in Figure 19 and Figure 20. The difference between 10th and 11th grade test score differences in reading was significant ($\rho = 0.002$), in addition to other differences also approaching significance. In sum, for both test subjects, 10th grade students appeared to have varied difference scores compared to 9th and 11th grade students.

Discussion

Overall, both the reading and math models overestimated the mid-pandemic winter test scores, supporting the suspected negative COVID-AAI. These values, mean differences of -1.04 for math differences and -1.87 for reading differences, indicate that although an average student may have fallen behind where they would have been projected to score in the absence of the COVID-19 pandemic, students were ultimately not impacted in their testing scores to the extent that many educators feared. To provide better context for the saliency of these score difference values, Table 21 and Table 22 contain approximate score bands for students in the 2019-2020 pre pandemic winter and 2020-2021 mid pandemic winter. From this data, it is important to consider that a difference of two test RIT points, close to the mean difference observed in reading scores, is close approaching 20% of a quintile band, and these differences could quite possibly be moving students between “average” and “high average” bands, for example.

It is entirely possible that many previous studies underestimated the resiliency of high school students to COVID-AAI. High school students may be better able to regulate their own learning, more technologically savvy, and have access to more social outlets than younger students. Another important note to the limited negative COVID-AAI on students is that students within the sample had already begun receiving academic support through various services such as tutoring and after school activities as early as the beginning of the 2020-2021 school year. The extent to which these services may have mitigated student losses in achievement due to COVID-19 are unknown, but it is likely losses would have been greater if not for assistance from these activities.

In order to better determine the extent to which model predictions were reliable and to investigate possible effects of the academic support, projections and score comparisons to fall 2020 test scores were run post-testing. Correlations between predicted and actual student scores were similar between both fall and winter, indicating a fairly reliable model. Differences between actual and predicted scores were similarly spread among achievement percentiles, though score differences from fall testing tended to be slightly lower than winter. These results, located in Table 25, support the notion that students were further behind following the lengthy summer break, but may have had a chance to catch up as they continued through the year. The study chose winter 2021 scores as the mid-pandemic comparison point in order to examine the continuing COVID-AAI and not limit the study to initial, early on impacts.

Another curious observation of the results in Table 2 reveals that not all students were impacted the same by COVID-19. Students in the 60th percentile and above in math test scores, or 80th percentile and above in reading test scores, actually outperformed the projection model. With values above 3.5 in the 80th percentile, this means more than twenty percent of students performed better than they would have been expected to without the pandemic. Though the cause of the performance is only speculative, it is likely that during the pandemic, these students were receiving additional educational attention from caregivers, boosting their learning and subsequent test scores. Given the results of score difference distributions being similar in the fall of 2020, it is likely that these impacts are a result of the pandemic, and not a result of student test score variance. It is important to note, however, that variance in student test scores from different test sessions is bound to happen, and can result in score fluctuations among students. Regardless of the reason for some students outperforming the model, the results are important in helping to determine individual student needs for remediation.

Simultaneously, the lowest percentiles of student test scores reveal that students at the bottom end of testing performance were impacted much more strongly than the average student. Students in the 20th percentile, for example, had scores underperforming projections by 5.7 in math and 7.3 points in reading. These disparities account for the majority of an achievement quintile and show a stark contrast to the students at the higher end of test scores who outperformed their projections. The deeper declines represent a much stronger negative COVID-AAI than other students faced and are important to consider when interpreting the overall results of the study.

A model from UNESCO details the four possible scenarios for COVID-19 needs, which supports the notion that in some scenarios, not all students will be needing assistance to stay on track while some students may need much greater help in mitigating negative COVID-AAI (2020). As described in the results of the current study, there is a large portion of students who have been largely unaffected or even positively affected by the COVID-19 disruption, at least in terms of their MAP test scores, and separate portion of students who were impacted far more severely. Though the overall negative COVID-AAI balances out to a mean loss of one to two points, the students on the high and low extremes of testing performance provide additional information from which educators can craft remediation policies. The results from the current study should be used to ensure educators do not overzealously apply academic support to students who do not need it, and instead apply remediation strategies towards the most severely affected students.

The current study attempted to further detail students who may be the most seriously affected by COVID-19, but ultimately the sample lacked statistical power to yield many statistically significant ANCOVA results. The eventual sample of students used to compare predicted student test scores and actual mid-pandemic test scores was relatively small. This was due to students in the sample moving in and out of the school system, in addition to a low number of students completing the tests in during the winter of 2021. It is also possible that students who did not return to complete winter testing were students who were more likely to exhibit stronger negative COVID-AAI, due to them being unable to even attend school at all or being forced to move out of the school. If student data was collected from multiple schools instead of just one, the sample would have been more robust, and statistical significance could have been achieved more easily.

As an example of how a greater sample could impact study results, consider that the current study's ANCOVA for math score differences by student gender had a power of $1 - \beta = 0.18$. Given a sample size of just 500, the test power would have increased to $1 - \beta = 0.41$. In the same manner, the ANCOVA test for reading test score differences among income group would jump from $1 - \beta = 0.52$ to $1 - \beta = 0.95$ given a sample size of 500.

Given the low power, further investigations of post hoc tests were warranted. The ability to determine differences among student characteristics is critical to determine the traits of students who may be severely underperforming their projections. These differences can also inform where remediation may have greater effects on student achievement. Though many of the ANCOVA tests used to determine significant differences between groups were not statistically significant, it is important to consider their findings, and understand why they did not achieve the level of statistical significance.

The first major observation was the impact of student SES on student achievement in reading scores. Students who were in the low income category performed worse than students who were not in the low income category. Students who were identified as homeless showed the same effects, but with even greater differences in scores compared to their peers who were not homeless. These effects were not found in math test score differences.

The effects of race appeared to vary, with white students performing slightly closer to their projected score than non-white students in math. However, in reading, non-white students appear to perform slightly closer to their projected score than white students. Ethnic differences between Hispanic and non-Hispanic students revealed that Hispanic students tend to be lower than their projected scores compared to non-Hispanic students in math, but near even in reading. These results may indicate that non-white and Hispanic students may be facing a larger drop in test scores than their peers, though the low study sample size hampers these conclusions. Additional studies including greater representations of non-white students could yield valuable information.

When investigating gender differences among student test score achievement, it was revealed that male students fell below their predicted test scores by a greater number than female students in math testing, while the opposite was true for reading testing. Though these results were not statistically significant, they appear to support the notion that male students may need additional support in math subjects, while female students need additional support in reading subjects.

The extent to which students were absent in years prior to the pandemic showed that absences may be a key to student reading test achievement: students in the lowest quintile of absences exceeded projections for reading tests, while all other quintiles averaged scores below 2 points of their projections. These results may indicate that students who were attending school more frequently prior to the pandemic may be more inclined to continue gaining reading skill during the challenges of the pandemic, while other students may not be able to do so as easily.

Overall, results did not match the expectations and hypotheses posited prior to the study. Previous educational research has placed an immense amount of attention on the investigation of student characteristics and achievement, which provided much of the foundation for the current study's hypotheses. In addition to the previous research, anecdotal evidence suggested that students of certain backgrounds were sure to see disparaging COVID-AAI. Though further examination is needed, the results of the study found very little significant differences between student groups. These findings speak to the necessity for educators to view students as individuals rather than assume characteristics based on their group identities. Assumptions should not be made about a student based on their group identities, but rather based on data examined on the individual student's achievement in order to identify their unique needs and offer solutions to support their academic growth.

In conclusion, though much of the literature and prior studies suggested that students may be facing severe learning impacts as a result of COVID-19, the current study showed student experience COVID-AAI at a relatively small extent, on average. The average, however, is not indicative of the overall findings of the study; that students on the lower and upper ends of testing performance were far more severely impacted, both positively and negatively, than students near the center of performance. Students in the upper percentiles of testing scores, who managed to surpass their pre-COVID testing trajectories, pulled up the average COVID-AAI score, indicating that not all students were negatively impacted by COVID-19. Most individual student characteristic differences yielded statistically insignificant results, which indicate that they may not be the best way to identify student COVID-AAI. Additional studies should follow the same analytical methods as the current study with larger samples of students with varying demographic characteristics in order to further identify the types of students who have been most impacted by the pandemic. Educators should use the findings of the current study to inform their ongoing remediation efforts to ensure students of all grades do not fall behind as a result of the COVID-19 pandemic.

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Appendix A

Tables

Table 1

Summary of Test Data Used For Modeling

Grade Level	Math Test			Reading Test		
	n	*Mean*	*SD*	*N*	*Mean*	*SD*
5	239	205	15.1	239	204	14.0
6	453	211	13.8	454	213	12.5
7	681	217	13.6	698	216	12.8
8	886	222	14.4	*899*	*220*	*12.3*
9	669	226	14.6	666	223	12.6
10	469	231	15.4	464	227	13.0
11	203	233	16.5	203	226	13.4

Table 2

Comparison of Prediction Model Estimates and Actual Mid-Pandemic 2020-2021 Scores

Measure	Math Test: *Prediction*	Math Test: *Actual Winter Score* [a]	Math Test: *Difference*	Reading Test: *Prediction*	Reading Test: *Actual Winter Score* [a]	Reading Test: *Difference*
n	412	414		414	414	
Mean	231	223	-1.04	228	220	-1.87
Median	231	223	-0.82	228	220	-2.06
SD	14.7	16.3	6.09	11.8	14.9	6.54
Min	180	168	-30.9	185	158	-18.7
Max	271	281	14.7	256	255	21.8
20th Percentile	219	210	-5.66	218	208	-7.3
40th Percentile	227	219	-1.86	225	217	-3.29
60th Percentile	235	227	0.56	231	224	-0.7
80th Percentile	244	235	3.65	238	232	3.51

[a] indicates the actual winter scores did not contain data from 12th grade students in 2021, while projections did include 12th grade students. This results in actualized scores being lower than predicted scores, which take into account the predicted scores of 12th grade students which would be higher following the upward trajectory of students over time

Table 3

Academic Characteristics of Students Who Completed Winter 2020-2021 MAP Tests

Academic Characteristic	Winter 2021 Test Score Data				
	n	Mean	SD	Min	Max
Yearly GPA	184	3.18	0.64	1.01	4.00
Yearly Absences	184	7.23	5.28	0.00	38.5

Table 4

Sociodemographic Characteristics of Students Used in Test Comparisons

Demographic Characteristic	*n*	%
Gender		
Female	94	51
Male	91	49
Ethnicity		
Hispanic	3	1.6
Not Hispanic	182	98.4
Race		
White	183	98.9
Not White	2	1.1
Low Income Status		
Yes	50	27
No	75	40.5
Fluctuating	59	31.9
Missing	1	0.5
Homeless Status		
Yes	4	2.2
No	119	64.3
Fluctuating	61	33
Missing	1	0.5
Grade Level 2021		
9th	60	32.4
10th	66	35.7
11th	59	31.9

Table 5

Summary of Math Test Modeling Results

Model	*AIC*	*BIC*	*Dev*	*P-R2 Fix*	*P-R2*	*ICC*	*Intercept*	*R-Int SD*	*Residual SD*
				Level One Prediction Models					
Random Intercepts	26411	26429	26504	0	0.78	0.78	217.4	14.70	7.8
Fixed Time	24254	24279	24246	0.1	0.89	0.88	228.4	14.83	5.56
Random – Diagonal	24226	24257	24126	0.1	0.89	0.88	209.6	14.48	5.43
Random - UN	24235	24272	24223	0.12	0.87	0.85	177.8	13.34	5.50
				Level Two Prediction Models					
Grade Level	24167	24205	24155	0.22	0.89	0.86	175.3	13.37	5.45
Grade Level * Time Interaction	24154	24197	24140	0.23	0.89	0.86	179.5	13.40	5.44
GPA	24108	24145	24096	0.31	0.89	0.84	189.7	12.49	5.41
GPA * Time Interaction	24087	24130	24073	0.29	0.89	0.84	186.7	12.60	5.42
Absences	24157	24194	24145	0.12	0.89	0.87	231.2	14.35	5.43
Absences* Time Interaction	24152	24196	24138	0.12	0.89	0.88	231.6	14.38	5.43
Grade Level & GPA	23972	24016	23958	0.49	0.89	0.78	117.3	10.38	5.44
Grade Level * GPA Interaction [a]	23842	23998	23924	0.48	0.89	0.79	117.9	10.47	5.43

[a] Designates the model ultimately chosen to predict student math scores

Table 6

Summary of Reading Test Modeling Results

Model	*AIC*	*BIC*	*Dev*	*P-R2 Fix*	*P-R2*	*ICC*	*Intercept*	*R-Int SD*	*Residual SD*
Level One Prediction Models									
Random Intercepts	25694	25713	25688	0.00	0.77	0.77	219.0	12.71	6.93
Fixed Time	24592	24617	24584	0.06	0.84	0.83	224.2	12.81	5.83
Random – Diagonal	24514	24545	24504	0.07	0.84	0.83	224.2	12.29	5.58
Random - UN	24517	24554	24505	0.06	0.87	0.85	224.1	13.22	5.53
Level Two Prediction Models									
Grade Level	24474	24511	24462	0.15	0.84	0.81	185.8	11.50	5.61
Grade Level * Time Interaction	24447	24491	24433	0.17	0.84	0.81	191.0	11.58	5.60
GPA	24431	24474	24417	0.22	0.84	0.8	195.6	11.04	5.59
GPA * Time Interaction	24433	24482	24417	0.22	0.84	0.8	195.1	11.02	5.58
Absences	24460	24497	24448	0.07	0.84	0.83	224.7	12.28	5.59
Absences * Time Interaction	24461	24504	24447	0.07	0.84	0.83	224.6	12.28	5.59
Grade Level & GPA	24344	24388	24330	0.35	0.84	0.75	142.6	9.67	5.61
Grade Level * GPA Interaction [a]	24317	24367	24301	0.37	0.84	0.75	147.8	9.72	5.60

[a] Designates the model ultimately chosen to predict student math scores

Table 7

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score Among Historical Absence Quintiles

Absence Quintile	*Absence Quintile*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
0-20%	20-40%	0.78	1.3	178	0.6	0.055	0.874	0.13
	40-60%	-1.32	1.39	178	-0.95	0.344	0.878	0.22
	60-80%	1.36	1.37	178	0.99	0.325	0.861	0.23
	80-100%	1.89	1.5	178	0.26	0.209	0.715	0.32
20-40%	40-60%	-2.1	1.32	178	-1.59	0.144	0.508	0.36
	60-80%	0.57	1.3	178	0.44	0.661	0.992	0.10
	80-100%	1.11	1.43	178	0.77	0.441	0.938	0.19
40-60%	60-60%	2.67	1.39	178	1.93	0.056	0.308	0.45
	80-100%	3.21	1.51	178	2.19	0.036	0.217	0.54
60-80%	80-100%	0.53	1.49	178	0.36	0.72	0.996	0.09

Note. Historical student absences were categorized by quintile rather than treated as a continuous variable to reduce the impact of outliers and maintain consistency with other results. Comparisons of scores reveal no difference between treating absences as a categorical or continuous variable.

Table 8

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score Among Historical Absence Quintiles

Absence Quintile	*Absence Quintile*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
0-20%	20-40%	2.14	1.43	178	1.497	0.136	0.566	0.33
	40-60%	2.503	1.53	178	1.637	0.103	0.476	0.38
	60-80%	3.017	1.5	178	2.01	0.046	0.265	0.46
	80-100%	2.689	1.64	178	1.637	0.103	0.476	0.41
20-40%	40-60%	0.362	1.46	178	0.248	0.805	0.999	0.06
	60-80%	0.877	1.43	178	0.612	0.541	0.973	0.13
	80-100%	0.549	1.58	178	0.347	0.729	0.997	0.08
40-60%	60-60%	0.514	1.53	178	0.337	0.737	0.997	0.08
	80-100%	0.186	1.67	178	0.112	0.911	1	0.03
60-80%	80-100%	-0.328	1.64	178	-0.2	0.842	1	0.05

Note. Historical student absences were categorized by quintile rather than treated as a continuous variable to reduce the impact of outliers and maintain consistency with other results. Comparisons of scores reveal no difference between treating absences as a categorical or continuous variable.

Table 9

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score Among Income Levels

Low Income Category	*Low Income Category*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Fluctuating	Missing	-12.045	5.99	180	-2.01	0.046	0.188	2.05
	No	2.429	1.02	180	2.37	0.019	0.086	0.41
	Yes	0.542	1.17	180	0.46	0.644	0.967	0.09
Missing	No	14.475	5.97	180	2.42	0.016	0.076	2.46
	Yes	12.587	5.96	180	2.11	0.036	0.154	2.14
No	Yes	-1.888	1.1	180	-1.72	0.088	0.318	0.32

Note. Student income data was not entirely consistent, causing summary categories to be made as described in the text.

Table 10

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score Among Income Levels

Low Income Category	*Low Income Category*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Fluctuating	Missing	-4.42	6.54	179	-0.676	0.5	0.906	0.68
	No	-1.75	1.13	179	-1.547	0.124	0.412	0.27
	Yes	1.04	1.29	179	0.801	0.424	0.854	0.16
Missing	No	2.67	6.52	179	0.409	0.683	0.977	0.41
	Yes	5.46	6.55	179	0.833	1.406	0.839	0.84
No	Yes	2.79	1.21	179	2.313	0.022	0.099	0.43

Note. Student income data was not entirely consistent, causing summary categories to be made as described in the text.

Table 11

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score Among Homelessness Levels

Homeless Category	*Homeless Category*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Fluctuating	Missing	-12.811	6.086	180	-2.105	0.037	0.155	2.15
	No	0.168	0.961	180	0.175	0.861	0.998	0.03
	Yes	2.942	3.14	180	0.937	0.785	0.785	0.49
Missing	No	12.979	6.034	180	2.151	0.141	0.141	2.18
	Yes	15.753	6.677	180	2.359	0.089	0.089	2.64
No	Yes	2.774	3.06	180	0.906	0.801	0.801	0.46

Note. Student homelessness data was not entirely consistent, causing summary categories to be made as described in the text.

Table 12

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score Among Homelessness Levels

Homeless Category	*Homeless Category*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Fluctuating	Missing	-5.47	6.41	179	-0.854	0.394	0.829	0.86
	No	-2.45	1.03	179	-2.383	0.018	0.084	0.39
	Yes	7.36	3.29	179	2.238	0.026	0.117	1.16
Missing	No	3.02	6.38	179	0.474	0.636	0.965	0.48
	Yes	12.82	7.1	179	1.807	0.072	0.274	2.02
No	Yes	9.8	3.23	179	3.037	0.003	0.014	1.54

Note. Student homelessness data was not entirely consistent, causing summary categories to be made as described in the text.

Table 13

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score by Student Ethnicity

Ethnicity	*Ethnicity*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Hispanic	Not Hispanic	-2.8	3.52	182	-0.795	0.428	0.428	0.47

Note. The sample contained extremely limited representation of Hispanic students.

Table 14

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score by Student Ethnicity

Ethnicity	*Ethnicity*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Hispanic	Not Hispanic	0.382	3.83	181	0.099	0.921	0.921	.06

Note. The sample contained extremely limited representation of Hispanic students.

Table 15

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score by Student Racial Group

Race		*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
White	Not White	-1.05	4.28	182	-0.245	0.807	0.807	0.17

Note. The sample contained extremely limited representation of non-White students.

Table 16

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score by Student Racial Group

Race	*Race*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
White	Not White	-2.77	4.28	181	-0.594	0.553	0.553	0.42

Note. The sample contained extremely limited representation of non-White students.

Table 17

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score by Student Gender

Gender	*Gender*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Female	Male	0.905	0.885	182	1.02	0.308	0.308	0.15

Table 18

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score by Student Gender

Gender	*Gender*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
Female	Male	-0.969	0.964	181	-1.01	0.316	0.36	0.15

Table 19

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score Among Historical GPA Quintiles

GPA Quintile	*GPA Quintile*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
0-20%	20-40%	-1.966	1.79	179	-1.1	0.274	0.807	0.33
	40-60%	0.578	1.83	179	0.32	0.753	0.998	0.09
	60-80%	1.24	1.85	179	0.67	0.502	0.962	0.21
	80-100%	0.64	1.98	179	0.33	0.745	0.998	0.11
20-40%	40-60%	2.54	1.53	179	1.67	0.097	0.457	0.42
	60-80%	3.21	1.54	179	2.08	0.039	0.234	0.54
	80-100%	2.61	1.69	179	1.54	0.125	0.537	0.44
40-60%	60-60%	0.67	1.36	179	0.49	0.625	0.988	0.11
	80-100%	0.07	1.44	179	0.05	0.964	1.00	0.01
60-80%	80-100%	-0.6	1.23	179	0.63	0.627	0.988	0.10

Note. Absences are calculated as the average for a student over their academic career. Lower percentiles indicate the student has been absent less often.

Table 20

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score Among Historical GPA Quintiles

GPA Quintile	*GPA Quintile*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
0-20%	20-40%	-0.7	2.01	178	-0.35	0.728	0.997	-0.11
	40-60%	0.01	2.04	178	0	0.998	1	0.00
	60-80%	1.73	2	178	-0.87	0.387	0.909	0.26
	80-100%	-1.07	2.13	178	-0.5	617	0.987	-0.16
20-40%	40-60%	0.71	163	178	0.43	0.665	0.993	0.11
	60-80%	-0.03	1.56	178	-0.66	0.509	0.964	0.00
	80-100%	-0.37	1.69	178	-0.22	0.828	1	-0.06
40-60%	60-60%	-1.74	1.47	178	-1.18	0.238	0.761	-0.26
	80-100%	-1.07	1.54	178	-0.7	0.486	0.957	-0.16
60-80%	80-100%	0.66	1.36	178	0.49	0.628	0.989	0.10

Note. GPAs were calculated as the average for a student over their academic career. Lower percentiles indicate the student has a lower GPA.

Table 21

ANCOVA Post Hoc Comparison Test for Mean Differences in Math Score Among Student 2021 Grade Level

Grade Level	*Grade Level*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
9	10	1.26	1.12	181	1.12	0.264	0.502	0.21
	11	-0.3	1.19	181	-0.25	0.802	0.966	0.05
10	11	-1.56	1.08	181	-1.4	0.151	0.321	0.26

Table 22

ANCOVA Post Hoc Comparison Test for Mean Differences in Reading Score Among Student 2021 Grade Level

Grade Level	*Grade Level*	*Mean Difference*	*SE*	*df*	*t*	*p*	*p-tukey*	*d*
9	10	-1.88	1.19	180	-1.58	0.115	0.256	0.29
	11	1.73	1.26	180	1.37	0.172	0.358	0.27
10	11	3.61	1.16	180	3.1	0.002	0.006	0.56

Table 23

Band Differences in Math Testing Pre and Post COVID-19

Achievement Level	9th Grade		10th Grade		11th Grade	
	Pre COVID	*Post COVID*	*Pre COVID*	*Post COVID*	*Pre COVID*	*Post COVID*
Low	<217	<213	<216	<215	<218	<219
Low Average	217-227	213-223	216-226	215-226	218-228	219-228
Average	228-237	224-234	227-236	227-236	229-239	229-239
High Average	238-239	235-244	237-148	237-248	240-251	240-251
High	250+	245+	249+	249+	252+	252+

Note. Bands were created using limited scoring data and represent approximate cutoffs.

Table 24

Band Differences in Reading Testing Pre and Post COVID-19

Achievement Level	9th Grade		10th Grade		11th Grade	
	Pre COVID	*Post COVID*	*Pre COVID*	*Post COVID*	*Pre COVID*	*Post COVID*
Low	<209	<206	<209	<217	<210	<210
Low Average	209-217	206-216	210-217	217-218	211-217	210-221
Average	218-225	217-225	218-225	219-227	218-227	222-229
High Average	226-235	226-234	226-235	228-239	228-236	230-239
High	236+	235+	236+	240+	237+	240+

Note. Bands were created using limited scoring data and represent approximate cutoffs.

Table 25

Comparison of Fall 2020 and Winter 2021 Prediction/Actual Score Differences

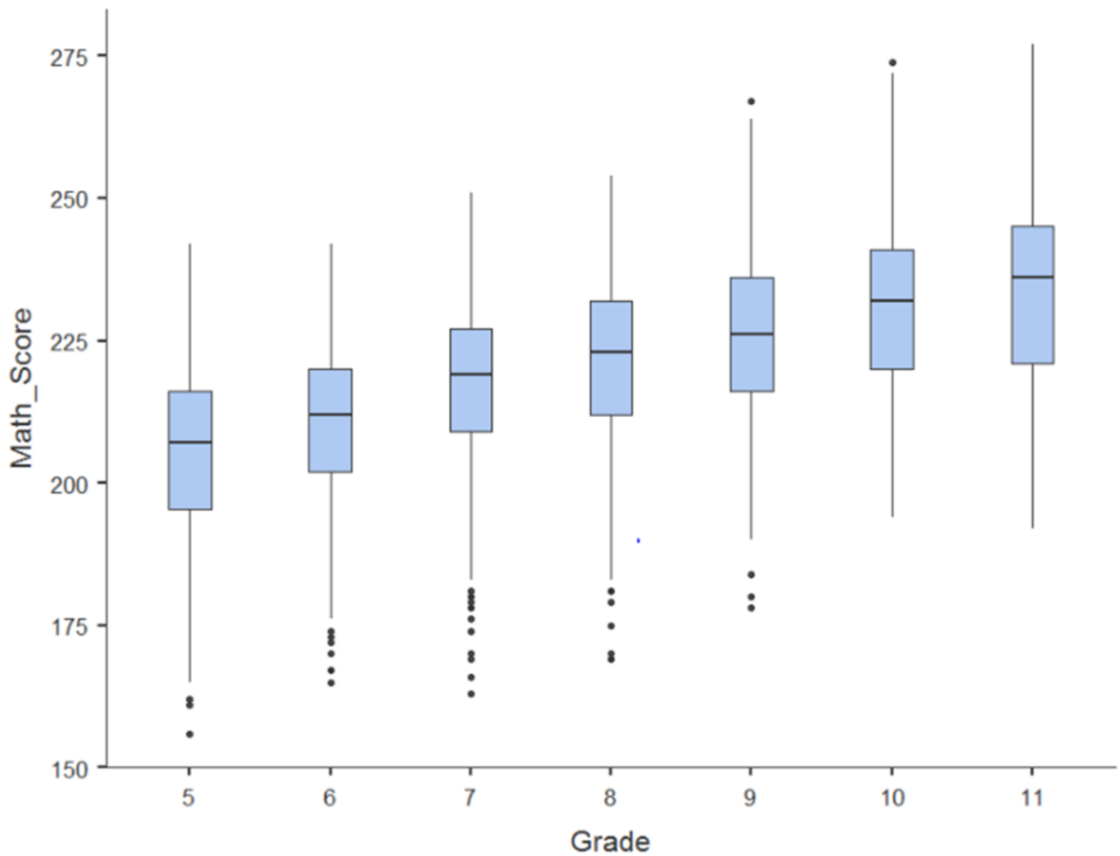
	Fall 2020		Winter 2021	
Measure	*Math Predicted/Actual Difference*	*Reading Predicted/Actual Difference*	*Math Predicted/Actual Difference*	*Reading Predicted/Actual Difference*
Mean	-3.51	-2.03	-1.04	-1.87
Median	-3.15	-1.88	-0.82	-2.06
SD	5.5	7.1	6.09	6.54
Min	-25	-32.1	-30.9	-18.7
Max	11.1	14.3	14.7	21.8
20th Percentile	-8.04	-7.27	-5.66	-7.3
40th Percentile	-4.2	-3.04	-1.86	-3.29
60th Percentile	-1.62	-0.53	0.56	-0.7
80th Percentile	0.7	3.7	3.65	3.51

Appendix B

Figures

Figure 1

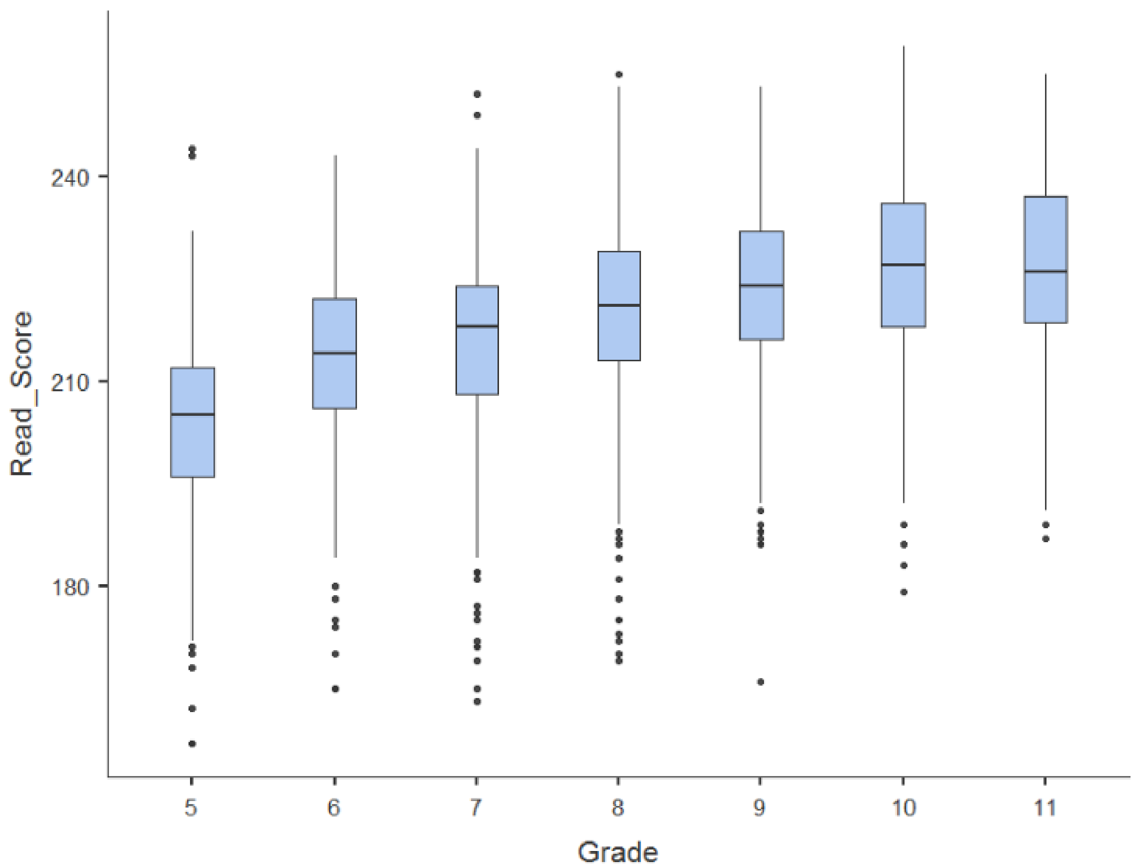
Summary of Grade Distributions of Test Scores Used for Math Modeling



Note. Data included in the figure displays distribution of test scores by grade level which were used to develop projection models. Only data from 2021 high school students with both projected and realized winter 2021 scores was used in comparisons.

Figure 2

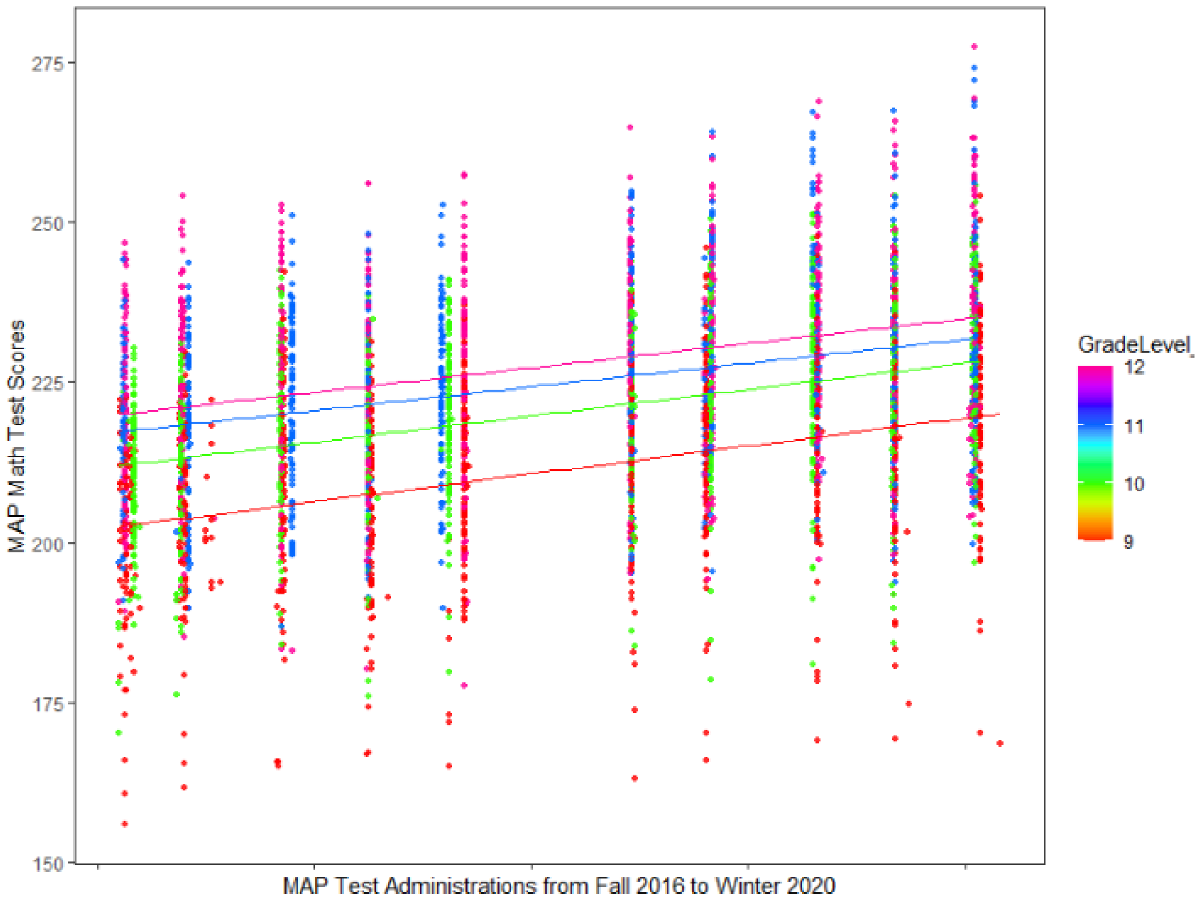
Summary of Grade Distributions of Test Scores Used for Reading Modeling



Note. Data included in the figure displays distribution of test scores by grade level which were used to develop projection models. Only data from 2021 high school students with both projected and realized winter 2021 scores was used in comparisons.

Figure 3

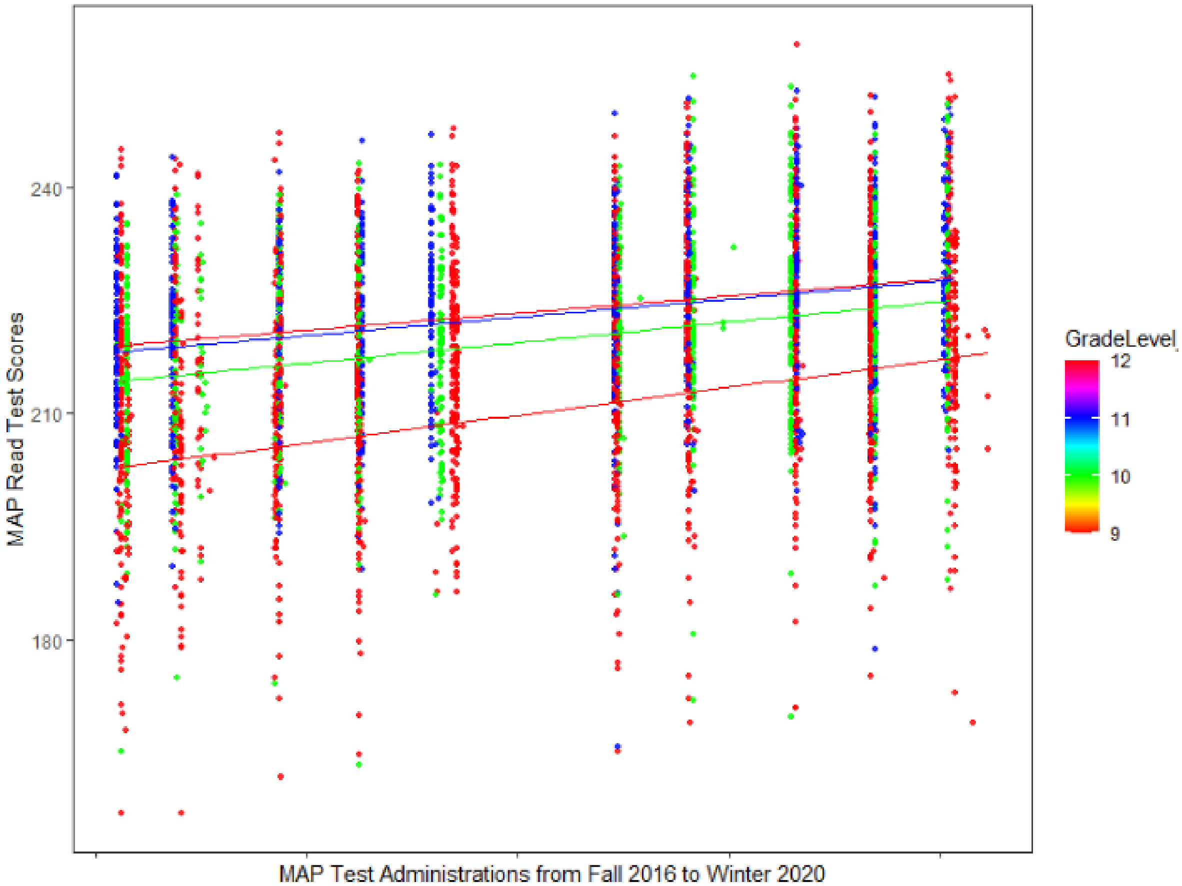
Math Map Test Score Trajectories from Fall 2016 to Winter 2020 Among Grade Levels



Note. All data points represent an individual student score. Trend lines represent average student growth by grade level.

Figure 4

Reading Map Test Score Trajectories from Fall 2016 to Winter 2020 Among Grade Levels



Note. All data points represent an individual student score. Trend lines represent average student growth by grade level.

Figure 5

Estimated Marginal Means Among Math Score Differences by Absence Quintile

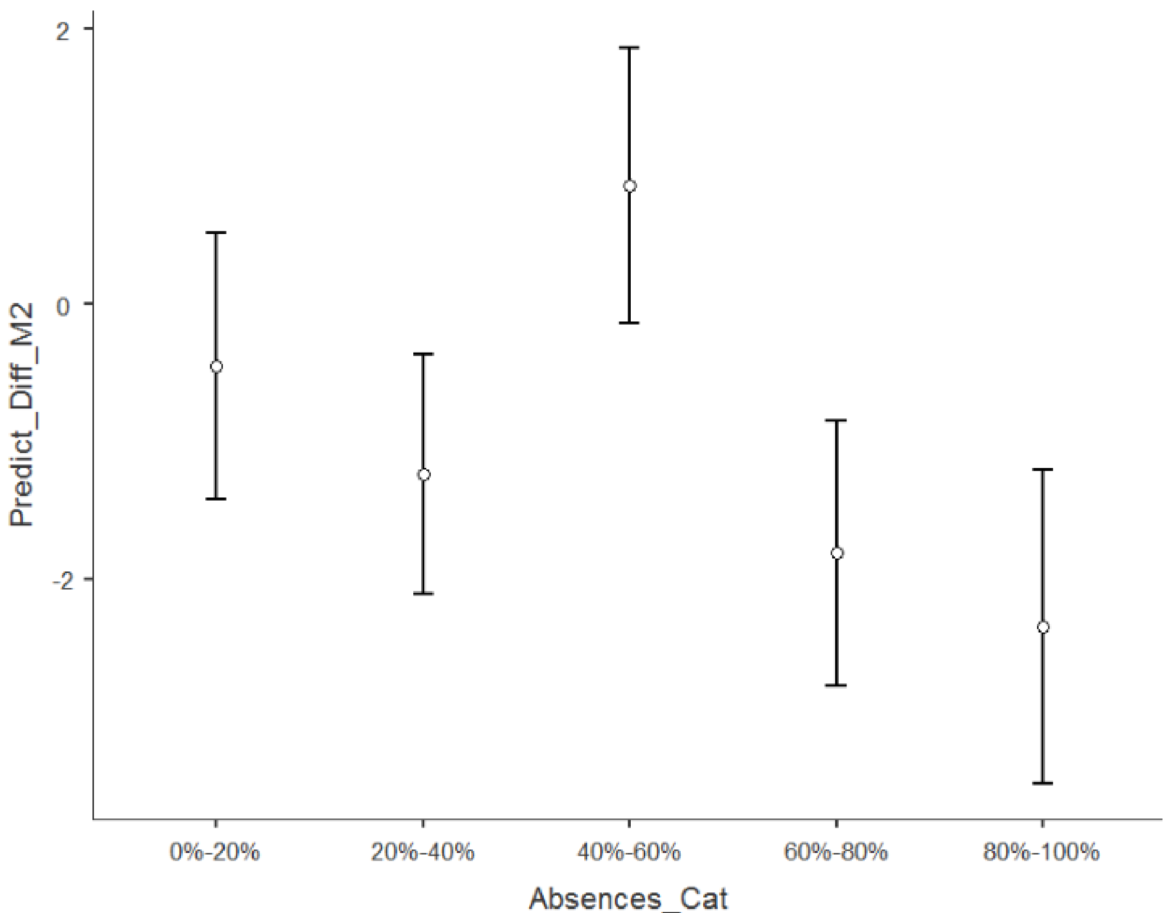


Figure 6

Estimated Marginal Means Among Reading Score Differences by Absence Quintile

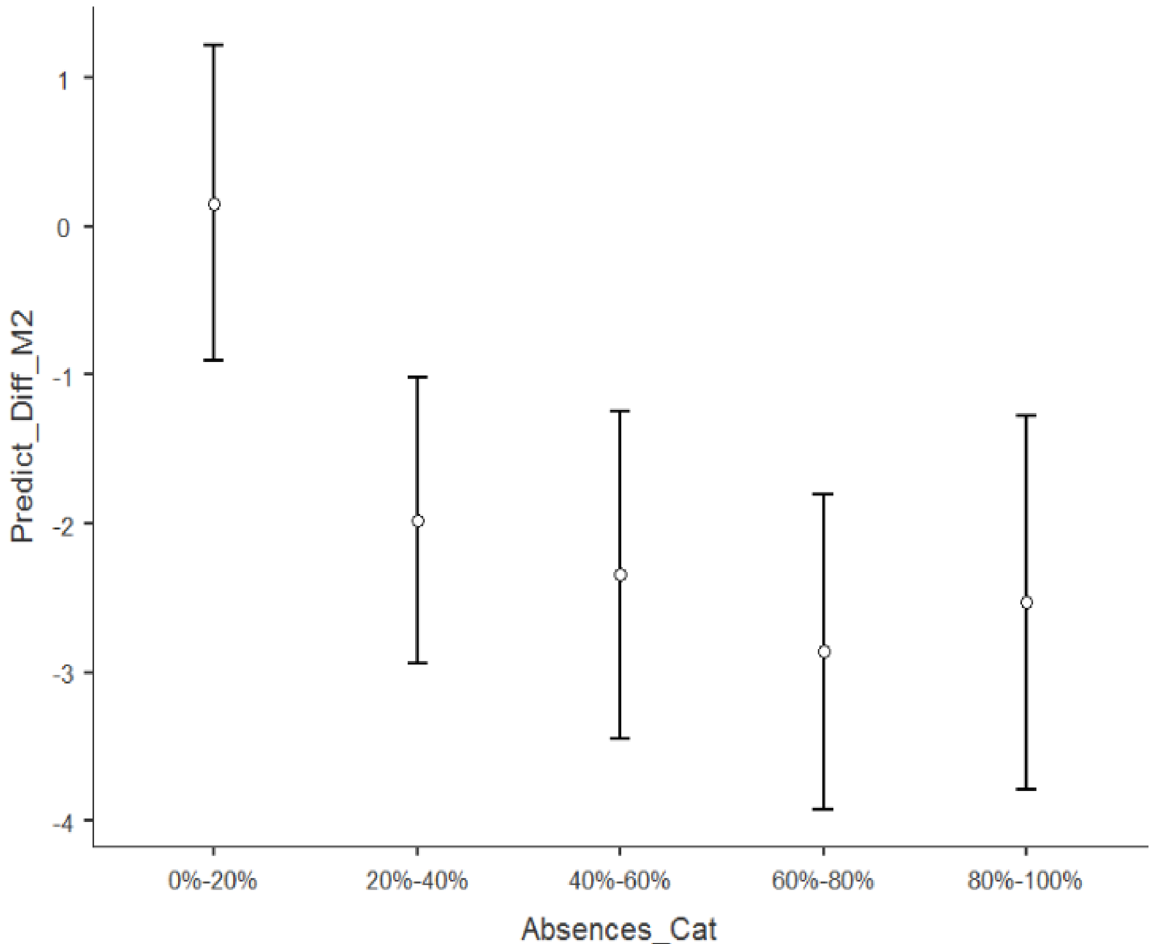
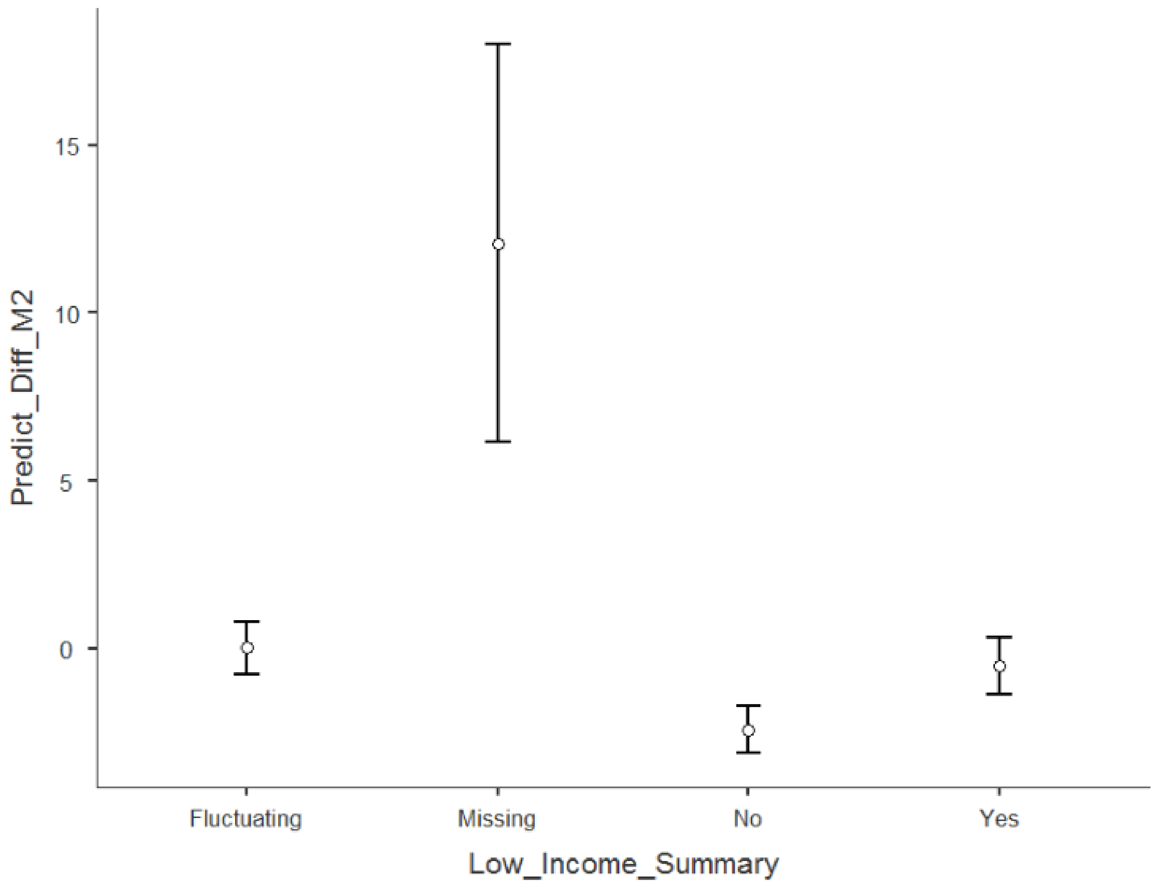


Figure 7

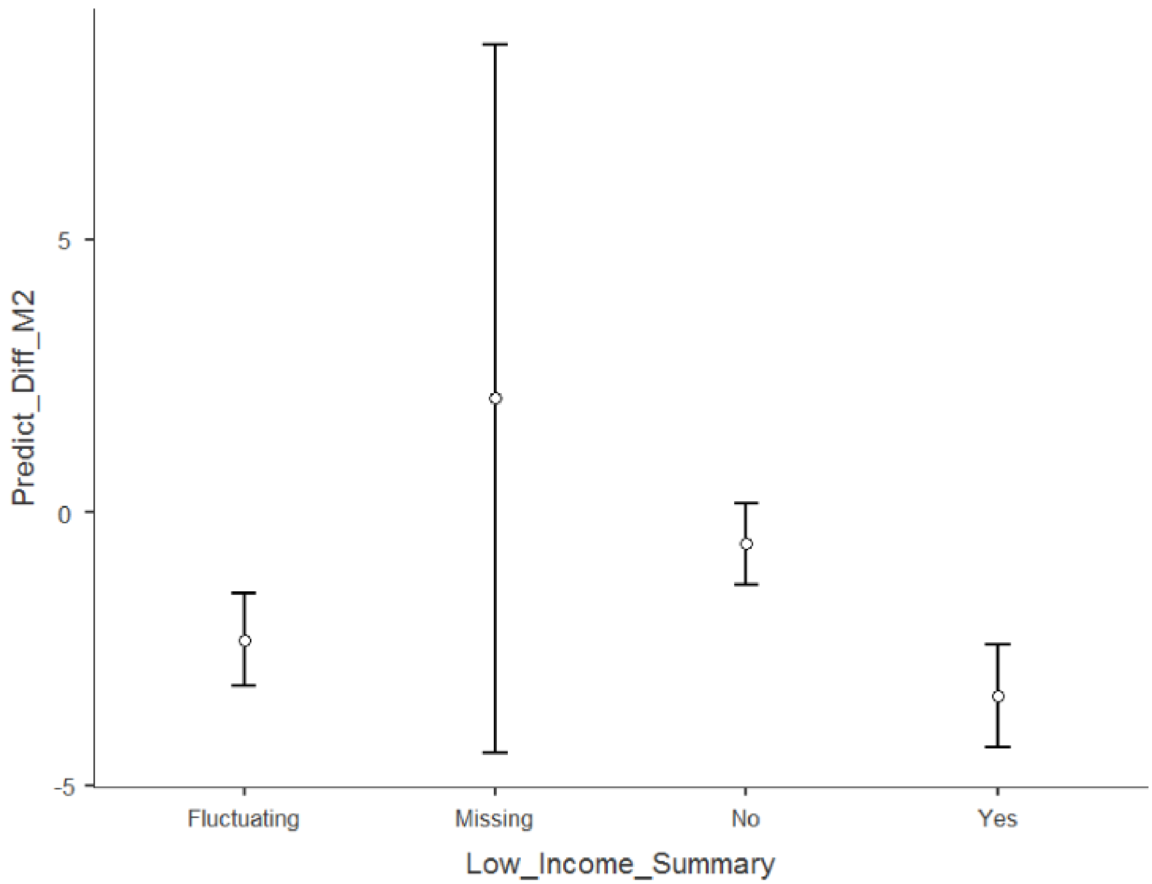
Estimated Marginal Means Among Math Score Differences by Low Income Categorization



Note. Sample size of "Missing" categorization was *n*=1.

Figure 8

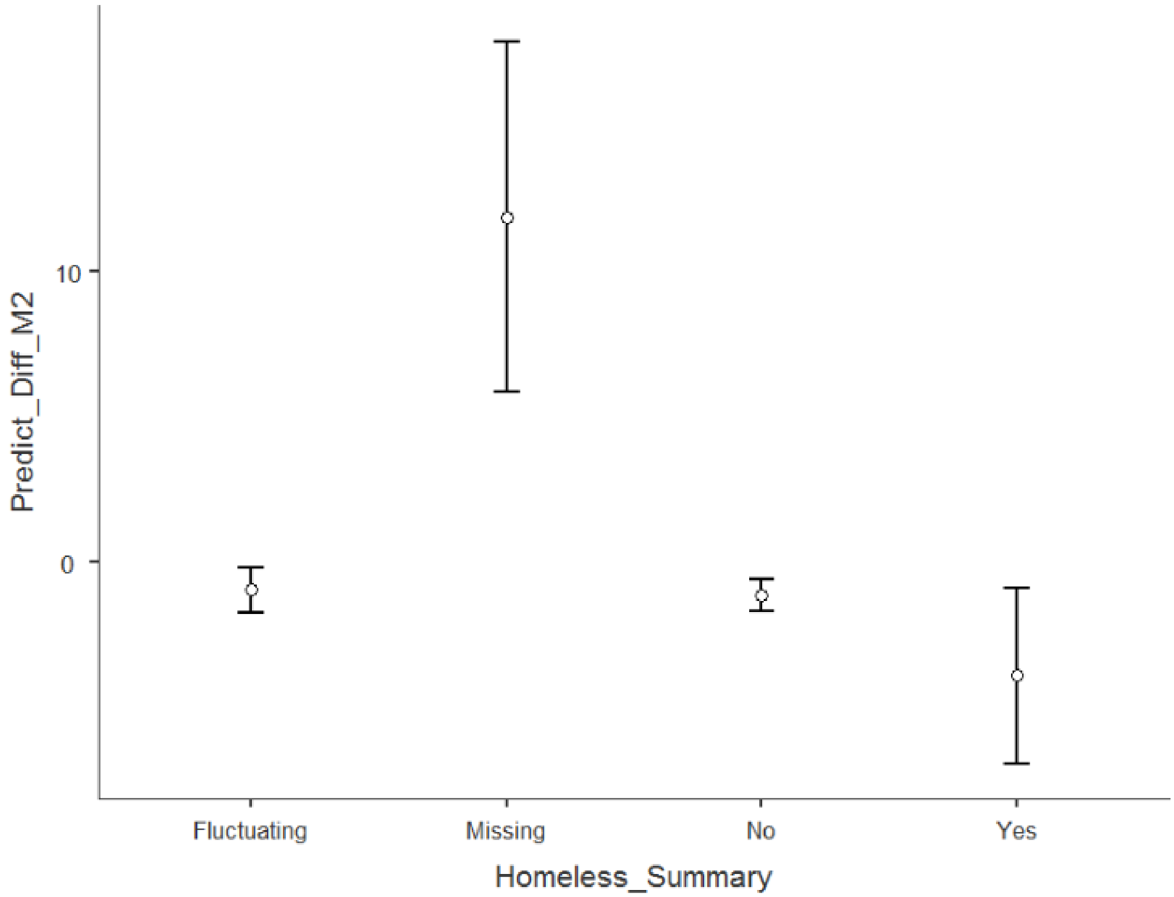
Estimated Marginal Means Among Reading Score Differences by Low Income Categorization



Note. Sample size of "Missing" categorization was *n*=1.

Figure 9

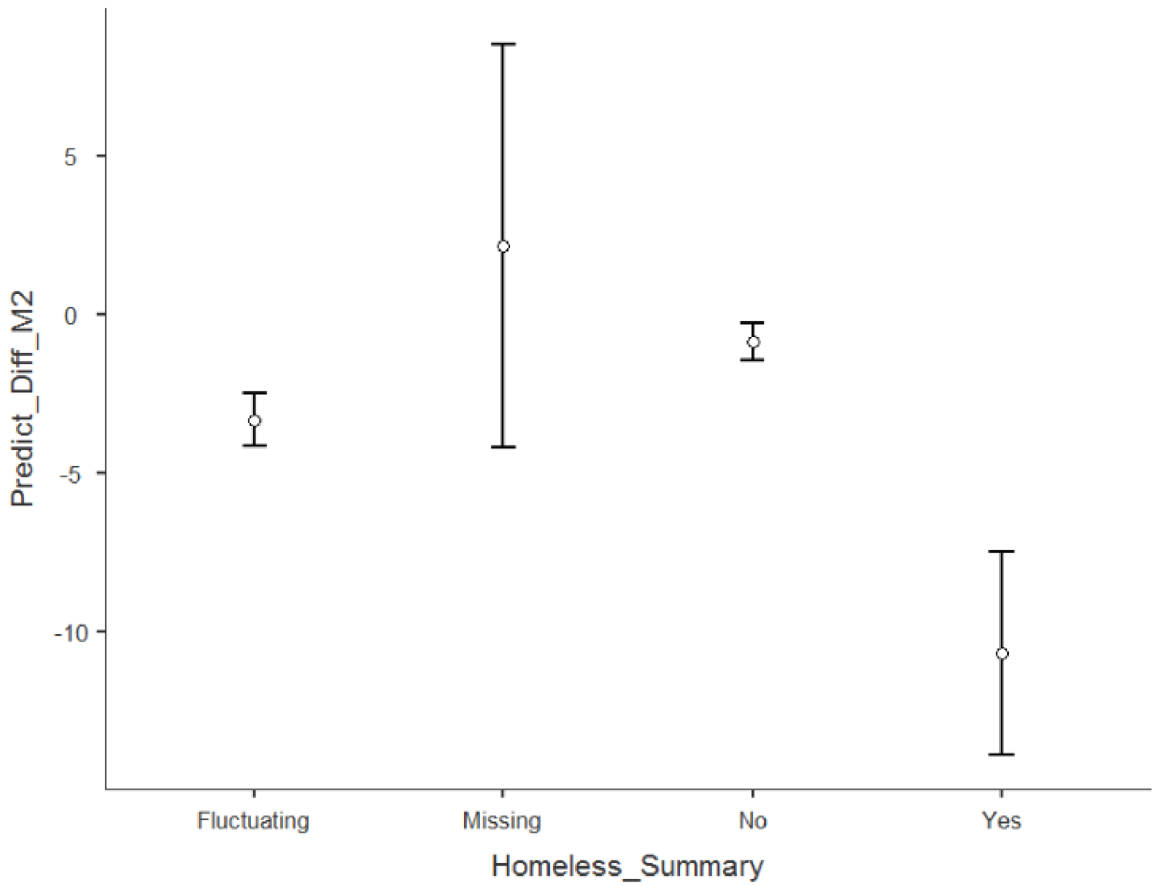
Estimated Marginal Means Among Math Score Differences by Homeless Categorization



Note. Sample size of "Missing" categorization was n=1.

Figure 10

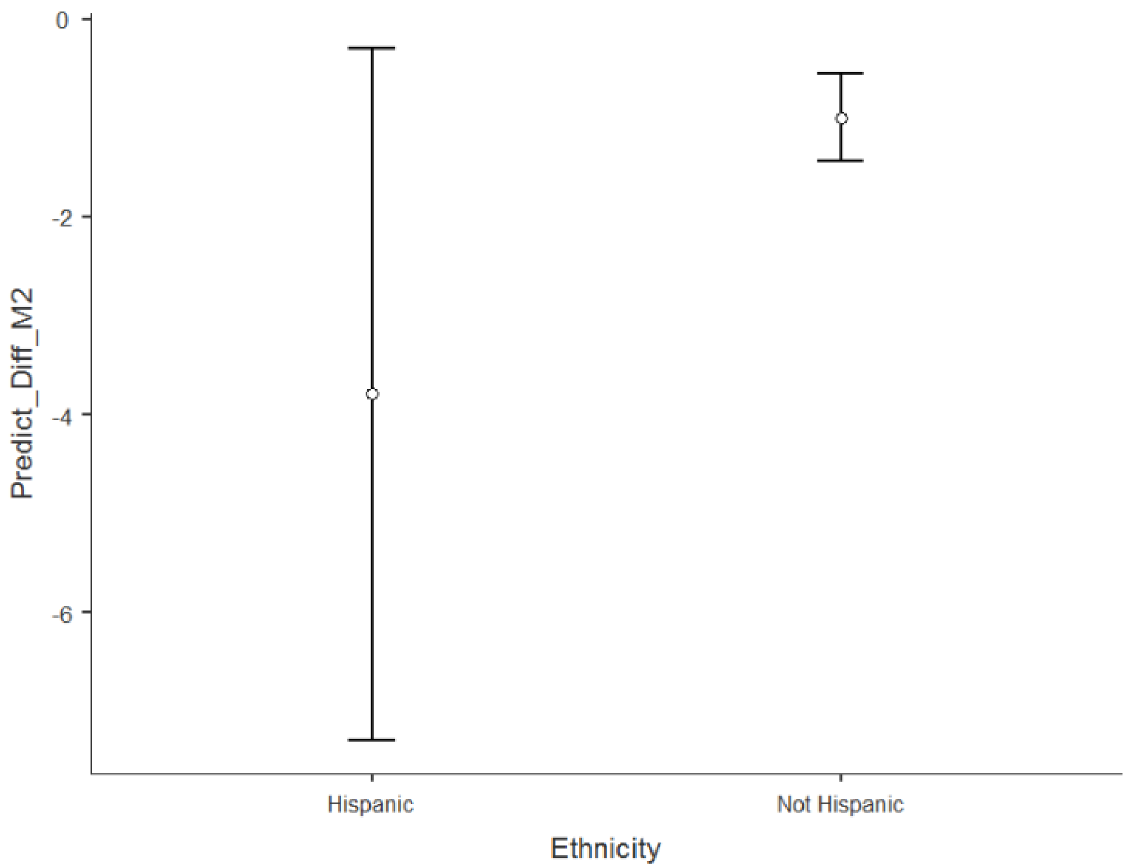
Estimated Marginal Means Among Reading Score Differences by Homeless Categorization



Note. Sample size of "Missing" categorization was n=1.

Figure 11

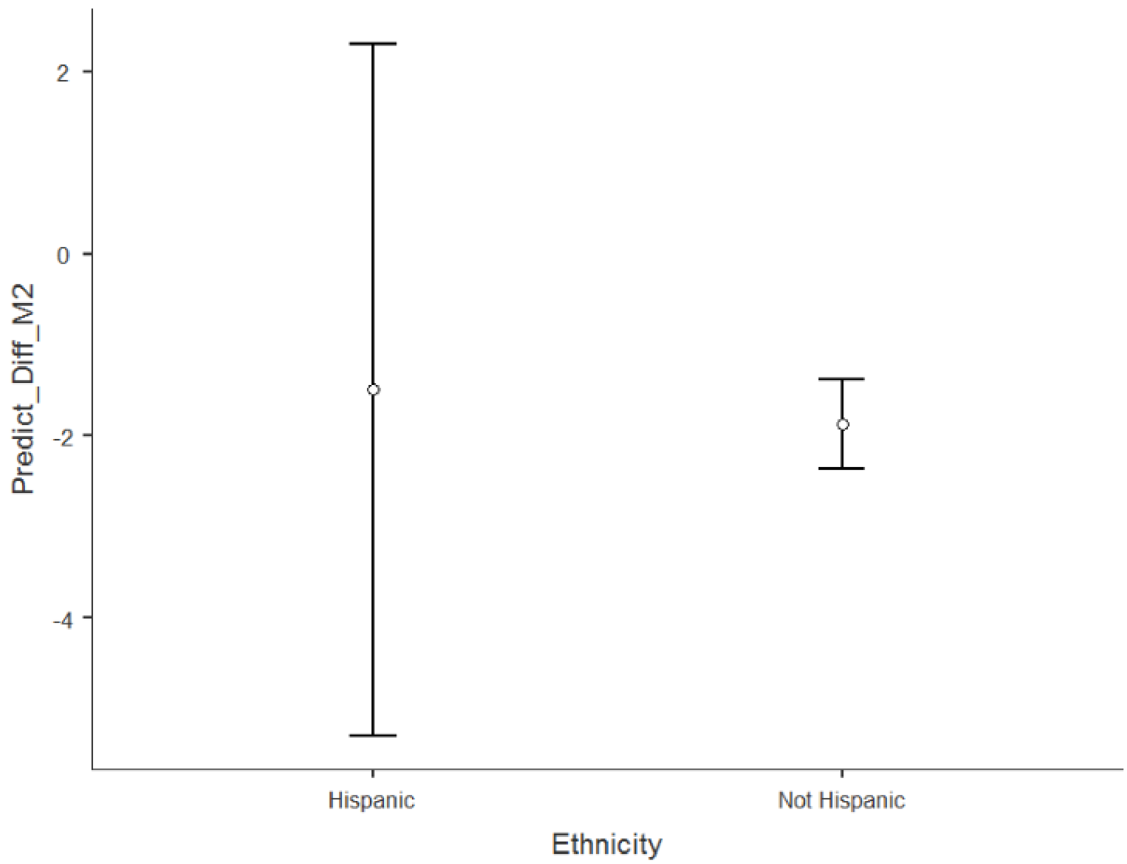
Estimated Marginal Means Among Math Score Differences by Student Ethnicity



Note. Sample size of Hispanic students was was n=3.

Figure 12

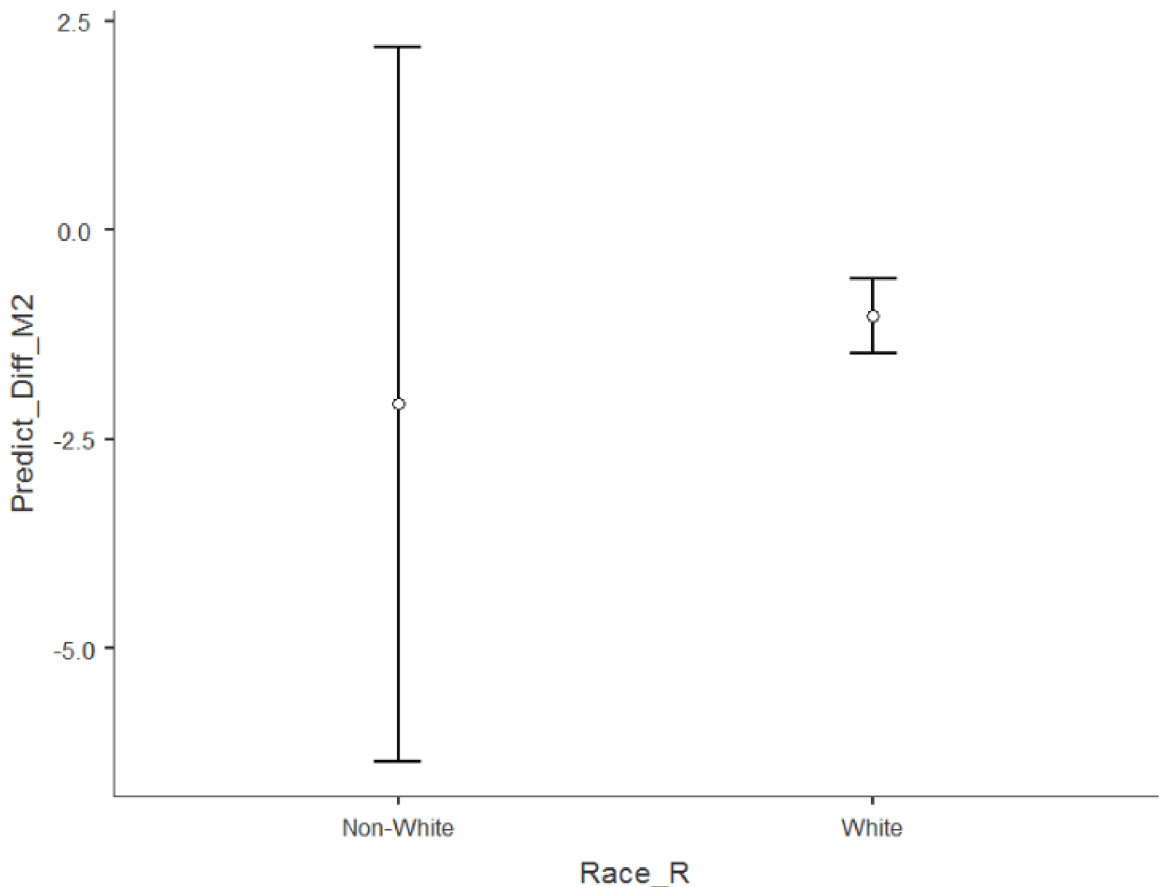
Estimated Marginal Means Among Reading Score Differences by Student Ethnicity



Note. Sample size of Hispanic students was n=3.

Figure 13

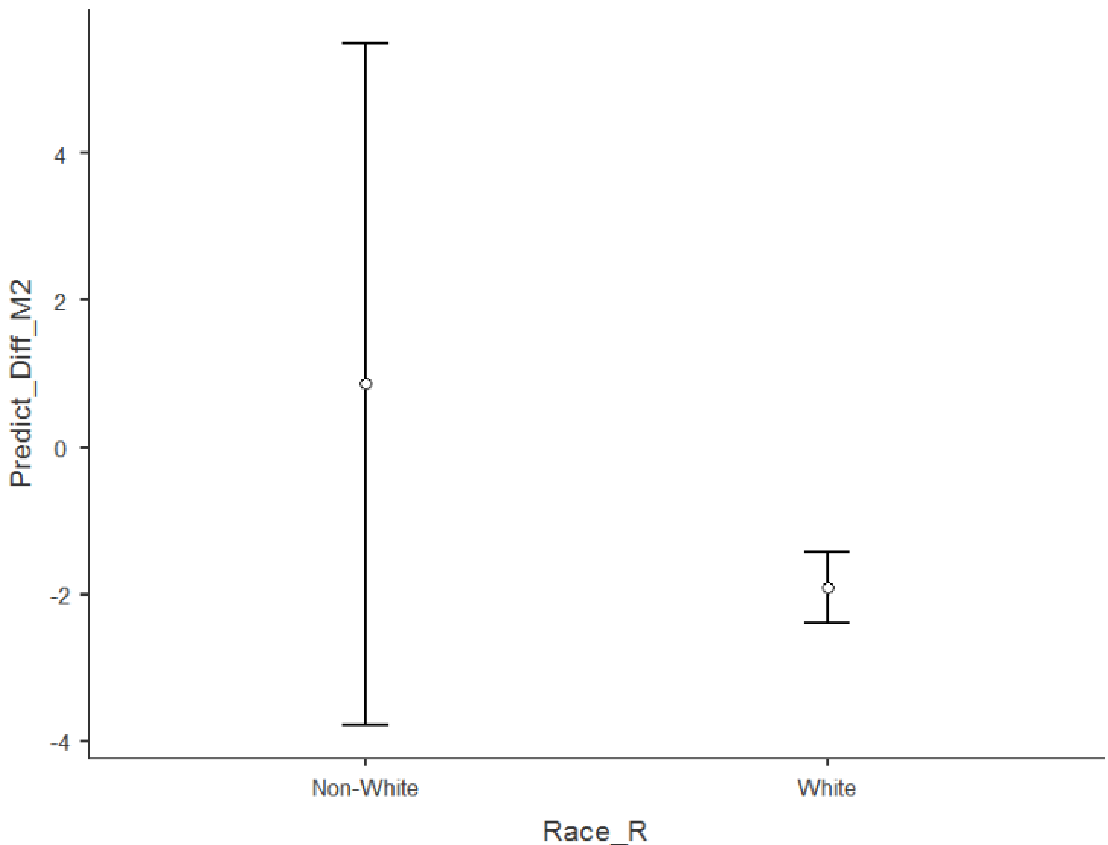
Estimated Marginal Means Among Math Score Differences by Student Racial Group



Note. Sample size of Non-White students was *n*=2.

Figure 14

Estimated Marginal Means Among Reading Score Differences by Student Racial Group



Note. Sample size of Non-White students was n=2.

Figure 15

Estimated Marginal Means Among Math Score Differences by Student Gender

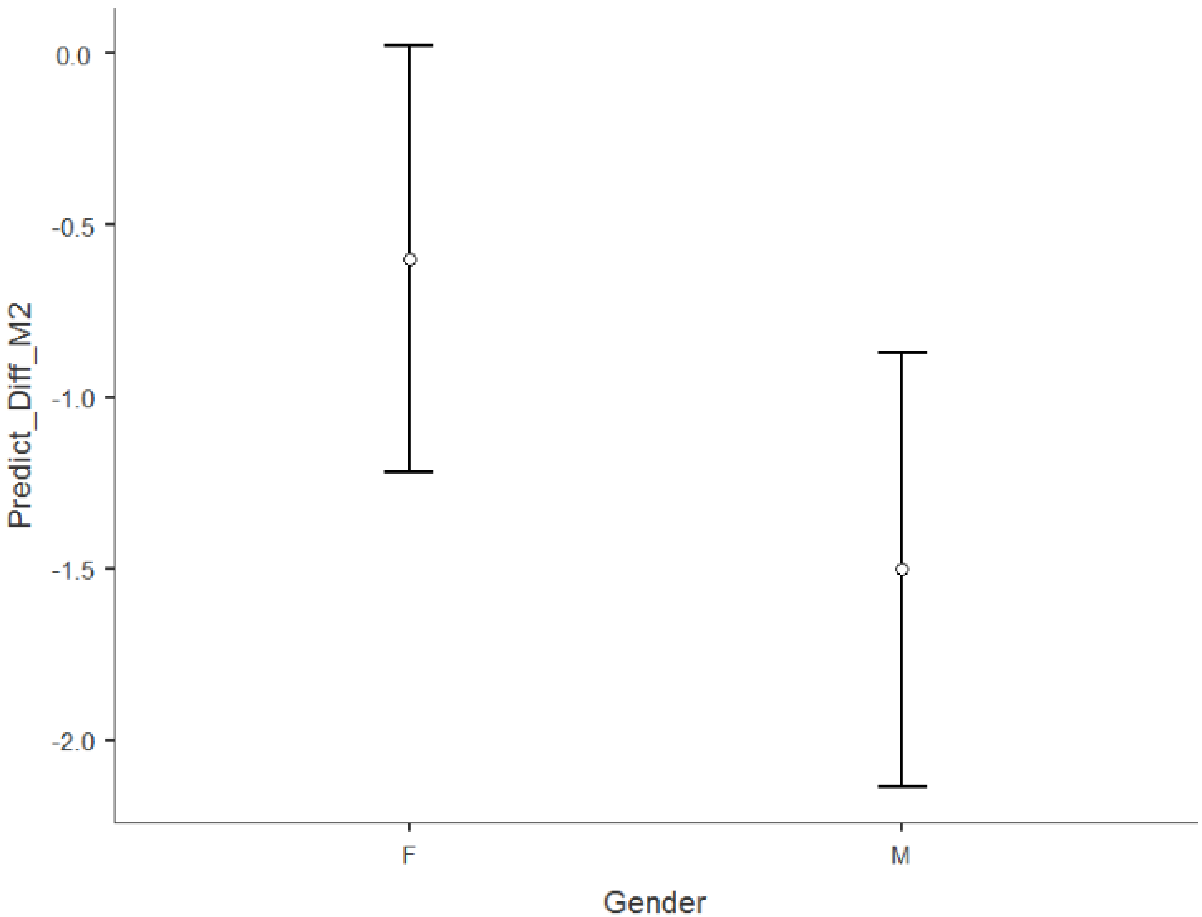


Figure 16

Estimated Marginal Means Among Reading Score Differences by Student Gender

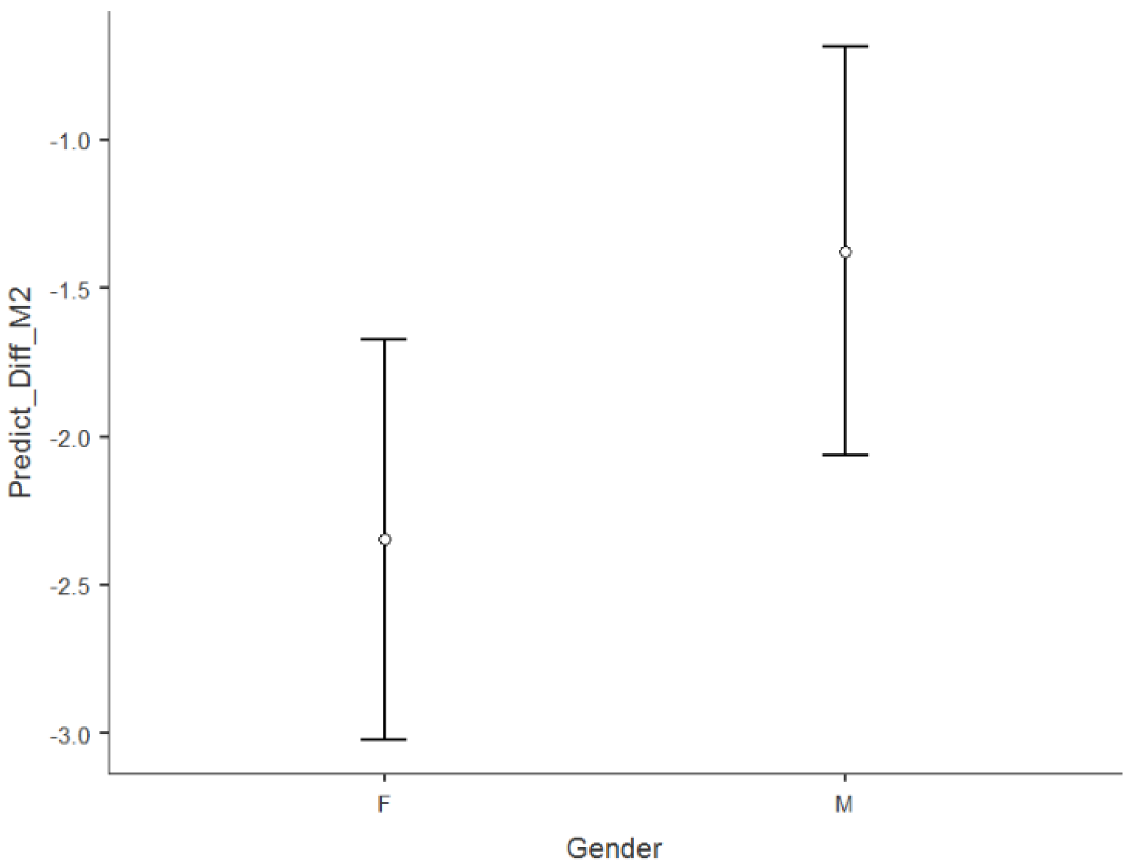


Figure 17

Estimated Marginal Means Among Math Score Differences by Student GPA Category

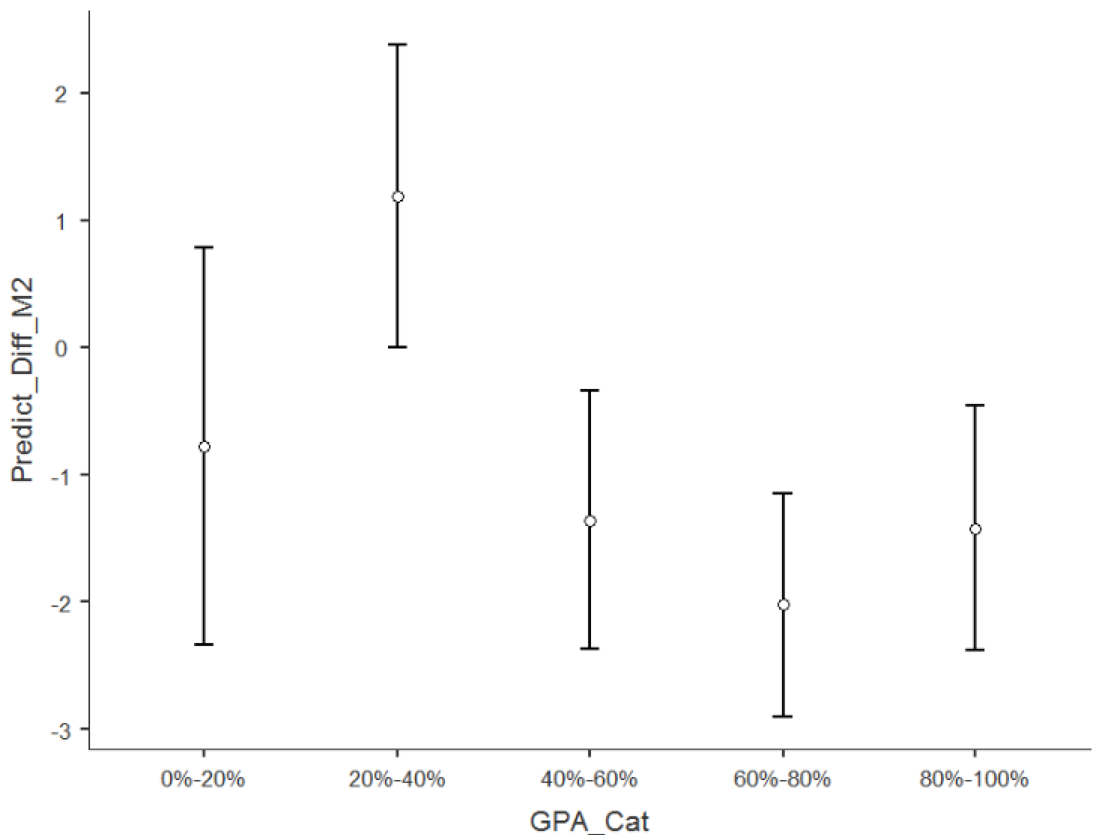


Figure18

Estimated Marginal Means Among Reading Score Differences by Student GPA Category

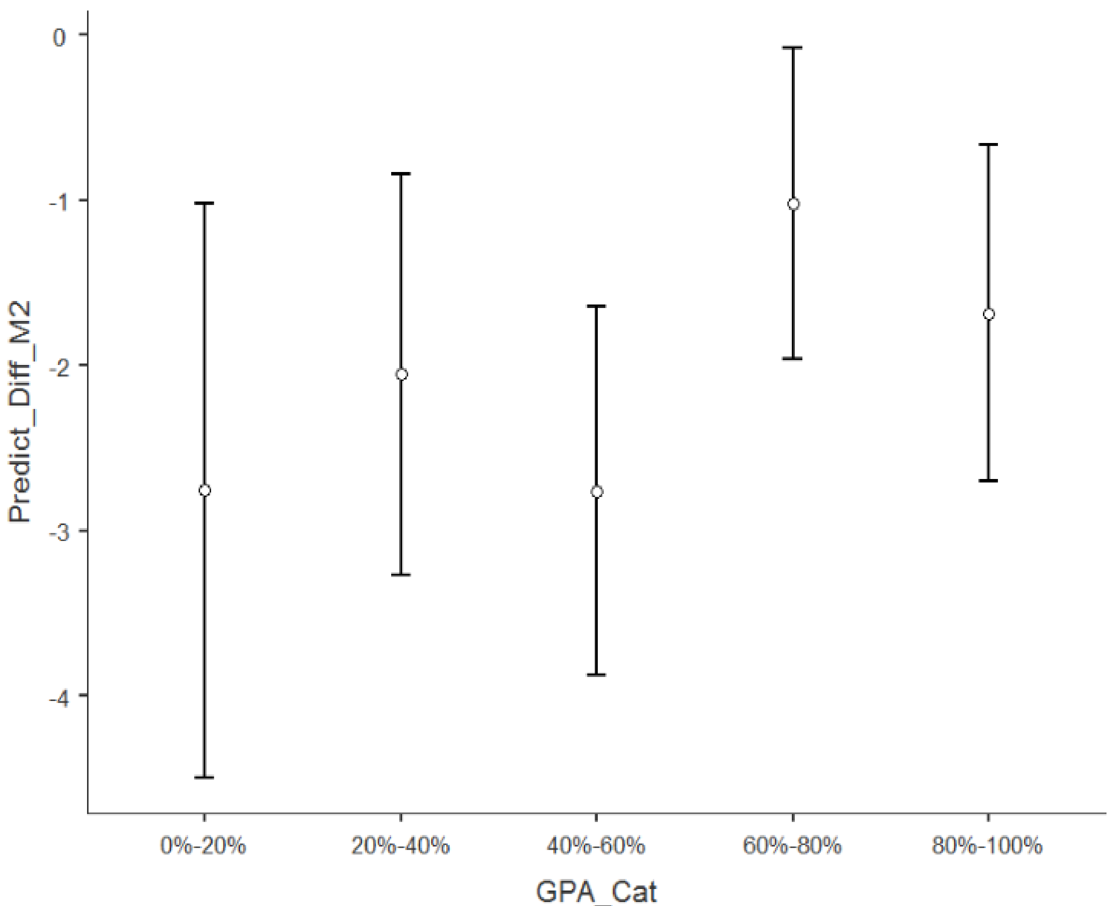


Figure 19

Estimated Marginal Means Among Math Score Differences by Student 2021 Grade Level

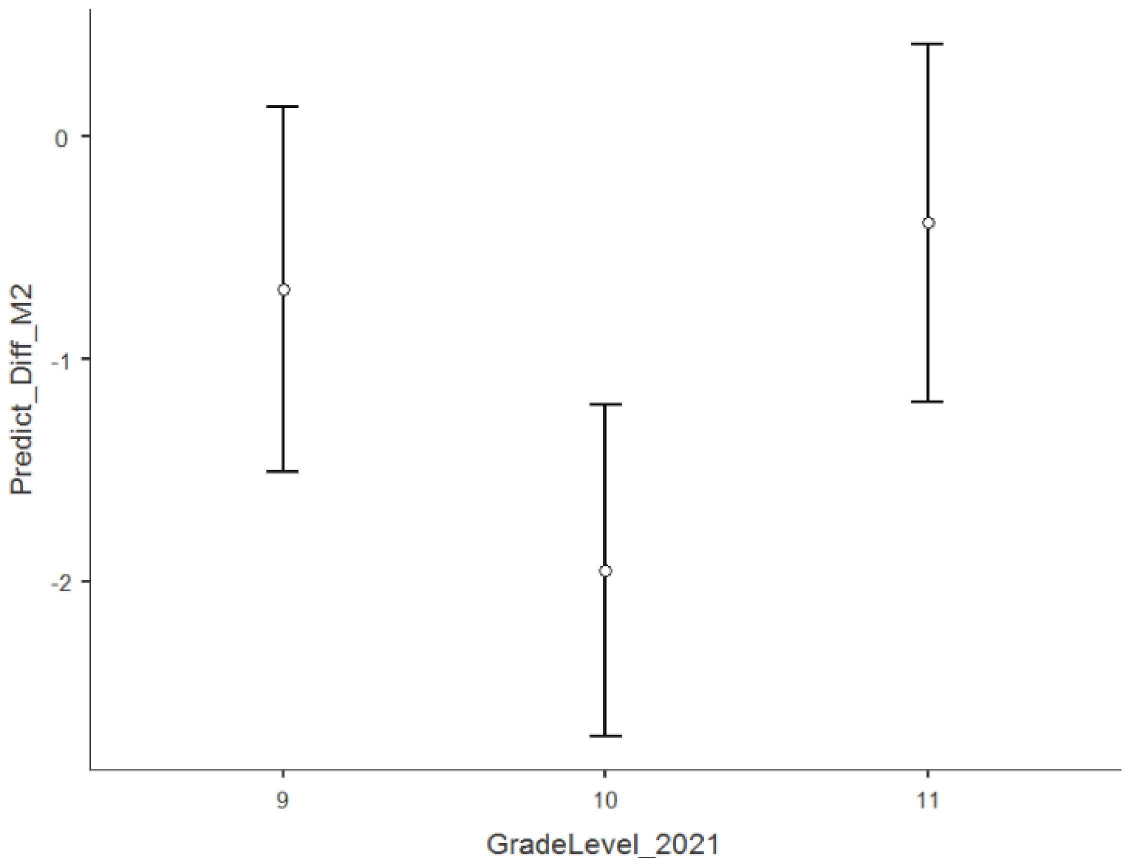
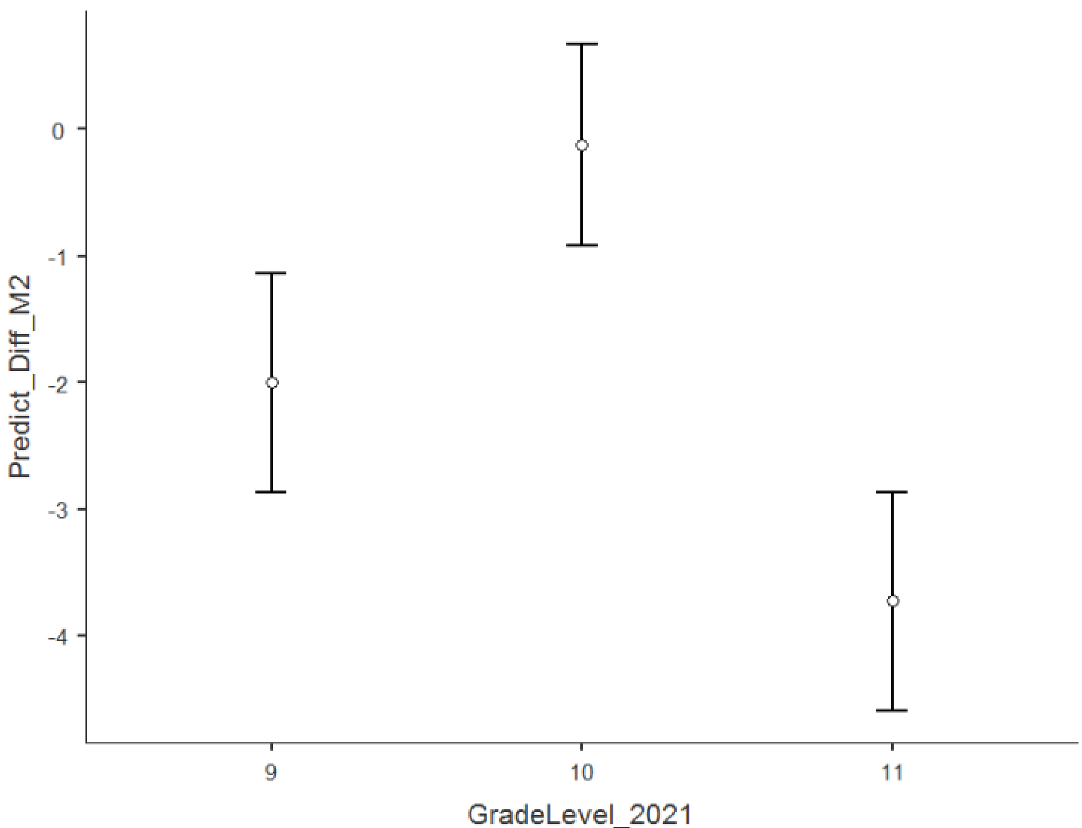


Figure 20

Estimated Marginal Means Among Reading Score Differences by Student 2021 Grade Level



Vita

Austin Melzer started his academic career at North Carolina State University in 2014, graduating in three years with a bachelor's degree in psychology. After requiring additional time to consider doctoral and master's options for graduate school, he participated in the Disney College Program, which inspired him to pursue a master's degree Industrial Organizational Psychology. He attended Appalachian State University from 2019-2021, earning a master's in Industrial Organizational Psychology and Human Resource Management. Throughout the program, he worked on various professional projects, including leading educational analytics initiatives, interning at Training Industry, and assisting in the creation and instruction of a new undergraduate course.