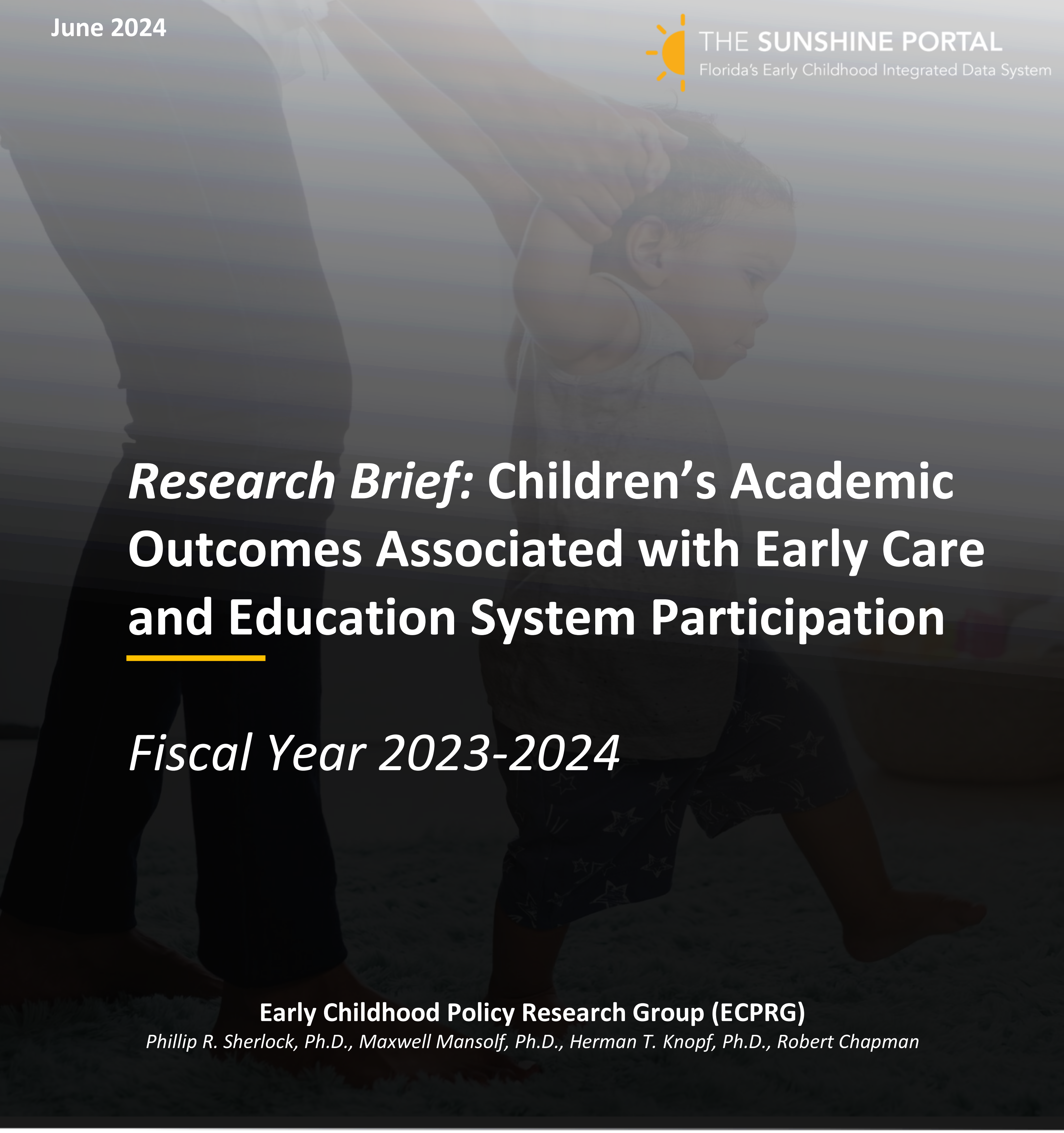

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THE SUNSHINE PORTAL
Florida's Early Childhood Integrated Data System

# *Research Brief:* Children's Academic Outcomes Associated with Early Care and Education System Participation

## *Fiscal Year 2023-2024*


**Early Childhood Policy Research Group (ECPRG)**

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DIVISION OF Early Learning
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# Children's Academic Outcomes Associated with Early Care and Education System Participation

## Introduction

The Early Childhood Policy Research Group (ECPRG) used the Early Childhood Integrated Data System linked dataset to investigate kindergarten readiness (KR) among students enrolled in the Voluntary Prekindergarten Education Program (VPK) across Florida. Specifically, the ECPRG used machine learning to detect and describe KR growth patterns characterized by individual-, household-, and classroom-level features. Children have different experiences—both negative and positive—as members of their respective families and peer groups.[1,2] Within education and numerous other fields, Bronfenbrenner's bioecological systems framework attributes differential outcomes to different combinations of exposures, such that each exposure is considered in context.[1,2] Children who attended VPK exhibited differential learning trajectories depending on family, peer and classroom context, with varying effects on development and preparation for kindergarten.

**Table of Acronyms**

| | |
|---|---|
| *Classroom Assessment Scoring System* | CLASS |
| *Early Childhood Policy Research Group* | ECPRG |
| *Florida Assessment of Student Thinking* | FAST |
| *Kindergarten Readiness* | KR |
| *Voluntary Prekindergarten Education Program* | VPK |

In this study, we investigated the effects of children's home- and school-based learning environments on their academic growth. Kindergarten Readiness (KR) is a term used to characterize the learning outcomes among children in the VPK program and was operationalized by (1) children's initial scores on the Florida Assessment of Student Thinking (FAST) upon entering VPK and (2) their growth (difference between initial and end-of-year FAST assessment). We first identified contexts under which children are likely to be ready for kindergarten. Future work will leverage lessons learned from this study to elucidate mechanisms of kindergarten readiness, motivating targeted interventions focusing on well-defined populations.

## Methods

### *Sample*

The analytic sample included 93,584 children born in Florida, enrolled in VPK during the 2022-2023 program year, and with at least two FAST assessments during that school year.

[1] Bronfenbrenner & Morris (2006)
[2] Elder Jr. (1998)

### *Kindergarten Readiness Scores*

Each of the children included in these analyses had one to three screening windows, with the number of assessments and time between first and last available assessment varying across children. Given these longitudinal data and the importance of the developmental period around kindergarten entry, our team constructed a single model to predict both initial score (the first available score for each child) and the expected monthly change in FAST score while the child was in VPK. To calculate the latter, the team first restricted the sample to children with at least two FAST scores, where there were at least 45 days between the first and last assessment dates. We then used all available FAST scores to calculate the increase in FAST score per month. Using the multivariate approach (i.e., simultaneously modeling two outcome variables) allowed us to consider not only the level of child ability before the start of VPK, but also the trajectory of learning while each child participated in VPK.

### *Understanding Classroom Context*

To understand the potential associations between the Classroom Assessment Scoring System (CLASS) and kindergarten readiness among VPK attendees, the ECPRG included the individual CLASS dimension scores in the machine learning model. This decision was made to allow for the discovery of associations between specific CLASS dimensions and differential kindergarten readiness among subgroups of children. To this end, we investigated how much the constituent dimensions of the CLASS were a (potentially complex) function of child, family and classroom characteristics using machine learning.

### *Brief Overview of Machine Learning Pipeline*

Analyses followed the steps established in the previous study, *Using Machine Learning Approaches to Describe Factors that Related to Kindergarten Readiness,* that were conducted as a component of the 2023 Sunshine Annual Report.[3] These analyses proceeded in three successive steps, firstly missing data handling using stacked multiple imputation, followed by selection of analysis variables with random forest regression, and lastly classification and regression trees to explain kindergarten readiness subgroups.[3] Once missing data were accounted for, random forest regression trimmed the large set of predictor variables to only the most important variables for predicting KR subgroups.[4,5] In the final step, a conditional inference regression tree model was used to predict KR subgroups, which was then pruned and examined to characterize these profiles in terms of data subpopulations. For a more detailed description of the machine learning methods, please see the 2024 Annual Sunshine Portal Progress Report.[6]

## Results

[3] ECPRG (2023)
[4] Gislason, Benediktsson, & Sveinsson (2006)
[5] Pal (2005)
[6] ECPRG (2024)

These findings reflect preliminary descriptions of child, household, and classroom factors that predict initial FAST scores and expected child academic growth. These fall under two broad categories: the influence of early learning experiences outside of formal schooling and classroom environment. While we do not have a direct measure of a family's support for their children's education, maternal education, maternal pre-pregnancy body mass index, Supplemental Nutrition Assistance Program participation and maternal country of origin are all associated with significantly negative initial FAST scores and significantly positive academic growth over the VPK year.

Children were more likely to have had experiences that were conducive to learning outside of formal education when their mothers had higher levels of education, healthy pre-pregnancy body mass indexes, and economic self-sufficiency. This was evidenced by the differences in final FAST scores primarily being a function of initial score rather than meaningful differences in academic growth across the VPK year. To that end, learning is a skill extending beyond the acquisition of any specific knowledge, and posits that information is organized into schemas, "organized units of knowledge for a subject or event based on past experience."[7] Children and all people leverage schemas to understand new information and create knowledge. Thus, the richer children's early experiences, the more schemas, formal and informal, can guide their learning. This can have an exponential effect on learning over a lifetime when established at a young age.

Children in classrooms with *instructional learning format* and *behavioral management* scores that of at least six on the 7-point scale of the CLASS experienced greater academic growth. VPK was particularly beneficial for children with socioeconomic vulnerabilities related to maternal education and family income. Targeted professional learning interventions should prioritize performance related to these two aspects of teacher practice.

## Future Directions

To fully leverage the results from this analysis, the ECPRG will spend the next year developing an interactive website to allow stakeholders to explore the findings. This website will feature executive summaries at both the state and coalition levels. Moreover, the coalition-specific summaries will be accompanied by in-depth reporting of the machine learning results to highlight the most salient contexts in which VPK attendees are exhibiting differences with respect to initial FAST scores and growth on that same measure. Furthermore, predictive insights based on results from the machine learning analysis will be used to suggest potential interventions. Finally, the ECPRG will create accompanying maps that will allow local stakeholders to visualize the zip-code-level placement of VPK students in order to inform their decisions for delivering targeted interventions.

[7] Pankin (2013)

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