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Examining the relation between PASS cognitive processes and superior reading and mathematics performance

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Abstract

Although several studies have shown that planning, attention, simultaneous, and successive (PASS) cognitive processes—operationalized with the cognitive assessment system (CAS; Naglieri & Das, 1997)—are significant predictors of academic performance in the general population, little is known about their role among children with superior academic skills. Thus, the purpose of this study was to examine whether PASS processes can predict superior performance in reading and mathematics. We used the standardization sample of CAS ($n = 1210$) and further identified children with superior reading ($n = 62$) and mathematics ($n = 73$) performance on Woodcock–Johnson Tests of Achievement–Revised (Woodcock & Johnson, 1989). Results of the initial regression analyses showed that the PASS processes were significant predictors of superior reading and mathematics performance. Next, a classification and regression tree approach showed that the PASS scores could classify superior or not-superior readers and mathematicians with 89% and 82% accuracy, respectively. Theoretical and practical implications of our results are discussed.

KEYWORDS

information processing, intelligence, mathematics, neurocognitive processes, PASS processes, reading

1 | INTRODUCTION

Several studies have established that planning, attention, simultaneous, and successive (PASS) neurocognitive processes as measured by the cognitive assessment system (CAS; Naglieri & Das, 1997) are significant predictors of academic achievement across languages (e.g., English: Das et al., 2008; Greek: Papadopoulos, 2001; Chinese: Wang et al., 2012), ethnicities (e.g., Naglieri et al., 2007), and developmental levels (e.g., Naglieri & Rojahn, 2004). Importantly, Georgiou et al. (2020) reported meta-analytic results showing correlations between PASS scores and reading or math that were significantly stronger than correlations reported in previous meta-analyses for other measures of intelligence. They concluded that "there are significant benefits if we conceptualize intelligence as a constellation of cognitive processes that are linked to the functional organization of the brain" (p. 10). However, their study, like those noted above, did not study individuals with very high levels of academic achievement. Thus, the purpose of this study was to examine whether PASS processes are related to superior performance in reading and mathematics.

This is important for both theoretical and practical reasons. From a theoretical point of view, any test of intelligence—particularly if it claims to predict academic achievement better than other tests of intelligence—should explain individual differences in reading or mathematics at different levels of their distribution. To date, most research on PASS theory has focused on the low ends of the reading or mathematics distributions (see Cai et al., 2013; Huang et al., 2010; Naglieri & Reardon, 1993). In addition, in today's educational climate, attention to the learning needs of children with superior academic achievement is too often pushed aside, and additional research focused on theoretical models, such as PASS could help to remind everyone of this subgroup's experiences and needs. In what follows, we briefly describe the PASS theory of intelligence, then we review previous studies on PASS and superior reading or mathematics performance, and finally we present the rationale of the present study.

2 | THE PASS THEORY OF INTELLIGENCE

PASS theory is based on the conceptualization of brain function presented by Alexander R. Luria, a Russian neuropsychologist. In his influential book, *The working brain: An Introduction to neuropsychology*, Luria (1973) described four neurocognitive processes associated with different parts of the brain. The first is Planning, which is a mental activity that provides cognitive control; use of processes, knowledge, and skills; intentionality; organization; and self-regulation. This processing ability is closely aligned with frontal lobe functioning (third functional unit). Attention is the ability to demonstrate focused, selective, sustained, and effortful activity over time and resist distraction associated with the brain stem and other subcortical aspects (first functional unit). Simultaneous processing ability provides a person the ability to integrate stimuli into interrelated groups or a whole usually found in tasks with strong visual-spatial demands. Finally, Successive processing ability involves working with stimuli in a specific serial order including the perception of stimuli in sequence and the linear execution of sounds and movements.

This theory of brain function provided a blueprint for test development, which excluded traditional, academically-laden subtests that demand knowledge (e.g., Vocabulary, Arithmetic) and allowed more equitable measurement. Although the evidence of validity and reliability as well as clinical utility of PASS scores is beyond the scope of this study, Naglieri and Otero (2017) have reported that PASS scores (a) are more predictive of achievement test scores than any other ability test (see also Georgiou et al., 2020, for recent evidence from a meta-analysis); (b) show distinctive profiles for different children with different disabilities; (c) can be used for specific learning disabilities eligibility determination consistent with Federal Law using the discrepancy consistency method of analyzing a pattern of strengths and weaknesses in PASS and achievement scores; (d) can be readily used for instructional planning and interventions and, perhaps most importantly for gifted students, (e) offer the most equitable way to measure diverse populations (Naglieri & Otero, 2017).

One of the greatest differences between traditional intelligence tests and the CAS, is its reliance on the PASS theory and the inclusion of subtests that were developed explicitly to measure basic neurocognitive processes in a way that does not rely on verbal and quantitative knowledge (e.g., vocabulary, similarities, information, arithmetic). The composition of the two ability tests most often used to identify gifted students (CogAT and Wechsler intelligence scale for children, fifth edition [WISC-V]; Kurtz et al., 2019) influences which students are selected. Ford (2013) and Naglieri and Ford (2003) have argued that the verbal and quantitative content of such tests are an avoidable obstacle to traditionally underrepresented populations in gifted education. Naglieri and Otero (2017) estimated that approximately 750,000 Black, Hispanic, and English Language Learner students in grades K-12 in US would qualify for gifted programs but were not, in part, because the most widely used tests for the identification of gifted students demand verbal and quantitative knowledge. It is important to note that according to the *Standards for Educational and Psychological Testing* (AERA APA NCME, 2014) a test can be considered socially unjust for a person who has had limited opportunities to learn the content of the test questions. Moreover, that test may be considered unfair because it penalizes students for not knowing the answers even if there is no evidence of psychometric test bias. This issue is a fundamental problem for equitable identification of gifted students.

Researchers have also found a mean difference of about 12–15 points between African Americans and Whites on measures of IQ that include verbal, quantitative, and nonverbal tests (Kaufman & Lichtenberger, 2006), which has had considerable impact on the composition of students in gifted programs. In contrast, Naglieri et al. (2005) reported a CAS full scale mean score difference of only 4.8 between African Americans and Whites, and Naglieri et al. (2007) found a 4.8-point difference between Hispanic and White children. Finally, small differences between PASS full scale scores and factorial invariance were reported using the Italian and English versions of the CAS (Naglieri et al., 2013). These findings suggest that PASS theory provides an option for fair assessment of students for gifted programs while remaining highly correlated with achievement without having tests that measure vocabulary, knowledge, and quantitative skills.

Importantly, researchers have proposed specific links between the PASS processes and academic achievement. In regard to reading, Das et al. (1994) proposed that Successive processing contributes to word reading through the effects of phonological recoding and Simultaneous processing contributes to word reading through the effects of orthographic knowledge. Planning and Attention are supposed to play an auxiliary role in that they enable the deployment of phonological recoding and orthographic knowledge. In regard to mathematics, Das and Janzen (2004) proposed that change in strategies (e.g., shifting from counting with fingers to conceptualizing basic operations in mental arithmetic) or flexibility in strategy use is a central requirement of planning. Likewise, they proposed that seeing similarities between two problems and transferring procedures learned from one problem to another, falls into the realm of Simultaneous processing. Finally, Das and Janzen (2004) argued that Successive processing is important when information has to be processed in a certain order, as in counting.

3 | PASS PROCESSES AND SUPERIOR READING OR MATHEMATICS PERFORMANCE

To date, the majority of studies on the relationship between PASS scores with reading and mathematics performance have been conducted either with typically developing children (e.g., Cai et al., 2018; Das et al., 2008; Georgiou et al., 2015; Kroesbergen et al., 2010; Papadopoulos, 2001; Wang et al., 2012) or with children experiencing reading or mathematics disabilities (e.g., Cai et al., 2013; Das et al., 2007; Iglesias-Sarmiento & Deaño, 2011; Joseph et al., 2003; Kroesbergen et al., 2003). For example, in a study with Grade 3 English-speaking children, Das et al. (2007) reported that the probability of a child being a poor reader if his or her standard score in successive processing was below 80 was 0.76. The corresponding probability for simultaneous processing was 0.50. In a study with Grades 6 to 8 Chinese children, Cai et al. (2013) also found that children with mathematics learning disabilities (MLD) were performing lower than their chronological-age controls on all PASS processes. However, only Planning and Simultaneous processing significantly predicted their group membership (MLD vs. no MLD).

The first study to examine the association between PASS processes and superior academic performance was part of the standardization of CAS (Naglieri & Das, 1997). More specifically, Naglieri and Das (1997) reported descriptive statistics on the PASS processes from 173 gifted children ages 8 to 15. The children were identified as gifted on the basis of state and federal definitions of giftedness by multidisciplinary teams in their schools. These teams used teacher referrals, achievement test scores (Italics added by authors to give emphasis), and intelligence test scores as the criteria for identification. As a group, the gifted children obtained a standard score of 111.9 in Planning, 111.0 in Attention, 117.7 in simultaneous processing, and 115.8 in Successive processing. Naglieri and Das (1997) pointed out that the high scores in Simultaneous and Successive processing scales could be attributed to the fact that these CAS scales are most similar to the traditional IQ tests used to identify these children.

Studies on PASS processes with superior readers are scarce (see Dunn et al., 2019; Papadopoulos et al., 2020, for exceptions). Dunn et al. (2019) compared a group of children with superior reading performance (standard score on Broad Reading[1] higher than 130) to a group of children with average reading performance (standard score on Broad Reading between 85 and 115) and found that the two groups differed significantly in Simultaneous and Successive processing. Papadopoulos et al. (2020), in turn, conducted a study with precocious readers (kindergarten children who were reading words before receiving any formal reading instruction) in Greek and found that they also performed better than controls in Simultaneous and Successive processing. Although both aforementioned studies suggest that Simultaneous and Successive processing are key predictors of superior reading, they did not specify what scores in Successive and Simultaneous processing would have to be achieved for a child to be correctly identified as a superior reader.

To our knowledge, only one study has examined the PASS processes in children with superior mathematics performance. More specifically, Iglesias-Sarmiento et al. (2020) compared the performance of high achieving children in mathematics (n = 26) on PASS processes to that of a group of average performing children (n = 58) and children with math difficulties (n = 26). Children with math difficulties obtained significantly lower scores than the high achieving children in Planning, Simultaneous processing, and Successive processing. The group of average performing children performed more poorly than the high achieving group only in Simultaneous processing. Certainly, more research is needed on PASS and superior mathematics performance.

4 | THE PRESENT STUDY

The present study aimed to answer the following three research questions:

(1). What PASS processes explain individual differences in reading and mathematics performance? Addressing this study question will allow us to establish the relationship between PASS processes and student performance in reading and mathematics. On the basis of previous studies with superior readers (Dunn et al., 2019; Papadopoulos et al., 2020), we expected that Simultaneous and Successive processing would predict superior reading performance. In addition, we expected that Simultaneous processing and Planning would predict superior mathematics performance.

(2). What combination of PASS processing scores predicts superior academic performance? No specific hypothesis could be formulated for this question because this is the first time the classification and regression tree (CART) approach (see below for details) is used to predict superior academic performance.

[1]Broad Reading is a cluster score derived from Letter-Word Identification, Reading Fluency, and Passage Comprehension (Woodcock, McGrew, & Mather, 2001).

(3). How accurate a model with PASS processes is in predicting membership to superior reading or mathematics groups? Based on the findings of previous studies highlighted above, we hypothesized that the model with PASS processes would accurately differentiate children with and without superior reading or mathematics performance.

We chose to examine these questions using the standardization and validity study data from the original version of the CAS because of (a) the size and representative nature of the sample (*n* = 1,210); and (b) the fact that this is the largest study on PASS and academic achievement conducted thus far. Despite the publication of the second edition of the CAS2 (Naglieri et al., 2014), the correlation between the first and second edition is very high (*r* = .88; Naglieri et al., 2014).

The findings of the present study are expected to contribute to the literature in three important ways. First, examining the role of PASS processes in superior reading or mathematics performance fills an important gap in research on PASS theory that has focused mostly on the lower end of the reading or mathematics performance continuum (see Naglieri & Otero, 2018, for a review). In light of evidence that intelligence—operationalized as a set of neurocognitive processes—plays an important role in learning disabilities (e.g., Naglieri & Reardon,1993), we have good reasons to believe that a similar role may be played in superior academic performance. Second, our findings can provide direction to instructional programming of children with superior academic performance because PASS theory has direct links to intervention (e.g., Das & Misra, 2015; Naglieri & Otero, 2017). Obviously, this is not the place to discuss how gifted children are identified (see e.g., Pfeiffer, 2012, for a discussion on this issue), but to the extent such identification is influenced by potential to learn (e.g., PASS) and children's scores in reading or mathematics,[2] then our findings can give direction to educational programming of these children.

5 | METHODS

5.1 | Participants

The participants for this study were 1,210 children and adolescents (590 males, 620 females) ages 8 to 17 years, who participated in the CAS standardization sample (Naglieri & Das, 1997). The sample was representative of the general population in US on the basis of gender, race, parental education, geographic region, and the community setting they came from (see Naglieri & Das, 1997, for details). To be included in this study, participants had to have been individually administered the reading and math subtests of the Woodcock–Johnson Tests of Achievement—Revised (WJ-R; Woodcock & Johnson,1989) by a trained examiner, following the administration of the CAS.

6 | MATERIALS

6.1 | Academic achievement

To measure academic achievement the WJ-R (Woodcock & Johnson, 1989) was administered. For the purpose of this study two cluster scores were of interest: Broad reading which is composed of scores from the letter-word

[2]For example, in Alberta (Canada), Code 80 suggests that gifted children can be identified, among other criteria, on the basis of their academic achievement (Alberta Education, 2014).

identification and passage comprehension subtests, and broad math which is composed of scores from the calculation and applied problems subtests.

6.2 | PASS processes

PASS processing scores were obtained using the CAS (Naglieri & Das, 1997). This individually administered test of neurocognitive functioning was standardized for use with children and adolescents ranging from 5 to 17 years of age. The four PASS scales have a mean of 100 and a standard deviation of 15. Scores from the CAS Standard Battery which consists of all 12 subtests (three for each PASS scale) were used. A description of these subtests can be found in the Appendix. The average internal consistency (i.e., coefficient alpha) values for the PASS Standard (all 12 subtest) battery are as follows: Planning = 0.88; attention = 0.88; simultaneous = 0.93; and successive = 0.93.

6.3 | Data analysis

To answer our first research question, we performed multiple regression analyses in which the WJ-R Broad Reading and Broad Math scores were used as dependent variables and the PASS standard scores were used as predictor variables. This regression model can be written as:

$$Y_i = b_0 + b_1X_{iPL} + b_2X_{iAT} + b_3X_{iSM} + b_4X_{iSC} + \varepsilon_i, \tag{1}$$

where Y_i is person i's Broad Reading (or Broad Math) score; X_{iPL}, X_{iAT}, X_{iSM}, and X_{iSC} are person i's standard scores in Planning, Attention, Simultaneous and Successive processing, respectively; $b_0$is the intercept, $b_1$to b_4 are the regression weights for the PASS processing standard scores; and ε_i is the error term for person i. The multiple regression models were estimated using the R software program (R Core Team, 2019). Statistical significance, magnitude, and direction of the estimated regression coefficients and the total variance explained by the models (i.e., R^2) were evaluated.

To answer the second research question, we first identified individuals from the whole sample with a standard score in Broad Reading and Broad Math at or above 130 (indicating superior reading/math performance). This resulted in 62 superior readers and 73 superior mathematicians. Then, a CART approach was used to predict superiority status for individuals (1 = superior, 0 = not superior). CART is a widely used data mining technique that employs a set of independent variables for predicting a dependent variable characterized as either continuous or categorical. This approach relies on binary splitting of a prediction space into a number of smaller and non-overlapping branches of the data, which are also known as decision nodes. Then separate predictions (i.e., regressions) are made by going through the branches of a decision tree and a prediction is made for the dependent variable in the final nodes, which is also known as leaf nodes. The estimated CART model yields a tree-like structure with many branches created based on the predictors (see Loh (2011) for a detailed review).

In the current study, the standard scores of the four PASS processes were used to create a series of branches in the decision tree model and the final nodes were used to predict whether individuals were superior in reading and math based on their WJ-R scores. Separate decision trees were built for reading and mathematics. The CART models were estimated using the *rpart* (Therneau & Atkinson, 2019) and *rpart. plot* (Milborrow, 2019) packages in R (R Core Team, 2019). The resulting CART models were subsequently evaluated based on their classification accuracy, sensitivity, and specificity (this answers our third research question). Table 1 demonstrates a 2 × 2 table of binary classification categories required to compute accuracy, sensitivity, and specificity indices.

TABLE 1 Evaluating the accuracy of a binary classification model

	Actual classification	
Predicted classification	**Gifted in reading (or math)**	**Not gifted in reading (or math)**
Gifted in reading (or math)	True positive (TP)	False positive (FP)
Not gifted in reading (or math)	False negative (FN)	True negative (TN)

Note: Sensitivity = TP/TP+FN; specificity = TN/TN+FP; accuracy = TP+TN/(TP+TN+FN+FP).

7 | RESULTS

7.1 | Multiple regression analysis

Before conducting multiple regression analyses, the linear relationships among the broad reading, broad math, and PASS standard scores were visually inspected. Figure 1 depicts a scatterplot matrix that contains all the pairwise scatterplots of the scores in a matrix format. The lower triangular portion shows the pairwise relations among the scores, the diagonal portion shows a histogram showing the distribution of each score, and the upper triangular portion shows the Pearson correlations among the scores. The scatterplots suggest that the PASS processes had a positive, linear relation with Broad Reading and Broad Math. The correlations among the scores were mostly moderate to strong.

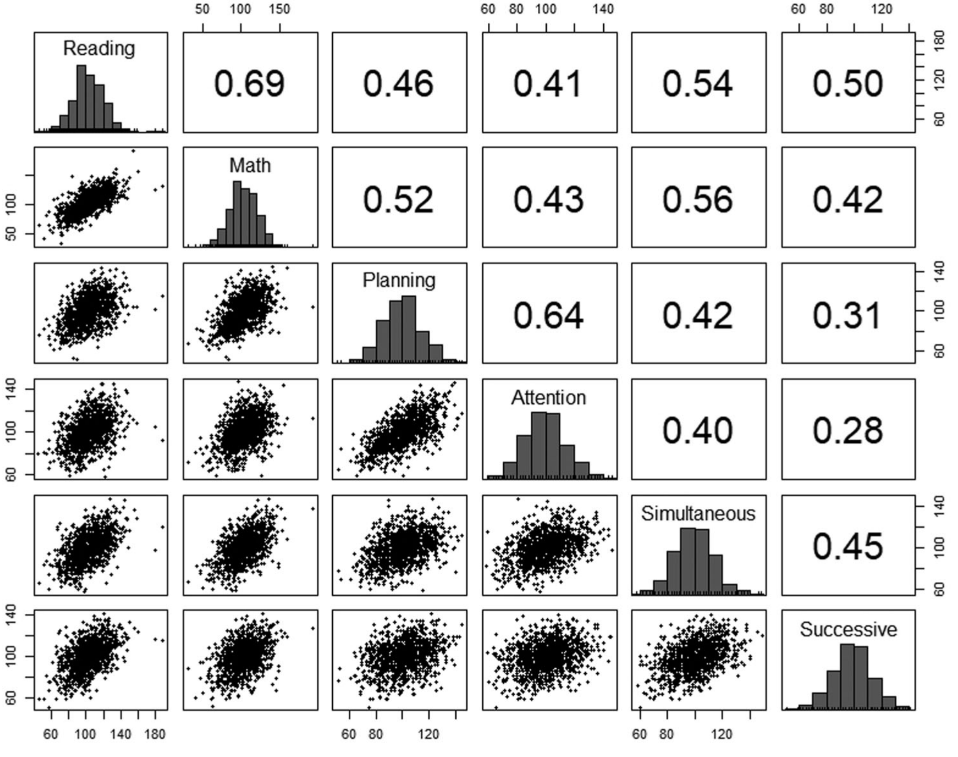

FIGURE 1 A scatterplot matrix of the pairwise relationships among broad reading, broad math, and planning, attention, simultaneous, and successive (PASS) sores

TABLE 2 Results for the regression model predicting Broad Reading

Predictor	*b*	*b*95% CI	*β*	*β* 95% CI	sr^2	sr^2 95% CI	Fit
Intercept	3.14	(−3.56, 9.85)					
Planning	0.21**	(0.15, 0.28)	.18	(0.13, 0.24)	0.02	(0.01, 0.03)	
Attention	0.11**	(0.05, 0.18)	.10	(0.04, 0.16)	0.01	(−0.00, 0.01)	
Simultaneous	0.34**	(0.28, 0.40)	.29	(0.24, 0.34)	0.06	(0.04, 0.08)	
Successive	0.33**	(0.28, 0.39)	.28	(0.24, 0.33)	0.06	(0.04, 0.09)	
							R^2 = .426**
							95% CI (0.39, 0.46)

Note: A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *β* indicates the standardized regression weights. sr^2 represents the semi-partial correlation squared. 95% CI indicates the lower and upper limits of a confidence interval.

Abbreviation: CI, confidence interval.

**$p < .01$.

After inspecting the pairwise correlations, we performed multiple regression analyses to answer our first research question. Tables 2 and 3 show the results from the multiple regression models for reading and mathematics, respectively. The regression model for broad reading was statistically significant ($F(4, 1203) = 223.36$, $p < .001$) and explained a large proportion of variance (43%). In the model, the effects of all PASS standard scores were positive and statistically significant at the significance level of $\alpha = .01$. Based on the standardized regression coefficients (β), Simultaneous and Successive processing were stronger predictors of Broad Reading than the other two PASS processes.

TABLE 3 Results for the regression model predicting Broad Math

Predictor	*b*	*b*95% CI	*β*	*β* 95% CI	sr^2	sr^2 95% CI	Fit
Intercept	−3.53	(−10.68, 3.62)					
Planning	0.36**	(0.29, 0.43)	0.29	(0.23, 0.35)	0.05	(0.03, 0.06)	
Attention	0.08*	(0.01, 0.15)	0.06	(0.01, 0.12)	0.00	(−0.00, 0.01)	
Simultaneous	0.43**	(0.37, 0.49)	0.34	(0.29, 0.39)	0.08	(0.06, 0.11)	
Successive	0.20**	(0.14, 0.26)	0.16	(0.11, 0.21)	0.02	(0.01, 0.03)	
							R^2 = .437**
							95% CI (0.40, 0.47)

Note: A significant *b*-weight indicates the beta-weight and semi-partial correlation are also significant. *b* represents unstandardized regression weights. *β* indicates the standardized regression weights. sr^2 represents the semi-partial correlation squared. 95% CI indicates the lower and upper limits of a confidence interval.

Abbreviation: CI, confidence interval.

*$p < .05$.

**$p < .01$.

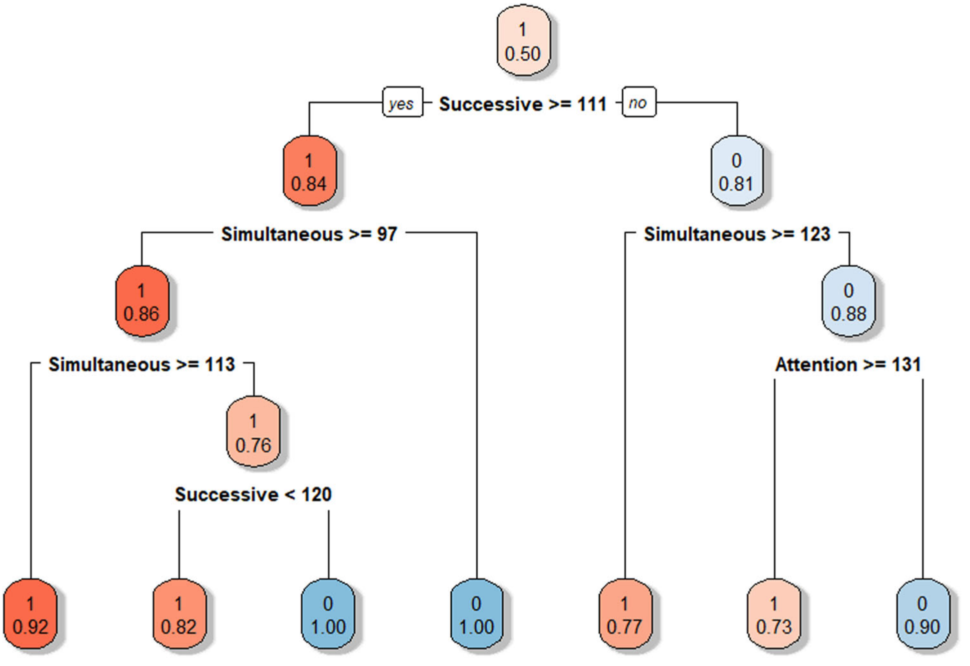

FIGURE 2 Decision tree of the PASS scores in predicting gifted students in reading. Note: 1 = superior; 0 = not superior; the values at the bottom of red and blue boxes are the probability of a student falling into 1 = superior or 0 = not superior status, respectively. PASS, planning, attention, simultaneous, and successive processing [Color figure can be viewed at wileyonlinelibrary.com]

The multiple regression model predicting Broad Math scores also explained a significant proportion of total variance (44%); $F(4, 1201) = 233.26$, $p < .001$. The effects of all PASS standard scores were positive and statistically significant at the significance level of $\alpha = .05$. Based on the standardized regression coefficients (β), simultaneous processing and planning appeared to be the strongest predictors of broad math. Overall, these findings suggest that the PASS processes can be used as predictors of students' performance in reading and mathematics.

7.2 | Classification and regression trees

To answer our second research question, we performed CART analyses. Figures 2 and 3 show the classification trees generated for reading and math, respectively. Each tree starts with a root at the top and then splits into multiple branches based on a PASS scale's score. The leaf nodes (i.e., colored boxes) show predicted superior status (1 = superior; 0 = not superior) and the probability of that status for the predicted status. Each red box represents 1 = superior; whereas each blue box represents 0 = not superior. Within the boxes, the values at the bottom indicate the probability of a student falling into either superior or not superior category given the PASS score conditions in the branches (e.g., simultaneous ≥113 in Figure 2). Furthermore, each tree splits into multiple branches where the left branches indicate the PASS score condition being met; whereas the right branches indicate the PASS score condition not being met. For example, the branches on the left-hand side of Figure 2 show that a student whose scores in successive processing and simultaneous processing are larger than 111 and 113, respectively would have an 92% probability of being superior in reading (shown as "1" in the figure). A similar interpretation can be made for the left-hand side of Figure 3. An individual whose scores in simultaneous

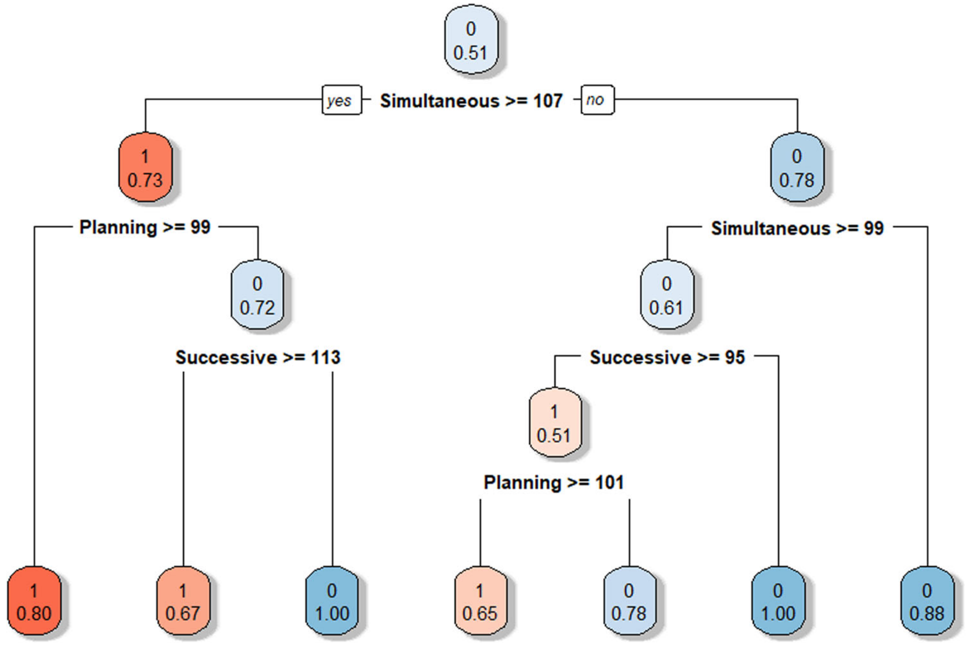

FIGURE 3 Decision tree of the PASS scores in predicting gifted students in math. Note: 1 = superior; 0 = not superior; the values at the bottom of red and blue boxes are the probability of a student falling into 1 = superior or 0 = not superior status, respectively. PASS, planning, attention, simultaneous, and successive processing [Color figure can be viewed at wileyonlinelibrary.com]

processing and planning are larger than 107 and 99, respectively would have an 80% probability of being "superior" in mathematics (shown as "1" in the figure).

To examine how accurate a model with PASS processes is in predicting membership to superior reading or mathematics groups, we inspected the classification accuracy indices for the CART models generated for reading and math (see Table 4). The overall accuracy of the classification was rather similar between the two academic domains (89% for reading and 82% for math). The CART model for reading had high values for both sensitivity and specificity, suggesting that the model performs quite well at detecting both "superior" status and "not superior" status. The CART model for math was stronger in detecting the "superior" status (i.e., higher sensitivity) than in detecting the "not superior" status (i.e., specificity). Overall, both CART models had a decent rate of accuracy in classifying "superior–not superior" readers and mathematicians given that we had only a limited number of predictors (notice that similar coefficients have been reported in the literature when predicting membership to poor/at-risk vs. not-poor/not at-risk readers' groups; see Adlof et al., 2010; Catts et al., 2016). Further analysis of the CART models indicated that successive and simultaneous processing were the strongest predictors of superior reading performance, while the other two processes were relatively less influential. For math, simultaneous

TABLE 4 Classification evaluation indices for the estimated CART models for reading and math

Subject	Accuracy	Sensitivity	Specificity	Kappa
Reading	0.89	0.92	0.86	0.77
Math	0.82	0.91	0.74	0.64

Abbreviation: CART, classification and regression tree.

processing and planning were the strongest predictors while the other two processes (attention and successive processing) seemed to be less important in the prediction process. These findings align well with the previous findings from the multiple regression analyses.

8 | DISCUSSION

The objective of this study was to examine whether PASS processes could be used to predict superior academic performance. This is important in light of the dispute around the role of IQ in high achievement (e.g., Naglieri, 2008; Rowe et al., 2012) and the ever-increasing attention of research to the role of neurocognitive processes (e.g., Naglieri & Otero, 2018). Our results showed that the four PASS processes were significantly related to both reading and mathematics and could accurately classify the children in the superior or non-superior categories. Simultaneous and successive processing were the strongest of the four neurocognitive processes in predicting superior reading performance (see Dunn et al., 2019, for similar findings) and simultaneous processing and planning were the strongest of the four in predicting superior mathematics performance (simultaneous processing was important in Iglesias-Sarmiento et al.'s, 2020, study as well).

The same set of cognitive processes has been found to predict individual differences in reading or mathematics performance in the general population (e.g., Das et al., 2008; Georgiou et al., 2015; Kroesbergen et al., 2010; Papadopoulos, 2001) and in children with reading or math disabilities (e.g., Cai et al., 2013; Das et al., 2007; Joseph et al., 2003; Kroesbergen et al., 2003). This suggests that the same cognitive processes can explain individual differences across the continuum of reading or mathematics performance. At the same time, these findings suggest that there is diversity in the role of PASS processes in reading and mathematics. Obviously, successive processing is important in decoding and simultaneous processing is important in seeing the whole picture when reading passages, which then supports reading comprehension. In turn, planning is important in problem solving where children must come up with a plan on how to answer the problem (and revise it if it proves to be ineffective), and simultaneous processing is important in seeing similarities between problems and in integrating information from different problems into a whole.

The fact that simultaneous processing predicted both Broad Reading and Broad Math is interesting in view of discussions around the role of fluid-crystallized abilities in academic achievement (see Cattell, 1971; Kaufman et al., 2009; Zaboski et al., 2018). We argue here that the fluid-crystallized division has less explanatory power than Simultaneous and Successive processing, if only because the concept of crystallized intelligence is confounded mostly by knowledge. In addition, from PASS theory we posit that Simultaneous processing predicts both Broad Reading and Broad Math because the essential characteristic of Simultaneous processing is processing of logical–grammatical relationships that is integral to both reading comprehension and problem solving (Das et al., 1979).

Our results have significant psychoeducational implications. First, given that CAS offers a culturally fair way of assessing cognitive abilities (e.g., Das et al., 2013; Naglieri et al., 2013), this means we can assess children of diverse linguistic backgrounds and predict their group membership without being constrained by the verbal demands of popular IQ tests (e.g., WISC). Second, assuming superior academic performance is one way of identifying gifted and talented children (see Footnote 2), our results suggest that scores in the four PASS processes can be used to identify students who would likely do very well in reading and math. Clearly, this is an area of future research using the most recent editions of CAS and WJ. Finally, given that encouraging students to more effectively use their PASS cognitive processes is associated with improved academic performance (e.g., Iseman & Naglieri, 2011; Mahapatra et al., 2010; Naglieri & Johnson, 2000), knowing the PASS scores of superior readers or mathematicians may have instructional implications. Cognitive stimulation has been at the forefront of many intervention studies with gifted children (e.g., Smutny, 2003; Venville & Oliver, 2015). If we know that Simultaneous Processing and Planning are important predictors of mathematics in high achieving children, then we can develop programs to stimulate children's Simultaneous Processing and Planning. Naglieri and Johnson (2000), for example, showed that engaging children in self-reflection and verbalization of strategies about how an arithmetic computation problem could be solved improved both their planning and arithmetic computation performance.

Some limitations of the present study are worth mentioning. First, our study is correlational and any associations do not imply causation. Here, the term prediction refers to the statistical relationship of scores obtained at the same period of time, not prediction over time. Second, we used the data that were collected as part of the standardization of CAS in 1997 (Naglieri & Das, 1997). Although a few changes have been made to both CAS and WJ since then, our goal here was to examine the utility of the PASS constructs notwithstanding which version was used. Notice also that the scores in CAS and CAS2 correlate 0.88 with each other. Third, our findings are based on data collected in US and may not generalize in other countries or languages. Finally, another limitation to consider is the complexity of using PASS as opposed to traditional IQ, such as the WISC-V to inform gifted eligibility determination when an individually administered test of intelligence is desired. Naglieri et al. (2009) described gifted students as those who have potential (i.e., high intellect) and could achieve advanced academic skills if they were afforded the opportunity to learn, regardless of the amount of knowledge they may have at the time. The current results suggest that students with very high PASS scores would likely also have high achievement, but we anticipate that those from disadvantaged background would likely have poor academic skills but could still have high PASS scores. This would likely result in lower scores on measures of vocabulary, information, word similarities and arithmetic word problems included in traditional IQ tests. In these instances, PASS and traditional IQ scores could be very different (see Naglieri & Rojahn, 2001) and would require careful interpretation. We suggest that a gifted student with high PASS scores would indicate potential to learn and gifted instruction tailored to the student's needs would be appropriate. This is a topic for future research.

To conclude, our findings add to a growing body of research on the role of PASS cognitive processes in academic performance (e.g., Das et al., 2008; Georgiou et al., 2015; Joseph et al., 2003; Kroesbergen et al., 2010; Papadopoulos, 2001) suggesting that they can predict superior performance at least as good or better than other intelligence tests (e.g., Rowe et al., 2012; see also Hodges et al., 2018). However, using PASS scores to predict superior reading or mathematics performance has an added benefit; that PASS processes are rooted to a theory of intelligence (Luria, 1966) with close links to instruction (see Das & Misra, 2015). A future study may explore the effects of a cognitive intervention study based on PASS processes in children with superior reading and mathematics performance.

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APPENDIX

Below we describe the 12 measures used to operationalize the four PASS processes in CAS (Naglieri & Das, 1997).

Planning

Planning was measured with matching numbers, planned codes, and planned connections. In matching numbers, children were presented with four pages comprised of eight rows of numbers that increased in length. For each row, children were instructed to underline the two numbers that looked alike, as quickly as possible. In Items 1–3, children were allowed 150 s to complete the task and in Item four 180 s. One point was given for each correct pair of matched numbers with a maximum score of eight on each item. The time and number of correct matches for each item was added and converted to a ratio score to obtain a subtest score. In planned codes, children were asked to fill in as quickly as possible, and by using any strategy of choice (e.g. left to right, top to bottom, randomly), empty boxes with a combination of O's and X's printed on top of an empty box that each corresponded to a letter (e.g. A = XO, B = XX, C = OX, D = OO). The task contained two pages, each with a distinct set of codes arranged in seven rows and eight columns. A legend located at the top of each page indicated the combination of O's and X's that corresponded to each letter. Children were given 60 s to fill in as many empty boxes as possible. The time and number correct for each page were recorded and combined to obtain a ratio score. The ratio score was then converted to a subtest scaled score. In planned connections, children were asked to connect sequential stimuli. In Items 1 and 2, children were asked to connect numbers (1–25) that were semi-randomly arranged on a page. In Item 3, children were asked to connect 25 numbers (1–25) and 25 letters (A–Z) in successive order (1, A, 2, B, 3, C). The subtest score was the total time to complete all three items.

Attention

Attention was measured with expressive attention, number detection, and receptive attention. In expressive attention, children were given 180 s to complete ach item on three consecutive pages of increasing difficulty. On the first page, children were asked to read a sequence of color words (i.e., Blue, Yellow, Green, and Red) arranged in quasi-random order. On the next page, children were asked to name the color of a series of blocks printed as the colors mentioned on the previous page. On the final page, color words were printed in a color different from the word's name (e.g., the word green may appear in yellow ink). Children were then required to name the color of ink in which the word was presented (e.g., Blue appearing in red ink is read as “Red”). The time and number correct for each page were recorded and combined to obtain a ratio score. The ratio score was then converted to a subtest scaled score. In number detection, children were asked to identify as quickly as possible target numbers (i.e., the numbers 1, 2, and 3 printed in an open font) among distractors (i.e., the same numbers printed in a different font). The task contained two pages each with a 150 s time limit to complete. On the first page, children were asked to underline the target numbers 1, 2, and 3 arranged on a page that contained numbers 1 to 6 written in various fonts. Those numbers that were different from 1, 2, and 3 or the incorrect font were to be ignored. On the second page, children were required to underline the same numbers among distractors—4, 5, and 6 written in bold font. The time and number correct (total number correct minus the number of false detections) for each page were recorded and combined to obtain a ratio score. The subtest ratio score was then converted to a subtest scaled score. In receptive attention, children were asked to identify as quickly as possible target pairs of letters among distractors (i.e., the same letters printed in a different font). The time and number correct (total number minus the number of false detections) for each page were recorded and combined to obtain a ratio score. The subtest ratio score was then converted to a subtest scaled score.

Simultaneous processing

Simultaneous processing was measured with nonverbal matrices, verbal-spatial relations, and figure memory. In nonverbal matrices, children were presented with a variety of shapes and geometric designs that were spatially and logically interrelated within a visual matrix. For each item, children were required to decode the relationships and choose from a list of six possible answers to complete the picture. The task consisted of 33 items and was discontinued after four consecutive errors. The subtest score was the total number of correct answers. In verbal-spatial relations, children were presented with six drawings (pictures of objects and shapes) and with a printed question that was dictated by the examiner (e.g. Which picture shows a circle to the left of a cross under a triangle above a square?). Given a 30 s time limit to respond to each item, children were instructed to identify the correct drawing from a selection of six choices. The test consisted of 27 items and was discontinued after four consecutive errors. The subtest score was the total number correct. In figure memory, children were presented with geometric designs, such as a triangle or a square, one at a time for a period of five seconds each. Following the presentation of a target design the child was given a more complex design in which the target design was embedded. The child then was asked to use his color pencil to outline the original target. The test consisted of 20 items and was discontinued after four consecutive errors. The subtest score was the total number of items correctly reproduced.

Successive processing

Successive processing was measured with word series, sentence repetition, and sentence questions. In Word Series, children were read a series of single-syllable, high frequency words, varying in length from four to nine words: “Book,”“Car,”“Cow,”“Dog,”“Girl,”“Key,”“Man,”“Shoe,” and “Wall,” and then asked to repeat the words in the same order. The test consisted of 27 items and was discontinued after four consecutive errors. The subtest score was the total number of correctly repeated word series. In sentence repetition, participants were read 20 sentences aloud and then required to repeat each sentence verbatim. The sentences consisted of color words (e.g., the blue is yellowing) and increased in length from 4 to 19 words. The number of sentences repeated correctly was recorded. The test consisted of 20 items and was discontinued after four consecutive errors. The subtest score was the total number of correctly repeated sentences. Finally, in sentence questions, children had to answer questions about the same nonsensical sentences that were used in the Sentence Repetition task (e.g., The blue is yellowing red. Who is yellowing red?). The children could use syntactic cues but no semantic cues to answer the questions. The task was discontinued after four consecutive errors. The subtest score was the total number of correctly answered questions.