GRIT AND ATTITUDE: A PREDICTABILITY STUDY OF COMMUNITY COLLEGE STUDENT PERFORMANCE IN COREQUISITE MATH COURSES

by

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ABSTRACT

Many community colleges are providing accelerative interventions for underprepared students by allowing them to enroll in corequisite math and English courses. These courses allow students to enroll in both remediation and college-level math and English and complete them within a semester. However, no studies have looked at how noncognitive factors like Grit and attitudes towards mathematics (ATM) of students influence their success in corequisite gateway math courses.

This non-experimental study examined the relationship and extent to which noncognitive factors, like Grit and ATM, influence student success in corequisite math gateway courses. Grit and ATM were found to be correlated to academic performance (AP) in both college-math ready (CR) and not college-math ready (NCR) students. These two noncognitive factors also moderately predicted AP in the corequisite math courses for both student groups. The distribution of ATM significantly varied between the two student groups whereas Grit was not distributed significantly differently between CR and NCR students.

These findings illustrate the need for teachers to be aware of the importance of the role of noncognitive factors in the AP of CR and NCR students.

KEY WORDS: Grit, mathematics, corequisites

DEDICATION

With deep gratitude and humble reflection, I dedicate this doctoral dissertation to the pillars of my life, each playing an indispensable role in my scholarly journey. First and foremost, I want to thank my loving wife, Uzo, whose unwavering patience and support sustained me through the arduous, extended years of research and writing. This achievement is as much yours as it is mine.

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CHAPTER ONE: INTRODUCTION

INTRODUCTION

Midwest Community College (MCC) is an open-access institution. Like any other typical community college, it enrolls many students who are either low income or underprepared for college (Bers & Schuetz, 2014; Callan, 1997; Hardy & Katsinas, 2007; Roueche, 1968; Ryu et al., 2022). These students share several demographic characteristics that identify them as academically at-risk students. These shared characteristics include financial-aid dependence, low completion and graduation rates, part-time enrollment, part-time or full-time employment, family responsibilities, etc. (Bragg & Durham, 2012; Kantrowitz, 2012). Of this population, a majority will take at least one developmental math class.

The terms *at-risk*, *remedial*, *developmental*, or *underprepared students* are used to designate this student population (Bailey & Smith Jaggars, 2016). They are assessed as underprepared for gateway college-level math and/or English through placement exams such as Accuplacer, Scholastic Aptitude Test (SAT), or American College Testing (ACT) (Barnes et al., 2010; Mattern et al., 2016). Among MCC's fall 2019 cohort enrollees, 73.2% of first-time degree-seeking college students tested into the developmental math course sequence (Breer, 2019, 2021). A 2016 national study reports that 59% of poorly prepared community college students enrolled in developmental math courses (X. Chen, 2016).

The last decade has been characterized by two sweeping higher education reforms at the national level: college access and the completion agenda. Community colleges respond to these challenges by providing various targeted initiatives to facilitate the advancement of underprepared students throughout college. Some of these initiatives include delineating STEM and non-STEM math pathways, implementing internally customized placement tests, establishing multiple-measures placement, incorporating accelerative interventions, and even instituting the cessation of placement testing (Jaggars, et al., 2015).

I focused on one specific accelerative intervention for this study. In this intervention, despite being placed into a developmental math sequence by placement exams like SAT and Accuplacer, underprepared students are allowed to enroll directly into introductory or gateway college-level math or English courses. However, due to their low placement scores, they are also simultaneously enrolled in a paired concurrent remediation or support course during the same semester (Bailey & Smith Jaggars, 2016; Park et al., 2018). This intervention allows the underprepared students to begin gateway college-level courses earlier than they should have given their placement scores, while also providing the just-in-time support or supplemental instruction they need to succeed at the college-level curriculum.

Studies indicate that underprepared students taking college-level math corequisite courses have been successful (Complete College America [CCA], 2012; Fair, 2017; Vandal, 2014). Comparable results are observed at MCC with its six-year-old corequisite program. In the academic year 2017–18 alone, 79% of underprepared students successfully passed introductory statistics and quantitative literacy math corequisite courses, while 78% of college-math ready (CR) students passed the introductory statistics and quantitative literacy math courses (Cole, 2022a).

Between fall 2018 and summer 2022, 71% of 696 underprepared students who assessed into developmental math successfully passed the same introductory math corequisite courses.

Comparably in the same period, 77% of 1,636 CR students passed the same introductory math courses (Cole, 2022a). This evidence suggests that underprepared students, with the help of supplemental instruction, not only can pass college-level gateway math classes but also, in some cases, can even surpass CR students in the same college-level courses when given the opportunity of enrolling in a corequisite course (Bailey & Smith Jaggars, 2016; Breer, 2018a; Park et al., 2018).

BACKGROUND

Over the last several years, community colleges, like most higher learning institutions, have been thrust with the challenge of improving accountability and success. One specific focus is to improve student retention, persistence, and completion rates, an area where community colleges suffer abysmal rates (Kantrowitz, 2012; Kotamraju & Blackman, 2011). Correlated to this focus is the lack of college readiness of most students graduating from high school who benefit from the privilege of open access to community colleges like MCC (Roderick et al., 2009). Of these incoming freshmen from MCC's district, about 73% test into developmental math education (Breer, 2021). One-third of these students testing into developmental math do not complete their education at MCC (Breer, 2018b). Some underprepared students are placed into between one to three developmental math classes below their college-level gateway math classes (Bailey, 2009; Breer, 2018a; Davidson & Petrosko, 2015).

At MCC, corequisite acceleration allows developmentally placed math students to enroll concurrently in a college-level gateway math course, such as statistics or quantitative literacy, with just-in-time support or a remediation class. This model enables the students to complete both remediation and a gateway math course in one semester instead of two or more.

Various studies indicate that students' success rates in corequisite math courses are encouraging (Hern, 2012; Jaggars et al., 2015; Vandal, 2014). Compared to college-level students, corequisite students who are not college-math ready (NCR) had comparable course success and completion rates (Vandal, 2014). At MCC, sometimes more corequisite-enrolled students achieved a grade of C or better in certain academic years than CR students who directly entered gateway math courses (Breer, 2018a).

These results and other studies point to two critical issues. First, underprepared-student success in corequisite math courses casts the spotlight on some of the inherent weaknesses and consequences of an overreliance on traditional placement testing. The second issue is the systemic overlooking of non-cognitive factors' contribution to student success in college-level math courses. Therefore, the college-level corequisite model at MCC has the potential to accelerate a significant proportion of the greater than 60% of underprepared students from enrolling into developmental math courses.

To better understand some of the factors contributing to the success rates of underprepared-corequisite students in gateway math courses, I have studied non-cognitive and non-academic student-related traits and their relationship to student success in corequisite gateway courses at MCC. The traditional placement model through high-stakes placement exams does not consider non-cognitive factors that may allow many more students to be successful in gateway courses within the corequisite model. For this study, two such non-cognitive factors are Grit and attitudes toward mathematics (ATM), which have been evaluated.

Grit is a non-cognitive personality trait defined as the "perseverance and passion for long-term goals" (Duckworth et al., 2007). Grit and its two subsidiary elements—perseverance of effort (POE) and consistency of interest (COI)—is postulated to build the attitudes and subsequent behaviors towards long-term goals and tasks (Duckworth et al., 2007; Duckworth & Quinn, 2009). The role Grit plays in college students' AP has been widely studied (Akos & Kretchmar, 2017; Bazelais et al., 2016; Wolters & Hussain, 2015).

Ma and Kishor (1997b) cite Neal (1967) as defining ATM as being "an aggregated measure of a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics, and a belief that mathematics is useful or useless" (p. 27). Studies have analyzed the impact of students' attitudinal disposition in math and subsequent math success (Al-Mutawah & Fateel, 2018; Fennema & Sherman, 1976; Nicolaidou & Philippou, 2003).

PROBLEM STATEMENT

There is a lack of studies related explicitly to the relationship of noncognitive factors such as Grit and ATM with student success in college-level corequisite math courses. This study addresses this knowledge gap in the literature and at a local policy level at MCC.

Some studies indicate that placement tests fail many students in the following ways: about 24% of students get misplaced into either gateway or developmental courses; at best, they are weak predictors of college AP relative to other indicators like high school GPA (Scott-Clayton & Stacey, 2015), and they do not assess non-cognitive factors that may allow many more students to be successful in their academics.

Many students perceive mathematics as challenging and are intimidated by courses or sequences in mathematics (Betz & Hackett, 1983; Ma & Kishor, 1997; Wallaert, 2018). This perception appears to be validated by the existing correlation between ATM and lower success rates in math courses (Hagedorn et al., 1999). These lower success rates in math are subsequently related to lower college completion or graduation rates (Ali & Jenkins, 2002).

Persistence and completion rates for underprepared students who are attending community colleges and are enrolled in developmental, or gateway, math courses are very low. The corequisite model at MCC is designed to mitigate these rates. In the last five years of the corequisite model implementation, results indicate that 71% of underprepared students advanced successfully through their math sequence despite being designated underprepared by traditional placement tests (Cole, 2022a). This trend has been corroborated by other studies that show students can persist successfully through challenges; this includes academic challenges and may in part be influenced by non-cognitive aspects like mindset type (Dweck et al., 2011), Grit (Duckworth & Seligman, 2005), and attitude towards mathematics (Al-Mutawah & Fateel, 2018).

More than 60% of students test into developmental math courses in any given academic year at MCC. Yet, the majority of corequisite math students are passing their first college-level math courses. Therefore, it is imperative to understand what makes these students successful despite their underprepared-for-math designation. Developing a deeper understanding of the non-cognitive factors could contribute to the development of better support and pedagogical interventions for these at-risk students.

PURPOSE OF THE STUDY

The primary purpose of this study is to explore the relationships between noncognitive factors such as Grit and ATM with student success in college-level corequisite math courses. Additionally, it will examine if there are differences in Grit and ATM between underprepared students who are NCR and CR students enrolled in college-level corequisite math courses. Furthermore, the study also explores the relationship between the individual subscales of Grit: the COI, and the POE, with AP in college-level math courses.

This study will help MCC understand the importance of non-cognitive factors in developing more substantial support initiatives for its student population. It may involve implementing specific psychosocial interventions applied in high school, orientation, or during their first college semester to help them assume more of a resilient attitude toward their academics (Yeager & Walton, 2011). This would also serve as another avenue for any college to improve college readiness and effectively address at-risk students' success rates.

RESEARCH QUESTIONS

For this study, the following questions will be addressed:

1. Do non-cognitive factors, Grit, and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses?
2. Does the non-cognitive factor, Grit, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?
3. Does the non-cognitive factor, ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?

SIGNIFICANCE OF THE STUDY

Achievement of academic success is a profound challenge for both underprepared students and the community colleges that support them. Developmental math education comes at a high dollar cost and time investment for 60% or more of incoming first-year students in community colleges. This sequence of courses and the student population invariably lower course retention, persistence rates, and graduation rates at colleges implementing corequisites models. With corequisite student success seemingly mitigating the traditional metrics associated with developmental education, there appears to be a lack of knowledge of how Grit and ATM may contribute to the observed student success.

Therefore, administrators and educators in community colleges need to recognize and understand the role non-cognitive factors play in student academic success. It is especially true for the underprepared student population facing the arduous challenge of getting through math courses. A working comprehension of the roles and extent that Grit and ATM play in the success of students in college-level corequisite math courses could potentially serve as a foundation for developing a more nuanced and individualized approach to

- identifying the non-cognitive factors that NCR students need to develop to augment their cognitive skills for academic success,
- designing and implementing specific pedagogical interventions that would improve retention among NCR students in challenging gateway courses, and
- advising and supporting NCR students based upon their identified predictors of success, thus improving student success and overall institutional success.

Collectively, this platform would serve as another avenue for any college to improve college readiness, support student success rates in math courses, and improve persistence and completion rates.

DELIMITATIONS

Numerous delimitations are associated with this study. The student population comes from a single community college campus; also, the population size is limited to only those students enrolled in a college-level gateway math course such as statistics or quantitative literacy concurrently with just-in-time support or in their respective standalone gateway courses during the Fall 2019 semester. The results of this study are therefore only generalizable to MCC.

LIMITATIONS

As with any self-reporting survey instrument, implicit limitations may include social biases and inaccurate self-estimations by the subjects (Fisher, 1993; Nederhof, 1985). They would impact both the Grit and ATM survey instruments. With students indicating their names on the survey instruments, their answers may be influenced despite being informed that no identifiable information will be published.

For the ATM, the researcher used the TIMSS survey instrument written at the eighth grade reading level and employed primarily in elementary schools. The impact of its use on college students is yet to be determined.

Definitions

The study will use the following variables, which are defined as follows:

Academic Performance (AP). The student's final letter grade earned in the gateway math courses studied in this research.

Attitudes Towards Mathematics (ATM). An aggregated measure of a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics, and a belief that mathematics is useful or useless. It is measured using the adapted Trends in International Mathematics and Science Study (TIMSS) scale.

College-Math Ready Student (CR). A student who has met the college readiness standards in mathematics as assessed by a placement exam score determined by MCC.

Corequisite Course. A college-level course in which academically underprepared students are enrolled while receiving additional just-in-time support or remediation through a paired course or lab (Vandal, 2014).

Grit. The "perseverance and passion for long-term goals" (Duckworth et al., 2007) measured using the Grit-S Scale.

Not-College-Math Ready Student (NCR). A student who has not met the college readiness standards as assessed by a placement exam score determined by MCC. They may also be referred to as underprepared, developmental, or remedial students.

SUMMARY

With more than 60% of students entering a developmental math sequence and less than 30% of them completing community college education, corequisite interventions appear to offer a viable solution to both students and colleges (Bailey et al., 2008). Since little is known about the role non-cognitive factors play in students' AP in corequisite math courses, this study will attempt to explore their possibility as potential indicators of AP.

Chapter Two will further explicate the concepts introduced in the current chapter. Additionally, Chapter Two will review the existing and relevant literature on cognitive and non-cognitive factors and their relationship to AP. The review will specifically look at the primary affective factors of this research: Grit and ATM.

CHAPTER TWO: LITERATURE REVIEW

INTRODUCTION

The inability of traditional developmental math programs to adequately prepare students for college-level course work has been a persistent challenge as highlighted in Chapter One. This chapter explores literature that critiques these traditional approaches, while examining their limitations and far-reaching consequences that they pose for students trapped within developmental education systems. This chapter will also synthesize research findings that shed light on how non-cognitive interventions are emerging as significant areas of inquiry. Such interventions offer promising avenues for enhancing student success, particularly for those enrolled in gateway corequisite math courses.

WHAT IS DEVELOPMENTAL EDUCATION?

The term "developmental" education, as defined by Roueche (1968), involves "the development of skills or attitudes and may or may not have anything to do with making a student eligible for another program" while referring to "remedial" education as "the remediation of student deficiencies in order that the student might enter a program for which he was previously ineligible" (p. viii). Today, the distinction between these two terms depending on the venue, is generally blurred (Payne & Lyman, 1996). Wading into the academic debate of their definitions is beyond the scope of this research.

In either case, there is a tacit acknowledgment of a student's need, deficiency, or weakness. This study is based on the understanding that some students lack the mathematical skills or knowledge necessary to succeed at college-level mathematics. NCR students are assessed as underprepared for college-level math through traditional placement exams like SAT and ACT etc. (Barnes et al., 2010; Mattern et al., 2016). The terms *developmental* or *remedial education* are used interchangeably and refer to programs, courses, and support provided to college students identified as having deficiencies or as underprepared in their prerequisite mathematical skills and knowledge as determined by the policies of MCC.

A BRIEF HISTORY OF DEVELOPMENTAL EDUCATION

Developmental education's historical roots in America can be traced to the 1800s when college preparatory programs were required for students of middle-class families lacking the college-level prerequisite reading, writing, and mathematical skills (Payne & Lyman, 1996). Two specific federal policies have been credited with significantly expanding developmental education in higher education: the GI Bill Act of 1944 and the Civil Rights Act of 1964. These federal policies democratized higher education in America; both led to World War II veterans and then low-income students, respectively, gaining access to higher education which was previously a domain for the middle class (Higbee & Dwinell, 1996).

As four-year institutions became more selective in their admissions, community colleges carried most of the burden of open-access admissions for the masses (Roueche, 1968). At the turn of the last century, four of the eight Ivy League schools had student populations, with more than half requiring developmental education (Wyatt, 1992). During the last decade, the majority of community college bound students, more than 59% by some estimates (Jaggars & Stacey, 2014), needed developmental education, while about 21% of those bound for public four-year institutions required some form of developmental education (Attewell et al., 2006; Bailey et al., 2008; CCA, 2012).

This historical view of developmental education informs anyone of the deep-rooted mission that community colleges play in providing the masses a pathway to a better life through education via open-access admissions. Since open access does not define student success, community colleges must continue working for the masses across the socioeconomic spectrum to facilitate building the skills students did not acquire through high school. It is also important to be cognizant that individuals from the lower end of the socioeconomic scale are more likely to need developmental education (Rutschow & Cormier, 2019). Community colleges serve as the needed springboard to propel the students they serve to a better life (Roueche, 1968).

THE PREVALENCE OF DEVELOPMENTAL EDUCATION

Remedial math education and its policies were developed and implemented to provide NCR students with the necessary skills to succeed before enrolling in future college-level math courses. Traditional placement exams usually determine their specific entry point into the sequence of math courses either below or at the college level. Several studies differ in their estimates of the prevalence of remedial education across the United States. However, the collective message is that remedial education is the inescapable pathway for a significant proportion of college-bound students (Cullinan et al., 2018; Rutschow, 2019). One annual estimate for the country is that 1.7 million students begin college by being referred to at least one area of remediation each year (CCA, 2012). The Achieving the Dream study of first-time community college students from 57 colleges across seven states revealed that 59% of sampled students beginning their postsecondary education in 2004 were referred to a developmental path (Bailey, 2009, p. 3).

Community college enrollment harbors the majority of NCR students in the United States. The CCA project studied 10 million students in public institutions across the nation. They found that students in public two-year institutions were 2.5 times more likely to enroll in a developmental course than their counterparts in four-year institutions (CCA, 2012, p. 6). Close to 70% of community college students were placed into developmental education relative to 40% of students enrolling directly into four-year institutions between 2003 and 2009 as reported in Chen's national longitudinal study of the class of 2003–04 (Chen, 2016). This translates to 1.75 times more likely that community college-bound students will enroll in developmental courses.

Chen also noted that this prevalence of developmental math across community colleges is also high when explicitly viewed through the lens of mathematics and NCR students. Of community college-bound students, 59% are referred to a remedial math pathway versus 33% of all four-year university students. This higher proportion of remedial math students in community colleges relative to remedial reading, writing and English students has also been verified by numerous other studies (Attewell et al., 2006; Bailey et al., 2008; CCA, 2012).

Challenges of Traditional Developmental Math Education

Research by Park et al. (2018) and Rutschow and Cormier (2019) reveals the near-impossible situation NCR students face in college while trying to navigate through remedial math education. These include course misplacement (Scott-Clayton & Stacey, 2015), delayed progression to college-level math courses (Brathwaite et al., 2020), lower graduation or transfer rates (Bailey, 2009), the financial penalty for taking additional non-credit courses, and higher than typical college dropout rates relative to CR students (Bailey & Smith Jaggars, 2016) as well psychological costs (Bailey, 2009).

Is Open Access Admission Synonymous with Developmental Education Placement?

Community colleges have long been identified as carrying the majority of the burden of developmental education relative to four-year institutions (Roueche, 1968). This may be attributed to the open access or the non-selective nature of the admission policies of community colleges. Community colleges cater to an expanded swathe or heterogeneous population of student academic aptitudes relative to traditional or selective four-year institutions. In a National Educational Longitudinal Study (NELS:88) of a weighted sample of two million students, students attending community colleges were found to be more than twice as likely (58%) to be enrolled in a remedial sequence than students at four-year public institutions (26%) (Attewell et al., 2006, p. 186). This is similar to the ATD ratio referred to earlier. According to Attewel et al. (2006), even after controlling for socioeconomic background and AP in high school, community college-bound students are still 11% more likely to be enrolled in developmental education than their equal counterparts at four-year institutions.

Consequently, as noted in Brathwaite et al.'s work (2020), there is a moral burden by two–year open-access institutions to understand their students better to provide multiple pathways or ramps to succeed through or past the associated developmental education challenges.

Course Misplacement

The ATD study (CCA, 2012) reported that of the 59% NCR math students, 24%, 16%, and 19% of students were placed into one, two, and three levels, respectively, below their college-level gateway math course. Scott-Clayton and Stacey (2015) noted that high-stakes college placement exams like SAT and ACT have been reported to misplace 25% of students into the wrong level of their math sequence. Depending upon the college curricular structure, students can be placed anywhere between one to three or more levels of remedial math education.

Scott-Clayton et al. (2014) posit that placement exams fail at accurately predicting student success in college-level courses. Bailey (2009), describes the blind inefficacy of placement cut-off scores to college success in general:

> To a large extent, the distinction between developmental and non-developmental students is arbitrary—the dichotomous categorization does not match the underlying continuity. Thus, some students placed in remediation do succeed in college-level courses even when they do not enroll in remediation, while many students who score well above the cut-off scores struggle in their college courses. (p. 23)

Misplacement may be due to underplacement, in which the student, based upon traditional placement mechanisms, is placed into a remedial class. Yet, statistically, other variables indicate they would have likely attained a passing grade if placed directly into a college-level course (Scott-Clayton et al., 2014; Scott-Clayton & Stacey, 2015). Underplacement is found to occur 3.8 times more frequently than overplacement, according to Scott-Clayton's study (2015, p. 1). It could be argued, then, that the underplaced student population may immensely benefit from the accelerated intervention to college-level math courses offered by corequisites interventions.

Another focus on placement challenges is that 25-35% of remedially referred students do not enroll in any remedial courses within three years of initial registration. This is evident in institutions with policies that allow for students to make the choice on whether to enroll into a remedial course or not after referral to remediation. According to Bailey (2009), 17% of these students bypass their remedial math class and enroll directly into a college-level math class, with 12% passing it. Contrast this with a meager 20% pass rate of students who first took a remedial math class before the college-level course. It would seem by this data that students who first enroll into a remedial course do not enjoy a lucrative advantage of passing a future college-level math class. This highlights a population of students that will have to navigate the challenges inherent in developmental math education despite their likely ability to succeed at college-level math (CCA, 2012).

DELAYED ACCESS AND PROGRESS TO COLLEGE-LEVEL MATH COURSES

Many of the referred developmental students will likely not succeed in completing their developmental education (Adelman, 1999; Bailey et al., 2008; Fong et al., 2015). Jaggars and Stacey (2014) found that of almost 64,00 students, only 11% of NCR students testing into three levels of developmental math education can reach a gateway college-level math course (p. 4). Given a three-year time frame to reach a math college-level course, Bailey (2009) indicates that this trend improves to only 16% of NCR students (p. 14). Attwell et al. (2006) emphasize that only one third of NCR students successfully pass their developmental math education courses. According to a CCA report, *Remediation: Higher Education's Bridge to Nowhere* (2012) only 22.3% of community college students are able to persist from developmental education through to their college-level course within two years. This trend disproportionately impacts non-traditional and students of color (CCA, 2012, p. 8).

Some studies encourage a more nuanced approach to better understand community colleges' poor completion rates of developmental math education (Fong et al., 2015). One such study by Fong et al. (2015) suggests that lower math placement levels of NCR students do not automatically lead to certain failure at completing developmental education. Instead, the level of accuracy of math placement has a more significant impact on their ability to succeed at the subsequently higher math courses. However, this trend was not observed for students placing below beginning or pre-algebra.

Bailey et. al (2008) identified a population of NCR students who, despite being successful through developmental education, did not subsequently enroll into a college-level course they were likely to pass. Evidence suggests that a student accurately placed into an appropriate math course is more likely to succeed at it and then persist successfully in subsequent math courses (Jaggars & Stacey, 2014; Rutschow, 2019). Persistence and earned success of community college NCR students were also found to likely improve their chance of graduation (Attewell et al., 2006), regardless of the lower graduation rates associated with remediation (Adelman, 1999). This suggests that any academic momentum generated by NCR students within the developmental pathway may be critical to their success.

Pre-College Variables and Noncognitive Aspects of Underprepared Students

Community colleges need to understand better how pre-college factors and high school preparation influence college-bound students' potential success in mathematics via their noncognitive or non-academic preparation (Carey et al., 2016; Li et al., 2020; Szczygieł, 2020). Bailey and Smith Jaggars (2016) state, "Traditional remediation is designed to address academic weaknesses in math and English, yet non-cognitive and metacognitive skill weaknesses may be more serious barriers to student success" (p. 17). Without a holistic student-centered approach to developmental education reform, institutional and classroom interventions may likely still be successful yet limited in their potential impact to address some of the barriers that vulnerable students carry (Goudas, 2018).

Results from Li et al.'s exploratory study (2020) show that a family's socioeconomic background partly predicts junior high school students' AP via the noncognitive factor of self-efficacy concerning AP in math; other studies have linked students' math anxiety, an emotional noncognitive disposition, to parental and teacher math anxiety (Casad et al., 2015; Szczygieł, 2020), gender and culture pressures (Casad et al., 2015), negative experiences, and very importantly, self-efficacy or appraisal (Dowker et al., 2016) of math competencies.

Regardless of the sources of math anxiety, this emotional aspect negatively and indirectly impacts AP in math (Jansen et al., 2016; McAnally, 2019) through its mediating effects on the students' self-appraisal towards mathematics. Dowker et al. (2016) state that, "People who think that they are bad at mathematics are more likely to be anxious. Most studies indicate a negative relationship between mathematics self-concept and mathematics anxiety" (p. 3). NCR students are known to self-report higher math anxiety levels than CR students. Furthermore, math anxiety exerts its influence by negatively moderating academic learning, behaviors, working memory functionality, and math-related strategies, which all fuel a vicious cycle of impaired mastery for these NCR students (Dowker et al., 2016; Ramirez et al., 2018; Yu et al., 2021).

Implicit in these findings is the notion that a student's family background, academic skills, experiences, and high school performance in mathematics may all contribute to the student developing weak noncognitive skills that may, in turn, lead to their placement into developmental education and, ultimately, to the struggle to succeed through developmental math education (McAnally, 2019). Consequently, this study attempts to fill gaps in the literature on the role noncognitive factors play in students' success in math corequisite courses which are part of the overall developmental math education reform.

ADVANCING DEVELOPMENTAL MATH REFORM-COREQUISITES

A broad coalition of educational and research institutions, policy organizations, and educators have long advocated for institutions nationally to implement several remedial education changes to help students reach and successfully complete college-level math classes (Bailey, 2009; CCA, 2012; Jaggars & Stacey, 2014; Roueche, 1968; Vandal, 2014). One such structural change away from traditional developmental education has been the implementation of corequisite courses (Hern, 2012; Ryu et al., 2022). NCR students can enroll directly into a gateway college-level math course with a paired just-in-time support or remediation course, usually within the same semester or year. The corequisite intervention gained prominence after promising results from earlier interventions in Baltimore and California were made widely available in 2010 (Bailey & Smith Jaggars, 2016; Hern, 2012; Jaggars et al., 2015).

For statistics and quantitative literacy gateway courses especially, which are the focus of this study, the corequisite interventions are based on the fundamental assumption that most of the algebra-based prerequisite skills of developmental math sequence aren't directly applicable to these courses (Hern, 2012). The traditional remedial approach of enrolling NCR students in up to three non-credit courses of mostly non-pre-requisite knowledge differs widely from the general corequisite model. The corequisite courses were designed to provide the students struggling with a specific statistical or quantitative mathematical skill the targeted and needed support to succeed in their time of need from their instructors (Vandal, 2014).

Corequisite Models

The existing corequisite models across the country exist either as a single or two-semester intervention (Daugherty et al., 2018; Vandal, 2014). Students complete both the remediation intervention and the college-level math course within the same semester in the former model, while the latter model involves two sequenced courses across two semesters. The single-semester intervention pairs the college-level math course with any of three support mechanisms:

1. Additional seat time dedicated to providing students with individually needed support, typically supervised by the same instructor
2. Mandatory tutoring or labs utilizing software, adjuncts, or capable students to assist the NCR students with the necessary skills to succeed
3. A preceding remedial intervention course that helps the NCR students strengthen the basic skills they can utilize to succeed in the subsequent college-level course.

The two-semester sequence is closer to a traditional approach to sequencing courses. However, in this corequisite model, the two-semester course sequence is redesigned to streamline mathematical skill acquisition across two semesters and introduce holistic-based skills a college student needs to succeed at the college-level course (Vandal, 2014).

The college in this study employed the single-semester corequisite model with the additional seat time scheduled as lab time and taught by the same instructor (Kashyap & Mathew, 2017). Each corequisite section was also scheduled identically to a college-level section. This effectively mixed NCR with CR students within the same class, which is considered a benchmark practice (Ryu et al., 2022). NCR students attended both the college-level lecture and stayed back for the additional seat time or lab, while the CR students departed after the initial 50-minute college-level instruction.

THE IMPACT OF COREQUISITE INTERVENTION

The unfolding of the corequisite intervention has been to mitigate some of the adverse effects of the traditional multi-semester sequenced progression of math developmental education.

ACCELERATING PAST DEVELOPMENTAL MATH EDUCATION

Front and center is a 2006 study by Attewell et al. that revealed that developmental math students were between 2.3 and 2.6 times less able to complete their math sequence of courses relative to developmental writing and reading students, respectively. There has been strong evidence from several studies showing that through corequisite math courses, NCR students are able to succeed in their first gateway math courses at comparative rates to CR students taking the same college-level math course (Ponder, 2018; Wikstrom, 2018).

Mitigating Delayed Access of Underplaced Students to College-Level Courses

NCR students who marginally missed the cut-off placement score end up placed into traditional developmental math education, therefore, delaying their access to college-level math courses by at least a semester (Brathwaite et al., 2020; Rutschow & Cormier, 2019). The tragedy here is amplified by J. Scott-Clayton and Stacey (2015), who estimated that up to 25% of NCR students "… could have passed college-level courses with a B or better… if placed directly into college-level courses" (p. 1).

Therefore, corequisite math courses appear to be the natural panacea for this delayed access to college-level courses. Being that access is not tantamount to success, the corequisite design of providing as-needed remediation concurrently with the college-level course work has been proven to be a significantly successful intervention in getting NCR students to pass their first college-level course and progress in their programs without delay of taking the traditional developmental math course across a semester or more. Ran and Lin's (2019) study concluded that:

> Compared with their counterparts placed directly into college-level courses, students placed into corequisite remediation had similar gateway course completion rates and were about eight percentage points more likely to enroll in and pass a subsequent college-level math course after completing gateway math. (p. 33)

Improving Graduation and Transfer Rates

It should be noted that despite the accelerative benefits of corequisites, some longitudinal studies suggest that student corequisite success is not far-reaching as to have corresponding impacts on graduation rates (Goudas, 2018; Meiselman & Schudde, 2022). Ryu et al. (2022) suggest in their study that shorter-term gains in persistence and retention were correlated to increases of almost ten times the levels associated with longer-term gains like transfer and completion. Similar to the non-algebra corequisite courses in this study, any long-term student success metrics in these course types were, at best, limited compared to students taking algebra-based corequisite courses (Ran & Lin, 2019).

These positive results of corequisite interventions are very encouraging; however, caution is advised as numerous areas still need to be explored. Causal studies of the impact of corequisite studies pale in comparison to the rich body of correlation and comparative studies. A more holistic understanding of how these reforms impact NCR students of varying levels of developmental placement is not fully developed yet.

NONCOGNITIVE SKILLS ASSOCIATED WITH STUDENT SUCCESS IN COREQUISITE COURSES

There is currently a strong body of evidence elucidating the relationships between various noncognitive attributes of students and subsequent academic success (Bowman et al., 2019; Robbins et al., 2004; Sisk et al., 2018; Wanzer et al., 2019a). Wilson (2018) identified the importance of further studying corequisite success from an adult learning framework. McAnally (2019) studied the association of NCR student self-efficacy in corequisite interventions and concluded the importance of the noncognitive aspect to their long-term success. The study identified a potential gap: “Instructors should help their students with time management, study skills, and with building up their own persistence and Grit” (p. 115). Farrington (2012) concludes in his study that: “By helping students develop the noncognitive skills, strategies, attitudes, and behaviors that are the hallmarks of effective learners, teachers can improve student learning and course performance while also increasing the likelihood that students will be successful in college” (p. 74). With these acknowledgments of the necessity to take an integrated approach to student success, this study directly explored the relationship between noncognitive or affective factors of college students and AP in corequisite math courses.

Several studies have established that Grit (Cross, 2014; Duckworth et al., 2007; Duckworth et al., 2010; Nagaoka et al., 2013; Stoffel & Cain, 2018; Tang et al., 2019) and attitudes towards mathematics (Al-Mutawah & Fateel, 2018; Chen et al., 2018; Hodges & Kim, 2013; Mazana et al., 2019) can be used to explain variance in AP of students at different levels of education. However, the role of Grit and attitude towards mathematics in explaining students' AP in college-level math corequisite courses has not been investigated. This study attempted to address the following gaps: explore the relationships between Grit and ATM with student success in college-level corequisite math courses. Additionally, it examined if Grit and ATM differ significantly between CR and NCR students.

GRIT

Grit is a noncognitive personality trait defined as the "perseverance and passion for long-term goals" (Duckworth, 2016; Duckworth et al., 2007, p. 1087). Implied in this definition is sustained interest and effort applied towards a demanding activity or task (Stoffel & Cain, 2018). A mathematics course, by its very nature, can be described as both an academic and cognitive challenge for many students (Carey et al., 2016) and that passing the course may also be viewed as relatively a long-term goal. Studying the relationship between the two constructs thus seems of practical value to understanding needs and variables that are associated with NCR student success in corequisite math courses.

Grit, as studied by Duckworth et al. (2007), was originally focused on achievement of individuals' controlling for intelligence. This study has become one of the seminal noncognitive studies in deconstructing intelligence from achievement in various domains. Since then, Grit and its application has been very widely studied. Literature is varied on the strength of Grit's relationship to various domains as evaluated by Grit focused meta-analytic studies (Credé et al., 2017; Datu et al., 2017).

The Grit construct is postulated to exist as a combination of two subsidiary attributes—COI and POE (Duckworth et al., 2007; Duckworth & Quinn, 2009). They will be referred to as subscales of the overall Grit Scale. COI describes an individual's ability to sustain interest on a long-term goal or aspiration (Duckworth et al., 2007). Conversely, in the face of a challenging task, POE is the sustained labor needed to achieve long-term goals or aspirations (Duckworth et al., 2007). Collectively, these build the attitudes and subsequent behaviors towards long-term goals and tasks and are assessed by the original Grit-O Scale or the updated Grit-S (Duckworth et al., 2007; Duckworth & Quinn, 2009).

The Grit-S scale and its subscales were shown to demonstrate high internal consistency: Overall Grit-S ($\alpha = .85$); COI, ($\alpha = .84$); and POE, ($\alpha = .78$) (Duckworth et al., 2007; Duckworth & Quinn, 2009).

Grittiness is known to have numerous positive relationships to important attributes related to higher success and productivity: task or competitive performance (Ackermann, 2018; Duckworth & Quinn, 2009), lasting commitment to career paths (Duckworth et al., 2007), engagement (Hodge et al., 2018; Von Culin et al., 2014), greater AP (Williams, 2017; Wolters & Hussain, 2015), course persistence (Rogalski, 2018), self-efficacy (Usher et al., 2019) and superior self-regulation (Wolters & Hussain, 2015) among other additional individual traits.

Numerous Grit studies have led to mixed results regarding the strength and stability of its relationship to productivity and performance levels. Moderating variables such as the nature or difficulty level of the task or domain may or may not contribute to the positivity of the relationship between Grit and performance. However, because mathematics is an established complex domain, this study expects results that would overcome this limitation of the Grit construct.

The Grit-AP construct is also suggested to be moderated by the interaction of student ability as well as self-appraisal of the student in that academic domain (Usher et al., 2019). In essence, Grittiness may have a limited consequential relationship to AP levels in a domain in which the individual lacks ability or self-belief (Farrington et al., 2012). This study attempts to fill a void in the literature concerning corequisite math courses. It explores the differences in the levels of noncognitive attributes, Grit and ATM, and their subsequent relationships to AP in college-level math courses between the NCR students with lower math abilities and CR students with higher math abilities.

Attitudes Towards Mathematics

The explanation of what an attitude is by Joseph (2013) (as cited by Mazana et al. (2019) is as follows:

> Attitude refers to a learned tendency of a person to respond positively or negatively towards an object, situation, a concept, or a person. It is also regarded as a belief held by individuals that reflects their opinions and feelings and can be sometimes manifested in behaviour. (p. 210)

Ma and Kishor (1997b) cite Neal (1967) as defining attitude toward math as being "an aggregated measure of a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics, and a belief that mathematics is useful or useless" (p. 27). The attitude construct thus appears to have three subsidiary attributes to it–affective or emotional, behavioral, and cognitive or belief attributes (Albarracin & Shavitt, 2018; Hannula, 2002). These three attributes were applied to the mathematics domain when designing the attitude towards mathematics survey instrument used in this study. These subsidiary attributes or subscales will be discussed.

The Trends in International Mathematics and Science Study (TIMSS) survey has a long historical and global development and deployment in 70 countries in the field of education, dating to 1995 (Martin & Preuschoff, 2007). It is the leading study of the International Association for the Evaluation of Educational Achievement (IEA) and is managed by TIMSS & Progress in International Reading Literacy Study (PIRLS) International Study Center at Boston College (Mullis et al., 2015). This instrument was designed to be deployed every four years to assess student achievement in mathematics and science at the fourth and eighth grades. Its background indices or context questionnaires attached to the cognitive assessment survey undergo a four-year cycle of continuous development, field testing, statistical validation (Martin & Preuschoff, 2007), and improvement to keep it relevant to educational and supportive trends needed to develop a holistic view of mathematical and science trends (Martin et al., 2016).

The TIMSS ATM scale was developed consistent with the body of research on the attitude construct that identifies the three subsidiary attributes. It is designed to assess the total ATM of an eighth grade participant. For this study, the three subscales assessing the three attitude attributes were used, leaving out two additional scales assessing other affective attributes not relevant to the scope of this work. Thus, the adapted ATM scale was aligned strongly with the established traditional construct of attitude. The indices or attributes of interest on the TIMMS ATM (Martin & Preuschoff, 2007) that form the adapted ATM scale for this study therefore include

- Positive affect: measured by the Positive Affect Toward Mathematics (PATM) Index, referred to as Liking Math

- Self-confidence: measured by the Self-Confidence in Learning Mathematics (SCM) Index, referred to as Confidence in Math Skills
- Valuing the subject: measured by the Students' Valuing Mathematics (SVM) Index, referred to as Value towards Math. (Martin & Preuschoff, 2007)

The ATM scale is subjected to cyclical exploratory, validation, and reliability analyses by the study's authors to ensure its relevance to the current body of research as well as to improve the scale. Each of the indices mentioned above is specifically assessed using Cronbach's alpha to determine the internal consistency and reliability of the scale and questions. Total ATM scale confirmatory analyses are completed to determine the accuracy of how the indices measure the theoretical construct of each of the three attributes. Finally, correlation studies between the indices and math achievement are also conducted to assess their individual relationship to achievement. According to, at the eighth grade level, the median Cronbach's alpha scores across countries are: PATM scale (α = .81); SCM scale (α = .73); SVM scale (α = .70) while the median multiple correlation scores of the indices to achievement in mathematics are PATM scale (R = .28); SCM scale (R = .46); SVM scale (R = .19) (Martin & Preuschoff, 2007). The ATM scale thus lends itself as a potentially viable scale to be used to assess students' affective state toward mathematics.

SUMMARY

The inability of developmental math education to effectively transition vulnerable, mathematically underprepared for college-level math education is evident. Its limitations have far-reaching consequences for students who cannot escape it. With the limitations of cognitive interventions to improve the success rates of NCR students, recognizing the potential impact that noncognitive interventions may have in strengthening student success initiatives is vital.

Providing college instructors information that sheds light on how students' academic mindsets, such as ATM, may interact with academic Grit, which in turn influence academic learning and behaviors, may be profitable to assist them in designing effective just-in-time remediation strategies for students enrolled in gateway corequisite math courses.

CHAPTER THREE: METHODOLOGY

INTRODUCTION: OVERVIEW TO THE STUDY

This non-experimental quantitative research design attempted to understand the role of Grit or ATM on the AP of college students enrolled in corequisite gateway math courses. The participants were NCR and CR students simultaneously enrolled in the same gateway general education math courses. Three sources of data were utilized in this study. Two instruments were employed, namely: the 8-Item Grit Scale (Grit-S) instrument (Duckworth et al., 2007) and the adapted TIMSS Scale instrument (LaRoche et al., 2015). In addition, student information data of the participants were obtained and included demographic, placement, and final grade in the corequisite or gateway math course. Institutional research staff from MCC provided these data sets to the researcher.

RESEARCH DESIGN

The non-experimental research design was appropriate for this study since it explored the individual relationship between the IVs, Grit and its subscales, as well as ATM with the dependent variable, AP in the corequisite gateway math courses. The primary research questions were limited to observing the relationship, not the causal nature, between the variables. The study also explored if any differences existed in the levels of these non-cognitive factors between CR and NCR students.

RESEARCH QUESTIONS AND HYPOTHESES

For this study, the following questions were addressed:

1. Do non-cognitive factors, Grit, and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses?
2. Does the non-cognitive factor, Grit, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?
3. Does the non-cognitive factor, ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?

The following are the overarching null and alternative hypotheses for this study:

H1O: Grit and ATM have no significant relationship to the AP of students enrolled in a college-level corequisite math course.

H11: Grit and ATM have significant relationship to the AP of students enrolled in a college-level corequisite math course.

H2O: Grit does not differ significantly between CR and NCR students.

H21: Grit differs significantly between CR and NCR students.

H3O: ATM does not differ significantly between CR and NCR students.

H31: ATM differs significantly between CR and NCR students.

SETTING OF THE STUDY

MCC is a mid-size rural community college located in the Midwest and is the setting for this study. The college district is a 4,000-square-mile area comprising 32 feeder school districts across 15 mainly rural agrarian counties (Breer, 2013). In Fall 2019, MCC enrolled 4,466 students. MCC had the state's largest population of Department of Correction (DOC) students, with an additional 3,253 students in the Fall 2019 semester (note that this population will be excluded from this study and any generalizations). The college reflects the district's lack of diversity in its population: white students consisted of 88% of enrolled students, black 3.7%, Hispanic 3%, Asian 1%, Native Indian 0.3%, and unknown 4%. Of the college students in the

Fall 2019 semester, 71% were traditional-aged students between 16 and 22 years of age, with an average age of 22.7 years; 64% of the total students enrolled in the Fall 2019 semester were male; 89% of students were classified as in-district, while 11% were a combination of out-of-district, out-of-state, and international students. Only 60% were degree-seeking students, while the remaining student population were comprised of dual credit, adult education, technical skills, and course enrollees. Of the MCC student population, 2,082 (47%) of the students were full-time, while 2,384 (53%) attended college as part-time students. Additionally, 87.8% of the in-district students enrolled were first-time degree-seeking (Breer, 2019; Cole, 2022b).

POPULATION CHARACTERISTICS

The total population consisted of freshmen or sophomore students enrolled in either of two identified college-level gateway math courses offered by MCC: Statistics (S) and Quantitative Literacy (QL). During Fall 2019, 187 NCR and CR students enrolled in the same in-person general education math courses through normal course registration processes by the tenth-day census (Cole, 2022a). These students enrolled in either course, S or QL, based upon the academic requirement of their specific majors.

A total of 15 in-person sections of S and QL math sections were selected to disseminate the instrument surveys to ensure a higher response rate. Seven of these sections (4S & 3QL) were corequisite courses with the additional 100 minutes of lab per week built-in for just-in-time support for the NCR students. Five of the seven sections (2S & 3QL) enrolled with up to 15 NCR students were paired to meet in the same classroom, and time with five corresponding sections enrolled with 15 CR students taking the same S and QL courses.

Table 1: Response Rates from Math Sections Surveyed

NCR Sections	Students Enrolled	Respondents	Response Rate %	Sections
Quantitative Literacy (QL)	35	24	67.99	3
Statistics (S)	52	44	85.83	4
NCR Total	87	68	78.16	7
CR Sections	Students Enrolled	Respondents	Response Rate %	Sections
Quantitative Literacy (QL)	33	26	86.16	3
Statistics (S)	67	61	91.36	5
CR Total	100	87	87.00	8
Grand Totals	187	155	82.89	15

The CR students would depart after the 50-minute lectures, while the NCR would remain for the additional 100 minutes of lab per week. The sixth corequisite section was a standalone S section with only 20 NCR students enrolled. In addition, there were two other S sections and one QL section with only CR students enrolled in them.

Sampling

According to Ma and Kishor (1997b), an ideal sample size would be less than 300 and randomly selected to maximize the effect of non-cognitive factors on student performance in mathematics. However, due to the scope of the study, the small population, and the unique population characteristics, the nonprobability sampling method-purposive sampling was used. Therefore, 187 students enrolled in 15 in-person S and QL math sections in the Fall 2019 semester were purposively sampled. The sample size inadvertently limits the generalization of the findings to a larger population beyond this study.

This study excluded two online S and QL math courses offered in the Fall 2019 semester due to their online format, aiming to eliminate any potential variability associated with course modality. Two groups of students were identified: 87 (47%) NCR students who enrolled in the corequisite-supported S and QL math courses and 100 (53%) CR students who tested directly into the college-level S and QL math courses and received no remediation support. Students from the identified 15 sections were all invited to participate in this study. To be included in this study, the subjects were freshmen or sophomore degree-seeking students who completed both the Grit-S and the Mathematics Attitude surveys in their entirety. Of the 187 students enrolled in the in-person sections of S and QL, 82.89% (n = 155) participated in the study. The two instrument surveys and two additional demographic questions were handed to each student present in the classrooms to ensure a strong response rate.

INSTRUMENTS FOR DATA COLLECTION

The 8-Item Grit-S Scale survey (Duckworth & Quinn, 2009) employed in this study was designed and validated to detect and measure the level of Grit an individual possesses. This Likert-scaled Instrument has choices ranging from 1 (not at all like me) to 5 (very much like me) and is a self-reported survey by subjects. Dr. Angela Duckworth has granted permission for non-commercial uses of the Grit-S scale as published on her website (https://angeladuckworth.com/research/). Appendix E includes the 8-Item Grit-S questionnaire as published by Duckworth.

The original 27 questions of the Grit scale were narrowed down to 24 items and then to the 12 specific items that now form the 12-Item Grit-O Scale (Duckworth et al., 2007). This scale was found to consist of the total Grit score and possess two subscales, namely COI and POE. In a subsequent study investigation, Duckworth et al. (2009) developed and validated a more efficient measure of Grit with the Grit-S scale, which today is the 8-item Grit-S scale. They concluded:

> …the Grit–S, a more efficient measure of Grit. The 8-item Grit–S is both shorter and psychometrically stronger than the 12-item Grit–O. In confirmatory factor analyses, the Grit–S fit the data better than did that of the Grit–O. (Duckworth & Quinn, 2009, p. 174)

Regarding validation metrics, the Grit-S scale and its subscales were shown to demonstrate high internal consistency: Overall Grit-S (α = .85); COI, (α = .84); and POE, (α = .78) (Duckworth et al., 2007; Duckworth & Quinn, 2009). Despite the reduction to eight items, the results infer that the Grit-S scale maintains its two-factor modality's validity.

Some studies do indicate the potential for non-invariance of the Grit-S Instrument concerning nonhomogeneous age groups or nationalities (Ackermann, 2018). According to Duckworth and Quinn (2009), the Grit-S instrument is thought to be a more appropriate scale for a more diverse population across varying levels of development. I, therefore, selected the Grit-S Instrument to accommodate the relative potential of a community college class to have a more diverse population across varying levels of development.

The ATM survey was adapted from the TIMSS 2019 Context Questionnaires (Mullis et al., 2017). It consists of 42 questions in six categories. For the purpose of this study, 27 question items from groups 20, 22, and 23 were selected that explore the level that students like mathematics, their perceived level of self-confidence in mathematics, and their perceived value towards mathematics, respectively (Appendix E). This instrument employs a four-choice Likert range from 1 (disagree a lot) to 4 (agree a lot) and is self-reported by subjects.

Despite being designed and validated for eighth graders, this study used the ATM for college freshmen and sophomores to determine the perception of mathematics by the respondents. I chose the ATM instrument for three reasons:

1. The participants include NCR students who had test scores in math placement exams that were not college-level and thus possessed math levels equivalent to high school students.

2. The study was designed to use a survey tool that measured ATM in general and not within specific domains of college math.
3. The TIMMS ATM instrument undergoes periodic robust design and validation techniques employed "to provide valid and reliable measurement of trends in student achievement in countries around the world" (LaRoche et al., 2015, p. 3.1).

According to LaRoche et al. (2015):

> Developing the TIMSS 2015 context questionnaires was a collaborative process involving multiple rounds of reviews by staff at the TIMSS & PIRLS International Study Center, policy analysis experts on the TIMSS 2015 Questionnaire Item Review Committee (QIRC), and the NRCs from the participating countries. (p. 2.1)

ADMINISTRATION OF THE INSTRUMENTS

Students received a copy of the consent form for the survey completion through Canvas learning management system mail before the designated class meeting. They also received a hard copy in class to sign indicating their agreement to participate in the study prior to receiving the survey instruments. Students who returned signed consent forms were each handed the surveys to fill out and return to me in 15–20 minutes.

The two survey instruments that were disseminated in the classrooms by the researcher also included additional basic demographic questions such as name, age, socioeconomic status (Pell grant recipient or not), and work status (number of hours a week) for the initial identity verification of participants for the completion of respondent profile. Participants were given an additional choice to withdraw or not submit their data. The participating students in each class were informed of the opportunity to be included in a raffle to win up to two $20 gift cards from the gas station next to MCC.

METHOD OF DATA COLLECTION

All demographic and participant profile data used in this study was collected from the survey and the student information management system with the help of the institutional research and financial aid offices. Previous research has shown that variables such as gender, age, socioeconomic status, student employment status, and high school GPA can be associated either with student success measured as GPA (Nakajima et al., 2012) or as determinants of at-risk profiles of students (Horton, 2015). This study collected some of this additional information to develop a nuanced understanding of the results in a future follow-up study.

Once the results and additional data were collected, any identifying personal information from the student data was stripped, and students were coded to provide anonymity in accordance with IRB approval guidelines. All data collected with non-identifiable information was saved as a raw data file which was then stored on a password-encrypted cloud storage platform called Dropbox.

INDEPENDENT AND DEPENDENT VARIABLES

The study used the following variables, which are defined as follows:

Independent Variable (IV)
This is a measured variable assigned as X in the correlational analyses. The IVs will be referred to as Predictor Variables (PV) in the regression analyses.

Dependent Variable (DV)
This is a measured variable assigned as Y in the correlational analyses. The DVs will be referred to as Outcome Variables (OV) in the regression analyses.

Academic Performance (AP)
The student's final letter grade earned in the gateway math courses studied in this research is the DV.

Completion of a Math Course
In the additional analyses, completing a math course is defined as when a student earned a grade of A, B or C. This DV is coded as 1 if the participant received a passing grade (A, B, or C) and 0 if they withdrew or received an F or D.

Attitudes Towards Mathematics (ATM)
This an aggregated measure of a liking or disliking of mathematics, a tendency to engage in or avoid mathematical activities, a belief that one is good or bad at mathematics, and a belief that mathematics is useful or useless (Ma & Kishor, 1997, p. 27). It is measured

using the adapted TIMSS scale. This IV is determined by the total score a student earns on the adapted ATM scale.

Corequisite Course
This is a college-level course in which academically underprepared students are enrolled while receiving additional just-in-time support or remediation through a paired course or lab (Vandal, 2014).

Grit
The "perseverance and passion for long-term goals" (Duckworth et al., 2007) were measured using the Grit-S Scale. This IV is defined as the total score a student earns on the Grit-S Scale.

Consistency of Interest (COI)
This IV is determined by a student's score on the subscale of the Grit-S Scale, which measures a student's tendency to maintain focus and not lose interest in a difficult task or circumstance.

Perseverance of Effort (POE)
This IV is determined by a student's score on the subscale of the Grit-S Scale, which measures a student's tendency to maintain an adequate level of effort in order to persist through a difficult task or circumstance.

College-math Ready Student (CR)
This IV is determined as "yes" if the participants have met the college readiness standards as assessed by a placement exam score determined by MCC. Placement status was obtained for each participant from the student information system. College readiness status was determined by SAT, ACCUPLACER, and ACT scores.

Not College-math Ready Student (NCR)
This IV is determined as "no" if the participants have not met the college readiness standards as assessed by a placement exam score determined by MCC. Placement status was obtained for each participant from the student information system. College readiness status was determined by SAT, ACCUPLACER, and ACT scores. They may also be referred to as underprepared, developmental, or remedial students.

Gender
This IV is defined as male or female as recorded in the college student information system.

STATISTICAL ANALYSIS APPROACH

The statistical analyses for this study was performed using the statistical analysis program R/R studio. The data were analyzed at confidence levels of $\alpha = 0.05$ and 0.01 for statistical significance. R is able to perform both inferential and descriptive statistical tests to determine levels of consistency and validity.

The first research question explored the relationship of IV Grit and ATM and their subscales with the AP DV (defined as a final letter grade in math class) of students in a college-level gateway math course. The IVs were obtained from subscale scores from the Grit-S scale. Multilevel linear and logistic regression models were used to examine the relationships between the variables ATM and Grit with the DV AP. This was repeated for the subsets of Grit and ATM, respectively.

The second and third research questions explored whether non-cognitive factors, Grit and ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses. Independent samples t-test and multilevel linear regression models were used to examine differences between the two student groups.

Table 2: Research Questions and Variables

Q	Research Questions	Independent Variable	Dependent Variable	Data Analysis
Q1	Do non-cognitive factors, Grit and Attitude Towards Math (ATM), have a significant predictive relationship to academic performance (AP) for college-math ready (CR) and not-college-math ready (NCR) students enrolled in college-level corequisite math courses?	Grit S-Scores and ATM Scores	Academic Performance	Multilevel Linear and Logistic Regression models
Q2	Does the non-cognitive factor, Grit, differ significantly between college-math ready (CR) and not-college-math ready (NCR) students enrolled in college-level corequisite math courses?	College readiness (CR vs NCR)	Grit S-Scores	Independent samples t-test and Multilevel Linear Regression models

Q	Research Questions	Independent Variable	Dependent Variable	Data Analysis
Q3	Does the non-cognitive factor, Attitude Towards Math (ATM), differ significantly between college-math ready (CR) and not-college-math ready (NCR) students enrolled in college-level corequisite math courses?	College readiness (CR vs NCR)	ATM Scores	Independent samples t-test and Multilevel Linear Regression models

Limitations

Various limitations exist in this study due to its design. The use of self-reporting survey instruments (Grit-S and ATM) introduces respondent biases and inaccurate self-estimations (Fisher, 1993; Nederhof, 1985). In choosing the population of students for this study, the inherent limitations of purposive sampling cannot be totally avoided. Generalization to the entire MCC student population would not be feasible though still valid for the defined population of students who are enrolled in in-person QL and S math courses at MCC (Etikan et al., 2016). The experimental implementation of the ATM instrument for surveying college students is unique. As a result, there is a scarcity of validation studies addressing its application specifically to college students. Finally, college readiness, as defined through established placement exams scores has been established as being problematic. Standard placement exams are not accurate indicators of AP in college or college readiness. The misplacement of students due to their placement score can impact up to 30% of students taking these exams, and therefore, have a significant impact on the veracity of this study.

SUMMARY

Chapter Four presents the data and results from the implemented research design as discussed in the current chapter. The results will be applied to and answer the three research questions and subsequent hypotheses related to exploring the relationship between Grit and ATM with AP for CR and NCR students enrolled in college corequisite math courses.

CHAPTER FOUR: DATA ANALYSIS

INTRODUCTION

The non-experimental research design investigated the individual relationship between the independent variables (IVs)—Grit and its subscales, along with ATM—and the dependent variable (DV), academic performance (AP), within the context of corequisite gateway math courses. The study examined whether any differences existed in the levels of these non-cognitive factors between CR and NCR students.

The data collected was analyzed with the statistical analysis program R/R studio, and the results are presented in this chapter. The overall chapter organization includes the following sections: purpose of study, theoretical perspective, summary of results and findings, and detailed results.

PURPOSE OF THE STUDY

This study aimed to explore the relationship of noncognitive factors such as Grit and ATM with community college student AP in college-level corequisite math courses. Additionally, it examined whether differences exist in Grit and ATM between underprepared students who are NCR and CR students enrolled in college-level corequisite math courses. Furthermore, the study also explored the relationship between the individual subscales of Grit: the COI, and the POE, with AP in college-level math courses.

THEORETICAL PERSPECTIVE

Previous studies have established that Grit and academic attitudes amongst other non-cognitive factors can be used to explain AP at multiple levels of education (Chen et al., 2018; Datu et al., 2017; Aiken, L. R., Jr., 1976; Rogalski, 2018; Sedlacek & Adams-Gaston, 1992; Wanzer et al., 2019b).

Collectively, this body of work has been synthesized into The Noncognitive Framework, which was developed to integrate this varied and extensive research space. Grit forms the *academic perseverance* subset of the framework while academic attitudes, in this case ATM, may be categorized as a subset of *academic mindset* (Farrington et al., 2012). According to the noncognitive framework, a student's level of applied tenacity through challenging tasks or subjects, mathematics in this case, may be related to their preceding mindset or attitudes towards that task or challenge (Wanzer et al., 2019a). In addition, this framework redefines college readiness holistically beyond the narrow boundaries of only placement exam scores. It incorporates a perspective that also takes into account the grade point average of graduating high schoolers. This longitudinal approach to college readiness then allows for the cumulative interactions of the various subsets of the noncognitive framework with academic effort and performance of students:

> The prevailing interpretation is that, in addition to measuring students' content knowledge and core academic skills, grades also reflect the degree to which students have demonstrated a range of academic behaviors, attitudes, and strategies that are critical for success in school and in later life, including study skills, attendance, work habits, time management, help-seeking behaviors, metacognitive strategies, and social and academic problem-solving skills that allow students to successfully manage new environments and meet new academic and social demands. (Farrington et al., 2012, p. 5)

RESEARCH QUESTIONS

This study addresses the following gaps: To what extent can Grit and ATM predict academic performance (AP) in college-level math corequisite courses, and do Grit and ATM exhibit significant differences between CR and NCR students?

For this study, the following questions were addressed:

1. Do non-cognitive factors, Grit and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses?
2. Does the non-cognitive factor, Grit, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?
3. Does the non-cognitive factor, ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?

RESULTS

DEMOGRAPHIC RESULTS FROM SAMPLE

Of the general population, 155 students were present physically in class and completed the survey instruments, thus providing a response rate of 82.9%. Demographically, there were 63% (*n* = 98) females compared to 37% (*n* = 57) males. The median age was 20.94 years (SD = 6.84) and spanned a range of between 17–80 years old. More than half of the participants were CR (57%) students relative to NCR (43%) students. More than two-thirds were Pell recipients totaling 68% (*n* = 106) of the participants, while 94.82% (*n* = 147) were working. Of the working students, almost two thirds were employed part-time (70%) while 39% were employed full-time. Of the participants, 72% earned a grade of C or higher. See Table 3.

Table 3: Participants Demographics Table

	n = 187	*n* = 155[1]
CHARACTERISTIC	*n*	PERCENTAGE
Age (median)	20.94 (6.80)	
Gender		
Female	98	63%
Male	57	37%
Student Level		

	$n = 187$	$n = 155$[1]
CHARACTERISTIC	*n*	PERCENTAGE
Freshman	91	59%
Sophomore	64	41%
Employment Status		
FT	39	25%
PT	108	70%
Unemployed	8	5%
College Readiness		
NCR	67	43%
CR	88	57%
Math Grade		
A	48	31%
B	33	21%
C	31	20%
D	10	6.5%
F	10	6.5%
W	23	15%

[1]Mean (SD)

The next step involved performing a correlation analysis to determine the relationship between all the variables associated with the research questions. The outcome of this part of the analyses is to determine the strength and direction of the relationship between the IVs and the DV.

The strength of the relation is derived from the value of the *r*, the Pearson correlation coefficient, which ranges from 0, an indication of no relationship between the variables, to ±1, which is a strong or perfect relationship. A strong relationship is synonymous with strong predictability. The value of *r* is either positive or negative which provides information of the direction of relationship. A positive value informs that there is a directly proportional relationship between the two values while a negative value reports an indirectly proportional relationship.

Specifically, the Pearson correlation coefficients were generated to examine the relationship and interaction that AP in math has with Grit, ATM, and their subscales. The DV, AP in math, has a small to moderately positive correlation with the main IVs, Grit ($r = .26$, p

<.01) and the overall ATM (r = .29, p <.01). The small to moderate positive relationship was similar for the subscales of Grit, COI (r = .22, p <.01), and POE (r = .21, p <.01), with AP. The subscales of ATM also share a similar correlation with AP, namely liking mathematics (r = .24, p <.01), and confidence in math skills (r = .32, p <.01) with AP. See Table 4 for further information.

Pearson's correlation coefficients were also conducted for the subsets of the participants, namely CR and NCR students. The correlation analyses revealed similar results for the NCR participants. Explicitly, the small to moderate positive relationships to AP were also observed for all variables at the 0.05 confidence level, the only exceptions were POE (a subscale of Grit) and value towards math (a subscale of ATM) that were not significant. For CR participants, the only two positive significant correlations to AP at the 0.05 confidence level were Grit and COI. See Tables 5 and 6 for further information.

Table 4: Correlation Matrix of Study Variables – Entire Sample

VARIABLE	M	SD	1	2	3	4	5	6	7	8
1. Grit Total	3.43	0.56	--							
2. COI	1.49	0.38	.88**	--						
3. POE	1.94	0.3	.79**	.39**	--					
4. ATM Total	68.63	16.02	.37**	.29**	.33**	--				
5. Liking Math	21.46	6.88	.36**	.30**	.30**	.90**	--			
6. Confidence	21.77	7.03	.37**	.31**	.31**	.85**	.69**	--		
7. Value Towards	25.36	5.52	0.15	0.09	.18*	.69**	.49**	.31**	--	
8. Age	20.94	6.8	0.08	0.15	-0.03	-0.07	-0.02	-0.14	0.02	--
9. AP (Math Grade)	4.18	1.76	.26**	.22**	.21*	.29**	.24**	.32**	0.12	-0.06

**p<.05, **p<.01 Note. ATM = Attitude Towards Mathematics, COI = consistency of interest, POE = perseverance of effort, Confidence = Confidence in Math Skills, Value = Value towards Math, AP = Academic Performance.*

Table 5: Correlation Matrix of Study Variables – NCR Students

VARIABLE	M	SD	1	2	3	4	5	6	7	8
1. Grit Total	3.40	0.60	--							
2. COI	1.48	0.40	.85**	--						
3. POE	1.92	0.33	.77**	.31*	--					
4. ATM Total	63.52	14.89	.41**	.31**	.36**	--				
5. Liking Math	19.90	6.97	.36**	.26*	.33**	.91**	--			
6. Confidence	19.12	6.18	.44**	.36**	.35**	.81**	.67**	--		
7. Value Towards	24.51	5.35	0.18	0.12	0.18	.66**	.44**	0.23	--	
8. Age	21.80	8.94	0.09	0.13	0.01	0.07	0.12	-0.05	0.11	--
9. AP (Math Grade)	3.58	1.72	.27*	.24*	0.2	.28*	.24*	.34**	0.07	-0.08

**p<.05, **p<.01 Note. ATM = Attitude Towards Mathematics, COI = consistency of interest, POE = perseverance of effort, Confidence = Confidence in Math Skills, Value = Value towards Math, AP = Academic Performance.*

Table 6: Correlation Matrix of Study Variables –CR Students

VARIABLE	M	SD	1	2	3	4	5	6	7	8
1. Grit Total	3.45	0.54	--							
2. COI	1.49	0.36	.90**	--						
3. POE	1.96	0.27	.81**	.48**	--					
4. ATM Total	72.56	15.82	.34**	.29**	.29**	--				
5. Liking Math	22.66	6.60	.35**	.33**	.27*	.90**	--			
6. Confidence	23.78	7.00	.34**	.30**	.28**	.84**	.69**	--		
7. Value Towards	26.01	5.59	0.12	0.06	0.16	.71**	.50**	.32**	--	
8. Age	20.30	4.54	0.09	0.19	-0.09	-0.19	-0.18	-.22*	-0.06	--
9. AP (Math Grade)	4.64	1.65	.24*	.22*	0.19	0.18	0.16	0.19	0.09	0.04

**p<.05, **p<.01 Note. ATM = Attitude Towards Mathematics, COI = consistency of interest, POE = perseverance of effort, Confidence = Confidence in Math Skills, Value = Value towards Math, AP = Academic Performance.*

The scatter diagrams for both AP (math grade) and Grit as well as AP (math grade) and ATM suggest a positive linear relationship between these non-cognitive variables and AP in math corequisite courses for both CR and NCR participants. See Figures 1 and 2.

Figure 1. Scatter diagram for AP (Math Grade) and Grit.

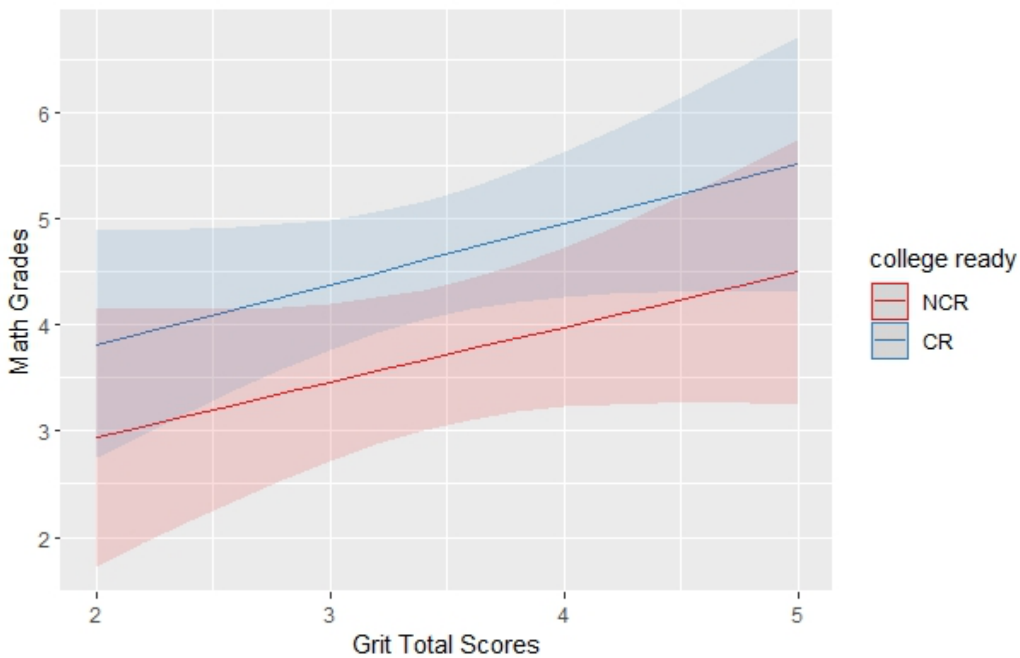
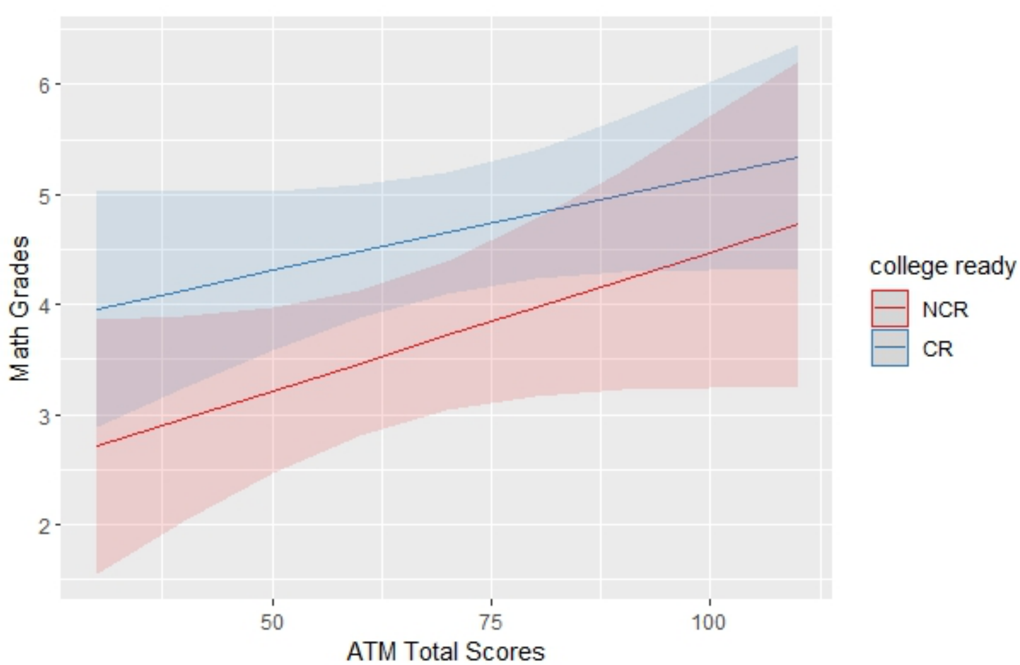


Figure 2. Scatter diagram for AP (Math Grade) and ATM.



To complete this phase of the analyses, a series of Fisher's *Z* tests were conducted to examine if there is a significant difference between two correlation coefficients, r_{NCR} and r_{CR}, found in the NCR and CR participant samples respectively. Put differently, I examined if the correlation relationship between Grit and ATM with respect to AP differed between the two student groups NCR and CR. None of the correlations were found to be statistically different between the two groups. See Table 7.

Table 7: Differences in Correlations Between NCR and CR Groups

GROUPS	N	X-Y	R	Z	P
NCR	67	Grit-AP (Math Grade)	0.27	0.21	0.831
CR	88	Grit-AP (Math Grade)	0.24		
NCR	67	POE-AP (Math Grade)	0.20	0.02	0.985
CR	88	POE-AP (Math Grade)	0.19		
NCR	67	COI-AP (Math Grade)	0.24	0.16	0.873
CR	88	COI-AP (Math Grade)	0.22		
NCR	67	ATM-AP (Math Grade)	0.28	0.60	0.548
CR	88	ATM-AP (Math Grade)	0.18		
NCR	67	Liking Math-AP (Math Grade)	0.24	0.54	0.588
CR	88	Liking Math-AP (Math Grade)	0.16		
NCR	67	Confidence in Math Skills-AP (Math Grade)	0.34	0.97	0.332
CR	88	Confidence in Math Skills-AP (Math Grade)	0.19		
NCR	67	Valuing towards Math-AP (Math Grade)	0.07	-0.17	0.865
CR	88	Valuing towards Math-AP (Math Grade)	0.09		

In the following sections, inferential statistics were utilized to answer the three research questions as well as test their respective null hypotheses.

PRIMARY FINDINGS

Based upon the results of examining the first research question, there is evidence that there is a significant relationship between non-cognitive factors, Grit and ATM, to AP for CR and NCR students enrolled in college-level corequisite math courses.

The results from examining the second research questions provide evidence that there is a significant difference in levels of ATM between CR and NCR students. This was not observed in the distribution or existence of levels of Grit between CR and NCR students.

Research Question One

The first research question examines if non-cognitive factors, Grit and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses.

Multilevel linear and logistic regression models were used to examine the relationships between these variables, accounting for similarity in variance for participants in the same classes. Multilevel regression models are statistical tests examining the relationships between predictor and outcome variables while accounting for complex patterns of variance that can occur due to either similarity of responses from group membership or repeated measures (Finch et al., 2019). The alpha level used to determine statistical significance for study results is the general standard of .050 (Agresti, 2018).

Regarding multilevel linear regression interpretation, the *p*-value for each predictor describes whether the variable is a significant predictor of the outcome variable. A variable is a significant predictor of the outcome when its p-value is less than .050. *P*-values are the probability of finding statistical results as, or more extreme than, observed results assuming the null hypothesis is true (Agresti, 2018). For regression, a *p*-value less than .05 indicates the slope of the predictor is statistically different from 0 and is a significant predictor of the outcome variable. The beta value (slope) in the multilevel regression model is the average change of the outcome variable for every one-point increase of the predictor variable while keeping all the other predictor variables in the model constant (Agresti, 2018). The LLCI and ULCL values are the 95% confidence interval of each predictor's beta value. The confidence intervals are a range of values indicating 95% certainty that the true population beta value is within.

Relationship between Grit and ATM with AP

A multilevel linear regression analysis was conducted to examine whether Grit and ATM can predict the college students' AP in the corequisite math courses in the sample. The results show that Grit (β = .53, *CI* = [0.06, 1.01], *p* = .028) and ATM (β = .02, *CI* = [0.01, 0.04], *p* = .011) are significant positive predictors of AP in the corequisite math courses. This demonstrates that a one-unit increase in either Grit or ATM are associated with corresponding .53-unit and .02-unit increases, respectively in AP in the math corequisite courses. See Table 8.

Table 8: Multilevel Linear Regression Table of Grit and ATM Predicting AP

PREDICTORS	BETA	SE		*DF*	*P*	LLCI	ULCL
Intercept	0.83	0.88	0.95	148.51	0.35	-0.90	2.56
Grit Total	0.53	0.24	2.22	140.88	0.03	0.06	1.01
ATM Total	0.02	0.01	2.57	147.07	0.01	0.01	0.04

Relationship between Grit Subscales and Academic Performance

A multilevel linear regression model was conducted to examine whether Grit-S subscales predict the college students' AP in the corequisite math courses in the sample. The results show the subscales COI (β = .39, *CI* = [-0.36, 1.14], *p* = .30) and POE (β = .66, *CI* = [-0.29, 1.61], *p* = .170) are not significant positive predictors of AP in the corequisite math courses. See Table 9.

Table 9: Multilevel Linear Regression Table of Grit-S Subscales Predicting AP

PREDICTORS	BETA	SE	*T*	*DF*	*P*	LLCI	ULCL
Intercept	0.85	1.02	0.83	146.93	0.410	-1.17	2.86
COI	0.39	0.38	1.03	139.39	0.300	-0.36	1.14
POE	0.66	0.48	1.37	139.49	0.170	-0.29	1.61

Relationship between ATM Subscales and AP

A multilevel linear regression model was conducted to examine whether any of the ATM subscales predict the college students' AP in the corequisite math courses in the sample. The results show that two of the three ATM subscales Liking Math (β = .00, *CI* = [-0.04, 0.06], *p* = .91) and Value towards Math (β = .01, *CI* = [-0.04, 0.06], *p* = .66) are not significant positive predictors of AP in the corequisite math courses. Whereas Confidence in Math Skills (β = .05, *CI* = [0.00, 0.11], *p* = .05) is, at best, a significant, yet a weakly positive, predictor of AP in corequisite math courses. This demonstrates that a one-unit increase in Confidence in Math Skills is associated with a corresponding.05-unit increase in AP in the math corequisite courses. See Table 10.

Table 10: Multilevel Linear Regression Table of ATM Subscales Predicting Academic Performance

PREDICTORS	BETA	SE	T	DF	*P*	LLCI	ULCL
Intercept	0.85	1.02	0.83	146.93	0.410	-1.17	2.86
Liking Math	0.00	0.03	0.12	142.05	0.910	-0.05	0.06
Confidence in Math Skills	0.05	0.03	1.97	144.06	0.050	0.00	0.11
Value towards Math	0.01	0.03	0.44	142.86	0.660	-0.04	0.06

RESEARCH QUESTION TWO

The second research question examines data to determine if the noncognitive factor, Grit differ significantly between CR and NCR students enrolled in college-level corequisite math courses. A series of independent samples *t*-tests and multilevel linear regression models were used to examine differences in the noncognitive factor, Grit, between the two independent groups categorized as CR and NCR students.

Relationship Between Grit with College-Math Readiness

The independent sample *t*-tests demonstrated no significant difference in the levels of total Grit between CR (M = 3.45, SD = 0.54) and NCR (M = 3.40, SD = 0.59) students; t (153) = -0.51, p < .001, d = -.08). The null hypothesis was accepted for Grit and for the two subscales of Grit, COI and POE. Altogether, these results suggest that CR students do not report a higher mean value of Grit or its subscales than the NCR students taking math corequisite courses. See Tables 11 and 12.

Table 11: Independent Samples *t*-test Table

DV	*t*	DF	*p*	D	95% CI
Grit Total	-0.51	153	.614	-0.08	[-0.40, 0.24]
COI	-0.12	153	.906	-0.02	[-0.34, 0.30]
POE	-0.81	153	.419	-0.13	[-0.45, 0.19]

Table 12: College-Math Ready Group Descriptive Results of Non-Cognitive Variables Table

College -Math Readiness	DV	*n*	M	SD
NCR	Grit Total	67	3.40	0.59
CR	Grit Total	88	3.45	0.54
NCR	COI	67	1.48	0.40
CR	COI	88	1.49	0.36
NCR	POE	67	1.92	0.33
CR	POE	88	1.96	0.27

Research Question Three

Relationship between Attitude Towards Mathematics with College-Math Readiness

The independent sample *t*-tests demonstrated a significant difference in the levels of ATM between CR (M = 72.56, SD = 15.82) and NCR (M = 63.52, SD = 14.89) students; t (152) = -3.61, p < .001, d = -.59). The alternative hypothesis was accepted for ATM. The results suggest that CR students tend to have a higher mean value of ATM than the NCR students taking math corequisite courses. Specifically, our results suggest that CR students may view mathematics with higher positive attitudes than do the NCR students. See Tables 13 and 14.

Table 13: Independent Samples *t*-test Table

DV	T	DF	*p*	D	95% CI
ATM Total	-3.61	152	< .001	-0.59	[-0.91, -0.26]

Table 14: College-Math Ready Group Descriptive Results of Non-Cognitive Variables Table

College-Math Readiness	DV	*n*	M	SD
NCR	ATM Total	67	63.52	14.89
CR	ATM Total	88	72.56	15.82

Finally, a series of multilevel linear regression models were conducted to further examine if there are differences in the study's non-cognitive variables between CR and NCR students enrolled in college-level corequisite math courses, while holding the other IVs constant. The multilevel level regression models accounted for a similar variance of the DVs for each student group. The only significant effect of college readiness on any non-cognitive variables was on ATM ($\beta = 8.12$, $CI = [1.48, 14.75]$, $p = .020$). The alternative hypothesis was accepted when CR students were again found to have higher positive ATM compared to NCR students while accounting for the shared variance of participants in the same group had with each other. This demonstrates that college readiness is associated with a corresponding 8.12-unit increase in ATM. Specifically, this means that being college ready predicts a student will have an 8.12-unit increase in their ATM than NCR students. See Table 15 and Figures 3 and 4.

Table 15: Multilevel Linear Regression Table Predicting Non-Cognitive Variables

DV	Predictors	Beta	*SE*	*t*	*DF*	*p*	LLCI	ULCI
Grit Total	Intercept	3.41	0.08	41.09	12.20	< .001	3.23	3.59
	College Ready	0.03	0.11	0.28	14.33	.784	-0.20	0.26
COI	Intercept	1.48	0.05	30.28	11.35	< .001	1.38	1.59
	College Ready	0.00	0.06	0.07	13.17	.944	-0.13	0.14
POE	Intercept	1.92	0.05	42.31	12.07	< .001	1.82	2.02
	College Ready	0.03	0.06	0.48	14.27	.642	-0.10	0.15
ATM Total	Intercept	63.82	2.38	26.87	12.02	< .001	58.64	68.99
	College Ready	8.12	3.10	2.62	14.30	.020	1.48	14.75

Figure 3. Grit Scores Histogram by College-math Ready Status.

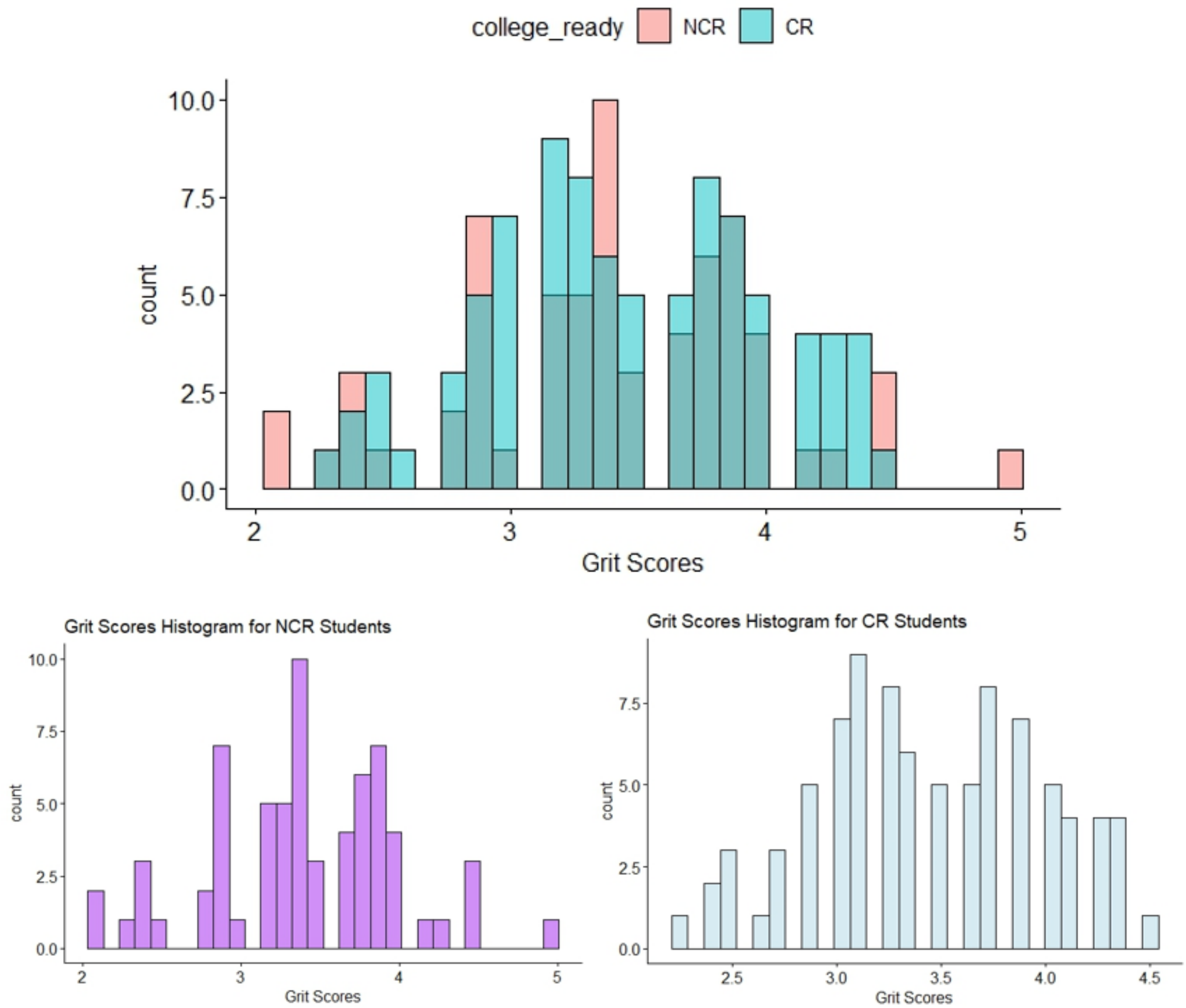
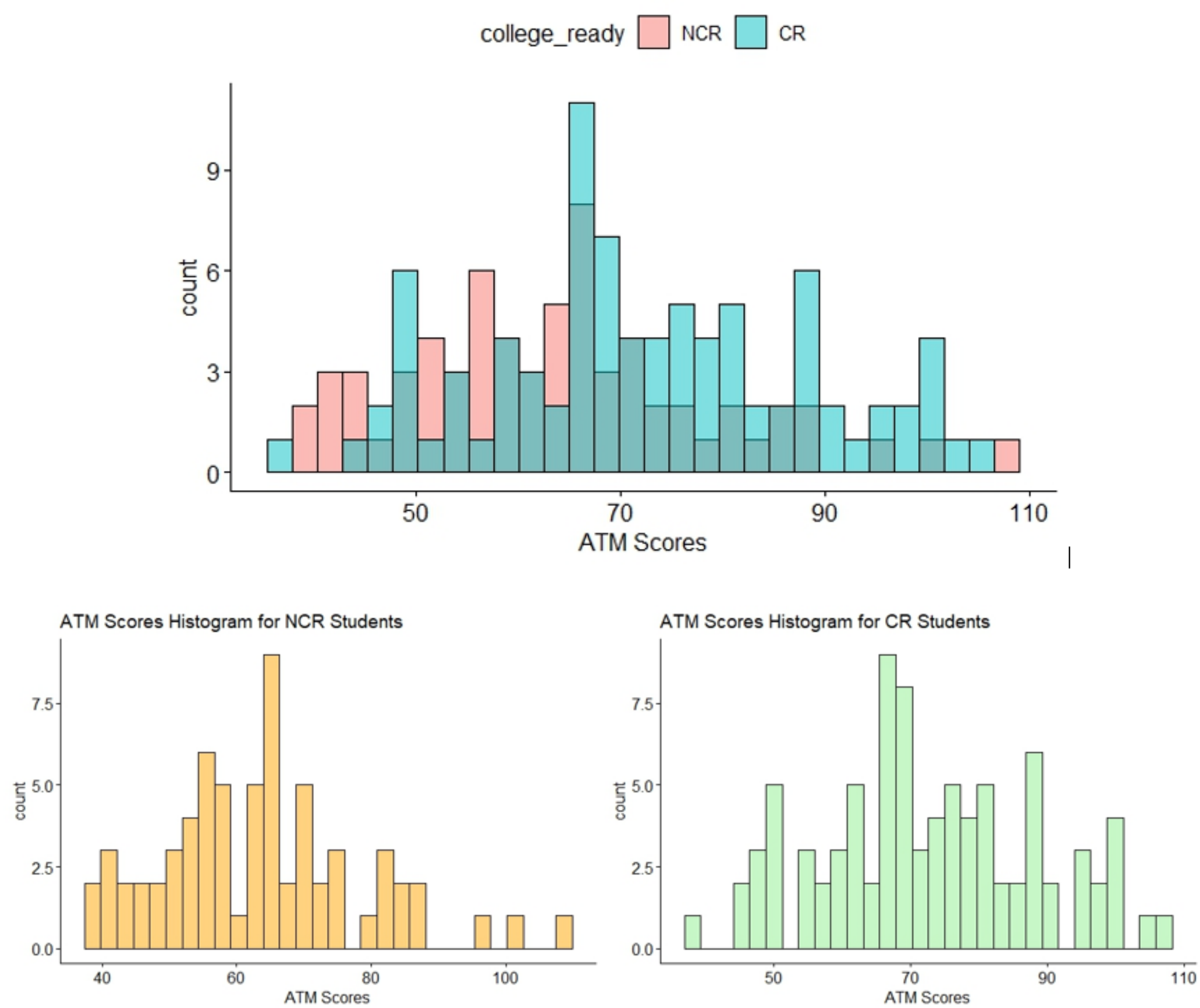


Figure 4. ATM Scores Histogram by College-math Ready Status.



SUMMARY

Results from this study lead to the rejection of the first null hypothesis ($H1_0$) because there are small-to-moderately positive, but yet statistically significant, correlations between participants' Grit, ATM, and their Academic Performance (AP) in corequisite math courses. Consequently, the acceptance of the first alternative hypothesis ($H1_1$) follows, due to the significant relationship between Grit, ATM, and the AP of students in college-level gateway math courses. The second null hypothesis ($H2_0$) is accepted due to the results indicating the levels of Grit or its subscales demonstrated no statistically significant variance between the NCR and the CR student groups. While the third alternative hypothesis ($H3_1$) is accepted due to the results indicating the levels of ATM demonstrated a statistically significant variance between the NCR and the CR student groups.

The findings of the descriptive and inferential statistical procedures performed in this study demonstrate clear evidence that Grit and ATM have a measurable impact on AP of students enrolled in math corequisite courses. However, the data suggests that levels of Grit and the implied sustenance of effort applied by college students does not differ between CR and NCR students. Conversely, the data also suggests that levels of ATM perceived by college students do differ between CR and NCR students.

CHAPTER FIVE: CONCLUSION

INTRODUCTION

This study explored the relationship between noncognitive factors such as Grit and ATM and student success in college-level corequisite math courses taught at MCC. The following three research questions were proposed and examined:

1. Do noncognitive factors, Grit and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses?
2. Does the non-cognitive factor, Grit, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?
3. Does the non-cognitive factor, ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?

The null and alternative hypotheses for research question one in this study are:

- H1O: Grit and ATM have no significant relationship to the AP of students enrolled in a college-level corequisite math course.
- H11: Grit and ATM have a significant relationship to the AP of students enrolled in a college-level corequisite math course.

The null and alternative hypotheses for research question two in this study are:

- H2O: Grit does not differ significantly between CR and NCR students.
- H21: Grit differs significantly between CR and NCR students.

The null and alternative hypotheses for research question three in this study are:

- H3O: ATM does not differ significantly between CR and NCR students.
- H31: ATM differs significantly between CR and NCR students.

In the Fall 2019 semester, freshman and sophomore students attending MCC and enrolled in both Statistics and Quantitative Literacy math courses were selected as participants and invited to complete the Grit-S and the ATM survey adapted from the Trends in International Mathematics and Science Study (TIMSS) 2017 Context Questionnaires. Results from both surveys were examined to understand the relationship between Grit, ATM, and AP of the student participants, as measured by the final letter grade the students earned in either the Statistics (S) or Quantitative Literacy (QL) math course they were enrolled in.

The Pearson correlation coefficient was used to measure the strength and direction of the relationships between Grit, ATM, and AP of the participants. The Pearson correlation analyses were also repeated separately for CR and NCR participants. The obtained *r*-values were then examined using the Fisher Z test to determine if there was a difference between the correlation coefficients of the two subsets of participants, CR and NCR students. The analyses were also repeated to include the subscales of Grit and ATM and all the variables associated with the research questions. To better understand the overall relationships between the two main noncognitive variables and AP between CR and NCR participants, independent-*t*-tests and additional regression analyses were performed to determine if there was a significant difference across the two subsets of participants.

SUMMARY OF FINDINGS

The findings from the descriptive and inferential statistical procedures performed in this study demonstrate that both Grit and ATM have moderately positive yet statistically significant correlations to AP as measured by the final grades in the corequisite math courses earned by the community college students. The data also suggest that both Grit and ATM are significant predictors of AP for the participants. Based on these findings, the first alternative hypothesis, H11, was accepted, confirming that: Grit and ATM have significant relationships to the AP of students enrolled in a college-level gateway math course.

Grit levels were not significantly different between the CR and NCR students in this study. The second alternative hypothesis H21, was rejected in favor of the null hypothesis H20. The data further indicated that ATM levels were found to be statistically significantly higher in CR students than in NCR students. The third alternative hypothesis, H31, was accepted.

RESEARCH QUESTION ONE

Question one examined whether noncognitive factors Grit and ATM have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses. The null hypothesis was rejected in favor of the alternative hypothesis.

The Pearson correlation coefficients demonstrated statistically significant positive correlations between AP and noncognitive factors Grit and ATM for the entire sample. With the sample divided into two groups, CR and NCR students, and the same analyses repeated, the Pearson correlation coefficients also demonstrated statistically significant positive correlations between AP and noncognitive factors Grit and ATM for NCR students. However, for CR students, the only demonstrated statistically significant positive correlation was between AP and the noncognitive factor Grit. The correlation results support studies that suggest NCR students may have stronger negative ATM. Negative attitudes of math have been studied and correlated to corresponding levels of higher math anxiety, leading to poorer math AP (Meece et al., 1990; Necka et al., 2015; Ramirez et al., 2018; Yu et al., 2021). Thus, affective dispositions and attitudes have a stronger relationship to AP in mathematics in NCR students than observed in CR students.

Additionally, the multilevel linear regression beta values for Grit and ATM suggest they are both significant predictors of the DV, AP, for the entire sample. The observed data showed that for each additional unit increase in Grit or ATM, CR and NCR students are likely to earn a net increase in their AP in a math corequisite course. These findings confirm the alternative hypothesis (H11) that Grit and ATM have a significant relationship to the AP of students enrolled in a college-level gateway corequisite math course.

This study's finding is comparable to findings from other studies. Grit-S scores have been found to be moderately associated with levels of academic success (Credé et al., 2017; Strayhorn, 2014). Grit's positive relationship to varying metrics of academic success was consistent across several studies (Rogalski, 2018; Tang et al., 2019; Williams, 2017). Students with higher levels of math-specific Grit also had higher AP in mathematics (Yu et al., 2021).

A study conducted by Al-Mutawah and Fateel (2018) yielded results indicative of a parallel constructive association between Grit and AP in mathematics. Their study also highlighted the same trend for ATM and AP in mathematics. Other studies utilized different instruments to study the relationship between attitude as it related to math and AP in math with similar results to the TIMSS instrument in this study (Chen et al., 2018; Dogbey, 2010; Fennema & Sherman, 1976; Jansen et al., 2016).

This established net positive relationship of noncognitive variables with AP is summarized by Nagaoka et al. (2013):

> There is also a growing recognition that being ready for college means not only building students' content knowledge and academic skills, but also fostering a host of noncognitive factors–sets of behaviors, skills, attitudes, and strategies that are crucial to students' academic performance and persistence in post-secondary education. (p. 46)

Since the level of AP in adult students can be mediated through the relationship to or interactions between behavior and a multitude of other cognitive and noncognitive factors, it is not unusual to have obtained low to moderate correlation coefficients between the IVs of Grit and ATM with the DV of AP. These specific results only confirm that Grit and ATM, together with their subscales, do not explain the majority of the variability associated with AP in CR and NCR participants (Farrington et al., 2012; Ma & Kishor, 1997).

Additionally, the results of this study need to be balanced with other studies finding results and consequential implications inconsistent with this study. As with any realm of academic research, alternative viewpoints exist regarding the correlation between noncognitive factors and AP. These studies have yielded results that deviate from this study's observed relationship between noncognitive factors and academic achievement. Grit was nonpredictive of AP in the Bazelais et al. (2016, p. 33) study. Datu et al. (2017) found in multiple studies that the Grit subscale, POE, had a stronger predictive outcome to AP than did the total Grit-S scale. Ackermann (2018) found that using the Grit-S scale across diverse age groups is potentially problematic due to non-invariance between different age groups. This cautionary aspect may be relevant to a typical community college class with a mixture of traditional and non-traditional-aged students. The median age in this study was 20.94 years (SD = 6.84), with a range of students between 17–80 years old.

In their meta-analysis study, Akos and Kretchmar (2017) summarized their findings on Grit and AP as follows… "In sum, although noncognitive factors and Grit specifically show promising in predicting college success, many questions still remain" (p. 167).

Research Question Two

The focus of question two was to examine if the noncognitive factor Grit differs significantly between CR and NCR students enrolled in college-level corequisite math courses. The null hypothesis was accepted based upon observed results. An independent sample *t*-test was conducted to compare CR and NCR students' levels of Grit. There was no observed significant difference in the levels of Grit between CR and NCR students.

Despite Grit being a facet of perseverance that was found to be predictive of higher AP in this study, Grit distribution between CR and NCR students was not significantly different. A possible explanation is that Grit is domain-general rather than domain-specific (Credé et al., 2017; Duckworth & Quinn, 2009). As such the survey instrument design may inherently be unable to effectively evaluate Grit from a domain-specific construction of mathematics. It is explained analogously as a soccer player may exhibit Grittiness in all things soccer but fail to show the same levels of Grit in music studies. Thus, to be able to better measure the soccer-domain specific Grittiness may require a domain-specific Grit instrument relative to the original instrument.

In addition, a multiple linear regression was also used to predict levels of Grit based on students' college-math readiness coded as 1 = CR, 2 = NCR. The examination of the relationship between college-math readiness and levels of Grit among student participants also did not uncover any significant correlation. Thus, there is no material relationship between the degree of preparedness for college-level mathematics and the levels of Grit displayed by the students. As stated earlier perhaps the confounding aspect of the results is laid bare by a domain-general construct used to elucidate a domain-specific variable.

Other explanations for these results may stem from the fact that average community college class is typically diverse in terms of student demographics. Reflecting on the demographic summary of the participants in this study, it is likely the varying experiences, age, socioeconomic, and diverse high school educations (MCC serves 32 high school districts), may all interplay to make it challenging to observe concise results or differences between groups in this population (Horton, 2015; Von Culin et al., 2014).

Research Question Three

The objective of question three was to investigate the potential disparity in the noncognitive factor known as ATM between CR and NCR, both of whom were enrolled in college-level corequisite math courses. The null hypothesis, advancing no significant difference in ATM levels between the two groups, was rejected in favor of the alternative hypothesis. To assess the difference, an independent samples *t*-test was conducted, revealing a statistically significant distinction in the levels of ATM. Specifically, CR students demonstrated higher levels of positive ATM in comparison to NCR students.

This finding corroborates the work from numerous studies (Carey et al., 2016; Jansen et al., 2016; Park et al., 2018) as well as that of Farrington et al.'s (2012) noncognitive framework or model associated with AP. The model explains that students who possess stronger academic skills in a specific domain, in turn, are more likely to possess more positive attitudes or mindsets towards that domain which collectively correlates to stronger academic performances in that domain (Farrington et al., 2012; Wanzer et al., 2019a); in this study the domain is mathematics (Chen et al., 2018; Dogbey, 2010).

In addition, a multiple linear regression was also used to predict levels of ATM based on students' college-math readiness coded as 1 = CR, 2 = NCR. The observed data predicts that CR students were more likely to have higher levels of ATM than NCR students. These findings confirm the alternative hypothesis, H21, that ATM significantly differs between CR and NCR students.

These findings are comparable to other studies that have also determined that students who are identified to have the prerequisite skills tended to have more favorable attitudes to mathematics than students who don't (Hembree, 1990; Hodges & Kim, 2013; Nicolaidou & Philippou, 2003). Students with lower math skills are likely to have higher levels of math anxiety and interpret their math-related experiences differently from those with higher math skills (Ramirez et al., 2018). Carey et al. (2016) posited a bidirectional relationship between the affective state of a student and AP in mathematics. According to Farrington et al. (2012), "the degree to which students value an academic task strongly influences their choice, persistence, and performance at the task" (p. 31). Therefore, compared to NCR students, CR students with stronger math skills, more positive mindsets towards math, and better academic behaviors related to learning math, are likely to coalesce to provide the basis for a higher AP in mathematics. This understanding was further explored with additional analyses beyond these three questions.

Additional Analyses

Both Grit and ATM are moderately correlated to AP and function as predictors of AP in a math course. With the availability of the participants' letter grades in the data set, I planned to explore the strength and direction of the relationship between the IVs, Grit, and ATM, with a subset of the original DV, AP, as an additional analysis. This subset of AP is the Completion of a Math Course and is defined as a student successfully completing a math course with an earned A, B, or C grade. The purpose of the analyses was to understand if any noncognitive factors in the study are related or can predict if a student can successfully pass a math course with a C or better.

Relationship of Grit or ATM With Completion of a Math Course

The multilevel linear regression analyses indicate that higher Grit and positive ATM are linked with a greater AP in the math corequisite course, so further multilevel logistic regression analyses were carried out. An Odds Ratio (OR) was used to determine whether Grit or ATM can also predict college students' completion of the math course with a C or higher. The OR is the probability of the target event (AP of C or better) occurring for every one-point increase of the predictor variable (Grit or ATM) while keeping all the other predictors constant within the model. OR greater than one (OR > 1) predicts that higher scores of the predictor variable relate to a greater chance of the event occurring. OR less than one (OR < 1) predicts that the higher predictor scores relate to a lower chance of the event occurring.

The first multilevel logistic regression results show that ATM (OR = 1.03, CI = [1.00, 1.06], p = .044) is a significant positive predictor of completing the math course with a C or better. A higher positive ATM is associated with greater odds of passing the math course with a C or better. Specifically, the data suggests a 3% increase in the odds of successfully completing the math course with a C or better based on the student's level of ATM. See Table 17.

Table 17: Multilevel Logistic Regression Table of Grit and ATM Predicting Completion of a Math Course

PREDICTOR	OR	SE	WALD	P	LLCI	ULCI
Intercept	0.09	0.13	-1.75	0.08	0.01	1.34
Grit Total	1.56	0.61	1.14	0.25	0.73	3.35
ATM Total	1.03	0.01	2.02	0.04	1.00	1.06

These results reinforce the primary findings for the third research question that the academic mindset or affective nature of a student plays an important role in the eventual performance of the student in an academic domain, regardless of college readiness (Horton, 2015).

A second multilevel logistic regression model was also conducted to examine whether Grit and ATM subscales predict college students' ability to complete a math course with a C or better. The results show that confidence in math skills (OR = 1.1, CI = [1.01, 1.20], p = .030) is the only significant positive predictor of completing the math course with a C or better. Higher confidence in math skills is associated with greater odds of passing the math course with a C or better. Specifically, the data suggests a 10% increase in the odds of passing the math corequisite course with a C or better based on the student's confidence level in math skills. See Table 18.

Table 18: Multilevel Logistic Regression Table of Grit and ATM Predicting Course Performance

PREDICTOR	OR	SE	WALD	p	LLCI	ULCI
Intercept	0.09	0.15	-1.49	0.140	0.00	2.12
COI	1.38	0.82	0.54	0.590	0.43	4.40
POE	1.62	1.22	0.64	0.520	0.37	7.07
Liking Math	0.98	0.04	-0.54	0.590	0.89	1.07
Confidence in Math Skills	1.10	0.05	2.18	0.030	1.01	1.20
Valuing Math	1.02	0.04	0.51	0.610	0.94	1.11

Students with a more positive ATM had a 3% better chance of successfully persisting through the corequisite math courses. While at the subscale level, a 10% better chance of successfully persisting through the corequisite math courses is observed in those students with higher levels of confidence in their math skills. These results are congruent with a meta-analytic study on the role that noncognitive factors play in moderating AP which reported that when students face difficult tasks or domains, the self-confidence construct of a student in that specific domain is one of the strong predictors of their likelihood of succeeding in that difficult or challenging domain (Farrington et al., 2012).

IMPLICATIONS FOR PRACTICE

This study can provide three significant conclusions that educators at MCC can use to help their NCR students become more successful through the developmental math reform and the scaling of their math corequisite programming.

First, noncognitive factors, Grit and ATM, significantly mediate persistence and success in a college-level math corequisite course. Despite Duckworth and Quinn (2009) presenting Grit as a more inherently stable factor in people, some studies propose the malleability of Grittiness from a teaching and learning perspective (Tang et al., 2019; Williams, 2017).

Math teachers should also recognize the role and potential impact of inculcating strategies into their pedagogical plans to specifically address and strengthen NCR students' ATM. Math anxiety is all too commonly identified with NCR students (Dowker et al., 2016; Meece et al., 1990). In turn, it may impede the math learning strategies of NCR students by inhibiting their working memory (Carey et al., 2016). Given that these corequisite sections have a weekly additional 100 minutes on top of the math content lecture time, it may be profitable for MCC math teachers to develop intentional strategies to support and strengthen the ATM of their students. According to Bowman et al. (2019), "… noncognitive factors are influential only insofar as they contribute to positive academic behaviors within and outside of the classroom" (p. 137).

Second, NCR students are more likely to see potential gains in AP if carefully designed interventions are effectively employed to enhance the positive levels of ATM in this vulnerable group of underprepared students. As reported by Farrington et al. (2012) and Wanzer et al. (2019a), the indirect causal nature of ATM mediates AP through its subsequent influence on academic perseverance and secondary academic activities that impact learning and comprehension strategies. Based upon the stronger correlation between AP in mathematics and

ATM for NCR students than CR students and that CR students possess higher positive levels of ATM, as well as confidence in math skills, any net increase in ATM, would effectively improve academic course behaviors, persistence, and ultimately, AP in students regardless of college readiness.

Finally, based on the results of this study, the TIMSS ATM survey instrument is a potentially viable tool that can provide MCC math teachers with knowledge of individual students' levels of ATM. Since affective and noncognitive factors are subject to individual experiences, an individualized approach to supporting each NCR student may be important yet limited due to class size and time. This study also validates the current instructors' corequisite course designs, keeping the corequisite courses' support section to 15 students each. The corequisite course design at MCC and the ATM survey instrument provide an effective pedagogical platform to provide an individualized and more integrated approach for each NCR student.

Effectively describing the challenges between two student groups in terms of Grit entails considering several additional factors. Some obstacles associated with studying the effects of Grit on student groups include the following.

Measurement and Assessment

Grit is a multidimensional construct that can be challenging to measure accurately. Researchers often employ self-report questionnaires or scales, which may introduce biases or limitations in capturing the complexity of Grit. Ensuring reliable and valid measures of Grit across diverse student populations can be a challenge.

Contextual Factors

Grit's influence on student groups can be influenced by various contextual factors such as cultural background, socioeconomic status, and educational environment. These factors may interact with Grit differently across different groups, making it challenging to generalize findings across diverse populations.

Identifying Causal Relationships

Determining a causal relationship between Grit and student outcomes is challenging due to the possibility of reverse causality or the presence of confounding variables. For instance, it is difficult to ascertain whether high levels of Grit lead to improved AP or if high achievers tend to exhibit higher levels of Grit.

External Influences

Grit is not solely influenced by internal factors but can also be shaped by external influences such as family support, teacher-student relationships, and socio-cultural norms. Understanding and accounting for these external influences on Grit can be challenging when comparing student groups.

Longitudinal Studies

Assessing the long-term impact of Grit on student groups requires longitudinal studies that track participants over an extended period. Conducting such studies can be time-consuming and resource-intensive, posing logistical challenges.

Addressing these challenges requires careful study design, rigorous measurement techniques, and the consideration of various contextual factors. By acknowledging these obstacles, researchers can strive to develop comprehensive investigations that provide a more accurate understanding of the challenges associated with Grit among different student groups.

RECOMMENDATIONS FOR RESEARCH

The results of this study suggest a positive statistically significant predictive relationship between Grit and ATM and the AP of CR and NCR students enrolled in corequisite math courses. Other significant findings are the overall ATM and the sense of mathematical efficacy in mediating AP in mathematically vulnerable NCR students. It is beyond the scope of this study to elucidate more precisely the mediating mechanisms and relationships between these variables in addition to other underlying factors.

SAMPLE SIZE AND GENERALIZABILITY

The sample size limits the generalization of the findings to a larger population beyond this study. The ability to replicate this study with a sufficient sample size would benefit community colleges in this state, which are mandated to adopt and scale corequisite education in mathematics.

TIMING OF MEASUREMENT OF VARIABLES

There may be additional variance in the correlation between noncognitive factors and AP based on whether the survey instruments are employed before or when the student's final grades are available. The impact of this study's non-experimental design in surveying the students at the beginning of the course and not the end may play an unknown role in the strength of the interacting variables. In addition, there may be value in understanding if levels of Grit and ATM change between the start and end of the semester because participants' self-appraisal or reporting of these IVs may be influenced by current performance.

Gender

In light of providing practical information to help shape a future integrated approach to enhancing students' noncognitive skills to improve learning in mathematics, it is vital to understand if and how gender and gender-related educational experiences influence noncognitive mediation in AP. This is especially important for a number of reasons. There has been a notable shift in higher education enrollment demographics, with a higher proportion of females enrolling (Snyder et al., 2019). Additionally, there has been an increase in female degree attainment since 1979 (Perry, 2019). Furthermore, females who are vulnerable to stereotypical gender differences in AP in math are more likely to perform poorly compared to those females who are not receptive to this stereotype belief (Szczygieł, 2020). Despite the favorable gender gap, females still lag behind men in STEM enrollments and careers (Makarova et al., 2019). Further research in the relationship of gender and noncognitive mediation in AP in mathematics may provide inroads to supporting females' enrollment and achievement in STEM education.

Corequisite English and Other Academic Disciplines

Noncognitive factors like Grit and attitude are not academically domain-specific; however, the use of the domain-specific ATM was invaluable in providing insight into students' attitudes toward mathematics. Another study showed promising results by adapting the Grit-S scale to a math-specific Grit S-scale (Yu et al., 2021). Therefore, this study opens the door to applying this methodology to other gateway academic domains, such as English composition, where corequisite interventions are being employed.

Pre-College Demographic Factors

The average MCC college class is populated by students from a 4,000 square mile district, who therefore, reflect a broad swathe of diversity in age, socioeconomic factors, parental education levels, high school preparation, and college readiness. This would be typical for most open-access community colleges. Future research in this domain should explore if some of these pre-college factors interact in mediating the role of noncognitive factors in students' AP.

CONCLUSION

This study explored the relationship between noncognitive factors such as Grit and ATM with community college student AP in college-level corequisite math courses. It also explored whether differences existed in Grit and ATM distribution between CR and NCR students enrolled in college-level corequisite math courses. This study's theoretical framework was based on Farrington et al.'s (2012) evidenced-based model of noncognitive factors and AP. The literature review exposed a knowledge gap in the relationship between noncognitive factors such as Grit and ATM and AP in college-level corequisite math courses.

In addressing this knowledge gap, the study was designed to explore these specific research questions: do non-cognitive factors, Grit, and ATM, have a significant predictive relationship to AP for CR and NCR students enrolled in college-level corequisite math courses; and do either non-cognitive factors, Grit or ATM, differ significantly between CR and NCR students enrolled in college-level corequisite math courses?

The results from this study provide a better understanding of some of the noncognitive factors contributing to the success rates of underprepared-corequisite students in gateway math courses. This study highlights the value and importance of a student's level of Grit and ATM in explaining the success of underprepared students attempting college-level math courses that they did not place into using the traditional placement tests.

Grit and ATM are both significantly correlated and function as predictors of AP in mathematics for students enrolled in math courses. CR students possess higher positive ATM than NCR students, while Grit was not significantly different between the two groups. However, with NCR students, ATM has a stronger correlation to AP. Of these two noncognitive factors, this study highlights the significance of ATM in explaining the success of underprepared students.

This finding introduces to the body of work the importance of considering Grit as a domain-specific construct within the realm of any domain-specific academic investigation. Specifically, it emphasizes the need to measure Grit in a domain-specific context, especially when seeking to establish correlations between Grit and performance within a particular domain. When examining the correlation between Grit and performance in mathematics, it is evident from the results between Grit and ATM, that it is crucial to capture the nuances of Grit that are specifically relevant to this mathematics. This can easily be achieved by rephrasing the Grit survey to mirror the ATM construct in terms of mathematical tasks than domain agnostic questions.

By recognizing the domain-specific nature of Grit, researchers and educators can gain deeper insights into the role of Grit in mathematics achievement. It allows for a more precise assessment of the relationship between the various dimensions of Grit and the specific challenges encountered in the mathematics domain.

With this new information, math educators and administrators at MCC's offering corequisite math courses could develop better support and pedagogical interventions by including a component that evaluates and strengthens the attitudes towards math of these at-risk students.

This study sheds light on the intrinsic worth and profound significance of a student's level of Grit and attitudes towards mathematics when it comes to comprehending the academic success of underprepared students who choose to embark upon college-level math courses despite not meeting the customary placement criteria through traditional placement tests.

By delving into the notion of Grit, which encompasses traits such as perseverance, resilience, and passion for long-term goals, researchers have acknowledged its pivotal role in influencing students' ability to navigate the rigorous demands of college-level mathematics. The possession of Grit empowers these underprepared students to confront challenges head-on, persist in the face of setbacks, and maintain a fervent dedication to mastering mathematical concepts.

Additionally, the attitudes that students harbor towards mathematics play an instrumental role in their academic trajectory. Positive attitudes foster an environment conducive to learning, enabling students to approach mathematical tasks with enthusiasm, curiosity, and an eagerness to acquire knowledge. Conversely, negative attitudes may impede progress, hindering students' engagement, motivation, and overall performance in the field of mathematics.

Understanding the interconnectedness of Grit and attitudes towards mathematics enables researchers and educators to identify key factors that contribute to the success of underprepared students. By recognizing and fostering these traits, educational institutions can provide targeted support and tailored interventions to empower underprepared students to thrive in college-level math courses. This research emphasizes the need to consider both Grit (math-domain-contextualized) and ATM as vital components in understanding and promoting the academic achievement of underprepared students in the realm of higher-level mathematics education.

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APPENDIX A: LAKE LAND COLLEGE RBB APPROVAL

LAKE LAND
COLLEGE

May 1, 2019

Ike Nwosu
5001 Lake Land Blvd
Mattoon, IL 61938

Dear Mr. Nwosu,

Lake Land College's Research Review Board (RRB) has received and reviewed your request to conduct research at Lake Land College for your dissertation through Ferris State University. The RRB has approved your research to be conducted at Lake Land College for spring 2019 and fall 2019. However, data collection CANNOT begin until an official approval letter has been received from Ferris State University's Institutional Review Board (IRB). Once you have received approval for your research from Ferris State University's IRB, the RRB agrees to provide access for the approved research project. If we have any concerns or need additional information, we will contact you or Ferris State University's IRB.

Sincerely,

M. Lynn Breer

M. Lynn Breer, Ph.D.
Director of Institutional Research
Lake Land College

Lake Land College

Research: Authorization to Conduct Human Subject Research Procedures and Documentation

To receive proper authorization to conduct human subject research as defined by the Department of Health and Human Services Protection of Human Subjects Act with Lake Land College students and/or staff, the ***Request to Conduct Research at Lake Land College*** forms, along with all additional documentation, must be completed and submitted to the Director of Institutional Research at Lake Land College. Upon receipt of the documentation, the Director of Institutional Research will convene the Research Review Board (RRB) to review the submission and provide the RRB's recommendation to the College President or appropriate Vice President who has final approval for all research requests. The Director of Institutional Research will then communicate all final decisions related to Authorization to Conduct Human Subject Research with the requester and will maintain all related records on behalf of the Research Review Board This procedure is intended to ensure that college staff and students who may be affected by the research can be certain that the research is sound and in accordance with board policy, college operating procedures, and federal regulations concerning protection of human subjects.

Please submit the completed form as well as the required documentation below to Lynn Breer, the Director of Institutional Research at Lake Land College. Please email all documentation to mbreer@lakelandcollege.edu.

Required Documentation:

1. Copy of the IRB approval letter from an accredited institution
2. Copy of completed IRB submission forms from accredited institution
3. Copies of all data collection instruments and requisite informed consent forms.
4. Completed Request to Conduct Human Subject Research at Lake Land College Submission Form
5. Data Agreement
6. Any other supportive documentation

Request to Conduct Human Subject Research at Lake Land College Submission Form

Title of Project: ______________________________

Person(s) Conducting Research:

Ikemefuna Nwosu inwosu@lakelandcollege.edu 217-234-5309

(name) (e-mail) (Phone)

____

(name) (e-mail) (Phone)

Affiliated With: ____Ferris State University, Big Rapids, MI______________

(i.e., educational institution)

Director of Institutional Review Board at affiliated institution

___ Susan DeCamillis ,Ph.D___________________IRB@ferris.edu/ decamis@ferris.edu

(name) (e-mail)

Abstract:

Many community colleges are providing accelerative interventions for underprepared students by allowing them to enroll in corequisite math and English courses. These courses allow students to enroll into both remediation and college-level math and English and complete within a semester. However, there no studies that have looked at how affective factors like either grit and attitudes towards mathematics (ATM) of students influence their success in corequisite gateway math courses. This study attempts to explore the relationship and the extent that affective factors like grit and ATM, influence student success in co-requisite math gateway course.

Data Agreement

All researchers requesting to conduct research with Lake Land College current or former students and/or staff must agree and comply with the following conditions:

1. The researcher(s) will conduct research in accordance with federal regulations concerning protection of human subjects and established college policies regarding the protection of student rights.
2. The researcher(s) must notify study participants that this research has been approved by the college but is in no way sponsored by the college.
3. The researcher(s) must provide a written summary of results to Lake Land College's Director of Institutional Research. If appropriate, a copy of the publication in which the results of the research are published should be supplied to the Director of Institutional Research.
4. Lake Land College will not be named in any published results.
5. The researcher(s) must provide research data, if the Research Review Board requests a copy of the data collected from Lake Land College.
6. The researcher(s) agree to destroy all ***identifiable*** data (i.e., names, contact information, etc.) within 24 months after completion of data collection.
7. Participants must be informed that participation is voluntary.
8. Participants must be informed that participation or non-participation will not impact their status in any way with Lake Land College.
9. Research may not begin until all required documentation has been submitted.

The researcher(s) has submitted the required documentation, written information, and agrees to the five items listed above.

___IKEMEFUNA NWOSU__________________________ _____4/23/2019_______

Person(s) requesting authorization | Date

APPROVE ☐ | APPROVED WITH RECEPT OF IRB LETTER ☒ | DENY ☐

______________________________ 5/1/2019

Chair, Research Review Board | Date

______________________________ 5/1/2019

President or Vice President, Lake Land College | Date

APPENDIX B: FERRIS STATE UNIVERSITY IRB APPROVAL

FERRIS STATE UNIVERSITY
INSTITUTIONAL REVIEW BOARD FOR HUMAN SUBJECT RESEARCH
1010 Campus Drive FLITE 410 Big Rapids, MI 49307 | (231) 591-2553 | www.ferris.edu/irb

Date: May 21, 2019
To: Sandra Balkema
From: Gregory Wellman, R.Ph, Ph.D, IRB Chair
Re: IRB Application *IRB-FY18-19-93 The Influence of GRIT and Attitude to Mathematics on Academic Performance.*

The Ferris State University Institutional Review Board (IRB) has reviewed your application for using human subjects in the study, *The Influence of GRIT and Attitude to Mathematics on Academic Performance.(IRB-FY18-19-93)* and approved this project under Federal Regulations Exempt Category 1. Research, conducted in established or commonly accepted educational settings, that specifically involves normal educational practices that are not likely to adversely impact students' opportunity to learn required educational content or the assessment of educators who provide instruction. This includes most research on regular and special education instructional strategies, and research on the effectiveness of or the comparison among instructional techniques, curricula, or classroom management methods.
Category 2.(ii). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording).
Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.

Approval has an expiration date of one year from the date of this letter. **As such, you may collect data according to the procedures outlined in your application until May 20, 2020**. Should additional time be needed to conduct your approved study, a request for extension must be submitted to the IRB a month prior to its expiration. Your protocol has been assigned project number IRB-FY18-19-93. Approval mandates that you follow all University policy and procedures, in addition to applicable governmental regulations. Approval applies only to the activities described in the protocol submission; should revisions need to be made, all materials must be reviewed and approved by the IRB prior to initiation. In addition, the IRB must be made aware of any serious and unexpected and/or unanticipated adverse events as well as complaints and non-compliance issues.

Understand that informed consent is a process beginning with a description of the study and participant rights, with the assurance of participant understanding followed by a signed consent form. Informed consent must continue throughout the study via a dialogue between the researcher and research participant. Federal regulations require each participant receive a copy of the signed consent document and investigators maintain consent records for a minimum of three years. As mandated by Title 45 Code of Federal Regulations, Part 46 (45 CFR 46) the IRB requires submission of annual reviews during the life of the research project and a Final Report Form upon study completion. Thank you for your compliance with these guidelines and best wishes for a successful research endeavor.

Regards,

Gregory Wellman, R.Ph, Ph.D, IRB Chair
Ferris State University Institutional Review Board

APPENDIX C: IEA PERMISSION REQUEST FORM

Number IEA-22-070 (to be filled by IEA)

IEA

Researching education, improving learning

PERMISSION REQUEST FORM

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*Enter a space if no text is needed on a specific section

1. Requested IEA material

1.1. Please indicate the source of the requested IEA material:

Author/editor: Click or tap here to enter text.

Title: Click or tap here to enter text.

ISBN: Click or tap here to enter text.

Date of publication: Click or tap here to enter text.

URL: file:///C:/Users/inwosu/Dropbox/dccl/ResearchPapers/ATM/T19_StuQ_SepSc_8.pdf

1.2. Please provide information about the requested IEA material:

Language of requested materials: Click or tap here to enter text.

NOTE: Translated study materials are jointly owned by IEA and the National Study Center in the respective country. IEA will take the needed steps to acquire joint permission.

Description of requested IEA material (add information only on the requested materials):

- ☐ Assessment items (add the block or ID number): Click or tap here to enter text.
- ☐ Background questionnaires (e.g., home, teacher, school, or student): Items: 16, 19, 20
- ☐ Text excerpt (e.g., chapter number): Click or tap here to enter text.
- ☐ Figure/table: Click or tap here to enter text.
- ☐ TIMSS 2019 ePLAYER, Restricted Use Items (add Grade 4 and/or Grade 8, with or without PSI items): Click or tap here to enter text.
- ☐ Other: Click or tap here to enter text.

NOTE: Only restricted use items of assessment/test items can be requested. Please visit the relevant study website for this information. For further information, email permission.requests@iea.nl.

2. How IEA material will be used

2.1. Information about your intended use (select all that apply):

☒ Non-commercial ☐ Commercial

☒ Thesis (Bachelor, Master, Doctoral) ☐ Publication (e.g., article, book)

☒ Data collection (if known, please complete below):

•Sample size: 155 •Data collection window: Fall 2019

☐ Other, please specify: Click or tap here to enter text.

If applicable, please provide sufficient information about:

- Your research question(s): THE INFLUENCE OF GRIT AND ATTITUDE ON THE PERFORMANCE OF MIDWEST COMMUNITY COLLEGE STUDENTS ENROLLED IN COREQUISITE MATH COURSES
- The methodology to be used: I used valuing, liking and confidence in mathematics items and created a survey for 155 sophmore/freshmen students.
- The intended use of data and plans for reporting it: I am working on my dissertation since fall of 2019. I am now only beginning to analyze the data obtained. I wish to complete my thesis this year in December.

2.2. Information about where the requested materials or research results will appear:

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- ☐ Print publication
- ☐ Website (URL:Click or tap here to enter text.)
- ☐ Online publication (e.g., online journal)
- ☒ Other, please specify: Ferris state University Thesis repository.

2.3. Additional information about the planned publication (if applicable):

Author: Click or tap here to enter text.
Title: Click or tap here to enter text.
Publisher or sponsor: Click or tap here to enter text.
Language of publication: Click or tap here to enter text.
Intended audience: Click or tap here to enter text.
Number of copies for distribution: Click or tap here to enter text.
Retail price: Click or tap here to enter text.
Release date: Click or tap here to enter text.
Additional comments: Click or tap here to enter text.

3. Requestor information

First name: Ike
Last name: Nwosu
Name of institution or organization: Lake Land College
City and zip code: Mattoon, IL 61822
Country: USA
Email: inwosu@lakelandcollege.edu

Signature: INwosu

Date of request:20 September 2022

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To be completed by IEA

4. Permission

☒ Granted ☐ Denied

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☒ Free ☐ Agreed Fee (payable to NL63ABNA0481961968)

Signature: D. Hastedt Date: 25 November 2022

Name: Dirk Hastedt

Title: Executive Director

[1] Cf. ECJ 16 July 2009, Case C-5/08 (Infopaq I).

APPENDIX D: DUCKWORTH RESEARCH PERMISSION

Angela Duckworth

THE BOOK FAQ RESEARCH ABOUT CHARACTER LAB

Research

My research focuses on two traits that predict achievement: grit and self-control. Grit is the tendency to sustain interest in and effort toward very long-term goals (Duckworth et al., 2007). Self-control is the voluntary regulation of impulses in the presence of momentarily gratifying temptations (Duckworth & Seligman, 2005; Duckworth & Steinberg, 2015). On average, individuals who are gritty are more self-controlled, but the correlation between these two traits is not perfect: Some individuals are paragons of grit but not self-control, and some exceptionally well-regulated individuals are not especially gritty (Duckworth & Gross, 2014).

Measures

Researchers and educators are welcome to use the scales I have developed for non-commercial purposes.

On a cautionary note, these scales were originally designed to assess individual differences rather than subtle within-individual changes in behavior over time. Thus, it's uncertain whether they are valid indicators of pre- to post-change as a consequence of interventions.
I also discourage the use of these scales in high-stakes settings where faking is a concern (e.g., admissions or hiring decisions). Please see the article Measurement Matters for more information.

If you are interested in grit in particular, I encourage you to use the 12-item Grit Scale since the 8-item questionnaire omits items that, in my current view, are important in underscoring goal pursuit over extended time frames.

These scales are copyrighted. They cannot be published or used for commercial purposes or wide public distribution. Therefore, journalists and book authors should not reproduce these scales nor any part of them.

Grit

12-Item Grit Scale
8-Item Grit Scale
Biodata Grit Activities Grid

Other

Academic Diligence Task
Mirror Tracing Frustration Task
Measures from Gates College Persistence Study
Self-Control Scale (For Children)

APPENDIX E: STUDENT DEMOGRAPHIC INFORMATION

Student Demographic Information

Last Name _________________________ First Name_____________________

In this part of the survey, you will find two basic questions about your student profile. Please answer them as accurately as you can.

1. Do you receive financial aid? e.g. Pell Grant ___________ (yes or no)
2. Do you work part-time or full time hours? ____________(Part-time = less than 40hrs a week OR Full-time = 40 or more hours a week)

8-Item Grit Scale

Directions for taking the Grit Scale:

Respond to the following 8 items. Be honest – there are no right or wrong answers.

1. New ideas and projects sometimes distract me from previous ones. *
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
2. Setbacks do not discourage me.
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
3. I have been obsessed with a certain idea or project for a short time but later lost interest. *
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
4. I am a hard worker.
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
5. I often set a goal but later choose to pursue a different one. *
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
6. I have difficulty maintaining my focus on projects that take more than a few months to complete. *
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not much like at all
7. I finish what I begin.
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all
8. I am diligent.
   - ☐ Very much like me
   - ☐ Mostly like me
   - ☐ Somewhat like me
   - ☐ Not much like me
   - ☐ Not like me at all

Attitude Toward Mathematics (ATM) Survey

In this survey, you will find questions about yourself. Some questions ask for facts while other questions ask for your opinion. Each question is followed by a number of answers. Fill in the circle next to the answer of your choice.

How much do you agree with these statements about your mathematics lessons?				
	Agree a lot	Agree a little	Disagree a little	Disagree a lot
I enjoy learning mathematics	○	○	○	○
I wish I did not have to study mathematics	○	○	○	○
Mathematics is boring	○	○	○	○
I learn many interesting things in mathematics	○	○	○	○
I like mathematics	○	○	○	○
I like any schoolwork that involves numbers	○	○	○	○
I like to solve mathematics problems	○	○	○	○
I look forward to mathematics class	○	○	○	○
Mathematics is one of my favorite subjects	○	○	○	○

How much do you agree with these statements about mathematics?				
	Agree a lot	Agree a little	Disagree a little	Disagree a lot
I usually do well in mathematics	○	○	○	○
Mathematics is more difficult for me than for many of my classmates	○	○	○	○
Mathematics is not one of my strengths	○	○	○	○
I learn things quickly in mathematics	○	○	○	○
Mathematics makes me nervous	○	○	○	○
I am good at working out difficult mathematics problems	○	○	○	○
My teacher tells me I am good at mathematics	○	○	○	○
Mathematics is harder for me than any other subject	○	○	○	○
Mathematics makes me confused	○	○	○	○

How much do you agree with these statements about mathematics?				
	Agree a lot	Agree a little	Disagree a little	Disagree a lot
I think learning mathematics will help me in my daily life	○	○	○	○
I need mathematics to learn other school subjects	○	○	○	○
I need to do well in mathematics to get into the college or university of my choice	○	○	○	○
I need to do well in mathematics to get the job I want	○	○	○	○
I would like a job that involves using mathematics	○	○	○	○
It is important to learn about mathematics to get ahead in the world	○	○	○	○
Learning mathematics will give me more job opportunities when I am an adult	○	○	○	○
My parents think that it is important that I do well in mathematics	○	○	○	○
It is important to do well in mathematics	○	○	○	○