Examining Predictors of Math Ability Among Students with Autism

by

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Abstract

A widely held, stereotyped belief is that students with autism tend to be mathematically gifted. This stereotype has some support in the annals of autism research, but more recently, researchers have revealed that the rates of both math giftedness and math weakness and/or disability among students with autism are higher than we would expect in a typical population (Chiang & Lin, 2007; Mayes & Calhoun, 2006; Oswald et al., 2015). More research is needed to determine how students who share a common diagnosis can have such disparate outcomes in the same area of academic performance. In the present study, I examine the role that restricted, repetitive behaviours and interests (RRBIs) have in predicting the math abilities of students with autism. I hypothesize that students' consistent, systematic, and uniquely autistic engagement with RRBIs, such as special interests, leads to improved math reasoning abilities. Forty-nine students with autism completed standardized assessments of IQ and language. Scores from the *Social Responsiveness Scale, Second Edition* Restricted Interests and Repetitive Behaviours subscale were used as a measure of students' RRBI symptomology. A standardized measure of foundational math ability was administered as the outcome measure. I present the results from a hierarchical regression analysis, which revealed that RRBIs did not account for a significant amount of the variance in participants' math ability scores above and beyond IQ and language. I discuss the limitations of the measures used in this study as well as the value of these nonsignificant results, which may help to dismantle stereotypes and shape future research to better understand the academic achievement of students with autism.

Preface

This thesis is an original work by Lauren Trafford. The research conducted for this thesis was supervised by Dr. Heather M. Brown at the University of Alberta. The broader research project of which this thesis is a part was developed by Dr. Heather M. Brown, who designed the research study and selected the measures used. I reviewed the literature to formulate hypotheses for selecting the predictor measures of interest, collected data on those measures, maintained a database of those measures, and completed and interpreted the data analysis described in this thesis. This study received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Developing a Model of Mathematical Ability for Children with ASD”, No. 58795, April 20, 2016.

Dedication

This thesis is dedicated to my parents, Doris and Kevin Trafford. Without their support and encouragement, this work would not be possible. Thank you for cheering me on.

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Introduction

Hollywood has partly shaped the stereotype of math giftedness in people with autism spectrum disorder (autism). The portrayal of mathematical savants—such as Raymond in the movie *Rain Man*—perpetuates a stereotype that autistic individuals are typically mathematically gifted. The stereotype of math giftedness could negatively impact students with autism if expectations for their math performance are inaccurately inflated (Draaisma, 2009). While there is some support for this stereotype in the extant literature (e.g., Baron-Cohen et al., 2007), what seems to be more accurate is that while some students with autism are indeed mathematically gifted, the majority have average to below-average math abilities (e.g. Chiang & Lin, 2007; Mayes & Calhoun, 2006; Oswald et al., 2015). Researchers have attempted to understand how students who share a diagnosis of autism can have widely different math abilities. Two existing studies examined the role that autism symptomology itself may play in math ability development (Miller et al., 2017; Oswald et al., 2015). Both studies suggest that a diagnosis of autism predicted poorer math skills, but the amount of unique variance in math scores explained by a diagnosis was either small (Oswald et al., 2015) or subsumed by other predictors (Miller et al., 2017). However, when examining the relationship between autism symptoms and math abilities, neither study partitioned the two core symptoms of autism: (a) social communication; and (b) restricted, repetitive behaviours and interests (RRBIs).

Although it has been suggested that social communication deficits inhibit math learning (Miller et al., 2017), students' engagement in RRBIs may play an important role in supporting math learning for two reasons. First, RRBI behaviours, such as special interests, tend to involve gathering and sorting large amounts of data (Klin et al., 2007) and may be regarded as a form of naturalistic learning, requiring students to constantly engage in categorizing and systemizing processes (Atwood, 2003). These processes engage the same thinking as the logical reasoning required to master foundational math concepts (Schwank & Schwank, 2015). Second, experiential learning theory (Kolb et al., 2001) posits that students' experiences are a core component of acquiring new skills. Therefore, autistic students' intense engagement in RRBIs may provide them with more experience categorizing and systemizing, skills that support math reasoning, whereas students who engage in these behaviours less frequently may have fewer opportunities to practice this type of thinking. The purpose of the present quantitative study is to explore the relationship between (a) students' RRBIs and (b) math abilities in a sample of autistic students by asking the following research question: *in a sample of students with autism, how much of the variance in math ability can be explained by the severity of students' RRBI symptomology*?

Autism

Definition & Prevalence

Autism spectrum disorder was first conceptualized by psychiatrist Leo Kanner in 1943. Presented as a collection of case studies, Kanner's 1943 publication described several children who shared the same *inborn autistic disturbances of affect*, defined as an "inability to form the usual, biologically provided affective contact with people" (p. 250). The clinical definition of autism has evolved and changed considerably since that time. Currently, autism spectrum disorder is a neurodevelopmental disorder listed in the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition* (*DSM-5*; American Psychiatric Association [APA], 2013). Today, the diagnostic criteria for autism spectrum disorder includes a set of symptoms in two core domains—social communication and restricted, repetitive behaviours and interests (RRBIs; APA, 2013). Individuals must meet both criteria in order to receive a diagnosis.

Research on the topic of autism spectrum disorder has grown considerably as global awareness increases. This growth in literature may be related to the disorder's rising prevalence. The most up to date prevalence estimates among Canadian youth aged 5–17 years indicate that 1 in 66 students in Canada lives with an autism spectrum disorder (Ofner et al., 2018). As researchers have worked to understand the disorder, advocates have worked to dismantle stereotypes and harmful stigma that can accompany this diagnosis.

Neurodiversity & Supporting People with Autism

A recent open-access publication documents the experiences of autistic people in light of the *neurodiversity movement*, a social activism movement that aims to integrate the social and medical models of disability to support the autonomy of individuals with autism (Kapp, 2020). Proponents of the neurodiversity movement recognize autism as a neurological divergence from what is considered typical social communication and behaviour, as opposed to a pathologized disorder. To honour and respect this perspective, the remainder of this thesis will refer only to "autism" as a broad category of identity encompassing many specific diagnoses, symptoms, and strengths. Similarly, it should be noted that this thesis intersperses both person-first (e.g. "student with autism") and identity-first (e.g. "autistic student") language to respect that individuals who identify as autistic can have preferences for adopting either type of language (see Callahan, 2018, for a discussion).

Despite the preference to abandon deficit-based perspectives on autism, advocates have acknowledged the utility of interventions that support autistic people's functioning in society, so long as those interventions are not framed "in unnecessarily medical or clinical ways" (Kapp, 2020, p. 8). This shift in thinking—from disorder to divergence—has taken place over many years and is still in progress, especially given the reality that current societal structures are not tailored to the needs of people with autism. Similarly, existing stereotypes of autism have made it difficult for autistic people to be accepted and understood.

Stereotypes of Autism

Plenty of stereotypes exist in media and literature that lead to the inaccurate description of autistic people as highly homogenous—all persons with autism are supposed to have the same quirks, characteristics, and personality traits. What is perhaps most harmful is the portrayal of autistic characters as belonging only to the very extremes of society. In his review of the stereotypes of autism in the media, Draaisma (2009) provides the following observation regarding the typical roles for an autistic character to occupy in movies and television:

> There are two options for an autistic person: either he [*sic*] is mentally handicapped, an egghead reading geek magazines, or he [*sic*] is a savant with mental powers exceeding those of two Cray supercomputers spinning numbers 24 hours a day. It is either diminished capacity or superhuman capacity, but nothing in between. (p. 1477)

This statement highlights the disparity in how autistic characters can be portrayed. More importantly, however, it also alludes to the harm that could arise from these stereotypes creating inaccurate expectations of people with autism. These stereotypes may result in people with autism not being expected to achieve much at all, or being expected to possess expert savant abilities (Draaisma, 2009). Evidence from the research suggests that teachers have also adopted misconceptions about students with autism. While most studies examine teacher's perceptions of the behavioural problems of students with autism, one study revealed that teachers of autistic students feel ill-prepared to understand the *academic* abilities of students with autism in the general education classroom (Soto et al., 2012), and this lack of understanding may have negative consequences for teaching and learning. Thus, it is important to present accurate information about the range of academic abilities among students with autism. Breaking down stereotypes may help students with autism get the support they need in the classroom based on their individual areas of strength and weakness, which in turn supports optimal outcomes later in life.

Outcomes for Autistic People

As scholars work to dismantle stereotypes, research is also being conducted to determine how best to support the well-being of autistic people in the world today considering the challenges this population faces throughout the lifespan. Explorations of the outcomes for people living with an autism diagnosis reveal a troubling pattern of difficulties. Adults with autism continue to be severely disadvantaged in the job market; this includes documented difficulties finding permanent employment, consistently earning lower wages than their neurotypical peers, and experiencing instability and unpredictability with respect to securing employment opportunities (Dudley et al., 2015; Howlin et al., 2004). Baldwin and colleagues (2014) presented a particularly sobering statistic, finding that 46% of their sample of adults with autism were considered underemployed. While these outcomes are at least partly the result of the social pressures and stigmatization this population faces (Kapp, 2020), it is important to ensure that these difficulties are not compounded by other challenges this population may face. For example, supporting young students with autism in the classroom to ensure they experience academic success may enhance their employability.

Math abilities and numeracy appear to be particularly important to support, given that poor numeracy and low math ability has been linked to life difficulties, poorer mental health, earning lower wages as an adult, and lower rates of full-time employment (Butterworth, 2008; Bynner & Parsons, 1997; Gillum, 2014). Furthermore, the argument has been made that children of all demographics have a right to access education that supports the development of math abilities specifically (Munn, 2005). Thus, it is important to establish whether autistic students' numeracy and math abilities are as developed as their peers. This endeavour is especially important given the perpetuated stereotype of increased mathematical prowess among students with autism, which has been upheld in media and some research studies.

Math Abilities & Autism

Rates of Math Giftedness & Math Learning Disorders

To discuss the math abilities of students with autism, it is important to first review the math achievement profiles of the general population. Accurate prevalence rates for math giftedness are difficult to find, given the controversy among scholars about how giftedness itself ought to be defined (Bicknell, 2009). For example, Bélanger and Gagné (2006) demonstrated that the various available definitions of “giftedness,” ranging from more conservative to more liberal, make it nearly impossible to calculate the rate of giftedness in the general population. Structural equation modelling used by Bélanger and Gagné (2006) demonstrated how severely under- or over-reported rates of giftedness could be, with estimates ranging from as low as 0% to as high as 74% depending on the giftedness classification criteria used. Without a clear operationalization of giftedness, it is difficult to say how many students are typically identified as mathematically gifted. From a psychometric perspective, between 2%–5% of the population would score in the top percentiles on any skill or ability assessment, and thus this range is often reported as an estimate for the rate of giftedness among school-age students (e.g., Hutchinson & Specht, 2020, Chapter 3; Winzer, 2008, Chapter 9).

As is the case with identifying math giftedness, the variety of methods that may be used when identifying learning disorders (LDs) makes it difficult to pinpoint how common these disorders are in the general population. Rates of math LDs among school-age students in the United States have been estimated to fall in the range of 5.9%–13.8%, depending on the method used to classify students with a math LD (Barbaresi et al., 2005).

Autism & Math Giftedness

Some previous research has concluded that autism is indeed linked to increased mathematical talent. For example, Baron-Cohen et al. (2007) suggested a relationship between having an autism diagnosis and being more likely to enrol in a math-based post-secondary program. However, this study did not include a direct measure of students’ math abilities, instead relying on the assumption that students enrolled in math-based programs would perform better on math assessments. Other research published by Baron-Cohen and colleagues have proposed a link between mathematical prowess and autistic traits (Baron-Cohen et al., 1998, 2001). More recently, Wei and colleagues (2015) reported on the rates of *hypercalculia* among students with autism, which was defined as having a math calculation score at least 1 *SD* higher than scores in any other academic achievement area. In their sample, 20% of students with autism fit the profile of hypercalculia (Wei et al., 2015). Jones et al. (2009) categorized students with autism based on their achievement profiles, noting that a large portion of their sample (16.2%) had above average math achievement, while the smallest category (6.1%) had unexpectedly low math achievement. While these studies provide some compelling evidence for the claim that heightened math abilities are linked to having an autism diagnosis, further evidence suggests that this does not accurately capture the spectrum of math achievement among students in this population.

Autism & Math LD

Several researchers have reported high rates of math weakness among students with autism. Oswald and colleagues (2015) identified math LD in 22% of a predominantly-male sample of 27 adolescents with autism. Furthermore, only 4% of their sample was identified as having math giftedness (Oswald et al., 2015). Mayes and Calhoun (2006) identified the rate of math LDs in several clinical populations, including a sample of 124 students with autism aged 6–16 years, and found that 23% of these students would meet criteria for a math LD based on the discrepancy between their cognitive ability and math ability. Other researchers have conversely looked at the rates of autism among students with math LDs. Morsanyi and colleagues (2018) sampled 139 elementary school students with a math LD and determined that these students were 4.48 times more likely to also have a co-occurring autism diagnosis than students without a math LD. Taken together, the results from these studies indicate that the rate of math LD among students with autism is likely higher than the 5.9–13.8% estimate of math LDs among the general population. A review conducted by Chiang and Lin in 2007 examined 18 studies on the math abilities of students with autism, concluding that autistic students did tend to have a weakness in math relative to other areas of academic achievement. However, Chiang and Lin (2007) also acknowledged that reported ranges of math ability scores included scores above the 99th percentile, indicating that at least some participants in these samples were mathematically gifted autistic students. Several studies include similar observations of highly variable math scores, as evidenced by wide ranges and large *SD*s in the math scores of their autistic samples (e.g. Griswold et al., 2002; Titeca et al., 2015).

Towards an Understanding of Divergent Math Profiles

This review of the research reveals that although math giftedness is present—and may be more common—among students with autism than in the general population, concurrently, math LDs also appear to be more common. It remains unclear how a shared diagnosis can lead to such distinctive math ability profiles that differ so greatly from the expected normal distribution of math achievement; as discussed, estimated rates of math giftedness and math LD in the general population more closely resemble the tail ends of a normal distribution (~5%). It is important to clarify the underlying factors contributing to elevated rates of math giftedness and math weakness to identify potential targets for intervention for the groups that require the most support. It is also important to dismantle stereotypes that suggest

- *all* autistic students are mathematically gifted,
- *all* autistic students are math learning disabled, or
- *all* autistic students are no different than their peers—which researchers suggested ought to comfort parents "to know that no additional concerns should be raised" about their academic abilities (Titeca et al., 2017, p. 287).

These inaccurate assumptions may make accessing necessary supports more difficult for students and families.

The literature on predictors of math ability in the general population is extensive (see Bull et al., 2008; Byrnes & Miller, 2007; Garon-Carrier et al., 2018; Lefevre et al., 2010; Weber et al., 2013, for examples). However, the key predictors of math ability in the general population do not explain the same amount of variance when applied to autistic samples (cf. Bae et al., 2015; Oswald et al., 2015). To date, few researchers have tried to understand the specific factors that contribute to the development of such varied math abilities in this unique population.

Predictors of Math Abilities in Autism

Oswald et al. (2015)

Oswald and colleagues (2015) examined several predictors of math abilities in a sample of adolescents with autism. This study included cognitive predictors—perceptual reasoning, working memory, and verbal ability—as well as a single *clinical predictor* measure of test anxiety. Oswald and colleagues (2015) used the term clinical predictor to define psychological variables outside of the domain of cognitive predictors. Perceptual reasoning and verbal ability, two cognitive predictors, were named as the strongest predictors of math problem solving abilities among teen learners with autism. However, test anxiety also accounted for unique variance in math problem solving abilities in this sample; this is noteworthy because no research had previously examined clinical predictors of the math abilities of students with autism. Overall, Oswald and colleagues (2015) highlighted the value of understanding a clinical predictor for its potential to be targeted in treatment. In this case, Oswald et al. (2015) argued that treating students' test anxiety would not only reduce an unpleasant and stressful experience, but could also support their math abilities.

Miller et al. (2017)

Miller et al. (2017) also studied predictors of math ability in a younger, school-aged sample of students with autism. Like Oswald et al. (2015), Miller and colleagues (2017) found IQ explained the most variance in the math scores of their autistic sample. When other predictors were added to the model, including motor abilities and verbal abilities, IQ continued to be the strongest predictor. Miller and colleagues (2017) maintained that although the other predictors were largely subsumed by participants' IQ scores, motor and verbal abilities still had a key role to play in the development of students' math abilities.

Changing the Lens: Clinical Predictors of Math Abilities in Autism

Autism Symptomology

Given that having an autism diagnosis seems to increase the likelihood of both math giftedness and math LD, the core symptoms of autism may play a role in explaining autistic students' math abilities. The studies conducted by Oswald and colleagues (2015) and Miller et al. (2017) used different approaches to explore whether autism could be a clinical predictor of math ability. Oswald et al. (2015) included a dichotomous predictor to denote "having" or "not having" a diagnosis of autism and included this predictor in their regression model. A diagnosis of autism was a significant predictor of lower math problem solving scores, but this predictor accounted for the smallest amount of variance in the model. Additionally, Oswald and colleagues (2015) made no attempt to interpret this finding aside from suggesting a possible relationship between autism and inattention, although the authors acknowledged that inattention was not explicitly measured.

On the other hand, Miller et al. (2017) included a measure of autism symptomology that generated a continuous variable, which allowed the authors to "quantify ASD severity" (p. 389). Overall, Miller and colleagues (2017) initially found that participants who were rated as having more severe autistic symptoms had lower math scores. Much like the other predictors included in their study, Miller and colleagues (2017) found that the relationship between autism symptomology and math scores was subsumed by IQ, meaning that when IQ was added to their models, autism symptomology was no longer predicting any unique variance in participants' math scores. However, Miller et al.'s (2017) study used a measure that included autism symptomology across both core symptom domains. Neither of the studies broke down the symptoms of autism to separate out those related to social communication versus RRBIs. The consolidation of both sets of symptoms may be masking the unique influence that these individual symptoms have on autistic students' math ability, which may in turn affect the regression results. Although it has been suggested that social communication deficits can be disruptive to math learning (Miller et al., 2017), it is unclear whether increased engagement in RRBIs positively or negatively affects math learning. Nevertheless, RRBIs could be an important predictor of math abilities in students with autism.

RRBIs

According to the *DSM-5*, RRBIs cover a wide range of behaviours including repetitive motor movements, difficulty with transitions, rigid thinking, “excessively” perseverative interests, and hypersensitivity to sights, sounds, and other stimuli (APA, 2013). RRBIs are often seen as highly negative and impairing, and are often characterized in terms of their relationship to poor outcomes (e.g. Anthony et al., 2013; Troyb et al., 2016). Furthermore, this pathologizing perspective posits RRBIs as harmful experiences requiring treatment (Lin et al., 2018).

On the other hand, a more neurodivergent perspective suggests that RRBIs, particularly special interests, are areas of strength for people with autism. Many autistic children view their special interests as core to who they are; they acknowledge that although the intensity of their engagement in these behaviours is different from that of their peers, it is a vital part of how they define themselves (Winter-Messiers, 2007). As students with autism spend time engaging in their special interests, they not only grow their sense of identity, but they are also engaging in more enriching learning experiences than we might expect. Klin and colleagues (2007) detailed the numerous ways that autistics engage with a restricted set of interests, including collecting information and developing expert knowledge in a wide array of topics. Atwood (2003) also explained that special interests involve constantly engaging in processes of categorization and calculation, such as collecting sports statistics. In this sense, special interests may be a facet of RRBIs that provide autistic children with enriching math learning experiences.

Two theoretical perspectives of how children acquire fundamental math skills may explain how RRBIs could provide more opportunities for math learning for students with autism. First, Schwank and Schwank (2015) found *predictive-logical reasoning* to be an underlying principle that contributes to the development of math reasoning. Math competencies can develop when students are engaged in predictive-logical reasoning, which is "a type of inferential logical thinking that establishes relations by focusing on similar or identical components of objects" (Schwank & Schwank, 2015, p. 773). Namely, the ability to determine patterns in objects and categorize shapes as belonging or not belonging together is foundational to the development of math reasoning. Students who are intensely engaged in a special interest are regularly engaging in processes of categorization and systemizing—processes which may mimic predictive-logical reasoning tasks. This regular engagement presents many opportunities for practicing these reasoning skills, which may further support autistic students' math ability development.

Second, Byrnes and Miller's (2007) study on the predictors of high school math achievement was based on the *opportunity-propensity model*. The opportunity-propensity model includes predictors related to both opportunities for learning and an individual's propensity for learning that skill. Given that up to 95% of students with autism engage with a special interest (Turner-Brown et al., 2011), RRBIs may help to explain the discrepant math ability profiles in populations of students with autism. Namely, the frequency and intensity with which students engage with their special interest may play a role in the development of their math ability. Students engaging in special interests more frequently and intensely are encountering more experience with categorization and systemizing, two tasks that enhance one's predictive-logical reasoning. Additionally, one might argue that these students also have the propensity to learn math more readily due to the intensity of their special interest, which involves processes so similar to math reasoning. Thus, it was critical to explore whether or not RRBI symptomology plays a role in the development of math ability for students with autism.

Current Study

As discussed, students with autism have both well documented variability in math skills, and a shared clinical characteristic that varies in its presentation and intensity—RRBIs. A hierarchical multiple regression analysis is used to determine the amount of unique variance in math abilities that can be predicted by the severity and frequency of students' RRBIs after including predictors of IQ and language, which have already been established as predictors of math ability (e.g. Miller et al., 2017; Oswald et al., 2015). Potential links between the RRBIs of autistic students and their math abilities are examined here for the first time to address the following research question: *in a sample of students with autism, how much of the variance in math ability can be explained by the severity of students' RRBI symptomology*? The current study contributes to the literature by further exploring the underlying factors that explain the variable math abilities of students with autism.

Method

Participants & Procedures

The sample used in this study was drawn from a larger study aimed at developing a model of math ability in students with autism. For recruitment, a cluster sampling method was used. First, the research team identified local organizations in Edmonton, Alberta that service populations of students with autism, including the Centre for Autism Services Alberta, the Autism Research Centre, the Glenrose Rehabilitation Hospital, and social media groups for parents of students with autism. Next, families within these organizations who have children with autism aged 4–18 years were invited to participate in the study via an advertisement shared to social media and organization websites. Thus, participants in this sample were self-selected. Participants were offered $10 gift cards for each 60-minute research session completed, as indicated in the recruitment advertisement.

Information about participants' specific diagnoses were based on parents' or caregivers' recollection of diagnostic information, including the source of their child's diagnosis. Diagnostic information and other demographic characteristics of the sample are presented in Table 1. Diagnoses were not independently confirmed by the research team; instead, participant eligibility was determined by scores on the *Social Responsiveness Scale, Second Edition* (*SRS-2*; Constantino & Gruber, 2012). The *SRS-2* is a 65-item parent-report questionnaire used to identify the presence of social and behavioural symptoms most associated with autism. Prior to study enrolment, parents or caregivers of potential participants completed the *SRS-2* School-Age Form, which is suitable for use with students aged 4–18 years. A total *SRS-2* T score of 60 or greater was required for inclusion in the study, in accordance with the *SRS-2*'s cutoff score for social impairments consistent with a diagnosis of autism spectrum disorder (Constantino & Gruber, 2012).

In addition to meeting the *SRS-2* cutoff criteria for inclusion, participants were also required to speak fluent English to provide responses to the research team. Similarly, although there were no minimum IQ or language criteria, students had to be able to supply responses to the standardized measures used in this assessment. If students were recruited and could not provide the verbal or gestured responses needed for each respective measure, their data were excluded from the study. Based on this inclusion criteria, 49 participants (4 female) aged 5–16 years (M = 9.97, SD = 3.34) participated in the sample presented in this thesis.

Table 1

Demographic Characteristics of Participants

Characteristic	*n*	% of total sample
Gender		
Male	45	92
Female	4	8
Diagnosis[a]		
ASD	19	39
Autism	21	43
High-functioning autism/Asperger's	6	12
Source of diagnosis[a]		
Multidisciplinary team or clinic	34	69
Neuropsychologist	1	2
Pediatrician	4	8
Psychiatrist	6	12
Psychologist	1	2
Comorbid diagnoses[b]		
None	24	49
Attention-deficit hyperactivity disorder (ADHD)	12	25
Anxiety disorder	1	2
Communication/language disorder	1	2
Mood disorder	1	2
>1 comorbid disorder[c]	8	16

Note. All information is self-reported according to participants' parent(s)/caregiver(s). Where possible, specific verbiage was retained to create the categories reported in this table (i.e. care was taken to respect use of either "ASD" or "Autism").

[a] Missing responses n = 3

[b] Missing responses n = 2

[c] Among the eight total participants, reported comorbid disorders included ADHD (n = 6), anxiety (n = 4), communication/language disorder (n = 1), math learning disorder (n = 1), other learning disorder (n = 2), obsessive compulsive disorder (n = 2), sensory processing disorder (n = 2), and Tourette syndrome (n = 2).

A power analysis was conducted *a priori* using G*Power (Version 3.1.9.3; Faul et al., 2009) to determine the minimum number of participants needed for the intended analysis. Oswald et al. (2015) were able to detect an effect size classified by Cohen (1988) as moderate to large (ES = .29) in their analysis of test anxiety as a predictor of math problem solving abilities. To detect a similar effect size, this study required a sample size of 48 participants according to G*Power. Thus, the sample of 49 students recruited for this study was considered adequate for the purpose of the planned analysis.

Sampling was conducted cross-sectionally. All variables were intended to be measured at a single point in time, from one sample of participants, during an in-person administration of the measures. To ensure participants felt comfortable engaging with the research team, the research team offered participants the option to complete sessions at the team's research lab at the University of Alberta campus, or in the participant's own home. Data collection often occurred over a series of dates for each participant due to: (a) the number of variables measured as part of the larger study, bearing in mind the time required to administer each standardized test; (b) the availability of materials; and (c) the ethical obligation to minimize psychological fatigue for students, which was achieved by limiting each session to a maximum length of 60 minutes. Every reasonable effort was made to schedule subsequent required sessions as soon as possible following a completed session. This research design, including the sampling parameters described above, was approved by the University of Alberta's internal research ethics board prior to the start of data collection.

Predictor Measures

IQ

The inclusion of IQ as a predictor of math ability was considered necessary based on previous studies of math abilities (e.g., Miller et al., 2017; Oswald et al., 2015) and aligns with Byrnes and Miller's (2007) proposition for comprehensive studies of the predictors of math ability. Unlike previous studies (e.g. Bae et al.,2015; Oswald et al., 2015), IQ cutoff scores were not used to exclude any participants; instead, all participants who were able to comprehend and complete the standardized measures in this sample were chosen for inclusion to ensure that students of all ability levels were represented in this sample. Participants completed one of three potential IQ measures: *Raven's Educational Coloured Progressive Matrices* (*Raven's CPM*; Rust & Raven, 2008a), *Raven's Educational Standard Progressive Matrices-Plus* (*Raven's SPM+*; Rust & Raven, 2008b), or the *Leiter International Performance Scale, Third Edition* (*Leiter-3*; Roid et al., 2013). All three measures produce IQ composite scores with a mean of 100 and a standard deviation of 15.

The *Raven's CPM* and *Raven's SPM+* are two age-normed versions of a standardized, nonverbal fluid reasoning assessment, and each version is suitable for individuals of different ages. The *Raven's CPM* is appropriate for assessing students aged 4–11 years, contains 36 items, and takes approximately 30 minutes to complete (Rust & Raven, 2008a). On the other hand, the *Raven's SPM+* is used to assess students aged 7–18 years by having students complete 60 items in approximately 60–90 minutes (Rust & Raven, 2008b). An overlap in the intended age range of each measure meant that students aged 7–11 years could be assessed with either version. Following the advice of the publisher's product guidelines (Pearson Clinical, n.d.), the research team determined the most suitable version for each participant aged 7–11 years on a case-by-case basis. Each member of the research team used their best judgement to determine which version would be most appropriate to use based on: (a) the participant's ability to sustain their attention for longer than 30 minutes, (b) the amount of time available for each session, and (c) the participant's level of interest in the task. For both the *Raven's CPM* and the *Raven's SPM+*, students selected a response from several images, or "pieces," in order to complete a pattern, or "puzzle," arranged in a matrix as presented in a stimulus book. The language demands for this assessment are low; students completing either version of the *Raven's* are required to understand a set of scripted verbal instructions, but these instructions are also accompanied by pointing gestures to ensure students understand the tasks. The *Raven's CPM* contained coloured items, while the *Raven's SPM+* contained only black-and-white items. Evidence for the reliability of the *Raven's CPM*, as presented in the technical manual (Rust & Raven, 2008a), includes a reported split-half reliability of .97 and a standard error of measurement of 2.62. The *Raven's SPM+* manual (Rust & Raven, 2008b) includes a reported split-half reliability of .94 and a standard error of measurement of 3.79. Evidence for the validity of each measure is demonstrated by a collection of factor analysis studies, as well as robust correlations between the current version and previous, validated versions of each measure (Rust & Raven, 2008a, 2008b).

The *Leiter-3* is another age-normed measurement of nonverbal cognitive abilities appropriate for administering to individuals aged 3–75+ years (Roid et al., 2013). The *Leiter-3* includes four subtests which contribute to an individual's overall nonverbal IQ score. Like the *Raven's* measures, the language demands for completing the *Leiter-3* are low. Subtests are administered without any verbal instructions and require individuals to use manipulatives to indicate responses. Reliability evidence for the Leiter-3 includes reported internal consistency coefficients (α = .94 – .98) and test-retest reliability coefficients (α = .74 – .86). Roid and colleagues (2013) also provide evidence for the *Leiter-3*'s content, concurrent, and criterion validity. Content validity was established through expert reviews and item analysis during developing, including pilot testing of new items. Concurrent validity was evidenced by report correlations between a subsample of scores on the *Leiter-3* and scores on other well-established cognitive measures, including the *Stanford-Binet Intelligence Scales, Fifth Edition* (r = .77), the *Wechsler Intelligence Scales for Children, Fourth Edition* Perceptual Reasoning Index (r = .73), and the *Woodcock-Johnson Tests of Cognitive Abilities* Fluid Reasoning subtest (r = .74). Finally, evidence for the *Leiter-3*'s criterion validity includes a demonstration of the *Leiter-3*'s utility for correctly classifying individuals with intellectual disabilities. Overall, Roid and colleagues (2013) present compelling evidence for the reliability and validity of the *Leiter-3* as a measure of nonverbal cognitive abilities.

Like the *Raven's* assessments, the *Leiter-3* was used to determine each student's nonverbal fluid reasoning. Given the number of materials needed to administer, use of the *Leiter-3* in this study was limited to the availability of the test materials and the ability of each member of the research team to transport the materials needed for each session. For some participants (n = 28), time permitted the administration of both a *Raven's* measure and the *Leiter-3*, which allowed me to determine that the correlation between the composite IQ scores produced by each measure was strong (r = .75; see Dancey & Reidy, 2007). Thus, IQ scores are included for participants who completed either the *Raven's CPM*, the *Raven's SPM+*, or *Leiter-3*. This decision allowed for more data points to be included in the regression model. In cases where participants completed both a *Raven's* measure and the *Leiter-3*, a participant's *Raven's* score was selected for inclusion in this analysis. This decision was made based on the clarity and simplicity of the administration instructions provided in the *Raven's* technical manuals (Rust & Raven, 2008a, 2008b). In contrast, the *Leiter-3* may have been more prone to administrator error given: (a) the requirement to manage several manipulatives, (b) the potential variability in administrators' style of pantomime instruction delivery, and (c) the need for "considerable familiarity with the instructions" prior to administration (Drevon et al., 2017). As previously mentioned, scores from any of the three measures were considered appropriate to use as a measure of each participant's math score due to their high correlation and their similarly nonverbal nature. I present a comprehensive breakdown of the IQ measures included in this analysis in Table 2.

Table 2

Descriptive Table of IQ Measures Included for Analysis

IQ measure	*n*	%
Raven's CPM	23	47
Raven's SPM+	18	37
Leiter-3	6	12

Note. *n* = 2 participants (4% of sample) did not complete any IQ measure.

Language Ability

The inclusion of language as a predictor measure also aligns with Byrnes and Miller's (2007) proposition for comprehensive predictor models when examining math abilities. Additionally, language has been established as a predictor of math abilities in previous studies of students with and without autism (e.g., LeFevre et al., 2010; Oswald et al., 2015; Taub et al., 2008). Participants in this study completed subtests of the *Clinical Evaluation of Language Fundamentals, Fifth Edition* (*CELF-5*; Wiig et al., 2013), a standardized, norm-referenced assessment of core language abilities. The *CELF-5* is suitable for use with individuals aged 5 years to 21 years, 11 months. Subtests within the *CELF-5* are reported as scaled scores with a mean of 10 and a standard deviation of 3. Scores on the *CELF-5* subtests can also be used to calculate several language composites, including expressive and receptive language. However, to keep administration time within a reasonable limit, the decision was made to only administer a select few subtests. One of those subtests, the Formulated Sentences (FS) subtest, measured each participant's ability to construct sentences using a given word within the context of a presented illustration. Participants' responses on this subtest are provided verbally, which allowed for language to be measured without any potential impact due to students' fine motor skills. Among the 16 available subtests available in the *CELF-5* test battery, FS was chosen for this analysis for two reasons. First, most participants completed FS, which allowed me to include more data points in the analysis. Second, FS is a comprehensive, stand-alone measure of a student's ability to integrate multiple features of expressive language, including semantics, syntax, and pragmatics (Wiig et al., 2013). Intercorrelations between *CELF-5* subtests and available composites also revealed FS to have some of the strongest relationships to the broader language composites (r = .56–.70), further supporting its use as a valid measure of participants' language ability. The reliability of the FS subtest is supported by a strong average internal consistency coefficient (r = .86) as well as good inter-scorer agreement (r = .95). Evidence for the validity of the *CELF-5* overall test includes confirmatory factor analysis data, as well as the FS subtest's robust concurrent validity with the previous fourth edition (corrected r = .71; Wiig et al., 2013).

RRBI Symptomology

To gauge participants' RRBI symptomology, parents or caregivers were asked to complete the *SRS-2* (Constantino & Gruber, 2012). Among other scores, the *SRS-2* produces two subscale T scores compatible with the *DSM-5* criteria for autism, one of which is the Restricted Interests and Repetitive Behavior subscale (M = 50, SD = 10). Higher scores on this subscale represent more severe and frequently exhibited patterns of rigidity, rule-based insistence on sameness, and restricted interests. This score was used as a measure of students' RRBI symptomology. Although reliability coefficients are not reported for subscales, reliability for the *SRS-2* is evidenced by an overall internal consistency of .95 for the School-Age Form. The technical manual for the *SRS-2* also offers a range of validity evidence, including confirmatory factor analysis which supported the two-factor model of the two *DSM-5* symptom subscales, as well as expert review of the appropriateness of items based on what is known about children with autism (Constantino & Gruber, 2012).

Outcome Measure: Math Ability

The *KeyMath3 Diagnostic Assessment, Canadian Edition* (*KeyMath3 DA^{CDN}*; Connolly, 2008) assesses an individual's understanding of basic math concepts, as well as an individual's ability to apply their knowledge to solve math problems. This measure is appropriate for use with students aged 5 years to 17 years, 11 months, and covers three general math content areas including basic foundational concept knowledge, computation and operations, and problem solving (Connolly, 2008). The *KeyMath3 DA^{CDN}* is norm-referenced, and age norms were used for this analysis. Two parallel forms, Forms A and B, are available for this measure; all study participants completed Form A. All participants included in this analysis completed five subtests: (a) Numeration, (b) Algebra, (c) Geometry, (d) Measurement, and (e) Data Analysis and Probability. These five subtests make up the Basic Concepts composite (M = 100, SD = 15). Items from each of these subtests are delivered orally and are typically accompanied by supplemental visual stimuli. Unlike other standardized math measures—including other written subtests from the *KeyMath3 DA^{CDN}*—these subtests were intentionally chosen for their verbal response format; completing these items did not require students to have the fine motor abilities necessary to scribe their responses. This composite was also chosen for its comprehensive coverage of basic math abilities, as well as normative information indicating that this composite is highly correlated with *KeyMath3 DA^{CDN}* total test scores (r = .96–.97). The split-half reliability of the Basic Concepts composite reported in the technical manual includes reliability coefficients ranging from .83 to .97 across age bands. Test-retest reliability for the Basic Concepts composite is also established by reported reliability coefficients ranging from .81 to .93 across age bands. Validity evidence for the *KeyMath3 DA^{CDN}* includes comprehensive data on the test's content and construct validity. Specifically, the technical manual includes a description of the expert review and consultation with the National Council of Teachers of Mathematics in support of the test's development, as well as comparison studies between the *KeyMath3 DA^{CDN}*

and other validated measures of math ability. The Basic Concepts composite was used as the outcome measure of interest for this analysis to represent each participants' math ability.

Analysis

A hierarchical multiple regression analysis was used to determine the amount of unique variance in math ability—as measured by the *Keymath3 DA*^{CDN} Basic Concepts composite score—accounted for by participants' RRBI symptomology. This method of analysis is appropriate for examining the amount of unique variance in a continuous outcome variable that is explained by a set of continuous or dichotomous predictor variables. Given that the IQ composite scores, the *CELF-5* FS scaled score, the RRBI symptomology T score derived from the *SRS-2*, and the *KeyMath3 DA*^{CDN} Basic Concepts composite score are all continuous variables, a hierarchical multiple regression was deemed appropriate to answer the stated research question. Furthermore, this method was chosen to allow for known predictors to be held constant as the new variable of interest—RRBI symptomology—was added. Thus, IQ and language were added in the first model, given the existing empirical evidence for their capacity to predict math ability, whereas the second model examined the unique predictive power of students' RRBI symptomology. The decision was made to use pairwise deletion to address missing data in order to retain the largest number of data points possible. As suggested by Tabachnick and Fidell (2013), I repeated the analysis with listwise deletion and produced equivalent results; thus, the outcome from the models using pairwise deletion was not spurious. All figures and statistical results were generated using IBM SPSS Statistics (Version 24).

Results

Addressing Assumptions of Multiple Regression

Managing Outliers

Potential outliers in the dataset were investigated in several ways. First, boxplots were generated in SPSS for each variable included in the analysis, none of which revealed any outlier cases. Second, an analysis of the 5% trimmed mean was reviewed to determine the effect of removing any outliers on the mean scores. The 5% trimmed mean of each variable also indicated that potential outliers were unlikely and, if they did exist, did not have an influence on the mean scores (Table 3). Finally, no outliers were visible in the generated regression plots (Figures 1 & 2). Thus, the decision was made to confidently retain all cases in the analysis.

Table 3

Descriptive Statistics for Predictor and Outcome Variables

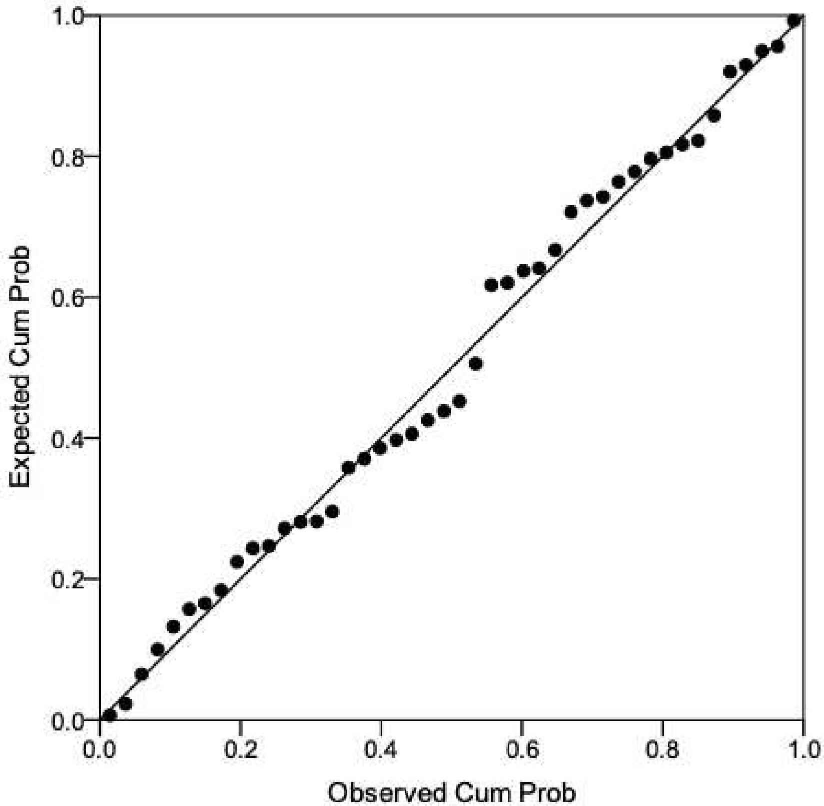
Variable	N	*M*	5% trimmed mean	*SD*	Min.	Max.	Skewness[b]	Kurtosis[b]
IQ	47	99.55	99.87	22.89	55	147	0.30	-0.47
Language ability	45	7.29	7.18	3.25	1	15	0.19	0.32
RRBI symptomology[a]	49	79.61	80.64	8.86	57	90	1.66	0.98
Math ability	49	92.12	91.88	27.21	55	145	1.18	1.05

[a] *SRS-2* total T score (to determine study eligibility) *M* = 78.69, *SD* = 7.79

[b] Represents absolute Z-score (i.e. value / standard error)

Figure 1

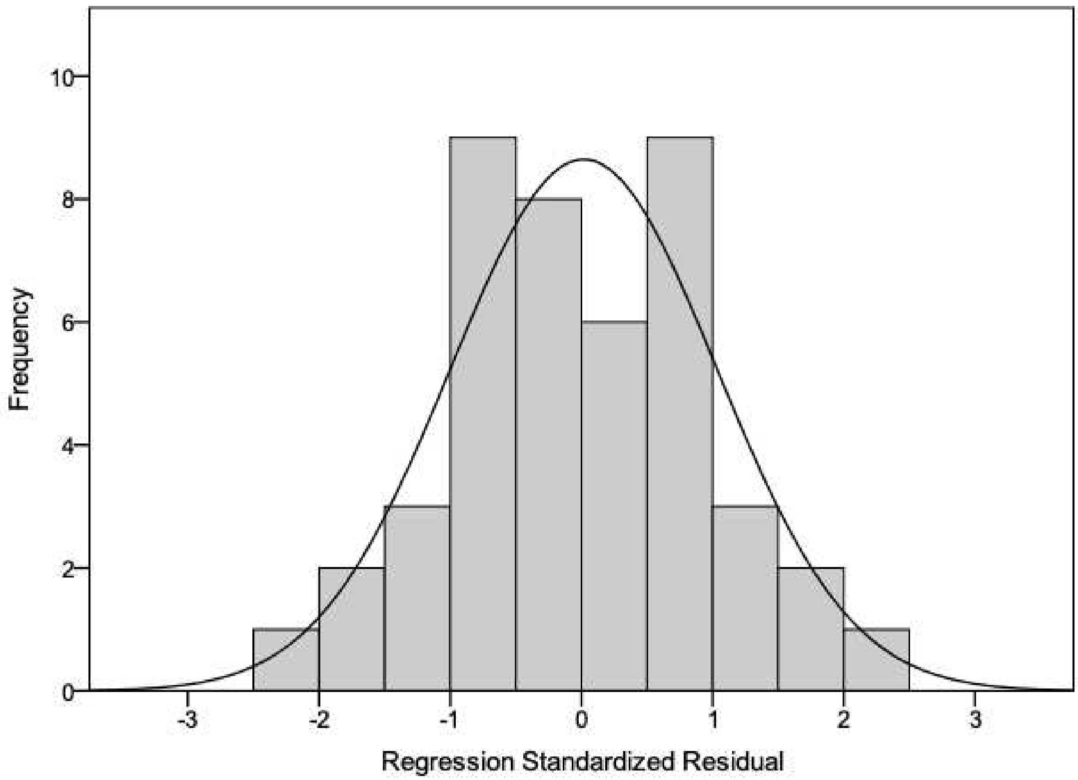
Normal P-P Plot of Standardized Residuals



Note. Outcome variable: Math ability.

Figure 2

Distribution of Standardized Residuals



Note. Outcome variable: Math ability.

Normally Distributed Errors

As pictured in Figures 1 and 2, the residuals were normally distributed around the predicted dependent variable scores. Thus, the errors were determined to be normally distributed.

Non-Zero Variance

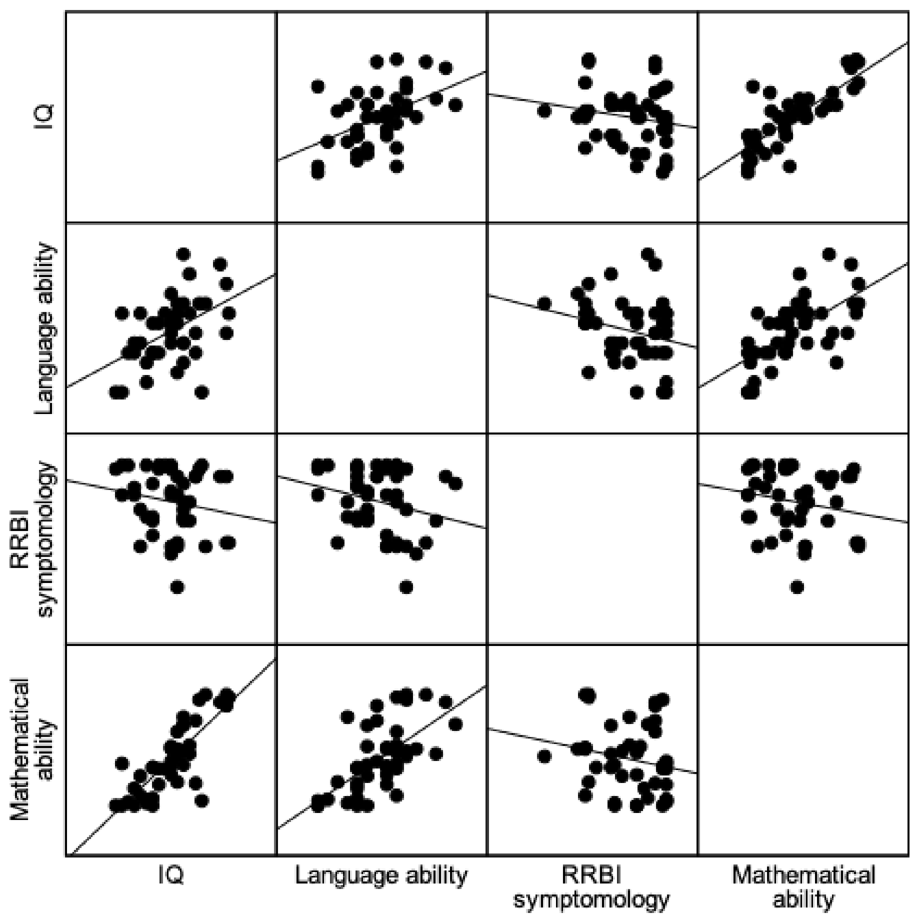
For the assumption of non-zero variance to be met, predictors must have some level of variance above zero. Descriptive statistics and a review of the range of scores (as described in Table 3) indicated that none of the score were constant and that there was variability in the value of each predictor variable. Thus, the assumption of non-zero variance was met for this analysis.

Linearity

The relationship between math ability and the three predictor variables was assessed by generating scatter plots of the relationships between each predictor variable and the dependent variable of *KeyMath3 DA*^{CDN} Basic Concepts scores. The scatterplot matrix portrayed in Figure 3 shows that while not all relationships were strong, all variables had linear relationships, providing evidence that this assumption of multiple regression was met.

Figure 3

Scatterplot Matrix of Relationships Between Study Variables



Note. Each scatterplot includes a fit line.

Independent Values

Logically, all predictor values and values of math ability came from independent participants, given that all measures were administered to each participant and entered into the data sheet only once. Thus, the assumption of each value being generated by independent participants was met.

Independent Errors

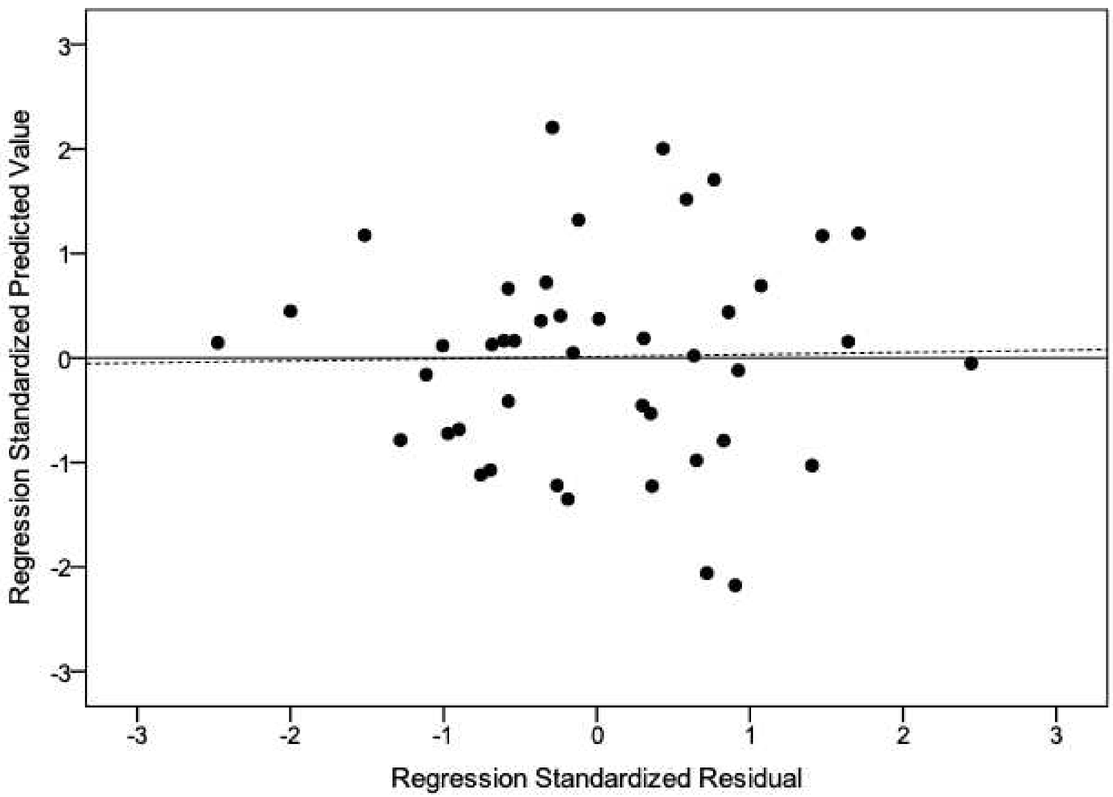
The assumption of independent errors was tested by assessing the Durbin-Watson statistic. The value of the Durbin-Watson statistic for the final regression model was 1.63, indicating that there was no significant autocorrelation within the data and that the error terms are uncorrelated for this analysis.

Homoscedasticity

To test for the assumption of homoscedasticity, the scatterplot of the relationship between the standardized residual values and the predicted values was reviewed. The scatterplot of the relationship between the standardized residuals and the predicted values from the model (Figure 4) revealed an even, horizontal distribution in the residuals, indicating that the error term was constant for each value of the predictor variables. Thus, the assumption of homoscedasticity was also met for this analysis.

Figure 4

Scatterplot of Standardized Residuals and Standardized Predicted Values



Note. Outcome variable: Math ability.

Absence of Multicollinearity

Several steps were taken to ensure that the variables entered into the regression model were not highly correlated. First, the correlation table (Table 4) revealed some strong correlations among the variables, with correlation coefficients ranging from -.11 to .80. However, additional reviews of collinearity statistics generated by SPSS revealed a sufficiently high Tolerance statistic (> .7) and a sufficiently low variance inflation factor (VIF; < 1.4). Taken together, these results suggest that although there were strong correlations among the variables, there was an absence of multicollinearity within this data set.

Table 4

Correlation Coefficients

Variable	IQ	Language	RRBI symptomology	Math ability
IQ	—			
Language ability	.48**	—		
RRBI symptomology	-.11	-.27	—	
Math ability	.80***	.63***	-.11	—

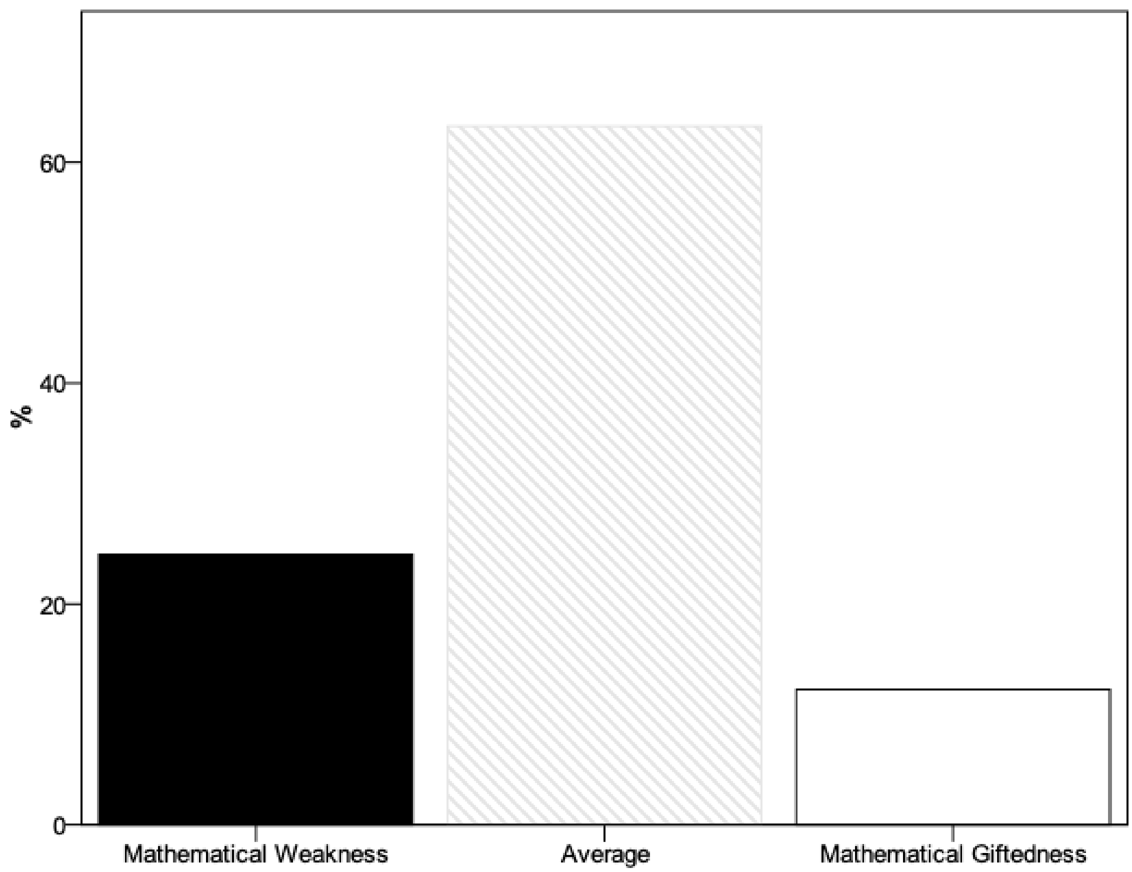
* $p < .05$ ** $p < .01$ *** $p < .001$

Distribution of Math Abilities

Although the aim of this study was not to examine the distribution of math ability scores in this sample, especially given the relatively small sample size, it is worth mentioning that the distribution of math ability scores was not statistically different from normal, as evidenced by the skewness and kurtosis values of the math ability scores (see Table 3; Kim, 2013). However, an evaluation of the proportion of students with high math ability compared to low math ability provides evidence against the stereotype of math giftedness among autistic students, as well as support for the higher rates of math weakness in this population. Conservative cutoffs of ±2 *SD* above or below the *KeyMath3 DA*^{CDN} Basic Concepts mean score of 100 were applied to determine the number of students in the sample who had math giftedness and math weakness, respectively. Twice as many students were categorized as having a math weakness (24.5%) compared to the number of students categorized as having math giftedness (12.2%), as demonstrated in Figure 5. Altogether, results from this sample support previous findings (e.g., Mayes & Calhoun, 2006; Oswald et al., 2015) that a greater proportion of autistic students have below average math abilities rather than mathematical giftedness. While the distribution of math ability scores was not statistically different from normal, the proportions of both math giftedness and math weakness were much higher than expected.

Figure 5

Distribution of Math Ability Scores Among Sample



Note. Math weakness = Math ability score < 70; Average = Math ability score 70–130; Math giftedness = Math ability score > 130.

Predictors of Math Ability

Correlational analyses indicated that RRBI symptomology scores were not statistically significantly correlated with math ability scores (see Table 4). Results from the hierarchical multiple regression were used to assess the amount of unique variance in math ability scores that could be explained by students' RRBI symptomology. The model summary is presented in Table 5. A review of the first model revealed that, together, IQ and language ability accounted for 72.4% of the variance in math ability scores (R^2 = .724). After RRBI symptomology scores were entered into model 2, the total amount of variance explained by the model increased to only 72.6% (R^2 = .726), $F(1, 40) = .359$, $p = .552$. Thus, the ΔR^2 after adding the RRBI symptomology predictor was .002, indicating that RRBI symptomology accounted for only .2% of the variance in math ability scores. Thus, RRBI symptomology does not significantly predict the math ability scores of students with autism ($p > .05$). Both IQ ($\beta = .65$, $p < .001$) and language ability ($\beta = .34$, $p = .001$) remained statistically significant positive predictors of math ability in the second model.

Table 5

Hierarchical Regression Coefficients Summary

Variable	*B*	*SE B*	β	R^2	ΔR^2
Model 1				.724	.724***
Constant	-4.150	9.970			
IQ	.769***	.111	.647		
Language ability	2.703**	.783	.323		
Model 2				.726	.002
Constant	-17.449	26.005			
IQ	.767***	.113	.644		
Language ability	2.824**	.823	.336		
RRBI symptomology	.158	.285	.035		

Note. Pairwise deletion used for analysis. RRBI symptomology was added as a predictor in Model 2. Dependent variable for both models: math ability.

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

This means that students with better nonverbal fluid reasoning abilities and better language abilities had better overall math abilities as measured by the *KeyMath3 DA*^{CDN} Basic Concepts score. Variance in the math ability scores of students with autism was better explained by IQ and language ability, whereas RRBI symptomology did not significantly predict math abilities. Moreover, the correlation between RRBI symptomology and math ability was nonsignificant, which was surprising given the initial hypothesis that engaging in more rule-based, repetitive behaviours supports autistic students' proficiency in foundational math concepts.

Discussion

Overall, the findings of this study did not support the hypothesis that autistic students who had more frequent or more intense RRBI engagement would have higher math ability. The amount of variance in students' math ability scores explained by RRBI frequency and intensity was not significant, as demonstrated by the results of the hierarchical multiple regression. However, these results did support earlier research on the significant role that IQ and language ability both play in predicting math ability in students with autism (Miller et al., 2017; Oswald et al., 2015). Additionally, an exploration of the distribution of math ability scores in this sample was congruent with earlier findings that math weakness is more common than math giftedness in autistic students (e.g. Chiang & Lin, 2007; Mayes & Calhoun, 2006; Oswald et al., 2015). Namely, 24.5% of students had a math weakness based on math ability scores ≤2 *SD* below the mean of the *KeyMath3 DA*^{CDN}. In contrast, only 12.2% of the sample had math ability scores ≥2 SD above the mean of the *KeyMath3 DA*^{CDN}. Although applying formal criteria for math LD was outside the scope of this paper, the results from this study supply further evidence that stereotypes of math giftedness in autism are unwarranted and inaccurate.

Limitations & Future Directions

A major limitation of this study is that the *SRS-2* scale used to measure RRBIs in this sample is not a highly specific measure, given that it includes every possible RRBI associated with the *DSM-5*'s criteria for autism spectrum disorder. In other words, the *SRS-2* Restricted Interest and Repetitive Behaviour subscale does not distinguish between items measuring "lower-order" versus "higher-order" RRBIs (Lin & Koegel, 2018). "Lower-order" RRBIs are limited to those in the domain of motor-sensory symptoms, such as self-injury and self-soothing rocking behaviours. On the other hand, "higher-order" RRBIs describe those that are more cognitive in nature, such as engaging in special interests and adhering to rule-based thinking. Further evidence for distinct RRBI subtypes has been published in the years since the creation of the *SRS-2*. Three total "subtypes" of RRBIs have been identified through exploratory factor analysis: (a) special interests, (b) insistence on sameness, and (c) repetitive motor behaviours (Lam et al., 2008).

The *SRS-2*'s use of a single RRBI scale amalgamates all possible subtypes of RRBI to produce a single score. For example, ratings of one student's frequent self-stimulatory behaviours in the absence of special interest engagement may produce a score equally as high as the rating of another student who displays intense engagement in a special interest. Thus, students' RRBI symptomology scores in this sample may not differentiate RRBI engagement. As South and colleagues (2007) noted with respect to RRBI measurement, "[s]ome… behaviors are best measured in terms of frequency or duration, while others are better measured by the impairment they cause" (p. 447). This could also be framed more positively to propose that engagement in a higher-order RRBI like a special interest may be better measured by the *method* with which students engage with their special interest area (Klin et al., 2007). For example, it may be that a subset of students with autism are meaningfully and regularly engaged in organizing and systematizing information about their intense special interest—and as a result of having these consistent learning opportunities involving the same processes that support math learning (Schwank & Schwank, 2015), these students are mathematically gifted. To more clearly understand the relationship between special interest engagement and math ability development, researchers must first develop more specific measures focused exclusively on special interest engagement. In this way, future studies can assess whether or not special interest engagement in particular contributes to math ability development, without confounding these cognitive-based RRBI behaviours with more physical, “lower-order” RRBI behaviours.

It is also important to address several limitations related to the current study’s sample:

1. The sample is quite small. This is not uncommon in research on a special population such as autism—however, having fewer participants reduced the number of predictors that could reasonably be added to the regression analysis without sacrificing statistical power. This made it difficult to further explore other potential cognitive or clinical predictors, as suggested by Byrnes and Miller (2007). Future studies should endeavour to recruit more participants so that a more varied set of predictors can be tested.
2. The sample was predominantly male and required participants to engage with an English-speaking team of researchers, which greatly limits the generalizability of these findings to autistic females or people with autism who speak a language other than English. Future studies should include more female participants and more culturally diverse representation.
3. This sample required students to be able to complete standardized tests; although measures were chosen which reduced demands for reading and writing, and participants with a wide range of IQ scores were included, it could be argued that the sample still fails to represent students with autism who are unable to participate in standardized testing, especially given that some items used in this study required verbal responses. Future studies should explore more inclusive measurement tools to assess participants of all ability levels who may be unable to adhere to standardized testing (e.g. incorporating gaze tracking software to gather responses that are less reliant on providing verbal responses).
4. The generalizability and interpretability of these results may be limited based on the potential for participants’ diagnoses to be misrepresented. Parents’ and caregivers’ self-

reports of their child's diagnoses—including any comorbid conditions—may have been false or inaccurate, especially if the diagnosis occurred in the distant past. If students without autism were mistakenly included in this sample, the results would no longer be describing predictors of math ability unique to this population. Future studies should include independent confirmation of participants' diagnosis by the research team, using an existing diagnostic measure of autism (e.g. the *Autism Diagnostic Observation Schedule, Second Edition*; Lord et al., 2012).

5. The decision to include all participants regardless of comorbid diagnoses may have also impacted the generalizability and interpretability of these results. Namely, the possible inclusion of students with existing LD diagnoses may have inflated the reported rates of math weakness in the sample. Future studies should endeavour to recruit larger sample sizes so that potential comorbid diagnoses can be examined separately.
6. Self-selection bias in this sample may have led to an inflated number of under- and over-achieving math students (i.e. parents who were invested in learning more about their child's known giftedness or weakness in math may have been more interested in participating in this math study). Future studies should employ more purposeful methods of sampling to ensure parents of children with average math abilities are not overlooked for participation in a study aimed at understanding math achievement.

Contribution & Significance of Findings

Despite the lack of support for the original hypothesis, this study still makes an important contribution to the literature on math abilities in autism. Although rarely acknowledged, the *file drawer problem* in research publications can lead to misleading biases. The file drawer problem refers to the concept that only statistically significant results are accepted for publication, resulting in numerous studies being tucked away in researchers' "file drawers." This is particularly problematic when conducting meta-analyses (Pautasso, 2010). While the current study did not find support for its original hypotheses, the statistical values reported in the hierarchical regression models are important to acknowledge if future researchers were ever to publish a meta-analysis on the math abilities of students with autism. If nonsignificant results were never published, meta-analyses may draw false conclusions from published literature.

Results from this study also help to continue dismantling stereotypes of enhanced mathematical talent in students with autism. Findings from other researchers on the elevated rates of math weakness in autistic students were supported and replicated in the current sample. Although RRBIs were not found to significantly predict math ability in this sample, limitations of the RRBI measure used here were revealed. This discussion promotes a critical call to action for researchers to develop more focused RRBI assessment tools. If RRBIs more specifically predict math ability, interventions can be developed to promote special interest engagement. Commenting on the environments that best promote math learning, Gillum (2014) advocates that educators ought to “teach the skill in an accessible way.” Special interests may provide an accessible pathway to better math learning for students who struggle with math concepts.

In that same spirit, this study helps to advocate for a more strengths-based approach to autism research. Although RRBIs can be considered impairing for some students, they can also enrich the lives of others. Students with autism should be supported to pursue interests that are meaningful and contribute to their self-image. While more concentrated research is needed to determine whether special interest engagement specifically predicts math ability, this study enriches the discussion of how RRBIs can be seen as a benefit and strength for autistic people.

Conclusion

Previous studies provide evidence for the divergent profiles of math abilities in students with autism (Chiang & Lin, 2007); however, the mechanisms underlying these differences are still unclear. Researchers have demonstrated that certain cognitive abilities are predictive of math abilities (LeFevre et al., 2010); however, these cognitive models have not been replicated in autistic samples (e.g. Bae et al., 2015; Oswald et al., 2015), and there is a paucity of quantitative research exploring clinical predictors of math abilities (e.g., RRBIs). Although my results indicated that RRBIs were not significant predictors of math abilities, the results of this study refute the potentially harmful stereotype that autistic students are typically mathematically gifted. Rather, students with autism tend to have below average math abilities. This is important to acknowledge in our understanding of how math ability develops for students with autism—students with autism who struggle with math have a right to access interventions that support their academic achievement. This study also includes a call to action for future researchers to develop tools to more accurately assess the multifaceted concept of RRBIs and to adopt a more strength-based approach when working with neurodivergent populations.

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