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Effects of Extreme Prematurity on Numerical Skills and Executive Function in Kindergarten Children: An Application of Partially Ordered Classification Modeling

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Abstract

Although mathematics disabilities (MD) are common in extremely preterm/extremely low birth weight (EPT/ELBW) children, little is known about the nature of these problems. In this study partially ordered set (POSET) models were applied to classify 140 EPT/ELBW kindergarten children (gestational age <28 weeks and/or birth weight <1000 g) and 110 normal birth weight (NBW) controls into profiles of numerical and cognitive skills. Models based on five numerical skills and five executive function and processing speed skills provided a good fit to performance data. The EPT/ELBW group had poorer skills in all areas than NBW controls but the models also revealed substantial individual variability in skill profiles. Weaknesses in executive function were associated with poorer mastery of numerical skills. The findings illustrate the applicability of POSET models to research on MD and suggest distinct types of early numerical deficits in EPT/ELBW children that are related to their impairments in executive function.

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Keywords

preterm birth; early school age outcomes; mathematics disabilities; executive function; partially ordered classification modeling

1. Introduction

Most extremely preterm/extremely low birth weight (EPT/ELBW) children, with gestational age (GA) <28 weeks and/or birth weight <1000 g, have some form of cognitive, learning, or behavioral disorder (Aylward, 2005; Hack et al., 2005; Simms, Cragg, Gilmore, Marlow, & Johnson, 2013). Mathematics disabilities (MD) are especially common in EPT/ELBW children relative to term-born, normal birth weight (NBW) peers and cannot be fully accounted for by global reductions in cognitive ability (Simms et al., 2013; Taylor, Espy, & Anderson, 2009). EPT/ELBW children also have deficits in cognitive skills closely associated with mathematics achievement, such as executive function and processing speed (Mulder, Pitchford, & Marlow, 2010).

However, we know little about the nature of MD in EPT/ELBW children. Most studies that have examined MD in preterm samples have administered standardized tests that assess composites of mathematics skills (Simms et al., 2013; Taylor et al., 2009). Reliance on these omnibus measures precludes identification of the types of mathematics skills adversely affected by prematurity. At early school age these “domain-specific” skills include rapid recognition of small quantities (i.e., subitizing), counting, simple addition and subtraction, recognition of numerals, and matching of number sets to numerals (Fuchs, Geary et al., 2010a; Geary, 2011a; Guarini et al., 2014; Simms et al., 2015).

1.1. Recent studies of early numerical skills in preterm children

In their study of early numerical skills, Guarini et al. (2014) compared preterm groups of 6- and 8-year-olds (GA 33 weeks) to age-matched controls on magnitude comparison tasks (identification of the larger of two sets of dots or Arabic digits) and on several measures of early number knowledge. Despite the absence of group differences in IQ, the younger preterm group was slower and less accurate than the controls on some of the magnitude comparison tasks and did less well on tests of number knowledge. Most of these differences were no longer evident at the older age level; the older preterm group had slower response times than their controls on some of the magnitude estimation tasks but this difference was attributed to a deficit in processing speed rather than in number sense.

In a related study, Simms et al. (2015) compared a group of 8- to 10-year-old very preterm children (GA <32 weeks) to term controls on tests of several specific mathematics skills as well as on measures of domain-general cognitive abilities. The preterm group had lower scores on multiple tests of early numerical skills. Differences in digit recognition, counting, and arithmetic strategies remained when controlling for non-verbal IQ. In contrast, these differences were not significant when controlling for working memory and visuospatial skills, suggesting that these cognitive abilities were contributing to the preterm group's lower test scores.

1.2. Domain-general cognitive correlates of mathematics disabilities

Findings from the latter study also highlight the importance of examining cognitive correlates of MD in EPT/ELBW children. Measures of processing speed and executive function, including working memory, inhibition, and cognitive flexibility/set shifting, are among the “domain-general” cognitive functions most closely related to mathematics achievement in the general population of school-age children (Blair & Razza, 2007; Bull, Espy, & Weibe et al., 2008; Bull & Scerif, 2001; Berg, 2008; Cirino, 2011; Clark, Pritchard, & Woodward, 2010; Clark, Sheffield, Weibe, & Espy, 2013; Espy, Bull, Martin, & Stroup, 2006; Fuchs et al., 2006; Geary, 2011a, 2011b; Gilmore et al., 2013; Simmons, Willis, & Adams, 2012). Additional predictors include phonological short-term memory and attention (Geary, Hoard, Byrd-Craven, Nugent, & Numtee, 2007; LeFevre et al., 2010; Meyer, Salimpoor, Geary, & Minon, 2010). Several studies document associations of specific cognitive abilities in young children with mathematics competencies. Examples include studies showing associations of auditory working memory and phonological processing with the ability to solve single-digit addition problems in 5- to 6-year-olds (Simmons et al., 2012), associations of inhibition in preschoolers with later mathematics skills (Blair & Razza, 2007; Clark et al., 2010), and prediction of magnitude estimation in kindergarteners from earlier measures working memory (Kolkman, Hoijtink, Kroesbergen, & Leseman, 2013).

1.3. Study aims and the applicability of partially ordered set (POSET) models

The primary aims of this study were to examine early numerical skills, related cognitive abilities, and their association in a sample of EPT/ELBW children and NBW controls assessed during their first year of formal schooling (kindergarten). The children were recruited for a study of early school-age outcomes of extreme prematurity. Previous reports document deficits in the EPT/ELBW group relative to NBW classmates on measures of mathematics achievement and domain-general cognitive skills, including assessments of processing speed, executive function, and attention (Orchinik et al., 2012; Taylor et al., 2011). Because scores on mathematics tests represented skill composites it was unclear how component skills were affected by extreme prematurity. Additionally, distinctions between different aspects of executive function (e.g., working memory, inhibition, set shifting) were based on assumptions about test content that were not subjected to empirical confirmation. The previous reports also failed to examine associations between MD and domain-general cognitive deficits.

To address these limitations, partially ordered set (POSET) model classification methods (Jaeger, Tatsuoka, Berns, & Varadi, 2006; C. Tatsuoka, 2002; C. Tatsuoka, 2014; C. Tatsuoka & Ferguson, 2003; C. Tatsuoka, Tseng et al., 2013, C. Tatsuoka, Varadi, & Jaeger, 2013) were applied to test a model of the numerical skills contributing to children’s performance on individual test items from a mathematics achievement test. Based on item content, these skills included subitizing, counting more than four objects (cardinality), and single-digit subtraction and addition. This same approach was applied in modeling aspects of domain-general cognitive skills related to mathematics achievement. Although deficits in multiple skills contribute to MD, emphasis was placed on executive function because of the strong association of this ability domain with numerical abilities in preterm children

(LeFevre et al., 2010; Simms et al., 2013). Modeling of both domains in parallel made it possible to examine associations of the numerical and cognitive skills.

A major advantage of POSET models is that they explicitly acknowledge the polyfactorial nature of test performance, with multiple skills making varying contributions to performance on any given test item or score. Posterior probabilities of “state” membership, representing skill profiles into which children are classified, are computed based on test performance across different items or tests. The states are partially ordered by skill sets, ranging from states in which all or most skills are mastered to states in which no skill is mastered. One state is considered at a higher level than another if it subsumes all the mastered skills of the other state.

1.4. Hypotheses

We hypothesized that POSET modeling of early numerical skills and associated cognitive skills would reveal generalized deficiencies in the EPT/ELBW group compared to NBW controls, as well as heterogeneity of skill profiles within the EPT/ELBW group (Simms et al., 2013; Taylor et al., 2009). We further hypothesized that domain-specific numerical skills would be positively associated with domain-general cognitive skills (Berg, 2008; Bull et al., 2008; Cirino, 2011; DeSmedt, Verschaffel, & Ghesquiere, 2009; Fuchs et al., 2006).

2. Material and Methods

2.1. Participants

As described in previous reports (Orchinik et al., 2011; Taylor et al. 2011), 148 EPT/ELBW children without congenital conditions unrelated to preterm birth were recruited from cohorts born 2001–2003 and treated in the neonatal intensive care unit of Rainbow Babies & Children’s Hospital in Cleveland, Ohio. Fifty additional survivors were not recruited because of refusals, residence outside the region, failure to locate families, questions regarding custody, or non-English-speaking parents. The non-participants did not differ from participants in sex, race, or neonatal characteristics. Although some children were in full-time special education programs ($n=16$) or home schooled ($n=3$), most attended regular education classrooms ($n=129$). The control group consisted of 111 term-born NBW children ($GA >36$ weeks, birth weight >2500 g) matched individually to EPT/ELBW children. NBW controls were from the same classrooms ($n=93$) or other classrooms ($n=18$) in the same or demographically similar schools as the EPT/ELBW children and were the closest matches on sex, race, and age at assessment. NBW controls were recruited only for the EPT/ELBW children attending regular classrooms and were not available for 18 of these children because of school refusals/inaccessibility or difficulty recruiting appropriate matches. All children were assessed during their first year in kindergarten.

Children who were unable to complete achievement testing because of inattentiveness, lack of cooperation, or inability to understand basic test demands were excluded from this study, resulting in a final sample of 140 EPT/ELBW children and 110 NBW controls. Additional children were untestable on some of the cognitive tasks, further reducing sample size for the cognitive model to 121 EPT/ELBW children and 100 NBW controls. Table 1 summarizes

group demographic and neonatal characteristics. The groups did not differ significantly in sex, race, age at assessment, or level of maternal education. The EPT/ELBW had higher rates of delayed school entry than the NBW group (21% vs. 3%, $p<.001$) but the groups did not differ in rates of preschool attendance (84% vs. 86%). Because each EPT/ELBW child had to be assessed before recruitment of the NBW control could be initiated, controls were assessed an average of 9 weeks later in the school year.

2.2. Procedures and measures

Kindergarten assessments included tests of academic achievement and neuropsychological skills completed to examine learning, cognitive, and behavior outcomes of extreme prematurity (Orchinik et al., 2011; Scott et al., 2012; Taylor et al., 2011). The children were tested during half-day sessions by examiners who were not informed of group status. The research was approved by the institutional review board of University Hospitals Case Medical Center. Informed parental consent was documented prior to participation.

The Applied Problems test from the Woodcock Johnson Tests of Achievement, 3rd Edition (Woodcock, McGrew, & Mather, 2001a) was administered to assess early numerical skills. The items from this test consist primarily of showing children a series of pictured objects and asking them to solve problems involving number or measurement. The test has good reliability and validity in younger children (Clark et al., 2013). The focus of this study was on the first 17 items (from the initial set of 20) that involved numerical operations on pictured objects.

Cognitive skills included four experimental tasks of executive function developed for young children by Espy and colleagues (Espy & Cwik, 2004; Espy et al., 2006): (1) The Test of Inhibition and Attention is a computerized task requiring the child to press the space bar for target stimuli but not for non-targets. Performance is scored using a d' -prime measure of target detectability. (2) Shape School requires children to follow rules for naming cartoon-like figures by their shape or color. Inhibition is assessed by a condition requiring naming of smiling figures but not sad ones, and set switching by a condition requiring naming some figures by shape and others by color. (3) The Preschool Trails Test—Revised requires that the child stamp cartoons of dogs and their corresponding bones in ascending order by size. Inhibition is assessed by having the child focus on the dogs while ignoring distractors, and set switching by having the child alternate between stamping the dogs and their bones. Both accuracy and completion time were taken into account in computing scores for Shape School (accuracy/time) and Preschool Trials-Revised $[(1/\text{time})/(\text{square root}(\text{errors}+1)) \times 100]$. (4) Nebraska Barnyard is a computerized test of working memory in which the child is shown cartoon animals on a touch screen, each of which is associated with a unique location and color. The examiner then reads lists of animal names of increasing length and the child attempts to touch the colors/locations of the names in order. The score is the maximum list length correctly recalled. The Digit Span subtest of the Comprehensive Test of Phonological Processing (Wagner, Torgesen, & Rashotte, 1999) provided an additional measure of auditory working memory. This task involves oral repetition of increasing series of numbers, with scores reflecting the maximum number of digits correctly recalled in order. Processing speed was assessed using the Visual Search subtest from the Woodcock Johnson Tests of

Cognitive Abilities, 3rd edition (Woodcock, McGrew, & Mather, 2001b), a timed task requiring the child to match numbers from printed number sets.

Previous group comparisons revealed that the EPT/ELBW group performed more poorly than NBW controls on scores adjusted for time in grade on Applied Problems and on age-adjusted scores on the above-mentioned neuropsychological measures (Orchinik et al., 2011; Taylor et al., 2011). Group comparisons on these measures for the sample of children included in this study revealed similar differences (data not shown). Mean standard scores for age on an abbreviated measure of global cognitive ability, the Brief Intelligence Assessment from the Woodcock Johnson Tests of Cognitive Abilities, 3rd Edition, were 87.45 (SD=19.82) for the EPT/ELBW group and 105.90 (SD=16.65) for NBW controls, $t(244)=-7.78$, $p<.001$.

2.3. Partially ordered set (POSET) modeling and classification methods

Responses to the 17 items from Applied Problems (scored 0 or 1) were modeled to reflect five types of early numerical skills included in the POSET model: (1) recognition of quantities of 4 or less, a skill potentially involved in any counting task (subitizing, labeled “C1,” 17 items), (2) counting of quantities >4 (cardinality, labeled “C2,” 4 items), (3) quantity remaining when specified number are taken away (subtraction, labeled “A1,” 4 items), (4) providing total quantity when two smaller sets are combined (addition, labeled “A2,” 2 items), and (5) performing these operations on objects embedded in visual distractors (spatial organization, labeled “N1,” 8 items). Because subitizing items were untimed and subitizing implies immediate recognition of small quantities, the term as used here refers to a more general ability to identify small quantities that may include counting as well as immediate recognition of numerosity. A focus on these skills was justified by research indicating that they are distinct facets of early numerical competence (Clements & Sarama, 2009; Fuchs et al., 2010a; Guarini et al., 2014; Simms et al., 2015). Table 2a presents the hypothetical item-attribute mappings, or “Q-matrix,” relating each test item to the five hypothesized numerical attributes or skills (K. Tatsuoka, 1995). The model was based on the authors’ consensus regarding the functions required to answer each test item and validated as described by C. Tatsuoka (2002).

In similar fashion, performance on the neuropsychological tests was assumed to reflect several key skills associated with mathematics achievement: processing speed, working memory, inhibition, selective attention (referred to here as “attention”), and set switching (Berg, 2008; Bull et al., 2008; Bull & Scerif, 2001; Cirino, 2011; Clark et al., 2010; Geary et al., 2007; Gilmore et al., 2013; LeFevre et al., 2010; Meyer et al., 2010; Mulder et al., 2010; Simms et al., 2013). Table 2b presents the hypothetical Q-matrix mapping each test score to the five cognitive skills. The mappings were based on neuropsychological expert opinion (HGT) and assume that multiple cognitive skills can contribute to accuracy on any given test. Responses were categorized by the quartile into which each score fell relative to scores for the total sample. Probabilistically, response distributions are viewed as multinomial and do not rely on specific parametric response models.

POSET modeling was then applied to generate a collection of “states,” representing profiles of mastery of numerical or cognitive skills into which the children could be classified.

Tatsuoka and colleagues established the statistical framework for this modeling approach, including validation of the Q-matrix specifications (Jaeger et al., 2006; C. Tatsuoka, 2002; C. Tatsuoka, 2014; C. Tatsuoka & Ferguson, 2003; C. Tatsuoka, Tseng et al., 2013; C. Tatsuoka, Varadi et al., 2014). In brief, math item and cognitive test response distributions were estimated using Bayesian Markov Chain Monte Carlo methods to classify children into states. Prior probabilities of state membership (i.e., those applied to model performance profiles) were initially assigned to each child in a manner that made each state in the model equally likely to apply. Probabilities of state membership were then updated by taking into account the observed responses. Once a child's posterior state membership probabilities for all the states in the model were calculated based on observed responses, the child was classified into the most probable state (i.e., one with the largest posterior probability).

Classification results indicate how well a model fits the child's performance profile (C. Tatsuoka, 2002). Ideally, classification of each child results in posterior probability mass for state membership suggesting one state (i.e., with a probability near 1 for one state and 0 for all others after observing responses from the child). Large posterior probability values aggregating on one state (or two) indicates that the observed item responses are consistent with the model specifications. After classification, for each child and each skill, a mastery probability value can be derived by summing the posterior probability values of all the states associated with a mastery of that skill. Higher values indicate higher probability that a child has mastery of that skill. These probabilities were computed for each child for each of the five numerical and five cognitive skills. Profiles sometimes cannot be statistically distinguished by the available item pool. This phenomenon, known as "confounding," occurs when the role of a skill in the profile (i.e., whether mastered or not) is unclear from patterns of responses to test items or test scores (C. Tatsuoka, 2002). Profiles that cannot be distinguished because of confounding are combined into one state, and the skills in question are referred to as "indeterminant" for that profile. Group comparisons of the respective numerical and cognitive skill probabilities were conducted using two-sided Mann-Whitney U tests. A Bonferroni corrected alpha level of 0.01 (.05/5) was used to adjust for the number of comparisons within each skill domain.

3. Results

3.1. Model descriptions

The POSET model for numerical skills comprises 11 states, as shown in Table 3a and graphically depicted as a Hasse diagram in Figure 1a. State 1 is the highest state in the model, representing mastery of all five numerical skills, whereas State 11 is the lowest state and indicates non-mastery of these skills. For the in-between states, at least one skill is not mastered. As depicted in the diagram, connections between states indicate ordering, with the higher states indicating greater functionality than the lower ones with respect to the skills needed for successful performance on the achievement test items. The model for cognitive skills comprised the 13 states presented in Table 3b and is represented by the Hasse diagram in Figure 1b. As in the numerical skills model, State 1 represents higher functioning across all cognitive skills, whereas State 13 indicates pervasive weaknesses.

Response distribution estimates for the numerical and cognitive skills models support model fit, in that probabilities of good performance are higher for states in which all skills are mastered than for states in which at least one skill is not mastered. In the model representing numerical skills, the mean (standard deviation) of the largest posterior probability for state membership and sum of the first and second largest values were 0.738 (0.227) and 0.887 (0.126), respectively, indicating that the model specifications were reasonably good in simulating actual item response patterns. Corresponding mean (standard deviation) values in the model for cognitive skills were 0.569 (0.214) and 0.678 (0.198), respectively. The latter values were not as large as those for the numerical skills model but they indicate acceptable fit.

3.2. Group comparisons of model-based numerical and cognitive skills

Figures 2a and 2b display the distributions of classified states by group for model-based numerical and cognitive skills, respectively. Both figures indicate a shift toward lower states in the EPT/ELBW group, with associated lower posterior probabilities of higher test scores. The model for numerical skills suggests that many EPT/ELBW children failed to master numerical skills other than subitizing, while a large number of NBW children demonstrated mastery of all numerical skills. These distributions also illustrate variability in skill profiles for both groups, with many children from both groups displaying varying combinations of partial skill sets. In the model for cognitive skills, NBW children had relatively few deficits compared to the EPT/ELBW group and were most frequently classified to State 1, representing mastery of all skills. State 2 was the next most frequent state into which NBW children were classified, indicating proficiency in all skills except set switching. In contrast, EPT/ELBW children were most often classified to State 13, signifying generally low skills, whereas two of the next most frequent states to which they were classified represented limited mastery (working memory in State 7 and selective attention and inhibition in State 12).

The EPT/ELBW group had lower probabilities of mastery than the NBW group for all of the numerical skills: subitizing, $U(248)=4770.5$, $p<.001$, cardinality, $U(248)=4666.5$, $p<.001$, subtraction, $U(248)=4453.5$, $p<.001$, addition, $U(248)=4509$, $p<.001$, and spatial organization, $U(248)=4332.5$, $p<.001$. The EPT/ELBW group also had lower probabilities of mastery for all cognitive skills: processing speed, $U(211)=7729.5$, $p<.001$; working memory, $U(211)=7104.5$, $p<.001$; inhibition, $U(211)=8236.5$, $p<.001$, attention, $U(211)=8092.0$, $p<.001$, and set switching, $U(211)=6756.0$, $p=.007$. The average group differences of probabilities of mastery are graphed in Figures 3a and 3b for numerical and cognitive skills, respectively.

3.3. Associations of model-based numerical and cognitive skills

To examine associations between model-based numerical and cognitive skills, children were grouped into high vs. low posterior probabilities for each cognitive skill. Cut-off probabilities were selected at approximately 0.2 to 0.3 to distinguish children with relatively low as compared to higher estimated performance while insuring reasonable numbers of children in each group. Mann-Whitney U tests were then conducted comparing these groupings on the probabilities of each numerical skill. Findings failed to reveal associations

of processing speed or set switching with any of the numerical skills. However, working memory was positively associated with subtraction, $U(176)=1588.5$, $p=.006$, addition, $U(176)=1467.0$, $p=.001$, and spatial organization, $U(176)=1592.0$, $p=.006$; inhibition with subitizing, $U(176)=1933.0$, $p=.002$, and subtraction, $U(176)=1426.5$, $p<.001$; and attention with subitizing, $U(176)=523.0$, $p<.001$, cardinality, $U(176)=2470.0$, $p=.018$, and spatial organization, $U(176)=418.0$, $p=.001$.

4. Discussion

This study addresses the call for research into the nature of early MD in children with extreme degrees of prematurity and the cognitive factors associated with specific numerical deficits (Simms et al., 2013; Taylor et al., 2009). Findings from POSET modeling support the hypothesis that multiple early numerical skills contributed to the performance of EPT/ELBW and NBW children on individual items from a mathematics achievement test administered in kindergarten. These skills included subitizing, cardinality as required to count >4 pictured objects, and simple subtraction and addition. The good fit of the model to item performance also supports the viability of the fifth “spatial organization” skill that was hypothesized to come into play on items requiring the child to distinguish to-be-counted objects within more complex visual arrays. Compared to NBW controls, the EPT/ELBW children had lower levels of functioning across all of the model-based numerical skills. The results are consistent with recent evidence for pervasive deficits in preterm children’s early numerical competencies, including counting and single-digit arithmetic (Guarini et al., 2014; Simms et al., 2015). Studies of other at-risk populations, such as children with cerebral palsy and genetic disorders, reveal similar deficits (Henik, Rubinsten, & Ashkenazi, 2011; van Rooijen, Verhoeven, & Steenbergen, 2010).

A unique aspect of the current study is the demonstration of impaired numerical skills based on modeling of item-level performance on a commonly used achievement test. Another contribution is the model’s support for variability in the early numerical skills in EPT/ELBW children. Although the most common state into which the EPT/ELBW children were classified was the second lowest one, signifying multiple skill deficits, many of these children were classified into states representing a more limited set of numerical deficiencies. The variability in these profiles underscores the importance of evaluating multiple numerical skills (Guarini et al., 2014; Simms et al., 2013) and shows that individual differences can be characterized by patterns of strengths and weaknesses in these skills rather by low standard scores on composite measures of achievement. Potential antecedents of MD in preterm children, such as neonatal complications and brain abnormalities, could then be examined in relation to skill profiles (Clark et al., 2013; Guarini et al., 2014; Simms et al., 2013; Simms et al., 2015).

POSET modeling also supported the hypothesis that multiple domain-general cognitive skills contributed to performance on the neuropsychological test battery. Consistent with other research, the EPT/ELBW group functioned at lower levels in processing speed, working memory, inhibition, attention, and set switching than the NBW controls (Mulder et al., 2010; Taylor et al., 2011). As for the model-based numerical skills, the EPT/ELBW children were more often lacking in multiple cognitive skills compared to the NBW group.

Although this finding accords with the lower global cognitive functioning of the EPT/ELBW group, many of these children were classified to states that represented more selective deficits.

Findings additionally revealed associations of weaknesses in executive function and attention with lower numerical skills. These results are consistent with research on school-based samples (Blair & Razza, 2007; Bull et al., 2008; Clark et al., 2013; Clark et al., 2010; Espy et al., 2006; Geary et al., 2007; LeFevre et al., 2010), as well as with evidence indicating that MD in EPT/ELBW children are related to domain-general deficits in executive function (Assel et al., 2003; Litt et al., 2012; Simms et al., 2013; Taylor et al., 2009). Deficits in executive function in the latter population can be attributed brain abnormalities secondary to preterm birth, particularly in subcortical and fronto-parietal regions that subserve these abilities (Orchinik et al., 2011), and are also implicated in arithmetic performance (Dahaene, Molko, Cohen, & Wilson, 2004; Meyer et al., 2010). The absence of a relation between set switching and early numerical skills may reflect underdevelopment of set shifting ability at early school age or minimal demand for this skill in solving the types of mathematics problems examined in this study (Clark et al., 2010; Lee, Bull, & Ho, 2013). The lack of association of processing speed with numerical skills contrasts with findings from Mulder et al. (2010) but may be explained on similar grounds, as well as by the fact that achievement test items were untimed. Conversely, the positive associations observed in this study may become less evident with advancing age as children gain greater mastery of lower-level numerical skills (Meyer et al., 2010; Simmons et al., 2012).

Discovery of deficits in early numerical skills and related cognitive functions in EPT/ELBW group indicates that many of these children are at risk for later MD (Mazzocco & Thompson, 2005), an expectation confirmed by previous research (Litt et al., 2012; Simms et al., 2013; Taylor et al., 2009). Difficulties in lower-level numerical skills predict MD in community samples (DeSmedt et al., 2009; Fuchs et al., 2006), and risks for persisting MD are even higher for children who have deficits in both numerical skills and domain-general cognitive abilities (Fuchs et al., 2010; Geary, 2011a; LeFevre et al., 2010). Identification of profiles of strengths and weaknesses across subtypes of numerical skills and different aspects of executive function may improve the accuracy of these predictions and help in targeting interventions (Guarini et al., 2014; Simms et al., 2013). Research suggests that targeted interventions can improve beginning numerical skills and foster emerging mathematics achievement (Clark et al., 2013; Geary, 2011b; Kolkman et al., 2013). Similar interventions may be useful in designing mathematics interventions for preterm children (Clark et al., 2010). Effective instruction of these children will likely require highly structured approaches that hold children's attention, reduce demands on working memory, and provide ample practice, concrete illustrations of number concepts, and explicit strategies for solving problems. This approach is illustrated by methods validated by Fuchs, Powell et al. (2010) for teaching number combination skills to early school-age children with MD.

One limitation of the study is that the group differences in model-based numerical and cognitive skills did not take into account the shorter time that EPT/ELBW children were in kindergarten compared to the NBW controls or correct for the shorter GA of the EPT/ELBW

group. Some of the group differences in skills could be reflect the EPT/ELBW group's younger GA and lesser exposure to academic instruction. However, group differences in mathematics achievement and cognitive abilities were significant in comparisons that took into account time in school, and cognitive differences remained even when correcting for GA (Orchinik et al., 2011; Taylor et al., 2011). Group comparisons also failed to control for other demographic factors or for previous educational experiences, though the groups were well matched on these characteristics. Further limitations include the relatively small pool of achievement test items and the fact that two of the cognitive tests (Digit Span and Visual Search) required either recall or matching of digits. Although none of the numerical test items involved digits, weakness in digit knowledge associated with generalized MD may have contributed to the group differences and to associations between the numerical and cognitive skill sets. Finally, although the models tested were viable and empirically validated by the classification methods, more comprehensive conceptualizations may enhance our understanding of numerical skills.

5. Conclusion

To our knowledge this is first study to demonstrate the utility of POSET modeling in examining numerical skills in EPT/ELBW children. A model that assumed distinct types of numerical skills provided a good fit to item-level data from an achievement test administered during the first year of formal schooling.. A second model that hypothesized multiple domain-general cognitive skills also fit data from tests of processing speed and executive function. Although model-generated estimates for all numerical and cognitive skills were lower for the EPT/ELBW group compared to NBW controls, substantial variability in skill profiles highlighted individual differences in the nature of MD in the EPT/ELBW group and in related cognitive abilities. Associations between the two skill sets suggested that deficits in executive function in the EPT/ELBW group contributed to their deficiencies in numerical skills. The results support the utility of assessing multiple numerical and cognitive skills in identification of MD in EPT/ELBW children at school entry. Further research is warranted to determine how deficit profiles change with age, investigate the factors related to variability in skill profiles, and examine the effectiveness of interventions targeted to core deficiencies (Geary, 2010; Geary, 2011b, Geary et al., 2007; Gersten, Jordan, & Flojo, 2005; Goswami, 2006; Keller-Margulis, Dempsey, & Llorens, 2011; Mazzocco, 2005).

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Highlights

- Multiple numerical skills contribute to mathematics achievement in young children.
- Preterm children have generalized deficits in these skills and executive functions.
- Preterm children vary in profiles of numerical skills and executive functions.
- Deficient executive functions are associated with non-mastery of numerical skills.
- Partially ordered classification modeling can be applied to examine skill profiles.

Figure 1.

Hasse diagrams of the classification states included in the partially ordered set (POSET) model for: (a) five numerical skills assessed by 17 numerical test items from Applied Problems, Woodcock Johnson Tests of Achievement, 3rd Edition (C1=subitizing; C2=cardinality; A1=subtraction; A2=addition; N1=spatial organization); and (b) five cognitive skills assessed by tests of processing speed and executive function (PS=processing speed; WM=working memory; INH=inhibition; ATT=attention; SET=set switching). Skills with indeterminate states are not included in the model.

Figure 2.

Frequency distribution of states with largest posterior probabilities for the EPT/ELBW and NBW groups for (a) numerical skills model and (b) cognitive skills model.

(a)

(b)

Figure 3.

Estimated marginal mean probabilities for the EPT/ELBW and NBW groups for models of (a) numerical skills (C1=subitizing; C2=cardinality; A1=subtraction; A2=addition; N1=spatial organization) and (b) cognitive skills. Error bars are one standard error in width.

Table 1

Demographic and neonatal characteristics of EPT/ELBW and NBW groups.

	EPT/ELBW Group (n=140)	NBW Group (n=110)
Demographic characteristics:		
Age in years at testing, mean (SD)	5.94 (0.34)	5.96 (0.31)
Months in school at testing, mean (SD) *	4.23 (2.34)	6.38 (1.72)
Males sex, n (%)	64 (46%)	50 (45%)
African American, n (%)	84 (60%)	60 (55%)
Maternal education:		
<High school, n (%)	19 (14%)	14 (13%)
High school or GED, n (%)	30 (21%)	15 (14%)
>High school, n (%)	91 (65%)	81 (74%)
Median family income, ^a mean (SD)	60 (33)	56 (24)
Neonatal characteristics:		
Birth weight in grams, mean (SD) *	819 (172)	3387 (446)
Gestational age, mean (SD)	25.9 (1.6)	---
Bronchopulmonary dysplasia (BPD), ^b n (%)	74 (53%)	---
Neonatal infection, n (%)	56 (40%)	---
Severely abnormal cranial ultrasound, ^c n (%)	12 (9%)	---
Severe retinopathy of prematurity, ^d n (%)	25 (18%)	---
Neurosensory abnormality at 20 months corrected age, ^e n (%)	12 (9%)	---

*
p<.05.

^aIncome in thousands of dollars based on family's census tract.

^bBPD defined as supplemental oxygen at 36 weeks corrected age.

^cSeverely abnormal defined as Grade III/IV intraventricular hemorrhage, periventricular leukomalacia, or ventricular dilatation at discharge.

^dSevere retinopathy defined as Stage 4 or 5 retinopathy or treatment with cryotherapy or laser therapy.

^eNeurosensory abnormality defined as cerebral palsy or visual or hearing impairment.

GED=general education degree certificate.

Table 2

a. Q-matrix for numerical skills associated with 17 numerical test items from Applied Problems, Woodcock Johnson Tests of Achievement, 3rd Edition.

Item	C1	C2	A1	A2	N1
03	1	0	0	0	0
04	1	0	0	0	1
05	1	0	0	0	0
06	1	0	0	0	0
07	1	0	0	0	1
08	1	0	0	0	1
09	1	0	0	0	0
10	1	0	0	0	1
11	1	0	0	0	1
12	1	0	0	0	1
13	1	0	0	0	0
14	1	0	1	0	0
15	1	1	1	0	0
16	1	0	1	0	0
17	1	1	0	1	1
18	1	1	0	1	0
20	1	1	1	0	1

b. Q-matrix of cognitive skills associated with tests of executive function and processing speed.

Test (age standardized)	Process- ing Speed	Working Memory	Inhibition	Sustained Attention	Set Switching
CTOPP Memory for Digits	0	1	0	0	0
WJ-COG Visual Matching	1	0	0	1	0
Nebraska Barnyard	0	1	0	1	0
Shape School:					
Color Naming Condition	1	0	0	1	0
Shape Naming Condition	1	0	0	1	0
Inhibition Condition	1	0	1	1	0

b. Q-matrix of cognitive skills associated with tests of executive function and processing speed.

Test (age standardized)	Process- ing Speed	Working Memory	Inhibition	Sustained Attention	Set Switching
Switching Condition	1	0	0	1	1
Preschool Trails:					
Control Condition	1	0	0	1	0
Inhibition Condition	1	0	1	1	0
Switching Condition					
Test of Inhibition and Attention:	1	0	0	1	1
Go No-Go Condition	0	0	1	1	0
CPT Condition	0	0	1	1	0

CI=subitizing; C2=cardinality; A|=subtraction; A2=addition; N1=spatial organization.

CTOPP=Comprehensive Test of Phonological Processing; WJ-COG=Woodcock Johnson Tests of Cognitive Abilities, 3rd Edition; CPT=Continuous Performance Test.

Table 3

a. POSET classification states and associated profiles of skill mastery for 17 numerical test items from Applied Problems, Woodcock Johnson Tests of Achievement, 3 rd Edition.						
State	C1	C2	A1	A2	N1	
1	1	1	1	1	1	
2	1	1	1	0	1	
3	1	0	1	*	1	
4	1	1	0	1	1	
5	1	0	0	0	1	
6	1	1	1	1	0	
9	1	1	0	1	0	
7	1	1	1	0	0	
8	1	0	1	*	0	
10	1	0	0	0	0	
11	0	0	0	0	0	

b. POSET classification states and associated profiles of skills on tests of processing speed and executive function.						
State	PS	WM	INH	ATT	SET	
1	1	1	1	1	1	
2	1	1	1	1	0	
3	1	1	0	1	1	
4	1	1	0	1	0	
5	0	1	1	1	*	
6	0	1	0	1	*	
7	*	1	*	0	*	
8	1	0	1	1	1	
9	1	0	1	1	0	
10	1	0	0	1	1	
11	1	0	0	1	0	
12	0	0	1	1	*	
13	0	0	0	0	0	

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Entries denoted as *,** indicate that modeling was unable to determine the skill level associated with that state (i.e., the skill was “indeterminant”).

CI=subitizing; C2=cardinality; A1=subtraction; A2=addition; N1=spatial organization.

Entries denoted as **, indicate that modeling was unable to determine the skill level associated with that state (i.e., the skill was “indeterminant”).

PS=processing speed; WM=working memory; INH=inhibition; ATT=attention; SET=set switching.