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Developmental Differences in Classifiers of Low and High Mathematics Performance: A Classification and Regression Tree Analysis

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Supplementary Materials: Code, Materials [see Index of Supplementary Materials]

Abstract

Background: Given the contribution of domain-general and domain-specific skills to children's mathematics performance and the importance of children's early mathematical skills for future success, it is imperative to determine and compare the predictive skills that classify children's mathematical performance. Previous efforts examining classifiers of mathematics performance have focused on development within a year (e.g., preschool; Purpura et al., 2017) or general predictive relations (e.g., Jordan et al., 2002). The question remains whether the classifiers of low and high mathematics performance differ across multiple years.

Method: The current study used data from a longitudinal project that assessed children on a number of academic and behavioral measures across four time points spanning preschool and kindergarten. The analytic sample for this study consisted of 322 children (T1 M_{age} = 4.81 years; *SD* = 0.30; 50.6% female) from three cohorts.

Results: Prior mathematics performance was the most consistent classifier for low and high mathematics performance at the end of kindergarten. Broad school readiness at the beginning of preschool was also a consistent classifier of low and high mathematics at the end of kindergarten. A consistent classifier of only low mathematics performance at the end of kindergarten was behavioral self-regulation skills in the spring of preschool. Further, reading skills at the beginning of kindergarten were a consistent classifier of only high mathematics performance.
Conclusion: Findings can guide researchers and educators in identifying the important skills at different developmental periods in early schooling to support children at risk of low mathematics performance or those with exceptionally high mathematics performance.

Keywords

low and high math performance, CART, developmental differences

Individual differences in early mathematical skills are evident as early as preschool and are strong predictors of later mathematical skills (Clements & Sarama, 2007; Duncan et al., 2007; Watts et al., 2014) and college attendance (e.g., Davis-Kean et al., 2022). Given that early mathematical skills lay the foundation for later mathematical skills and achievement, to best support positive development, it is important to understand which skills and abilities (both domain-specific and domain-general) are related to low and high mathematical performance early in childhood. Identifying classifiers of both extremes of mathematical achievement could provide evidence to guide effective, high-quality, differentiated early mathematical instruction and intervention.

Prior research examining differences in mathematical performance has found domain-general (e.g., working memory), domain-specific (e.g., verbal counting), and overlapping (e.g., mathematical language) skills to be predictive of later mathematical achievement (Koponen et al., 2019; Kroesbergen & van Dijk, 2015; Purpura & Ganley, 2014; Purpura, Logan, et al., 2017). However, these efforts examining classifiers of mathematical status have focused on specific developmental periods (Purpura, Day, et al., 2017) or general predictive relations (e.g., Jordan et al., 2002). The current study addresses longitudinal domain-specific and domain-general predictors of children's mathematical skills at the end of their first formal school year (i.e., kindergarten) and uses classification and regression trees (CART) as a data-driven, nonparametric approach to identify classifiers of later low and high performance in mathematics. We focus specifically on mathematics achievement at the end of kindergarten, as children who continue to demonstrate low mathematical performance after a year of kindergarten instruction may require additional support to build foundational skills prior to formal arithmetic instruction in first grade (Jordan et al., 2009).

Developmental Periods

Children's mathematical skills in kindergarten are important for later mathematical achievement (e.g., Jordan et al., 2009). Using sequential process growth curve models across five time points from first through third grade, Jordan et al. (2009) found that kindergarten number sense predicted later mathematics achievement while accounting for child age, gender, and family income. However, even before that, preschool skills predict later mathematics outcomes throughout childhood and adolescence. For example, Watts et al. (2014) demonstrated that preschool mathematics predicted achievement in second grade, fifth grade, and at age 15, even after controlling for a broad set of child and family characteristics, including early reading skills, vocabulary, attention, general cognitive skills, behavior ratings, demographic factors, and home environment quality. Taken together, these findings suggest that early mathematics skills follow a developmental trajectory, meaning that early competencies provide a foundation that supports subsequent skill acquisition over time. Although prior work has examined this trajectory longitudinally, given children's rapid skill development, more assessments over a shorter time frame are needed to better understand these periods (e.g., the beginning of preschool and the end of kindergarten).

One essential question yet to be addressed by prior research is whether classifiers of high or low mathematical performance at the end of kindergarten (6 – 8 years old) change from the beginning of preschool (3 – 5 years old), end of preschool (4 – 6 years old), or beginning of kindergarten (5 – 7 years old)? Addressing these questions can provide teachers and practitioners with more information about which types of activities or instruction may be most appropriate for a specific developmental period. Thus, an important contribution of including multiple developmental time points across multiple years would be to provide more precise information regarding appropriate developmental instruction. For example, Purpura, Day, et al. (2017) found that children's mathematical language skills at the beginning of preschool were an important predictor of low mathematics performance at the end of preschool. However, a different cognitive skill (other than mathematical language) at the end of preschool may serve as an important classifier for mathematics at the end of kindergarten. Therefore, examining multiple developmental time points will be informative about which skills to focus on and when.

Predictors of Mathematics Performance

Given that early childhood mathematics performance is predictive of later college attainment (e.g., Davis-Kean et al., 2022) and income (Rose & Betts, 2004), it is important to identify best practices for promoting positive mathematical development early on in a child's life. Research on children's reading skills has used information to specifically target important predictors of later reading in early childhood (Carlisle, 2003; Tyler et al., 2002). However, unlike reading research, less is known about the specific skills that inhibit or advance children from succeeding in mathematics. Not necessarily the skills that predict mathematical giftedness or disabilities, but the skills that may hinder or advance children on a typical trajectory. With information about domain-specific and domain-general skills that contribute to mathematics, we can better specify which skills are most important at particular developmental periods, informing learning trajectories that support children who may struggle. Understanding these predictors is especially important in the context of socioeconomic differences in early mathematics, as children from lower-income backgrounds tend to show lower average performance (Purpura & Reid, 2016; Starkey et al., 2004) but substantial heterogeneity in developmental pathways (Jordan et al., 2009), highlighting the need to identify skills that may serve as targets for early intervention and support.

Although much of the literature focuses on predictors of low mathematics achievement (Jordan et al., 2002; Purpura, Day, et al., 2017), evidence also suggests that high mathematics performance is associated with early domain-general (e.g., executive function; Ribner et al., 2023), domain-specific (e.g., numeracy; Nguyen et al., 2016), and overlapping skills (e.g., mathematical language; Purpura, Day, et al., 2017). Importantly, predictors of high performance may reflect both areas for intervention and the presence of qualitatively distinct strengths, emphasizing the need for analytic approaches that identify classifiers across the full distribution of mathematics achievement.

Domain-General Skills

Differences in learning mathematics can often be explained by various cognitive skills (Jordan et al., 2002; Mazzocco & Myers, 2003; Purpura, Day, et al., 2017). Domain-general skills have been linked to general mathematical performance, including children's executive function (Ahmed et al., 2019), language (Xenidou-Dervou et al., 2015), and general school readiness (Duncan et al., 2007). Children's executive functioning and behavioral self-regulation skills include cognitive processes that allow children to inhibit, pay attention to, and remember a task at hand (Diamond, 2013; Miyake et al., 2000), which are particularly important for solving mathematical problems (Devlin et al., 2024; McClelland et al., 2007). For example, Ribner et al. (2023) found that children who started kindergarten with higher levels of executive function skills also developed math skills faster through second grade, suggesting that children who enter school with high executive function but low math skills may be able to catch up to their peers. Language skills, or the linguistic pathway, provide the foundation for children's mathematics development, connecting non-symbolic and symbolic development (LeFevre et al., 2010; Scalise & Purpura, 2022). Finally, children's abilities, as assessed by a general school readiness assessment (e.g., letter knowledge, number knowledge), have been shown to predict children's readiness ratings and teachers' decisions to retain or refer for services (Panter & Bracken, 2009). We conceptualize school readiness as a domain-general composite. Although some items involve number knowledge, they serve as indicators of broad cognitive preparedness rather than domain-specific math skills.

Domain-Specific Skills

Children's prior mathematics knowledge is a strong classifier of later mathematics achievement (Devlin et al., 2022; Purpura, Day, et al., 2017). Broadly, prior mathematics skills can be assessed by measuring the same skills at a previous time point to capture time-varying differences in those skills. However, this can also include a more fine-grained approach to understanding children's mathematical trajectories. For example, components of children's numeracy skills (i.e., cardinality, ordinality) are especially important for general mathematical development, such that children's numeracy skills serve as a prerequisite for understanding more complex or advanced mathematics (Aunio & Niemivirta, 2010). Evidence suggests that these numeracy components may be particularly predictive during the preschool years (e.g., Duncan et al., 2007), when children are transitioning from informal to more formal numerical understanding, and may function differently as children enter kindergarten and receive formal mathematics instruction (e.g., Rittle-Johnson et al., 2017). Thus, beyond the same assessment, numeracy skills may play a role in classifying children's later general mathematical performance.

Overlapping Skills

Finally, mathematical language may be conceptualized as an overlapping skill as it combines key mathematical concepts with precise verbal terms (Purpura & Reid, 2016; Purpura et al., 2019). Mathematical language refers to the broader linguistic framework used to express mathematical ideas, relationships, and reasoning (Purpura et al., 2019). It includes words, phrases, and structures that describe quantities (e.g., more, fewer, many), relationships (e.g., before, after, in front of, below), comparisons (e.g., less than, greater than), and sequences (e.g., first, second, third). These terms often serve a relational function, connecting objects, quantities, and concepts rather than naming them directly. Specifically, research supports the theory that mathematical language provides children with a potential connection between nonsymbolic and symbolic mathematics understanding (Scalise & Purpura, 2022).

A previous study examined preschool classifiers of both high and low future mathematical achievement from a range of factors, including non-symbolic mathematics skills, executive functioning, and language performance (Purpura, Day, et al., 2017). In that study, children were assessed in the fall of preschool on a battery of predictors, which were used to classify mathematics performance in the spring of the same year using classification and regression tree analyses. Constructs were operationalized to capture multiple aspects of early development, including domain-general, domain-specific, and overlapping skills. Findings suggested that the most common predictors of children's later low mathematics performance for younger children (ages 3-4) were prior general mathematics, mathematical language, print knowledge, and response inhibition assessments, whereas for the older children (ages 4-5), the most common predictors were prior general mathematics, mathematical language, and definitional vocabulary. By conducting separate analyses by age group, Purpura, Day, et al. (2017) demonstrated that skill classification differed developmentally, with mathematical language emerging as a consistent classifier across both age groups beyond prior mathematics. Further, Hornburg et al. (2024) also found that math language in the fall of preschool predicted development in most early numeracy skills in the spring of the same year. Together, this evidence suggests that mathematical language skills may serve as a risk classification for both low and high mathematics performance during early childhood.

Classification of Low Mathematics Performance Using Classification and Regression Tree Analyses

Classification and regression tree (CART) analyses present an ideal modeling approach for identifying children at the high and low ends of mathematics performance. CART is a technique that uses recursive partitioning to create more alike groups of children from a larger sample using a range of skills as predictor variables (Gruenewald et al., 2008). Unlike multivariate regression, CART models create data-driven split points (or nodes) based on a continuous outcome variable to partition it into categories such as “high risk” and “low risk.” These models are inherently non-parametric; thus, they can include any number of possible predictors (Lewis, 2000).

Importantly, CART is designed for prediction and classification rather than modeling relations among constructs (Strobl et al., 2009). This approach allows for the identification of complex interactions and nonlinear relations among predictors without requiring these to be specified a priori, which would be necessary in approaches such as structural equation modeling. Because CART is data-driven, it identifies combinations of predictors that best classify outcomes based on observed data and detects meaningful cut points that may not be captured using traditional continuous modeling approaches.

Finally, CART also facilitates communication through its tree format (see Figure 1), allowing teachers and practitioners to better translate results into practice and determine which skills are more important than others for classifying math ability. In Figure 1, the full sample of 140 children was first split based on Bracken. Children with a score of 41 or lower had the lowest average mathematics score (Terminal Node 1), whereas children with a score above 58 on Bracken and above 32 on HTKS had the highest average mathematics score (Terminal Node 5).

Given the benefits of CART as a methodological approach for identifying risk classifiers, it is not surprising that prior work has leveraged this technique. Specifically, CART has been used in both mathematics and reading. Some studies have used CART analyses to determine classifiers of reading difficulties (Compton et al., 2006; Koon et al., 2014). Notably, Purpura, Day, et al. (2017) used CART to determine predictors of high and low mathematics performance between fall and spring of preschool. Finally, other studies have found that CART results are consistent with logistic regression results when more potential predictor variables are considered, and fewer assumptions are made about the model framework (Koon & Petscher, 2015).

Current Study

The current study extends Purpura, Day, et al. (2017) by examining predictors across multiple developmental time points spanning preschool through kindergarten in an independent sample and builds upon previous research examining classifiers of later low and high mathematics performance in early childhood. Given that prior research has been limited by developmental timing (Jordan et al., 2002; Purpura, Day, et al., 2017), this study specifically extends prior work by using four (rather than two) developmental time points across years to identify classifiers of low and high mathematics performance. Notably, these four time points span the early years of children's educational experiences in the United States and capture the critical transition from preschool to kindergarten: fall of preschool (Time 1), spring of preschool (Time 2), fall of kindergarten (Time 3), and spring of kindergarten (Time 4). All children were assessed on the same battery of measures at each time point (with math performance as the outcome at Time 4), but the developmental timing of these assessments allows us to examine how predictors operate differently across educational transitions. To do this, we examined three CART analyses that differed in the range of time points. The first assessed classifiers of initial school entry skills (using data from Time 1 to Time 4). The second assessed classifiers of kindergarten readiness skills (Time 2 to Time 4). The final assessed classifiers of kindergarten entry skills (Time 3 to Time 4). Based on results from Purpura, Day, et al. (2017), we expected children's previous mathematics achievement and mathematical language skills (domain-specific and overlapping) to be consistent classifiers of later low mathematical skills across all time points; however, we did not explicitly expect this to differ from high mathematical skills. Further, given results from Purpura, Day, et al. (2017) suggesting that classifiers differ by children's age, we also expected domain-general classifiers to differ across time points for both high and low mathematical skills.

Method

Participants

Data came from a larger study evaluating a state-funded preschool program that was approved by the Institutional Review Board [#1807020801] and represents a quasi-experimental study in which a state-developed preschool program was designed to offer high-quality early education to children from families with low incomes. However, there were no significant differences in outcomes between the treatment and control groups, so we combined them into a single sample in this study. The original study consisted of N = 684 children; however, CART methods require complete case analysis, resulting in listwise deletion of all variables included in the models up to the final time point. As reported in studies using the same dataset, the data met the criteria for missing at random (Ehrman et al., 2025). Thus, the present sample included 322 children (50.6% female) from three cohorts (i.e., year of entry into preschool 2015, 2016, and 2018, respectively). To participate in the original study, all children's families met an income-eligibility requirement of a family income at or below 127% of the federal poverty level. At the first time point (fall of preschool), children ranged in age from 3.74 to 5.45 years (M_{age} = 4.81 years; SD = 0.30). Per the parent report, the sample was 41% Black or African American, 35.1% White, 12.4% Hispanic or Latine, 10.5% multiracial, and 1% Asian. Further, children had no known diagnoses of developmental, neurological, or sensory differences.

Procedure

Children were assessed at four time points: the fall and spring of preschool and kindergarten. The time between assessments during the school year was approximately 6 months (M = 5.56 months; SD = 0.79 months). Executive function, global school readiness, early literacy, receptive vocabulary, mathematical language, and early numeracy variables were each assessed at the first three time points following the same procedure at each time point. Early mathematics was assessed at all four time points following the same procedure at each time point. Assessments were administered one-on-one by a trained research assistant in a quiet area at the child's school.

Measures

Early Mathematics

Woodcock-Johnson Applied Problems (WJAP) — The Applied Problems subtest from the standardized Woodcock-Johnson IV Tests of Achievement battery (Schrank et al., 2014) assessed mathematics achievement, including counting, addition, and subtraction. Children solved practical problems by answering questions about pictures or word problems. A stop rule was applied, and the assessment was discontinued after five consecutive incorrect responses. We used children's raw scores as a measure of mathematics performance in the spring of kindergarten. We do not have item-level data for this study; however, the Applied Problems has demonstrated high reliability, with a median reported Cronbach's alpha of α = 0.89 (Villarreal, 2015).

Preschool Early Numeracy Skills (PENS) — The Preschool Early Numeracy Skills-Brief Version (Purpura et al., 2015) assessed early numeracy knowledge. Twenty-five items on the PENS are ordered by difficulty and cover content, including set comparisons, number order, cardinality, ordinality, numeral identification, and number combinations. Children were either shown a picture and asked to point to a correct response or to give a verbal response, and the assessment was discontinued after three consecutive incorrect responses. Children received a point for every correct answer, with a maximum score of 24, since the first question was not included in the total because it asked how high a child could count and was therefore not dichotomous. Raw scores were used for analysis instead of aged norms because the study from which these data came used the pre-published version of the PENS-B, and norms could not be calculated. Internal consistency was high across time points for this sample, with α = .89 in the fall of preschool, .90 in the spring of preschool, and .84 in the fall of kindergarten. The first item is not included in the total score, so a possible score of 0 to 24 was used.

Executive Function

Head-Toes-Knees-Shoulders (HTKS) — The Head-Toes-Knees-Shoulders task measured children's behavioral self-regulation (McClelland et al., 2014). The task taps all three components of executive function (inhibitory control, cognitive flexibility, and working memory) through overt behavior. Children were asked to participate in a game where they paired combinations of rules ("*touch your head," "touch your toes," "touch your knees,"* and "*touch your shoulders"*) for a practice round and three testing sections. Children were first asked to respond to the directions naturally, then were asked to respond in an opposite way (e.g., to touch their heads when the assessor says, "*touch your toes*"). They received feedback for practice items. The testing sections consisted of 10 items each and grew increasingly complex. Children had to correctly answer at least 4 items in a testing section to move on to the next section. Each item was scored as 0 if the child was incorrect, 1 if the child self-corrected after being incorrect, or 2 if the child was correct. Internal consistency was high across time points for this sample, with α = .98 in the fall of preschool, α = .97 in the spring of preschool, and α = .97 in the fall of kindergarten. To increase scale variability, we used a sum score that included practice items.

Day-Night Stroop (DNS) — The Day Night Stroop task primarily measures the inhibitory control component of executive function (Gerstadt et al., 1994). Children were shown a card with a picture of either a sun or moon and were asked to say the opposite (i.e., saying "day" when shown the moon and "night" when shown the sun). Each item was scored as 0 if the child was incorrect, 1 if the child self-corrected or provided a response that was similar to the correct response (e.g., saying "sun" instead of "day"), and 2 if the child was correct. Internal consistency was high across time points for this sample, with α = .92 in the fall of preschool, α = .91 in the spring of preschool, and α = .91 in the fall of kindergarten.

Early Literacy and Vocabulary

Get Ready to Read (GRTR) — The Get Ready to Read was used to assess emergent literacy skills (Lonigan & Wilson, 2008). Children were shown a page with four pictures and asked to point to the correct response after a verbal prompt. Items on the measure were focused on print knowledge (e.g., “Find the picture that has letters in it”) and phonological awareness (e.g., “Find the one that rhymes with arm”). Internal consistency was high across time points for this sample, with α = .82 in the fall of preschool, .85 in the spring of preschool, and .78 in the fall of kindergarten.

Woodcock-Johnson Letter-Word Identification (LWID) — The Letter Word Identification subtest from the standardized Woodcock-Johnson IV Tests of Achievement battery (Schrank et al., 2014) was used to assess early literacy skills. Children were asked to identify letters and read words for 76 total possible items, and a stopping rule was applied after six consecutive incorrect responses. We used children’s raw scores as a predictor of mathematics performance in the spring of kindergarten. Similar to Applied Problems, we do not have item-level data for this study; however, in prior work, the LWID demonstrated strong internal consistency (α = .84-.94 [Villarreal, 2015]).

Peabody Picture Vocabulary Test (PPVT) — The Peabody Picture Vocabulary Test is a standardized measure of children’s receptive vocabulary (Dunn & Dunn, 2007). Children were shown four pictures and asked to point to the picture that matched a word the assessor said aloud. The assessment was discontinued after eight consecutive incorrect responses. Internal consistency for this sample was high across time points, α = .97 in the fall of preschool, α = .97 in the spring of preschool, and α = .96 in the fall of kindergarten.

Mathematical Language

The Preschool Assessment of the Language of Mathematics was used to assess children’s understanding of comparative (e.g., more, less) and spatial (e.g., near, before) language (Purpura & Logan, 2015; Purpura & Reid, 2016). Children were shown a picture and asked to point to the correct response for 16 items. Internal consistency was acceptable across time points for this sample: α = .79 in the fall of preschool, α = .73 in the spring of preschool, and α = .70 in the fall of kindergarten.

School Readiness

The Bracken School Readiness Assessment was used to measure children’s global school readiness (Bracken, 2002). The measure includes five subtests: colors, letters, numbers, size/comparisons, and shapes. Children were shown four pictures and asked to point to the correct response. A stop rule was applied, and the assessment was discontinued after three consecutive incorrect responses. Internal consistency was high across time points for this sample, with α = .96 in the fall of preschool, .95 in the spring of preschool, and .92 in the fall of kindergarten.

Demographic Variables

In all classification and regression trees, we also included child sex and child age at the time points when predictors were assessed. Both variables were collected via parent reports.

Analytic Strategy

We used CART analyses in IBM SPSS 28.0 to identify predictors of high and low mathematics performance using a data-driven approach. Sum scores of children's executive function, global school readiness, early literacy, receptive vocabulary, mathematical language, and early numeracy, as well as sex and age were used to predict low and high performance in mathematics in the spring of kindergarten. CART analyses consist of both trees and forests (Gruenewald et al., 2008). A tree represents a series of hierarchical decision rules in which the sample is repeatedly split into more homogeneous subgroups based on predictor variables, resulting in terminal nodes that represent groups of children with similar mathematics performance. Each split is selected to maximize differences between groups while minimizing differences within groups. A forest is a collection of trees trained on the same set of predictors but with different random subsamples of the data, allowing for the evaluation of the stability and replicability of classification patterns (Gruenewald et al., 2008). Rather than relying on a single tree, examining a forest of trees reduces the likelihood that results are driven by sample-specific variation. Given the non-parametric nature of CART, a traditional power analysis is not appropriate, as it relies on hypothesis testing. However, SPSS automatically adjusts for multiple comparisons using a built-in Bonferroni correction, as indicated in our syntax (ADJUST = BONFERRONI), which we have made publicly available (https://osf.io/t6dp9/files/52xmu). Accordingly, significance values for both merging and splitting criteria were adjusted using the Bonferroni method.

We generated three forests of 25 trees each: a) predicting mathematics performance in the spring of kindergarten using predictors from the fall of preschool, b) predicting mathematics performance in the spring of kindergarten using predictors from the spring of preschool, and c) predicting mathematics performance in the spring of kindergarten using predictors from the fall of kindergarten. The use of 25 trees per forest follows prior developmental CART applications and provides a balance between model stability and interpretability (e.g., Purpura, Day, et al., 2017). We used split-sample validation by growing a training tree on a randomly selected 60% of participants and replicating it with a test tree on the remaining 40%.

After generating forests of 25 trees for each time point of predictors, we used three criteria to choose the final representative trees for each forest (Day & Dotterer, 2018).

First, we determined whether any trees had a terminal node (i.e., the children with the lowest mathematics scores) that contained less than 10% of the sample. Such trees were cut, as they were determined to be non-replicable. Next, we compared the mean mathematics score in spring kindergarten for children in the lowest terminal node across training and test tree pairs. Those with significantly different mean scores were excluded because they were non-replicable. Finally, we calculated the proportion of variance in mathematics achievement in the spring of kindergarten explained by each test tree. We excluded any that explained a substantially low proportion of variance (20%). For more information about CART, see Breiman and Ihaka (1984) and Purpura, Day, et al. (2017) for a closer example of using CART to classify low mathematics performance.

Results

Classification and Regression Tree Analyses

Descriptive statistics are presented in Table 1. All variables demonstrated adequate variability, with no evidence of floor or ceiling effects. Low mathematical performance was determined by focusing on the terminal node with the lowest mean mathematical score at the end of kindergarten in each individual tree; high mathematical performance was determined by focusing on the terminal node with the highest mean mathematical score. Full trees across all time points are shown in the appendix. Given the data-driven nature of CART analyses, it is best not to rely upon single trees, but rather to consider the entire forest to identify consistent classifiers. In this instance, after the exclusions listed above, there were 23 trees in the forest at the beginning of preschool classifications, 24 at the end of preschool classifications, and 19 at the beginning of kindergarten classifications. See (Ellis, 2026S) for syntax, output, and supplemental materials.

Table 1

Descriptive Statistics

Variable Name	*N*	*Min*	*Max*	*M*	*SD*
Female	322	0	1	.51	.50
Age T1	322	3.74	5.45	4.81	.30
WJAP T1	322	0	20	10.39	3.83
PENS T1	322	0	22	9.81	4.95
MLA T1	322	0	16	10.48	3.31
Bracken T1	322	0	80	49.83	17.39
WJLW T1	322	0	41	7.84	4.70
GRTR T1	322	1	25	14.62	4.95
PPVT T1	322	4	120	70.76	21.47
DNS T1	322	0	32	20.23	8.34
HTKS T1	322	0	90	24.83	26.74
Age T2	322	4.12	5.78	5.23	.29
WJAP T2	322	0	21	12.00	3.58
PENS T2	322	0	24	12.98	5.37
MLA T2	322	0	16	11.94	2.77
Bracken T2	322	0	83	59.20	14.76
WJLW T2	322	0	47	10.67	5.62
GRTR T2	322	2	25	17.31	4.88
PPVT T2	322	14	144	80.87	21.98
DNS T2	322	0	32	22.26	7.25
HTKS T2	322	0	94	37.03	29.38
Age T3	322	4.73	6.48	5.76	.31
WJAP T3	322	3	24	14.80	3.56
PENS T3	322	1	24	17.26	4.70
MLA T3	322	3	16	13.64	2.20
Bracken T3	322	10	85	69.11	10.95
WJLW T3	322	0	52	14.98	7.25
GRTR T3	322	3	25	21.08	3.30
PPVT T3	322	34	140	91.75	20.28
DNS T3	322	0	32	24.94	5.60
HTKS T3	322	0	93	56.44	28.21
WJAP T4	322	5	28	17.43	3.50

Note. T1 = Time 1; T2 = Time 2; T3 = Time 3; T4 = Time 4. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; MLA = Math Language Assessment; WJLW = Woodcock-Johnson Letter Word ID; GRTR = Get Ready to Read; PPVT = Peabody Picture Vocabulary Test; DNS = Day Night Stroop; HTKS = Head-Toes-Knees-Shoulders.

Classifiers at the Beginning of Preschool

Six of the eleven possible variables appeared in at least one pathway when predicting children's low mathematical performance, and eight appeared for high mathematical performance from the beginning of preschool to the end of kindergarten (see Table 2). The most common predictors across all trees were prior mathematics scores (WJAP and PENS) and the school readiness assessment (Bracken). Trees assessing classifiers from the beginning of preschool accounted for 19.98-41.47% of the variance in the end of kindergarten mathematics scores. Tree 5 accounted for the most variance (41.47%) in later mathematics performance (Figure 1). In this tree, a score below 41 on the school readiness assessment was associated with a low mathematics score (14.09), and a score above 58 on the school readiness assessment and above 32 on behavioral self-regulation (HTKS) was associated with a high mathematics score (20.97) at the end of kindergarten. These results suggest that the combination of low levels of prior mathematics achievement and low levels of school readiness skills is a strong classifier at the beginning of preschool for low math performance at the end of kindergarten.

Classifiers at the End of Preschool

At the end of preschool, seven of the eleven possible variables appeared in at least one pathway when predicting children's low and high mathematical performance at the end of kindergarten (see Table 3). All the same variables from the fall of preschool were present except the reading measure (GRTR), and instead, children's behavioral self-regulation (HTKS) and inhibitory control (DNS) skills were included. This time, the most common predictors across all trees were prior mathematics scores (mainly PENS) and low scores on the behavioral self-regulation assessment (HTKS). A consistent classifier of only low mathematics performance at the end of kindergarten was behavioral self-regulation skills (HTKS) at the end of preschool. Trees assessing classifiers at the end of preschool accounted for 29.22-59.37% of the variance in the end of kindergarten mathematics scores. Tree 24 accounted for the most variance (59.37%) in later mathematics performance (Figure 2). In this tree, a score below or equal to 10 on prior mathematics scores (WJAP) in combination with a score below or equal to 10 on early numeracy skills (PENS) was associated with a low mathematics score (12.67), and a score of greater than 15 on early numeracy skills (PENS) and a score above 13 on math language (MLA) was associated with a high mathematics score (21.04) at the end of kindergarten. These results suggest that the combination of low levels of prior mathematics achievement and low levels of numeracy knowledge are strong classifiers at the end of preschool of low math performance, and high mathematics achievement, numeracy knowledge, and math language are strong classifiers at the end of preschool of high math performance at the end of kindergarten.

Table 2

Forest of Trees for Beginning of Preschool Variables Predicting Mathematical Performance at the End of Kindergarten

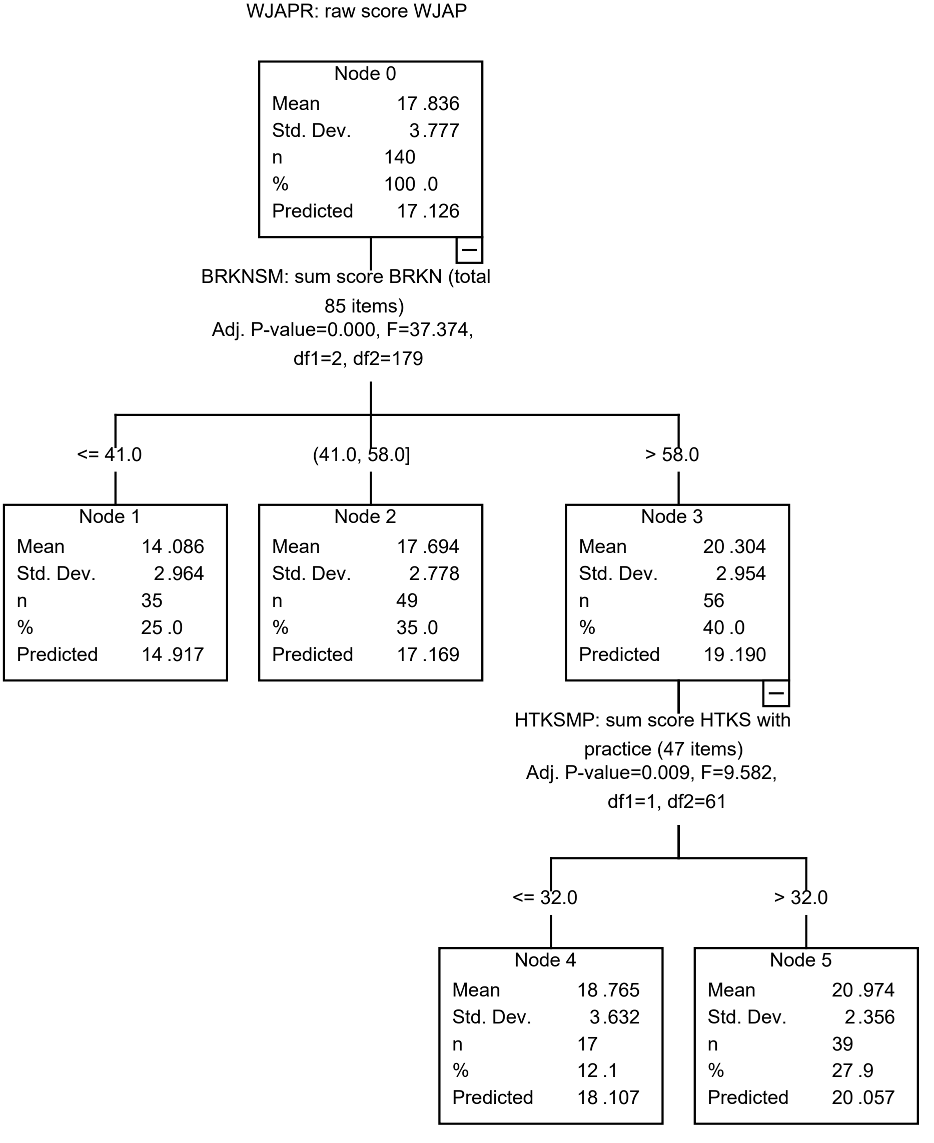
Beginning of Preschool (T1)	*R2*	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of Low Mathematical Performance												
Tree 5	41.47	14.09				≤ 41						
Tree 2	40.25	14.03	≤ 9		≤ 9							
Tree 20	40.17	13.96	≤ 9					≤ 11				
Tree 12	39.15	14.00	≤ 8									
Tree 1	38.06	15.02		≤ 7								
Tree 17	37.95	14.47		≤ 7								
Tree 7	37.83	14.58	≤ 9			≤ 43						
Tree 21	37.79	14.61	≤ 0	≤ 7								
Tree 4	35.89	14.75	≤ 8									
Tree 22	35.19	14.97				≤ 42						
Tree 18	34.78	14.68		≤ 8					≤ 66			
Tree 19	34.75	14.36		≤ 7					≤ 63			
Tree 8	34.50	15.57						≤ 11				
Tree 23	34.04	14.69		≤ 7				≤ 12				
Tree 6	33.38	14.17	≤ 9			≤ 42						
Tree 10	32.68	14.60	≤ 9			≤ 42						
Tree 16	31.16	14.61		≤ 7								
Tree 3	29.45	15.43			≤ 9							
Tree 14	25.96	15.32				≤ 42						
Tree 15	25.87	15.23		≤ 7								
Tree 9	24.51	14.74	≤ 9					≤ 11				
Tree 11	23.58	15.00				≤ 42						
Tree 13	19.98	14.93			≤ 9	≤ 43						

Beginning of Preschool (T1)	*R2*	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of High Mathematical Performance												
Tree 5	41.47	20.97				> 58					> 32	
Tree 2	40.25	20.49	> 11	> 11								
Tree 20	40.17	20.53	> 11	> 11								
Tree 12	39.15	20.63	> 11		> 12							
Tree 1	38.06	21.07		> 11				> 17				
Tree 17	37.95	20.32		> 12							> 32	
Tree 7	37.83	21.04	> 12									
Tree 21	37.79	20.45	> 11	> 11								
Tree 4	35.89	21.00	> 11	> 12								
Tree 22	35.19	19.92				> 60						
Tree 18	34.78	21.47		> 12								
Tree 19	34.75	21.46	> 12	> 11								
Tree 8	34.50	21.07			> 12			> 16				
Tree 23	34.04	21.83	> 12					> 17				
Tree 6	33.38	19.85	> 12									
Tree 10	32.68	20.49	> 11					> 17				
Tree 16	31.16	20.00		> 11						> 26		
Tree 3	29.45	20.08			> 12							
Tree 14	25.96	19.89				> 59				> 26		
Tree 15	25.87	19.55		> 11								
Tree 9	24.51	19.57	> 11						> 77			
Tree 11	23.58	19.35				> 59						
Tree 13	19.98	19.44				> 60						

Note. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; MLA = Math Language Assessment; WJLW = Woodcock-Johnson Letter Word ID; GRTR = Get Ready to Read; PPVT = Peabody Picture Vocabulary Test; DNS = Day Night Stroop; HTKS = Head-Toes-Knees-Shoulders.

Figure 1

The Tree That Accounted for the Most Variance Classifying High and Low Mathematics Performance From the Beginning of Preschool to the End of Kindergarten



Note. WJAP = Woodcock-Johnson Applied Problems; BRKN = Bracken School Readiness ; HTKS = Head-Toes-Knees-Shoulders.

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Table 3

Forest of Trees for End of Preschool Variables Predicting Mathematical Performance at End of Kindergarten

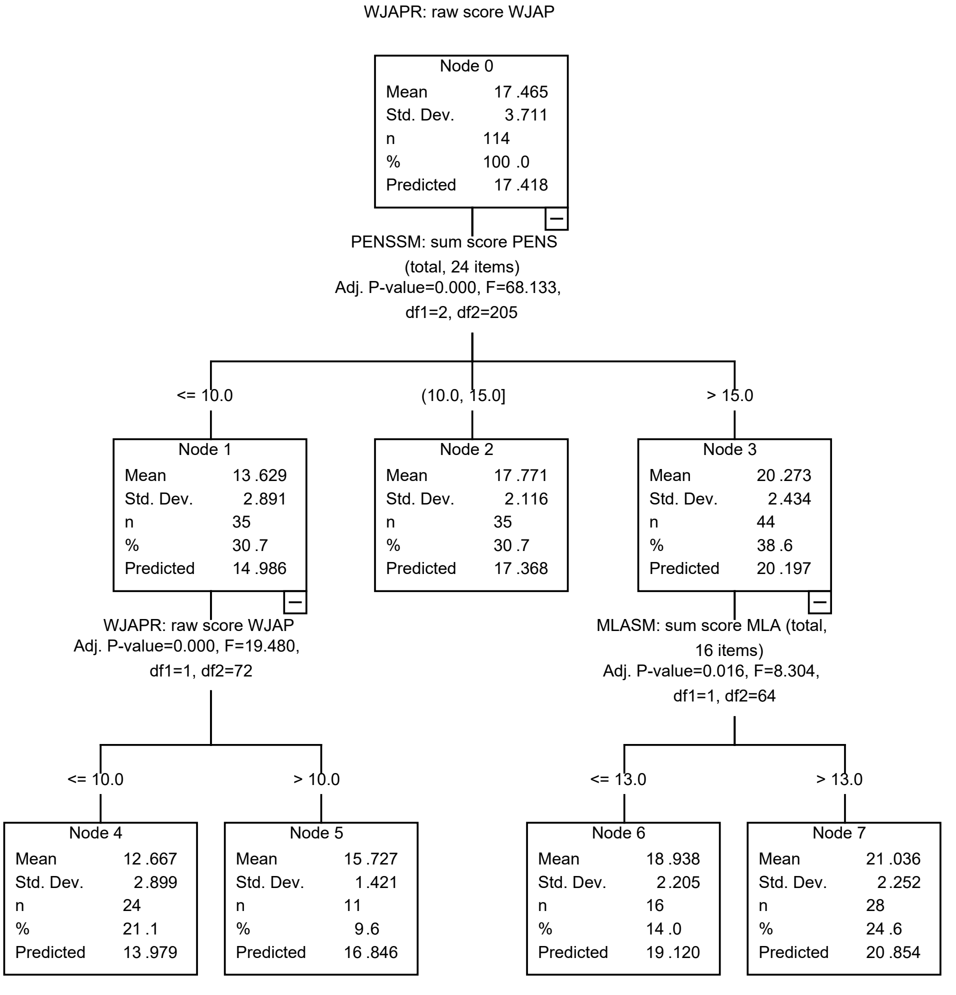
End of Preschool (T2)	R2	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of Low Mathematical Performance												
Tree 24	59.37	12.67	≤ 10	≤ 10								
Tree 15	51.71	13.71		≤ 10							≤ 12	
Tree 21	50.13	13.78		≤ 10							≤ 12	
Tree 19	49.94	14.03		≤ 9								
Tree 18	49.33	13.10		≤ 10							≤ 12	
Tree 1	49.26	13.09	≤ 10	≤ 10								
Tree 3	48.61	13.71		≤ 10	≤ 11							
Tree 13	47.09	13.78		≤ 10	≤ 11							
Tree 12	46.96	14.11		≤ 10					≤ 68			
Tree 4	45.50	14.73		≤ 10						≤ 21		
Tree 5	45.06	13.85		≤ 9							≤ 12	
Tree 10	44.05	14.28		≤ 10							≤ 15	
Tree 20	42.98	13.96		≤ 10	≤ 11							
Tree 6	42.86	14.79		≤ 10								
Tree 9	42.19	14.73		≤ 10								
Tree 16	42.15	13.69	≤ 10						≤ 72			
Tree 7	41.44	15.08		≤ 10								
Tree 17	41.25	14.54		≤ 10	≤ 11							
Tree 23	38.89	14.31	≤ 10	≤ 11								
Tree 22	38.51	13.75		≤ 10							≤ 12	
Tree 8	37.10	14.19		≤ 10							≤ 11	
Tree 14	35.10	15.02	≤ 10									
Tree 2	32.63	14.98				≤ 54						
Tree 11	29.22	14.52		≤ 10							≤ 11	

End of Preschool (T2)	R2	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of High Mathematical Performance												
Tree 24	59.37	21.04		> 15	> 13							
Tree 15	51.71	20.31		> 15								
Tree 21	50.13	20.89		> 15	> 13							
Tree 19	49.94	20.54		> 15								
Tree 18	49.33	20.27		> 15					> 90			
Tree 1	49.26	20.17	> 13									
Tree 3	48.61	20.10		> 15								
Tree 13	47.09	20.63		> 15					> 91			
Tree 12	46.96	20.31		> 15								
Tree 4	45.50	21.30	> 13	> 15								
Tree 5	45.06	19.82		> 15								
Tree 10	44.05	20.36		> 16								
Tree 20	42.98	20.81		> 15				> 20				
Tree 6	42.86	20.33		> 16								
Tree 9	42.19	19.94		> 15							> 58	
Tree 16	42.15	20.42	> 13			> 67						
Tree 7	41.44	21.30		> 15		> 67						
Tree 17	41.25	20.85		> 15	> 14							
Tree 23	38.89	20.61		> 16								
Tree 22	38.51	20.43		> 15								
Tree 8	37.10	20.30	> 13	> 15								
Tree 14	35.10	20.39	> 13									
Tree 2	32.63	20.46			> 13	> 66						
Tree 11	29.22	19.61		> 15								

Note. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; MLA = Math Language Assessment; WJLW = Woodcock-Johnson Letter Word ID; GRTR = Get Ready to Read; PPVT = Peabody Picture Vocabulary Test; DNS = Day Night Stroop; HTKS = Head-Toes-Knees-Shoulders.

Figure 2

The Tree That Accounted for the Most Variance Classifying High and Low Mathematics Performance From the End of Preschool to the End of Kindergarten



Note. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; MLA = Math Language Assessment.

Classifiers at the Beginning of Kindergarten

Finally, at the beginning of kindergarten, seven of the eleven possible variables appeared in at least one pathway when predicting children's low and high mathematical performance at the end of kindergarten (see Table 4).

Table 4

Forest of Trees for Beginning of Kindergarten Variables Predicting Mathematical Performance at End of Kindergarten

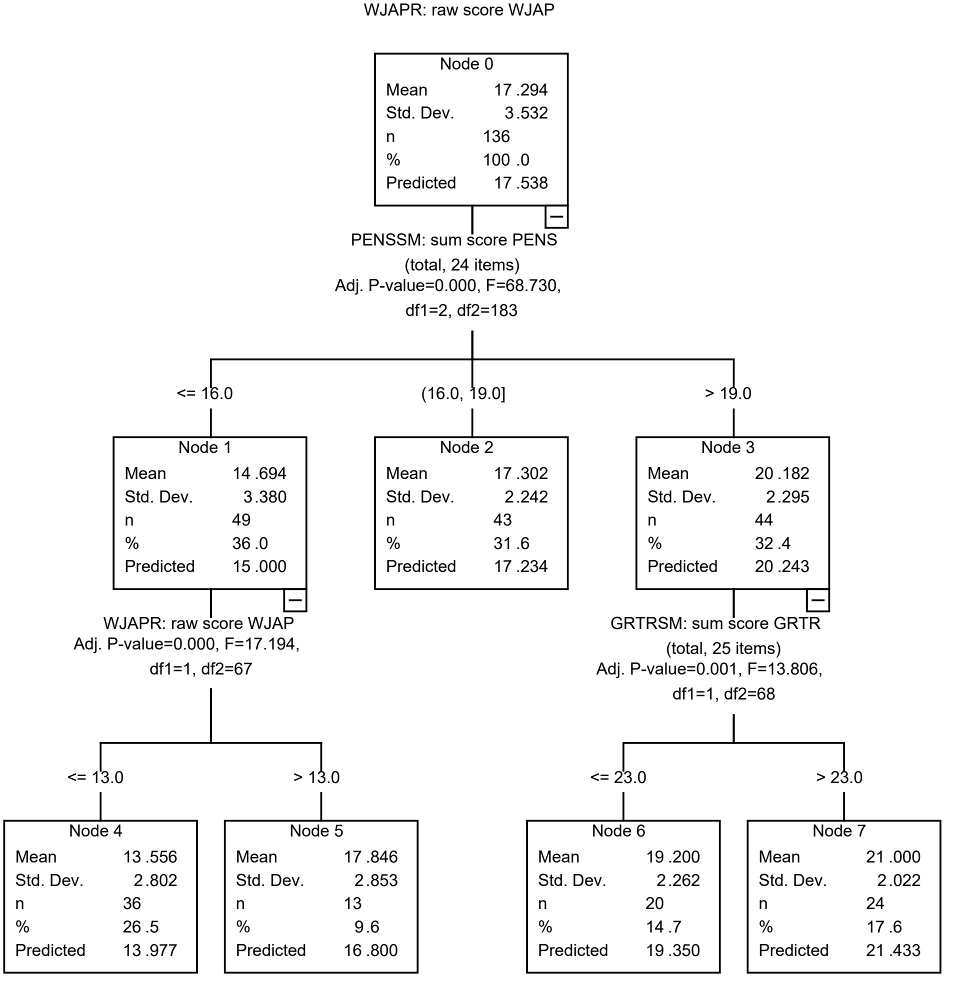
Beginning of Kindergarten (T3)	*R2*	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of Low Mathematical Performance												
Tree 8	52.81	13.56	≤ 13	≤ 16								
Tree 5	49.90	13.52	≤ 13					≤ 20				
Tree 2	49.01	13.32	≤ 13					≤ 19				
Tree 20	48.54	13.41	≤ 13	≤ 15								
Tree 7	48.36	13.37	≤ 13					≤ 20				
Tree 23	47.36	14.40	≤ 12									
Tree 14	46.10	14.43		≤ 16	≤ 13							
Tree 12	45.95	14.25	≤ 13	≤ 16								
Tree 9	44.95	13.84	≤ 12		≤ 12							
Tree 24	43.83	13.96	≤ 12	≤ 16								
Tree 3	43.56	14.90		≤ 15								
Tree 15	42.93	14.21				≤ 65						
Tree 13	41.84	13.77	≤ 12									
Tree 18	41.66	14.00		≤ 15					≤ 81			
Tree 10	41.57	14.32		≤ 16							≤ 50	
Tree 25	40.20	14.11				≤ 66						
Tree 22	39.45	14.65		≤ 15								
Tree 17	39.33	15.00		≤ 15								
Tree 19	36.48	14.83	≤ 12									

Beginning of Kindergarten (T3)	*R2*	*M* T4 WJAP	WJAP	PENS	MLA	Bracken	WJLW	GRTR	PPVT	DNS	HTKS	Age (mo)
Predictors of High Mathematical Performance												
Tree 8	52.81	21.00		> 19				> 23				
Tree 5	49.90	21.50	> 16					> 23				
Tree 2	49.01	20.53	> 16					> 22				
Tree 20	48.54	20.97	> 16					> 22				
Tree 7	48.36	20.50	> 16						> 103			
Tree 23	47.36	21.20	> 16			> 75						
Tree 14	46.10	21.32		> 19				> 23				
Tree 12	45.95	20.77	> 16					> 22				
Tree 9	44.95	20.13	> 16									
Tree 24	43.83	20.71	> 16	> 19								
Tree 3	43.56	20.16		> 19								
Tree 15	42.93	20.42		> 19		> 73						
Tree 13	41.84	20.72	> 16				> 15					
Tree 18	41.66	20.11		> 19								
Tree 10	41.57	21.19		> 20								
Tree 25	40.20	19.83				> 74						> 70.65
Tree 22	39.45	20.94	> 16	> 19								
Tree 17	39.33	21.12		> 19		> 75						
Tree 19	36.48	20.35	> 16									

Note. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; MLA = Math Language Assessment; WJLW = Woodcock-Johnson Letter Word ID; GRTR = Get Ready to Read; PPVT = Peabody Picture Vocabulary Test; DNS = Day Night Stroop; HTKS = Head-Toes-Knees-Shoulders.

Figure 3

The Tree That Accounted for the Most Variance Classifying High and Low Mathematics Performance From the Beginning of Kindergarten to the End of Kindergarten



Note. WJAP = Woodcock-Johnson Applied Problems; PENS = Preschool Early Numeracy Screener; GRTR = Get Ready to Read.

The most common predictors across all of the trees were prior mathematics scores (WJAP and PENS). A consistent classifier of only high mathematics performance at the end of kindergarten was reading skills (GRTR) at the beginning of kindergarten. Trees assessing classifiers from the beginning of kindergarten accounted for 36.48-52.81% of the variance in the end of kindergarten mathematics scores. Tree 8 accounted for the most variance (52.81%) in later mathematics performance (Figure 3). In this tree, a score below or equal to 13 on prior mathematics scores (WJAP) in combination with a score below or equal to 16 on early numeracy skills (PENS) was associated with a low mathematics score (13.56) at the end of kindergarten. A score above 19 on prior mathematics scores (WJAP) in combination with a score above 23 on reading skills (GRTR) was associated with a high mathematics score (21.00) at the end of kindergarten. These results suggest that the combination of low levels of prior mathematics achievement and low levels of numeracy knowledge is a strong classifier at the beginning of kindergarten of low math performance, and high levels of numeracy knowledge and high levels of reading skills are strong classifiers of high math performance.

Discussion

In this study, we used CART models to identify and compare classifiers of low and high mathematical performance across four developmental time points in early childhood. We hypothesized that classifiers would differ across time points and that mathematical performance would be a consistent predictor of later mathematical performance (e.g., Purpura, Day, et al., 2017). Results revealed that consistent skill classifiers for high and low mathematics performance shared some similarities (e.g., prior mathematics and school readiness) and some differences (e.g., behavioral self-regulation for low performance and reading for high performance). Although different classifiers emerged at different time points, a consistent classifier across all time points was children's prior mathematical performance.

Prior studies examining predictors of later mathematical achievement have also found that earlier mathematics predicts later mathematics achievement (Devlin et al., 2022; Jordan et al., 2009). Not surprisingly, findings from the current study suggest that these domain-specific skills remain important classifiers across all time points. Not only was children's performance on the general mathematics achievement assessment a classifier that recurred, but the more numeracy-specific mathematics assessment was also a classifier that showed up across all three predictive time points. This suggests that domain-specific skills provide evidence of children who may be at risk for mathematical difficulties at the end of kindergarten.

Purpura, Day, et al. (2017) found that mathematical language was an important classifier of later mathematics performance. Consistent with this work, the current findings suggest that mathematical language most frequently emerged as a classifier at the end of preschool for both high and low mathematics achievement; however, it did not emerge as consistently as domain-specific numeracy skills or domain-general behavioral self-regulation skills across developmental periods. Together, these findings suggest that the relative importance of mathematical language may be developmentally specific and, in some contexts, may be explained by children's foundational numeracy skills as mathematics learning becomes more formal. Differences between the current study and Purpura, Day, et al. (2017) may also reflect variation in sample characteristics, including socioeconomic background, as well as methodological differences. Notably, early numeracy skills were not included in Purpura, Day, et al. (2017), limiting direct comparisons and underscoring the importance of including domain-specific numeracy measures when examining longer-term mathematics outcomes. Thus, mathematical language as an overlapping skill may serve as an important classifier during the preschool period, particularly for certain populations, while its relative predictive role may change as children transition into formal mathematics instruction.

Beyond children's prior mathematical performance, some important classifiers of later mathematical performance emerged at different time points. At the beginning of preschool, children's school readiness skills were consistently in the forest for both high and low performers. Given that the Bracken assessment covers five subtests that capture a range of skills, these findings suggest that at the earliest developmental period, this assessment provides the top classifier of later performance in mathematics. At this early age, these general school readiness skills share a substantial amount of variance (Duncan et al., 2023), and few specialized skills explain distinct variance as classification abilities yet.

At the beginning of preschool, children's self-regulation skills appear important for later high mathematical performance, and then, at the end of preschool, they switch to becoming a consistent classifier of later low mathematical performance. There could be many explanations for this finding; however, one focuses on children's experiences in the preschool classroom, which may help children to better understand how to control their bodies (Bull & Lee, 2014; McClelland et al., 2014). Children learning self-regulation skills are inherently important for their mathematical skills, as they may complete their work and attend to classroom instruction. Thus, instructional practices could play a role in this result, particularly for low-performing math students. This result may also align with research indicating that although self-regulatory skills are highly related to early mathematics performance, children begin to rely on them less as they become more proficient in mathematics (Chan & Scalise, 2022; Dong et al., 2022).

Finally, at the beginning of kindergarten, a consistent classifier of high mathematical performance was children's reading skills. This finding is consistent with research demonstrating a strong schooling effect on children's literacy development (Burrage et al., 2008), given the instructional focus during the kindergarten school year. Further, this finding is consistent with the literature suggesting that math and literacy co-develop, as children who are high performers in one skill may also be high performers in mathematics skills (Schmitt et al., 2017). The developmental shift from domain-general skills to reading as a classifier of later mathematics may reflect developmental changes in the cognitive and instructional demands across early schooling. Early mathematics relies heavily on domain-general processes, such as executive function skills (Ribner et al., 2023), whereas kindergarten mathematics increasingly requires language comprehension, print knowledge, and vocabulary (Purpura et al., 2011). Reading skills may therefore be important for classifying high mathematics performance because they overlap with symbol mapping (e.g., letters to sounds and numerals/words to quantities), and because of the increased need to interpret mathematical vocabulary and problem contexts, particularly as children encounter tasks with fewer visual scaffolds.

Developmental Theory

From a broader developmental perspective, these findings align with transactional and systems-based theories of development, which emphasize that children's skills emerge through dynamic interactions between individual characteristics and environmental contexts across time (Bronfenbrenner & Morris, 2007; Sameroff, 2010). The shifting importance of domain-specific, domain-general, and overlapping skills across developmental periods, as shown in this study, underscores the idea that early mathematics development is not driven by a single skill or pathway, but rather by multiple changing abilities and contexts that reflect children's developmental stage and educational context. In particular, the consistent role of prior mathematics performance across time points is consistent with models of development (Duncan et al., 2007; Watts et al., 2014), whereas the time-specific emergence of school readiness, self-regulation, and reading skills highlights the importance of developmental timing and schooling experiences in shaping mathematics outcomes (Morrison et al., 2019). Together, these findings support a developmental systems view in which early competencies both scaffold and are reorganized by subsequent learning experiences, including formal instruction.

Future Research and Practice

The current findings have implications for future research and practice. From a research perspective, identifying age-specific classifiers highlights the importance of examining developmental timing in studies of early mathematics achievement, rather than assuming the same predictors remain important across childhood. Future work should continue to examine how domain-specific and domain-general skills interact across developmental periods, particularly in more diverse and nationally representative samples, and whether similar classification patterns emerge when different instructional contexts or curricula are considered. From a practice perspective, these findings may suggest that early mathematics support may be most effective when aligned with children's developmental age. For example, broad school readiness and self-regulation skills may be particularly important for identification in early preschool, whereas domain-specific numeracy skills may warrant greater emphasis as children approach and enter formal schooling. Although the current study does not test interventions directly, identifying developmentally sensitive classifiers provides a framework for informing differentiated instruction and early screening efforts to support children at risk for low mathematics performance.

Limitations

A couple of limitations of the present study should be noted. First, CART is a data-driven analytic approach that may be susceptible to sample-specific biases. While many of our results are consistent with prior findings and theoretical evidence (Duncan et al., 2007; Purpura et al., 2011), there are limitations specific to our sample. For example, the analytic sample of this paper included children whose families met a specific income-eligibility requirement, and therefore, it does not capture the full range of possible educational and home experiences. Relatedly, although socioeconomic status (SES) is known to be associated with children's language, literacy, and mathematics development, the SES variables in this dataset had substantial missing values. As CART requires complete cases, including SES would have reduced the analytic sample, making it infeasible to incorporate SES as a covariate in the present analysis. As a result, SES could not be directly examined in this study. However, one interesting future direction could be to use CART analyses with nationally representative data (i.e., Early Childhood Longitudinal Study-Kindergarten) to examine low and high mathematics performance across multiple time points and compare results.

Second, although the current study identifies classifiers of low and high mathematical performance, mathematical difficulties or giftedness could not be determined from these data. Math difficulty is often defined by low performance despite access to adequate instruction, resistance to intervention, or a specific math learning disability such as dyscalculia (Chan & Wong, 2020). Math giftedness has received more attention over recent years (Leikin, 2020), and although a precise definition remains lacking, it is often perceived as a person with high mathematical abilities and a strong inborn mathematical promise (Leikin, 2009). Importantly, including a broader range of learners may increase variability in math performance while also limiting conclusions drawn from more homogeneous samples. Despite this limitation, the current study can identify possible antecedents to children's low and high performance represented in this sample. This information, used in conjunction with other important factors, can help better identify children who may experience difficulties or giftedness in math. Future research should also examine whether specific components of early numeracy (e.g., magnitude, cardinality, or symbolic knowledge) differentially classify later mathematics outcomes across developmental periods and levels of performance.

Conclusion

The current study assessed domain-specific, domain-general, and overlapping classifiers of low and high mathematics performance across different developmental periods. Findings from this study suggested that classifiers may differ depending on developmental period and performance level, such that domain-specific factors serve as classifiers across all developmental periods, whereas domain-general skills serve as important classification capabilities at different time points and performance levels. Moving forward, this methodological approach and understanding of domain-specific and domain-general skills should inform our research, policies, and practices to better identify and support children at risk of low mathematics performance.

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Competing Interests: Alexa Ellis is an Associate Editor for the *Journal of Numerical Cognition* but played no editorial role for this particular article or intervened in any form in the peer review procedure.

Data Availability: The datasets analyzed for the current study are not publicly available. The data that support the findings of this study are available on request from the corresponding author, Alexa Ellis. The research team will consider the data request and approve it only if the proposed use aligns with data protection regulations and the consent provided by study participants.

Supplementary Materials

The Supplementary Materials include output and syntax for all analyses. Further, they contain Figure 1, a histogram of the end of kindergarten mathematics scores (for access, see Ellis, 2026S).

Index of Supplementary Materials

Ellis, A. (2026S). *CART predictors of low and high math* [Syntax, results, and materials]. OSF. https://osf.io/dpn2x/

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