Identifying psychological factors that improve mathematics achievement in Grade 9 pupils from Gauteng

by

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ABSTRACT

The South African mathematics pass rate is below par when compared to international benchmarks, a trend that continues to negatively impact tertiary education opportunities and the national economy. This study aimed to investigate the unique contribution of mindset, study orientations, and personality traits in influencing the mathematics performance of grade nine learners, over and above the predictive value explained by fluid intelligence. A sample of grade nine learners from various schools across the Gauteng province provided their latest mathematics marks. Furthermore, learners completed the Raven's Standard Progressive Matrices, Implicit Theories of Intelligence, Study Orientation Questionnaire in Mathematics, and Basic Traits Inventory. Logistic regressions reported that study orientations, such as learner study attitudes, mathematics anxiety, study habits, and problem-solving behaviour, as well as the study milieu, directly predict mathematics marks. Additionally, hierarchical regression models demonstrated that facets of conscientiousness, extraversion, and agreeableness moderate the influence of study orientations to predict mathematics performance. Overall, it is concluded that fluid intelligence, study orientations, and personality add significant value in predicting grade nine learners' mathematics performance. Therefore, this study calls for a multidisciplinary approach where psychological and educational bodies collaborate to better understand at which stages of learners' scholastic careers study orientations and personality dispositions shape mathematics performance. Additionally, it is recommended that a longitudinal study, using larger learner samples, be conducted in both rural and urban areas to further understand the impact of study attitudes and mathematics anxiety on mathematics performance.

***Keywords*:** fluid intelligence, mathematics performance, mindset, personality, study orientations

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DECLARATION

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ETHICS STATEMENT

I, **Pakeezah Rajab**, student number **21779806**, have obtained ethical approval for the research titled: *Identifying psychological factors that improve mathematics achievement in Grade 9 learners from Gauteng*.

On 1 August 2022, I received ethical approval (reference number: **HUM035/0721**) from Prof Karen Harris, Chair of the Research Ethics in the Faculty of Humanities at the University of Pretoria.

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GLOSSARY

Term	Definition
Agreeableness	Propensity to get along with, and show compassion for, others.
Conscientiousness	Disposition of individual to plan and organise, with prudence and self-discipline.
Extraversion	Extent to which individual enjoys the stimulation provided by their environment and others' company.
Fluid intelligence	Innate patterns of thinking and novel problem-solving, independent of acquired skill and socioeconomic or educational context.
Mathematics anxiety	Panic, anxiety, and concern felt towards mathematics.
Mindset	Also known as implicit theories of intelligence, mindset relates to one's beliefs about their intelligence, abilities, and capacity to grow and learn.
Neuroticism	Tendency to get easily upset, depressed, anxious, or overly self-conscious.
Openness to experience	Degree to which an individual enjoys novelty, unconventionality, and are curious about the world.
Problem-solving behaviour	Thinking about one's cognitive processes when solving mathematical problems.
Study attitude	Confidence, enjoyment, and motivation towards mathematics.
Study habits	Willingness to learn and consistently practice mathematics.
Study milieu	Sociocultural and physical environments that support or hinder learners' study efforts.
Study orientations	Learners' approaches, motives, styles, study methods, and attitudes towards a particular subject at school.

Chapter One: Establishing the Research Objectives

Introduction

Slightly over a decade ago, South Africa had set the goal of enabling approximately 90% of grade nine learners to achieve 50% or more in the annual national mathematics assessments (National Development Plan [NDP] 2030, 2012). Moreover, the NDP (2012) set the goal of increasing the number of learners eligible for further mathematics and science-based degrees. The World Economic Forum (WEF) Global Information Technology Report (Baller et al., 2016) indicated that South Africa (65th) was one of the top ten upward movers in terms of readiness for innovation in the digital economy.

Unfortunately, current realities do not align with these visionary goals, with the quality of South African mathematics education being on par with low-income nations, rather than that of a middle-income nation (Van der Berg et al., 2020). Although there have been incremental improvements in the number of learners passing the National Senior Certificate (NSC) mathematics examination, it is not a direct indication of learners having mastered the concepts taught within the curriculum (Taylor, 2021). Despite the Trends in International Mathematics and Science Study (TIMSS) benchmarking mathematics performance of grades four and eight globally, grades five and nine were assessed in South Africa to allow fair benchmarking (Mullis et al., 2020). Furthermore, South Africa subsequently performed third lowest globally in the TIMSS with learners scoring slightly lower than in 2015 (Mullis et al., 2020). Given the importance of mathematics for growth within the science, technology, engineering, and mathematics (STEM) fields, these trends are concerning. At an individual level, lower mathematics performance limits career options post-matric. At the national economic level, the decline in adequately qualified graduates and employees to progress South African innovations to align with global leaders is lacking.

Background to the Research Problem

The preliminary report on the 2022 NSC examination outcomes disclosed a national pass rate of 80.1%, with 38.4% of learners achieving a Bachelor's pass (Mweli, 2023). This report also indicates that despite a 3.9% increase in mathematics enrolments and 38% of learners writing the NSC examination, the national mathematics pass rate was 55.0%, a drop from 57.6% achieved in 2021 (Mweli, 2023). In comparison, enrolments in mathematics literacy increased by 1.6% and illustrated a significant improvement in the mathematics literacy pass rate from 74.5% in 2021, to 85.7% in 2022 (Mweli, 2023). Examining these pass rates further, it is reported that only 2.7% of learners who wrote mathematics passed with distinction (a mark of 80% or higher), while only 1.7% of learners who completed the mathematics literacy examination passed with distinction (Mweli, 2023). A more detailed description of the Gauteng province learner sample, where the current study has been conducted, shows that Gauteng learners achieved an average of 62.7% (7.7% higher than the national average), with independent schools performing better (77.0%) than both public fee-paying (66.4%) and non-fee-paying (51.5%) schools (Mweli, 2023).

Mweli (2023) highlighted that since 2020, learners have had to adjust to increased load-shedding, protests, declines in service delivery, as well as the aftermath of the Covid-19 pandemic and subsequent disruptions to classes. However, the low rates of mathematics distinctions specifically limit how many learners are eligible for enrolment in STEM-related undergraduate courses. Mweli (2023) therefore sets the current context in which this study was conducted, and from which several questions arise. The discrepancy between the mathematics pass rate and the low number of mathematics distinctions, compared to the pass rates and distinctions across subjects, is also apparent. Such findings suggest that the concern is less with the intellectual ability of learners impacting performance across subjects, but rather the environmental and personal factors related to mathematics performance (Mabena et al., 2021).

In acknowledging environmental factors, learners with higher socioeconomic standing, perform significantly better in mathematics (Echazarra & Radinger, 2019). Furthermore, the trend of low mathematics performance could be attributed to teachers in lower socioeconomic standing schools not having adequate resources, not receiving adequate training, or lacking the capacity to provide personal attention to large numbers of learners (Du Plessis & Mestry, 2019). Some of these concerns are relevant even in higher socioeconomic schools, as learners who do not share their concerns with teachers are unlikely to be supported. Further exploring the influence of teachers, Arends and Visser (2019) found that learners' relationships with teachers positively contributed to mathematics performance, even after considering socioeconomic status. As such, the learners' willingness to ask questions when unsure and motivation to understand the subject material, likely aids in building a relationship with teachers, in turn positively influencing mathematics performance.

Moving the emphasis to personal factors, seeing more learners enrolling for mathematics, instead of mathematics literacy, is suggestive of a positive attitude and motivation towards the subject. This is in contrast with the observations by Mabena et al.

(2021, p. 460), who stated that “learners show no interest in learning mathematics”. In exploring the lack of interest and disengagement of learners towards mathematics, Anson (2021) cautioned that the role of mathematics anxiety should not be underestimated, and that it is not that learners do not see the value of the subject, but rather that learners lack self-confidence in their mathematics abilities. Garba et al. (2020) further highlighted that mathematics anxiety is displayed as a fear of mathematical problems and in some cases, learners may experience physical pain, discomfort, or cognitive confusion. Therefore, mathematics anxiety can cause temporary forgetfulness of learnt materials, due to the high levels of learner stress and worry when confronted with such material. There is therefore value in exploring whether learners who naturally have a more anxious personality profile might experience exacerbated mathematics anxiety, and how these learners could be supported. While O’Hara et al. (2022) underlines the importance of a supportive classroom learning environment in mitigating mathematics anxiety, Cheema and Sheridan (2015) found that positive habits such as spending sufficient time studying mathematics, can mitigate the influence of mathematics anxiety on mathematics performance, even when accounting for learner socioeconomic status. In promoting positive study habits, many learners will grow in confidence in their mathematics abilities, thereby motivating them to persist with difficult material despite possible fears of failure (Özcan & Gümüs, 2019).

Therefore, to appreciate the variability in factors that underly mathematics performance, the benefit can be seen in understanding the dynamic interplay between psychological factors (intellectual ability and personality), behavioural factors (mindset, study attitudes, and study habits), and environmental factors (study support). It is therefore the aim of this study to investigate the predictive value of these intellectual and non-intellectual factors in enabling learners to achieve adequate mathematics performance in secondary school.

The motivation for such an investigation is guided by the need to develop targeted interventions and strategies to improve mathematics performance for learners. By determining the relative value of psychological, behavioural, and environmental factors and how they relate to mathematics performance, a holistic and multidisciplinary approach can be taken. This approach would not only incorporate the curriculum and learner motivation to perform, but also the psychological well-being of learners to enhance learning experience, confidence, and success in mathematics. Moreover, the findings of the study will add to the supporting body of evidence that guides policymakers in enhancing interventions to improve mathematics performance more systemically. Mathematics education relates to developments and innovations within the STEM fields, skills that are scarce and critical in South Africa for a more employable workforce and prosperous economy (WEF, 2016). As such, this study stands to benefit learners, teachers, parents, and the larger society by equipping learners with the skills deemed essential for future success within the STEM fields.

Setting the Research Objectives

Contributing mathematics performance to a single factor, such as learner intellectual ability or teaching efficiency, neither motivates nor encourages learners to exhibit any effort. Furthermore, it is incorrect to assume that a single factor fully explains the multi-faceted reality of learner mathematics performance. Therefore, this study aims to determine which non-intellectual psychological factors (mindset, study orientation to mathematics, and personality) best predict mathematics performance effectively in South African grade nine learners, whilst accounting for fluid intelligence. Identifying these factors will attribute to the existing body of literature, while also directing practical initiatives to improve the general understanding of mathematics performance in South Africa.

While the relationship between intelligence and mathematics has been comprehensively explored by previous studies (Hilbert et al., 2019; Abin et al., 2020), considering the impact of mindset, study orientations, and personality factors on mathematics performance, without accounting for intelligence, would not provide practical and meaningful insights. Study orientations are malleable in that learners can adjust their approaches, motivations, study methods, and attitudes towards mathematics (Maree, 1997; Maree et al., 2011). In contrast, personality traits are relatively stable across adolescence and throughout the individual lifespan (De Moor et al., 2023; Goldstein et al., 2022). Therefore, two key objectives for the current study have been formulated:

1. To determine the relationship between mindset and aspects of study orientation towards mathematics (study attitude, mathematics anxiety, study habits, problem-solving behaviours, and study milieu) with mathematics performance, whilst accounting for fluid intelligence;

2. To investigate the moderating influence of the five-factor model of personality on mindset, study orientation towards mathematics, and mathematics performance, whilst accounting for fluid intelligence.

Given the two study objectives, the moderating role of more malleable mindsets and study orientations will first be explored in the relationship between fluid intelligence and mathematics performance. Following the analyses of these relationship, the long-term influence of personality on the relationships investigated in objective one will be considered.

From the two study objectives and clarifying the various factors encompassed in study orientation and personality, a total of 15 hypotheses will be tested to fill gaps or address contradictions in existing literature, which will be explored further in Chapter Two.

For the current study, the hypotheses are:

H_O1: A growth mindset does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A1: A growth mindset moderates the positive relationship between fluid intelligence and mathematics performance.

H_O2: A fixed mindset does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A2: A fixed mindset moderates the negative relationship between fluid intelligence and mathematics performance.

H_O3: Study attitude does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A3: Study attitude moderates the positive relationship between fluid intelligence and mathematics performance.

H_O4: Mathematics anxiety does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A4: Mathematics anxiety moderates the negative relationship between fluid intelligence and mathematics performance.

H_O5: Study habits do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A5: Study habits moderate the positive relationship between fluid intelligence and mathematics performance.

H_O6: Problem-solving behaviours do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A6: Problem-solving behaviours moderate the positive relationship between fluid intelligence and mathematics performance.

H_O7: The study milieu does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A7: The study milieu moderates the positive relationship between fluid intelligence and mathematics performance.

H_O8: Openness to experience does not interact with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A8: Openness to experience interacts with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

H_O9: Openness to experience does not interact with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A9: Openness to experience interacts with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

H_O10: Conscientiousness does not moderate mindset’s relationship with fluid intelligence and mathematics performance.

H_A10: Conscientiousness moderates mindset’s relationship with fluid intelligence and mathematics performance.

H_O11: Conscientiousness does not interact with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A11: Conscientiousness interacts with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

H_O12: Extraversion does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A12: Extraversion interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_O13: Agreeableness does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A13: Agreeableness interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_O14: Neuroticism does not interact with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A14: Neuroticism interacts with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

H_O15: Neuroticism does not interact with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A15: Neuroticism interacts with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

Synthesis of Chapter One

The present study argues that in addition to intelligence, the mindset, study orientations, and personality of grade nine learners significantly influence mathematics performance. After establishing the predictive strength of fluid intelligence on mathematics performance in grade nine learners in the Gauteng province, the moderating effects of adaptable behaviours, such as learner mindset and study orientations, will be explored. Thereby establishing where efforts should be invested if the South African educational system is to effectively guide learners in mastering mathematics. Secondly, the role of more stable traits throughout adolescence, such as learner personality, will then be factored in to consider the influence on learner mindset, study orientations, and the relationship between fluid intelligence and mathematics performance.

Chapter One provided context to the study, highlighting the importance of understanding factors within learners that influence their mathematics performance. The discussion leads to research objectives centred around the learner's intelligence, study orientations towards mathematics, and personality factors that each predicts mathematics performance. These objectives are further argued based on their theoretical and practical contributions. The chapter concludes with a summary of this introductory chapter, leading into Chapter Two, which is a comprehensive literature review of these elements.

Thesis Structure and Layout

Chapter One positioned the problem statement within the South African context, establishing an argument for several factors to be considered when addressing the concerning mathematics performance of South African grade nine learners. Chapter Two commences with a literature review of the various factors, starting with a summary of literature supporting the underlying assumption that intelligence predicts learner mathematics performance. This is followed by an operationalisation and discussion of growth and fixed mindset, the five study orientations under consideration, and the five factors of personality, which leads to the formulation of the 15 hypotheses being investigated. Chapter Three covers the study methodology utilised – the theoretical paradigm, sampling, data collection, analytic methods, and ethical considerations. Chapter Four reports on the results of the respective hypotheses, followed by a discussion in Chapter Five of the theoretical and practical implications of the study findings for improving mathematics performance in secondary school learners in South Africa.

Chapter Two: Literature Review

Introduction

Mathematics proficiency and engagement is a core skill that impacts individual learners' career choices and successes, as well as those of the national (and international) economy (Lipnevich et al, 2016; Priess-Groben & Hyde, 2017). However, the mathematics performance of South African learners is concerning, as the Trends in International Mathematics and Science Study (TIMSS) (Mullis et al., 2020) found that South African grade nine learners scored the second lowest globally in mathematics. This is in line with previous literature, as the United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute of Statistics (2019) reported that only 34% of South African learners in grades seven to 10, achieved a minimum proficiency level in mathematics. Furthermore, the World Economic Forum (WEF) ranked South Africa 139th, the lowest possible ranking, in mathematics and science education worldwide (Baller et al., 2016). Since education in mathematics is one of the pillars of a society's readiness for innovation in the digital age, learners should be empowered with the competence to achieve in mathematics. This is especially important if South Africa wants to position itself as a leader in areas such as artificial intelligence, robotics, and genetics (Baller et al., 2016).

The reductionist view that attributes academic performance to either intellectual or non-intellectual (situational) factors, does not reflect the complexity of mathematical learning (Harris, 2018). Cognitive ability has already been established as a key determinant of academic performance and intellectual potential (Furnham & Chamorro-Premuzic, 2006). However, cognitive ability alone does not fully explain individual differences in academic performance (Furnham & Chamorro-Premuzic, 2006). Non-cognitive factors that have consistently shown to impact academic performance are, among others, planning and organisation abilities, self-discipline, self-concept, learning routines and habits, stress management, and test anxiety (McClure et al., 2011; Wehner & Schils, 2021).

Personality dimensions, which highlights individual traits and how individuals approach tasks, have also received more attention in recent years (Poropat, 2009; Richardson et al., 2012). Locally, the research on study orientations is limited (Erasmus, 2013; Maree et al., 2014), with no known research to date investigating the concurrent contribution of mindset, study orientations towards mathematics, and personality dimensions on mathematics performance, whilst accounting for cognitive potential.

Although the focus of the current study is on non-intellectual factors that influence learner mathematics performance, these factors will be evaluated while accounting for fluid intelligence. Therefore, this chapter will provide an overview of the relationship between intelligence and mathematics performance, before reviewing literature pertaining to mindset, study orientations towards mathematics, and the five-factor model of personality, and their established or hypothesised relationships with mathematics performance.

Intelligence and Mathematics Performance

Over the past century, the use of intelligence measures to predict academic performance has become a well-established procedure (Brown & French, 1979; Furnham & Chamorro-Premuzic, 2006; Spearman, 1904). This relationship has not always shown the same effect across the lifespan of an individual. However; Jenson (1980) found that the strength of the positive relationship between academic performance and intelligence declined as learners progressed from primary to tertiary education. Furthermore, Laidra et al. (2007), noted how increasing biological age reduced the positive relationship between academic performance and intelligence. Nevertheless, Strenze (2007) was able to demonstrate how intelligence consistently indicated a relationship with academic performance during the educational years, and later with occupational prestige and status.

The relationship between cognitive abilities and mathematics performance specifically, has been studied in various contexts (Hilbert et al., 2019; Abin et al., 2020). Locally, to progress to grades 10 to 12, learners need to showcase their proficiency in perceiving, illustrating, and exploring patterns and quantitative connections in both tangible and intangible mathematical concepts during grades seven to nine (Department of Basic Education [DBE], 2011). As such, a shift from comprehending concrete patterns and relationships, to applying them more abstractly during the subsequent phases of education, is required of learners.

Acknowledging that the mathematics curriculum strives to cultivate a learners' critical thinking and abstract problem-solving skills, it is necessary to examine theories of adolescent cognitive development., This will allow for a holistic comprehension of the significance of non-intellectual factors, which will be discussed later in this chapter.

Cognitive Development Theory

Piaget (1928, 1960), an early theorist who studied cognitive development in children, proposed that children constructed cognitive development by moving through four sequential and universal development stages. These four stages consisted of: 1) sensorimotor stage, from birth to two years of age, 2) preoperational stage, ages two to seven years, 3) concrete operational stage, ages seven to 11 years, and 4) formal operational stage, ages 11 years and older. The key attainments during the formal operational stage, are that firstly, adolescents' problem-solving processes commence with a hypothesis or prediction where inferences can logically be deduced and confirmed (Inhelder & Piaget, 1958). Secondly, these inferences can be evaluated without reference to real-world circumstances (Inhelder & Piaget, 1958), creating cognitive capacity for abstract and systematic thought processes which are required of learners from grades seven to nine and onwards. In this study, it is therefore assumed that South African grade nine learners, between the ages of 14 and 16 years, are functioning at this formal operational development stage.

However, Piaget's stages have been countered by studies that found that cognitive development is a constant acquisition and modification of thought process throughout childhood and adolescence (Bjorklund, 2012; Case & Okamoto, 1996). Abstract reasoning has also been found to develop as an individual receives extensive exposure, guidance, and practice in the use thereof (Kuhn, 2008), contradicting Piaget's acceptance that the formal operational stage is invariant and occurs naturally once an individual's prefrontal cortex matures. In this regard, Bolton and Hattie (2017) noted that the relationship between genetics and the development of executive functioning, performed by the prefrontal cortex and which includes skills such as planning and adaptive thinking, had yet to be determined. Therefore, Bolton and Hattie (2017) suggests that children may not develop the required biological structures at the same rate and within the provided age brackets, to fit into the proposed four-stage theory of Piaget (1928).

Juraschek (1983) notes that by age fifteen, only some learners are functioning at a formal operational level, which is key to understanding concepts such as proportions and probability. Such findings raise the question of how much learning is demonstrated in being able to follow through on mathematical rules (formulae), when compared to abstract and complex problem-solving. This concept is addressed in section 2.4.4, where orientations towards developing problem-solving behaviours specific to mathematics are covered. Keating (2004) further highlighted that the use of formal operations was specific to contexts and tasks, rather than a general way of thought. Despite the contradictory evidence to

Piaget's (1960) theory, Piaget's constructive vision of a child's cognitive development laid the general foundation for the current study to understand cognitive development in learners.

Sociocultural Theory

While Piaget's (1960) work emphasised the active role of the individual child in developing their thought processes, Vygotsky (1978) underlined the effect of social and cultural influences on a child's cognitive development. Vygotsky's (1978) theory postulates that meaningful learning occurs in the zone of proximal development, where adults and peers assist with tasks that a child would otherwise find too difficult to accomplish independently. From an educational standpoint, Vygotsky's theory promotes assisted discovery and peer collaboration, showcasing the value of teachers and the larger schooling system (Berk, 2013). Roth (2012, 2018) highlights that while it is generally accepted that mathematics is a more abstract subject than most, these complex concepts are concrete in society. Therefore, mathematical concepts are observable and available for learning as per Vygotsky's model, with the use of language giving these abstract concepts meaning.

However, Newman and Latifi (2021) critique that while efforts to collaborate and imitate may lead to an improved understanding of a concept, the zone of proximal development provides less insight into initial learning, unless it is assumed that all learning begins as an imitation attempt. Additionally, Swanson and Williams (2014) query how the Vygotskian principles can be applied within the educational (or other institutionalised) systems. This is due to the uncertainty of whether a child's performance is an indication of their understanding of a mathematical concept, or whether they have simply been able to accurately 'imitate' and follow through by using an equation or formulae previously demonstrated to them, which is more commonly referred to as rote learning (Swanson & Williams, 2014).

Both the Piagetian 'milestone' approach and Vygotsky's perspective add valuable insights when the South African context is considered, where there are still notable disparities in socioeconomic conditions and quality of education (DBE, 2019). Subject curricula are based on the principle of progression, which includes empowering learners to acquire specific skills, develop understanding, and competently apply these skills. However, drawing parallels with elements of Piaget's theory, the quality of the exposure of these skills and how confidence is developed depends on the social resources available. Therefore, as per Vygotsky's premise, a possible explanation for individual differences in cognitive development is provided.

General Intelligence Theory

Keeping in mind the theoretical foundations of cognitive development and the subsequent practical and predictive implications of assessing learners' cognitive potential or general intelligence (*g*), an attractive attribute of assessing fluid intelligence is its stability, irrespective of socioeconomic variables. Fluid intelligence assessments, by their nature, measures the 'raw' intelligence of individuals and relates to information processing, working memory, and the ability to establish relationships between concepts, without educational influences. In contrast, crystallised intelligence measures are influenced by environmental and cultural factors such as acquired skills, learnt knowledge, and social and environmental status (Brown, 2016; Cattell, 1940).

Floyd et al. (2003) highlighted that fluid intelligence assessments measure patterns of thinking that are transferrable to mathematics performance, tapping into elements of problem-solving and strategic, abstract thinking. Geary et al. (2019a) noted that both fluid and crystallised intelligence contributed to the mathematics performance of adolescents, however, the ability to grasp and understand the novel concepts that are continuously introduced is related solely to fluid intelligence. Furthermore, evidence obtained across varying age groups and ethnicities in schools indicated that fluid intelligence is a better predictor of mathematics performance in a diverse context like South Africa (Cormier et al., 2017; McGrew & Wendling, 2010).

Mindset and Mathematics Performance

Identity construction – determining the goals, values, and beliefs one is committed to – is a concept that is a key developmental focus of adolescence (Erikson, 1968). Beliefs about one's intelligence, abilities, and capacity to grow are known as implicit theories of intelligence or, more commonly, as mindsets (Blackwell et al., 2007; Dweck, 2000). Moreover, mindsets are also shaped during adolescence, which in turn influence how learners react to academic challenges (Blackwell et al., 2007; Dweck, 2000). Mindset depends on the skill or subject under consideration (Scott & Ghinea, 2014), therefore having practical implications, since studies should preferably modify the questions posed to individuals to be as specific as possible to capture individuals' beliefs towards the specific skillset.

Dweck and Leggett (1988) simplify the concept of mindset by dividing individuals according to two theories of intelligence – entity (fixed) and incremental (growth). Entity theorists believe that intellectual ability is innate or fixed, regardless of whether individuals expend effort to be successful. In other words, entity theorists suppose that individuals are either competent at something or not, and that no amount of effort or practice will change that. In this respect, individuals with a high perceived competence are more likely to have a mastery orientation when confronted with new tasks, generally looking forward to the challenge. Inversely, individuals with low perceived competence are more likely to have a helpless orientation, believing that they will struggle with the task at hand irrespective of the effort they put into it (Dweck & Master, 2009). In contrast to entity theorists, incremental theorists believe that intellectual ability is malleable and that increased effort and practice will improve one’s performance until the skill is mastered.

In developing these mindsets, Haimovitz and Dweck (2016) found that when parents and teachers praise the child’s processes (effort and strategies used), the child developed a growth mindset, while praising the child (telling the child they are smart) predicted a fixed mindset (Gunderson et al., 2013; Gunderson et al., 2018). Despite teachers and parents influencing, but not passing on, their own mindsets to learners or children (Haimovitz & Dweck, 2016), a study by King (2019) found that fixed mindsets can be transferred between peers. This transfer of mindsets among peers could have negative influences in subjects like mathematics (King, 2019), which often has a reputation for being difficult (Usta, 2014). To reduce an increase in fixed mindsets in South African high school learners, schools should invest in workshops focused on teaching learners to persist when confronted with challenging tasks. Given that Haimovitz and Dweck (2017) demonstrated that growth mindsets could be taught, Boaler et al. (2018) showed that growth mindsets could be successfully developed by presenting a six-module online course aimed at school-going mathematics learners. This was supported by the findings of Yeager et al. (2019), despite them noting that the intervention had a weaker effect on grade nines in high-achieving schools.

If a learner has a fixed mindset and low perceived competence towards mathematics, it can negatively impact their motivation and perseverance to continue expending energy towards mathematics homework and examinations (Greene et al., 2004). Additionally, individuals with a fixed mindset are more likely to procrastinate (Howell & Buro, 2009), drop out, or deregister from mathematics altogether (Dai & Cromley, 2014), thereby validating their beliefs of not being capable (Haimovitz et al., 2011). Inversely, if the learner believes that they can master a skill, they are more likely to persist and continue to exert effort when they are confronted with difficult concepts in mathematics (Boaler, 2015). Furthermore, learners will be more likely to learn for the sake of mastery rather than achieving high marks (DeBacker et al., 2018), to collaborate, and to attempt alternative problem-solving strategies when existing methods fail (Campbell, 2019).

Li et al. (2021) found that during schooling, learners tend to experience a consistent decline in competence beliefs in mathematics. This decline may be because self-belief becomes more accurate and realistic during adolescence (Chiu & Klassen, 2010). Despite learners' mindsets influencing their behaviours and the effort they put into a subject, a consistent relationship between growth mindsets and higher academic performance has not been established (Burnette et al., 2013; Li & Bates, 2017). It is also suggested that a growth mindset by itself is not sufficient to ensure academic success, even if it does increase motivation (Aditomo, 2015). Jones et al. (2012) found a moderate relationship between effort beliefs (r = .30) and weak relationships between marks and low helplessness (r = .26), interest (r = .24), positive strategies (r = .21), and incremental theory (growth mindset) (r = .17). Moreover, no significant relationship with mastery and learning goals was found (Jones et al., 2012), indicating that while growth mindset may influence mathematics marks in grade nine, other factors better predict mathematics performance. Nevertheless, a meta-analysis by Sisk et al. (2018) found that mindset was a stronger predictor of academic performance than socioeconomic status, albeit a notable yet small effect of growth mindset on performance. A study by Hwang et al. (2019) also found that minority groups and lower socioeconomic status learners in the United States of America were less likely to endorse a fixed mindset towards mathematics. The findings of Hwang et al. (2019) is promising for Africa, given Africa's diverse cultures and economic inequalities. However, a meta-analysis by Costa and Faria (2018) highlighted the influence of cultural differences on how mindsets associate with performance. Furthermore, Liu (2021) commented that while Eastern collectivist countries encourage learning over performance, European countries emphasise outcomes over knowledge.

Within the South African context, Campbell (2019) highlighted that in addition to mindset, the role of effective learning habits (covered in section 2.4.3) and persistence (covered in section 2.5.2) should be explored in relation to academic performance. This is due to improvement in academic performance only being possible if learners engage effectively with the learning materials (Campbell, 2019). The non-intellectual factors of effective learning habits and persistence, and their influence on academic performance, will be covered in upcoming sections. However, the following sets of hypotheses were formulated for this study given the role of cognitive potential (as discussed in section 2.2) in relation to mindset within the South African context:

H_O1: A growth mindset does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A1: A growth mindset moderates the positive relationship between fluid intelligence and mathematics performance.

H_O2: A fixed mindset does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A2: A fixed mindset moderates the negative relationship between fluid intelligence and mathematics performance.

Study Orientations Towards Mathematics and Mathematics Performance

Grobler et al. (2001) and Maree (2009) assert that attributing underachievement in mathematics solely to intelligence might oversimplify a multiplexed issue, especially in Africa. More recently, Campbell (2019) stressed the limited application of looking at the relationship between mathematics performance and mindsets in isolation, within South African universities. Maree (2009) recommends that factors such as intervention strategies aimed at study orientations to mathematics could help remedy the national problem around mathematics education. Building on the definition of Schmeck (1988), Maree (1997) defines study orientation as the factor that summarises learners' approaches, motives, and styles, as well as study methods and attitudes towards a particular subject at school. Maree (1997) further distinguishes between six underlying factors of study orientations towards mathematics, namely study attitude, mathematics anxiety, study habits, problem-solving behaviour, study milieu, and information processing.

Information processing is a concept most relevant to the grade 10-12 syllabus, and will therefore not be discussed further. However, study attitude, mathematics anxiety, study habits, problem-solving behaviour, and study milieu will be discussed in the below sections. Thereafter, several hypotheses regarding the interactive effects of fluid intelligence and study orientations on mathematics performance will be presented. Even though the relationship between study orientation towards mathematics and mathematics performance is established (Maree et al., 2011), research is scarce on the relationship between study orientations towards mathematics while controlling for intelligence. More specifically, the interactive effects between fluid intelligence and the five factors of study orientations towards mathematics on mathematics performance have received limited attention to date (Taylor et al, 2019). Lastly, when proposing this research study, it appeared to be the first in the South African context to determine the relationship between mathematics mindset and study orientations towards mathematics, whilst accounting for fluid intelligence and mathematics performance.

Study Attitude

Maree et al. (2014) operationalised study attitude as the enjoyment of mathematics, self-confidence in the subject, and the belief that the subject is useful and challenging, thereby affecting motivation and interest towards learning mathematics. Theoretically, whilst this definition appears to be nested in Dweck's (2000) implicit theories of intelligence model (discussed in section 2.3), some aspects also link it to Bandura's social cognitive theory (Bandura et al., 1996). Bandura's (1996) theory postulates that self-efficacy, or the belief in one's capabilities to perform, involves cognitive, motivational, affective, and selection processes. While Dweck's (2000) mindset theory suggests that individuals with a growth mindset will be inclined to exert more effort towards challenging tasks until they are mastered, Bandura argues that belief alone does not result in more effort being put into a task, and that individual interpretations of past experiences also serve as motivation for present behaviours (Bandura, 1997; Chen & Tutwiler, 2017).

Bandura's theory suggests that behaviours, such as choosing to put effort into studying mathematics, are the result of the individual's choices (persistence, choosing studying over exciting tasks) as well as environmental factors, such as being rewarded or supported while working (Bandura, 1977). While mindset may be influenced by how parents and teachers praise learners (person versus process-based), self-efficacy beliefs are formed by learners reflecting on how their behaviours were previously reinforced (Bandura, 1977). Reinforcement takes place either directly, by parents and teachers rewarding learners or punishing them for their performance, or vicariously by learners seeing another child (likely a classmate or sibling) being rewarded or punished for their behaviours (Bandura, 1977). Moreover, self-reinforcement can take place by a learner wanting to feel pride, rather than shame or disappointment, or rewarding oneself for achieving a goal (Bandura, 1977).

There are often strong relationships between previous and current academic performances. A study by Hemmings and Kay (2010), found a relationship (r = .77) between year seven and 10 mathematics marks, and between year 10 mathematics marks and mathematics attitudes (r = .44). Therefore, how achievement is recognised in a child's earlier years could shape how they work towards achieving the same result, if not improving it, in the future. Priess-Groben (2018) assessed the mindset and self-concept of ability in grade nine learners, and found that self-concept was a greater predictor of mathematics motivation and courses chosen in further education than mindset.

However, there is evidence of some overlap between these two theories, as Chen (2012) found that mindset could influence cognitive processing, which in turn affects learners' beliefs of self-efficacy. Furthermore, the sense of mastery that is based on the achievement of challenging goals could be considered a characteristic of a growth mindset that increases self-efficacy (Bandura, 2013). Implicit theories of intelligence and social cognitive theory agree that it is unlikely that learners will effectively motivate themselves, or regulate their behaviours, to focus on mathematics, if they do not value or expect themselves to achieve in the subject (King et al., 2012; Zimmerman et al., 1992).

Practically, both concepts (mindset and self-efficacy) are subject or task-specific, rather than a general self-perception (Marsh et al., 2016). Given some key similarities and underlying motives between the two theoretical models, and the seeming overlap with study attitude, how mindset and study attitude differ in their strength in predicting mathematics performance will be explored as part of the current study.

Considering previous research on study attitudes, Mazana et al. (2019) found that high school learners, when compared to primary school learners, had lower positive study attitudes. Additionally, the study attitudes of high school learners was lowest by the time they left for college, blaming negative school experiences and increased mathematics anxiety for the decline (Mazana et al., 2019). Ma (1997) proposed that mathematics attitudes and abilities reciprocally strengthened each other within high school learners. Beal et al. (2008) further highlighted the influence of internal beliefs on learner behaviour, by concluding that learners who displayed higher motivation levels were more likely to ask for assistance with mathematics. This is in line with the findings of Crumpton and Gregory (2011), which demonstrated that grade nine learners who believed that school was relevant had higher levels of engagement and motivation, regardless of their ethnic or gender group. The meta-analysis by Richardson et al. (2012) revealed that performance self-efficacy explains the most variance in academic performance at the university level, after accounting for intellectual factors. The subsequent meta-analysis by Muenks and Miele (2017) reaffirmed that as learners' competence grows towards a certain subject, the more likely learners are to see its value, use self-regulatory strategies to meet subject-based goals, and perform better academically. Furthermore, learners responded less negatively to failures and persisted when faced with challenges (Muenks & Miele, 2017). Chen et al. (2018) added to this by finding that positive attitudes appear to activate the hippocampal learning-memory system, which in turn could positively influence mathematics performance if learners possess positive attitudes towards the subject.

Building on this relationship, Willingham et al. (2002) found that positive study attitudes independently predicted academic performance, even after accounting for intelligence. Locally, Erasmus (2013) found a significant relationship (r = .41) between study attitude and mathematics performance, while assessing the influence of study orientations and emotional intelligence on mathematics performance. Moreover, Maree et al. (2014)

reported a positive, yet slightly weaker, relationship (r = .25) between study attitude and mathematics performance in South African grade nine learners, but did not account for intelligence or personality, a gap that the current study wishes to close.

As such, the following alternate hypothesis proposes that, in addition to learners' intelligence, learners are less likely to achieve in mathematics if they do not have a positive study attitude towards mathematics.

H_O3: Study attitude does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A3: Study attitude moderates the positive relationship between fluid intelligence and mathematics performance.

Mathematics Anxiety

Mathematics anxiety is operationally defined as the panic, anxiety, and concern that presents as aimless and repetitive behaviours such as nail-biting, scrapping of correct answers, and inability to speak clearly (Maree et al., 2014). Previous studies have suggested that there are both cognitive and affective facets that relate to mathematics anxiety (Eysenck et al., 2007; Li et al., 2021). Cognitive facets are worrying over the consequences of poor performance or engagement and self-deprecatory thoughts, while affective facets are feelings of nervousness, discomfort, and fear towards mathematics tasks (Namkung et al., 2019).

While Casbarro (2005) proposes that moderate anxiety levels positively influence pupil performance, increased levels of mathematics anxiety generally negatively impact mathematics performance across ages (Maree et al., 2013; Pekrun et al., 2017; Zhang et al., 2019). However, the extent of mathematics anxiety, and how it affects learning and performance, depends on the individual learner. Individual learner factors which could potentially contribute to the level of mathematics anxiety are general abilities and mathematics skill (discussed in section 2.2), mindsets and attitude towards mathematics (discussed in sections 2.3 and 2.4.1), response to stress and challenging stimuli, previous learning experiences, and personality profile especially in relation to conscientiousness (discussed in section 2.5.2), and emotional stability (discussed in section 2.5.5) (Ramirez et al., 2018a; Wehner & Schils, 2021).

Mathematics Anxiety and Cognition. Ashcraft (2002) notes that mathematics anxiety is not an innate trait, but rather an acquired response to threatening school situations that negatively influence cognitive processing. Building on this, Beilock (2008) postulated that learners with higher mathematics anxiety reduced their working memory capacity, leaving fewer mental resources available for problem-solving and reasoning, especially under pressure. Furthermore, Soltanlou et al. (2019) suggested that low visuospatial memory, rather than verbal working memory, is the most significant factor impairing mathematical learning attempts.

Apart from the biological level, higher levels of mathematics anxiety can debilitate learners' courage to ask for help or take risks when solving novel mathematical problems, which could delay learners' cognitive development in numerical reasoning (Maree et al., 2011; Ramirez et al., 2018b). Ramirez et al. (2016) noted that, paradoxically, learners in primary school with a higher cognitive ability are more likely to avoid mathematical problem-solving when anxious. As a result, learners with a higher cognitive ability might be the most likely to underperform due to mathematics anxiety (Ramirez et al., 2016). Schillinger et al. (2018) found that, while numerical and figural intelligence had a negative relationship with mathematics anxiety, verbal intelligence had no relationship with mathematics anxiety. Therefore, Schillinger et al. (2018) postulates that highly mathematics-anxious learners struggle with the general processing of numerical reasoning. Locally, Maree et al. (2014) found a significant relationship (r = .45) between mathematics anxiety (reversed) and mathematics performance, second only to study milieu (r = .49). However, Maree et al. (2014) did not account for general intelligence, mindset, or personality influences. The current study's alternate hypothesis, therefore, postulates that mathematics anxiety negatively impacts mathematics performance, even after accounting for learners' fluid intelligence.

H_O4: Mathematics anxiety does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A4: Mathematics anxiety moderates the negative relationship between fluid intelligence and mathematics performance.

Mathematics Anxiety and Mindset. It would be meaningful to discuss learners' struggles with mathematics as part of learning, particularly after difficult class tests or examinations. Such precautions are needed, especially considering the findings of Ramirez et al. (2016), where mathematics anxiety made high cognitive potential learners want to avoid the subject. This was evident even at elementary school level, potentially having lifelong negative implications (Ramirez et al., 2016). Li et al. (2021) further reported a significant, negative relationship (*r* = -.48) between mathematics anxiety and self-concept. While a learner with a growth mindset would perceive failure as an opportunity to enhance learning, a learner who has developed a negative mindset towards mathematics would perceive failure as debilitating (Park et al., 2014). Johnston-Wilder and Lee (2010) believe that mathematical resilience, a positive emotional stance towards mathematics, can be developed over time, similar to how a growth mindset develops. Reframing struggle as a challenging learning opportunity, rather than inability or failure, reinforces self-efficacy and growth mindset perceptions (Ramirez et al., 2018b). Teachers and parents should also be mindful of continuing to promote process-focused, rather than ability-focused (rote learning) teaching of mathematics, as this could lead to fixed mindsets and lower self-efficacy in learners (Ramirez et al., 2018a). As such, the current study will add to the existing body of literature, by determining whether mathematics anxiety or mindset is a stronger predictor of mathematics performance, while accounting for intelligence and personality, using regression analysis.

Mathematics Anxiety and Study Attitude. Mathematics has a reputation for being a difficult subject to master, due to the complex skills that need to be demonstrated and the generally negative attitudes associated with the learning of these skills (Mammarella et al., 2019). Like study attitude, mathematics anxiety seems to increase as learners are more formally exposed to mathematics (Ganley & McGraw, 2016; Lu et al., 2021; Mutegi et al., 2021). Since study attitude and mathematics anxiety are both facets of study orientation, Maree et al. (2014) previously found a moderate relationship (r = 0.39) between mathematics anxiety and study attitude in a local grade nine sample. Internationally, high mathematics anxiety has also been associated with avoidance of mathematics-related tasks (Brown et al., 2008), negative mathematics attitude (Lee, 2009), and low engagement with mathematics (Henschel & Roick, 2017). Abin et al. (2020) also found that learners perform better in mathematics when they demonstrate higher cognitive ability, higher perceived mathematical competence, higher motivation, higher interest in mathematics, lower mathematics anxiety, and perceived mathematics as useful. However, Dowker et al. (2016) cautions that despite the numerous studies that have found statistically significant relationships between mathematics anxiety and mathematics attitudes, the cognitive and motivational facets of study attitudes and the emotional facets of mathematics anxiety, warrant separate evaluation. Therefore, the current study aligns with Maree's (1997) conceptualisation and the summary of Dowker et al. (2016). Regression analysis will be employed to determine whether mathematics anxiety or study attitude is a stronger predictor of mathematics performance, while accounting for intelligence, mindset, and personality, thereby adding to existing literature.

Mathematics Anxiety and Personality. To approach mathematics with confidence, learners need to articulate their ideas fearlessly, which will build their mathematical resilience (Johnston-Wilder & Lee, 2010). Mathematical resilience refers to the persistence to pursue mathematics, being willing to reflect and research alternative solutions, believing that the subject can be learnt, and actively engaging in mathematical reasoning (Johnston-Wilder & Lee, 2010; Rodarte-Luna & Sherry, 2008). This resilience, or grit, can be developed and is malleable, like a growth mindset. However, mathematics resilience requires a learner's willingness to first attempt learning mathematics. In investigating the relationship between mathematics performance, resilience, and mindsets, Kaya and Karakoc (2022) found that grit mediated the relationship between a growth mindset and mathematics achievement, as positive mindsets supplement grit. Resilience is a concept best related to emotional intelligence (EI), and locally, Erasmus (2013) established relationships between mathematics anxiety (reversed, to reflect mathematics confidence) and adaptability (r = .26), stress management (r = .20), EI (r = .29), and mathematics performance (r = .37). These relationships were echoed by Donolato et al. (2020), who found that resiliency aided learners to focus when needing to perform under pressure, aided quicker adjustment, facilitated persistent and flexible problem-solving strategies, and protected learners against mathematics anxiety. While EI and personality are separate constructs, there is nevertheless a relationship between EI and the five factors of personality (Alegre et al., 2019; Stols & Van Lill, 2022). The relationship between EI and the five factors of personality will be discussed in detail in section 2.5, given that personality factors serve as moderators of the study orientations towards mathematics.

Study Habits

Maree et al. (2014) defines study habits as a learner's willingness to focus on learning mathematics by consistently working through homework, assignments, and past tests and examination papers. Acido (2010) provides a clearer indication of the concept, summarising that study habits encompass elements of: 1) organisation of study materials, 2) regularly prioritising studies, with a specified time and place for studying, 3) consistent parental supervision, with parents modelling positive and conducive learning behaviours, and 4) personal responsibility over one's learning and how it is approached.

Maree et al. (2014) further highlights the relationship (r = .73) between study attitude and study habits, emphasising that this facet of study orientation relates to the behaviours that learners choose to engage in as a means of manifesting their study attitude. This further corresponds to Dweck's mindset theory, wherein learners with a growth mindset are inclined to invest effort in learning new concepts, while learners with a fixed mindset view learning efforts as futile and may opt to pursue more enjoyable tasks instead (Dweck & Master, 2009). Additionally, it aligns with Bandura's self-efficacy theory, as learners who hold positive attitudes towards mathematics are more likely to employ self-regulatory strategies and persist in solving challenging problems, thereby reinforcing their positive emotional outlook (Bandura, 2013). This was in part replicated by Islam (2021), who found a positive relationship between study habits and academic achievement (r = .27), self-esteem and academic achievement (r = .29), and study habits and self-esteem (r = .28).

Teachers and parents should emphasise learner efforts to motivate learners to perform well in mathematics, since such motivation will make it substantially easier for learners to implement regular study habits and improve mathematics performance (Akben-Selcuk, 2017). Having a personal interest and getting joy out of learning mathematics may also be a useful driver in implementing time management strategies with learners, to ensure that learners have enough time to focus on studying mathematics alongside other subjects and extramural activities (Aeon & Aguinis, 2017). Having the time to focus on mathematics for a set period every day also makes it easier to form a habit, since that time cannot be attributed to another activity. Maree et al. (2014) suggests that implementing routines for studying mathematics would result in learners becoming more competent at solving mathematical problems, given the regular time and attention dedicated to learning mathematics. In a meta-analysis, Cooper et al. (2006) found that 50 out of 69 studies show a positive relationship between homework and academic performance.

Following on from time spent doing homework, simply allocating time to practice mathematic skills might not be sufficient, as the type of skill that is learnt is equally important. For example, Sauls and Beeson (1976) considered the habit of finger counting (working out mathematical sums by counting on fingers) in primary school learners, and found that the habit inhibited development and was considered a ‘crutch’. Sauls and Beeson (1976) observed that learners who frequently worked out mathematics problems, by counting or tapping out on their fingers, had slightly lower intelligent quotient scores. Trautwein and Lüdtke (2007) further highlighted the effect of conscientiousness and self-discipline (discussed in section 2.5.2) on learner performance, and that homework effort, rather than time spent on homework, was a better predictor of learner performance. This was echoed in the local study by Goodman et al. (2011), which found that effort mediated the relationship between both intrinsic and extrinsic motivation, and academic performance, although intrinsic motivation explained more variance in performance. In the same vein, Akinsola et al. (2007) discovered that procrastination had a negative relationship with mathematics performance, highlighting the need for active learning to occur for improved academic results. Moreover, a study by Acido (2010) found that learners with below-average reasoning ability had poor study habits, while learners with average and above-average reasoning endorsed more positive study habits. In the same study, learners with below-average reasoning also had negative attitudes towards learning, providing further support to the role of self-efficacy and mindset in determining whether learners put in effort when studying (Acido, 2010).

Regarding the relationship between study habits and test anxiety, Tuncay (2011) discovered that study habits had a negative relationship with test anxiety, and a positive relationship with achievement motivation. Therefore, the findings of Tuncay (2011) adds further support to previous studies which proposes that effective study habits improve learners' confidence, thereby reducing test anxiety. Furthermore, improved learner confidence will internally motivate learners to achieve, therefore ensuring learners will continue to engage in productive study habits (Tuncay, 2011). Regarding mathematics performance locally, Erasmus (2013) reported a moderate (r = .46) relationship between study habits and performance, which is significantly higher than the findings of Maree et al. (2014), who found a weaker (r = .19) relationship between the two constructs. As mentioned earlier, no local studies have accounted for the learners' fluid intelligence and mindset, therefore, the current study aims to investigate the role of study habits between the two constructs (fluid intelligence and mathematics performance) with the following set of hypotheses:

H_O5: Study habits do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A5: Study habits moderate the positive relationship between fluid intelligence and mathematics performance.

Problem-Solving Behaviour

The concept of problem-solving relates to the underlying cognitive and meta-cognitive learning strategies that learners rely on when solving mathematical problems. These strategies include planning which calculation to conduct for a certain mathematical problem, evaluating those choices, abandoning strategies that do not work, estimating and approximating answers, deciding on the method of calculation, following through, and being able to make generalisations and inferences for future mathematical problems (Maree et al., 2014).

This idea of metacognitive learning, or thinking about how one is thinking and learning, has been accepted to contribute to effective mathematical problem-solving (Özsoy, 2011; Morosanova et al., 2016), with a differentiation being drawn between metacognitive knowledge and metacognitive skills. Metacognitive knowledge is a reflective skill that refers to the learners' beliefs towards mathematics and awareness of their cognitive strengths and shortcomings to effectively apply the resources and strategies available to them (Schneider & Artelt, 2010). Therefore, metacognitive knowledge could relate to mindset and study attitude, as discussed above, and the amount of effort the learner is willing to invest in solving the mathematics equation they are faced with. Metacognitive skill, on the other hand, refers to the learners' ability to execute (Azevedo, 2009). As such, metacognitive skill is the learners' ability to actively engage in learning, recognising familiar or easy versus new or difficult concepts, persisting with more challenging tasks, analysing the content effectively to retrieve previously learnt knowledge, and effectively applying the relevant domain-specific problem-solving strategies to the task (Azevedo, 2009).

However, in examining the relationship between mathematics anxiety and metacognition, Erickson and Heit (2015) found that high school learners, despite experiencing high levels of mathematics anxiety, also expressed overconfidence in their mathematics-related metacognition. Moreover, Erickson and Heit (2015) explained that mathematics anxiety could arise from high school learners not putting in enough effort when studying due to insufficient practice with more challenging mathematical problems, and then realising too late that they are not adequately prepared. These studies further promote the current study's stance to consider problem-solving behaviour's relationship with mathematics anxiety, study attitudes, and mindset, while also accounting for cognitive potential.

Ideally, although the knowledge learnt in mathematics curricula is domain-specific, it is expected that learners should be able to apply mathematical knowledge and skills acquired in the classroom to problems in real-life contexts (Meijer & Riemersma, 2002). However, as learners progress through high school, they become less optimistic towards difficult mathematical problems and their belief that mathematics is useful also decreases (Mason, 2003). For learners to remain positive towards mathematics and continue to see its value, learners need to understand mathematical concepts, rather than simply repeat procedures. However, understanding mathematical concepts may be difficult in environments where: 1) mathematics is taught as a system of instructions with inflexible rules and processes (Cobb & Bauersfeld, 1995), 2) the emphasis is often on performance rather than comprehension (Haimovitz & Dweck, 2017), and 3) the principles are not taught using relatable real-life contexts where more than one approach to solving the problem is accepted (Xin & Zhang, 2009). In this respect, the current study assesses learners' mathematics-specific problem-solving behaviours to evaluate learner orientation towards drawing comparisons to previous situations where learners had to solve similar problems, thereby making the process of problem-solving part of real-life rather than a skill only relevant to mathematics class.

Pennequin et al. (2010) investigated the relationship between metacognition and mathematics performance in learners aged eight to 10 years and found that metacognition training improved metacognitive knowledge, metacognitive skill, and mathematical problem-solving, in low-mathematics-achieving learners. However, metacognition training did not improve knowledge or skills in average mathematics-achieving learners (Pennequin et al., 2010). Zhao et al. (2019) further found that problem-solving strategies mediated the relationship between metacognition and learning performance, but that there was no direct relationship between metacognition and learning performance. In conflict with the above findings, Baten and Desoete (2019) observed that metacognition was a significant predictor of mathematics accuracy, however, the relationship between motivation, study attitudes and mathematics accuracy was not significant.

Local studies, such as Desoete and de Craene (2019), have also reported mixed findings on the role of problem-solving behaviour, mediated by study attitudes or effort, in influencing mathematics performance. However, this may be due to differences in executive function development in adolescence, or because metacognition is taught differently across various regions, if at all (Desoete & De Craene, 2019). Maqsud (1998) found that providing extensive feedback on incorrect answers aided mathematics teaching strategies and increased learners' metacognitive awareness, attitude towards mathematics, and mathematics performance, while accounting for general ability. Although a study by Maree et al. (2014) did not assess cognition, findings indicated significant positive relationships between problem-solving behaviour and study attitudes (r = .60) and study habits (r = .67). Therefore, if learners are motivated to achieve mathematics goals and make a habit of attempting more mathematics problems, learners will become better at solving such problems, thereby improving overall mathematics performance (Maree et al., 2014). Additionally, Moodaley et al. (2006) found that problem-solving behaviour and the social milieu were the most significant predictors of mathematics performance in Northern Cape grade nine learners. The findings of Moodaley et al. (2006) were replicated by in a study Erasmus (2013), which found a relationship (r = .42) between problem-solving behaviour and mathematics marks. However, Maree et al. (2014) reported no significant relationship between problem-solving behaviour and mathematics performance. As such, the question of whether problem-solving behaviours moderates the relationship between cognition and mathematics marks arise. Therefore, the current study is testing the hypotheses that:

H_O6: Problem-solving behaviours do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A6: Problem-solving behaviours moderate the positive relationship between fluid intelligence and mathematics performance.

Study Milieu

Study milieu encompasses the sociocultural and physical environments that learners are exposed to when growing up, including both home and school settings (Maree et al., 2014). Exposure to less stimulating environments before entering school has a positive relationship with the restricted development of mathematics and reading skills in children (Caughy et al., 1994). Furthermore, physical problems such as eyesight and hearing difficulties, reading problems, and language problems also limit the learner’s performance at school across subjects (Maree et al., 2011). Conversely, learners who come from higher socioeconomic backgrounds are more likely to demonstrate goal-setting skills, confidence, and ability in asking questions, and are ultimately more motivated to perform better in mathematics (Claro et al., 2016; Church et al., 2001).

A large number of South African learners are confronted with a study milieu that has the potential to negatively impact their mathematics performance. An estimated 18.2 million South Africans live below the national poverty line of R945 per month, with an official unemployment rate of 33.9% (roughly eight million workers) being reported during the second quarter of 2022 (Statistics South Africa [StatsSA], 2022). These financially crippling circumstances at home lead to non-stimulating learning and study environments, since the focus is on survival and basic needs. Given the financial struggles the parents are already grappling with, additional communication, learning, mental, and physical health problems faced by the learner may go unnoticed, increasing the challenge these learners must overcome to translate their cognitive potential into mathematics performance (Jensen, 2009). Nevertheless, the study by Kapp et al. (2014) is somewhat assuring, as it illustrated that South African learners could still position themselves as learning agents despite their low socioeconomic status when they had cultural and religious support. Williams (2016) further cautions against hyperawareness of socioeconomic disparities, warning that in the process of amending curricula to meet the needs of the disadvantaged, the system further alienates learners and inadvertently increases the developmental gaps.

In a meta-analysis on the relationship between socioeconomic status and academic achievement, Sirin (2005) found that the relationship strengthened across primary and middle school, but the pattern did not continue into high school. A study by Hu et al. (2018) later examined mathematics performance in 51 countries and found that after controlling for socioeconomic status, national Gross Domestic Product (GDP) per capita, and gender, that national culture accounted for 23.9% of country differences in mathematics performance. Additionally, Zhang et al. (2019) observed that varied cultural and educational contexts influenced the relationship between mathematics anxiety and performance. Similarly, the Organisation for Economic Cooperation and Development (OECD) (2019) evaluated of over 10 million learners globally and highlighted that, although social disadvantage does contribute to poor educational performance in 15-year-olds, the value of growth mindset, resilience, stress management, parental support, and a positive school environment should not be underestimated. For the South African population, these findings theoretically highlight the importance of a growth mindset, positive study attitude, low mathematics anxiety, and consistent study habits. Such a mindset and positive study orientation can buffer learners from certain struggles that accompany a lower socioeconomic status and assist them to persevere and perform well academically. It is one of the aims of the current study to determine which of these facets is most relevant to focus on developing, relative to the others.

Teachers, and the classroom environment they create, can initiate the development of mathematics anxiety, which as discussed above can lead to a fixed mindset, negative study attitude, decreased interest in studying mathematics, and a rote-learning problem-solving style (Arslan, 2020). Locally, Maree et al. (2014) have also found a strong relationship between mathematics anxiety and social milieu (r = .72), and a weak relationship between social milieu and problem-solving behaviour (r = .19). Therefore, the findings of Maree et al. (2014) reiterate international findings that lower environmental support can lead to lower resilience and cause challenges in mathematics classrooms. Teachers may be perceived as non-supportive if they do not provide learners with a chance to question methods, evaluate the practical value of concepts, and understand the strategic process. If educators teach mathematics concepts purely as a method to be repeated or only accept one way of answering questions, it can create mathematics anxiety and foster an environment in which rote learning thrives (Savaş et al., 2010; Uçar et al., 2010). Similarly, to increase learners' internal motivation to learn mathematics, teachers should aim to increase perceptions of the attractiveness of better mathematics marks, arguing for its relevance in the real, post-school world (Gagné & Deci, 2005; Vansteenkiste et al., 2012).

How teachers explain phenomena also has implications for learners' study habits and problem-solving skills. For example, Meijer and Riemersma (2002) found that using experimental mathematics problem-solving instruction methods, which make use of both indicative and problem-specific hints during teaching and testing, enhances mathematics problem-solving ability. Another suggestion would be to teach learners several strategies to solve the problem, since often, the issue with mathematics is not the mathematical problem itself, but understanding how the equations and processes work to get to the answer (Geary et al., 2019b). Therefore, parents and teachers should be wary of imposing their way of problem-solving as the only way of answering the question, since this could demotivate and reduce the enthusiasm of learners to continue forming certain study habits, and foster negative study attitudes and fixed mindsets towards mathematics (Xin & Zhang, 2009; Sisk et al., 2018). As discussed, when considered separately, a growth mindset is a better predictor of mathematics performance than socioeconomic status (Claro et al., 2016; Gunderson et al., 2018), however, this will also be explored further in the current study.

As mentioned above, parents may already be overburdened with their financial realities, and as a result, may either not have the capacity to guide their children, or may place unnecessary pressures on the child to perform well at school. Therefore, the teacher, as a more objective stakeholder, should be held accountable for coaching learners to achieve realistic, albeit challenging, academic goals (Murayama et al., 2016). Indeed, while parents' attitude towards mathematics has a positive relationship with learners' mathematical performance, assisting their children with homework did not (Ashim & Sahin, 2018) This suggests that parents need to empower their children with confidence and problem-solving skills, rather than protect them from failing by doing their work for them. This is in line with comments by Clark et al. (2019) on developing learners' resilience, where it was noted that perceived parental and classmate social support had a significant relationship with learners' grit and effort perseverance.

To boost engagement between classmates and to facilitate learners supporting each other rather than relying on their parents, lessons could be restructured (Sekao, 2004). The restructured lessons will enable learners to work in cooperative learning groups that are fit-for-purpose and heterogeneous in terms of personality and study orientations in mathematics; a tactic that may be helpful in crowded classrooms typically found in public schools (Sekao, 2004). Such engagement could also serve as a potential buffer in rural schools, where mathematics performance and participation are consistently lower than in schools found in metropolitan areas (Ashim & Sahin, 2018; Murphy, 2019). Furthermore, this type of engagement will allow learners to discuss the topic using jargon that makes sense to them, especially if the language of instruction is a concern.

Locally, the relationship between study milieu and mathematics performance has been consistently significant (ranging between r = .32 and r = .68) (Erasmus, 2013; Maree et al., 2014; Moodaley, 2006). Moreover, study milieu has been found to be the strongest facet of the study orientation towards mathematics to predict mathematics performance (Maree et al., 2014). However, none of these studies accounted for the role of intelligence and personality factors, and therefore, with the literature discussed in this section in mind, this study contributes new insights by testing the set of hypotheses that:

H_O7: Study milieu does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A7: Study milieu moderates the positive relationship between fluid intelligence and mathematics performance.

Personality Factors and Mathematics Performance

Furnham and Chamorro-Premuzic (2006) argued that knowledge acquisition is dependent on cognitive ability, self-efficacy, and personality. Cognitive ability and self-efficacy have already been discussed, therefore, the remainder of this chapter will focus on the five-factor (also referred to as the Big Five) model of personality. Previously, Farsides and Woodfield (2003) performed a hierarchical regression to investigate the incremental validity of the Big Five personality model factors when added to the predictive model for academic performance, accounting for cognitive ability. Farsides and Woodfield (2003) found that the Big Five personality model factors added an additional 5% of the variance in academic performance, above that already predicted by cognitive ability (which accounted for 4%). Additionally, Lounsbury et al. (2003), performed a hierarchical regression analysis and found that general intelligence accounted for 16% of the variance in academic performance, with the Big Five personality model factors adding 7% variance.

Practically, this is why personality is targeted in development interventions, as focusing on learners' social-emotional aspects have been shown to enhance learner scholastic performance (Damgaard & Nielsen, 2018). As O'Connor and Paunonen (2007) argue, personality traits are reflected in behavioural traits that can influence the development of habits or approaches to learning and studying. Therefore, even if personality and intelligence are separate concepts that influence mathematics performance, learners' personality traits may impact their study orientations, which has been considered as a moderator in the relationship between intelligence and mathematics performance (O'Connor & Paunonen, 2007).

The Big Five personality model integrates a wide variety of constructs while remaining uncomplicated enough for researchers to easily communicate findings to the public (Furnham & Chamorro-Premuzic, 2004; Saucier & Goldberg, 1996; Taylor & De Bruin, 2013). As per this lexical approach, the dimensions of the five-factor model of personality relates to behaviours and outcomes that have been recognised as important, resulting in this personality model being one of the most widely researched in relation to academic performance (Poropat, 2009). The Big Five personality model covers personality traits such as openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, each of which will be discussed in further detail below.

Locally, the Big Five personality model has been comprehensively used and researched in industrial settings and has consistently been found to predict job performance (Van Aarde et al., 2017). Furthermore, when the Big Five personality model is applied locally to academic performance, it is generally in relation to undergraduate students (Heuchert et al., 2016; Laher & Dockrat, 2019; Schoeman & Kotzee, 2022; Zhang & Akande, 2002). This may be due to personality being somewhat unstable during the phase between childhood and young adulthood, when compared to other time brackets in the lifespan (Soto & Tackett, 2015). However, personality is not rigid and may be more malleable towards development initiatives, such as imposing more homework on learners to foster desired levels of conscientiousness (Cooper et al., 2006; Trautwein et al., 2009).

Limited local options are available to assess adolescent personality as per this five-factor model, which may be due to the underwhelming volume of local adolescent studies. In the South African context, norms for the 16pf Adolescent Personality Questionnaire are not yet available, and preliminary research on the Revised NEO Personality Inventory-3 showing less satisfactory psychometric properties for adolescents (Boshoff & Laher, 2015). Additionally, the psychometric properties and norms for an adolescent sample on the Basic Traits Inventory (BTI) was only recently launched (De Bruin et al., 2022; Taylor & De Bruin, 2017). As will be discussed in Chapter Three, the BTI was used in the current study, given its flexibility in providing both factor- and facet-level insights. This differentiation between personality factors and facets allows for increased predictive accuracy, which adds practical value (Paunonen & Ashton, 2001; Taylor & De Bruin, 2017). Paunonen (1998) found that the facets increased the prediction of academic performance by an additional 5-7% in variance over considering only the Big Five personality model factors. This is, therefore, the first local study to consider the moderating effects of the five-factor model of personality (and its facets) on study orientation towards mathematics, whilst accounting for mindset and fluid intelligence.

However, this is not the first study to consider how other factors can influence the relationship between study orientations towards mathematics and mathematics performance. In this regard, Erasmus (2013) assessed how study orientations towards mathematics and EI each influence mathematics performance in grades nine and 11 learners. While EI and personality are separate concepts, given the relationships between EI with openness to experience (r = .26), conscientiousness (r = .40), extraversion, (r = .47), agreeableness (r = .39), and neuroticism (r = -.68) (Alegre et al., 2019), there is value in building on Erasmus's (2013) work, albeit from a different perspective. While Erasmus (2013) considered how EI skills and study orientations related to mathematics performance, the current study builds on these findings by considering the role of the five factors of personality as moderators in the relationship between study orientation and mathematics performance.

Openness to Experience

Openness to experience relates to the extent that individuals are curious, seek out novelty, and enjoy new and unconventional ideas and experiences (Taylor & De Bruin, 2017). Taylor and De Bruin (2017) further distinguishes the five facets of behaviour relating to this factor of personality. The first facet of *aesthetics* relates to a person's appreciation for art in its various forms, even if the person is not artistically gifted (Taylor & De Bruin, 2017). Second, the facet of *actions* is defined by a person's drive to experience novelty as much as possible, and a general restlessness with stability and keeping the status quo (Taylor & De Bruin, 2017). *Values* make up the third facet of openness to experience and regards how comfortable the person is with challenging societal, political, or religious values (Taylor & De Bruin, 2017). The fourth facet, *ideas*, is operationalised by a person's intellectual curiosity to understand how things work (Taylor & De Bruin, 2017). Lastly, the facet of *imagination* pertains to the individual's tendency to creatively (or realistically) solve problems (Taylor & De Bruin, 2017).

Although earlier studies found a significant relationship between openness to experience and intelligence (Chamorro-Premuzic & Furnham, 2005; Holland et al., 1995; McCrae, 1993), subsequent studies found weaker, or no relationships between the personality factor and academic performance (Ackermann & Heggestad, 1997; O'Conner &

Paunonen, 2007; Paunonen & Ashton, 2001). As such, Chamorro-Premuzic and Furnham (2008) suggest that the way intelligence and openness to experience interact to influence academic achievement might be more dynamic than initially conceived, explaining that the various methodologies employed to study the relationship impact the observations. In this regard, learners who are more open to experience tend to be more intellectually curious (higher on the facet of *ideas*) and generally report higher critical thinking scores (Bidjerano & Dai, 2007). Learners with higher openness to experience might have a stronger inclination to be internally motivated to learn about a certain subject, and because of their enjoyment of learning, this trait could translate their cognitive potential into academic achievement (Caprara et al., 2011; Chamorro-Premuzic & Furnham, 2008). Openness to experience might also enable learners to perceive challenging learning experiences as less threatening, thereby increasing their self-efficacy, resulting in increased mathematics performance (Di Giunta et al., 2013). Subsequently, when investigating the moderating effect of study attitude on the relationship between cognitive potential and mathematics performance, a learner's openness to experience is also worth considering, leading to the of hypotheses that:

H_O8: Openness to experience does not interact with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance, or

H_A8: Openness to experience interacts with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

Jensen (2015) further found that openness to experience has a positive relationship with intrinsic motivation and learning for the sake of maximising understanding. Moreover, openness to experience has a negative relationship with a surface learning approach, or learning just for the sake of solving the problem (Jensen, 2015). Such relationships suggest that learners scoring higher on openness to experience will gain a more detailed understanding of concepts, making it easier to solve problems based on the concept. Furthermore, it was found that learners who were more open to problem-solving (potentially the work of their *imagination*) achieved higher mathematics marks (Akben-Selcuk, 2017).

Subsequently, it will be explored whether openness to experience moderates problem-solving behaviours, by testing the below pair of hypotheses.

H_O9: Openness to experience does not interact with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A9: Openness to experience interacts with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

Conscientiousness

A learner scoring higher on conscientiousness is more likely to plan, organise, and conduct tasks like studying and homework effectively and efficiently (Taylor & De Bruin, 2017). According to Taylor and De Bruin (2017), this factor of personality can also be subdivided into five facets, namely: order, self-discipline, dutifulness, effort, and prudence. *Order* is the degree to which the environment should be kept neat and tidy, and to which degree a process is followed methodically. *Self-discipline* relates to the tendency to commence tasks immediately and follow through until completion, with the ability to self-motivate. *Dutifulness* is the inclination to be reliable, dependable, and the willingness to fulfil moral obligations. *Effort* is associated with how often a learner works diligently to meet ambitious goals. Lastly, *prudence* is the tendency to carefully check the facts and think things through before making decisions.

While openness to experience consistently has the strongest significant relationships with intelligence compared to the other personality factors, conscientiousness (r = .21) and its facets of achievement-orientation (r = .26) and effort (r = .26), frequently have the strongest relationship with academic performance (O'Conner & Paunonen, 2007; Paunonen & Ashton, 2001). These findings were echoed in a study by MacCann et al. (2009), which found that each facet of conscientiousness adds incremental predictive value towards performance, above and beyond general cognition. Wehner and Schils (2021) agree, suggesting that high conscientiousness almost always guarantees better performance. With regards to academic performance in adolescence, studies have found that self-discipline accounts for more than twice as much variance as intelligence (Duckworth & Seligman, 2005). Furthermore, self-discipline tends to correlate with magnitudes similar to that of intelligence (Poropat, 2009). Despite this, studies have found no relationship between conscientiousness and intelligence, or a weak, negative relationship (Rikoon et al., 2016). Furthermore, a study by Akben-Selcuk (2017) found no statistically significant relationship between perseverance and academic achievement in mathematics in their sample of 15-year-old learners.

Poropat (2009) highlights the practical value of assessing conscientiousness, whilst accounting for intelligence, in academic contexts to identify high performance. This is due to conscientiousness consistently predicting performance across educational (and work) levels, while the magnitude of the relationship between intelligence and performance declines as age or experience increases (Conard, 2006). Chamorro-Premuzic and Furnham (2005) have suggested that more conscientious learners tend to be more internally motivated to perform well. Given the literature on study habits, the findings indicate that the more disciplined and diligent learners are, the more effort learners will invest in studying mathematics, and the more likely learners are to achieve mathematical success (Bauer & Liang, 2003; Göllner et al., 2017). Additionally, highly self-disciplined learners are absent less often, spend more time studying, and are less likely to procrastinate than their more impulsive peers (Ducksworth & Seligman, 2005). Similarly, Cho and Park (2016) have demonstrated that learners that score lower on impulsivity and higher on persistence, are more likely to successfully retrieve information from their long-term memory, suggesting that practice does help with performance. Furthermore, Seo (2018) argues that study time planning improves mathematics performance, as does participating in additional mathematics tutoring. As such, the next two sets of hypotheses to follow from the literature are:

H_O10: Conscientiousness does not moderate mindset's interaction with fluid intelligence and mathematics performance.

H_A10: Conscientiousness moderates mindset's interaction with fluid intelligence and mathematics performance.

H_O11: Conscientiousness does not interact with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A11: Conscientiousness interacts with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

Extraversion

The personality factor of extraversion refers to the extent to which an individual enjoys excitement and stimulation in their environments, especially in the company of others (Taylor & De Bruin, 2017). Extraversion can also be further differentiated by five underlying facets. *Ascendance* relates to one's interest in entertaining and dominating others. A person's *liveliness* can be measured by how bubbly and energetic the person typically is. *Positive affectivity* is linked to the tendency to be optimistic, enthusiastic, and experience happy emotions. *Gregariousness* is defined as one's preference for frequent social interaction and being in the company of others. The last facet, *excitement-seeking*, is the degree to which one needs intense stimulation and adrenaline-spiking experiences (Taylor & De Bruin, 2017).

O'Connor and Paunonen (2007) summarised that literature examining the role of extraversion as a predictor of academic performance provides mixed results, with the majority of studies reporting no relationship between this personality trait and academic performance. Additionally, the relationship between academic performance and extraversion was negligible when intelligence was controlled for in the meta-analysis of Poropat (2009). Earlier, a study by Eysenck and Eysenck (1985) found a negative relationship between extraversion and academic performance in high school learners, and later (Eysenck, 1992) argued that more extroverted learners were more likely to pursue other activities than study. Awuondo et al. (2019) further evaluated Eysenck's model with Kenyan Form 3's (grade 10 equivalent), and found a significant relationship (r = .35) between extraversion and mathematics performance, a direct contradiction to Eysenck's works.

As such, most of the existing literature provides no support for a relationship between extraversion and mathematics performance.The operationalisation of extraversion and its facets for the current study also suggest that other personality factors better explain mathematics performance. Therefore, the current null hypothesis relating extraversion to academic performance echoes the results found by previous studies (Conard, 2006; Farsides & Woodfield, 2003; John et al., 2020; Lounsbury et al., 2003), that:

H_O12: Extraversion does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

Should the current study, however, find a moderation effect, the alternate hypothesis to be accepted is that:

H_A12: Extraversion interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

Standardised assessment administration processes will be discussed in more detail in Chapter Three. However, at this point, it may be prudent to note that a five-factor model of personality assessment was administered to learners, thereby assessing their levels of extraversion. Given the existing literature, the current study proposes that at the factor level, extraversion will not influence mathematics performance, either directly or as a moderator, pre-empting support for the null hypothesis. The null hypothesis is also in line with Brandt et al. (2019), who commented that the sociability element of extraversion is associated less with mathematics performance than the energy element. However, given that different questionnaires vary as to how they assess extraversion, results may differ.

Agreeableness

Taylor and De Bruin (2017) explain that agreeableness can be defined as the tendency of a person to get along with, and show compassion for, others. This factor too can be more intricately described using five facets. First, *straightforwardness* is one's disposition for honesty and sincerity. Second, *compliance* is one's inclination to forgive and forget, being able to inhibit aggression, and defer to others. *Prosocial tendencies*, the third facet, is the degree to which one cares about helping their community and peers. A person scoring high on the *modesty* facet is humble. Lastly, *tendermindedness* relates to one's concern and sympathy towards others.

Like extraversion, the literature on agreeableness as a predictor of academic performance is mixed. However, when controlling for the contribution of intelligence, the results are stable and indicative of a negligible relationship (Poropat, 2009; Splenger et al., 2013). A study by O'Connor and Paunonen (2007) indicated no significant relationship between agreeableness and academic performance (r = .06), a finding replicated by Westphal et al. (2020) with grade seven and nine learners (r = -.01). Yet Paunonen (1998) had previously suggested that low agreeableness was the best personality predictor of academic performance. Additionally, a study by Brandt et al. (2019) found that throughout school, agreeableness had a negative relationship with academic performance. Contradictory to this, a study by John et al. (2020) found that agreeableness was had a positive relationship with academic performance. Moreover, Vermetten et al. (2001) explains that agreeableness may be associated with academic performance, given how agreeableness results in learners being more cooperative and compliant with teachers' instructions.

Considering the operationalisation of agreeableness, and its facets for the current study, there is more support for the null hypothesis that:

H_O13: Agreeableness does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

Should a moderation effect be found, however, the alternate hypothesis will be supported.

H_A13: Agreeableness interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

Neuroticism

A higher score on neuroticism suggests an individual's tendency to get upset easily, feel depressed, and a general sense of anxiety and self-consciousness (Taylor & De Bruin, 2017). Of the five factors, neuroticism is the only factor that Taylor and De Bruin (2017) further defined by only four facets; namely: affective instability, depression, anxiety, and self-consciousness. *Affective instability* is observed as the individual's tendency to be emotionally volatile and easily upset. *Depression* relates to an individual's experience of dejection, discouragement, sadness, and hopelessness. *Anxiety* is one's inclination to feel nervous, apprehensive, and tense. *Self-consciousness* is the degree to which individuals feel shame and embarrassment, as well as how they respond to criticism.

The literature on the role of neuroticism's effects on academic performance is mixed. In the O'Conner and Paunonen (2007) meta-analysis, neuroticism had a population correlation coefficient of -0.03 with academic performance, arguing that overall, neuroticism plays a relatively insignificant role in influencing academic performance. Poropat's (2009) meta-analysis further found that the relationship between academic performance and neuroticism (phrased positively as emotional stability) was significantly reduced when intelligence was controlled for. This is followed by minimal evidence for the incremental validity of neuroticism in predicting mathematics achievement specifically (Gilles & Bailleux, 2001; Marsh et al., 2006; Spinath et al., 2010).

Nevertheless, research by Chamorro-Premuzic and Furnham (2003), Migali and Zucchelli (2017), and Poropat (2014) found that neuroticism is negatively associated with academic performance and participation in class, implying that emotionally stable learners tend to perform better than their more anxious, depressed, or otherwise neurotic peers. This is typically most observable during tests and other forms of evaluation, where anxiety impairs learners' performance (Chamorro-Premuzic & Furnham, 2005). From a cognitive perspective, more anxious learners may struggle to pay adequate attention to a task and focus more of their mental capacity on their emotional state, negatively impacting performance (Judge & Bono, 2002). Individuals scoring higher on neuroticism facets also typically use emotion-focused coping strategies, such as procrastination or avoidance, which has a negative influence on study habits (Campbell-Sills et al., 2006; Connor-Smith & Flachsbart, 2007). These negative coping strategies and decreased effort results in lower mathematics performance, from which a destructive self-fulfilling prophecy develops – where learners become nervous when faced with mathematics content, struggle to find the motivation to put in the effort to master the subject or employ effective learning strategies, and continue to perform poorly (Wehner & Schils, 2021). Inversely, more emotionally stable learners are likely to have higher self-esteem, which has been found to positively correlate with academic performance (Cervone & Pervin, 2013; Robbins et al., 2004). Therefore, although neuroticism has not consistently been found to serve as a strong independent predictor of mathematics performance, higher levels of neuroticism might make individuals more vulnerable to anxiety-provoking factors in mathematics, thereby increasing the negative effect on mathematics performance (Cupani & Pautassi, 2013; Dobson, 2000). The set of hypotheses that follow from this review is therefore:

H_O14: Neuroticism does not interact with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A14: Neuroticism interacts with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

Although not a direct consideration of this study, given that data collection predominantly occurred in the 'post-pandemic' period, the impact of the Covid-19 pandemic was felt more strongly by learners scoring lower on emotional stability. Learners indicated that the need to learn remotely due to the closure of schools and social distancing protocols had a negative influence on their academic performance (Iterbeke & de Witte, 2020). This highlights how environmental changes can significantly influence both emotional stability and academic performance. Furthermore, as highlighted above, learners with low social support are more likely to struggle with self-esteem, motivation, and resilience (Claro et al., 2016; OECD, 2019). It is therefore hypothesised that learners with a perceived non-supportive milieu and high neuroticism score will struggle even more to achieve adequately in mathematics.

H_O15: Neuroticism does not interact with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A15: Neuroticism interacts with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

Chapter Synthesis

Several variables have been proposed to investigate and offer a comprehensive model of predictors of mathematics performance that accounts for non-intellectual psychological moderators, which might prevent or enable learners to achieve in mathematics in secondary school. Practically, such an investigation provides learners and their support networks (parents, teachers, and other mentors) with more individual strengths to explore, beyond the intention to improve cognitive potential alone. This chapter served to define the various concepts under consideration in this study – fluid intelligence, mindset, study attitude, mathematics anxiety, study habits, problem-solving behaviour, study milieu, openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Furthermore, this chapter provided a review on existing literature evidencing the predictive value of these concepts in mathematics performance.

Therefore, the aim of this study is to investigate a model of factors hypothesised to influence mathematics performance in grade nine learners in the Gauteng province. In this respect, the primary moderating effect of study orientations in mathematics on the relationship between fluid intelligence and mathematics performance was reviewed and summarised above. In turn, the effect of the five factors of personality on the primary moderating effect of study orientations in mathematics was also considered. By evaluating the incremental predictive value of each variable in the model of mathematics performance, the findings of this study can guide stakeholders in the education realm to focus energy on psychological strategies that are the most likely to yield improvements in mathematics performance.

Chapter Three will focus on the methodology employed to investigate the numerous hypotheses that followed the literature discussed in this chapter.

Chapter Three: Study Methodology and Ethical Considerations

Introduction

In Chapter Two, several hypotheses were proposed to investigate the two overarching objectives of the current study, which are to:

1. Determine how study orientation towards mathematics and mindset towards mathematics moderate the established relationship between fluid intelligence and observed mathematics performance, and
2. Investigate the secondary moderating influence of the five-factor model of personality on these primary moderated relationships.

Chapter Three will systematically discuss the research paradigm, research approach, and research design chosen for the current study. Moreover, the process of sampling, participant recruitment, data collection, and the instruments used to measure the various latent variables under consideration will be discussed. Additionally, the data analysis process, including the rationale for using specific statistical techniques to investigate the 15 hypotheses that followed from the literature review, will be detailed. Finally, the chapter will conclude with the ethical considerations for this study.

Theoretical Paradigm

The current study relies on psychometric measurements of multiple psychological variables in an objective and quantitative manner, positioning the research questions within the positivist paradigm (Çüm & Demir, 2020). The positivist paradigm emphasises the use of empirical data when testing hypotheses and establishing relationships (Chilisa & Kawulich, 2012; Kivunja & Kuyini, 2017), which is instrumental to the aim of the current study. Studies guided by the positivist paradigm assumes a realist ontology, taking the view that reality is objective and can be precisely observed and verifiably measured. Furthermore, findings reported from such a study can be shown to be valid and reliable, and can be robustly replicated in future research (Mazur, 2020).

The positivist paradigm, and therefore the current study, is aligned with the hypothetico-deductive model of science (Park et al., 2020). This methodology is a somewhat circular process that commences by familiarising oneself with existing literature and theories, to: 1) build testable hypotheses about relationships between independent variables and outcome variables from gaps in the literature, as the current study did in Chapter Two, 2) design a research study by identifying variables to operationalise, manipulate, or measure, as the current study does in this chapter by defending a selection of psychometric assessments used, and 3) conduct an empirical study that experiments or evaluates these variables, by means of a data analysis process which the current study details in this chapter and which is interpreted in Chapter Four. The goal of such evaluation is to establish relationships that better explain and predict phenomena. Additionally, the findings of these experiments further aid in building and refining theory, thereby renewing this cycle of knowledge creation.

Positivism is commonly used to study social phenomena using the empirical, scientific method (Alakwe, 2017). The scientific method requires that a study fulfils the requirements of replicability, precision, falsifiability, and parsimony (Alakwe, 2017; Iso-Ahola, 2020). As such, studies should systematically gather empirical, objective data which future research can replicate to obtain similar, if not identical findings. This is one of the core functions of Chapter Three, to provide readers with a detailed discussion of the research methodology followed in the current study, for later replication should it be required. There should also be minimal uncertainty about the authentic objectivity of the data collected, with little or no allowance for personal biases, values, or subjective interpretation, thereby allowing for a precise, reliable, and valid measurement and subsequent interpretation. In this regard, the psychometric measures used in this study were chosen given their reliability and validity merits. By assuming a deterministic viewpoint, findings indicate predictive relationships between phenomena, thereby creating capacity for the results to be further investigated, and either further supported or refuted. It is the aim of the current study to establish a number of causal relationships and moderation effects on these relationships. Lastly, speaking to the principle of parsimony, or reductionism, positivism allows for complex phenomena to be broken down into more manageable units for study. For the current study, the measurements selected further enables reductionism by often providing a general score of a construct (for example, neuroticism) as well as further nuanced, facet scores.

In critique of the positivist paradigm, post-positivism acknowledges the role of subjectivity and interpretation in research, suggesting that the researcher’s perspectives, as well as social and cultural contexts, add biases to the analyses (Turyahikayo, 2021). While the researcher recognises that contextual factors may have contributed to the selection of assessments, it is believed that the aim of the current study better aligns with the positivist paradigm.

Research Strategy

Quantitative studies involve systemically collecting numerical datasets from standardised measures and employing statistical techniques to objectively evaluate and analyse relationships between variables, to potentially make generalisable predictions about future behaviour (Wagner et al., 2012). This study was quantitative in nature and investigated the psychological factors that influence mathematics performance in a sample of 187 grade nine learners. Given the nature of the hypotheses to investigate numerous relationships between mindset, study orientation, and personality, together with the need to deduce preliminary generalisations about these relationships, a quantitative research approach was deemed more appropriate (Park et al., 2020).

The following section discusses how this quantitative study was operationalised and provides a description of the participating sample. Moreover, an indication is given on how the data was collected, and how the assessment tools were chosen.

Research Design

An analytical cross-sectional study is a non-experimental, quantitative research design that aims to collect data from a single group of participants at a single point in time, without any manipulation of the independent variables or any intervention that warrants a pre- and post-measurement (Schmidt & Brown, 2019). The focus of such a research design is to examine relationships or associations between variables within that specific time frame.

For the current study, learners were only assessed once between August and October 2022 for the current study to adequately establish whether the hypothesised relationships between variables exist (Lavrakas, 2008). Collecting data within a single timeframe was adequate given the purpose of the study. Further benefits of a cross-sectional study for the participating learners included the convenience of not needing to find a second opportunity to be assessed, thereby ensuring less disruption of learner study time. Whilst there was an intervention in the sense that learners were provided with feedback on their cognitive potential, study orientations, and personality profiles, the subsequent stability or changes in behaviour following the feedback were not assessed. Furthermore, evaluating the impact of the feedback was not within the scope of the current study. In this regard, a limiting functionality of a cross-sectional design to be considered is that the findings of the study would only be providing evidence for differences between learners' intellectual and non-intellectual profiles.

Target Population and Sampling Strategy

The population of the present study were adolescents registered as grade nine learners in secondary schools across the Gauteng province of South Africa. Grade nine learners were targeted as it is the final senior phase year in a learner's scholastic career before entering the stage of further education and training. By the end of the grade nine school year, learners should have demonstrated competence in a variety of mathematical concepts (Department of Basic Education [DBE], 2011). Understanding why learners are not demonstrating competence at this level is a key motivation behind the current study.

G*Power v3.1 was used to determine the minimum acceptable sample size required for a linear multiple regression (moderation analysis), with three predictor variables under consideration (fluid intelligence, a study orientation facet, and a personality factor). G*Power is a freely available tool that helps researchers determine appropriate minimum sample sizes for several statistical techniques, after considering the alpha level and statistical power of the analysis (Faul et al., 2007). The resulting calculation suggested that 119 participants should be sufficient ($\alpha = 0.05$; power = .95). When contemplating sample size for a hierarchical multiple regression considering the predictive value of each of the study orientations, mindset, and personality factors over fluid intelligence, the suggested sample size rose to 184 ($\alpha = .05$; power = .95). The researcher therefore proposed to assess a minimum of 200 learners, in line with the requirements to conduct statistically powerful analyses.

Initially, a cluster sampling strategy was employed to gain access to participants registered as grade nine learners within the Ekurhuleni region of the Gauteng province in 2022. Cluster sampling involves identifying pre-existing heterogeneous groups and drawing some of these groups or clusters randomly to build a sample (Laher & Botha, 2012). After receiving approval from the Gauteng Department of Education and the University of Pretoria's Ethics Committee to collect data from schools in the Ekurhuleni North region, 20 quintile-five high schools (where the medium of instruction is English) were contacted by the researcher. The emails sent enquired whether the schools would be interested in participating in the study during a time that suited them between August and September 2022, and the email template can be found in Appendix A. A total of four schools responded positively, and thereafter assisted in communicating the participant information sheet, parental information sheet, and informed assent and consent forms to grade nine learners and their parents or guardians within their email database. The information sheets, informed assent form, and informed consent form templates can be found in Appendices B and C. A total of 186 learners and parents across these four schools provided their consent to be assessed.

However, during the data collection phase, an unexpected snowballing of interest in the study followed. Snowball sampling is a method of sampling where existing study participants recruit additional participants from among their acquaintances. Also known as chain sampling or network sampling, snowball sampling begins with one or more study participants. It then continues on the basis of referrals from those participants (Tenzek, 2017). Given that the contact with these subsequent learners stemmed from the initial sample, however, an element of snowball sampling was present. The context of the current study was such that all participants were provided with feedback reports based on their personality and study orientations, as well as a group feedback session and an opportunity to confidentially discuss their personal report with the researcher, as a token of the researchers' appreciation for their participation. Parents who heard about this study from participants within their communities and who wanted their children to benefit from the feedback provided, contacted the researcher. This resulted in 53 grade nine learners who were not registered with the schools that were initially contacted, being part of the final sample analysed. It can be argued that this deviation from cluster sampling is not standard research procedure. However, the parents requested that the assessments be completed, provided consent, the participants also provided assent, and benefitted from feedback on their personality and study orientations.

Therefore, a total of 239 Gauteng grade nine learners and their parents or guardians consented to participate in the study, of which 22% were not learners registered with the initial cluster of schools contacted. The unit of analysis for this study is each learner – their mathematics marks, fluid intelligence score, mindset, study orientations, and personality trait profile (Salkind, 2010).

Data Collection Procedure

The majority of learners were assessed on the school premises under the supervision of the researcher and school staff. Assessments were completed after-hours, to not affect teaching time or cause non-participating learners to feel excluded. Equivalent physical copies of the questionnaires were available for learners to complete if that was their preference. However, given that the schools had made their computer rooms available for use on the days of data collection, all learners indicated a competence with computer usage and preference to be assessed on the electronic versions of the assessments. Learners read and answered the questions at their own pace, with the researcher only providing interpretation support on some of the personality questionnaire items, for example, when learners asked for the meaning of a word to be clarified. Learners that were absent or had conflicting schedules on the day of the assessment were invited to complete the assessments electronically at a time that was convenient to both them and the researcher. These individual online administrations were supervised by the researcher, by requesting the learner to keep his or her camera on and use the screen-share functionality on Google Meet.

Data Collection Instruments

The psychometric measures used have been developed or validated for the South African context to objectively assess aspects of the target populations' fluid intelligence, mindset, study orientations, and personality. The commercial versions of the Raven's Standard Progressive Matrices (SPM), Study Orientation Questionnaire in Mathematics (SOM), and Basic Traits Inventory (BTI) were administered and scored as per instruction provided in their assessment manuals. The researcher adapted the Implicit Theories of Intelligence Scale for Children – Self Form (ITISC - SF) to be specific to mathematics mindset. Moreover, to ease administration, the researcher set up SurveyMonkey to automatically redirect learners to the six ITISC - SF items after completing the SOM questionnaire. None of the assessments had administration time limits, and only the electronic versions were completed by the participants.

ITISC – SF. The ITISC - SF is a six-item, publicly available (RAND, n.d), internationally developed scale that assesses children's growth or fixed mindset (Dweck, 2000). This is the only instrument in the current study that has not been developed, and validated for, South African populations specifically. Although the psychometric properties of the original items have been determined as acceptable (Cronbach $\alpha > .70$) for multiple contexts outside South Africa (Abd-El-Fattah & Yates, 2006; Dweck et al., 1995; Karlen & Hertel, 2021; Liu, 2021), the original items were not used for this study, and therefore, these coefficients do not apply to the version used for this study. For the current study, the researcher adapted the items to refer specifically to mathematical intelligence, in line with Dweck's (2000) note that words can be replaced or substituted to their original items. The adaptation was also made in line with Costa and Faria's (2018) recommendation that specific academic scales better moderated the relationship between implicit intelligence theories and performance. The suggested adapted items were approved by the University of Pretoria's Ethics Committee, upon recommendation by an initial proposal reviewer.

Although previous research has adapted the original ITISC - SF questionnaire to be applied specifically to mathematics (Bostwick et al., 2017; Jones et al., 2012; Priess-Groben

& Hyde, 2017), only sample items were provided in their publications, making it difficult to confidently confirm that the wording used in the current study is identical to that used previously. Since it cannot be determined whether the wording of the items used in the current study was exactly the same as these previous works, and given the different sample demographics, it cannot be assumed that the adapted items identically replicate those used previously, and therefore previous internal consistencies do not apply to the current items. The original ITISC - SF items proposed by Dweck (2000), and the adapted versions used for this study, can be seen in Table 1. Learners were asked to rate their agreement with each of the six items (1 – *strongly agree*; 6 – *strongly disagree*).

Table 1

ITISC - SF Item Comparison

Original item (Dweck, 2000)	Adapted item
1. You have a certain amount of intelligence, and you really can't do much to change it.	1. You have a certain amount of mathematics intelligence, and you really can't do much to change it.
2. Your intelligence is something about you that you can't change very much.	2. Your mathematics intelligence is something about you that you can't change very much.
3. You can learn new things, but you can't really change your basic intelligence.	3. You can learn new things, but you can't really change your basic mathematics intelligence.
4. No matter who you are, you can change your intelligence a lot.	4. No matter who you are, you can change your mathematics intelligence a lot.
5. You can always greatly change how intelligent you are.	5. You can always greatly change how intelligent you are in mathematics.
6. No matter how much intelligence you have, you can always change it quite a bit.	6. No matter how much mathematics intelligence you have, you can always change it quite a bit.

The internal consistency reliability of this adapted version was evaluated using the *psych* package in *R* (Revelle, 2019), using the responses of 187 learners, and was found to be acceptable (Cronbach's α = .77). The item-to-rest of scale correlation coefficients, and Cronbach's α if the item had to be dropped, are reported in Table 2. As can be seen in Table 2, each item contributes to the overall Cronbach's α, as their removal will decrease the overall internal consistency reliability (Cronbach, 1970). The results obtained from the adapted ITISC - SF will therefore be considered to reliably assess mindset for subsequent analyses.

Table 2

Internal Consistency Coefficients of Adapted ITISC - SF Items

		If item dropped
	Item-rest correlation coefficient	**Cronbach's α**
ITIS1	.557	.720
ITIS2	.613	.703
ITIS3	.576	.714
ITIS4	.440	.750
ITIS5	.463	.744
ITIS6	.415	.755

Raven's SPM. The Raven's SPM is an internationally recognised, locally normed measure of general intelligence (NCS Pearson, 2018). The Raven's SPM consists of 60 patterns of figures, which become progressively more difficult and must be completed. Each puzzle has a piece missing, and the learner had to find the exact fitting piece among six to eight alternatives presented. The instruction video participants had to watch to explain the exercise can be viewed at https://youtu.be/Rgr3V35fQDE, which also shows two sample items. One of two of the example items presented to the learners can be seen in Figure 1, which has been shared with the permission of JVR Psychometrics, the local distributor of the Raven's SPM for Pearson. With the example item, participants are guided to select option 4 as completing the pattern.

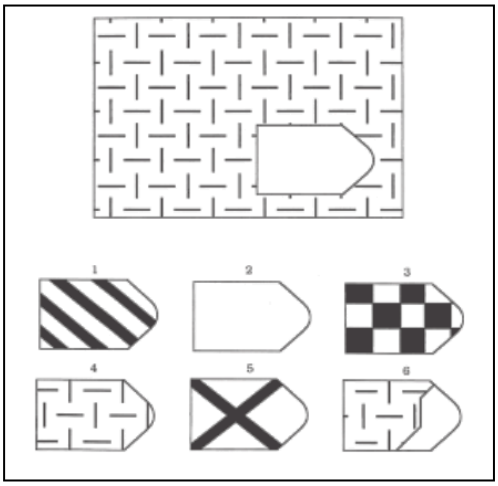

Figure 1

Example Raven's SPM Item

The electronic version of the Raven's SPM requires answers to all items for successful submission, thereby reducing the frequency of non-responses. All items load onto a general factor, or single scale score. South African adolescent norms are available, for which internal consistency reliability coefficients (Cronbach α) are .90 for both boys and girls, .90 for White adolescents and .88 for Black adolescents (NCS Pearson, 2018). Since there is no significant difference between ethnic groups, there is only one South African norm for adolescents.

Both the raw total scores and percentile scores were provided from the assessment platform, JVROnline, for subsequent analyses. The non-verbal nature of the questions provides users with a culturally fair, language-free gauge of the participant's fluid intelligence and abstract thinking ability, making it more applicable to our diverse, multilingual South African learner population. Previous local and international studies have shown that learners' performance on the Raven's SPM is unaffected by their level of schooling (De Bruin et al., 2005; Lewis, 1974; Taylor, 2008). Furthermore, Raven's SPM scores have been shown to predict mathematics performance specifically (Maqsud, 1998; Skagerlund & Träff, 2016; Taylor, 2008), making it suitable for the current study. In the current study, the Ravens SPM scores will be used as an indicator of the learners' fluid intelligence.

SOM. The SOM is a 76-item South African-developed assessment for learners from grades seven to 12. The assessment measures study attitude (14 items), mathematics anxiety (14 items), study habits (17 items), problem-solving (18 items), study milieu (13 items), and information processing (16 items – only for grades 10, 11 and 12) (Maree et al., 2011). Learners are asked to rate their frequency of behaviours (1 – *rarely*, 2 – *sometimes*, 3 – *frequently*, 4 - *generally*, 5 – *almost always*) across items. Examples of items that the grade nines answer include:

Study attitude: *I enjoy solving mathematics problems*.

Mathematics anxiety: *While answering tests or exams in mathematics, I panic*.

Study habits: *I catch up lost work in mathematics*.

Problem-solving behaviour: *I can think of examples where I use mathematics outside the class*.

Study milieu: *My mathematics teacher uses words that I do not know and that confuse me*.

For grade nine learners, the SOM has internal consistency reliabilities (Cronbach α) of between .72 and .79 on the individual scales, and an overall reliability of .95 as a measure with English and Afrikaans speaking learners, and an overall reliability of .89 for learners speaking African languages. The SOM is available electronically via SurveyMonkey, and the researcher was able to calculate raw and percentile scores to use for analyses. Questionnaires that were not completed in their entirety could not be scored.

The current study uses these measured SOM scales as primary moderating variables, treating each scale as a factor for analysis purposes. The SOM scales were previously found to predict mathematics performance in grade nine and 11 learners (Erasmus, 2012, 2013; Maree et al., 2014).This study aims to build on those findings while accounting for fluid intelligence, as well as the non-intellectual influences of personality and mindset.

BTI. The BTI is a South African developed personality questionnaire assessing the Big Five factors of personality: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (Taylor & De Bruin, 2017). The assessment was chosen because the items were developed with the diversity of languages and cultures in South Africa in mind and is one of the few local personality trait questionnaires with updated norms for high school learners aged 13-18 (De Bruin et al., 2022). The inventory consists of 193 statements that describe specific behaviours related to the five factors. Examples of items include:

Openness to experience: *I have a lot of different interests*.

Conscientiousness: *I double-check my work for mistakes*.

Extraversion: *When I tell a joke or story, everybody listens*.

Agreeableness: *I am a friendly person*.

Neuroticism: *I often feel sad for no reason*.

Participants respond to these statements using a 5-point Likert scale (1- *strongly disagree*; 5 – *strongly agree*). Internal consistency reliability coefficients (Cronbach's α) across the five factors range between .86 and .95 in younger adolescents (ages 13-15), in which Black and White learners were evenly represented. Stanine and percentile scores are provided from the electronic scoring system, JVROnline, for analyses. Reports can be generated from JVROnline if more than 80% of the items per scale have been answered.

Given that the BTI's adolescent norms were published recently (2022), it has mostly only been used in personal development initiatives. Given that the preceding literature review chapter highlights the value of assessing personality traits in relation to mathematics performance, the BTI was selected for this study to inspect the secondary moderating relationships of personality on the relationships between the study orientation factors, fluid intelligence, and mathematics performance.

Data Analysis

Before data analysis could commence, the datasets for each of the assessments (ITISC - SF, Raven's SPM, SOM, and BTI) needed to be merged into a single data file. Once merged, it was verified that a total of 231 learners had completed at least one assessment, with only eight learners not being able to participate after providing consent. After cleaning the datasets for completed assessments, however, the number of completions was reduced to 187 learners. Forty-four learners were removed from the subsequent analysis dataset due to these learners not having a 100% completion rate on either, or both, the BTI or SOM questionnaires, in line with their assessment interpretation guidelines (Maree et al., 2014; Taylor & de Bruin, 2017). Incomplete questionnaires render results an inaccurate or incomplete reflection of their personality or study orientations, and imputation methods for these variables would also be inadequate (Tran et al., 2018). The sample size was still adequate as per the G*Power suggestion discussed above in section 3.3.1.

The analyses on the dataset of 187 learners were performed using Jamovi version 2.2.5 (The jamovi project, 2021). The R packages used within the Jamovi programme for specific analyses are discussed in the sections below. It should also be noted that for all analyses, only raw scores were used, given that the mindset items have no standardised or normed scores, and that the BTI does not report on percentile scores like the SPM and SOM. From this point forward, all raw score totals will be referred to as factors or variables for analysis, rather than derivatives from the instruments they come from.

Descriptive Statistics

The preliminary step of inspecting the data in relation to the research objectives was running univariate and multivariate descriptive statistics, by considering the sample demographics and range across variables. These data inspections were performed with the Jamovi '*jmv*' R package 2.2.5.

The range and score distribution of each of the variables were evaluated by obtaining the means, standard deviations, range, multivariate skewness, and multivariate kurtosis to determine whether the data points were normally distributed or not. Each variables' minimum and maximum scores were checked, which served as an internal check that all data was scored correctly, given that the range of computed total raw scores needed to be within the range of number of items for that scale, multiplied by the number of response options for that scale.

Regression Analyses

Inter-Factor Correlation Matrices. Before more complex relationships were explored, Pearson correlation coefficients were calculated using the *jmv* package to determine inter-factor Pearson correlation coefficients between the variables across the various assessments, since the variables are measured on an interval scale. These inter-factor Pearson correlation coefficients serve to inform whether the hypothesised statistical relationships directly exist between the variables (Schober et al., 2018). The strength and direction of the relationships between variables were interpreted using the guideline of correlation coefficients in the range of .1 to .3 to represent small (weak) magnitudes, .3 to .5 medium (moderate) magnitudes, and .5 to 1.0 large (strong) magnitudes (Cohen, 1992; Gignac & Szodorai, 2016). In addition, the statistical significance of relationships, regardless of strength and direction, was also noted, and p-values are interpreted alongside magnitude. These inter-factor correlation matrices were inspected for potential multicollinearity, or the investigation of relationships between independent variables, before being investigated further with a multiple regression to test the specific hypotheses in relation to moderation. Multicollinearity was accounted for to ensure that the statistical significance of the independent variables was not undermined in the moderation and regression models (Siegel, 2016).

Moderation Analyses. Moderation analysis examines how a relationship between a predictor and outcome variable is influenced by a third variable, known as the moderator. The results of such analysis can determine whether the relationship between predictor and outcome variables weakens, strengthens, or exists at all in the presence of the moderating variable (Hair et al., 2021). The inter-factor correlation analysis provided insight into the variables which would be theoretically meaningful to include to test for the existence of moderating relationships (Hayes, 2018; Little et al., 2007). The existence of these moderating relationships was tested using the *medmod* module on Jamovi, to provide support for, or against, the seven primary moderator hypotheses arising from the literature reviewed in Chapter Two. The *medmod* module enables simple mediation and moderation analyses when considering a single mediator or moderator variable in relation to a predictor and outcome variable, without needing to manually mean center the variables (Selker, 2017). Mean centering involves computing a new variable by deducting the mean score of that scale from each instance, to minimise multicollinearity, to reduce the instability added to the regression model (Iacobucci et al., 2017).

For the set of primary moderating analyses, the fluid intelligence factor was set as the predictor variable, mathematics marks were set as the outcome variable, and the study orientation factors were each tested as an independent moderator variable. In cases where the interaction effects were significant, the simple slope analyses would also be reported, to further describe how different levels in the moderator variable affect how the predictor variable influences the outcome variable (Robinson et al., 2013). In cases where the interaction effects were found to be nonsignificant, the consideration of the different levels of moderation was less relevant for the current study, and therefore the simple slope analyses were not reported.

The alternate hypotheses evaluated using direct moderation were:

H_A1: A growth mindset moderates the positive relationship between fluid intelligence and mathematics performance.

H_A2: A fixed mindset moderates the negative relationship between fluid intelligence and mathematics performance.

H_A3: Study attitude moderates the positive relationship between fluid intelligence and mathematics performance.

H_A4: Mathematics anxiety moderates the negative relationship between fluid intelligence and mathematics performance.

H_A5: Study habits moderate the positive relationship between fluid intelligence and mathematics performance.

H_A6: Problem-solving behaviours moderate the positive relationship between fluid intelligence and mathematics performance.

H_A7: Study milieu moderates the positive relationship between fluid intelligence and mathematics performance.

Hierarchical Regressions. Hierarchical regression analysis is a statistical technique used to examine incremental contributions of levels of independent variables towards the prediction of the dependent variable, whilst accounting for the effects of other variables in the model (Gelman & Hill, 2007). To test the indirect effects of secondary moderations using *jmv*, interaction terms first needed to be created after mean centering the predictor and moderator variables under consideration. An interaction term is then created by multiplying a centered predictor variable (in this case, one of the study orientation factors) with a centered moderator variable (one of the personality factors).

These interaction terms were then added into a hierarchical regression together with the centered predictor and centered moderator variables, to determine whether a secondary moderating effect was present. Mathematics marks was set as the dependent variable and added covariates were the centered predictors (study orientation factor and fluid intelligence factor), centred moderator (personality factor), primary interaction term (fluid intelligence factor*study orientation factor) for the primary moderation, and second interaction term (study orientation factor*personality factor) for the secondary moderation. These covariates were then added into the hierarchical regression model builder, with the centred predictors and moderator variables being added first, followed by the first interaction term as the second-order variable, and the second interaction effect being added as the third-order hierarchical level (Hair et al., 2021).

The secondary moderations and interaction terms that were investigated by these regressions provided support or rejection for these alternate hypotheses:

H_A8: Openness to experience interacts with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A9: Openness to experience interacts with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A10: Conscientiousness moderates mindset’s relationship with fluid intelligence and mathematics performance.

H_A11: Conscientiousness interacts with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A12: Extraversion interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A13: Agreeableness interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A14: Neuroticism interacts with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A15: Neuroticism interacts with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

Ethical Considerations

Throughout the planning, data collection, data analysis, and reporting stages of this study, actions were taken with utmost care to ensure the beneficence of this study, while keeping the psychological safety and confidentiality of the participants in mind. Grade nine learners are considered vulnerable, according to the Children's Act 38 of 2005 since they are under 18 years of age. Therefore, while applying for ethical clearance from the University of Pretoria to conduct this study (clearance document can be viewed in Appendix D), permission was concurrently obtained from the Gauteng Department of Education (Appendix E) to contact schools in the Gauteng province with the proposal of conducting research with their learners who voluntarily agreed to participate. Prior to the learner participating in the study, the researcher had to obtain: 1) ethical approval from the University of Pretoria's Ethics Committee, 2) permission to conduct research in high schools from the Gauteng Department of Education, 3) permission from the school principals, 4) parental consent, and 5) pupil assent. The voluntary nature of the assessment was made clear at all stages of approval and consent. Furthermore, the aim of the study, time and tasks involved, and the declaration of use of the results for research purposes were made clear at all stages of approval and consent. Moreover, it was also communicated that the assessment provider, JVR Psychometrics, has a legal obligation to keep the data collected and scored on their systems (JVR Online and SurveyMonkey) for seven years, unless asked to delete the data earlier. Additionally, the data collected during this study will be kept electronically, in a password-protected folder on OneDrive that can only be accessed by the researcher and the research supervisor, for 15 years should the analyses in this report need to be replicated.

Whilst planning the study, care was taken at a practical level to keep participants physically safe given the Covid-19 pandemic. This meant considering assessments that could be completed electronically and virtually if needed, while also maintaining psychometric integrity. The researcher was available during all assessment completions to answer any questions or provide support. Moreover, the researcher and their supervisors' contact details were made available on the information sheets. For assessment administrations done on school premises, a teacher was present to support the administrative process. Care was taken to ensure that, despite it being a voluntary study, participants found value in participation, and as such, each participant received an interpretive learner insights report, providing them with a personality profile and development tips based on their cognitive, personality, and study orientation results. The majority of learners also received group feedback to guide their interpretation of these insight reports, and the opportunity for individual feedback was communicated. All learners that participated outside of the participating schools received individual feedback. It is within the researcher's scope as an independent psychometrist, and research psychologist, registered with the Health Professions Council of South Africa to provide such feedback reports. Furthermore, the narratives of these reports were reviewed by a team of four psychologists with extensive experience with the assessments used. Finaly, the present study was conducted under the supervision of research practitioners associated with the University of Pretoria.

Chapter Summary

Chapter Three discussed the process undertaken to investigate the hypotheses formulated from the literature review detailed in Chapter Two. In this regard, a cross-sectional, quantitative, positivist approach was deemed best suited to determine the psychological factors that influence mathematics performance in grade nine learners, a cohort annually faced with the choice of taking mathematics or mathematics literacy to their matric year. This chapter also provided a summary of the psychometric properties and reasoning for choosing the Raven's SPM, BTI, SOM, and ITISC - SF used in this study. The data obtained from these assessments were then used to conduct descriptive and inferential regression analyses with the *jmv* package, details of which were discussed in section 3.4. The outputs of these analyses are reported and interpreted in Chapter Four, presenting evidence to accept or disprove the hypotheses set based on existing literature, in accordance with the research objectives of this study.

Chapter Four: Analysis and Interpretation

Introduction

Several hypotheses were derived from the literature review covered in Chapter Two. Chapter Three continued to describe how these hypotheses would be practically operationalised and evaluated. After describing the sample demographics, Chapter Four reports on the results following the statistical analyses conducted, to provide support for, or reject the hypotheses proposed. These results are supplemented with corroborating, or where necessary, contradictory findings from previous studies.

Sample Description

A total of 187 grade nine learners make up the sample data used for analysis in this study. The majority of learners were 15 years of age, and more females than males participated in this study. Almost half of the sample indicated that they were Black African, with the other ethnicities fairly represented, in line with their representation in the Gauteng province (Statsistics South Africa [StatsSA], 2016). Most of the sample indicated their home language as English, followed by Afrikaans. For interest, it should also be noted that no learners indicated isiNdebele as their home language, despite a fair representation of the racial group (Black African) most likely to speak this language at home. A summary of the learner demographic details is reported in Table 3 on the next page.

Table 3

Participant Demographics

Variable	Category	Frequency (*N*)	Percentage of total (%)
Age	14	18	9.6
	15	150	80.2
	16	19	10.2
Total		187	100
Gender	Female	113	60.4
	Male	74	39.6
Total		187	100
Racial Group	Black African	88	47.1
	Prefer not to say	43	23.0
	White	29	15.5
	Indian/Asian	16	8.6
	Coloured (Mixed Ethnicity)	10	5.3
	Other	1	0.5
Total		187	100
Home Language	English	97	51.9
	Afrikaans	25	13.4
	Sesotho	15	8.0
	Setswana	13	7.0
	Prefer not to say	8	4.3
	siSwati	8	4.3
	isiZulu	6	3.2
	Northern Sotho	6	3.2
	Xitsonga	5	2.7
	Other	3	1.6
	Tshivenda	1	0.5
Total		187	100

Intelligence and Mathematics Performance

This study aims to investigate the moderating influence of mindset, study orientations, and personality on the relationship between fluid intelligence and mathematics performance. Determining this relationship within the current sample is therefore a cornerstone of this chapter. In examining this relationship, it was found that despite most psychometric assessment scores being normally distributed, the mathematics marks were slightly skewed and did not meet the assumption of normal distribution according to the significant Shapiro-Wilk test (W[185] = 0.95, $p < .001$ (Ramachandran & Tsokos, 2021). However, the Central Limit Theorem states that the distribution approaches normality as the sample size increases (normally above 30) (Acra, 2020; Gao et al., 2017). As such, parametric testing can still be performed on this sample of 187 learners.

The mean raw fluid intelligence score was 42.3 out of a possible 60 (*SD* = 7.4), while the mean mathematics marks was 57% (*SD* = 6.0), reflecting a slightly above-average performing sample. A statistically significant, moderate, positive relationship ($r = .387$, $p < .001$) between fluid intelligence and grade nine mathematics marks was observed.

The remainder of Chapter Four will consider how the non-intellectual factors moderate this relationship, to further explain significant influences on mathematics performance.

Objective One: Primary Moderation Relationships - Role of Mindset and Study Orientations Towards Mathematics

The following section seeks to investigate whether mindset and study orientations significantly moderates the relationship between fluid intelligence and mathematics marks, by testing hypotheses one to seven. Before assessing the moderating role of the study orientation factors, the strength and direction of the direct relationships between the variables were tested. These relationships are reported in Table 4 below.

Table 4

Primary Moderator Factor Correlation Coefficients

	FM	**GM**	**SA**	**MA**	**SH**	**PSB**	**SM**
Mathematics marks	-.261***	-.271***	.506***	-.356***	.461***	.467***	.408***
Fluid Intelligence	-.132	-.158*	.265***	-.123	.227**	.29***	.289***
M	6.35	6.63	38.00	15.20	46.20	39.90	42.00
SD	4.03	3.12	9.09	8.78	11.60	11.50	6.84

Note. FM = Fixed Mindset, GM = Growth Mindset, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu.
**p* < .05, ***p* < .01, ****p* < .001.

Both fixed ($r = -.26$, $p < .001$) and growth mindset ($r = -.27$, $p < .001$) have statistically significant weak, negative relationships with mathematics marks. It is somewhat contradictory that both mindsets have negative relationships with observed performance, given their polarity.

The five study orientation factors had statistically significant, moderate relationships with mathematics marks, with only mathematics anxiety indicating a negative relationship. Study attitude, study habits, problem-solving behaviour, and study milieu also have statistically significant, weak, positive relationships with fluid intelligence, and therefore, the moderation and regression models discussed later in this chapter have been performed with mean-centered variables to reduce this multicollinearity effect.

Study attitude reflected a statistically significant, strong, positive relationship with mathematics marks ($r = .51$, $p < .001$), as well as a statistically significant, weak, positive relationship with fluid intelligence ($r = .27$, $p < .001$). The relationship between study attitude and fluid intelligence suggests that the self-insight into one's abilities likely positively influences one's study attitudes.

Given the only negative statistically significant moderate relationship, between mathematics anxiety and mathematics marks ($r = -.36$, $p < .001$), the relationship supported the hypothesis that anxiety negatively influences performance. The relationship between mathematics anxiety and fluid intelligence was not significant ($r = -.12$, $p > .05$), as expected, given that the fluid intelligence questionnaire did not have mathematical content. Additionally, the non-significant relationship provides support for mathematics anxiety only impacting mathematics performance, while not impacting performance in other domains.

The relationship between study habits and mathematics marks is statistically significant, moderate, and positive ($r = .46$, $p < .001$), supporting the view that positive study habits positively influence mathematics performance. The statistically significant, weak, positive relationship between study habits and fluid intelligence ($r = .23$, $p < .01$) could be indicative of learners higher on fluid intelligence realising sooner that they do not understand concepts, and in turn, putting in more study effort to grasp the concept confidently.

Problem-solving behaviour displayed a statistically significant, moderate, positive relationship with mathematics marks ($r = .47$, $p < .001$), the second strongest after study attitude. This facet of study orientation also showed the highest, albeit weak, statistically significant positive relationship with fluid intelligence ($r = 0.29$, $p < .001$). Given that problem-solving behaviour relates to metacognition and applying cognitive strategies effectively to solve problems, it is evident that individuals who apply problem-solving skills towards mathematics problems, applied similar skills during the completion of the fluid intelligence assessment.

The last study orientation scale, study milieu, also had statistically significant positive relationship with both mathematics marks ($r = .41$, $p < .001$) and fluid intelligence ($r = .29$, $p < .001$), supporting the hypothesis that study milieu relates to mathematics performance.

Hypothesis One: Moderating Role of Growth Mindset

In Table 5 the moderation test conducted is reported, with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and growth mindset as the moderator variable. Table 5 therefore illustrates the analyses for the following hypotheses:

H_O1: A growth mindset does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A1: A growth mindset moderates the positive relationship between fluid intelligence and mathematics performance.

Table 5

Direct Effects and Moderation Model: Growth Mindset

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.763	0.142	0.485	1.041	5.371	< .001
Growth Mindset (GM)	-1.097	0.336	-1.756	-0.438	-3.261	.001
f x GM	0.016	0.045	-0.073	0.105	0.352	.725

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

There was a significant, positive main effect found between fluid intelligence and mathematics marks (b = 0.763, 95% CI [0.485, 1.041], z = 5.371, p < .001), indicating that higher fluid intelligence scores predict higher mathematics marks. There was also a significant, negative main effect found between growth mindset and mathematics marks (b = -1.097, 95% CI [-1.756, -0.438], z = -3.261, p = .001). This finding can be interpreted as growth mindset predicting mathematics marks, with higher growth mindset scores resulting in lower mathematics marks. This supports findings by Aditomo (2015) and Li and Bates (2017), which indicated that growth mindset does not consistently exhibit a positive relationship with academic success, despite increasing motivation. However, the interaction effect is non-significant (b = 0.016, 95% CI [-0.073, 0.105], z = 0.352, p > .05), indicating that despite each variable independently predicting mathematics marks, the relationship between fluid intelligence and mathematics marks is not moderated by growth mindset. As such, the findings in Table 5 fail to reject the null hypothesis (H_O1).

Hypothesis Two: Moderating Role of Fixed Mindset

In Table 6 the moderation test conducted is reported, with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and fixed mindset as the moderator variable. The hypotheses being tested were:

H_O2: Fixed mindset does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A2: Fixed mindset moderates the negative relationship between fluid intelligence and mathematics performance.

Table 6

Direct Effects and Moderation Model: Fixed Mindset

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.770	0.143	0.491	1.050	5.398	< .001
Fixed Mindset (FM)	-0.833	0.260	-1.343	-0.322	-3.197	.001
f x FM	0.015	0.029	-0.042	0.073	0.522	.602

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

Table 6 illustrates a significant, positive main effect between fluid intelligence and mathematics marks (b = 0.770, 95% CI [0.491, 1.050], z = 5.398, p < .001), again supporting the theory that higher fluid intelligence scores predict higher mathematics marks. There was also a significant negative main effect found between fixed mindset and mathematics marks (b = -0.833, 95% CI [-1.343, -0.322], z = -3.197, p = .001), suggesting higher fixed mindset predicts lower mathematics marks, which supports the findings of Greene et al. (2004) and Dweck and Master (2009). However, the interaction effect is non-significant (b = 0.015, 95% CI [-0.042, 0.073], z = 0.522, p > .05), indicating that despite each variable independently predicting mathematics marks, the relationship between fluid intelligence and mathematics marks is not moderated by fixed mindset. As such, the findings fail to reject the null hypothesis (H_O2).

Hypothesis Three: Moderating Role of Study Attitude

The moderation analysis conducted with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and study attitude as the moderator variable, is reported in Table 7. Therefore, in Table 7 the results of the following hypotheses is displayed:

H_O3: Study attitude does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A3: Study attitude moderates the positive relationship between fluid intelligence and mathematics performance.

Table 7

Direct Effects and Moderation Model: Study Attitude

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.596	0.131	0.340	0.852	4.563	< .001
Study Attitude (SA)	0.773	0.106	0.566	0.981	7.312	< .001
f x SA	0.010	0.015	-0.020	0.040	0.662	.508

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

A significant, positive main effect was found between fluid intelligence and mathematics marks (b = 0.596, 95% CI [0.340, 0.852], z = 4.563, p < .001). The positive main effect between study attitude and mathematics marks was also significant (b = 0.773, 95% CI [0.566, 0.981], z = 7.312, p < .001), supporting previous studies that study attitude predicts mathematics marks (Lipnevich et al., 2016; Muenks & Miele, 2017). However, the interaction effect is non-significant (b = 0.010, 95% CI [-0.020, 0.040], z = 0.662, p > .05), indicating that despite each variable independently predicting mathematics marks, the relationship between fluid intelligence and mathematics marks is not moderated by study attitude. As such, the findings fail to reject the null hypothesis (H_O3).

Hypothesis Four: Moderating Role of Mathematics Anxiety

In Table 8 the moderation test conducted is reported, with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and mathematics anxiety as the moderator variable, which tested the following hypotheses:

H_O4: Mathematics anxiety does not moderate the negative relationship between fluid intelligence and mathematics performance.

H_A4: Mathematics anxiety moderates the negative relationship between fluid intelligence and mathematics performance.

Table 8

Direct Effects and Moderation Model: Mathematics Anxiety

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.757	0.138	0.488	1.027	5.502	< .001
Math Anxiety (MA)	-0.568	0.116	-0.795	-0.341	-4.904	< .001
f x MA	-0.003	0.016	-0.034	0.029	-0.159	.874

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

A significant, positive main effect was found between fluid intelligence and mathematics marks (b = 0.757, 95% CI [0.488, 1.027], z = 5.502, p < .001). The negative main effect between mathematics anxiety and mathematics marks was also significant (b = -0.568, 95% CI [-0.795, -0.341], z = -4.904, p < .001), providing further support to the findings of Ramirez et al. (2016) that higher levels of mathematics anxiety predict lower mathematics marks. However, the interaction effect is non-significant (b = 0.003, 95% CI [-0.034, 0.029], z = -0.159, p > .05), demonstrating that, although each variable independently significantly predicts mathematics marks, the relationship between fluid intelligence and mathematics marks is not moderated by math anxiety. As such, the hypothesis that mathematics anxiety moderates the relationship between fluid intelligence and mathematics marks is not supported, and the findings fail to reject the null hypothesis (H_O4).

Hypothesis Five: Moderating Role of Study Habits

The moderating relationship tested with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and study habits as the moderator variable, is reported in Table 9. Here, the hypotheses being tested were:

H_O5: Study habits do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A5: Study habits moderate the positive relationship between fluid intelligence and mathematics performance.

Table 9

Direct Effects and Moderation Model: Study Habits

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.633	0.136	0.366	0.899	4.653	< .001
Study Habits (SH)	0.543	0.085	0.377	0.709	6.409	< .001
f x SH	-0.005	0.011	-0.027	0.017	-0.425	.671

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

A significant, positive main effect was again found between fluid intelligence and mathematics marks (b = 0.633, 95% CI [0.366, 0.899], z = 4.653, p < .001). The positive main effect between study habits and mathematics marks was significant, supporting existing literature which found that study habits positively predict mathematics marks (Cooper et al., 2006; Islam, 2021). However, as per preceding study orientation interactions, the interaction effect is non-significant (b = -0.005, 95% CI [-0.027, 0.017], z = -0.425, p > .05). The non-significant interaction effect illustrates that, whilst both fluid intelligence and study habits independently predict mathematics marks, the relationship between fluid intelligence and mathematics marks is not moderated by study habits. As such, the results fail to reject the null hypothesis (H_O5).

Hypothesis Six: Moderating Role of Problem-Solving Behaviour

By setting mathematics marks as the dependent variable, fluid intelligence as the predictor variable, and problem-solving behaviours as the moderator variable, the moderation relationship between these variables was tested. These results are reported in Table 10, which tested the following hypotheses:

H_O6: Problem-solving behaviours do not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A6: Problem-solving behaviours moderate the positive relationship between fluid intelligence and mathematics performance.

Table 10

Direct Effects and Moderation Model: Problem-Solving Behaviour

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.602	0.141	0.326	0.878	4.270	< .001
Problem-Solving Behaviour (PSB)	0.538	0.086	0.369	0.707	6.242	< .001
f x PSB	0.002	0.011	-0.020	0.025	0.198	.843

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

A positive main effect between fluid intelligence and mathematics marks was significant (b = 0.602, 95% CI [0.326, 0.878], z = 4.270, p < .001). Additionally, the positive main effect between problem-solving behaviour and mathematics marks was significant (b = 0.538, 95% CI [0.369, 0.707], z = 6.242, p < .001), signifying that problem-solving behaviours predict mathematics marks. This finding adds further support to the findings of Moodaley (2006) and Erasmus (2013), while refuting the findings of Maree et al. (2014). However, despite the two variables independently predicting mathematics marks, the interaction effect is non-significant (b = -0.002, 95% CI [-0.020, 0.025], z = -0.198, p > .05). As such, there is no support for the alternate hypothesis (H_A6) that the relationship between fluid intelligence and mathematics marks is moderated by problem-solving behaviour. Therefore, the results fail to reject the null hypothesis (H_O6).

Hypothesis Seven: Moderating Role of Study Milieu

The moderation analysis conducted with fluid intelligence as the predictor variable, mathematics marks as the dependent variable, and study milieu as the moderator variable , is reported in Table 11, to test the following hypotheses:

H_O7: Study milieu does not moderate the positive relationship between fluid intelligence and mathematics performance.

H_A7: Study milieu moderates the positive relationship between fluid intelligence and mathematics performance.

Table 11

Direct Effects and Moderation Model: Study Milieu

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Fluid Intelligence (*f*)	0.703	0.139	0.431	0.976	5.060	< .001
Study Milieu (SM)	0.822	0.146	0.535	1.109	5.620	< .001
f x SM	0.044	0.017	0.011	0.077	2.600	.009

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

The positive main effect between fluid intelligence and mathematics marks was significant (b = 0.703, 95% CI [0.431, 0.976], z = 5.060, p < .001). Furthermore, the positive main effect between study milieu and mathematics marks was also significant (b = 0.822, 95% CI [0.535, 1.109], z = 5.620, p < .001), noting that study milieu does predict mathematics marks, which is in line with existing literature (Claro et al., 2016). Furthermore, in addition to the two direct significant effects, the interaction effect is significant (b = 0.044, 95% CI [0.011, 0.077], z = 2.600, p < .01). Therefore, there is support for H_A7 – study milieu moderates the relationship between fluid intelligence and mathematics marks, and the results therefore reject the null hypothesis (H_O7).

In Table 12, this interaction effect is further described, showing the effect of fluid intelligence on mathematics marks at different levels of study milieu scores.

Table 12

Simple Slope Analysis: Fluid Intelligence and Study Milieu Interaction Effect

			95% CI			
	Estimate	**SE**	**Lower**	**Upper**	**z**	**p**
Average	0.703	0.141	0.428	0.979	5.000	< .001
Low (-1SD)	0.405	0.160	0.091	0.720	2.530	.010
High (+1SD)	1.001	0.201	0.606	1.396	4.970	< .001

Note. SE = Standard Error of the Estimate, CI = Confidence Interval.

From Table 12, it can be interpreted that learners who reported higher than average levels of study milieu were able to achieve higher mathematics marks in accordance with their fluid intelligence potential (b = 1.001, 95% CI [0.606, 1.396], z = 4.970, p < .001), when compared to average or lower than average levels of study milieu (b = 0.703, 95% CI [0.428, 0.979], z = 5.000, p < .001 and b = 0.405, 95% CI [0.091, 0.720], z = 2.530, p = .01, respectively). As such, it can be concluded that the more learners perceive a positive study milieu, the more likely learners are to achieve in mathematics and actualise their cognitive potential, as assessed by fluid intelligence.

Synthesis of Hypotheses Outcomes for Objective One

Objective One of this study aimed to investigate whether mindset and study orientations significantly moderate the relationship between fluid intelligence and mathematics marks. Following from this objective there arose seven specific hypotheses to be tested. The results of these analyses are summarised as:

There are statistically significant, weak, negative relationships between growth mindset, and mathematics marks (r = -.271, p < .001) and fluid intelligence (r = -.158, p < .05), respectively. Furthermore, although fluid intelligence and growth mindset each independently predict mathematics marks, the relationship between fluid intelligence and mathematics performance, in grade nine learners, is not moderated by a growth mindset. Therefore, the results fail to reject the null hypothesis (H_O1) in favour of the alternative hypothesis (H_A1).

A statistically significant, weak, negative relationship between fixed mindset and mathematics marks is present (r = -.261 p < .001). Despite fluid intelligence and fixed mindset each independently predicting mathematics marks, the relationship between fluid intelligence and mathematics performance in grade nine learners, is not moderated by a fixed mindset. Therefore, the results fail to reject the null hypothesis (H_O2) in favour of the alternative hypothesis (H_A2).

A statistically significant, strong, positive relationship between study attitude and mathematics marks was present ($r = .506$, $p < .001$), as well as a statistically significant, weak, positive relationship between study attitude and fluid intelligence ($r = .265$, $p < .001$). However, while fluid intelligence and study attitude each independently predict mathematics marks, the relationship between fluid intelligence and mathematics performance, in grade nine learners, is not moderated by study attitude. Therefore, the results fail to reject the null hypothesis (H_O3) in favour of the alternative hypothesis (H_A3).

A statistically significant, moderate, negative relationship between mathematics anxiety and mathematics marks was observed ($r = -.356$, $p < .001$). Additionally, even though fluid intelligence and mathematics anxiety each independently predict mathematics marks, the relationship between fluid intelligence and mathematics performance, in grade nine learners, is not moderated by mathematics anxiety. Therefore, the results fail to reject the null hypothesis (H_O4) in favour of the alternative hypothesis (H_A4).

There were statistically significant positive relationships between study habits, and mathematics marks ($r = 0.461$, $p < .001$) and fluid intelligence ($r = .227$, $p < .01$), respectively. Furthermore, fluid intelligence and study habits each independently predict mathematics marks. However, the relationship between fluid intelligence and mathematics performance in grade nine learners, is not moderated by study habits. Therefore, the results fail to reject the null hypothesis (H_O5) in favour of the alternative hypothesis (H_A5).

There are statistically significant, positive relationships between problem-solving behaviours, and mathematics marks ($r = .467$, $p < .001$) and fluid intelligence ($r = 0.29$, $p < .001$), respectively. Adding to this, fluid intelligence and problem-solving behaviours each independently predict mathematics marks, however, this relationship, in grade nine learners, is not moderated by problem-solving behaviour. Therefore, the results fail to reject the null hypothesis (H_O6) in favour of the alternative hypothesis (H_A6).

Statistically significant, positive relationships were observed between study milieu, and mathematics marks ($r = 0.408$, $p < .001$) and fluid intelligence ($r = .289$, $p < .001$), respectively. In addition, fluid intelligence and study milieu each independently predict mathematics marks, as well as the interaction effect of the two variables. Therefore, the relationship between fluid intelligence and mathematics performance, in grade nine learners, was shown to be moderated by study milieu. Therefore, the null hypothesis (H_O7) is rejected in favour of the alternative hypothesis (H_A7).

Objective Two: Secondary Moderation Relationships - Influence of Personality on Mathematics Marks

Objective Two of the study is to investigate the secondary moderating role of personality on the study orientation factors, given that many of the study orientations were found to independently influence mathematics marks, as evidenced by their significant direct effects reported in section 4.3. Objective Two aims to add the most original contribution to literature on the topic of non-intellectual factors that influence mathematics marks, since both personality factors and facets are considered, whilst accounting for fluid intelligence and specific study behaviours, or orientations. Hypotheses eight to 15, test specific moderations to support or refute the influence of personality on study orientations, which influence mathematics performance.

Openness to Experience as a Moderator of Study Orientation Factors

The strength and direction of the direct relationships between openness to experience, study orientation factors, fluid intelligence, and mathematics marks are reported on first, followed by hierarchical regression models testing whether significant moderation effects exist between these variables to predict mathematics marks. The Pearson correlation coefficients between these variables are reported in Table 13.

Table 13

Correlation Coefficients Between Mathematics Marks, Fluid Intelligence, Study Orientations, and Openness to Experience

	OtE	Ae	Id	Ac	Va	Im
Maths Mark	.015	-.117	.089	.070	.036	.025
f	.034	-.057	.002	.096	.057	.049
SA	.132	-.004	.258***	.098	-.027	.151*
MA	.121	.107	.079	.051	.106	.075
SH	.302***	.137	.322***	.198**	.158*	.255***
PSB	.247***	.042	.302***	.208**	.087	.253***
SM	-.008	-.095	.171*	.028	-.123	.008
M	120.00	25.80	20.90	25.70	24.60	23.30
SD	15.40	5.76	4.13	4.48	3.60	4.30

Note. f = Fluid Intelligence, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, OtE = Openness to Experience, Ae = Aesthetics, Id = Ideas, Ac = Actions, Va = Values, Im = Imagination.

**p* < .05, ***p* < .01, ****p* < .001.

From Table 13, it can be noted that openness to experience and its facets do not have statistically significant relationships with either mathematics marks or fluid intelligence. Therefore, it can be preliminarily suggested that openness to experience does not have a direct moderation effect on the strength or direction of the relationship between mathematics marks and fluid intelligence, although this will be further explored in the regression models below. It should also be noted that aesthetics does not have statistically significant relationships with any of the study orientation facets – suggesting that the personality tendency to be drawn towards visually pleasing materials does not influence orientations towards studying mathematics.

As per hypothesis eight, that openness to experience moderates study attitude, there appears to be no significant relationship between the personality factor and study attitudes ($r = .13$, $p > .05$). However, the relationship between study attitude and two of the facets of openness to experience, namely ideas ($r = .26$, $p < .001$) and imagination ($r = .15$, $p < .05$), show a statistically significant, weak, positive relationship. The relationship and predictive value of the facets of openness to experience, with study attitudes, will be explored further below in section 4.4.1.1.

No relationships were hypothesised between openness to experience (and its facets) and mathematics anxiety. Additionally, the lack of statistically significant relationships in Table 13 further support the decision to not explore this relationship further for the current study.

There was no hypothesis set for the relationship between study habits and openness to experience. Therefore, this relationship will not be explored beyond the observed relationships of this study. However, statistically significant positive relationships are present between study habits and openness to experience ($r = .30$, $p < .001$), and the facets of ideas ($r = .32$, $p < .001$), actions ($r = .20$, $p < .01$), values ($r = .16$, $p < .05$), and imagination ($r = .26$, $p < .001$).

As per hypothesis nine, that openness to experience moderates problem-solving behaviour, statistically significant positive relationships were observed between problem-solving behaviour and the openness to experience factor ($r = .25$, $p < .001$), as well as the facets of ideas ($r = .30$, $p < .001$), actions ($r = .21$, $p < .01$), and imagination ($r = .25$, $p < .001$). These relationships and relative predictive values between the facets of openness to experience and problem-solving behaviours will be explored further in section 4.4.1.2.

Finally, a relationship between study milieu and openness to experience was not hypothesised and will not be discussed beyond the observed relationships of this study. Albeit small, the statistically significant positive relationship between study milieu and the ideas facet of openness to experience (*r* = .17, *p* < 0.05) is a note-worthy correlation. This relationship suggests that learners who perceive their social and study environments as supportive, find it easier to discover alternative solutions to mathematics problems. This is in line with literature covered in Chapter Two and will be discussed in more detail under Hypothesis 15.

Hypothesis Eight: Openness to Experience as a Moderator of Study Attitude. A hierarchical multiple regression was performed by adding fluid intelligence and study attitudes (since both have been established as independent predictors of mathematics marks), as well as openness to experience as a new independent variable into model one, to produce a baseline direct effects model. The interaction terms between these variables were added to model two, to determine whether openness to experience directly influenced study attitudes or fluid intelligence to predict mathematics marks (primary moderations), or whether the three-way interaction between openness to experience, study attitudes, and fluid intelligence predicts mathematics marks (secondary moderation). The analyses presented in Table 14 therefore served to test the following hypotheses:

H_O8: Openness to experience does not interact with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A8: Openness to experience interacts with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance.

Table 14

Hierarchical Regression Model: Fluid Intelligence, Study Attitude, Openness to Experience

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 - Direct	.573	.328	.317	29.8	3	183	< .001
2 - Interaction	.585	.342	.316	13.3	7	179	< .001
Model Comparison	ΔR^2	.014		0.937	4	179	.444

In Table 14, it is revealed that both regression models are statistically significant. While the direct effects model explained 32.8% of the variance (R^2 = .328, F(3, 183) = 29.8, p < .001), the interaction effects model explained 34.2% of the variance in mathematics marks (R^2 = .342, F(7, 179) = 13.3, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .014, F(4, 179) = 0.937, p > .05).

Table 15

Multiple Regression Model Coefficients: Openness to Experience as a Moderator of Study Attitude

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.986	0.968	65.076	68.897	69.192*		
f	0.589	0.136	0.321	0.857	4.331*	.069	0.272
SA	0.778	0.112	0.557	0.998	6.963*	.178	0.441
OtE	-0.054	0.063	-0.179	0.071	-0.852	.003	-0.052
2 - Interaction							
Intercept	66.863	1.013	64.864	68.862	66.002*		
f	0.592	0.138	0.320	0.863	4.301*	.068	0.273
SA	0.786	0.113	0.563	1.009	6.954*	.178	0.446
OtE	-0.079	0.065	-0.208	0.050	-1.210	.005	-0.076
f x SA	0.012	0.015	-0.019	0.042	0.772	.002	0.048
f x OtE	-0.010	0.009	-0.028	0.008	-1.114	.005	-0.070
SA x OtE	-0.003	0.007	-0.018	0.011	-0.433	.001	-0.028
f x SA x OtE	0.001	0.001	-0.001	0.004	1.019	.004	0.066

Note. *f* = Fluid Intelligence, SA = Study Attitude, OtE = Openness to Experience.

**p* < .001.

In Table 15, these models are further explored, revealing that 25.0% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (7.8%) of the variance. However, it should be noted that the contribution of openness to experience in the direct model is not significant. In the interaction model, the purpose of which is to test the various interaction effects, none of the interactions are significant. Furthermore, the interactions only contribute 1.2% to the overall variance explained by the model.

Therefore, there is no support for the alternate hypothesis that openness to experience moderates the interaction effect between fluid intelligence and study attitude to predict mathematics marks. However, before rejecting the alternate hypothesis, the facets of openness to experience were further explored in similar regression models. For the sake of brevity, only the facets of openness to experience that showed significant relationships with study attitude, namely ideas (r = .26, p < .001) and imagination (r = .15, p < .05), are reported below. It should also be noted that the regression models did not indicate statistically significant interaction effects with the remaining facets of aesthetics, actions, and values.

Ideas. A hierarchical multiple regression was performed by adding fluid intelligence, study attitudes, and ideas (a facet of openness to experience) into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether ideas influenced study attitudes or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between ideas, study attitudes, and fluid intelligence predicts mathematics marks.

Table 16

Hierarchical Regression Model: Fluid Intelligence, Study Attitude, Ideas

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.571	.326	.315	29.5	3	183	< .001
2 - Interaction	.574	.330	.304	12.6	7	179	< .001
Model Comparison	ΔR^2	.004		0.249	4	179	.910

In Table 16 it is revealed that both regression models are statistically significant. While the direct effects model explained 32.6% of the variance (R^2 = .326, F(3, 183) = 29.5, p < .001), the interaction effects model explained 33.0% of the variance in mathematics marks (R^2 = .330, F(7, 179) = 12.6, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .004, F(4, 179) = 0.249, p > .05).

In Table 17 these models are further explored. It is reported that 23.7% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (8.9%) of the variance. However, it must be noted that the contribution of ideas in the direct model is not significant. Moreover, none of the interactions are significant. Furthermore, the interactions only contribute 0.3% to the overall variance explained by the model. Therefore, the results in Table 17 provides no support that the ideas facet of openness to experience moderates the effect that fluid intelligence and study attitude have on mathematics marks. This is despite the statistically significant positive relationship between study attitude and ideas (r = .258, p < .001) reported in Table 13.

Table 17

Multiple Regression Model Coefficients: Ideas as a Moderator of Study Attitude

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr^2**	**Stand. Estimate**
1 - Direct							
Intercept	66.976	0.970	65.063	68.889	69.082*		
f	0.585	0.137	0.316	0.855	4.285*	.068	0.270
SA	0.778	0.115	0.551	1.005	6.758*	.168	0.441
Id	-0.099	0.244	-0.582	0.383	-0.407	.001	-0.026
2 - Interaction							
Intercept	66.863	1.052	64.787	68.939	63.552*		
f	0.561	0.146	0.272	0.849	3.834*	.055	0.259
SA	0.782	0.117	0.551	1.012	6.685*	.167	0.443
Id	-0.127	0.256	-0.632	0.377	-0.498	.001	-0.033
f x SA	0.014	0.018	-0.022	0.050	0.784	.002	0.057
f x Id	0.002	0.036	-0.069	0.072	0.053	.000	0.004
Id x SA	-0.009	0.027	-0.063	0.045	-0.326	.000	-0.023
f x SA x Id	0.002	0.004	-0.005	0.009	0.541	.001	0.043

Note. *f* = Fluid Intelligence, SA = Study Attitude, Id = Ideas.

*p < .001.

Imagination. A hierarchical multiple regression was performed by adding fluid intelligence, study attitudes, and imagination (a facet of openness to experience) into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether imagination directly influenced study attitudes or fluid intelligence to predict mathematics marks, or whether the three-way interaction between imagination, study attitudes, and fluid intelligence predicts mathematics marks.

Table 18

Hierarchical Regression Model: Fluid Intelligence, Study Attitude, Imagination

				Overall Model Test			
Model	R	R²	Adjusted R²	F	df1	df2	p
1 – Direct	.573	.328	.317	29.8	3	183	< .001
2 - Interaction	.589	.346	.321	13.6	7	179	< .001
Model Comparison	ΔR²	.018		1.23	4	179	.299

In Table 18 it is revealed that both regression models are statistically significant. While the direct effects model explained 32.8% of the variance (R^2 = .328, F(3, 183) = 29.8, p < .001), the interaction effects model explained 34.6% of the variance in mathematics marks (R^2 = .346, F(7, 179) = 13.6, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .018, F(4, 179) = 1.23, p > .05).

Table 19

Multiple Regression Model Coefficients: Imagination as a Moderator of Study Attitude

			95% CI				
Predictor	Estimate	SE	Lower	Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.966	0.968	65.056	68.875	69.190*		
f	0.590	0.136	0.322	0.859	4.341*	.069	0.272
SA	0.780	0.112	0.559	1.001	6.971*	.178	0.442
Im	-0.207	0.228	-0.657	0.243	-0.907	.003	-0.055
2 - Interaction							
Intercept	66.959	1.013	64.959	68.958	66.076*		
f	0.571	0.138	0.299	0.844	4.137*	.063	0.264
SA	0.779	0.113	0.556	1.002	6.888*	.176	0.442
Im	0.122	0.283	-0.436	0.680	0.432	.001	0.027
f x SA	0.009	0.016	-0.023	0.040	0.537	.001	0.034
f x Im	-0.055	0.035	-0.124	0.013	-1.592	.009	-0.104
Im x SA	0.024	0.033	-0.040	0.089	0.742	.002	0.049
f x SA x Im	-0.002	0.004	-0.010	0.006	-0.523	.001	-0.036

Note. *f* = Fluid Intelligence, SA = Study Attitude, Im = Imagination.

*p < .001.

In Table 19 it is demonstrated that, within the direct model, 25.0% of the unique variance is explained by each predictive variable, with the combination of the variables explaining the remainder (7.8%) of the variance. However, it must be noted that the contribution of imagination in the direct model is not significant. Moreover, none of the interactions are significant. Furthermore, the interactions only contribute 1.3% to the overall variance explained by the model. Therefore, there is no support that the imagination facet of openness to experience moderates the relationship between fluid intelligence and study attitude, despite the weak relationship reported between imagination and study attitude (r = .15, $p < .05$) in Table 13.

Based on the reported evidence, none of the interaction effects between openness to experience (or its facets) were significant. Therefore, openness to experience and its related facets do not moderate the interaction effect between study attitude and fluid intelligence in predicting mathematics marks. As such, the results fail to reject the null hypothesis, H_O8.

Hypothesis Nine: Openness to Experience as a Moderator of Problem-Solving Behaviour. A hierarchical multiple regression was performed by adding fluid intelligence and problem-solving behaviour (since both have been established as independent predictors of mathematics marks), as well as openness to experience as a new independent variable into a baseline direct effects model (model 1). This was followed by adding their interaction terms to model two, to determine whether openness to experience directly influenced problem-solving behaviours or fluid intelligence to predict mathematics marks (primary moderations), or whether the three-way interaction between openness to experience, problem-solving behaviours, and fluid intelligence predicts mathematics marks (secondary moderation). The results seek to provide evidence for one of the following hypotheses:

H_O9: Openness to experience does not interact with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A9: Openness to experience interacts with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance.

In Table 20 it is revealed that both regression models are statistically significant. While the direct effects model explained 29.5% of the variance ($R^2 = .295$, $F(3, 183) = 25.5$, $p < .001$), the interaction effects model explained 31.2% of the variance in mathematics marks ($R^2 = .312$, $F(7, 179) = 11.6$, $p < .001$). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects ($R^2 = .017$, $F(4, 179) = 1.12$, $p > .05$).

Table 20

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Openness to Experience

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.543	.295	.284	25.5	3	183	< .001
2 - Interaction	.559	.312	.285	11.6	7	179	< .001
Model Comparison	ΔR^2	.017		1.12	4	179	.350

Table 21

Multiple Regression Model Coefficients: Openness to Experience as a Moderator of Problem-Solving Behaviour

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr^2**	**Stand. Estimate**
1 - Direct							
Intercept	67.001	0.992	65.045	68.958	67.570*		
f	0.584	0.141	0.306	0.861	4.150*	.067	0.270
PSB	0.574	0.094	0.390	0.759	6.140*	.145	0.411
OtE	-0.099	0.067	-0.230	0.032	-1.490	.008	-0.095
2 - Interaction							
Intercept	67.141	1.066	65.037	69.245	62.972*		
f	0.621	0.152	0.321	0.920	4.093*	.065	0.287
PSB	0.601	0.095	0.414	0.788	6.332*	.154	0.430
OtE	-0.112	0.070	-0.251	0.026	-1.600	.010	-0.108
f x PSB	0.006	0.012	-0.017	0.029	0.500	.001	0.034
f x OtE	-0.015	0.010	-0.034	0.004	-1.577	.010	-0.105
PSB x OtE	-0.005	0.006	-0.018	0.007	-0.838	.003	-0.055
f x PSB x OtE	0.000	0.001	-0.002	0.002	0.007	.000	-0.001

Note. *f* = Fluid Intelligence, PSB = Problem-Solving Behaviour, OtE = Openness to Experience.
*p < .001.

These models are further explored in Table 21 and shows that 22.0% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (7.5%) of the variance. However, it must be noted that the contribution of openness to experience in the direct model is not significant. In the interaction model, the purpose of which is to test the various interaction effects, there are no significant interactions, and therefore, no significant moderations. Furthermore, the interactions only contribute 1.4% to the overall variance explained by the model.

Therefore, the results in Table 21 provides no support for the hypothesis that openness to experience moderates the relationship between fluid intelligence and problem-solving behaviour, or between these two independent variables and mathematics marks, despite the statistically significant relationship (r = .25, p < .001) reported in Table 13. However, before accepting the null hypothesis H_O9, the hierarchical regression models of the openness to experience facets that showed significant relationships with problem-solving behaviour, namely ideas (r = .30, p < .001), actions (r = .21, p < .01), and imagination (r = .25, p < .001) are reported below. Furthermore, despite the values facet of openness to experience having non-significant relationships with mathematics marks, fluid intelligence, or problem-solving behaviour, the facet was found to have a significant interaction effect with fluid intelligence, which will also be discussed in more detail below.

Ideas. A hierarchical multiple regression was performed by adding fluid intelligence, problem-solving behaviour, and ideas into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether ideas influenced problem-solving behaviour or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between ideas, problem-solving behaviour, and fluid intelligence predicts mathematics marks.

Table 22

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Ideas

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.536	.287	.276	24.6	3	183	< .001
2 - Interaction	.543	.294	.267	10.7	7	179	< .001
Model Comparison	ΔR²	.007		0.43	4	179	.784

In Table 22 it is revealed that both regression models are statistically significant. While the direct effects model explained 28.7% of the variance (R^2 = .287, F(3, 183) = 24.6, p < .001), the interaction effects model explained 29.4% of the variance in mathematics marks (R^2 = .294, F(7, 179) = 10.7, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .007, F(4, 179) = 0.43, p > .05).

In Table 23, these models are further explored and highlights that 19.8% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (8.9%) of the variance. However, it must be noted that the ideas facet of openness to experience does not significantly contribute to the model. There are no significant interactions, and as a result, no significant moderations. Furthermore, the interactions only contribute 0.4% to the overall variance explained by the model. Therefore, the ideas facet does not moderate the relationship between problem-solving behaviour and mathematics marks, despite the significant relationship (r = .30, p < .001) between ideas and problem-solving behaviour reported in Table 13.

Table 23

Multiple Regression Model Coefficients: Ideas as a Moderator of Problem-Solving Behaviour

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.983	0.997	65.016	68.949	67.193*		
f	0.586	0.142	0.306	0.866	4.129*	.067	0.271
PSB	0.554	0.096	0.365	0.744	5.770*	.130	0.397
Id	-0.122	0.255	-0.626	0.381	-0.478	.001	-0.031
2 - Interaction							
Intercept	67.228	1.101	65.055	69.401	61.051*		
f	0.580	0.157	0.270	0.891	3.688*	.054	0.268
PSB	0.563	0.097	0.371	0.755	5.778*	.132	0.403
Id	-0.143	0.273	-0.681	0.395	-0.525	.001	-0.037
f x PSB	0.003	0.012	-0.021	0.027	0.259	.000	0.018
f x Id	-0.004	0.036	-0.076	0.068	-0.112	.000	-0.008
PSB x Id	-0.023	0.024	-0.070	0.025	-0.945	.003	-0.065
f x PSB x Id	0.001	0.003	-0.005	0.007	0.417	.001	0.031

Note. *f* = Fluid Intelligence, PSB = Problem-Solving Behaviour, Id = Ideas.

*p < .001.

Actions. Fluid intelligence, problem-solving behaviour, and actions were added into a baseline, direct effects model. The interaction terms between these variables were added into model two. This addition aimed to determine, via means of a hierarchical regression model, whether actions influenced problem-solving behaviour or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between actions, problem-solving behaviour, and fluid intelligence predicts mathematics marks.

Table 24

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Actions

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.537	.288	0.276	24.7	3	183	< .001
2 - Interaction	.541	.293	0.265	10.6	7	179	< .001
Model Comparison	ΔR²	.005		0.30	4	179	.876

In Table 24 it is reported that both regression models are statistically significant. While the direct effects model explained 28.8% of the variance (R^2 = .288, F(3, 183) = 24.7, p < .001), the interaction effects model explained 29.3% of the variance in mathematics marks (R^2 = .293, F(7, 179) = 10.6, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .005, F(4, 179) = 0.30, p > .05).

In Table 25, these models were further explored, and it is reported that 20.7% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (8.1%) of the variance. However, it must be noted that actions do not significantly contribute to this direct model. There are no significant interactions or moderation effects, with the interactions only contributing 0.4% to the overall variance explained by model two. Therefore, there is no evidence to suggest that actions moderate any relationships between problem-solving behaviour, fluid intelligence, and mathematics marks.

Table 25

Multiple Regression Model Coefficients: Actions as a Moderator of Problem-Solving Behaviour

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.977	0.997	65.011	68.943	67.210*		
f	0.596	0.141	0.317	0.875	4.215*	.069	0.275
PSB	0.550	0.093	0.367	0.733	5.931*	.137	0.394
Ac	-0.138	0.228	-0.588	0.312	-0.604	.001	-0.039
2 - Interaction							
Intercept	67.104	1.067	64.999	69.210	62.899*		
f	0.616	0.153	0.313	0.918	4.020*	.064	0.285
PSB	0.564	0.095	0.376	0.753	5.921*	.138	0.404
Ac	-0.126	0.238	-0.596	0.344	-0.528	.001	-0.035
f x PSB	0.003	0.012	-0.020	0.026	0.274	.000	0.018
f x Ac	-0.007	0.033	-0.072	0.057	-0.229	.000	-0.015
PSB x Ac	-0.017	0.020	-0.057	0.024	-0.815	.003	-0.053
f x PSB x Ac	-0.002	0.003	-0.008	0.004	-0.574	.001	-0.037

Note. *f* = Fluid Intelligence, PSB = Problem-Solving Behaviour, Ac = Actions.

*p < .001.

Values. A hierarchical multiple regression was performed by adding fluid intelligence, problem-solving behaviour, and values into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether values directly influenced problem-solving behaviour or fluid intelligence to predict mathematics marks, or whether the three-way interaction between values, problem-solving behaviour, and fluid intelligence predicts mathematics marks.

In Table 26 it is revealed that both regression models are statistically significant. While the direct effects model explained 28.7% of the variance (R^2 = .287, F(3, 183) = 24.5, p < .001), the interaction effects model explained 30.7% of the variance in mathematics marks (R^2 = .307, F(7, 179) = 11.3, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .020, F(4, 179) = 1.29, p > .05).

Table 26

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Values

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.536	.287	.275	24.5	3	183	< .001
2 - Interaction	.554	.307	.280	11.3	7	179	< .001
Model Comparison	ΔR^2	.020		1.29	4	179	.275

Table 27

Multiple Regression Model Coefficients: Values as a Moderator of Problem-Solving Behaviour

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr^2**	**Stand. Estimate**
1 - Direct							
Intercept	66.982	0.997	65.014	68.950	67.158***		
f	0.594	0.141	0.314	0.873	4.196***	.069	0.274
PSB	0.541	0.092	0.361	0.722	5.918***	.136	0.388
Va	-0.059	0.279	-0.610	0.491	-0.213	.000	-0.013
2 - Interaction							
Intercept	66.892	1.039	64.842	68.941	64.404***		
f	0.624	0.150	0.328	0.920	4.161***	.067	0.288
PSB	0.541	0.092	0.360	0.721	5.904***	.135	0.387
Va	0.010	0.291	-0.565	0.585	0.034	.000	0.002
f x PSB	0.005	0.012	-0.018	0.027	0.399	.001	0.026
f x Va	-0.080	0.039	-0.157	-0.002	-2.020*	.016	-0.149
PSB x Va	0.033	0.030	-0.027	0.093	1.073	.005	0.071
f x PSB x Va	-0.006	0.004	-0.013	0.001	-1.593	.010	-0.117

Note. *f* = Fluid Intelligence. PSB = Problem-Solving Behaviour. Va= Values.

**p* < .05. ***p* < .001.

In Table 27, these models are further explored and indicates that 20.5% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (8.2%) of the variance. However, it should be noted that the values facet of openness to experience does not statistically significantly contribute to the direct or interaction model. However, there is a significant interaction effect between fluid intelligence and values, indicative of a primary moderation effect – the values facet moderates fluid intelligence, which in turn predicts mathematics marks. Even with this statistically significant interaction effect, however, the interactions only contribute 3.2% to the overall variance explained by the model. Therefore, although there is no support for values serving as a moderator of problem-solving behaviour, this facet does work as a moderator (of fluid intelligence) to predict mathematics marks.

Imagination. Fluid intelligence, problem-solving behaviour, and imagination were independently added into a baseline, direct effects model in a hierarchical regression model. Model two was created by adding the interaction effects between these variables, to determine whether imagination directly influenced problem-solving behaviour or fluid intelligence to predict mathematics marks, or whether the three-way interaction between imagination, problem-solving behaviour, and fluid intelligence predicts mathematics marks.

Table 28

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Imagination

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.543	.295	.283	25.5	3	183	< .001
2 - Interaction	.556	.309	.282	11.4	7	179	< .001
Model Comparison	ΔR²	.014		0.92	4	179	.452

In Table 28 it is revealed that both regression models are statistically significant. While the direct effects model explained 29.5% of the variance (R^2 = .295, $F(3, 183) = 25.5$, $p < .001$), the interaction effects model explained 30.9% of the variance in mathematics marks (R^2 = .309, $F(7, 179) = 11.4$, $p < .001$). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 =.014, $F(4, 179) = 0.92$, $p > .05$).

In Table 29 these two models are further explored and reports that 21.9% of the unique variance is explained by each predictive variable in the direct effects model. The combination of the variables explain the remainder (7.6%) of the variance. However, it must be noted that the contribution of the imagination facet of openness to experience is not significant in this direct model, nor the interactions model. There are no significant interaction effects, and therefore, no moderation effects to report on. Furthermore, the interactions only contribute 1.1% to the overall variance explained by the model. Therefore, there is no evidence to imply that imagination moderates the relationship between problem-solving behaviour and mathematics marks, despite the weak, positive relationship between problem-solving behaviour and imagination (*r* = 0.253, *p* < .001) reported in Table 13.

Table 29

Multiple Regression Model Coefficients: Imagination as a Moderator of Problem-Solving Behaviour

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.965	0.992	65.008	68.923	67.510*		
f	0.587	0.141	0.309	0.864	4.170*	.067	0.271
PSB	0.573	0.094	0.389	0.758	6.120*	.144	0.411
Im	-0.344	0.239	-0.815	0.128	-1.440	.008	-0.092
2 - Interaction							
Intercept	67.004	1.062	64.909	69.100	63.096*		
f	0.620	0.154	0.316	0.925	4.022*	.063	0.287
PSB	0.584	0.094	0.398	0.770	6.182*	.147	0.418
Im	-0.384	0.253	-0.883	0.115	-1.517	.009	-0.103
f x PSB	0.008	0.012	-0.015	0.032	0.695	.002	0.048
f x Im	-0.044	0.034	-0.111	0.022	-1.318	.007	-0.090
PSB x Im	-0.016	0.022	-0.059	0.026	-0.755	.002	-0.050
f x PSB x Im	0.001	0.003	-0.005	0.007	0.302	.000	0.021

Note. *f* = Fluid Intelligence. PSB = Problem-Solving Behaviour. Im = Imagination

**p* < .001.

Based on the reported evidence, none of the interaction effects between openness to experience (or its facets) and problem-solving behaviour were significant. Therefore, openness to experience, and its related facets, does not moderate the relationship between problem solving behaviour and mathematics marks. There was, however, a significant interaction effect observed between the values facet and fluid intelligence, providing support that the values facet moderates the influence of fluid intelligence on mathematics marks. This significant interaction effect provides new insights into the influence of openness to experience and its facets in relation to mathematics marks, regardless of how small this effect is. However, because there are no significant interactions with problem-solving behaviours as hypothesised, the results fail to reject the null hypothesis (H_O9).

Conscientiousness as a Moderator of Mindset and Study Orientation Factors. The strength and direction of the direct relationships between conscientiousness, mindset, study orientations, fluid intelligence, and mathematics marks are reported on first, followed by hierarchical regression models testing whether significant moderation effects exist between these variables to predict mathematics marks. The Pearson correlation coefficients between these variables are reported in Table 30.

Table 30

Correlation Coefficients Between Mathematics marks, Fluid Intelligence, Mindset, Study Orientations, and Conscientiousness

	Cons.	**Eff**	**Ord**	**Dut**	**Pru**	**S-d**
Maths marks	.253***	.244***	.207**	.178*	.188**	.200**
f	.033	.016	-.026	.121	.040	.008
FM	-.160*	-.052	-.142	-.175*	-.233**	-.086
GM	-.132	-.050	-.128	-.094	-.173*	-.110
SA	.430***	.371***	.377***	.287***	.346***	.352***
MA	-.047	-.002	-.078	.022	-.054	-.072
SH	.504***	.473***	.411***	.340***	.460***	.371***
PSB	.464***	.454***	.362***	.338***	.408***	.333***
SM	.225**	.136	.158*	.195**	.148*	.281***
M	146.00	27.60	35.00	34.20	22.20	27.00
SD	22.30	5.84	7.29	5.23	3.74	5.38

Note. f = Fluid Intelligence, FM = Fixed Mindset, GM = Growth Mindset, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, Cons. = Conscientiousness, Eff = Effort, Ord = Order, Dut = Dutifulness, Pru = Prudence, S-d = Self-Discipline.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

The results in Table 30 support existing literature that conscientiousness relates with academic performance, even if there is no relationship with intelligence (Rikoon et al., 2016; Wehner & Schils, 2021). In the current study, both the conscientiousness factor, as well as all its facets, have statistically significant positive, weak, relationships with mathematics marks, while there are no statistically significant relationships with fluid intelligence.

In support of hypothesis 10, there are statistically significant, weak, negative relationships between fixed mindset and conscientiousness (r = -.16, p < .05), and the facets of dutifulness (r = -.18, p < .05) and prudence (r = -.23, p < .01). There is also a statistically significant, weak, negative relationship between the prudence facet and growth mindset (r =

-.17, $p < .05$). The predictive value of these relationships will be explored further in section 4.4.2.1.

Statistically significant moderate, positive relationships are present between study attitudes and conscientiousness ($r = .43$, $p < .001$), as well as with all the conscientiousness facets, suggests that positive attitudes relate to better self-regulation and persistence. Given that conscientiousness as a moderator of study attitude was not a hypothesis for the current study, and considering that the existing literature adequately covers this, these relationships will not be explored further.

No statistically significant relationships between mathematics anxiety and conscientiousness were observed. This contradicts Johnston-Wilder and Lee (2010), who indicated that mathematics resilience, the inverse of math anxiety, relates to a persistent display of conscientiousness towards the subject.

The statistically significant, strong, positive relationship between study habits and conscientiousness ($r = .50$, $p < .001$), and moderate relationships with all the facets, supports the implication that learners scoring higher on discipline and diligence would invest more effort in studying. This relationship is explored further in section 4.4.2.2.

The statistically significant moderate relationships between problem-solving behaviour and conscientiousness ($r = .46$, $p < .001$), along with its facets, supports the hypothesis that higher persistence scores are related to improved information retrieval. If an individual scoring higher on conscientiousness puts in more effort in studying, they would, in time, be training their metacognitive knowledge and problem-solving abilities (Pennequin et al., 2010).

Lastly, the statistically significant, weak, positive relationships between study milieu and conscientiousness ($r = .23$, $p < .01$), as well as the facets of order ($r = .16$, $p < .05$), dutifulness ($r = .20$, $p < .01$), prudence ($r = 0.15$, $p < .05$), and self-discipline ($r = .28$, $p < .001$) highlights the value of being planful and disciplined even in unsupportive environments. In this regard, although this relationship will not be explored further in the current study, there is potential in following up on the study by Hu et al. (2018) that examined the role of conscientiousness in predicting mathematics performance while accounting for socioeconomic status, cultural influences, and fluid intelligence.

Hypothesis 10: Conscientiousness as a Moderator between Mindset and Mathematics Performance. A hierarchical multiple regression was performed by adding fluid intelligence, fixed mindset, and growth mindset (since they have all already been established as independent predictors of mathematics marks), as well as conscientiousness as a new independent variable into a baseline direct effects model. Model two was created by adding their interaction terms, making it possible to determine whether conscientiousness either directly influenced mindset or fluid intelligence to predict mathematics marks (primary moderations), or whether the three-way interaction between conscientiousness, mindset and fluid intelligence predicts mathematics marks (secondary moderation).

The hypotheses being tested here are therefore:

H_O10: Conscientiousness does not moderate mindset's interaction with fluid intelligence and mathematics performance.

H_A10: Conscientiousness moderates mindset's interaction with fluid intelligence and mathematics performance.

Table 31

Hierarchical Regression Model: Fluid Intelligence, Mindset, Conscientiousness

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 - Direct	.489	.239	.226	19.12	3	183	< .001
2 - Interaction	.501	.251	.222	8.59	7	179	< .001
Model Comparison	ΔR^2	.013		0.764	4	179	.550

The results in Table 31 conveys that both regression models are statistically significant. While the direct effects model explained 23.9% of the variance (R^2 = .239, F(3, 183) = 19.12, p < .001), the interaction effects model explained 25.1% of the variance in mathematics marks (R^2 = .251, F(7, 179) = 8.59, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .013, F(4, 179) = 0.764, p > .05).

These two models are further explored in Table 32, and reports that 18.7% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (5.2%) of the variance.

Table 32

Multiple Regression Model Coefficients: Conscientiousness as a Moderator of Mindset

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.986	1.019	64.975	68.998	65.71***		
f	0.732	0.140	0.455	1.010	5.21***	.111	0.338
FM	-0.559	0.268	-1.088	-0.031	-2.09*	.018	-0.141
GM	-0.774	0.346	-1.456	-0.091	-2.24*	.020	-0.151
Cons.	0.143	0.047	0.051	0.235	3.07**	.038	0.199
2 - Interaction							
Intercept	66.985	1.053	64.907	69.063	63.613***		
f	0.711	0.146	0.424	0.998	4.885***	.097	0.329
FM	-0.450	0.276	-0.995	0.095	-1.628	.011	-0.113
GM	-0.954	0.368	-1.681	-0.227	-2.590**	.028	-0.186
Cons.	0.172	0.050	0.074	0.270	3.473***	.049	0.240
f x FM	0.024	0.030	-0.036	0.084	0.795	.003	0.054
f x GM	-0.018	0.048	-0.112	0.077	-0.369	.001	-0.026
f x Cons.	0.008	0.006	-0.005	0.020	1.239	.006	0.087
FM x Cons.	-0.012	0.012	-0.036	0.013	-0.962	.004	-0.070
GM x Cons.	0.025	0.017	-0.008	0.058	1.469	.009	0.111
f x FM x Cons.	0.001	0.001	-0.002	0.004	0.646	.002	0.049
f x GM x Cons	0.002	0.002	-0.002	0.007	1.075	.005	0.083

Note. *f* = Fluid Intelligence. FM = Fixed Mindset, GM = Growth Mindset, Cons. = Conscientiousness.
*$p < .05$. **$p < .01$. ***$p < .001$.

Moreover, it should be noted from Table 32 that while variables add significantly to the direct model, fixed mindset does not contribute statistically significantly to the interaction model. There are also no significant interaction effects, and therefore, no moderation effects to report on. Furthermore, the interactions only contribute 3.0% to the overall variance explained by the interaction model. Therefore, despite the significant, weak, negative (r = -.16, $p < .05$) relationship reported in Table 30 between fixed mindset and conscientiousness, conscientiousness does not moderate the relationship between fixed mindset and mathematics marks. Additionally, conscientiousness does not moderate the relationship between growth mindset and mathematics marks.

However, before concluding that the results fail to reject the null hypothesis, H_O10, the hierarchical regressions were repeated by substituting the facets of conscientiousness in place of the factor, in both the direct and interaction models. These additional analyses were conducted after noting the relationships between all the conscientiousness facets and mathematics marks, despite minimal significant relationships with mindset or fluid intelligence. For the sake of brevity, only significant models are reported below.

Effort. A hierarchical multiple regression was performed by adding fluid intelligence, fixed mindset, growth mindset, and effort into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether effort influenced fixed or growth mindset, or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between effort, mindset, and fluid intelligence predicts mathematics marks.

Table 33

Hierarchical Regression Model: Fluid Intelligence, Mindset, Effort

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 - Direct	.520	.270	.254	16.83	4	182	< .001
2 - Interaction	.551	.304	.260	6.93	11	175	< .001
Model Comparison	ΔR^2	.034		1.20	7	175	.303

That both regression models are statistically significant was confirmed in Table 33. While the direct effects model explained 27.0% of the variance (R^2 = 0.270, $F(4, 182)$ = 16.83, p < .001), the interaction effects model explained 30.4% of the variance in mathematics marks (R^2 = .304, $F(11, 175)$ = 6.93, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .034, $F(7, 175)$ = 1.20, p > .05).

These two models were further examined in Table 34, and it was reported that 20.5% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (6.5%) of the variance. It should also be noted that all variables add significantly to both the direct and interaction models. There is also a significant interaction effect between fluid intelligence, growth mindset, and effort in predicting mathematics marks.

Table 34

Multiple Regression Model Coefficients: Effort as a Moderator of Mindset

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.967	1.012	64.971	68.963	66.18***		
f	0.730	0.139	0.455	1.005	5.24***	.110	0.337
FM	-0.629	0.264	-1.149	-0.108	-2.38*	.023	-0.158
GM	-0.827	0.342	-1.502	-0.152	-2.42*	.023	-0.161
Ef	0.610	0.174	0.267	0.954	3.51***	0.049	0.222
2 - Interaction							
Intercept	66.804	1.031	64.770	68.838	64.821***		
f	0.782	0.144	0.498	1.065	5.439***	.118	0.361
FM	-0.568	0.275	-1.110	-0.026	-2.069*	.017	-0.143
GM	-0.999	0.355	-1.700	-0.299	-2.817**	.032	-0.195
Eff	0.777	0.187	0.409	1.145	4.164***	.069	0.283
f x FM	0.060	0.036	-0.011	0.132	1.658	.011	0.136
f x GM	-0.041	0.050	-0.140	0.058	-0.814	.003	-0.059
f x Eff	-0.014	0.026	-0.066	0.037	-0.542	.001	-0.037
FM x Eff	-0.004	0.046	-0.095	0.088	-0.081	.000	-0.006
GM x Eff	0.072	0.062	-0.052	0.195	1.146	.005	0.085
f x FM x Eff	-0.006	0.006	-0.019	0.006	-0.978	.004	-0.085
f x GM x Eff	0.025	0.009	0.007	0.043	2.672**	.029	0.221

Note. *f* = Fluid Intelligence. FM = Fixed Mindset, GM = Growth Mindset, Eff = Effort.
**p* < .05. ***p* < .01. ****p* < .001.

Given that none of the simple, primary interaction effects are statistically significant, the results in Table 34 therefore provides support for the moderating effect of effort on the interaction between growth mindset and fluid intelligence, in predicting mathematics marks. However, the interaction between fluid intelligence, fixed mindset, and effort was not significant, and therefore, a moderation effect between the three variables is not present.

Order. A hierarchical multiple regression was performed by adding fluid intelligence, fixed mindset, growth mindset, and order to establish a baseline, direct effects model. This was followed by adding these variables' interaction terms to model two, to determine whether order directly influenced fixed or growth mindset, or fluid intelligence to predict mathematics marks, or whether the three-way interaction between order, mindset, and fluid intelligence predicts mathematics marks.

Table 35

Hierarchical Regression Model: Fluid Intelligence, Mindset, Order

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.501	.251	.234	15.23	4	182	< .001
2 - Interaction	.527	.278	.232	6.11	11	175	< .001
Model Comparison	ΔR²	.027		0.928	7	175	.486

Table 36

Multiple Regression Model Coefficients: Order as a Moderator of Mindset

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.999	1.025	64.977	69.022	65.36***		
f	0.755	0.141	0.476	1.034	5.33***	.117	0.349
FM	-0.581	0.269	-1.111	-0.051	-2.16*	.019	-0.146
GM	-0.776	0.348	-1.463	-0.090	-2.23*	.020	-0.151
Ord	0.388	0.143	0.105	0.670	2.70**	.030	0.176
2 - Interaction							
Intercept	66.793	1.068	64.686	68.900	62.566***		
f	0.791	0.150	0.495	1.086	5.285***	.116	0.365
FM	-0.506	0.275	-1.049	0.036	-1.842	.014	-0.128
GM	-0.949	0.360	-1.659	-0.239	-2.637**	.029	-0.185
Ord	0.430	0.149	0.137	0.723	2.895**	.035	0.196
f x FM	0.027	0.035	-0.041	0.096	0.788	.003	0.061
f x GM	-0.016	0.050	-0.114	0.082	-0.323	.000	-0.023
f x Ord	-0.001	0.021	-0.042	0.040	-0.060	.000	-0.004
FM x Ord	-0.036	0.035	-0.104	0.033	-1.026	.004	-0.071
GM x Ord	0.010	0.052	-0.093	0.112	0.185	.000	0.013
f x FM x Ord	-0.008	0.005	-0.011	0.009	-0.165	.000	-0.013
f x GM x Ord	0.013	0.007	-0.008	0.027	1.962*	.016	0.144

Note. *f* = Fluid Intelligence. FM = Fixed Mindset, GM = Growth Mindset, Ord = Order.
*p < .05. **p < .01. ***p < .001.

That both the direct and interaction regression models are statistically significant was revealed in Table 35. While the direct effects model explained 25.1% of the variance (R^2 = .251, $F(4, 182) = 15.23$, $p < .001$), the interaction effects model explained 27.8% of the variance in mathematics marks (R^2 = .278, $F(11, 175) = 6.11$, $p < .001$). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .027, $F(7, 175) = 0.928$, $p > .05$).

These two models are further examined in Table 36 and it is reported that 18.6% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (6.5%) of the variance. Additionally, it should be noted that all variables add significantly to the direct model. However, fixed mindset does not add a statistically significant contribution to the interaction effects model. There is also a significant interaction effect between fluid intelligence, growth mindset, and order in predicting mathematics marks.

Since none of the simple, primary interaction effects are statistically significant, the significant interaction term indicated in Table 36 supports the interpretation of order as a moderator of the relationship between growth mindset and fluid intelligence to predict mathematics marks. Furthermore, the interaction between fluid intelligence, fixed mindset, and effort was not significant, and therefore, a moderation effect between the three variables is not present. Similar hierarchical regression models were run for dutifulness, due to the significant relationships noted with fixed mindset ($r = .18$, $p < .05$) and mathematics marks ($r = .18$, $p < .05$) in Table 30. However, no significant interaction effects were flagged.

Likewise, despite the significant, weak relationships between prudence and fixed mindset ($r = -.23$, $p < .01$), growth mindset ($r = -.17$, $p < .05$), and mathematics marks ($r = .19$, $p < .01$), there were no significant interactions to suggest prudence acts as a moderator between mindset and mathematics marks. Although self-discipline did not have significant relationships with mindset, there was a significant relationship ($r = .20$, $p < .01$) with mathematics marks reported. However, self-discipline did not moderate mindset or fluid intelligence's effect on mathematics marks.

Therefore, in conclusion of hypothesis 10, it was found that effort and order both have significant interactions with fluid intelligence and growth mindset, although there are no significant interactions with fixed mindset. Consequently, there is evidence to reject the null hypothesis (H_O10) in favour of the alternative hypothesis (H_A10). Therefore, facets of conscientiousness moderates the influence of growth mindset and fluid intelligence in predicting mathematics marks.

Hypothesis 11: Conscientiousness as a Moderator of Study Habits. To test whether moderating relationships were present, a hierarchical multiple regression was conducted by adding fluid intelligence and study habits as established independent predictors of mathematics marks, as well as conscientiousness as a new predictor variable into a baseline direct effects model. Following this, the interaction terms between these independent variables were added to model two, to evaluate whether conscientiousness either moderated study habits directly to impact how study habits predict mathematics marks, or whether the three-way interaction between conscientiousness, study habits, and fluid intelligence predicts mathematics marks (indicative of a secondary moderation).

The hypotheses under investigation here is therefore:

H_O11: Conscientiousness does not interact with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A11: Conscientiousness interacts with study habits to moderate the positive relationship between fluid intelligence and mathematics performance.

Table 37

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Conscientiousness

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.548	.300	.288	26.1	3	183	< .001
2 - Interaction	.558	.312	.285	11.6	7	179	< .001
Model Comparison	ΔR²	0.012		0.761	4	179	.552

The variance explained by the direct and interaction models are reported in Table 37, both of which are statistically significant. While the direct effects model explained 30.0% of the variance (R^2 = .300, F(3, 183) = 26.1, p < .001), the interaction effects model explained 31.2% of the variance in mathematics marks (R^2 = .312, F(7, 179) = 11.6, p < .001). However, the interaction effects model does not significantly contribute further variance over and above the direct effects (R^2 = .012, F(4, 179) = 0.761, p > .05)..

Table 38

Multiple Regression Model Coefficients: Conscientiousness as a Moderator of Study Habits

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.984	0.988	65.034	68.934	67.782*		
f	0.656	0.138	0.384	0.929	4.753*	.086	0.303
SH	0.500	0.102	0.299	0.702	4.902*	.092	0.362
Cons.	0.043	0.052	-0.058	0.145	0.841	.003	0.061
2 - Interaction							
Intercept	66.755	1.146	64.494	69.016	58.264*		
f	0.547	0.153	0.246	0.848	3.588*	.050	0.253
SH	0.489	0.104	0.284	0.694	4.700*	.085	0.354
Cons.	0.018	0.059	-0.098	0.134	0.303	.000	0.025
f x SH	-0.009	0.012	-0.033	0.015	-0.707	.002	-0.048
f x Cons.	0.004	0.006	-0.009	0.016	0.605	.001	0.043
SH x Cons.	0.002	0.004	-0.006	0.010	0.569	.001	0.040
f x SH x Cons.	0.001	0.001	-0.003	0.002	1.536	.009	0.113

Note. *f* = Fluid Intelligence, SH = Study Habits, Cons. = Conscientiousness

**p* < .001.

Exploring these two models further, Table 38 reports that 18.1% of the unique variance is explained by fluid intelligence, study habits, and conscientiousness in the direct model, with the combination of the variables explaining the remainder (11.9%) of the variance. It should however be noted that conscientiousness is not a statistically significant predictor in either the direct or interaction models. Furthermore, none of the interaction effects add significantly to the interaction model, only contributing a total of 1.3% of variance to explaining the predictors of mathematics marks. Therefore, there are no moderating effects to report on, meaning that the conscientiousness factor does not moderate the relationship between study habits, fluid intelligence, and mathematics marks. Despite the significant relationship ($r = 0.50$, $p < .001$) between study habits and conscientiousness that was reported in Table 30.

However, before concluding that conscientiousness in its totality does not moderate study habits in predicting mathematics marks, the facets were substituted into the regression models in place of the conscientiousness factor. These analyses were performed considering the moderate relationships between all the conscientiousness facets and study habits, as well as with mathematics marks. For the sake of brevity of this report however, only the models that flagged significant interactions are reported below.

Dutifulness. To test whether dutifulness moderates how fluid intelligence or study habits predict mathematics marks, a hierarchical multiple regression was performed by comparing the direct and interaction effects regression models. Fluid intelligence, study habits, and dutifulness were added as independent predictor variables into the baseline direct effects model. The interaction terms between these independent variables were added to model two, to prove whether dutifulness directly moderated study habits or fluid intelligence to impact how they predict mathematics marks, or whether the three-way interaction between dutifulness, study habits, and fluid intelligence predicts mathematics marks (indicative of a secondary moderation).

That both the direct and interaction models are statistically significant is indicated in Table 39, explaining 29.7% (R^2 = .297, F(3, 183) = 25.8, p < .001) and 31.4% (R^2 = 0.314, F(7, 179) = 11.7, p < .001) of the variance in predicting mathematics marks, respectively. However, there is no statistically significant additional variance explained by the interaction model, over the direct effects model (R^2 = 0.017, F(4, 179) = 1.1, p > .05).

Table 39

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Dutifulness

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.545	.297	.286	25.8	3	183	< .001
2 - Interaction	.560	.314	.287	11.7	7	179	< .001
Model Comparison	ΔR²	.017		1.1	4	179	.357

These two models were further explored in Table 40, and it is reported that the total unique variance explained by the direct effects of the predictive variables is 21.4%, with the combination of the variables explaining the remaining 8.3% of the variance. It should be noted that dutifulness does not add statistically significant predictive value to either the direct or interaction effects models. There is, however, a statistically significant interaction effect between fluid intelligence and dutifulness, contributing 1.5% of the total 1.9% of the variance explained across interaction effects. Despite there being no significant relationship (r = .12, p > .05) between fluid intelligence and dutifulness reported in Table 30, the statistically significant interaction effect between these two variables suggests that dutifulness moderates the impact of fluid intelligence in predicting mathematics marks.

Table 40

Multiple Regression Model Coefficients: Dutifulness as a Moderator of Study Habits

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.983	0.990	65.029	68.936	67.654*		
F	0.644	0.138	0.372	0.916	4.672*	.084	0.298
SH	0.540	0.093	0.357	0.723	5.809*	.130	0.391
Duti.	0.029	0.202	-0.370	0.427	0.142	.000	0.009
2 - Interaction							
Intercept	67.021	1.059	64.931	69.111	63.280*		
F	0.587	0.149	0.294	0.881	3.948*	.060	0.271
SH	0.524	0.094	0.338	0.710	5.561*	.118	0.379
Duti.	0.094	0.218	-0.335	0.523	0.433	.001	0.031
f x SH	-0.012	0.012	-0.037	0.012	-1.016	.004	-0.069
f x Duti.	0.051	0.026	-0.005	0.103	1.955*	.015	0.146
SH x Duti.	-0.001	0.018	-0.037	0.034	-0.076	.000	-0.005
f x SH x Duti.	0.001	0.002	-0.004	0.005	0.323	.000	0.026

Note. *f* = Fluid Intelligence. SH = Study Habits, Duti. = Dutifulness.

$*p < .001$.

Self-Discipline. Another hierarchical multiple regression was conducted by adding the self-discipline facet of conscientiousness, with fluid intelligence and study habits, into a direct effects model to compare the interaction effects model. This was done to investigate whether moderation relationships were present between self-discipline, study habits, and fluid intelligence, and whether these moderations added significant value to the prediction model.

Table 41

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Self-Discipline

Model	R	R^2	Adjusted R^2	Overall Model Test F	df1	df2	p
1 - Direct	.548	.300	.289	26.2	3	183	< .001
2 - Interaction	.572	.327	.301	12.4	7	179	< .001
Model Comparison	ΔR^2	.027		1.79	4	179	.133

Both the direct and interaction models are statistically significant, according to Table 41. The direct effects model explained 30.0% of the variance in mathematics marks. (R^2 = .300, F(3, 183) = 26.2, p < .001). The interaction effects model explained 32.7% of the variance in mathematics marks (R^2 = 0.327, F(7, 179) = 12.4, p < .001). However, although the interaction effects model explained 2.7% more variance, this increase was not statistically significant (R^2 = .027, F(4, 179) = 1.79, p > .05).

Table 42

Multiple Regression Model Coefficients: Self-Discipline as a Moderator of Study Habits

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.986	0.988	65.037	68.936	67.801**		
F	0.655	0.138	0.383	0.928	4.753**	.086	0.303
SH	0.512	0.095	0.325	0.699	5.397**	.112	0.370
S-d.	0.178	0.199	-0.215	0.571	0.894	.003	0.060
2 - Interaction							
Intercept	67.026	1.067	64.920	69.131	62.820**		
F	0.558	0.144	0.274	0.841	3.878**	.057	0.258
SH	0.498	0.095	0.311	0.685	5.245**	.104	0.360
S-d.	0.040	0.230	-0.414	0.495	0.174	.000	0.014
f x SH	-0.016	0.012	-0.040	0.008	-1.325	.007	-0.089
f x S-d.	0.030	0.026	-0.021	0.081	1.171	.005	0.084
SH x S-d.	0.008	0.017	-0.025	0.041	0.476	.001	0.036
f x SH x S-d.	0.005	0.002	0.001	0.010	2.422*	.022	0.193

Note. *f* = Fluid Intelligence. SH = Study Habits, S-d. = Self-Discipline

*p < .05. **p < .001.

These two models were further examined in Table 42 and demonstrates that 20.1% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (9.9%) of the variance. Self-discipline does not add statistically significant value to either the direct or interaction effects models. None of the primary interaction effects are statistically significant. However, the interaction effect between fluid intelligence, study habits, and self-discipline was found to be significant, contributing 2.2% of the explained variance in the interaction model, where the total variance explained by the interaction effects was 3.5%. Therefore, the results in Table 42 provides support for a secondary moderation effect between fluid intelligence, study habits, and self-discipline to predict mathematics marks. This in in spite of there being no observed relationship between self-discipline and fluid intelligence (r = .01, p > .05) in Table 30, and a significant moderate relationship between study habits and self-discipline (r = .37, p < .001).

In summarising the findings for hypothesis 11, despite their significant relationships with both mathematics marks and study habits, the conscientiousness factor and the facets of effort, order, and prudence do not moderate study habits to predict mathematics marks. However, the facet of dutifulness was found to significantly moderate how fluid intelligence predicts mathematics marks. Furthermore, a significant interaction was also noted between fluid intelligence, study habits, and the facet of self-discipline. In conclusion, facets of conscientiousness were found to moderate study habits' influence in predicting mathematics marks. Therefore, the null hypothesis, H_O11, was rejected.

Hypothesis 12: Extraversion does not Moderate Study Orientations.

Given the consensus in the literature discussed in section 2.5.3, that extraversion does not impact academic performance, the hypotheses under investigation are:

H_O12: Extraversion does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A12: Extraversion interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

In examining the relationships between extraversion and study orientations, Pearson correlation coefficients were first evaluated, given that such results inform on the strength and direction of the direct relationships between extraversion, the study orientation factors, fluid intelligence, and mathematics marks. This result is reported on in Table 43.

There are no statistically significant relationships between extraversion (or any of its facets) and either mathematics marks, fluid intelligence, or mathematics anxiety. However, there are a number of statistically significant, weak, relationships between extraversion (and its facets) and other study orientations shown in Table 43.

Table 43

Correlation Coefficients Between Mathematics marks, Fluid Intelligence, Study Orientations, and Extraversion

	Ext.	Asc.	Liv.	Po. Af.	Gre.	Ex.Se
Maths marks	.130	.142	.133	.111	.089	-.011
F	.076	-.028	.086	.051	.038	.099
SA	.084	.157*	.108	.127	.102	-.158*
MA	-.126	-.027	-.069	-.128	-.153	-.053
SH	.101	.171*	.151*	.159*	.093	-.169*
PSB	.241***	.247***	.249***	.219**	.164*	-.017
SM	.156*	.073	.139	.208**	.171*	-.030
M	114	20.9	26.1	21.2	22.2	23.9
SD	17.5	4.86	5.05	4.25	5.62	6.04

Note. f = Fluid Intelligence, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, Ext. = Extraversion, Asc. = Ascendance, Liv. Liveliness, Po. Af. = Positive Affectivity, Gre. = Gregariousness, Ex. Se. = Excitement Seeking.
**p* < .05, ***p* < .01, ****p* < .001.

The relationship between study attitudes and extraversion is non-significant ($p > .05$). However, there is a significant, weak, positive relationship between study attitude and ascendance ($r = .16$, $p < .05$), and a significant, weak, negative relationship between study attitude and excitement-seeking ($r = -.16$, $p < .05$).

The different directions of the relationships between study habits and the facets of ascendance ($r = .17$, $p < .05$), liveliness ($r = .15$, $p < .05$), positive affectivity ($r =.16$, $p < .05$) and excitement-seeking ($r = -.17$, $p < .05$) provides a possible explanation why there is no relationship between study habits and the larger extraversion factor. An explanation may be that the effects of the relationships across the more nuanced facets of the behaviour potentially negate each other. In considering the weak positive relationships between study habits with ascendance and liveliness, these findings could suggest that learners scoring higher on ascendance and liveliness are able to ask questions about mathematics more readily than others when they are uncertain about a concept, or that they are more willing to suggest working in groups to boost understanding. With regards to the positive relationship between study habits and positive affectivity, learners who are more optimistic can view effective study habits positively, recognising that studying has worthwhile implications for their scholastic careers. Finally, learners who have higher levels of excitement-seeking personalities are less likely to be motivated to enforce routine study habits for a subject that has a reputation of being boring and anxiety-inducing.

Extraversion ($r = .24$, $p < .001$) and its underlying facets, apart from excitement-seeking, also have statistically significant relationships with problem-solving behaviour (correlation coefficients ranged from $r = .16$ to .25). This suggests that learners who are more comfortable communicating regularly are able to reflect on their thinking more readily, possibly identifying errors in reasoning or picking up misunderstood concepts quicker in their conversations with others.

Lastly, both the extraversion factor ($r = .16$, $p < .05$) and the facet of positive affectivity ($r = .21$, $p < .01$) correlate with study milieu. This suggests that learners are more likely to express their concerns readily when they feel they are in a socially supportive environment.

Extraversion as a Moderator of Study Orientations.

Study Attitudes. To test whether extraversion moderates how fluid intelligence or study attitudes predict mathematics marks, a hierarchical multiple regression was performed by comparing the direct and interaction effects regression models. Fluid intelligence and study attitudes, (as established independent predictors of mathematics marks) were added with extraversion as independent predictor variables into model one, to build a baseline direct effects model. The interaction terms between these independent variables were added to model two, to prove whether extraversion moderated study attitudes directly to impact how study attitudes predict mathematics marks, or whether the three-way interaction between extraversion, study attitudes, and fluid intelligence predicts mathematics marks, indicative of a secondary moderation.

Table 44

Hierarchical Regression Model: Fluid Intelligence, Study Attitudes, Extraversion

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.575	.331	.320	30.1	3	183	< .001
2 - Interaction	.583	.339	.314	13.1	7	179	< .001
Model Comparison	ΔR²	.009		0.581	4	179	.676

As reported in Table 44, both the direct and interaction models are statistically significant. The direct effects model explained 33.1% of the variance in mathematics marks (R^2 = .331, F(3, 183) = 30.1, p < .001). Furthermore, the interaction effects model explained 33.9% of the variance in mathematics marks (R^2 = .339, F(7, 179) = 13.1, p < .001). This increase in variance explained by the interaction effects model is not statistically significant when compared to what is already explained by the direct effects model (R^2 = .009, F(4, 179) = .581, p > .05).

In Table 45 these two models were further explored and informs that 24.3% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (8.8%) of the variance. It should be noted that extraversion does not add any statistically significant value to either the direct model or to the interaction effect model. Additionally, none of the interaction effects were shown to be statistically significant, which only adds 2.0% of variance in total across interaction effects to the second model. The absence of any interaction terms is indicative that no moderation effects are present, and therefore, it can be concluded that extraversion does not moderate study attitudes.

Table 45

Multiple Regression Model Coefficients: Extraversion as a Moderator of Study Attitude

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.963	0.966	65.056	68.869	69.31*		
f	0.580	0.136	0.312	0.848	4.27*	.067	0.268
SA	0.757	0.111	0.538	0.975	6.83*	.171	0.429
Extra.	0.067	0.056	-0.043	0.177	1.210	.005	0.073
2 - Interaction							
Intercept	66.901	1.014	64.899	68.902	65.950*		
f	0.565	0.139	0.291	0.839	4.065*	.061	0.261
SA	0.777	0.114	0.551	1.002	6.790*	.171	0.440
Extra.	0.070	0.058	-0.045	0.185	1.207	.005	0.077
f x SA	0.010	0.016	-0.021	0.041	0.634	.002	0.040
f x Extra.	-0.012	0.008	-0.028	0.005	-1.413	.007	-0.088
SA x Extra.	0.001	0.006	-0.011	0.012	0.121	.005	0.008
f x SA x Extra.	0.001	0.001	-0.002	0.002	-0.129	.006	-0.008

Note. *f* = Fluid Intelligence, SA = Study Attitude, Extra. = Extraversion.

**p* < .001.

Mathematics Anxiety. To establish a baseline, direct effects model for the hierarchical multiple regression performed, fluid intelligence, mathematics anxiety, and the extraversion factor were added into model one. This was followed by adding their interaction terms to model two, to determine whether extraversion moderated mathematics anxiety or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between extraversion, mathematics anxiety, and fluid intelligence moderates the relationship that predicts mathematics marks.

Table 46 reports that both the direct and interaction models are statistically significant. The direct effects model explained 31.6% of the variance in mathematics marks (R^2 = .316, F(3, 183) = 28.2, p < .001). Furthermore, the interaction effects model explained 32.8% of the variance in mathematics marks (R^2 = 0.328, F(7, 179) = 12.5, p < .001). The interaction effects model, however, does not explain significantly more variance than what has already been explained by the direct effects model (R^2 = .011, F(4, 179) = 0.749, p > .05).

Table 46

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Extraversion

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.563	.316	.305	28.2	3	183	< .001
2 - Interaction	.572	.328	.301	12.5	7	179	< .001
Model Comparison	ΔR²	.011		.749	4	179	.560

In Table 47 these models were further examined and reports that 20.8% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (10.8%) of the variance. However, it must again be noted that extraversion does not add any statistically significant value to either of the predictive models. Furthermore, the value of fluid intelligence also becomes non-significant in the interaction effects model, implying that math anxiety is the single predictor in the interaction model. There are also no significant interaction effects, and therefore no moderation effects to report on, with the interactions only contributing 1.5% to the overall variance explained by the model. In summary, extraversion does not moderate the relationship between math anxiety and mathematics marks.

Table 47

Multiple Regression Model Coefficients: Extraversion as a Moderator of Mathematics Anxiety

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	47.174	3.212	40.836	53.511	14.686*		
f	0.513	0.141	0.234	0.791	3.635*	.049	0.237
MA	0.774	0.120	0.538	1.010	6.468*	.156	0.424
Extra.	0.051	0.057	-0.061	0.163	0.901	.003	0.056
2 - Interaction							
Intercept	46.973	3.272	40.517	53.429	14.357*		
f	0.357	0.361	-0.356	1.070	0.989	.004	0.165
MA	0.781	0.121	0.542	1.020	6.453*	.156	0.428
Extra.	0.130	0.192	-0.249	0.508	0.675	.002	0.141
f x MA	0.005	0.014	-0.023	0.033	0.344	.000	0.057
f x Extra.	-0.034	0.024	-0.080	0.013	-1.421	.008	-0.252
MA x Extra.	-0.004	0.007	-0.019	0.010	-0.566	.001	-0.119
f x MA x Extra.	0.001	0.001	-0.007	0.003	1.238	.006	0.220

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Extra. = Extraversion.

*$p < .001$.

Study Habits. A hierarchical multiple regression was performed by adding fluid intelligence, study habits, and extraversion into model one, to establish a baseline direct effects model. This was followed by adding their interaction terms to model two, to determine whether extraversion influenced study habits or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between extraversion, study habits, and fluid intelligence predicts mathematics marks.

Table 48

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Extraversion

Model	R	R^2	Adjusted R^2	Overall Model Test F	df1	df2	p
1 - Direct	.549	.302	0.290	26.3	3	183	< .001
2 - Interaction	.563	.316	0.290	11.8	7	179	< .001
Model Comparison	ΔR^2	.015		0.968	4	179	.426

In Table 48 it is illustrated that both regression models are statistically significant. While the direct effects model explained 30.2% of the variance (R^2 = .302, F(3, 183) = 26.3, p < .001), the interaction effects model explained 31.6% of the variance in mathematics marks (R^2 = .316, F(7, 179) = 11.8, p < .001). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .015, F(4, 179) = .968, p > .05).

In Table 49 these models are further explored and demonstrates that 22.8% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (7.4%) of the variance. Extraversion does not add statistically significant value to either the direct or interaction effects models. Furthermore, none of the interaction effects are statistically significant and only add a cumulative 1.1% of variance explained to the interaction model. Therefore, it can be concluded that extraversion does not moderate study habits' influence on mathematics marks.

Table 49

Multiple Regression Model Coefficients: Extraversion as a Moderator of Study Habits

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.970	0.987	65.023	68.917	67.85*		
F	0.637	0.138	0.366	0.908	4.63*	,082	0.294
SH	0.536	0.088	0.362	0.709	6.09*	,141	0.388
Extra.	0.062	0.057	-0.050	0.175	1.090	,005	0.068
2 - Interaction							
Intercept	67.264	1.020	65.251	69.277	65.948*		
F	0.627	0.143	0.346	0.909	4.394*	.074	0.290
SH	0.557	0.090	0.379	0.734	6.179*	.146	0.403
Extra.	0.072	0.058	-0.042	0.186	1.254	.006	0.079
f x SH	-0.002	0.012	-0.026	0.021	-0.184	.000	-0.012
f x Extra.	-0.008	0.008	-0.024	0.009	-0.942	.003	-0.059
SH x Extra.	-0.006	0.005	-0.016	0.005	-1.049	.004	-0.068
f x SH x Extra.	-0.001	0.001	-0.003	0.001	-0.976	.004	-0.065

Note. *f* = Fluid Intelligence, SH = Study Habits, Extra. = Extraversion.

*p < .001.

Problem-Solving Behaviour. A hierarchical multiple regression was conducted by adding fluid intelligence and problem-solving behaviours as established independent predictors of mathematics marks, as well as extraversion as a new predictor variable into model one, to build a baseline direct effects model. Following this, the interaction terms between these independent variables were added to the interaction terms model two, to prove whether extraversion moderated problem-solving behaviour or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between extraversion, problem-solving behaviours, and fluid intelligence predicts mathematics marks, indicating a secondary moderation.

Table 50

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Extraversion

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.536	.287	.275	24.5	3	183	< .001
2 - Interaction	.546	.298	.271	10.9	7	179	< .001
Model Comparison	ΔR²	.011		0.715	4	179	.583

As can be seen in Table 50, both the direct and interaction models are statistically significant. The direct effects model explained 28.7% of the variance in mathematics marks (R^2 = .287, F(3, 183) = 24.5, p < .001). Additionally, the interaction effects model explained 29.8% of the variance in mathematics marks (R^2 = .298, F(7, 179) = 10.9, p < .001). The interaction effects model was further shown to not explain significantly more variance than what has already been explained by the direct effects model (R^2 = .011, F(4, 179) = 0.715, p > .05).

In Table 51 these models were further examined and reports that 19.6% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remaining 9.1% of the variance. It should be noted that extraversion does not add statistically significant value to either the direct or interaction models. There are also no statistically significant interaction effects, and therefore, no moderations are observed. The interaction effects only add a cumulative 1.0% of variance to the overall interaction model, a statistically non-significant amount. Therefore, it can be concluded that extraversion does not moderate the relationship between problem-solving behaviour and mathematics marks, despite the weak positive relationship (r = .24) reported in Table 43.

Table 51

Multiple Regression Model Coefficients: Extraversion as a Moderator of Problem Solving Behaviour

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.979	0.997	65.011	68.947	67.155*		
F	0.592	0.141	0.313	0.871	4.190*	.069	0.274
PSB	0.534	0.094	0.349	0.719	5.701*	.127	0.383
Extra.	0.015	0.059	-0.101	0.132	0.259	.000	0.017
2 - Interaction							
Intercept	67.242	1.067	65.137	69.348	63.014*		
F	0.595	0.157	0.286	0.904	3.803*	.057	0.275
PSB	0.559	0.096	0.370	0.748	5.827*	.133	0.400
Extra.	0.010	0.061	-0.111	0.130	0.158	.000	0.011
f x PSB	0.005	0.012	-0.018	0.029	0.449	.001	0.031
f x Extra.	-0.006	0.009	-0.025	0.012	-0.684	.002	-0.048
PSB x Extra.	-0.007	0.005	-0.018	0.004	-1.315	.007	-0.086
f x PSB x Extra.	0.000	0.001	-0.001	0.002	0.075	.000	0.005

Note. *f* = Fluid Intelligence, PSB = Problem Solving Behaviour, Extra. = Extraversion.

*p < .001.

Study Milieu. Lastly, to test the final possibility of a moderation effect between extraversion and study milieu, a hierarchical multiple regression was conducted by adding fluid intelligence and study milieu (as established independent predictors of mathematics marks), as well as extraversion as a new predictor variable into a baseline direct effects model. Following this, the interaction terms between these independent variables were added to the interaction terms model two, to prove whether extraversion moderated study milieu or fluid intelligence directly to predict mathematics marks, or whether the three-way interaction between extraversion, study milieu, and fluid intelligence predicts mathematics marks, indicating a secondary moderation.

In Table 52 it is illustrated that both the direct and interaction models are statistically significant, explaining 24.9% (R^2 = .249, F(3.183) = 20.3, p < .001) and 28.4% (R^2 = .284, F(7.179) = 10.1, p < .001) of the variance in predicting mathematics marks, respectively. However, statistically significant additional variance is not explained by the interaction model, over the direct effects model (R^2 = .035, F(4.179) = 2.17, p > .05).

Table 52

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Extraversion

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 - Direct	.499	.249	.237	20.3	3	183	< .001
2 - Interaction	.533	.284	.256	10.1	7	179	< .001
Model Comparison	ΔR^2	.035		2.17	4	179	.075

In Table 53 these models are further explored and indicates that 17.0% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (7.9%) of the variance. It should be noted that extraversion does not add any statistically significant value to either the direct model or to the interaction effect model. Additionally, the only statistically significant interaction effect is between fluid intelligence and study milieu, an interaction and moderation already discussed under section 4.3.7. in relation to hypothesis seven. In summary, extraversion does not moderate the relationship between study milieu or fluid intelligence and mathematics marks.

Table 53

Multiple Regression Model Coefficients: Extraversion as a Moderator of Study Milieu

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr^2**	**Stand. Estimate**
1 - Direct							
Intercept	66.954	1.023	64.935	68.973	65.427**		
f	0.632	0.145	0.346	0.918	4.362**	.078	0.292
SM	0.738	0.158	0.425	1.050	4.660**	.089	0.315
Extra.	0.054	0.060	-0.064	0.171	0.899	.003	0.058
2 - Interaction							
Intercept	66.553	1.055	64.472	68.635	63.098**		
f	0.685	0.148	0.393	0.977	4.629**	.086	0.317
SM	0.852	0.163	0.531	1.173	5.241**	.110	0.364
Extra.	0.045	0.060	-0.074	0.164	0.741	.002	0.049
f x SM	0.046	0.018	0.010	0.082	2.503*	.025	0.176
f x Extra.	-0.008	0.009	-0.025	0.010	-0.835	.003	-0.057
SM x Extra.	-0.011	0.009	-0.029	0.008	-1.128	.005	-0.075
f x SM x Extra.	-0.009	0.001	-0.003	0.002	-0.155	.000	-0.011

Note. *f* = Fluid Intelligence, SM = Study Milieu, Extra. = Extraversion.

**p* < .01. ***p* < .001

However, before failing to reject the null hypothesis, H_O12, the extraversion facets were investigated. As a result, a total of 25 hierarchical regressions were conducted to evaluate the moderating influence of the five extraversion facets with each of the five study orientations, given that all interactions were considered and not only the significant relationships, as reported in Table 43. In all hierarchical regression models, the extraversion factor was substituted with the facet, with fluid intelligence and the study orientation under consideration as the other two independent predictor variables. For the sake of brevity, only the significant regression models will be reported below.

Liveliness, Fluid Intelligence and Study Attitudes. Both the direct and interaction models are statistically significant, as indicated in Table 54. The direct effects model explained 32.9% of the variance in mathematics marks (R^2 = .329, F(3, 183) = 30.0, p < .001). The interaction effects model explained 37.3% of the variance in mathematics marks (R^2 = .373, F(7, 179) = 15.2, p < .001). The interaction model explains an additional 4.4% of variance, which is a statistically significant difference (R^2 = .044, F(4, 179) = 3.13, p < .05), suggestive of a significant moderating interaction.

Table 54

Hierarchical Regression Model: Fluid Intelligence, Study Attitudes, Liveliness

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.574	.329	.318	30.0	3	183	< .001
2 - Interaction	.611	.373	.349	15.2	7	179	< .001
Model Comparison	ΔR²	.044		3.13	4	179	.016

Exploring these direct and interaction models further, 23.6% of the unique variance is explained by fluid intelligence and study attitudes in the direct effects model. Liveliness explained a statistically non-significant 0.4% of variance, and the combination of the predictors explaining the remainder (8.9%) of the variance shown in Table 55. Liveliness independently does not add statistically significant value to the interaction effects model either, however, both the interaction between fluid intelligence and liveliness, and the three-way interaction including study attitudes, are significant. This result indicates that liveliness works as a moderator in the relationship between fluid intelligence and mathematics marks, as well as in the combined effects that study attitude and fluid intelligence have on mathematics marks. Overall, the interaction effects add a statistically significant 4.5% of variance to the second model, suggesting that liveliness is a statistically significant moderator, both on fluid intelligence directly, and the interaction between fluid intelligence and study attitudes in predicting mathematics marks.

Furthermore, liveliness was found to significantly interact with fluid intelligence directly in the study habits, problem-solving behaviour, and study milieu interaction models. However, no other interactions were significant, especially between liveliness and the study orientation facets, despite significant relationships with study habits ($r = .15$, $p < .05$) and problem-solving behaviour ($r = .25$, $p < .001$) reported in Table 43. As such, other models that reflected a statistically significant interaction between fluid intelligence and liveliness, has not been reported for the sake of brevity.

Table 55

Multiple Regression Model Coefficients: Liveliness as a Moderator of Study Attitude

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.976	0.967	65.068	68.884	69.25**		
f	0.581	0.136	0.312	0.849	4.27**	.067	0.268
SA	0.755	0.111	0.536	0.975	6.8**	.169	0.429
Liv.	0.202	0.194	-0.180	0.584	1.040	.004	0.064
2 - Interaction							
Intercept	67.021	0.990	65.068	68.974	67.722**		
f	0.625	0.139	0.351	0.899	4.504**	.071	0.289
SA	0.765	0.110	0.548	0.982	6.95**	.169	0.434
Liv.	0.237	0.195	-0.148	0.622	1.214	.005	0.075
f x SA	0.013	0.016	-0.019	0.044	0.809	.002	0.052
f x Liv.	-0.076	0.026	-0.128	-0.025	-2.944*	.030	-0.185
SA x Liv.	-0.007	0.021	-0.048	0.033	-0.356	.000	-0.022
f x SA x Liv.	-0.006	0.003	-0.013	0.000	-1.931*	.013	-0.128

Note. *f* = Fluid Intelligence, SA = Study Attitude, Liv. = Liveliness.

*p < .05. **p < .001.

Positive Affectivity, Fluid Intelligence, and Mathematics Anxiety. In interpreting Table 56, it can be summarised that both regression models are statistically significant. While the direct effects model explained 31.4% of the variance (R^2 = 0.314, F(3.183) = 27.9, p < .001), the interaction effects model explained 33.4% of the variance in mathematics marks (R^2 = .334, F(7, 179) = 12.8, p < .001). This additional 2.0% of explained variance is not a statistically significant improvement (R^2 = .020, F(4, 179) = 1.36, p > .05).

Table 56

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Positive Affectivity

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.560	.314	.303	27.9	3	183	< .001
2 - Interaction	.578	.334	.308	12.8	7	179	< .001
Model Comparison	ΔR^2	.020		1.36	4	179	.248

Table 57

Multiple Regression Model Coefficients: Positive Affectivity as a Moderator of Mathematics Anxiety

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr^2**	**Stand. Estimate**
1 - Direct							
Intercept	47.087	3.241	40.693	53.482	14.529**		
F	0.517	0.141	0.239	0.796	3.663**	.118	0.239
MA	0.778	0.121	0.539	1.016	6.445**	.091	0.426
Po. Af.	0.099	0.234	-0.364	0.561	0.420	.003	0.026
2 – Interaction							
Intercept	46.779	3.362	40.145	53.413	13.915**		
F	0.694	0.376	-0.047	1.435	1.849	.099	0.321
MA	0.779	0.124	0.535	1.022	6.304**	.090	0.427
Po. Af.	-0.594	0.799	-2.171	0.983	-0.743	.003	-0.158
f x MA	-0.007	0.015	-0.036	0.022	-0.462	.000	-0.079
f x Po. Af.	-0.180	0.079	-0.336	-0.024	-2.273*	.000	-0.379
MA x Po. Af.	0.020	0.030	-0.040	0.079	0.654	.008	0.134
f x MA x Po. Af.	0.008	0.004	0.001	0.015	2.255*	.001	0.358

Note. *f* = Fluid Intelligence, MA = Math Anxiety, Po. Af. = Positive Affectivity.

**p* < .05. ***p* < .001.

In Table 57 the findings indicate that within the direct model the variables explain 21.2% of the unique variance, with the combination of variables explaining the remainder (10.2%) of the variance, indicated in Table 56. However, it must be noted that the contribution of positive affectivity is not significant in either model. In addition, fluid intelligence is not a statistically significant independent contributor within the interaction effects model. Yet, the interaction effect between fluid intelligence and positive affectivity is significant, indicating that positive affectivity has a moderating impact on fluid intelligence's influence on mathematics marks.

Furthermore, the interaction between fluid intelligence, mathematics anxiety, and positive affectivity is also statistically significant, highlighting another moderation effect between the three variables to impact mathematics marks. Therefore, positive affectivity does have a moderating effect on the relationship between fluid intelligence, mathematics anxiety, and mathematics marks. Positive affectivity did not moderate any other variables or relationships, despite significant relationships with study habits (r = .16, p < .05), problem-solving behaviour (r = .22, p <.01), and study milieu (r = 0.21, p < .01) being reported in Table 43. As such, no other hierarchical regressions with positive affectivity will be further discussed.

Excitement-Seeking, Fluid Intelligence, and Study Habits. Both the direct and interaction models indicated in Table 58 are statistically significant, explaining 29.8% (R^2 = .298, F(3, 183) = 25.9, p < .001) and 34.2% (R^2 = .342, F(7, 179) = 13.3, p < .001) of the variance in predicting mathematics marks, respectively. Furthermore, this increase of 4.4% of variance explained is a statistically significant improvement over what is explained simply by the direct effects (R^2 = .044, F(4, 179) = 3.01, p < .05).

Table 58

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Excitement-Seeking

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.546	.298	.286	25.9	3	183	< .001
2 - Interaction	.585	.342	.316	13.3	7	179	< .001
Model Comparison	ΔR²	.044		3.01	4	179	.020

Table 59

Multiple Regression Model Coefficients: Excitement-Seeking as a Moderator of Study Habits

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.982	0.990	65.029	68.934	67.684**		
F	0.636	0.139	0.362	0.911	4.576**	.080	0.294
SH	0.552	0.090	0.375	0.729	6.153**	.145	0.399
Ex. Se.	0.073	0.168	-0.259	0.405	0.433	.001	0.028
2 - Interaction							
Intercept	66.817	1.021	64.803	68.831	65.464**		
F	0.515	0.146	0.227	0.802	3.531**	.046	0.238
SH	0.583	0.089	0.407	0.759	6.542**	.158	0.422
Ex. Se.	0.154	0.169	-0.180	0.488	0.910	.003	0.058
f x SH	-0.017	0.012	-0.041	0.007	-1.413	.007	-0.095
f x Ex.Se.	-0.033	0.025	-0.083	0.017	-1.318	.006	-0.090
SH x Ex.Se.	-0.029	0.015	-0.057	0.000	-1.962	.014	-0.128
f x SH x Ex.Se.	-0.006	0.002	-0.009	-0.002	-3.060*	.035	-0.221

Note. *f* = Fluid Intelligence, SH = Study Habits, Ex.Se. = Excitement Seeking.

**p* < .01. ***p* < .001.

In Table 59 these models are further explored, and reports that the total unique variance explained by the direct effects of the predictive variables is 22.6%, with the combination of the variables explaining the remainder (7.2%) of the variance explained by the direct model. It should be noted that excitement-seeking independently does not add statistically significant predictive value to either model. However, there is a statistically significant three-way interaction effect between fluid intelligence, study habits, and excitement-seeking, contributing 3.5% of the total 6.2% of the variance explained across interaction effects. Therefore, in providing further insight into the significant relationship between excitement-seeking and study habits ($r = -.17$, $p < .05$) as reported in Table 43, the statistically significant interaction effect between the three variables suggests that levels of excitement-seeking do moderate the impact of both fluid intelligence and study habits, in predicting mathematics marks.

In concluding the examination of the predictive variables and effects for hypothesis 12, none of the hierarchical regression models found the extraversion factor as a direct variable to statistically significantly add to the models predicting mathematics marks. However, after further examination of the extraversion facets, it was found that liveliness moderated the relationship between study attitudes and fluid intelligence in predicting mathematics marks. Liveliness also moderated fluid intelligence directly in impacting mathematics marks. Positive affectivity moderated the interaction between both mathematics anxiety and fluid intelligence in predicting mathematics marks. Additionally, positive affectivity had a direct moderation effect on fluid intelligence's role in predicting mathematics marks. Lastly, excitement-seeking moderated the interaction of both study habits and fluid intelligence to predict mathematics marks. In short, the facets of extraversion have an indirect, moderating influence on mathematics marks, despite Table 43 showing no direct, statistically significant relationship between any of the extraversion facets and mathematics marks. As such, the results of the hierarchical regression models support the rejection of the null hypothesis, H_O12.

Hypothesis 13: Agreeableness does not Moderate Study Orientations.

Similar to extraversion, previous studies have consistently found that the influence of agreeableness on academic performance is negligible (Westphal et al., 2020), as discussed in section 2.5.4. However, this study further explored the predictive power of the agreeableness facets in predicting mathematics performance. From the literature review, the hypotheses that followed was:

H_O13: Agreeableness does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

H_A13: Agreeableness interacts with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance.

Before considering the moderation effects, the direct relationships between agreeableness (and its facets), mathematics marks, fluid intelligence, and study orientations will be explored in Table 60, by reporting the Pearson correlation coefficients between the variables. In Table 60, no statistically significant relationships are reported between agreeableness and its facets, and either mathematics marks or fluid intelligence. There are, however, significant relationships between agreeableness and its facets with the study orientation facets.

Table 60

Correlation Coefficients Between Mathematics marks, Fluid Intelligence, Study Orientations, and Agreeableness

	Agr.	Str.	Com.	Pro.	Mod.	Ten.
Maths marks	.041	.033	.037	.007	-.025	.093
F	-.041	-.009	-.046	.002	-.031	-.072
SA	.241***	.316***	.143	.093	.167*	.167*
MA	.138	.033	.062	.096	.272***	.082
SH	.328***	.208**	.208**	.268***	.192**	.321***
PSB	.277***	.285***	.164*	.200**	.154*	.201**
SM	.043	.158*	.018	-.019	-.045	.031
M	129.00	22.50	28.20	27.00	24.50	26.90
SD	19.10	5.47	5.71	5.76	4.16	4.91

Note. f = Fluid Intelligence, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, Agr. = Agreeableness, Str. = Straightforwardness, Com. = Compliance, Pro. = Prosocial Tendencies, Mod. = Modesty, Ten. = Tendermindedness.
*p < .05. **p < .01. *** p < .001

Study attitude displays significant, weak relationships with the agreeableness factor (r = .24, p < .001), as well as the facets of modesty (r = .17, p <.05) and tendermindedness (r = 0.17, p < .05). There is also a significant, moderate relationship between study attitude and the facet of straightforwardness (r = .32, p < .001). These results suggest that learners who are more agreeable are more likely to have an increased positive study attitude towards mathematics. The significant, weak, positive relationship between mathematics anxiety and modesty (r = .27, p < .05) postulates that learners scoring higher on modesty, and are therefore more humble, are also likely to experience higher levels of mathematics anxiety. There are also significant positive relationships between study habits and the agreeableness factor (r = .33, p < .001) as well as all its facets (ranging from r = .19 to r = .32). Likewise, there are significant, weak, positive relationships between problem-solving and the factor of agreeableness (r = .28, p < .001) and all its facets (ranging from r = .15 to r = .29). Finally, the significant weak relationship between straightforwardness and study milieu (r = .16, p < .05), suggests that individuals who are more sincere are also more likely to experience supportive study environments. Given these relationships between agreeableness and its facets with study orientations, their impact as moderators of the study orientation factor in predicting mathematics marks will now be explored.

***Agreeableness as a Moderator of Study Attitude*.** To test whether agreeableness acts as a moderator of study attitude in predicting mathematics marks, a hierarchical multiple regression was conducted by adding fluid intelligence and study attitudes as established independent predictors of mathematics marks, as well as agreeableness as a new predictor variable into a baseline direct effects model. Following this, the interaction terms between these independent variables were added to model two, to prove whether agreeableness moderated study attitudes or fluid intelligence directly in predicting mathematics marks, or whether the three-way interaction between agreeableness, study attitudes, and fluid intelligence predicts mathematics marks, indicative of a secondary moderation.

In Table 61 the variance explained by the direct and interaction models is reported, both of which are statistically significant. While the direct effects model explained 32.8% of the variance (R^2 = .328, $F(3, 183)$ = 29.8, p < .001), the interaction effects model explained 35.0% of the variance in mathematics marks (R^2 = .350, $F(7, 179)$ = 13.8, p < .001). The interaction effects model, however, does not contribute statistically significant additional variance over and above the direct effects model (R^2 = .022, $F(4, 179)$ = 1.48, p > .05).

Table 61

Hierarchical Regression Model: Fluid Intelligence, Study Attitude, Agreeableness

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.573	.328	.317	29.8	3	183	< .001
2 - Interaction	.592	.350	.324	13.8	7	179	< .001
Model Comparison	ΔR^2	.022		1.48	4	179	.209

In Table 62 these two models were further explored and indicates that 24.3% of the unique variance is explained by the independent predictor variables in the direct model. The combination of variables explains the remaining 8.5% of the variance. It should, however, be noted that agreeableness is not a statistically significant predictor in either the direct or interaction models. Furthermore, none of the interaction effects add significantly to the interaction model, only contributing a total of 1.7% of variance to explaining the predictors of mathematics marks.

Table 62

Multiple Regression Model Coefficients: Agreeableness as a Moderator of Study Attitude

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.974	0.968	65.064	68.884	69.197*		
f	0.576	0.137	0.305	0.846	4.205*	.065	0.266
SA	0.792	0.115	0.566	1.019	6.903*	.175	0.449
Agree.	-0.047	0.053	-0.151	0.057	-0.889	.003	-0.056
2 - Interaction							
Intercept	66.680	1.034	64.639	68.721	64.459*		
f	0.577	0.138	0.305	0.850	4.182*	.064	0.267
SA	0.784	0.116	0.554	1.014	6.738*	.165	0.445
Agree.	-0.088	0.056	-0.198	0.022	-1.577	.009	-0.105
f x SA	0.015	0.016	-0.016	0.045	0.955	.003	0.059
f x Agree.	-0.007	0.007	-0.021	0.008	-0.894	.003	-0.058
SA x Agree.	-0.002	0.006	-0.014	0.010	-0.338	.000	-0.023
f x SA x Agree.	0.001	0.001	-0.006	0.003	1.734	.011	0.118

Note. *f* = Fluid Intelligence, SA = Study Attitude, Agree. = Agreeableness.

*$p < .001$.

There are therefore no moderating effects to report on from the analysis reported on in Table 62, and the agreeableness factor does not moderate the relationship between study attitudes and mathematics marks, despite the significant weak relationship between study attitudes and agreeableness ($r = .24$, $p < .001$) reported in Table 60.

***Agreeableness as a Moderator of Mathematics Anxiety*.** To examine whether moderation effects were present, a hierarchical multiple regression was conducted by adding fluid intelligence and mathematics anxiety as established independent predictors of mathematics marks, as well as agreeableness as a new predictor variable into a baseline direct effects model. Following this, the interaction terms between these independent variables were added to the interaction terms model two, to prove whether agreeableness moderated mathematics anxiety or fluid intelligence directly to impact how mathematics anxiety predicts mathematics marks, or whether the three-way interaction between agreeableness, mathematics anxiety and fluid intelligence predicts mathematics marks, which would provide evidence of a secondary moderation.

Table 63

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Agreeableness

				Overall Model Test			
Model	R	R^2	Adjusted R^2	F	df1	df2	p
1 – Direct	.562	.316	.304	28.1	3	183	< .001
2 - Interaction	.565	.319	.293	12.0	7	179	< .001
Model Comparison	ΔR^2	.004		0.257	4	179	.905

In Table 63 the variance explained by the direct and interaction models is reported, both of which are statistically significant. While the direct effects model explained 31.6% of the variance (R^2 = .316, $F(3, 183) = 28.1$, $p < .001$), the interaction effects model explained 31.9% of the variance in mathematics marks (R^2 = .319, $F(7, 179) = 12.0$, $p < .001$). The interaction effects model, therefore, does not significantly contribute further variance over and above the direct effects (R^2 = .004, $F(4, 179) = 0.257$, $p > .05$).

Table 64

Multiple Regression Model Coefficients: Agreeableness as a Moderator of Mathematics Anxiety

			95% CI				
Predictor	Estimate	SE	Lower	Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	46.940	3.198	40.630	53.250	14.678*		
f	0.522	0.141	0.243	0.800	3.696*	.051	0.241
MA	0.783	0.119	0.548	1.018	6.583*	.162	0.429
Agree.	0.039	0.052	-0.063	0.140	0.749	.002	0.046
2 - Interaction							
Intercept	47.442	3.386	40.761	54.123	14.013*		
f	0.556	0.387	-0.207	1.320	1.437	.008	0.257
MA	0.762	0.124	0.516	1.007	6.125*	.139	0.418
Agree.	-0.016	0.133	-0.278	0.246	-0.120	.001	-0.019
f x MA	-0.001	0.015	-0.030	0.029	-0.009	.006	-0.002
f x Agree.	-0.015	0.019	-0.053	0.022	-0.826	.002	-0.138
MA x Agree.	0.002	0.005	-0.008	0.012	0.348	.002	0.055
f x MA x Agree.	0.000	0.001	-0.001	0.002	0.589	.001	0.096

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Agree. = Agreeableness.

**p* < .001.

From the models reported in Table 63, 21.5% of the unique variance is explained by fluid intelligence, math anxiety, and agreeableness in the direct model, with the combination of the variables explaining the remaining 10.1% of the variance, as reported in Table 64. It should be acknowledged that agreeableness is not a statistically significant predictor in either the direct or interaction models. Furthermore, none of the interaction effects add significantly to the interaction model, only contributing a total of 1.1% of variance to explaining the predictors of mathematics marks. Therefore, agreeableness does not moderate mathematics anxiety.

***Agreeableness as a Moderator of Study Habits*.** Further hierarchical multiple regressions were conducted by adding agreeableness, fluid intelligence, and study habits, all as independent predictor variables into model one, to build a baseline direct effects model. The baseline model one was compared to the interaction effects, model two, to investigate whether moderation relationships were present between agreeableness, study habits, and fluid intelligence, and whether these moderations added significant value to the prediction model.

In Table 65 it is revealed that both regression models are statistically significant. While the direct effects model explained 30.4% of the variance (R^2 = .304, F(3, 183) = 26.6, p < .001), the interaction effects model explained 33.2% of the variance in mathematics marks (R^2 = .332, F(7, 179) = 12.7, p < .001). However, it should be noted that the 2.8% increase in variance explained by the interaction effects model did not contribute a statistically significant improvement over and above the direct effects (R^2 = .028, F(4, 179) = 1.88, p > .05).

Table 65

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Agreeableness

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.551	.304	.292	26.6	3	183	< .001
2 - Interaction	.576	.332	.306	12.7	7	179	< .001
Model Comparison	ΔR^2	.028		1.88	4	179	.115

In Table 66 it is shown that 23.3% of the unique variance is explained by each predictive variable in the model, with the combination of the variables explaining the remainder (7.1%) of the variance. Agreeableness does not add statistically significant value to either model. However, the three-way interaction between fluid intelligence, study habits, and agreeableness add statistically significant value to the second model, with the interaction effects model explaining 2.2% of the total 2.6% of variance explained by all the interaction effects. This indicates that agreeableness moderates the interaction between study habits and fluid intelligence in predicting mathematics marks, adding more context to the relationship between study habits and agreeableness (r = .33, p < .001) as reported in Table 60.

Table 66

Multiple Regression Model Coefficients: Agreeableness as a Moderator of Study Habits

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.980	0.986	65.035	68.924	67.960**		
f	0.623	0.138	0.350	0.895	4.500**	.077	0.288
SH	0.586	0.093	0.402	0.770	6.280**	.150	0.424
Agree.	-0.072	0.055	-0.181	0.037	-1.300	.006	-0.086
2 - Interaction							
Intercept	66.625	1.069	64.515	68.735	62.317**		
f	0.559	0.144	0.275	0.844	3.885**	.056	0.259
SH	0.594	0.093	0.410	0.777	6.367**	.151	0.429
Agree.	-0.111	0.057	-0.224	0.001	-1.951	.014	-0.132
f x SH	-0.004	0.012	-0.026	0.019	-0.319	.000	-0.021
f x Agree.	-0.005	0.008	-0.020	0.010	-0.687	.002	-0.046
SH x Agree.	0.004	0.005	-0.006	0.013	0.767	.002	0.050
f x SH x Agree.	0.002	0.001	0.000	0.003	2.433*	.022	0.167

Note. *f* = Fluid Intelligence, SH = Study Habits, Agree. = Agreeableness.

**p* < .001.

***Agreeableness as a Moderator of Problem-Solving Behaviour*.** Further hierarchical multiple regressions were conducted by adding fluid intelligence, problem-solving behaviour, and agreeableness into a baseline, direct effects model. This was followed by adding their interaction terms to model two, to determine whether agreeableness directly influenced problem-solving behaviour or fluid intelligence to predict mathematics marks, or whether the three-way interaction between agreeableness, problem-solving behaviour, and fluid intelligence predicts mathematics marks.

As indicated in Table 67, both regression models are statistically significant. While the direct effects model explained 29.0% of the variance (R^2 = .290, $F(3, 183) = 24.9$, $p < .001$), the interaction effects model explained 30.9% of the variance in mathematics marks (R^2 = .309, $F(7, 179) = 11.5$, $p < .001$). However, it should be noted that the interaction effects model did not contribute significantly to explaining further variance over and above the direct effects (R^2 = .020, $F(4, 179) = 1.27$, $p > .05$).

Table 67

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Agreeableness

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1 – Direct	.538	.290	.278	24.9	3	183	< .001
2 - Interaction	.556	.309	.282	11.5	7	179	< .001
Model Comparison	ΔR^2	.020		1.27	4	179	.285

As reflected in Table 68, in which these two models were further explored, 20.3% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remaining 8.7% of the variance. Agreeableness does not add statistically significant contributions to either the direct or interaction model. Additionally, there are no statistically significant interaction effects, and subsequently, no moderating effects to discuss. The interactions also only explained a total 1.5% of the variance of the interaction model. As such, even though a significant, weak, positive relationship ($r = .28$, $p < .001$) between problem-solving behaviour and agreeableness was reported in Table 60, this is not a moderating relationship.

Table 68

Multiple Regression Model Coefficients: Agreeableness as a Moderator of Problem Solving Behaviour

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.980	0.995	65.017	68.944	67.300*		
f	0.575	0.142	0.294	0.856	4.041*	.064	0.266
PSB	0.566	0.096	0.378	0.755	5.928*	.136	0.405
Agree.	-0.050	0.055	-0.158	0.058	-0.911	.003	-0.060
2 - Interaction							
Intercept	66.878	1.080	64.746	69.010	61.896*		
f	0.610	0.151	0.312	0.909	4.032*	.063	0.282
PSB	0.607	0.097	0.415	0.799	6.232*	.150	0.435
Agree.	-0.080	0.058	-0.195	0.035	-1.368	.007	-0.095
f x PSB	0.004	0.012	-0.020	0.027	0.303	.000	0.021
f x Agree.	-0.013	0.008	-0.028	0.002	-1.681	.011	-0.114
PSB x Agree.	-0.003	0.004	-0.012	0.006	-0.634	.002	-0.042
f x PSB x Agree.	0.000	0.001	-0.008	0.002	0.628	.002	0.042

Note. *f* = Fluid Intelligence, PSB = Problem Solving Behaviour, Agree. = Agreeableness * $p < .001$

***Agreeableness as a Moderator of Study Milieu*.** Lastly, to test whether agreeableness moderates how fluid intelligence or study milieu predicts mathematics marks, a hierarchical multiple regression was performed by comparing the direct and interaction effects regression models. Fluid intelligence and study milieu (as established independent predictors of mathematics marks), as well as agreeableness (as a new predictor variable) were added into a baseline direct effects model. The interaction terms between these independent variables were added to model two. Model two investigated whether agreeableness moderated study milieu or fluid intelligence directly to impact how they predict mathematics marks, or whether the three-way interaction between agreeableness, study milieu, and fluid intelligence predicts mathematics marks, indicative of a secondary moderation.

As reported in Table 69, both the direct and interaction models are statistically significant. The direct effects model explained 24.8% of the variance in mathematics marks ($R^2 = .248$, $F(3, 183) = 20.1$, $p < .001$). Furthermore, the interaction effects model explained 27.5% of the variance in mathematics marks ($R^2 = .275$, $F(7, 179) = 9.71$, $p < .001$). However, the increase in variance explained by the interaction effects model is not statistically significant when compared to the variance explained by the direct effects model ($R^2 = .028$, $F(4, 179) = 1.71$, $p > .05$).

Table 69

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Agreeableness

Model	R	R^2	Adjusted R^2	Overall Model Test			
				F	df1	df2	p
1 – Direct	.498	.248	.235	20.1	3	183	< .001
2 - Interaction	.525	.275	.247	9.71	7	179	< .001
Model Comparison	ΔR^2	.028		1.71	4	179	.150

In Table 70 these two models are further explored and informs that 17.6% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (7.2%) of the variance. It should be noted that agreeableness does not add any statistically significant value to either the direct model or to the interaction effect model. However, as has been previously observed, the interaction between fluid intelligence and study milieu is statistically significant, explaining an additional 1.6% of variance explained by the second model, when all interactions only explain a total variance of 1.9%.

Table 70

Multiple Regression Model Coefficients: Agreeableness as a Moderator of Study Milieu

Predictor	Estimate	SE	95% CI		t	sr^2	Stand. Estimate
			Lower	Upper			
1 - Direct							
Intercept	66.965	1.025	64.944	68.987	65.367**		
f	0.641	0.145	0.355	0.928	4.417**	.080	0.296
SM	0.752	0.157	0.442	1.062	4.784**	.094	0.321
Agree.	0.034	0.054	-0.073	0.140	0.622	.002	0.040
2 - Interaction							
Intercept	66.350	1.048	64.281	68.418	63.296**		
f	0.723	0.150	0.427	1.019	4.815**	.090	0.334
SM	0.786	0.167	0.457	1.115	4.715**	.090	0.335
Agree.	0.021	0.055	-0.087	0.129	0.381	.001	0.025
f x SM	0.037	0.019	-0.006	0.075	1.970*	.016	0.143
f x Agree.	-0.004	0.007	-0.019	0.011	-0.540	.001	-0.036
SM x Agree.	0.003	0.007	-0.011	0.016	0.408	.001	0.027
f x SM x Agree.	0.000	0.001	-0.002	0.002	0.452	.001	0.033

Note. *f* = Fluid Intelligence, SM = Study Milieu, Agree. = Agreeableness.

*$p < .001$.

Therefore, agreeableness does moderate the relationships between fluid intelligence or study milieu in predicting mathematics marks. At this point of the analysis, given that the agreeableness factor does moderate the interaction between fluid intelligence and study habits in predicting mathematics marks, there is already sufficient evidence to support the rejection of the null hypothesis, H_O13. Additionally, the 25 interactions between the five agreeableness facets and the five study orientations were also explored. To provide additional support of the alternate hypothesis, H_A13, the regressions with significant interactions are discussed further below. In all regressions, the agreeableness facet replaced the agreeableness factor in the setup of the hierarchical regression models.

Compliance with Study Orientations

Study Attitude

As can be observed in Table 71, both the direct and interaction models are statistically significant. The direct effects model explained 32.6% of the variance in mathematics marks ($R^2 = .326$, $F(3, 183) = 29.4$, $p < .001$). Comparatively, the interaction effects model explained 35.5% of the variance in mathematics marks ($R^2 = .355$, $F(7, 179) = 14.1$, $p < .001$). Despite the interaction effects model explaining 3.0% more variance than the direct model, the increase was not statistically significant ($R^2 = .030$, $F(4, 179) = 2.05$, $p > .05$).

Table 71

Hierarchical Regression Model: Fluid Intelligence, Study Attitude, Compliance

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.571	.326	.315	29.4	3	183	< .001
2 - Interaction	.596	.355	.330	14.1	7	179	< .001
Model Comparison	ΔR²	.030		2.05	4	179	.090

In Table 72 these two models were further investigated, and reports that 24.0% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remaining 8.6% of the variance. However, it must be noted that the contribution of compliance is not statistically significant in either the direct model or the interaction model.

Table 72

Multiple Regression Model Coefficients: Compliance as a Moderator of Study Attitude

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	66.975	0.970	65.061	68.888	69.055**		
f	0.587	0.137	0.317	0.857	4.289**	.068	0.271
SA	0.769	0.112	0.547	0.991	6.840**	.172	0.436
Com.	-0.035	0.173	-0.375	0.306	-0.201	.000	-0.012
2 - Interaction							
Intercept	66.799	1.005	64.816	68.783	66.448**		
f	0.627	0.136	0.359	0.896	4.607**	.077	0.290
SA	0.742	0.113	0.518	0.966	6.536**	.154	0.421
Com.	-0.209	0.186	-0.575	0.157	-1.125	.005	-0.074
f x SA	0.009	0.016	-0.021	0.040	0.595	.001	0.037
f x Com.	-0.012	0.023	-0.059	0.034	-0.529	.001	-0.035
SA x Com.	-0.015	0.020	-0.055	0.026	-0.726	.002	-0.051
f x SA x Com.	0.005	0.003	-0.004	0.011	1.921*	.013	0.139

Note. *f* = Fluid Intelligence, SA = Study Attitude, Com. = Compliance.

*p < .05. **p < .001.

However, there is a statistically significant interaction effect between fluid intelligence, study attitude, and compliance, explaining 1.3% of the total 1.7% of variance explained by all the interactions. Therefore, there is support that compliance moderates the relationship between fluid intelligence and study attitudes in predicting mathematics marks. Despite there being no relationship between compliance and study attitudes or fluid intelligence.

Mathematics Anxiety

Table 73

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Compliance

Model	R	R^2	Adjusted R^2	Overall Model Test F	df1	df2	p
1 – Direct	.561	.315	.304	28.0	3	183	< .001
2 - Interaction	.585	.342	.317	13.3	7	179	< .001
Model Comparison	ΔR^2	.027		1.87	4	179	.118

As can be observed in Table 73, both the direct and interaction models are statistically significant. The direct effects model explained 31.5% of the variance in mathematics marks (R^2 = .315, F(3, 183) = 28.0, p < .001). Furthermore, the interaction effects model explained 34.2% of the variance in mathematics marks (R^2 = .342, F(7, 179) = 13.3, p < .001). Despite explaining 2.7% more variance than the direct model, the increase explained by the interaction effects model was found to not be statistically significant (R^2 = .027, F(4, 179) = 1.87, p > .05).

Table 74

Multiple Regression Model Coefficients: Compliance as a Moderator of Mathematics Anxiety

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 – Direct							
Intercept	46.957	3.201	40.641	53.273	14.669***		
f	0.522	0.141	0.243	0.801	3.692***	.051	0.241
MA	0.783	0.119	0.548	1.018	6.572***	.162	0.429
Com.	0.108	0.172	-0.232	0.447	0.626	.001	0.038
2 - Interaction							
Intercept	47.827	3.237	41.440	54.214	14.776***		
f	0.870	0.388	0.103	1.637	2.239*	.019	0.402
MA	0.752	0.119	0.517	0.987	6.319***	.147	0.412
Com.	-0.310	0.489	-1.275	0.655	-0.634	.001	-0.110
f x MA	-0.010	0.015	-0.040	0.019	-0.676	.002	-0.116
f x Com.	-0.164	0.061	-0.284	-0.044	-2.700**	.027	-0.467
MA x Com.	0.010	0.019	-0.028	0.047	0.509	.001	0.087
f x MA x Com.	0.006	0.003	0.001	0.011	2.360*	.020	0.389

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Com. = Compliance.
*p < .05. **p < .01. ***p < .001.

In Table 74 the models were further explored, and it was found that 21.4% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remainder (10.1%) of the variance. The contribution of compliance is not statistically significant in either the direct model or the interaction model. However, the interaction between fluid intelligence and compliance was found to be statistically significant. Additionally, there was a statistically significant three-way interaction between fluid intelligence, mathematics anxiety, and compliance. This indicates that compliance moderates fluid intelligence, as well as the interaction between fluid intelligence and math anxiety, to influence mathematics marks. Given there were no statistically significant relationships between compliance and either mathematics anxiety, mathematics marks, or fluid intelligence reported in Table 60, this moderation effect adds new insights into how compliance indirectly impacts mathematics marks.

Study Habits

In Table 75 it is revealed that both regression models are statistically significant. While the direct effects model explained 29.8% of the variance (R^2 = .298, $F(3, 183)$ = 25.9, p < .001), the interaction effects model explained 34.1% of the variance in mathematics marks (R^2 = .341, $F(7, 179)$ = 13.2, p < .001). Additionally, the added variance explained by the interaction model is statistically significant (R^2 = .043, $F(4, 179)$ = 2.89, p < .05), suggesting that there are significant interactions to be explored in Table 76.

Table 75

Hierarchical Regression Model: Fluid Intelligence, Study Habits, Compliance

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 – Direct	.546	.298	.287	25.9	3	183	< .001
2 - Interaction	.584	.341	.315	13.2	7	179	< .001
Model Comparison	ΔR²	.043		2.89	4	179	.024

As illustrated by Table 76, 22.8% of the unique variance is explained by each predictive variable in model one, with the combination of the variables explaining the remainder (7.0%) of the variance. However, it must be noted that the contribution of compliance is not significant in either model. Additionally, the three-way interaction between fluid intelligence, study habits, and compliance was statistically significant, accounting for 3.2% of the total 4.2% explained across interaction effects. This significant interaction therefore demonstrates that compliance moderates the interaction between fluid intelligence and study habits to predict mathematics marks, adding more context to the significant weak relationship between compliance and study habits (r = 0.21, p < .01) observed in Table 60.

Table 76

Multiple Regression Model Coefficients: Compliance as a Moderator of Study Habits

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.979	0.990	65.027	68.931	67.693**		
f	0.638	0.138	0.365	0.911	4.614**	.082	0.295
SH	0.555	0.090	0.377	0.733	6.147**	.145	0.401
Com.	-0.091	0.179	-0.443	0.261	-0.512	.001	-0.033
2 - Interaction							
Intercept	66.952	1.024	64.931	68.973	65.370**		
f	0.627	0.139	0.353	0.900	4.523**	.075	0.290
SH	0.582	0.089	0.406	0.759	6.526**	.157	0.421
Com.	-0.295	0.186	-0.663	0.072	-1.586	.009	-0.105
f x SH	-0.017	0.012	-0.040	0.007	-1.405	.007	-0.092
f x Com.	-0.012	0.024	-0.060	0.036	-0.479	.001	-0.033
SH x Com.	0.011	0.017	-0.022	0.044	0.661	.002	0.046
f x SH x Com.	0.006	0.002	0.002	0.010	2.934*	.032	0.231

Note. f = Fluid Intelligence, SH = Study Habits, Com. = Compliance.

**p* < .01. ***p* < .001.

Tendermindedness

As can be seen in Table 77, both the direct and interaction models are statistically significant. The direct effects model explained 28.8% of the variance in mathematics marks (R^2 = .288, $F(3, 183) = 24.7$, $p < .001$). Furthermore, the interaction effects model explained 31.7% of the variance in mathematics marks (R^2 = .317, $F(7, 179) = 11.9$, $p < .001$). The interaction effects model, however, does not explain significantly more variance than what has already been explained by the direct effects model (R^2 = 0.029, $F(4, 179) = 1.90$, $p > .05$).

Table 77

Hierarchical Regression Model: Fluid Intelligence, Problem-Solving Behaviour, Tendermindedness

Model	R	R²	Adjusted R²	Overall Model Test F	df1	df2	p
1 – Direct	.537	.288	.276	24.7	3	183	< .001
2 - Interaction	.563	.317	.290	11.9	7	179	< .001
Model Comparison	ΔR²	.029		1.90	4	179	.113

Table 78 provides further exploration of these models, and reports that 19.4% of the unique variance is explained by fluid intelligence, problem-solving behaviour, and tendermindedness in the direct model, with the combination of the variables explaining the remainder (9.4%) of the variance. However, it should be noted that tendermindedness is not a statistically significant predictor in either the direct or interaction models.

Table 78

Multiple Regression Model Coefficients: Tendermindedness as a Moderator of Problem Solving Behaviour

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.987	0.997	65.021	68.953	67.216**		
f	0.604	0.143	0.323	0.886	4.236**	.070	0.279
PSB	0.527	0.094	0.342	0.712	5.624**	.123	0.377
Ten.	0.123	0.210	-0.291	0.537	0.585	.001	0.038
2 - Interaction							
Intercept	66.904	1.067	64.798	69.010	62.687**		
f	0.646	0.151	0.349	0.943	4.289**	.070	0.298
PSB	0.584	0.095	0.395	0.772	6.116**	.143	0.418
Ten.	0.027	0.224	-0.416	0.469	0.118	.000	0.008
f x PSB	0.003	0.012	-0.021	0.027	0.248	.000	0.017
f x Ten.	-0.076	0.032	-0.139	-0.013	-2.371*	.021	-0.176
PSB x Ten.	-0.008	0.020	-0.048	0.032	-0.397	.001	-0.027
f x PSB x Ten.	-0.001	0.003	-0.007	0.004	-0.447	.001	-0.034

Note. *f* = Fluid Intelligence, PSB = Problem Solving Behaviour, Ten. = Tendermindedness.
**p* < .05. ***p* < .001.

However, there is a statistically significant interaction between tendermindedness and fluid intelligence, with the effect contributing 2.1% of the total 2.3% variance explained across the interaction effects. Therefore, it can be concluded that tendermindedness moderates the influence of fluid intelligence on mathematics marks. Despite no statistically significant relationship between tendermindedness and either fluid intelligence or mathematics marks, as noted in Table 60.

Therefore, the above findings confirm that agreeableness does influence mathematics marks by acting as a moderator of other variables. Both the agreeableness factor, as well as the facets of compliance and tendermindedness, were found to demonstrate statistically significant interactions with fluid intelligence and study orientation facets. Therefore, there is sufficient evidence to reject the null hypothesis, H_O13.

Neuroticism as a Moderator of Study Orientation Factors

For the final personality trait under consideration, the strength and direction of the direct relationships between neuroticism, mindset, study orientations, fluid intelligence, and mathematics marks are summarised in the form of Pearson correlation coefficients in Table 79. The hierarchical regression models, to test whether significant moderation effects exist between these variables to predict mathematics marks, are then reported in the following sections.

Table 79

Correlation Coefficients Between Mathematics Marks, Fluid Intelligence, Study Orientations, and Neuroticism

	Neu.	**Aff.**	**Dep.**	**Sel.**	**Anx.**
Maths marks	-.149*	-.182*	-.161*	-.080	-.080
f	-.150*	-.143	-.163*	-.096	-.105
FM	.093	.081	.035	.124	.086
GM	-.078	-.019	-.066	-.101	-.082
SA	-.227**	-.238**	-.268***	-.144*	-.113
MA	.298***	.261***	.280***	.262***	.213**
SH	-.177*	-.194**	-.259***	-.111	-.023
PSB	-.208**	-.202**	-.246***	-.155*	-.095
SM	-.491***	-.394***	-.477***	-.406***	-.393***
M	102	21.7	25.7	30.1	24.2
SD	23.8	6.62	7.93	6.54	6.74

Note. f = Fluid Intelligence, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, Neu. = Neuroticism, Aff. = Affective Instability, Dep. = Depression, Sel. = Self-Consciousness, Anx. = Anxiety.

*$p < .05$. **$p < .01$. ***$p < .001$.

From Table 79, it is noted that neuroticism has significant, weak, negative relationships with mathematics marks ($r = -.15$, $p < .05$) and fluid intelligence ($r = -.15$, $p < .05$). In addition, the facets of affective instability ($r = -.18$, $p < .05$) and depression ($r = -.16$, $p < .05$) display significant, weak, negative relationships with mathematics marks. Moreover, depression has a significant negative relationship with fluid intelligence ($r = -.16$, $p < .05$). Furthermore, there are no relationships between neuroticism and its underlying facets and mindset.

Significant, weak, negative relationships are also observed between study attitudes and the neuroticism factor ($r = -.23$, $p < .01$), as well as the facets of affective instability ($r = -.24$, $p < .01$), depression ($r = -.27$, $p < .001$) and self-consciousness ($r = -.14$, $p < .05$) This suggests that as learners' emotional stability decreases, their motivation and positive attitudes towards studying also declines.

As hypothesised, there are notable weak, positive relationships between mathematics anxiety and all the facets of neuroticism, as well as the overarching factor (ranging from $r = .21$to $r = 0.30$), in line with what has been found previously (Cupani & Pautassi, 2013; Dowker et al., 2016). These relationships will be explored further by means of hierarchical regressions in section 4.4.5.1, to determine how neuroticism (and its facets) moderates the influence of mathematics anxiety on mathematics marks, whilst accounting for intelligence.

There are also statistically significant, weak, negative relationships observed between study habits and the facets of affective instability ($r = -.19$, $p < .01$) and depression ($r = -.26$, $p < .001$), in addition to the neuroticism factor ($r = -.18$, $p < .05$). This finding highlights that learners who already have a personality inclination to easily feel discouraged, upset, and hopeless are less likely to put in the consistent effort of studying. This will result in lower mathematics performance, resulting in further depression and feelings of helplessness.

Significant, weak, negative relationships between problem-solving behaviours and the neuroticism factor ($r = -.21$, $p < .01$), and the facets of affective instability ($r = -.20$, $p < .01$), depression ($r = -.25$, $p < .001$), and self-consciousness ($r = -.16$, $p < .05$) are also apparent.

Finally, significant moderate relationships between study milieu and all facets of neuroticism, in addition to the factor (ranging from $r = -.39$ to $r = .49$), are observed. The moderating effect of neuroticism in the relationship between study milieu and mathematics marks will be investigated in further detail in section 4.4.5.2. This is of particular interest, given that the study milieu has also been found to influence the impact of fluid intelligence in predicting mathematics marks.

Hypothesis 14: Neuroticism Interacting with Mathematics Anxiety. An initial hierarchical multiple regression was performed by adding fluid intelligence and mathematics anxiety, as established independent predictors of mathematics marks, as well as neuroticism as a new independent variable, into a baseline direct effects model. This was followed by adding their interaction terms to model two, to determine whether neuroticism moderated mathematics anxiety or fluid intelligence to directly predict mathematics marks (primary moderation), or whether the three-way interaction between neuroticism, mathematics anxiety, and fluid intelligence predicts mathematics marks (secondary moderation). In doing so, the results would provide evidence for the following hypotheses:

H_O14: Neuroticism does not interact with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A14: Neuroticism interacts with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance.

As indicated in Table 80, both regression models are statistically significant. While the direct effects model explained 32.2% of the variance (R^2 = .322, F(3, 183) = 29.0, p < .001), the interaction effects model explained 35.7% of the variance in mathematics marks (R^2 = .357, F(7, 179) = 14.2, p < .001). However, despite the interaction effects model explaining an additional 3.4% of variance, the contribution was not statistically significant (R^2 = .034, F(4, 179) = 2.38, p > .05).

Table 80

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Neuroticism

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.568	.322	.311	29.0	3	183	< .001
2 - Interaction	.597	.357	.331	14.2	7	179	< .001
Model Comparison	ΔR²	.034		2.38	4	179	.054

In Table 81 these two models are further discussed, and it is reported that 22.3% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remaining 9.9% of the variance. It should also be noted that, while fluid intelligence and mathematics anxiety add significantly to the direct model, neuroticism does not contribute statistically significant value to either model.

Table 81

Multiple Regression Model Coefficients: Neuroticism as a Moderator of Mathematics Anxiety

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	44.599	3.500	37.694	51.505	12.740***		
f	0.515	0.140	0.238	0.791	3.670***	.050	0.238
MA	0.875	0.132	0.616	1.135	6.650***	.164	0.480
Neuro.	0.072	0.046	-0.019	0.163	1.560	.009	0.106
2 - Interaction							
Intercept	44.473	3.940	36.699	52.247	11.288***		
f	2.536	0.953	0.656	4.416	2.662**	.026	0.474
MA	0.864	0.143	0.583	1.146	6.057***	.132	1.172
Neuro.	0.038	0.048	-0.057	0.133	0.785	.002	0.056
f x MA	-0.017	0.017	-0.050	0.016	-1.036	.004	-0.198
f x Neuro.	-0.015	0.007	-0.029	-0.001	-2.171*	.017	-0.767
MA x Neuro.	-0.004	0.004	-0.012	0.004	-0.992	.003	-0.070
f x MA x Neuro.	0.000	0.001	-0.003	0.001	0.242	.000	0.020

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Neuro. = Neuroticism.
*p < .05. **p < .01. ***p < .001.

There is also a statistically significant interaction effect between fluid intelligence and neuroticism, explaining 1.7% of the 2.4% total variance explained across the interaction effects. Therefore, there is support that neuroticism moderates the influence of fluid intelligence on mathematics marks, adding context to the significant, weak, negative relationships between neuroticism and fluid intelligence (r = -.15, p < .05) and mathematics marks (r = -.15, p < .05). This finding was echoed by Johann and Karbach (2022), who indicated that neuroticism had a negative relationship with intelligence, with the explanation that learners scoring higher on neuroticism likely felt higher test anxiety whilst completing the fluid intelligence assessment.

There is, however, no evidence that neuroticism has a moderating effect on mathematics anxiety, as was hypothesised. Despite the significant, weak, positive relationship (r = .30, p < .001) between neuroticism and mathematics anxiety reported in Table 79. Whether or not the facets of neuroticism moderate mathematics anxiety and its relationship in predicting mathematics marks, will now be investigated further, by substituting the facets and their interactions into the hierarchical regressions instead of the neuroticism factor. All factors are discussed below, given all facets demonstrated significant relationships with mathematics anxiety.

Affective Instability.

Table 82

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Affective Instability

Model	R	R²	Adjusted R²	Overall Model Test			
				F	df1	df2	p
1 - Direct	.560	.313	.302	27.9	3	183	< .001
2 - Interaction	.588	.346	.320	13.5	7	179	< .001
Model Comparison	ΔR²	0.032		2.19	4	179	.072

As can be observed in Table 82, both the direct and interaction models are statistically significant. The direct effects model explained 31.3% of the variance in mathematics marks (R^2 = .313, F(3, 183) = 27.9, p < .001). Furthermore, the interaction effects model explained 34.6% of the variance in mathematics marks (R^2 = .346, F(7, 179) = 13.5, p < .001). Despite the increase of 3.2% of variance explained by the interaction effects model, the contribution was not statistically significant (R^2 = .032, F(4, 179) = 0.032, p > .05).

Table 83

Multiple Regression Model Coefficients: Affective Instability as a Moderator of Mathematics Anxiety

Predictor	Estimate	SE	95% CI		t	sr²	Stand. Estimate
			Lower	Upper			
1 - Direct							
Intercept	46.727	3.380	40.058	53.396	13.824**		
f	0.517	0.141	0.238	0.796	3.660**	.050	0.239
MA	0.791	0.126	0.542	1.041	6.257**	.147	0.434
Aff.	0.021	0.159	-0.293	0.335	0.133	.004	0.009
2 - Interaction							
Intercept	46.974	3.609	39.852	54.097	13.014**		
f	0.981	0.432	0.128	1.833	2.270*	.019	0.453
MA	0.775	0.132	0.515	1.035	5.886**	.127	0.425
Aff.	-0.110	0.166	-0.438	0.218	-0.662	.002	-0.045
f x MA	-0.017	0.016	-0.049	0.015	-1.033	.004	-0.195
f x Aff.	-0.054	0.023	-0.100	-0.008	-2.322*	.020	-0.194
MA x Aff.	-0.008	0.014	-0.036	0.020	-0.569	.001	-0.039
f x MA x Aff.	0.000	0.002	-0.003	0.003	0.040	.000	0.003

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Aff. = Affective Instability.

**p* < .05. ***p* < .001.

In Table 83 these models are further explored, and reports that 20.1% of the unique variance is explained by fluid intelligence, mathematics anxiety, and affective instability in the direct model, with the combination of the variables explaining the remainder (11.2%) of the variance. However, it should be noted that affective instability is not a statistically significant predictor in either the direct or interaction models. The only statistically significant interaction effect observed was between fluid intelligence and affective instability, explaining 2.0% of the variance in the model (with the combination of interaction effects explaining a total of 2.5% of variance). As such, Table 83 adds context to the statistically significant relationships reported in Table 79 between affective instability and mathematics marks ($r = -.18$, $p < .05$). However, there is no support that affective instability moderates the influence of mathematics anxiety on mathematics marks, despite the significant, weak, positive relationship ($r = .26$, $p < .001$) between the two variables.

Depression.

In Table 84, it is indicated that both the direct and interaction models are statistically significant, explaining 31.9% ($R^2 = .319$, $F(3, 183) = 28.5$, $p < .001$) and 34.5% ($R^2 = .345$, $F(7, 179) = 13.5$, $p < .001$) of the variance in predicting mathematics marks, respectively. However, there is no statistically significant additional variance explained by the interaction model, over the direct effects model ($R^2 = .026$, $F(4, 179) = 1.80$, $p > .05$).

Table 84

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Depression

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.564	.319	.307	28.5	3	183	< .001
2 - Interaction	.587	.345	.319	13.5	7	179	< .001
Model Comparison	ΔR²	.026		1.80	4	179	.132

In Table 85 these models are further explored, and it is shown that 21.4% of the unique variance is explained by each predictive variable in the direct model, with the combination of the variables explaining the remaining 10.5% of the variance. However, it must be noted that the contribution of depression is not statistically significant in either the direct model or the interaction model. Furthermore, fluid intelligence does not add to the interaction effects model either. There were also no statistically significant interactions, contributing a total of only 1.5% to the overall variance explained by the model. Therefore, there are no moderating effects to report on, and subsequently no support that depression moderates the relationship between mathematics anxiety and mathematics marks, despite the statistically significant relationship (r = .25, p < .001) reported between the variables in Table 79.

Table 85

Multiple Regression Model Coefficients: Depression as a Moderator of Mathematics Anxiety

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr^2	Stand. Estimate
1 - Direct							
Intercept	45.285	3.464	38.450	52.120	13.07*		
f	0.519	0.141	0.242	0.797	3.69*	.051	0.240
MA	0.848	0.130	0.592	1.104	6.53*	.158	0.465
Dep.	0.161	0.137	-0.109	0.431	1.170	.005	0.080
2 - Interaction							
Intercept	44.480	4.005	36.576	52.384	11.105*		
f	0.730	0.424	-0.107	1.566	1.720	.011	0.337
MA	0.854	0.145	0.569	1.140	5.902*	.127	0.468
Dep.	0.077	0.147	-0.212	0.366	0.527	.001	0.038
f x MA	-0.008	0.016	-0.039	0.024	-0.482	.001	-0.088
f x Dep.	-0.033	0.021	-0.075	0.010	-1.521	.008	-0.119
MA x Dep.	-0.017	0.013	-0.044	0.009	-1.293	.006	-0.092
f x MA x Dep.	0.001	0.002	-0.003	0.005	0.351	.000	0.028

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Dep. = Depression.
*p < .05. **p < .01. ***p < .001.

Self-Consciousness.

Table 86

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Self-Consciousness

Model	R	R^2	Adjusted R^2	Overall Model Test F	df1	df2	p
1 - Direct	.573	.328	.317	29.8	3	183	< .001
2 - Interaction	.604	.364	.339	14.7	7	179	< .001
Model Comparison	ΔR^2	.036		2.53	4	179	.042

In Table 86 it is indicated that both the direct and interaction models are statistically significant, explaining 32.8% (R^2 = .328, F(3, 183) = 29.8, p < .001) and 36.4% (R^2 = .364, F(7, 179) = 14.7, p < .001) of the variance in predicting mathematics marks, respectively. The additional 3.6% of variance explained by the interaction model was a statistically significant contribution (R^2 = .036, F(4, 179) = 2.53, p < .05).

Table 87

Multiple Regression Model Coefficients: Self-Consciousness as a Moderator of Mathematics Anxiety

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	44.317	3.410	37.588	51.045	13.00**		
f	0.504	0.140	0.228	0.780	3.60**	.048	0.233
MA	0.885	0.128	0.633	1.137	6.93**	.176	0.485
Sel.	0.326	0.161	0.007	0.645	2.02*	.015	0.133
2 - Interaction							
Intercept	42.272	3.762	34.849	49.695	11.237**		
f	0.767	0.415	-0.052	1.586	1.849	.012	0.355
MA	0.940	0.135	0.674	1.207	6.961**	.172	0.515
Sel.	0.305	0.167	-0.025	0.636	1.824	.012	0.125
f x MA	-0.009	0.016	-0.039	0.022	-0.561	.001	-0.100
f x Sel.	-0.046	0.024	-0.094	0.002	-1.882	.013	-0.135
MA x Sel.	-0.026	0.017	-0.060	0.007	-1.571	.009	-0.108
f x MA x Sel.	0.001	0.002	-0.004	0.005	0.304	.000	0.023

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Sel. = Self- Consciousness.

**p* < .05. ***p* < .001.

From Table 87, in which the two models are further explored, it can be concluded that 23.9% of the unique variance is explained by each predictive variable in the direct effects model, with the combination of the variables explaining the remainder (8.9%) of the variance. However, it should be noted that neither fluid intelligence or self-consciousness added any statistically significant value to the interaction effect model. Additionally, none of the interaction effects were shown to be statistically significant, which only add 2.3% of variance in total across interaction effects to the model. Therefore, self-consciousness does not moderate mathematics anxiety's influence in predicting mathematics marks, despite the significant relationship (r = .26, p < .001) between the two variables reported in Table 87.

Anxiety.

Table 88

Hierarchical Regression Model: Fluid Intelligence, Mathematics Anxiety, Anxiety

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.571	.326	0.315	29.5	3	183	< .001
2 - Interaction	.589	.347	0.322	13.6	7	179	< .001
Model Comparison	ΔR²	.021		1.44	4	179	.223

Both the direct and interaction models are statistically significant, according to the results in Table 88. The direct effects model explained 30.0% of the variance in mathematics marks (R^2 = .300, F(3, 183) = 26.2, p < .001). The interaction effects model explained 32.7% of the variance in mathematics marks (R^2 = .327, F(7, 179) = 12.4, p < .001). However, although the interaction effects model explained 2.7% more variance, this increase was not statistically significant (R^2 = .027, F(4, 179) = 1.79, p > .05).

Table 89

Multiple Regression Model Coefficients: Anxiety as a Moderator of Mathematics Anxiety

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	44.717	3.378	38.053	51.381	13.240*		
f	0.510	0.140	0.234	0.786	3.640*	.049	0.236
MA	0.870	0.126	0.620	1.119	6.880*	.175	0.477
Anx.	0.288	0.155	-0.018	0.595	1.860	.013	0.121
2 - Interaction							
Intercept	44.169	3.821	36.629	51.709	11.560*		
f	0.857	0.438	-0.008	1.722	1.955	.014	0.396
MA	0.885	0.138	0.613	1.157	6.417*	.151	0.485
Anx.	0.240	0.164	-0.083	0.562	1.466	.008	0.101
f x MA	-0.012	0.017	-0.045	0.020	-0.751	.002	-0.142
f x Anx.	-0.041	0.024	-0.088	0.007	-1.691	.010	-0.133
MA x Anx.	-0.009	0.016	-0.041	0.022	-0.597	.001	-0.043
f x MA x Anx.	0.001	0.002	-0.003	0.004	0.310	.000	0.026

Note. *f* = Fluid Intelligence, MA = Mathematics Anxiety, Anx. = Anxiety.

*p < .001.

As demonstrated in Table 89, the unique variance explained by the independent predictive variables in the direct model is 23.7%, with the combination of variables explaining a further 8.9% of variance. Anxiety, however, does not statistically significantly add value to either the direct or interaction effects model Additionally, fluid intelligence also does not add statistically significant value to the interaction model. Furthermore, none of the interaction effects were found to be statistically significant, only contributing 1.3% to the variance explained in the interaction model. Therefore, it can be concluded that anxiety does not moderate mathematics anxiety, despite the significant weak relationship (r = .21, p < .05) (reported in Table 79) between the variables.

In conclusion, whilst neuroticism and affective instability were both statistically significant moderators, they did not moderate mathematics anxiety, but fluid intelligence's influence on mathematics marks. Therefore, there is no support that the facet of neuroticism moderates mathematics anxiety. Therefore, the null hypothesis, H_O14, was not rejected.

Hypothesis 15: Neuroticism Interacting with Study Milieu. An initial hierarchical multiple regression was performed by adding fluid intelligence and study milieu, as established independent predictors of mathematics marks (with an established interaction effect), as well as neuroticism as a new independent variable into a baseline direct effects model. This was followed by adding their interaction terms to model two. Model two aimed to determine whether neuroticism moderated study milieu, which would in turn predict mathematics marks (primary moderation), or whether the three-way interaction between neuroticism, study milieu, and fluid intelligence predicts mathematics marks (secondary moderation).

The hypotheses being investigated were:

H_O15: Neuroticism does not interact with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

H_A15: Neuroticism interacts with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance.

Table 90

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Neuroticism

Model	R	R²	Adjusted R²	Overall Model Test			
				F	df1	df2	p
1 - Direct	.500	.250	.238	20.3	3	183	< .001
2 - Interaction	.555	.309	.282	11.4	7	179	< .001
Model Comparison	ΔR²	.059		3.80	4	179	.005

Both the direct and interaction models are statistically significant, as indicated in Table 90. The direct effects model explained 25.0% of the variance in mathematics marks (R^2 = 0.250, $F(3, 183) = 20.3$, $p < .001$). The interaction effects model explained 30.9% of the variance in mathematics marks (R^2 = .309, $F(7, 179) = 11.4$, $p < .001$). The interaction model explains an additional 5.9% of variance, a statistically significant increase over the direct model (R^2 = .059, $F(4, 179) = 3.80$, $p < .01$).

Table 91

Multiple Regression Model Coefficients: Neuroticism as a Moderator of Study Milieu

Predictor	Estimate	SE	95% CI		t	sr²	Stand. Estimate
			Lower	Upper			
1 - Direct							
Intercept	66.976	1.023	64.958	68.995	65.472***		
f	0.638	0.145	0.352	0.923	4.404***	.080	0.295
SM	0.840	0.178	0.489	1.191	4.718***	.091	0.358
Neuro.	0.048	0.050	-0.050	0.146	0.970	.004	0.071
2 - Interaction							
Intercept	66.226	1.097	64.061	68.391	60.357***		
f	2.612	0.741	1.149	4.075	3.523***	.048	1.207
SM	0.901	0.187	0.532	1.269	4.822***	.090	0.384
Neuro.	0.035	0.049	-0.061	0.131	0.721	.002	0.052
f x SM	0.023	0.027	-0.031	0.077	0.842	.003	0.088
f x Neuro.	-0.019	0.007	-0.033	-0.005	-2.744**	.029	-0.982
SM x Neuro.	-0.001	0.005	-0.012	0.010	-0.208	.000	-0.015
f x SM x Neuro.	-0.008	0.001	-0.002	0.001	-1.043	.004	-0.110

Note. *f* = Fluid Intelligence, SM = Study Milieu, Neuro. = Neuroticism.

**p* < .05. ***p* < .01. ****p* < .001.

As observed in Table 91, 17.1% of the unique variance is explained by fluid intelligence and study milieu in the direct effects model, with neuroticism explaining a statistically non-significant 0.4% of variance. Additionally, the combination of the predictor variables explained the remaining 7.5% of the variance, shown in Table 90. Neuroticism did not add statistically significant value to the interaction effects model. However, the interaction between fluid intelligence and neuroticism was statistically significant. The interaction explained 2.9% of the variance, with all interaction effects contributing a total of 3.6% of variance. Furthermore, it should be noted that while fluid intelligence and study milieu usually indicates a statistically significant interaction, it was not observed in this model.

Additionally, there is no evidence that neuroticism moderates study milieu, despite the significant, moderate, negative relationship (r = -.49, p < .001) reported in Table 79. However, to confirm whether the data fails to reject the null hypothesis, H_O15, the neuroticism factor was substituted with the facets of neuroticism in the hierarchical regression models. All models will now be discussed below, given that all the facets of neuroticism demonstrated significant, moderate relationships with study milieu.

Affective Instability

The findings reported in Table 92 indicate that both the direct and interaction models are statistically significant, with the additional 5.1% variance explained by the interaction model also indicative of a statistically significant improvement (R^2 = .051, F(4, 179) = 3.25, p < .05). The direct effects model explained 24.6% of the variance in mathematics marks (R^2 = .246, F(3, 183) = 19.9, p < .001), with the interaction effects model explaining 29.7% of the variance in mathematics marks (R^2 = .297, F(7, 179) = 10.8, p < .001).

Table 92

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Affective Instability

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.496	.246	.234	19.9	3	183	< .001
2 - Interaction	.545	.297	.270	10.8	7	179	< .001
Model Comparison	ΔR²	.051		3.25	4	179	.013

From the models reported in Table 93, 15.9% of the unique variance is explained by fluid intelligence, study milieu, and affective instability in the direct model, with the combination of the variables explaining the remainder (8.7%) of the variance. However, it should be noted that affective instability is not a statistically significant predictor in either the direct or interaction models. The only statistically significant interaction effect observed was between fluid intelligence and affective instability, which has been discussed above, explaining 1.9% of the variance in the model (with the combination of interaction effects explaining a total of 2.4% of variance). Additionally, the interaction between fluid intelligence and study milieu was not significant. Lastly, despite the significant, moderate, negative relationship between study milieu and affective instability (r = -.39, p < .001) reported in Table 79, there is no evidence that affective instability moderates study milieu.

Table 93

Multiple Regression model coefficients: Affective Instability as a Moderator of Study Milieu

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.963	1.025	64.940	68.986	65.304**		
f	0.635	0.145	0.349	0.922	4.375**	.079	0.294
SM	0.744	0.169	0.410	1.078	4.394**	.080	0.317
Aff.	-0.037	0.169	-0.371	0.296	-0.221	.000	-0.015
2 - Interaction							
Intercept	66.087	1.072	63.971	68.203	61.621**		
f	0.715	0.158	0.403	1.027	4.521**	.080	0.330
SM	0.852	0.177	0.502	1.202	4.803**	.091	0.364
Aff.	-0.155	0.170	-0.489	0.180	-0.914	.003	-0.064
f x SM	0.015	0.027	-0.038	0.067	0.552	.001	0.056
f x Aff.	-0.049	0.023	-0.094	-0.005	-2.176*	.019	-0.177
SM x Aff.	-0.017	0.019	-0.054	0.020	-0.930	.003	-0.067
f x SM x Aff.	0.000	0.003	-0.005	0.005	0.018	.001	0.002

Note. *f* = Fluid Intelligence, SM = Study Milieu, Aff. = Affective Instability.

*p < .05. **p < .001.

Depression

In Table 94 it is demonstrates that both regression models are statistically significant, and that a statistically significant improvement of 5.6% was explained by the interaction model (R^2 = .056, F(4, 179) = 3.58, p < .01). While the direct effects model explained 24.8% of the variance (R^2 = 0.248, F(3, 183) = 20.1, p < .001), the interaction effects model explained 30.4% of the variance in mathematics marks (R^2 = .304, F(7, 179) = 11.2, p < .001).

Table 94

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Depression

Model	R	R²	Adjusted R²	Overall Model Test			
				F	df1	df2	p
1 - Direct	.498	.248	.236	20.1	3	183	< .001
2 - Interaction	.551	.304	.277	11.2	7	179	< .001
Model Comparison	ΔR²	0.056		3.58	4	179	.008

In Table 95 these models are further explored and demonstrates that 17.0% of the unique variance is explained by the direct predictors in the direct model, with the combination of the variables explaining the remaining 7.8% of the variance. However, it should be noted that depression is not a statistically significant predictor in either model. A statistically significant interaction effect was observed between fluid intelligence and depression, explaining 2.1% of the variance in the model (with the combination of interaction effects explaining a total of 4.7% of variance). However, despite the significant, moderate, negative relationship (*r* = -.48, *p* < .001) between study milieu and depression reported in Table 79, there is no evidence that depression moderates study milieu.

Table 95

Multiple Regression Model Coefficients: Depression as a Moderator of Study Milieu

Predictor	Estimate	SE	95% CI		t	sr²	Stand. Estimate
			Lower	Upper			
1 - Direct							
Intercept	66.967	1.024	64.947	68.987	65.394**		
f	0.639	0.145	0.353	0.925	4.410**	.080	0.295
SM	0.816	0.176	0.469	1.164	4.631**	.088	0.348
Dep.	0.107	0.147	-0.184	0.398	0.728	.002	0.053
2 - Interaction							
Intercept	66.018	1.112	63.823	68.214	59.346**		
f	0.595	0.163	0.273	0.917	3.644**	.052	0.275
SM	0.876	0.189	0.504	1.249	4.644**	.084	0.374
Dep.	0.125	0.147	-0.166	0.415	0.846	.003	0.062
f x SM	0.039	0.022	-0.004	0.083	1.797	.013	0.151
f x Dep.	-0.047	0.020	-0.088	-0.007	-2.319*	.021	-0.172
SM x Dep.	-0.002	0.017	-0.036	0.032	-0.089	.003	-0.006
f x SM x Dep.	-0.005	0.003	-0.010	0.001	-1.574	.010	-0.142

Note. *f* = Fluid Intelligence, SM = Study Milieu, Dep. = Depression.

**p* < .05. ***p* < .01. ****p* < .001.

Self-Consciousness

Table 96

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Self-Consciousness

				Overall Model Test			
Model	**R**	**R²**	**Adjusted R²**	**F**	**df1**	**df2**	**p**
1 - Direct	.504	.254	.241	20.7	3	183	< .001
2 - Interaction	.554	.307	.280	11.3	7	179	< .001
Model Comparison	ΔR²	.054		3.47	4	179	.009

As indicated in Table 96, both the direct and interaction models are statistically significant. Additionally, the increase of 5.4% of variance explained by the interaction model was statistically significant (R^2 = .054, $F(4, 179) = 3.47$, $p < .01$). The direct effects model explained 25.4% of the variance in mathematics marks (R^2 = .254, $F(3, 183) = 20.7$, $p < .001$). The interaction effects model explained 30.7% of the variance in mathematics marks (R^2 = .307, $F(7, 179) = 11.3$, $p < .001$).

Table 97

Multiple Regression Model Coefficients: Self-Consciousness as a Moderator to Study Milieu

			95% CI				
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**sr²**	**Stand. Estimate**
1 - Direct							
Intercept	66.950	1.020	64.937	68.963	65.61**		
f	0.631	0.144	0.346	0.916	4.37**	.078	0.292
SM	0.850	0.170	0.514	1.186	4.99**	.102	0.363
Sel.	0.234	0.171	-0.104	0.571	1.370	.008	0.096
2 - Interaction							
Intercept	66.294	1.087	64.148	68.439	60.966**		
f	0.673	0.158	0.362	0.985	4.272**	.071	0.311
SM	0.949	0.179	0.597	1.302	5.312**	.109	0.405
Sel.	0.255	0.169	-0.079	0.589	1.505	.009	0.104
f x SM	0.025	0.025	-0.024	0.074	1.022	.004	0.097
f x Sel.	-0.065	0.026	-0.116	-0.014	-2.510**	.024	-0.191
SM x Sel.	-0.007	0.022	-0.050	0.036	-0.317	.000	-0.022
f x SM x Sel.	-0.002	0.003	-0.008	0.004	-0.811	.003	-0.074

Note. *f* = Fluid Intelligence, SM = Study Milieu, Sel. = Self-Consciousness.

**p* < .01. ***p* < .001.

In Table 97 these two models are further explored, and states that 18.8% of the unique variance is explained by the direct predictors in the direct model, with the combination of the variables explaining the remaining 6.6% of the variance. However, it should be noted that self-consciousness is not a statistically significant predictor in either model. A statistically significant interaction effect was observed between fluid intelligence and self-consciousness, explaining 2.4% of the variance in the model (with the combination of interaction effects explaining a total of 3.1% of variance).

Therefore, despite the significant, moderate, negative relationship (r = -.41, p < .001) between study milieu and self-consciousness reported in Table 97, there is no evidence that self-consciousness moderates study milieu. Furthermore, it should be noted that, the interaction between fluid intelligence and study milieu was not statistically significant.

Anxiety

In Table 98 it is revealed that both regression models are statistically significant. While the direct effects model explained 25.3% of the variance (R^2 =.253, F(3, 183) = 20.7, p < .001), the interaction effects model explained 30.4% of the variance in mathematics marks (R^2 = .304, F(7, 179) = 11.2, p < .001). Furthermore, the interaction effects model contributes 5.1% more variance than the direct model, a statistically significant increase (R^2 = .051, F(4, 179) = 3.24, p < .05).

Table 98

Hierarchical Regression Model: Fluid Intelligence, Study Milieu, Anxiety

				Overall Model Test			
Model	R	R²	Adjusted R²	F	df1	df2	p
1 - Direct	.503	.253	.241	20.7	3	183	< .001
2 - Interaction	.551	.304	.276	11.2	7	179	< .001
Model Comparison	ΔR²	.051		3.24	4	179	.013

In Table 99 it is illustrated that 18.8% of the unique variance is explained by each predictive variable in the model, with the combination of the variables explaining the remaining 6.5% of the variance. However, it should be noted that the contribution of anxiety in the direct model is not significant. The only statistically significant effect is between fluid intelligence and anxiety, which explains 1.9% of variance in the model, while the other interactions explain an additional 2.4%. While the interaction between fluid intelligence and study milieu explains 1.2% of variance, it is not statistically significant. The interaction between study milieu and anxiety is not statistically significant, only explaining 0.1% of variance. Therefore, despite the significant relationship (r = -.39, p < .001) between anxiety and study milieu, anxiety was not found to moderate study milieu.

Table 99

Multiple Regression Model Coefficients: Anxiety as a Moderator of Study Milieu

Predictor	Estimate	SE	95% CI Lower	95% CI Upper	t	sr²	Stand. Estimate
1 - Direct							
Intercept	66.954	1.021	64.940	68.968	65.60**		
f	0.634	0.144	0.349	0.919	4.39**	.079	0.293
SM	0.843	0.169	0.510	1.177	4.99**	.102	0.360
Anx.	0.220	0.165	-0.106	0.546	1.330	.007	0.092
2 - Interaction							
Intercept	66.478	1.085	64.337	68.619	61.275**		
f	0.591	0.159	0.277	0.904	3.719**	.054	0.273
SM	0.896	0.179	0.542	1.250	4.994**	.097	0.382
Anx.	0.238	0.165	-0.087	0.563	1.445	.008	0.100
f x SM	0.046	0.027	-0.006	0.099	1.737	.012	0.177
f x Anx.	-0.053	0.024	-0.101	-0.005	-2.182*	.019	-0.172
SM x Anx.	0.008	0.021	-0.033	0.049	0.383	.001	0.027
f x SM x Anx.	-0.005	0.003	-0.011	0.001	-1.647	.011	-0.172

Note. *f* = Fluid Intelligence, SM = Study Milieu, Anx. = Anxiety.

*p < .01. **p < .001.

In summary of this hypothesis, the neuroticism factor and all its facets were found to have statistically significant interaction effects with fluid intelligence, but not with study milieu. In conclusion, there is no support that neuroticism or its facets moderate study milieu. Therefore, the null hypothesis, H_O15, was not rejected.

Synthesis of Hypotheses Outcomes for Objective Two

The second objective of this study was to investigate whether the five factors of personality, and their relative facets, moderate how study orientations influence mathematics marks. Following from this objective there arose eight specific hypotheses to be tested. The results of these analyses are summarised as follows:

Openness to experience did not demonstrate a statistically significant relationship with mathematics marks, fluid intelligence, or study attitude. Furthermore, none of the facets of openness to experience had statistically significant relationships with mathematics marks or fluid intelligence. However, the facets of ideas and imagination displayed significant, weak, positive relationships with study attitude. In addition, none of the interaction effects that included openness to experience, or any of its facets, were found to be statistically significant or contribute to the regression models in which they were added. Therefore, openness to experience does not moderate study attitude and the results fail to reject the null hypothesis H_O8.

A significant, weak, positive relationship was found between openness to experience and problem-solving behaviour. In addition, a moderate positive relationship between the ideas facet and problem-solving behaviour was observed. Moreover, weak positive relationships were observed between problem-solving behaviour and the facets of actions and imagination. Despite these relationships, the hierarchical regression model with openness to experience, problem-solving behaviour, and fluid intelligence found no statistically significant interaction effects, therefore providing no indication of moderation effects. When considering the models that included the facets of openness to experience, only the interaction between fluid intelligence and values was found to the statistically significant. This is indicative that the facet of values moderates the relationship between fluid intelligence and mathematics marks. Therefore, there is no support that openness to experience moderates problem-solving behaviour and as such, the null hypothesis H_O9 was not rejected.

Statistically significant, weak positive relationships were found between mathematics marks and conscientiousness and all five of its facets. In addition, weak negative relationships were reported between fixed mindset and conscientiousness, dutifulness, and prudence. A weak negative relationship was also found between growth mindset and prudence. There were no significant relationships found between fluid intelligence and conscientiousness or its facets. The hierarchical regression model between fluid intelligence, fixed mindset, growth mindset, and conscientiousness did not flag any statistically significant interaction effects. Therefore, the factor of conscientiousness does not moderate mindset.

However, the regression model with the facet of effort indicated that the interaction effect between fluid intelligence, growth mindset, and effort was statistically significant. Given that no other interactions were significant, there is evidence that the effort facet moderates how the interaction of fluid intelligence and growth mindset influences mathematics marks. In addition, the regression model with the order facet indicated that the interaction effect between fluid intelligence, growth mindset, and order was statistically significant. Given that no other interactions were significant, there is evidence that order moderates how the interaction of fluid intelligence and growth mindset influences mathematics marks. None of the other conscientiousness facets produced significant interaction effects. In conclusion, there is support that the conscientiousness facets of effort and order moderate the relationships between fluid intelligence, growth mindset, and mathematics performance. Therefore, sufficient evidence was presented to reject the null hypothesis H_O10.

In addition to the weak positive relationships between mathematics marks, conscientiousness, and its facets, a statistically significant, strong positive relationship was found between conscientiousness and study habits. Furthermore, moderate positive relationships were found between all five facets of conscientiousness and study habits. However, the hierarchical regression model between fluid intelligence, study habits, and conscientiousness found no statistically significant interaction effects. Therefore, there is no support that the conscientiousness factor moderates study habits' influence on mathematics performance. Yet, a statistically significant interaction was found between fluid intelligence and the facet of dutifulness, evidence that dutifulness moderates the relationship between fluid intelligence and mathematics marks. In addition, a statistically significant interaction effect between fluid intelligence, study habits, and self-discipline supports the interpretation that self-discipline moderates how fluid intelligence and study habits interact to predict mathematics marks. Therefore, the facets of dutifulness and self-discipline moderate relationships that impact mathematics marks, with self-discipline specifically moderating study habits. In conclusion, there is sufficient evidence to reject the null hypothesis H_O11.

The investigations that were conducted to determine whether extraversion moderates study orientations were exhaustive. All 30 relationships between extraversion and its five facets, and the five study orientation variables were explored:

- Considering statistically significant Pearson correlation coefficients, weak relationships were found between study attitudes and ascendance (positive) and excitement-seeking (negative); study habits and ascendance (positive), liveliness (positive), positive affectivity (positive), and excitement-seeking (negative); positive relationships between problem-solving behaviour and extraversion and all facets except excitement-seeking. Lastly, positive relationships between study milieu and extraversion, positive affectivity, and gregariousness. There were no statistically significant relationships with mathematics anxiety.

- Considering the hierarchical regressions for study attitudes – extraversion was not a statistically significant moderator; neither was ascendance, positive affectivity, gregariousness, or excitement-seeking. However, liveliness was found to moderate both the direct relationship between fluid intelligence and mathematics marks, as well as the interaction between fluid intelligence and study attitudes to predict mathematics marks. Therefore, there is support that liveliness moderates study attitudes.
- Considering the hierarchical regressions for mathematics anxiety – extraversion was not a statistically significant moderator; neither was ascendance, liveliness, gregariousness, or excitement-seeking. However, statistically significant interactions were found between fluid intelligence and positive affectivity, as well as fluid intelligence, mathematics anxiety, and positive affectivity, This is indicative that positive affectivity moderates both fluid intelligence and mathematics anxiety's relationships with mathematics marks.
- Considering the hierarchical regressions for study habits – extraversion was not a statistically significant moderator; neither was ascendance, positive affectivity, or gregariousness. However, a statistically significant interaction was reported between fluid intelligence and liveliness, indicating that liveliness moderates the relationship between fluid intelligence and mathematics marks. Furthermore, the statistically significant interaction between fluid intelligence, study habits, and excitement-seeking indicates that excitement-seeking moderates the interaction between fluid intelligence and study habits to predict mathematics marks.
- In summarising the regression results for problem-solving behaviour, extraversion does not moderate problem-solving behaviour. It was reported that ascendance, positive affectivity, gregariousness, and excitement-seeking did not have any statistically significant interaction effects either. However, the statistically significant interaction between fluid intelligence and liveliness, as mentioned earlier, was indication that liveliness moderates the direct relationship between fluid intelligence and mathematics marks.
- Extraversion did not moderate study milieu, neither did any of the facets of extraversion. The only statistically significant interactions were between fluid intelligence and study milieu (highlighted under objective one) and fluid intelligence and liveliness, discussed above.

In conclusion, there is support that extraversion facets moderate study attitudes, mathematics anxiety, and study habits, as well as fluid intelligence. Therefore, the null hypothesis H_O12 is rejected.

Similarly, whether agreeableness moderates study orientations has been extensively explored, considering all 30 possible moderating relationships between agreeableness and its five facets, and all five aspects of study orientation:

- There were no statistically significant Pearson correlation coefficients observed between agreeableness and its facets, and either mathematics marks or fluid intelligence. However, weak positive relationships were reported between study attitudes and agreeableness, modesty, and tendermindedness; a moderate relationship with straightforwardness was also observed. A weak positive relationship between mathematics anxiety and modesty was reported. Study habits had positive relationships with all facets of agreeableness (weak – straightforwardness, compliance, prosocial tendencies, modesty; moderate – tendermindedness), as well as the factor (moderate). Weak positive relationships between problem-solving behaviour and all facets of agreeableness, including the overarching factor, were described. Finally, a weak positive relationship between straightforwardness and study milieu was also communicated.
- Only the facet of compliance was found to have a statistically significant interaction between fluid intelligence and study attitudes to influence mathematics marks. No other facet of agreeableness, or the factor, were found to moderate study attitudes.
- Agreeableness and its facets did not moderate mathematics anxiety. The only statistically significant interaction effect observed in these regression models was between fluid intelligence and compliance, an indication that compliance moderates the direct relationship between fluid intelligence and mathematics marks.
- The three-way interaction between fluid intelligence, study habits, and agreeableness was statistically significant, indicating that agreeableness does moderate the interaction between fluid intelligence and study habits in predicting mathematics marks. Similarly, the three-way interaction between fluid intelligence, study habits, and compliance was also significant. Therefore, compliance moderates the interaction between fluid intelligence and study habits in impacting mathematics marks.
- No statistically significant interaction effects were reported between problem-solving behaviour and agreeableness, or any of the facets. The only statistically significant interaction reported was between fluid intelligence and tendermindedness, indicating that tendermindedness moderates the direct relationship between fluid intelligence and mathematics marks.

- Lastly, none of the interactions with agreeableness or its facets were found to be statistically significant with study milieu.

In summary, there is support that agreeableness moderates study habits, and that the facet of compliance moderates study attitudes and study habits. Additionally, agreeableness, compliance, and tendermindedness moderated fluid intelligence. Therefore, the null hypothesis H_O13 was rejected as the evidence shows that agreeableness is a moderator of study orientations.

In investigating neuroticism and mathematics anxiety, neuroticism displayed weak negative relationships with both mathematics marks and fluid intelligence. In addition, weak negative relationships between mathematics marks, and affective instability and depression, and fluid intelligence and depression were also reported. Weak positive relationships were observed between mathematics anxiety and neuroticism and all four of its facets. However, in the hierarchical regression between fluid intelligence, mathematics anxiety, and neuroticism, only the interaction between fluid intelligence and neuroticism was found to be statistically significant. Therefore, neuroticism does not moderate mathematics anxiety, but fluid intelligence's relationship with mathematics marks. Furthermore, affective instability was found to also moderate how fluid intelligence predicts mathematics marks. None of the other facets of neuroticism were found to moderate fluid intelligence or mathematics anxiety. Therefore, neuroticism does influence mathematics marks as a moderator, but of fluid intelligence and not mathematics anxiety. Therefore, despite the moderations observed, the null hypothesis H_O14 was not rejected.

Finally, in considering the interactions between neuroticism and study milieu, statistically significant moderate negative relationships were reported between study milieu and neuroticism and its four facets. However, only the interaction between fluid intelligence and neuroticism was found to be statistically significant. Therefore, the interpretation follows that neuroticism moderates the relationship between fluid intelligence and mathematics marks. Similarly, all the facets of neuroticism, namely affective instability, depression, self-consciousness, and anxiety were also found to moderate fluid intelligence's direct impact on mathematics marks, without moderating study milieu. Given neuroticism did not moderate study milieu, the null hypothesis H_O15 was not rejected.

Chapter Synthesis

Fifteen hypotheses, umbrellaed under two overarching objectives, were addressed in this chapter. When investigating these hypotheses, a number of relationships, moderation analyses, and hierarchical multiple regressions were performed. Table 100 summarises the statistically significant Pearson correlation coefficients (relationships) and significant moderation interactions, from which Chapter Five will offer concluding comments on. All relationships and moderations should be interpreted with the evidence that a statistically significant, moderate, positive relationship exists between fluid intelligence and mathematics marks.

Table 100

	Relationship	Moderation; Outcome
Objective One: Primary Moderations (Study Orientations)		
H_A1: GM moderates f - MM	MM - GM: weak f - GM: weak	Non-significant. Fail to reject H_O1.
H_A2: FM moderates f - MM	MM - FM: weak	Non-significant. Fail to reject H_O2.
H_A3: SA moderates f - MM	MM - SA: strong f - SA: weak	Non-significant. Fail to reject H_O3.
H_A4: MA moderates f - MM	MM - MA: moderate	Non-significant. Fail to reject H_O4.
H_A5: SH moderates f - MM	MM - SH: moderate f - SH: weak	Non-significant. Fail to reject H_O5.
H_A6: PSB moderates f - MM	MM - PSB: moderate f - PSB: weak	Non-significant. Fail to reject H_O6.
H_A7: SM moderates f – MM	MM-SM: moderate f - SM: weak	Significant. Reject H_O7.

	Relationship	Moderation; Outcome
Objective Two: Secondary Moderations		
(Personality)		
H_A8: OtE moderates SA - MM	OtE – SA: not significant	Non-significant.
	Id, Im – SA: weak	Fail to reject H_O8.
H_A9: OtE moderates PSB - MM	OtE – PSB: weak	Non-significant.
	Id, Ac, Im – SA: weak	Fail to reject H_O9.
H_A10: Cons. moderates FM - MM or GM - MM	Cons. – MM: weak	f*GM*Effort significant.
	All facets – MM: weak	f*GM*Order significant.
	Cons. – FM: weak	
	Dut, Pru – FM: weak	Reject H_O10.
H_A11: Cons. moderates SH - MM	Cons. – MM: weak	f*SH*Self-Discipline significant.
	All facets – MM: weak	
	Cons. - SH: strong	Reject H_O11.
	All facets – SH: moderate	
H_A12: Ext. does not moderate Study Orientations - MM	Asc., Ex.Se. – SA: weak	f*SA*Liv significant.
	Asc., Liv., Po. Af., Ex. Se – SA: weak	f*MA*Po. Af significant.
	Ext. and all facets – PSB = weak	f*SH*Ex. Se significant.
	Ext., Po. Af., Gre. - SM: weak	Reject H_O12.

	Relationship	Moderation; Outcome
H_A13: Agr. does not moderate Study Orientations - MM	Agr., Mod., Ten. – SA = weak	f*SA*Com significant.
	Str. – SA = moderate	f*MA*Com significant.
	Mod. – MA = weak	f*SH*Agr. significant.
	Agr., Ten. – SH = moderate	f*SH*Com significant.
	Str., Com., Pro., Mod. – SH = weak	
	Agr. and all facets – PSB = weak	Reject H_O13.
	Str. – SM = weak	
H_A14: Neu. moderates MA - MM	Neu., Aff., Dep. – MM = weak	Non-significant.
	Neu. and all facets – MA = weak	Fail to reject H_O14.
H_A15: Neu. moderates SM - MM	Neu., Aff., Dep. – MM = weak	Non-significant.
	Neu. and all facets – SM = moderate	Fail to reject H_O15.

Note. f = Fluid Intelligence, MM = Mathematics marks, FM = Fixed Mindset, GM = Growth Mindset, SA = Study Attitude, MA = Mathematics Anxiety, SH = Study Habits, PSB = Problem-Solving Behaviour, SM = Study Milieu, OtE = Openness to Experience, Cons. = Conscientiousness, Ext. = Extraversion, Agr. = Agreeableness, Neu. = Neuroticism.

Chapter Five: Discussion and Concluding Comments

Purpose of this Study

The primary aim of the study was to investigate the influence of non-intellectual factors on mathematics performance, whilst accounting for the role of fluid intelligence. There is a gap in existing literature exploring the interactions between fluid intelligence, mindset, and study orientations towards mathematics and mathematics performance, especially in South Africa (Taylor et al., 2019). Therefore, Objective One of the study endeavoured to establish whether mindset and elements of study orientations towards mathematics, moderate the relationship between fluid intelligence and mathematics performance. Furthermore, focusing on a learners' personality, or their socio-emotional traits, has been found to have substantiative developmental benefits (Damgaard & Neilsen, 2018). As such, understanding how learners' personalities interact with their mindset and study orientations to influence mathematics performance, while still accounting for their fluid intelligence, formed Objective Two of the study.

Figure 2 summarises the variables and relationships examined for the study under each objective. It should be noted that extraversion and agreeableness, whilst assessed as personality factors, were not hypothesised to moderate either the study orientations or the direct relationship between fluid intelligence and mathematics performance.

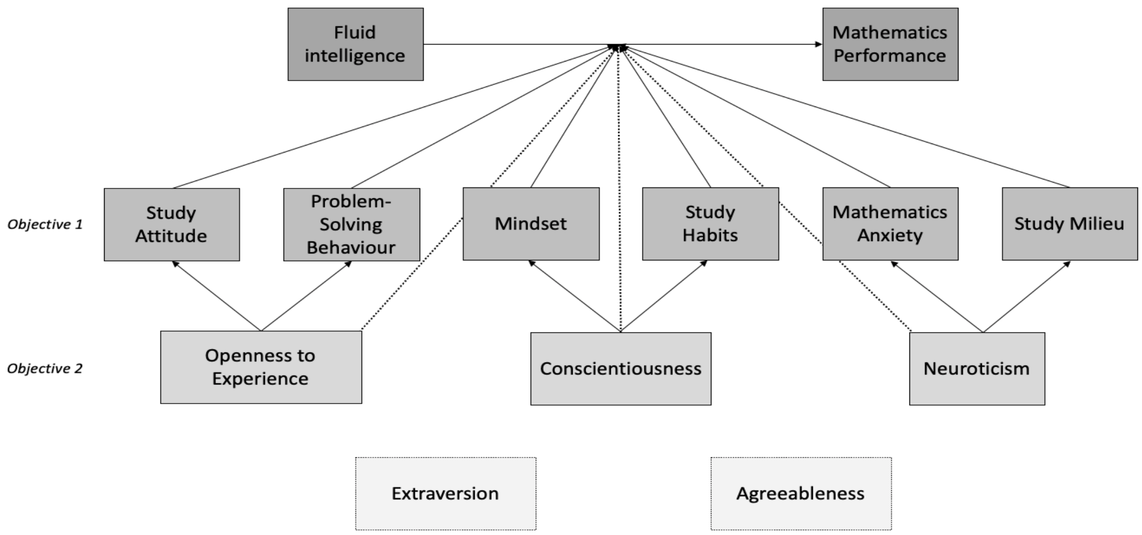

Figure 2.

Hypothesised Model Summary: Mindset, Study Orientations, and Personality Interaction Effects on the Relationship Between Fluid Intelligence and Mathematics Performance

Discussion of Objective One and its findings

Objective One was to determine if mindset and study orientations towards mathematics influence the relationship between fluid intelligence and mathematics performance, to better understand which elements to focus development initiatives on to improve the mathematics performance of South African high school learners. For the current study, a significant, moderate, positive (r = 0.39, p < .001) relationship was found between fluid intelligence and grade nine learner mathematics performance, replicating previous studies (Abin et al., 2020; Brandt & Lechner, 2022). The rest of the discussion of objective one relates to how mindset and study orientations strengthen or weaken this relationship.

Conclusion One: Growth Mindset Directly Predicts Mathematics Marks

For the current study, the null hypothesis (H_O1) was that the relationship between fluid intelligence and mathematics performance is not moderated by a growth mindset. The analyses showed that growth mindset has a statistically significant, yet weak, negative relationship with mathematics marks (r = -.27, p < .001). This finding provides support to Li and Bates (2017), who also found that growth mindset does not directly result in higher academic achievement. Only growth mindset had a statistically significant, weak, negative relationship with fluid intelligence (r = -.16, p < .05), which indicates that learners who believed they could master novel tasks eventually performed worse on the fluid intelligence assessment. Furthermore, the moderation analysis reported that growth mindset does not moderate fluid intelligence's influence in predicting mathematics performance. This finding differs from a study by Wang et al. (2022), which found an indirect moderation effect of growth mindset on academic performance via reasoning ability in an adolescent sample.

Although the findings fail to reject the null hypothesis (H_O1), the practical implication suggests that initiatives aimed at developing a growth mindset are valuable, given its direct influence on mathematics marks. In this regard, Haimovitz and Dweck (2017) had previously found that growth mindset could be learnt. Furthermore, Porter et al. (2020) found that growth mindset interventions were relatively low-cost ways to improve motivation, despite not directly improving mathematics grades, especially in schools in lower socioeconomic status areas in the Western Cape province. The reasoning, therefore, follows that if growth mindset increases motivation, with time, engagement with mathematics would increase (Wang et al., 2021), which in turn would increase mathematics performance.

Practically, if a school were only to focus on developing a learner's growth mindset towards mathematics, they would need to start by fostering a culture that embraces the belief that effort is meaningful, and that intelligence is not a fixed construct. Similarly, teachers should ideally refrain from suggesting that a learners' mathematics ability cannot be developed. Workshops and training sessions that introduce the concept of growth mindset to teachers, students, and parents, may be beneficial, but is only part of the solution. It is crucial that growth mindset principles are integrated into the curriculum, where teachers also consistently communicate to pupils that perseverance, resilience, and a positive attitude toward learning is more important to their academic achievement than just their innate, natural intelligence. Teachers should also be trained to model growth mindset behaviours, offering constructive feedback that focuses on effort and improvement, and creating a supportive environment where mistakes are viewed as opportunities to learn. Schools should also find ways to celebrate and reinforce effort and progress, set clear expectations for hard work, and incorporate growth mindset language into classroom discussions. Given that learning does not happen solely in the school setting, these initiatives may be more valuable if parents are also involved. Providing parents and guardians with resources that can support them in implementing growth mindset strategies contribute to the overall development of a growth mindset within the learner. This approach would not only enhance mathematics performance specifically, but if done correctly, has the potential to nurtures students' ability to face any challenge that they may be faced with in life with confidence and determination.

Conclusion Two: Fixed Mindset Directly Predicts Mathematics Marks

In the current study, the null hypothesis (H_O2) was that the negative relationship between fluid intelligence and mathematics performance is not moderated by a fixed mindset. Upon investigating the data, analyses found a statistically significant, weak, negative relationship between fixed mindset and mathematics performance (r = -.26, $p <$ .001). Moreover, fixed mindset was found to have a significant negative, direct effect in predicting mathematics performance. Furthermore, a non-significant interaction effect between fixed mindset and fluid intelligence means that fixed mindset does not moderate how fluid intelligence impacts mathematics performance. Therefore, based on this evidence, the results failed to reject the null hypothesis (H_O2).

Hwang et al. (2019) found that fixed mindset in grade 10 predicted lower academic achievement in grade 12. Nevertheless, the current findings also support Morse's (2022) conclusions that study orientation elements contribute more to mathematics performance than mindset. Although the current findings fail to reject the null hypothesis, the practical implications are like those previously mentioned under growth mindset and will also be explored further under developing study orientations.

There is value in reducing the effects of a fixed mindset, since it has a significant negative, direct influence on mathematics performance. By developing a growth mindset within learners, by virtue they would be less likely to have a fixed mindset. If learners are able to learn in an environment where mistakes are viewed as learning opportunities rather than indicators of innate ability, this will benefit their development of both growth mindset as well as buffer them from the negative effects of anxiety towards mathematics. Teachers should provide constructive feedback that focuses on effort and strategies, emphasising the notion that mathematical skills can be developed through dedication and perseverance, rather than suggesting that the learner just does not have the skills to do well in the subject. The curriculum should be designed in such a manner that highlights the relevance and real-world applications of mathematical concepts, making the subject more engaging and relatable. Encouraging collaborative learning, where students work together to solve problems, promotes a positive and supportive atmosphere. Additionally, incorporating diverse teaching methods, such as hands-on activities and real-life problem-solving scenarios, caters to different learning styles and helps students see the practicality of mathematics. Regularly celebrating students' progress and achievements, regardless of the level, contributes to building confidence and a positive attitude toward mathematical studies. Overall, by creating an environment that reinforces the principles of a growth mindset, schools can actively prevent the development of a fixed mindset toward mathematics and foster a culture where students embrace challenges and approach the subject with resilience and enthusiasm.

Conclusion Three: Study Attitude Directly Predicts Mathematics Marks

For the current study, study attitude reflected a statistically significant, strong, positive relationship with mathematics marks ($r = .51$, $p < .001$), as well as a statistically significant, weak, positive relationship with fluid intelligence ($r = .27$, $p < .001$). The relationship between study attitude and mathematics marks supports previous international studies by Chen et al. (2018) and Lipnevich et al. (2016). It is also in line with previous local studies by Erasmus (2013), which found a correlation coefficient of .41, and Maree et al. (2014), which found a correlation coefficient of .25, between the two variables. The relationship between study attitude and fluid intelligence suggests that the self-insight into one’s abilities likely positively influences one’s study attitudes.

It was further found that study attitude directly predicts mathematics performance but does not moderate the relationship. The current findings therefore failed to reject the null hypothesis (H_O3). This contradicts Erasmus (2013), who found that, whilst study attitude did correlate with mathematics performance, it did not predict it. However, Morse (2022) found that the interaction between mindset, mathematics anxiety, and study attitude predicted mathematics performance. The current findings also add context to studies such as Mazana et al. (2019), who found that study attitude declines from primary school to high school, while Mabena et al. (2021) noted disinterest towards mathematics. The current study therefore highlights the practical gains of improved performance, to mitigate the negative impact of declined interest in the subject.

The current study concludes that educators and parents should continuously cultivate positive study attitudes towards mathematics to create excitement and interest in the subject. In this regard, Ramirez et al. (2018b) suggested including mathematical board games, interactive classes, and even tuition to enhance study attitudes (whilst reducing mathematics anxiety and improving mathematics performance), especially when learners underperform and are unlikely to find mechanisms to motivate themselves to try again (King et al., 2012). Practical implications of this result again points at curriculum change. If the school can follow an engaging and interactive curriculum that highlights the real-world applications of mathematical concepts, students' interest and motivation is likely to be enhanced far more, regardless of whether they have the innate intelligence to perform well in mathematics.

Conclusion Four: Mathematics Anxiety Directly Predicts Mathematics Marks

The current study found that the only negative statistically significant moderate relationship, between mathematics anxiety and mathematics marks (r = -.36, p < .001), supported existing literature that stated that anxiety negatively influences performance (Zhang et al., 2019). The relationship between mathematics anxiety and fluid intelligence was not significant (r = -.12, p > .05), as expected, given that the fluid intelligence questionnaire did not have mathematical content. This finding does, however, contrast with Schillinger et al. (2018) who found that mathematics anxiety correlated with fluid intelligence. Nevertheless, the non-significant relationship between fluid intelligence and mathematics anxiety can be seen to provide support for mathematics anxiety only impacting mathematics performance, while not impacting performance in other domains. Therefore, given that this study assessed fluid intelligence, which is innate problem-solving ability, the findings do not support Ramirez et al. (2016) who postulated that learners with higher reasoning abilities still underperform due to high levels of anxiety.

The null hypothesis (H_O4) suggested that the positive relationship between fluid intelligence and mathematics performance is not moderated by mathematics anxiety. It was found that mathematics anxiety directly influenced mathematics performance, and that the interaction effect (or moderation) was not significant. In line with the finding that mathematics anxiety directly predicted mathematics performance, Anson (2021) argues that lowering mathematics anxiety has significant consequences for improved mathematics achievement and engagement. Especially in the South African context, where mathematics literacy is an alternative subject option. The alternative subject option may cause learners who are unable to cope with the affective symptoms of mathematics anxiety to opt for mathematics literacy, despite having the ability to perform well in mathematics. As such, as O’Hara et al. (2022) emphasised that teachers and others in education, together with the study environment, must focus on supporting those learners who display fear, nervousness, and discomfort when faced with mathematical problems. Mitchell (2018) found that by building a positive study attitude, sustainable and persistent study routines, and a growth mindset can counter the effects of mathematics anxiety in learners and build their confidence towards the subject over time.

By addressing mathematical anxieties with empathy, varied teaching approaches, and a focus on positive reinforcement, schools can create an environment that supports students in overcoming their apprehensions toward mathematics. Teachers should be coached on how to employ teaching methods that cater to different learning styles, incorporating hands-on activities, visual aids, and real-life examples to make mathematical concepts more accessible and relatable. Providing ample opportunities for practice and reinforcement allows students to build confidence gradually. Breaking down complex problems into smaller, manageable steps and offering regular, positive feedback on students' efforts fosters a sense of accomplishment. Encouraging collaborative learning, where students work together on problem-solving, promotes a shared understanding and reduces the fear of failure. Additionally, incorporating mindfulness and relaxation techniques during mathematics lessons can help students manage stress and anxiety.

Conclusion Five: Study Habits Directly Predicts Mathematics Marks

This study reported a statistically significant, moderate, positive relationship between study habits and mathematics marks ($r = .46$, $p < .001$), This finding mirrors Erasmus (2013), supporting the view that positive study habits positively influence mathematics performance (Aeon & Aguinis, 2017; Akben-Selcuk, 2017). The statistically significant, weak, positive relationship between study habits and fluid intelligence ($r = .23$, $p < .01$) could be indicative of learners higher on fluid intelligence realising sooner that they do not understand concepts, and in turn, putting in more study effort to grasp the concept confidently.

The current study set the null hypothesis (H_O5) that the positive relationship between fluid intelligence and mathematics performance is not moderated by study habits. The current study failed to reject the null hypothesis because study habits did not moderate the influence of fluid intelligence in predicting mathematics marks. This contradicts Bilalić et al. (2022), who concluded that practice and effort had indirect effects on academic performance. Study habits were instead found to directly predict mathematics marks, supporting Fernández-Alonso et al. (2015) who reported that effort put into homework positively influenced mathematics marks. The findings for the current study, therefore, highlight the direct influence that study habits have on mathematics marks, signifying the importance of learners creating and maintaining study schedules and consistently putting effort into studying mathematics. As suggested by Ramirez et al. (2018b), tuition would not only add mathematics more formally into learners' study schedules, but the supportive training environments can also improve study attitude, whilst reducing mathematics anxiety.

To foster positive and effective study habits toward mathematics, teachers should guide students in goal-setting, breaking down larger objectives into manageable tasks to enhance focus and organisation. Once again, by creating a supportive environment that encourages a growth mindset, students understand that effort leads to improvement, which can significantly impact study habits. Providing students with specific, constructive feedback on their work helps them identify areas for improvement and reinforces positive behaviours. Where feasible, schools should also offer resources such as additional practice materials, tutoring services, or online tools to support independent learning. Establishing a routine for studying mathematics and creating a dedicated study space can contribute to consistency and focus. Furthermore, promoting collaborative learning through group study sessions or peer support can enhance understanding and motivation. By emphasising the importance of practice, persistence, and a growth-oriented mindset, schools would be better equipped to empower students to succeed in their mathematics studies.

Conclusion Six: Problem-Solving Behaviour Directly Predicts Mathematics Marks

Problem-solving behaviour displayed a statistically significant, moderate, positive relationship with mathematics marks ($r = .47$, $p < .001$), the second strongest after study attitude. This relationship adds support to Erasmus's (2013) finding, while refuting the indication of Maree et al. (2014) that there is no significant relationship between problem-solving behaviour and mathematics performance. This facet of study orientation also showed the highest, albeit weak, statistically significant positive relationship with fluid intelligence (r =

0.29, $p < .001$). Given that problem-solving behaviour relates to metacognition and applying cognitive strategies effectively to solve problems, it is evident that individuals who apply problem-solving skills towards mathematics problems, applied similar skills during the completion of the fluid intelligence assessment.

The null hypothesis (H_O6) was that the positive relationship between fluid intelligence and mathematics performance is not moderated by problem-solving behaviours. Problem-solving behaviour was found to directly predict mathematics marks but did not moderate the effects of fluid intelligence in predicting mathematics marks. Therefore, the study failed to reject the null hypothesis (H_O6). Despite accepting the null hypothesis, the findings add to the research of Chytry et al. (2020). Chytry et al. (2020) stated that metacognitive knowledge, a component of problem-solving behaviour as it was operationalised for the current study, significantly impacts mathematical performance in schools. The current study also contradicts Van der Stel et al. (2010), who advised that while intelligence was the greatest predictor of mathematics performance in 13–14-year-olds, the unique contribution of metacognition outweighed intelligence in 14–15-year-olds.

To encourage positive and effective problem-solving behaviors in mathematics, schools can adopt various strategies, many of which have already been discussed above. Teachers should provide students with opportunities to engage in real-world problem-solving scenarios, fostering the application of mathematical concepts to practical situations. Encouraging a growth mindset, where challenges are viewed as opportunities for learning, can instil resilience and perseverance in students when faced with complex problems. Implementing collaborative learning environments, where students work together to solve mathematical problems, promotes the sharing of diverse perspectives and strategies. Offering constructive feedback on problem-solving processes, rather than solely on correct answers, reinforces the value of the problem-solving journey. Additionally, incorporating technology and interactive tools, where feasible can enhance students' engagement and interest in mathematical problem-solving. By integrating these strategies, schools can nurture a positive problem-solving mindset, equipping students with the skills and confidence to tackle mathematical challenges effectively.

Conclusion Seven: Study Milieu Directly Predicts, and Moderates Fluid Intelligence to Predict Mathematics Marks

This study's alternate hypothesis (H_A7) was that the study milieu moderates the positive relationship between fluid intelligence and mathematics performance. In assessing these relationships, study milieu had statistically significant positive relationship with both mathematics marks (r = .41, p < .001) and fluid intelligence (r = .29, p < .001). The moderate relationship with mathematics marks support previous findings that social and environmental factors influence mathematics marks (Erasmus, 2013; Moodaley, 2006). While the relationship between fluid intelligence and study milieu highlights how environmental factors influence intellectual growth in general (Maree et al., 2011), it contradicts the established theory that environmental factors do not influence fluid intelligence measures (Brown, 2016). Furthermore, study milieu was found to directly affect mathematics marks, with a larger estimate than fluid intelligence, as well as moderate the impact of fluid intelligence on mathematics marks, thereby rejecting the null hypothesis (H_A7) in favour of the alternative hypothesis.

Practically, this finding highlights how the support systems around learners influence their mathematics performance. Therefore, it is notable that even if learners possess higher levels of cognitive potential, if they do not have conducive learning environments their mathematics performance will ultimately be negatively impacted. This finding adds to the meta-analysis by Peng et al. (2019), which summarised that higher socioeconomic status boosts the effects of fluid intelligence on mathematics performance. Shamaki (2015) also demonstrated that the quality of classrooms, in terms of lighting and class sizes, influenced mathematics performance in secondary school. It should be noted that the current study was conducted in Gauteng, a province where both socioeconomic status and mathematics performance are generally higher, compared to other provinces in South Africa (apart from Western Cape) (Gondwe, 2022). Given that the results showed the effects of the study milieu in an urban area where learners had access to resources such as computer labs and internet connection, it is believed that the impacts will be more profound in a rural milieu. Therefore, this finding adds support to public pleas for more resources to be invested in educational systems, for learners to be able to actualise their potential. The above practical implications that discussed a number of strategies, from curriculum changes, to coaching teachers to be more approachable and supportive of a growth mindset, to making mathematical applications more practical, are then all smaller elements of the larger concept of study milieu.

Synthesis of Objective One

By reflecting on the influence of mindset and study orientations on mathematics performance, it was reiterated that mathematics performance cannot be solely attributed to cognitive abilities. In fact, study orientations were found to correlate stronger with mathematics marks than fluid intelligence.

Moreover, it was also found that, except for study milieu, none of the study orientations moderated fluid intelligence's impact on mathematics performance but added unique value in predicting mathematics performance. Therefore, it can be concluded that both study orientations and fluid intelligence are important, yet independent, factors that impact mathematics performance. Furthermore, the debilitating impact of a non-supportive study milieu was also made apparent, with learning environments moderating the influence of fluid intelligence in predicting mathematics performance. The findings also suggest that, depending on their study orientations, learners may require different interventions. As such, a single intervention targeted at the whole grade in a particular school may not be the solution, given that learners may have different areas of development. It is suggested that learners should rather attend workshops or receive resources for the area of study orientation they need the most development on, since the strengthening of one area is likely to positively impact other areas of study orientation.

Practically, the findings from the current study should be used to guide education and student support structures in enabling learners to perform better in mathematics. These findings confirm that mathematics achievement is dependent on more than purely the learner's cognitive potential (or fluid intelligence) to grasp mathematical concepts. In focusing on limited enrichment interventions for learners, these findings suggest that interventions should be focused on aspects of study orientations rather than attempts to shift learners to a growth mindset towards mathematics. Given limited resources, whether financially, lack of teacher or tutor support, or time constraints, the most pressing need is for local interventions to be focused on creating supportive study environments (or improving study milieu).

Part of fostering these environments include creating safe spaces where learners will not feel ridiculed for raising their concerns. The finding that mathematics achievement is not simply a reflection of intelligence should also be made known to learners, so that they can reframe their concerns. For example, when learners are struggling with a concept, they may believe that they are not intelligent enough to understand mathematics. It is then the duty of teachers and guardians to assist them in reframing their thoughts, that although they may be struggling with the concept, if they are persistent in their efforts, they will grasp the subject matter. Interventions focused on building confidence within learners may make it easier for them to reach out to teachers and guardians for help when they feel overwhelmed or confused with mathematical problems. In supporting their development of a positive attitude towards mathematics, with time the crippling effects of mathematics anxiety may also be lessened. Furthermore, there is value in implementing a sort of targeted support systems, such as mathematics clubs or tuition groups, that are specifically focused on reducing mathematics anxiety and fear. Such systems also need to normalise struggles with mathematics, so that learners can feel safe to discuss their concerns. By parents and teachers guiding learners through through their anxieties, focus can organically shift to constructive problem-solving methods. As learners become more comfortable with identifying which strategies need to be used with which types of mathematics problems, they will develop and strengthen the use of effective problem-solving strategies. As learners reflect on their problem-solving strategies more, they will be able to rely on their own skills whilst completing homework, thereby improving their study habit practices. In this regard, the value of resources that teach effective study techniques and time management should not be understated.

In summary, the conclusion of objective one supports the proposal that a holistic approach to mathematics achievement is needed. The change needs to start at a curriculum level, to make the subject more practical and engaging. Furthermore, educators need to be trained to model and support a growth mindset that can develop a learner's resilience towards mathematics. Educators and institutions should not only focus on academic content but also consider and address the psychological and environmental factors that impact students' mathematics performance. Implementing targeted interventions and creating a positive, supportive learning environment can contribute significantly to improved mathematics performance for grade nine.

Discussion of Objective Two and its findings

Objective Two was proposed to evaluate how personality (which was operationalised as specific, yet relatively stable behavioural traits) moderate the relationships between fluid intelligence, study orientations towards mathematics, and mathematics performance. This section summarises the relationships and interactions, or lack thereof, found between these independent concepts. As highlighted in earlier chapters, part of the unique contribution of the current study was evaluating the effects of the personality facets, as well as the more researched factors, on study orientations, fluid intelligence and mathematics performance.

Conclusion Eight: Openness to Experience does not moderate Study Attitude

The current study set the null hypothesis (H_O8) that openness to experience does not interact with study attitudes to moderate the positive relationship between fluid intelligence and mathematics performance. In this regard, the analysis found no significant relationships between openness to experience and its four facets, and either fluid intelligence or mathematics marks. Furthermore, the relationship between the openness to experience factor and study attitudes was not significant ($r = .13$, $p > .05$), despite significant relationship between study attitudes and the facets of ideas ($r = .26$, $p < .001$) and imagination ($r = .15$, $p < .05$). The relationship between ideas and study attitudes provides support to Di Giunta et al. (2013), who noted that higher openness to experience scores reduced the perceived threat of challenging learning experiences, which could be reframed as approaching the learning experience with a positive study attitude. Exploring the relationship further, only the facet of aesthetics was found to add significant, direct, negative value in a regression model predicting mathematics performance. However, none of the facets, or the factor of openness to experience, was found to have a moderating effect on either fluid intelligence or study attitudes in predicting mathematics performance. Overall, the current results failed to reject the null hypothesis (H_O8).

These findings refute Gatzka and Hell's (2018) meta-analysis, which found that the facets of ideas, values, and actions most influenced academic performance. Additionally, the current study does not align with Tjoe's (2016) conclusion that aesthetics positively impact mathematics learning experiences, given that for the current sample, it appears that learners who appreciate arts are less likely to achieve high mathematics marks. In summary, the findings of the current study are more aligned to provide subject-specific support to O'Conner and Paunonen (2007), who found no valuable relationships between openness to experience and academic performance. There is also no indication from the findings of the current study that more curious or creative individuals will perform any better or worse in mathematics, or that one's openness to experience has any impact on one's motivation and interest in mathematics, thereby conflicting with Jensen's (2015) finding of openness to experience improving intrinsic motivation.

Practically, these findings suggest that while openness to experience may influence performance in other subjects, a learner's openness to experience does not influence their mathematics performance. In this regard, the strategies discussed above for improving study attitudes towards mathematics still stand, and are not impacted by openness to experience.

Conclusion Nine: Openness to Experience does not moderate Problem-Solving Behaviour

The null hypothesis (H_O9) was that openness to experience does not interact with problem-solving behaviours to moderate the positive relationship between fluid intelligence and mathematics performance. Statistically significant, positive relationships were observed between problem-solving behaviour and the openness to experience factor ($r = .25$, $p < .001$), as well as the facets of ideas ($r = .30$, $p < .001$), actions ($r = .21$, $p < .01$), and imagination (*r* = .25, *p* < .001). The study by Köseoğlu (2016) had also found significant relationships between openness to experience, and processing and synthesis analysis, which are both elements of problem-solving behaviours. However, Köseoğlu (2016) had also noted that although openness to experience correlated with the methodical study learning style, conscientiousness explained significantly more variance (72%) than openness to experience (18%). Exploring the interactions of the current study further, the facet of aesthetics was found to add significant, direct, negative value in a regression model predicting mathematics performance. Moreover, the values facet was found to interact with fluid intelligence to have a moderating negative effect in predicting mathematics performance. Notably, this interaction effect did not extend to problem-solving behaviour. Overall, the findings of the current study failed to reject the null hypothesis (H_O9). Despite facets of openness to experience either directly, or indirectly, interacting with fluid intelligence, no moderating interactions between problem-solving behaviour and openness to experience and its facets are present.

As such, the current study does not align with suggestions from Akben-Selcuk (2017) that imagination towards problem-solving could result in higher mathematics marks. It also does not fit Bidjerano and Dai's (2007) conclusion that intellectually curious individuals are more likely to perform well in tasks that require critical thinking, such as questions posed in fluid intelligence questionnaires. The current findings do, however, highlight the interaction between values and fluid intelligence. Thereby indicating that learners who are more likely to challenge current processes may do so at the expense of evaluating the mathematical problem logically, which in turn results in poorer mathematics performance. This finding contradicts with suggestions (Akben-Selcuk, 2017) that teachers should be more open to alternative methods of solving mathematical problems, since the learners who are more likely to do so may have their need to challenge the status quo override their need to arrive at a correct answer.

Conclusion Ten: Conscientiousness moderates Growth Mindset, but not Fixed Mindset

The alternate hypothesis (H_A10) was that conscientiousness moderates mindset's interaction with fluid intelligence and mathematics performance. Despite there being no relationship between conscientiousness and fluid intelligence, as expected (Rikoon et al., 2016), significant (weak) relationships were observed between mathematics marks, the conscientiousness factor, and all of its facets. The significant relationship between conscientiousness and its facets is similar to what has been found in previous studies by

Göllner et al. (2017) and Wehner and Schils (2021). Conscientiousness (r = -.16, p < .05), and the facets of dutifulness (r = -.18, p < .05) and prudence (r = -.23, p < .01) relate negatively with fixed mindset, while prudence also has a negative relationship with growth mindset (r = -.17, p < .05). Additionally, conscientiousness as a factor, as well as the facets of effort, order, and self-discipline were found to directly predict mathematics marks. Furthermore, the significant interaction between fluid intelligence, growth mindset, and effort signifies that the facet of effort serves as a moderator of the fluid intelligence and growth mindset relationship, to predict mathematics marks. Similarly, the significant interaction between fluid intelligence, growth mindset, and order provides support that the facet of order moderates the relationship between fluid intelligence and growth mindset, to predict mathematics marks. Despite the conscientiousness factor and the facets of dutifulness, prudence, and self-discipline not contributing any significant interactions, it can be concluded that aspects of conscientiousness (namely effort and order) moderate growth mindset, and therefore, there is sufficient evidence to reject the null hypothesis (H_O10).

Practically, these findings add further context to the study of Rikoon et al. (2016), which reported that even when accounting for intelligence, conscientiousness adds significant incremental value in predicting mathematics performance. Furthermore, it highlights the need for parents and teachers to guide students in creating routine in their study practices and encourage continuous effort. Moreover, it is important for learners to have a space to study in, create an orderly environment to focus in, be disciplined, and create order for themselves. In this regard, Göllner et al. (2017) note that during adolescence, homework and chores help develop conscientiousness, particularly effort, a finding that parents and teachers should aim to incorporate into their children’s lives.

Conclusion Eleven: Conscientiousness moderates Study Habits

For hypothesis 11, the alternate hypothesis (H_A11) was that conscientiousness interacts with study habits to moderate the positive relationships between fluid intelligence and mathematics performance. The findings of this study reported that in addition to the relationships between conscientiousness and its facets with mathematics marks, fluid intelligence, and mindset, there were significant moderate relationships between conscientiousness and its facets with study habits. The statistically significant, strong, positive relationship between study habits and conscientiousness (r = .50, p < .001), and moderate relationships with all the facets, is in line with Göllner et al. (2017), that learners scoring higher on discipline and diligence would invest more effort in studying. These results support Seo’s (2018) findings, where planning and diligent behaviours, as demonstrated by those scoring higher on conscientiousness, resulted in improved study time and ultimately, mathematics performance. Considering the results from the regression models, the interaction effects including conscientiousness were found to be non-significant. Furthermore, the facets of effort, order, and prudence did not demonstrate any significant interaction effects with fluid intelligence or study habits, thereby giving no support that these facets moderate study habits. The prudence facet, however, indicated a positive interaction with fluid intelligence, whilst the three-way interaction effect between fluid intelligence, study habits, and self-discipline was significant.

Therefore, it can be concluded that prudence moderates the influence of fluid intelligence on mathematics marks, whilst self-discipline moderates the interaction between fluid intelligence and study habits in predicting mathematics marks. Therefore, the results of this study support the rejection of the null hypothesis (H_O11). Once again, the practical implications of how conscientiousness, as a behavioural trait, positively influences study habits is highlighted. As healthy, positive study habits are endorsed, they in turn result in improved mathematics marks. As such, when initiatives are undertaken to develop mathematical study habits, it would be helpful to consider the conscientiousness of the learner. The results suggest that learners lower on conscientiousness are more likely to benefit from such training, given that learners higher on conscientiousness are likely to already have effective study habits.

Conclusion Twelve: Extraversion moderates Study Orientations

The findings of this study demonstrated that extraversion facets do moderate study orientations and subsequently, affects mathematics performance. Therefore, the null hypothesis (H_O12) was rejected. In line with previous studies (John et al., 2020), extraversion did not have significant relationships with mathematics marks or fluid intelligence. However, a number of significant weak relationships between the study orientation factors and facets of extraversion were reported, which were further explored by considering interaction effects between fluid intelligence, study orientation facets, and extraversion.

The non-significant relationship between study attitudes and extraversion provides support to the study of Peklaj et al. (2015), which found a non-significant relationship (r = -.05) between extraversion and mathematics interest or motivation. The current results also supports the findings of Smith et al. (2021), who found no relationship between extraversion and interest in learning. Given that the operationalisation of study attitude for the current study includes learners' motivation and interest to study mathematics, these previous studies align with the current findings. The researcher was, however, unable to find any literature relating to the specific facets of extraversion to support or contradict the significant, weak, positive relationship between study attitude and ascendance (r = .16, p < .05), and the significant, weak, negative relationship between study attitude and excitement-seeking (r = -.16, p < .05) found in Table 43.

These relationships do, however, highlight the value of considering the faceted behaviours that group together within the factor of extraversion. As Taylor and De Bruin (2017) described, ascendance relates to dominating others – and as such, this relationship suggests that individuals who are more likely to want to lead groups at school, are also more likely to have more interest in studying, since they have the motivation of being considered as an achiever within their groups. In considering excitement-seeking, which is the need to have physiologically arousing experiences, the negative relationship with a facet that relates to interest and motivation towards mathematics makes sense, in that mathematics is not necessarily considered an exciting activity.

Erbas and Bas (2015) found weak relationships between extraversion, and knowledge and regulation of cognition, despite none of these factors statistically contributing to creative ability in mathematics. Having the awareness of one's cognitive processes, and being able to regulate them, relate to the metacognitive aspect underlying problem-solving behaviours. The relationships in Table 43 therefore support the findings of Erbas and Bas (2015). Extraversion (r = .24, p < .001) and its underlying facets, apart from excitement-seeking, also have statistically significant relationships with problem-solving behaviour (correlation coefficients ranged from r = .16 to .25). This suggests that learners who are more comfortable communicating regularly are able to reflect on their thinking more readily, possibly identifying errors in reasoning or picking up misunderstood concepts quicker in their conversations with others.

Lastly, both the extraversion factor (r = .16, p < .05) and the facet of positive affectivity (r = .21, p < .01) correlate with study milieu. This suggests that learners are more likely to express their concerns readily when they feel they are in a socially supportive environment. Consequently, given the number of significant correlations, the current study further evaluated evidence to determine whether extraversion moderates study orientations, and therefore influences mathematics marks.

Liveliness negatively influences study attitudes and mathematics marks, and therefore acts as a negative moderator. This finding can be interpreted as individuals looking for opportunities for adventure and socialisation are likely to be less motivated to study independently, especially when it is a subject as potentially overwhelming as mathematics.

Positive affectivity counters the influence of mathematics anxiety, allowing one to actualise one's cognitive potential. Furthermore, excitement-seeking negatively moderates the relationship between fluid intelligence and study habits, contradicting the findings of Poropat's (2009) meta-analysis, which found that extraversion had no influence on academic performance after accounting for intelligence. The current findings highlight the value of creating achievable, yet attractive study routines (from a conscientiousness perspective). When learners enjoy variety and seek entertainment, they are less likely to follow through with helpful study habits, and in doing so, may struggle to showcase their learning potential in mathematics. However, if learners feel more enthusiastic about mathematics and their study routines, they are more likely to follow through with their study plans. In turn, clear study plans would reduce their anxiety, which would ultimately result in improved mathematics marks.

As such, learners who enjoy socialising and excitement in general, should be guided and given more support in making mathematics meaningful and interesting. Their trait to look for external stimulation, in the form of other people or adventurous activities, may detract them from studying and putting in sufficient effort towards mathematics. As such, a learners' degree of extraversion should not be ignored when considering their mathematics potential and support initiatives. This is in line with findings by Awuondo et al. (2019), who found a significant relationship between extraversion and mathematics. It also contradicts Brandt et al. (2019), who commented that sociability (element of extraversion) does not influence mathematics performance. Therefore, the findings of this study recommend that extraversion be a consideration when planning classroom interactions. Learners who are less introverted may take longer to feel comfortable with group exercises, which can in turn influence their anxiety when working with mathematics within a team.

Conclusion Thirteen: Agreeableness moderates Study Orientations

The current study's null hypothesis (H_O13) postulated that agreeableness does not interact with study orientations towards mathematics to moderate the relationship between fluid intelligence and mathematics performance. Existing literature (Splenger et al., 2013; Westphal et al., 2020) suggests that the personality facet of agreeableness does not affect study orientations towards mathematics. However, in the current study, many statistically significant relationships were reported in Chapter Four between agreeableness and study orientations. In this respect, Ariani (2013) observed that agreeableness was positively related to the challenge and curiosity aspects of intrinsic motivation, but that there was no relationship with independent mastery of tasks. More recently, Swift and Peterson (2018) noted that in general, there has been little research indicating agreeableness to be a significant moderator of performance or motivation. This was one of the gaps that the current study aimed to address. Sekao (2004) also found that by facilitating and encouraging supportive study environments, engagement amongst learners would improve, which would result in improved mathematics performance.

Considering moderations, the current study demonstrated that compliance has a positive moderating effect on the relationship between study attitude and fluid intelligence, which predicts mathematics marks. Practically, this means that individuals that are more socially compliant and who display positive behaviour in class, are more likely to display increased enthusiasm and motivation towards studying, which in turn allows them to actualise their cognitive potential. Compliance also had a significant, positive interaction effect with fluid intelligence and mathematics anxiety. As such, it can be interpreted that individuals who are more cooperative in general may use this to their advantage in mathematics classrooms. This is especially relevant for those learners who feel more anxiety towards mathematics, and in conforming and following instructions, may achieve higher mathematics marks. The three-way interaction between fluid intelligence, study habits, and agreeableness was significant. As such, the conclusion follows that more pleasant, acquiescent learners are more likely to have productive study habits (rather than rebelling against the requests of their teachers and parents), which in turn allows them to capitalise on their cognitive potential and perform well in mathematics.

Overall, the moderating influence of compliance on study attitudes, mathematics anxiety, and study habits, as well as the moderating influence of agreeableness on study habits, provided sufficient evidence to reject the null hypothesis (H_O13) that agreeableness does moderate study orientations, and in turn, influences mathematics marks. Therefore, these results support John et al. (2020), who reported that agreeableness positively impacts academic performance. Furthermore, this study confirms the results of Vermetten et al. (2001), which suggested that compliant learners are more likely to follow teacher instruction, leading to improved mathematics performance. From this study, the key implication is that agreeableness and the ability to work and cooperate with others, is indeed a contributor to mathematics performance and should not be overlooked in initiatives seeking to improve mathematics marks. Practically, therefore, it can be noted that a learners' level of agreeableness will influence how they interact with initiatives aimed at developing positive study orientations. More agreeable learners will be more cooperative, which in turn helps educators make an environment safe and supportive for learning.

Conclusion Fourteen: Neuroticism does not moderate Mathematics Anxiety

For the current study, the null hypothesis (H_O14) was that neuroticism does not interact with mathematics anxiety to moderate the positive relationship between fluid intelligence and mathematics performance. When evaluating the relationships with mathematics marks and fluid intelligence, neuroticism was found to have significant, weak, negative relationship with both aspects. Furthermore, affective instability and depression also displayed significant weak relationships with mathematics marks. Additionally, depression had a significant, negative relationship with fluid intelligence. Overall, these weak relationships support findings by Migali and Zucchelli (2017), that neuroticism negatively affects mathematics performance and participation. Moreover, the significant, yet weak relationship between fluid intelligence and neuroticism is in line with the study of Judge and Bono (2002), which demonstrated that anxiety and depression reduced cognitive capacity, which in turn negatively impacted how much attention was available for the task at hand.

Moreover, the relationship between mathematics anxiety and neuroticism was explored. A logical argument was followed that more emotionally volatile learners would be even further impacted by anxiety brought on by mathematics specifically, which in turn would continue to make them more nervous towards the subject (Wehner & Schils, 2021). In this regard, the current study found significant, weak relationships between mathematics anxiety and all facets of neuroticism, as well as the neuroticism factor. Further exploration of significant interaction effects, however, found that neuroticism only moderates fluid intelligence (as suggested by Judge and Bono (2002)) and not the relationship between mathematics anxiety and fluid intelligence. Similarly, affective instability also only moderates the impact of fluid intelligence, but not the impact of mathematics anxiety, on mathematics marks. None of the other facets of neuroticism displayed any significant interactions. Therefore, neuroticism and its facets do not moderate mathematics anxiety, and as a result the null hypothesis (H_O14) was not rejected.

Conclusion Fifteen: Neuroticism does not moderate Study Milieu

Finally, given that neuroticism, especially the affective instability facet, relates to pessimism, it was hypothesised that individuals in unsupportive study environments would be more affected. Learners with unsupportive environments and higher levels of neuroticism would be more prone to believing that their situation would never improve, and as such, not display much resilience (Organisation for Economic Cooperation and Development, 2019). As such, the null hypothesis (H_O15) investigated was that neuroticism does not interact with study milieu to moderate the positive relationship between fluid intelligence and mathematics performance. In this regard, in addition to the significant weak relationships between neuroticism, mathematics marks, and fluid intelligence, moderate relationships were observed between study milieu and the neuroticism factor and facets.

These negative relationships were then further examined by means of interaction effects in regression models. As with hypothesis 14, it was found that neuroticism and affective instability negatively moderates how fluid intelligence predicts mathematics marks. Furthermore, when study milieu is part of the prediction model, the remaining facets – depression, self-consciousness, and anxiety – all moderate the influence of fluid intelligence. However, none of the neuroticism facets have a significant interaction with study milieu. In conclusion, there is no support that neuroticism and its facets moderate study milieu. Therefore, the null hypothesis (H_O15) was not rejected.

Synthesis of Objective Two

The relationships between the study orientation factors and mathematics performance were established for objective one. Objective two explored the moderating effects of personality traits on these relationships. While interventions to develop each of the study orientations were discussed under objective one, the purpose of objective two was to determine whether there is value in understanding learners' individual differences, in relation to personality. The findings confirm that personality does moderate the relationships between study orientation, fluid intelligence, and mathematics performance. Furthermore, when creating supportive learning environments, or providing resources to learners that can aid their mathematics performance, their personality profiles should also be considered. In this respect, the recommendation is that both study orientations and personality be considered before commencing with an intervention, given that a single approach to enhancing mathematics performance will likely be unsuccessful.

The moderating effect of openness to experience was evaluated in relation to two aspects of study orientation, namely study attitude and problem-solving behaviour, and was not found to moderate either aspect. The direct effect of aesthetics and indirect effect of values were both negative towards mathematics performance, suggesting that overall, lower scores on openness to experience may be better for mathematics performance. In this regard, previous suggestions that mathematics be taught with practical, realistic examples is further supported. However, the effects of openness to experience on the other aspects of study orientations should still be explored, to establish the overall contributions of openness to experience in predicting mathematics performance.

Conscientiousness was found to contribute to mathematics marks, both as a direct, and moderating predictor variable. Additionally, this study demonstrated the influence of effort and order, specifically in relation to mindset. The influence of prudence and self-discipline, in relation to study habits, was also illustrated. As such, it can be concluded that overall, conscientiousness facets have a positive influence on mathematics marks. Practically however, this does highlight a need for different study habit approaches depending on the learners' conscientiousness. Learners higher on conscientiousness may be able to enhance their study habits with a more self-directed approach, and providing them with access to supporting resources may be sufficient. However, learners who are lower on conscientiousness are likely to require more guidance and support when it comes to implementing effective study habits and may struggle if left to independently improve their study habits.

Extraversion, a personality factor that historically had minimal support for impacting mathematics marks, was found to be a significant moderator of study orientations in the current study. This was the first local study to explore how the different facets of extraversion influence the relationship between fluid intelligence and study orientations. The findings revealed that extraversion does moderate the impact of study attitudes, mathematics anxiety, and study habits on mathematics performance. The current study comprehensively evaluated all interaction effects between the facets of extraversion, as well as the factor more generally, with all five study orientations under investigation, and found that extraversion does indeed moderate study attitudes, mathematics anxiety, and study habits negatively. There is the suggestion that learners who tend to be more social should receive increased support to encourage their interest in mathematics; one possibility would be to create study groups, where they can keep their lessons interesting and engaging.

Similarly, the literature on agreeableness was also conflicted. However, the most recent studies argued that the effects of agreeableness was negligible when accounting for intelligence. Nonetheless, the current study found that the facet of compliance interacts with fluid intelligence, as well as study attitudes, mathematics anxiety, and study habits, to influence mathematics marks. Furthermore, the agreeableness factor also positively interacts with the relationship between study habits and fluid intelligence, to impact mathematics marks. Practically, these findings suggest that learners who are higher on agreeableness will likely contribute more to creating a supportive learning environment, which will not only benefit themselves, but their peers and educators alike. The approach taken for tuition and learning opportunities should likely also be adapted for students lower on agreeableness, so that they do not disrupt the safe environment for others.

Despite literature suggesting that neuroticism would moderate mathematics anxiety, there was no evidence to support this, despite the weak relationships between the constructs. Furthermore, the current study supported previous literature that found that neuroticism and its facets negatively moderate fluid intelligences' impact on mathematics marks, however, neuroticism does not interact with study milieu. The absence of evidence in this context suggests that emotionally unstable learners who reside in lower socioeconomic status areas, or in unsupportive study environments, are not necessarily more at risk of failure than learners with more resources. Nevertheless, the debilitating effects of neuroticism on fluid intelligence functioning was also made apparent, indicating that overall, less emotionally stable learners are less likely to perform optimally. Learners who struggle with emotional stability would therefore benefit from being able to work within a supportive classroom.

Study Limitations

The current study was limited to a quintile five sample of grade nine learners in the Gauteng province. As such, although the findings are insightful for learners and educators in the region, it is suggested that this study should serve as a preliminary motivation for similar research projects to be rolled out in rural areas across the country. A larger sample that is representative of a larger diversity of learners, across all grades, will help guide educators with interventions specific to their context. The need to develop study orientations and a growth mindset, that can be adapted depending on the personality profile of the learner, still exists and should be addressed with further research.

Data collection was also conducted during Term 3 of 2022. With many schools being concerned about the class time lost during the previous pandemic years, as well as learners not being adequately prepared for their final examinations, they elected to not be part of this study. Having only a single indication of a learners' mathematics achievement and study orientation is limiting. Noting the number of associations between variables, there are still unanswered questions relating to the stability of study orientations over an academic year, when it is expected that a learners' mathematics performance does fluctuate somewhat. While it is noted that Term 2 mathematics marks were requested, some pupils may have had subsequent mathematics tests post their mid-year examinations, and it cannot be said with certainty that they responded to the questionnaires with their Term 2 performance in mind. Additionally, the study primarily relies on self-report measures for personality traits and study orientations. Self-report measures can introduce bias, as participants may provide responses they believe are socially desirable or may not accurately reflect their behaviours.

The current study was not exhaustive in evaluating the impact of all factors and facets of personality on all elements of study orientations, due to investigating specific questions that arose from existing literature. There is potential in further exploring structural equation models with larger samples, where the interaction effects between each of the independent variables can be freely investigated without necessarily imposing assumptions on the relationships. Unfortunately, the sample size of the current study was a limitation to comprehensively evaluate the model fit of a structural equation model that factored in mathematics marks, fluid intelligence, the five study orientations, the five personality factors, and all 24 facets in a single model.

Similarly, the current study was also focused on specific hypotheses, and there were a number of meaningful relationships found between study orientations and facets of personality that were not explored beyond discussion of the relationship. Considering the moderating relationships between these constructs would further add to literature. Furthermore, examining the mediating role of these constructs is also an aspect that has not been explored at all for the current study, but can add an additional layer of interpretation and understanding of the interaction between these constructs.

Although there are a number of limitations to this study, the study still has both theoretical and practical value for the education system and its' stakeholders. The next section aims to recommend ways to improve the current study to have additional benefits.

Recommendations for Further Research

To enhance the generalisability of findings to advocate for curriculum change and psychometric profiling within schools, whilst also providing context-specific recommendations where possible, it is recommended that future research encompasses a more diverse and representative participant pool. Additionally, given the reliance on self-report measures for personality traits and study orientations in the current study, future research should explore alternative assessment methods, such as parent and teacher ratings, to mitigate potential biases. Incorporating objective measures or observational techniques could provide a more accurate representation of the dynamics underlying mathematics performance.

Whilst it is not an easy feat to improve the study milieu, the current study does highlight the positive impact that interventions aimed at developing study attitude, mitigating mathematics anxiety, teaching effective study habits, and training on thinking about one's thinking can have on learners. Therefore, future research should include a pre- and post-intervention assessment of study orientations, for a more pointed approach towards the factors that have the greatest impact on mathematics performance, beyond the study milieu. Additional studies could also explore specific aspects of milieu, and include teacher attitudes, parent socioeconomic status, and cultural influences.

As highlighted in the literature discussed in Chapter Two, it is also recommended that a longitudinal study be conducted to better identify at which stage of the learners' scholastic career study attitudes become more negative, or when mathematics anxiety starts crippling performance. Further longitudinal studies to investigate whether growth mindset initiatives eventually contribute to improved mathematics performance are still required in the local context. Additionally, longitudinal studies could examine whether the contribution of metacognition in predicting mathematics performance increases over learners' scholastic careers. Considering the potential fluctuations in learners' mathematics performance, collecting data at multiple points throughout the academic year may also offer a more comprehensive understanding of the dynamics involved.

Exploring intelligence more holistically, such as an objective, benchmarked numerical reasoning assessment, or verbal comprehension in the language of instruction, should also be considered in future studies. The nuanced impact of additional facets of personality and emotional intelligence on study orientations, learning approaches, and mathematics performance could contribute to a more nuanced and comprehensive understanding of the subject. Lastly, an investigation into the mediating role of all variables should be further explored, given this study's focus on moderating effects.

Concluding Remarks

The current study evaluated the influence of a number of non-intellectual factors that could impact mathematics performance. It was found that study attitude, mathematics anxiety, study habits, and problem-solving behaviour directly predicts mathematics performance, whilst accounting for fluid intelligence. Furthermore, it was found that study milieu both directly, and as a moderator of fluid intelligence, predicts mathematics performance. The study further demonstrated that a number of study orientations, as well as learners' general behavioural traits and mindset, play an invaluable role in predicting their mathematics performance. The unique value of openness to experience in predicting mathematics performance is negligible. However, there is some indication that learners with lower scores on openness to experience, who prefer the routine and ordinary, may perform better in mathematics.

This study, like previous studies, demonstrated the value of developing conscientiousness, given its direct and moderating influence towards mathematics marks.

Moreover, the study gave support for the moderating effect of agreeableness, especially the facet of compliance, in predicting mathematics marks. Much evidence was provided to suggest that more obliging learners are more likely to have better study attitudes, lowered mathematics anxiety effects, and improved study habits, which positively impact mathematics marks. Lastly, although one's general emotional stability does not moderate mathematics anxiety or study milieu, it does negatively moderate fluid intelligence. As such, more neurotic learners, similar to learners with high levels of mathematics anxiety, require a lot of support to perform well in mathematics.

Therefore, the current study adds to the literature on mathematics performance in South Africa, comprehensively noting the unique contributions of study orientations and personality in influencing mathematics performance. Furthermore, the present study provides evidence that creating positive and supportive learning environments, that teach learners the concepts of mathematics, would enhance learners' motivation, confidence, and critical metacognitive thoughts towards the subject. Given the study's results, educators, parents, and the entire educational system, are key in creating an environment (study milieu) that can build the youths' motivation, enthusiasm, and resilience. As such, a multidisciplinary approach where educational and psychological bodies better collaborate to support learners' optimal mathematical skills development is suggested. It is hereby recommended that longitudinal studies with larger samples in both rural and urban areas be conducted, to allow for the more nuanced evaluation of these relationships – by means of considering mediation relationships, as well as structural equation models where all constructs' influence on each other can be accounted for simultaneously. Such investigations will guide society in investing in learners' achievement, to better understand at which stage of the learners' scholastic career does study orientations and personality dispositions most shape mathematical performance, and subsequent career choices.

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Appendix A:

School Permission Email Template and Principal Permission Form

Gmail

Pakeezah Rajab <pakeezah93@gmail.com>

Maths Study Request: Principal's attention

Tue, 05 Apr 20223 at 15:23

Dear [redacted]

I hope you're well. If possible, could you please forward this email to your Principal?

I'm Pakeezah, currently a Research Psychologist completing my PhD in educational psychology through the University of Pretoria. I am requesting your permission to allow your Grade 9 pupils to participate in my study entitled "Identifying Psychological Factors that Improve Mathematical Achievement in South African High Schools' either online after hours, or during a Life Orientation/Mathematics period, if possible.

As part of the study, I will be requesting your pupil's latest Maths report mark, as well as asking them to complete cognitive, personality and study orientation questionnaires - it should not take them longer than 90 minutes to complete all 3 questionnaires, but I'd like to factor in 2 hours to be safe, in case of questions or other delays. Pupils should preferably be able to complete he assessments ONLINE, from home - making it safer for all of us during this time of Covid. So why should your pupils participate in this study? Of what benefit is to THEM if I need the data for MY PhD? As a thank-you for their time and efforts, I will provide each student with a profile of heir personality and study orientation to mathematics, as well as their fluid cognitive intelligence range - all in an understandable format that, together with their current Mathematics marks, will guide them in selection of Maths or Math Literacy (of course, this report will be provided free of charge). Should you wish, I can also provide a summary report to [redacted] as HoD of Mathematics.

Kindly advise whether this is something you would be interested in, as being proficient in Maths is very much becoming an essential skill to our youth being 'sellable' and job ready. If it **is** something you would be interested in, please find attached a letter of permission for your Principal's attention to be signed and returned. For your records, his study has obtained approval from the Gauteng Department of Education as well as the University of Pretoria's ethics approval.

Thank you, hope to hear from you soon!
For more information on the

study, please do not hesitate to

contact me. Kind regards

Pakeezah Rajab
Cell Number: (+27) 83 608 4090

Faculty of Humanities
Fakulteit Geesteswetenskappe
Lefapha la Bomotho

Department of Psychology

Humanities 100. Since 1919

April 2022

Dear Principal,

RE: REQUEST TO CONDUCT RESEARCH AT YOUR SCHOOL

I am Pakeezah Rajab, a PhD student at the University of Pretoria, in the Department of Psychology. As part of my PhD studies, I am interested in considering the impact of personality and study orientations on mathematics performance and would like to ask your school to participate. The title of my research is 'Identifying Psychological Factors That Improve Mathematics Achievement in South African pupils'. Participating in this data collection means that I would need to administer the assessments to your currently enrolled high school pupils, preferably Grade 9's since they will be selecting subjects later this year and the report feedback can be particularly valuable to them. Should your school participate, your school's management will also receive a group summary report, and a feedback session with you if you are interested. I would greatly appreciate it if your school could assist me with my data collection. The psychometric assessments, which will be used are as follows:

- **Implicit Theories of Intelligence Scale for Children (ITIS):** *this short questionnaire asks your pupils whether they believe they can develop their intelligence to perform better in mathematics if they put in the effort to do so.*
- **Basic Traits Inventory (BTI):** *this test measures the Big Five factors of personality; namely, Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. This test can normally be used by professionals to measure personality traits in teenagers and adults; it can also assist them in gaining insights into how to cope with the demands of school and explain some of their behaviours in interacting with others.*
- **Study Orientation to Mathematics (SOM):** *this assessment measures study attitude, mathematics anxiety, study habits, problem-solving, study milieu. Developed for South African schools, this assessment considers aspects that can have a negative impact on high school pupils' mathematics performance. The results can then be used to address the specific concerns.*
- ***Raven's Standard Progressive Matrices (SPM):*** *this non-verbal test assesses individuals' general mental ability, or fluid intelligence. This cognitive measure asks pupils' to complete a number of patterns.*

The administration of these assessments would be done in English and takes approximately 90 minutes. I can provide debriefing, should pupils require it. The assessments can be administered on a day that is suitable for your school, **or** after-hours to those pupils interested in participating on your premises. Ideally though, it would be preferred if pupils complete the assessments electronically from home at their leisure. If your school is willing to assist me in the process of data collection, I would also like to send out the necessary individual assent and consent forms to parents, as well as the learners, before going ahead with the assessments. I would preferably like to do this with the help of a school contact person if they are willing to assist. Participation is voluntary and no foreseeable harm will be caused to any learners during the administration.

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Email: pakeezah93@gmail.com or angela.thomas@up.ac.za| www.up.ac.za/psychology

Individual feedback reports will be provided to all participants, and group feedback sessions of approximately one hour regarding their mathematics profile will be provided at a later date that suits the school – possibly during a parent's evening, or a recorded presentation. The feedback sessions will provide an opportunity for the pupils to understand their personality and cognitive abilities in relation to mathematics – the reports will also guide them in their subject selection decisions; providing some tips into whether they should choose mathematics or mathematics literacy. If your school chooses to participate, you will also be provided with a group report on your students' overall profile.

If you require further information, please do not hesitate to contact me or my supervisor.

Yours sincerely,

Ms Pakeezah Rajab
PHD CANDIDATE
pakeezah93@gmail.com
+27 (0)83 608 4090

Dr Angela Tsholofelo Thomas
PHD SUPERVISOR AND LECTURER
angela.thomas@up.ac.za
+27 (0)12 420 2923

Principal Signature

____

Room 12-9, Humanities Building
University of Pretoria, Private Bag X20
Hatfield 0028, South Africa
Tel +27 (0)12 420 2923
Email: pakeezah93@gmail.com or angela.thomas@up.ac.za | www.up.ac.za/psychology

Appendix B:

Participant Information Sheet and Informed Assent

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Humanities 100.
1919 - 2019
Department of Psychology

PARTICIPANT INFORMATION SHEET

INFORMED ASSENT DOCUMENTATION

Hello, my name is Pakeezah Rajab, I am currently a PhD student at the Faculty of Humanities, University of Pretoria. You are being invited to take part in my research study. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. Please take some time to read the following information carefully, which will explain the details of this research project. Please feel free to ask the researcher if there is anything that is not clear or if you need more information.

I would like to invite you to take part in this research project. Please read this document that explains the research, carefully. Please also ask questions if there is any part of the study that you do not understand. Taking part in this research is voluntary, which means that you may say no if you do not want to take part. If you have started with the research and you feel that you no longer want to take part in the research, you may withdraw at any point. In cases where you withdraw or do not want to take part in the research, there will be no negative effects.

TITLE OF THE RESEARCH PROJECT:
Identifying psychological factors that improve mathematics achievement in South African Grade 9 pupils

WHAT IS THIS RESEARCH PROJECT ABOUT?
This research will be done online, from home, at a time that you and your parent/guardian find appropriate. You will be asked to complete a few tests that measure your personality, how you think about your intelligence, how you study mathematics and how you generally think about information. Two hundred (200) Grade 9's will be taking part in this study. With the results from these tests, we will be looking at ways of possibly making Mathematics easier to study, taking into account pupil's study styles and personalities.

THE RESEARCH TEAM
The people who are gathering the data are well-trained on how to use the tests. They have used tests like these many times before.

WHY YOU?
You are invited to take part in this study because you are in Grade 9. You also fit the research because you live in South Africa. We know that choosing subjects can be stressful sometimes, which is why we also want to give you a report that might help you choose between Mathematics and Mathematics Lit.

Departmental Research Committee (ResCom)
University of Pretoria, Faculty of Humanities, Department of Psychology
Humanities Building, Lynnwood Road, Hatfield, 0083, South Africa
Private Bag X20, Hatfield 0028, South Africa
Email: psychology.rescom@up.ac.za
Website: www.up.ac.za/psychology

Fakulteit Geesteswetenskappe
Departement Sielkunde
Lefapha la Bomotho
Kgoro ya Saekolotši

WHAT SHOULD YOU EXPECT?

You will be asked to complete a personality test, a test that looks at how you study Mathematics, a test that measures how you think about novel patterns, and a demographic questionnaire. This is not like the tests that you usually write in school that count for marks. It is rather tests that tell us about how you feel you do things, how you prefer to do things, and how you think about things. It will take between 90 minutes and two hours to complete. At a later stage, you will be invited to a group feedback session about the results of the questions that you answered, and you will also receive a report on your own results that you can read through, that will help you choose mathematics or mathematics literacy when you're asked to choose subjects for Grade 10 onwards. The time for the group feedback session will be arranged with your school.

WILL YOU GAIN ANYTHING FROM TAKING PART?

You will receive an individualised report that tells you a little bit about your personality, your study style and how you tend to think about new things. You will also receive a group feedback session that teaches you about what your group's answers to the questions tell us. In this group session, you will learn more about how you could change your study styles to make studying mathematics feel a bit less stressful, if it is something that normally stresses you. Learning about your own personality and study style can help you grow as a person. Research also tells us that this growth can help you stress less and succeed better with schoolwork. You can also contact me directly on pakeezah93@gmail.com for a one-on-one feedback session.

RISKS OF TAKING PART IN THIS RESEARCH

There are more gains for you in taking part in this study than there are risks but risks that can happen are as follows - We understand that completing a test that asks you about mathematics might cause some discomfort, especially if you don't like mathematics. If you feel emotional or uneasy at any point, there will be someone you can talk to.

Your friends and classmates may talk about this study. Please don't feel that you have to take part in the research because your friends or classmates are. Please do not feel pressured, because it is absolutely your choice to make. Taking part in the research will not cost you anything, except some of your time and data costs. We will not be able to pay you to take part in this research.

CONFIDENTIALITY

The answers that you give on the test will not be shared with anyone, except the researcher, Pakeezah Rajab, who will also be there while you complete the assessments. Your answers will be kept safe with passwords only known by the researcher. After the study your data may be used again, but it will not be connected to your name but to a number. In this way, no one will be able to see what you answered on the test. When we explain the findings in group feedback and in writing (reports, manuals, or articles), we will explain the total findings of the whole group.

We would really be grateful if you could help us with this research.
If you would like to ask any more questions or need more information from us, you may phone or email the number or address below.

Ms Pakeezah Rajab	**Dr Angela Tsholofelo Thomas**
PHD CANDIDATE	PHD SUPERVISOR AND LECTURER
pakeezah93@gmail.com	angela.thomas@up.ac.za
+27 (0)83 608 4090	+27 (0)12 420 2923

DECLARATION BY PARTICIPANT

By signing below, I ....agree to take part in the research study with the title:

'Identifying psychological factors that improve mathematics achievement in South African Grade 9 pupils'.

I declare that:

- I have read the information about this study - someone who I trust explained it to me in English. I understand English well;
- Someone told me what the research is about and what is expected of me;
- I could ask questions to the researcher. All the questions that I had were answered;
- I understand that I may take part in this study out of my own free will and that I was not pressured to take part;
- I may choose to leave the study at any time and will not be handled in a negative way if I leave;
- The researcher may ask me to leave the study before it is complete if the researcher feels it is better for me. I may also be asked to leave the study if I do not follow the instructions, as I agreed to.

Signed at (*place*) .... on (*date*) ....

....
Signature of Participant

....
Signature of Parent/Guardian

Appendix C:

Parent Information Sheet and Informed Consent

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Humanities 100.
1919 - 2019
Department of Psychology

PARENTAL INFORMATION SHEET

Identifying psychological factors that improve mathematical achievement in South African High Schools

Hello, my name is Pakeezah Rajab, I am currently a PhD student at the Faculty of Humanities, University of Pretoria. Your child is being invited to take part in my research study. Before you decide they can participate in this study, it is important that you understand why the research is being done and what it will involve. Please take some time to read the following information carefully, which will explain the details of this research project. Please feel free to ask the researcher if there is anything that is not clear or if you need more information.

WHAT IS THE PURPOSE OF THE STUDY?

The purpose of my study is to look at how personality and study orientations may influence your child's Mathematics marks. Understanding these relationships can help create a personalised study plan for your child that takes into account their personality and experience of Mathematics.

WHY HAVE THEY BEEN INVITED TO PARTICIPATE?

They have been invited to participate because they are a Grade 9 pupil in a Gauteng high school. They comply with the requirement of being a pupil in a regular school without severe learning difficulties that requires special school admission.

WHAT IS THE NATURE OF THEIR PARTICIPATION IN THIS STUDY?

As part of the study, I will be asking that they complete the following assessments.

- **Implicit Theories of Intelligence Scale for Children (ITIS):** *this short questionnaire asks them whether they believe they can develop their intelligence to perform better in mathematics.*
- **Basic Traits Inventory (BTI):** *this test measures the Big Five factors of personality; namely, Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. This test can normally be used by professionals to measure personality traits in teenagers and adults; it can also assist us in gaining insights into how your child copes with the demands of school and explains some of their behaviours in interacting with others.*
- **Study Orientation to Mathematics (SOM):** *This assessment measures study attitude, mathematics anxiety, study habits, problem-solving, study milieu. Developed for South African schools, this assessment considers aspects that can have their mathematics marks. The results can then be used to address the specific concerns.*

Departmental Research Committee (ResCom)
University of Pretoria, Faculty of Humanities, Department of Psychology
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Departement Sielkunde
Lefapha la Bomotho
Kgoro ya Saekolotši

- **Ravens Standard Progressive Matrices (SPM):** *this non-verbal test assesses their general mental ability, or fluid intelligence. This cognitive measure asks them to complete a number of patterns.*

Your child will be asked to complete a demographic questionnaire and the assessments mentioned above in English. The demographic questionnaire will ask for some biographical information as well as their mathematics marks. The assessments include statements where they must indicate the degree to which they can identify (Strongly Agree, Agree, Mostly agree, Mostly disagree, Disagree, Strongly Disagree – on the ITIS; Strongly Agree, Agree, Sometimes, Disagree, Strongly Disagree – on the BTI; Rarely, Sometimes, Frequently, Generally, Almost Always – on the SOM) with each statement. On the Ravens', they will be asked to complete the pattern. The tests will be administered electronically via an online link (with me supervising part of the session via Zoom/Google Meet, Microsoft Teams, according to social distancing protocols). The administration of the psychometric test will take approximately 90 minutes and will be scheduled in collaboration with you and your child. If you and your child are willing to assist me with the process of data collection, please complete the attached permission form and send it back to pakeezah93@gmail.com.

CAN THEY WITHDRAW FROM THIS STUDY EVEN AFTER HAVING AGREED TO PARTICIPATE?

Participating in this study is voluntary and your child is under no obligation to consent to participation. If you and they do decide to take part, you will be given this information sheet to keep and be asked to sign a written consent form. Your child is free to withdraw at any time and without giving a reason, if you/they decide not to take part in the study without negative consequences or being penalized.

WILL THE INFORMATION THAT THEY CONVEY TO THE RESEARCHER BE KEPT CONFIDENTIAL?

We would like to assure you that all information or data that is gathered during this project will be treated as confidential information. Only the researchers on this project will have access to the data. When the data is published in the form of a thesis, article, or conference proceeding, your child's name will not be mentioned or identified in any way. All electronic data will be anonymised after the project is complete, therefore, all information that could lead to them being identified through the data will be removed. If your child, at any stage during this time, wishes to withdraw the data, they may do so by contacting me using the contact information provided. Upon such a request the specific data will be destroyed.

WHAT ARE THE POTENTIAL BENEFITS OF TAKING PART IN THIS STUDY?

Within 48-72 hours after administration, your child will receive a personalised report with their results on the abovementioned assessments, sent to your email address. There will also be an opportunity for a one-on-one feedback session, where additional study suggestions can be provided, should you see benefit in such a session. Previous research has shown that these benefits may be related to academic success, improved well-being, decreased emotional stress, and positive social behaviours. These benefits may also have a positive influence on the school environment. Alternatively, this research will allow for improved interventions pertaining to mathematics confidence and performance in South Africa. Unfortunately, we will not be able to provide any financial compensation for your child's participation in the research. There will, however, be no financial expenses for you in this study apart from data used during the administration (and possible feedback) process.

WHAT ARE THE ANTICIPATED RISKS FROM TAKING PART IN THIS STUDY?

We understand that answering questions that relate to mathematics could potentially elicit an emotional reaction, especially for students that have generally performed poorly in the subject. In such an event, as a psychologist experienced in working with children, I will be available to provide debriefing and ensure that your child is left in a positive emotional state. Due to this potential risk of emotional discomfort or anxiety, we would like to request that if you know your child struggles with emotional or psychological distress, to not volunteer them for this study. The cognitive assessment will be completed under supervision (I would like to supervise virtually via Microsoft Teams/Google Chat), while the other assessments without further input from me.

WHAT WILL HAPPEN IN THE UNLIKELY EVENT THAT SOME FORM OF DISCOMFORT OCCUR AS A RESULT OF TAKING PART IN THIS RESEARCH STUDY?

Should your child have the need for further discussions after the assessments, I will be available, in my capacity as a research psychologist and psychometrist, to talk to them about the experience.

HOW WILL THE RESEARCHER(S) PROTECT THE SECURITY OF DATA?

Please note that electronic information will be stored for period of 15 years, and as such, if you agree to this study, you are also agreeing to the responses being de-identified, anonymised and reused if required over the 15 year period. If hard copy versions of the assessments are completed, they will be locked in the cabinet, and electronic data will be kept in a file that is password protected in the Department of Psychology.

WHAT WILL THE RESEARCH DATA BE USED FOR?

Your child's data, together with all other Grade 9 pupils who participate, will ultimately be used for my PhD dissertation, article publications, and national and international conference presentations. Your child's personal results will also be used to generate their personal report that highlights their personality, orientation towards mathematics, and whether they would benefit from taking Mathematics or Mathematics Literacy from Grade 10 onwards.

HAS THE STUDY RECEIVED ETHICS APPROVAL?

This study has received written approval from the Research Ethics Committee of Faculty of Humanities, University of Pretoria. A copy of the approval letter can be provided to you on request.

HOW WILL I BE INFORMED OF THE FINDINGS/RESULTS OF THE RESEARCH?

After the data collection and analysis phase of the research process has been completed with all interested Grade 9's, a feedback session will be arranged in collaboration with the school. You are welcome to attend this group feedback session with your child, which will serve as an opportunity for personal development. By this stage, your child will have also received their individual report pertaining to their results on the assessments and potentially an individual feedback session would have been conducted as well. These reports will also provide some guidance in terms of whether they should choose Mathematics or Mathematics Literacy as a subject going forward.

WHO SHOULD I CONTACT IF I HAVE CONCERN, COMPLAINT OR ANYTHING I SHOULD KNOW ABOUT THE STUDY?

If you have questions about this study or if your child has experienced adverse effects as a result of participating in this study, you may contact the researcher whose contact information is provided below. If you have questions regarding the rights as a research participant, or if problems arise which you do not feel you can discuss with the researcher, please contact the supervisor, and contact details are below

Thank you for taking time to read this information sheet and in advance for participating in this study.

Researcher
Pakeezah Rajab
+27 (0)83 608 4090
pakeezah93@gmail.com

Supervisor
Dr Angela Tsholofelo Thomas
+27 (0)12 420 2923
angela.thomas@up.ac.za

DECLARATION – PARENT/GUARDIAN

I, ____ (parent/guardian) hereby provides permission for ____________________________________ (child) to be assessed by Pakeezah Rajab on the following assessments:

- Implicit Theories of Intelligence Scale for Children
  YES ☐ NO ☐
- Basic Traits Inventory
  YES ☐ NO ☐
- Study Orientation to Mathematics
  YES ☐ NO ☐
- Raven's Standard Progressive Matrices
  YES ☐ NO ☐
- Biographical questionnaire asking for information about your child including their age, gender, nationality, home language, ethnicity, school grade, and Mathematics mark.
  YES ☐ NO ☐

I have also been informed of, and understand that:

1. Participation in this assessment process is voluntary. I have no objection for my child undergoing the paper and pencil or online assessment. I understand what the assessment intends to measure and what the purpose of the research is.
2. My child may withdraw from participation in the research at any time without negative consequences. In the case of withdrawal upon myself or my child's request, all data provided by my child will be removed/destroyed.
3. There are possible risks and potential benefits associated with participation in this research. I also understand what the risks and benefits entail.
4. The school is indemnified from any outcomes that may result from this research study.
5. I may contact the researcher if I have any further questions, telephonically or via email, using the information they provided on the information sheet.
6. I give permission that, within the parameters of confidentiality, results obtained may be used by the researcher for research purposes.
7. All information shared with the researcher is strictly confidential, except if the child poses a danger to her/himself or others; and consultations with other healthcare professionals are deemed to be necessary and in the best interest of the client;
8. It is my child's responsibility during the assessment session to inform the assessment administrator of anything that may negatively impact on his/her performance or assessment results.

______________________ ______________________ ______________________

PARENT SIGNATURE **DATE** **PLACE**

PARENT EMAIL ADDRESS: ____

Please note that your email address is required to electronically deliver your child's feedback report back to you.

Appendix D:

Ethics Clearance - University of Pretoria

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Humanities
Fakulteit Geesteswetenskappe
Lefapha la Bomotho

Humanities 100.
Since 1919

01 August 2022

Dear Miss P Rajab

Project Title:	Identifying psychological factors that improve mathematics achievement in Grade 9 pupils from Gauteng
Researcher:	Miss P Rajab
Supervisor(s):	Dr TA Thomas
Department:	Psychology
Reference number:	21779806 (HUM035/0721)
Degree:	Doctoral

I have pleasure in informing you that the above application was **approved** by the Research Ethics Committee on 01 August 2022. Please note that before research can commence all other approvals must have been received.

Please note that this approval is based on the assumption that the research will be carried out along the lines laid out in the proposal. Should the actual research depart significantly from the proposed research, it will be necessary to apply for a new research approval and ethical clearance.

We wish you success with the project.

Sincerely,

Prof Karen Harris
Chair: Research Ethics Committee
Faculty of Humanities
UNIVERSITY OF PRETORIA
e-mail: tracey.andrew@up.ac.za

Appendix E:

Gauteng Department of Education Permission

GAUTENG PROVINCE
Department: Education
REPUBLIC OF SOUTH AFRICA

8/4/4/1/2

GDE RESEARCH APPROVAL LETTER

Date:	**25 October 2021**
Validity of Research Approval:	**08 February 2022– 30 September 2022** **2021/323**
Name of Researcher:	**Rajab P**
Address of Researcher:	**Unit 4, Wyvenhoe Gardens**
	Sunny Road
	Leakefield
Telephone Number:	**083 608 4090**
Email address:	**pakeezah93@gmail.com , pakeezah@jvrafrica.co.za**
Research Topic:	**Identifying psychological factors that improve mathematics achievement in Grade 9 pupils from Gauteng**
Type of qualification	**PhD Psychology**
Number and type of schools:	**15 secondary Schools**
District/s/HO	**Ekurhuleni North**

Re: Approval in Respect of Request to Conduct Research

This letter serves to indicate that approval is hereby granted to the above-mentioned researcher to proceed with research in respect of the study indicated above. The onus rests with the researcher to negotiate appropriate and relevant time schedules with the school/s and/or offices involved to conduct the research. A separate copy of this letter must be presented to both the School (both Principal and SGB) and the District/Head Office Senior Manager confirming that permission has been granted for the research to be conducted.

26/10/2021

The following conditions apply to GDE research. The researcher may proceed with the above study subject to the conditions listed below being met. Approval may be withdrawn should any of the conditions listed below be flouted:

1. *Letter that would indicate that the said researcher/s has/have been granted permission from the Gauteng Department of Education to conduct the research study.*

1

Making education a societal priority

Office of the Director: Education Research and Knowledge Management
7th Floor, 17 Simmonds Street, Johannesburg, 2001
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Email: Faith.Tshabalala@gauteng.gov.za
Website: www.education.gpg.gov.za