WORKING WITH THE THRIVE BY FIVE INDEX 2024:
EXPLORATIONS OF EARLY LEARNING SYSTEMS IN SOUTH AFRICA

THE RELATIONSHIP BETWEEN RISKS TO CAREGIVER MENTAL HEALTH AND CHILD LEARNING OUTCOMES: AN ANALYSIS USING THRIVE BY FIVE INDEX DATA

JOHANNA BEUKES, ANATHI KWINANA

WORKING WITH THE THRIVE BY FIVE INDEX 2024:
EXPLORATIONS OF EARLY LEARNING SYSTEMS IN SOUTH AFRICA

THE RELATIONSHIP BETWEEN RISKS TO CAREGIVER MENTAL HEALTH AND CHILD LEARNING OUTCOMES: AN ANALYSIS USING THRIVE BY FIVE INDEX DATA

JOHANNA BEUKES[1], ANATHI KWINANA[2]

1 SAMRC Developmental Pathways for Health Research Unit, Department of Paediatrics, University of the Witwatersrand, Johannesburg, South Africa.
2 Centre for child, adolescent and family research, Department of Psychology, University of Cambridge, United Kingdom

Corresponding author

Johanna Beukes, johanna.beukes2@wits.ac.za, ORCID: 0000-0003-2644-7081

Funding

J.B. is supported by a postdoctoral fellowship from the Department of Science and Innovation and the National Research Foundation Centre of Excellence in Human Development at the Witwatersrand, Johannesburg, South Africa. A.K. is supported by the Oppenheimer Memorial Trust scholarship The funding sources had no role in the study design, data collection, analysis and interpretation of data or in writing the article.

Acknowledgements

The data used for this paper was provided by the Thrive by Five Index. The views and conclusions expressed in this paper are those of the author(s) and do not necessarily reflect the views of DataDrive2030, its partners, or the funders of the Thrive by Five Index.

Abstract

Background: The critical period of early childhood development is influenced by caregiver mental health and socioeconomic factors, yet information from low-resource settings remains scarce. This study explored how household- and caregiver-level risk factors relevant to caregiver mental health are associated with early learning outcomes in South Africa.

Methods: We conducted a secondary analysis of the nationally representative 2024 Thrive by Five Index, which included 3,841 children aged 50-59 months and their caregivers. The standardized Early Learning Outcomes Measure (ELOM) was used to measure child learning outcomes. In the absence of direct clinical measures of caregiver mental health, caregiver mental health risk was operationalized using proxy indicators of household food insecurity, perceived social support, and functional difficulties. Bivariate correlations and theory-driven multivariable linear regression models were estimated, with standard errors adjusted for clustering at the Early Learning Programme level.

Results: Multivariate analyses showed that higher household asset scores ($\beta = 1.00$, $p < .001$) and older child age ($\beta = 1.43$ per month, $p < .001$) were associated with higher ELOM total scores. Boys ($\beta = -3.54$, $p < .001$) and caregiver employment ($\beta = -0.46$, $p < .001$) were associated with lower ELOM scores. Household food insecurity ($\beta = -0.45$, $p = 0.582$) and perceived family support ($\beta = 0.25$, $p = 0.111$) were not independently associated with early learning outcomes after adjustment. The model explained approximately 12% of the variance in ELOM scores.

Conclusions: Early learning outcomes in South Africa appear to be shaped primarily by structural socioeconomic conditions and child characteristics. Addressing household-level constraints that influence caregiving environments may support both caregiver well-being and early childhood development in resource-constrained contexts.

Introduction

The first five years of life represent a critical period for cognitive, social, and emotional development (Aboud & Yousafzai, 2015; Goldfeld et al., 2022). During this critical window, a complex interplay of environmental, genetic, physiological, and psychological factors shapes developmental trajectories (Aranbarri et al., 2023; Chauhan & Potdar, 2022; Roberts et al., 2022). Caregiving environments profoundly shape developmental trajectories, yet many caregivers in low-resource contexts such as South Africa, face structural and psychosocial stressors such as poverty, food insecurity, and limited access to healthcare and education (Bluett-Duncan et al., 2021; Handa et al., 2024; Smith et al., 2023; Prom et al., 2022).

Globally, one in eight individuals experience mental health disorders (Dattani et al., 2023; WHO, 2022), with 16% of women developing a mental health disorder during pregnancy and 20% of them following childbirth in low-resource contexts (WHO, 2019). In South Africa, where 55% of households live below the poverty line and 50% are single parent headed (Statistics South Africa, 2023; Sulla, 2020), caregiver mental health challenges intersect with high unemployment, gendered caregiving burdens, and violence exposure. These factors collectively undermine caregivers' capacity for responsive, cognitively enriching interactions, potentially compromising children's school readiness and long-term wellbeing.

Socioeconomic status (SES), which encompass education, income, and occupation, is a well-established social determinant of both child development and caregiver mental health (Aranbarri et al., 2023; Marrie, 2011). Low parental education and unemployment create cumulative risks, potentially leading to maternal malnutrition, reduced parent-child interactions, and increased mental health challenges (Duncan & Magnuson, 2012; Ford & Stein, 2016). Beyond material resources, perceived social support is a key protective factor to child early learning. Studies have shown that stronger social networks are associated with better cognitive and socio-emotional development in young children and are negatively correlated with caregiver depressive symptoms (Shin et al., 2019; Surkan et al., 2023; Kang et al., 2016).

The home environment is consistently identified as the most influential setting for early development. Research from Brazil suggests that a high-quality home environment (characterized by family sensitivity, responsiveness, and availability of learning materials) can act as a powerful protective factor, potentially mediating the negative effects of low SES on child early learning (de Souza Morais et al., 2021). While home learning is a strong predictor of achievement, attendance at Early Learning Programmes (ELPs) has also been shown to be beneficial, particularly for high-risk children, helping to bridge developmental gaps associated with socioeconomic disadvantage (Burger, 2010; Rao et al., 2021).

Related to the home environment, boys were noted to be the most vulnerable to early life adversity during child rearing, affecting their inhibitory control and attention allocation skills (Coe et al., 2020). In a local study on sex differences in performances on early learning outcomes (ELOM 4&5), boys were reported to perform significantly poorer than girls, with 35% of girls being on track and only 30% falling behind while only 26% of boys are on track and as much as 41% falling behind in early learning outcome development (Tredoux et al., 2024).

Despite this growing body of evidence on child early learning, significant gaps remain, particularly in large-scale studies conducted in low-resource settings. Much of the existing literature on caregiver mental health relies on direct clinical measures (e.g., PHQ-9, GAD-7), which offer precise estimates of caregiver symptomatology. However, in large-scale national surveys in low-resource settings, such direct measures are often not feasible due to time, cost and ethical constraints. In these contexts, researchers have increasingly used household food insecurity, functional impairment, and perceived social support as indicators that are closely associated with caregiver psychological distress and well-being in low- and middle-income countries (Campisi et al., 2025; de Oliveira et al., 2020; George et al., 2020; Nair et al., 2025; Wawrziczny et al., 2020; Yuen et al., 2023). These proxy indicators do not capture mental health directly, but they reflect structural and relational conditions that are strongly linked to caregiver mental health risk.

Furthermore, while the broad roles of SES and home environment are acknowledged, their specific pathways and interactions within the high-stress, high-inequality context of South Africa are not fully elucidated. It remains unclear which specific socioeconomic and relational factors are the most robust predictors of child early learning outcomes when examined simultaneously, and whether these relationships are consistent across different subgroups (e.g., boys vs. girls, high vs. low SES households).

In this study, we therefore conceptualised “risks to caregiver mental health” pragmatically, as a constellation of household stressors and caregiver functional challenges that are theoretically and empirically associated with caregiver psychological well-being, rather than as diagnosed mental disorders. This approach aligns with calls to leverage routinely collected, policy-relevant indicators to understand how conditions that shape caregiver mental health may, in turn, influence child development in resource-constrained settings. Our interpretation of findings is accordingly cautious, as we focus on how these proxy risk factors to caregiver mental health relate to early learning outcomes, and we explicitly acknowledge that direct inferences about caregiver mental health disorders in the clinical sense cannot be made from the available data.

This study therefore aimed to address these gaps by leveraging South Africa's 2024 Thrive by Five Index dataset. Our research question was: How are household and caregiver-related risk factors that are associated with caregiver mental health risk related to early childhood learning outcomes in South Africa?

Conceptually, this study is guided by a bioecological framework that recognises child development as the product of multiple interacting systems. We posit that distal structural factors (e.g., SES and caregiver employment) influence proximal processes in the household (e.g., caregiver mental well-being and parent-child interactions), which in turn directly shape developmental outcomes. By utilising proxy indicators of risk to caregiver mental health available in the Thrive by Five Index dataset, this research offers a pragmatic and contextually relevant model for understanding how structural and relational conditions that affect caregiver well-being may be intertwined with child development in a resource-constrained setting, thereby informing targeted interventions and policies.

Methodology

Study Design

This study employed a quantitative, cross-sectional design comprising a secondary data analysis of the Thrive by Five Index data to investigate the association between caregiver mental health risk factors and child early learning within South Africa. Data was drawn from the 2024 Thrive by Five Index, a nationally representative survey conducted between September and November 2024. The Index assesses children aged 50-59 months, both enrolled in Early Learning Programmes (ELPs) and not enrolled, across all nine provinces of South Africa (Thrive by Five Index, 2022). This design allowed for the examining of relationships between key variables at a single time point.

Population and Sampling

The study population comprised of 3841 children aged 50-59 months and their caregivers. These participants were recruited across their 9 provinces of the country and using a multi-stage sampling strategy. For children enrolled in ELPs, a three-stage stratified sampling approach was used: 1. Selection of Primary Sampling Units (PSUs): 432 PSUs (wards/merged wards) were selected across all nine South African provinces, with each province allocated a minimum of 35 PSUs. PSUs were classified by a weighted school quintile based on Grade 3 enrolment. 2. Selection of ELPs: Within each selected PSU, ELPs meeting eligibility criteria (i.e., open 8 or more hours per week and having at least one child aged 50-59 months) were randomly selected. 3. Selection of Children: Within each selected ELPs, children aged 50-59 months were randomly selected, and consent was obtained from caregivers.

Data collection tools

The following measures were used to collect the data.

01. Child Early Learning Measures
Children's early learning was assessed using the Early Learning Outcomes Measure (ELOM 4&5 Years) direct assessment tool, a standardised, locally validated instrument (Dawes, et al., 2025; Mtati & Munnik, 2023; Munnik et al., 2021; Snelling et al., 2019). The ELOM 4&5 years measures multiple developmental domains, including cognition and executive functioning, emergent numeracy and literacy, fine and gross motor skills, and task orientation (Dawes et al., 2025; Mtati & Munnik, 2023; Munnik et al., 2021; Snelling et al., 2019). Domain scores and a composite ELOM 4&5 total score were derived to quantify children's developmental status relative to age-appropriate milestones.

02. Caregiver and Household Data
Primary caregivers were interviewed telephonically to collect sociodemographic information, household characteristics, and data on child-rearing practices (Petterson Gelander et al., 2025). Although direct clinical measures of caregiver mental health [such as PHQ-9; Kroenke et al. (2001) or GAD-7; Spitzer et al. (2006)] were not included in the 2024 survey, caregiver mental health risk factors were deduced using available variables reflecting household stressors and caregiver functioning with guidance of previous research. These risk factors include:

1. Household food insecurity, measured by the frequency of meal skipping due to food shortage among household members and children (Heany et al., 2021; Sansweet et al., 2024; Thielman et al., 2024).
2. Perceived social support, assessed through caregiver agreement with statements about family and friend support (Beharie et al., 2015; Panter-Brick et al., 2014; Seraj, 2025).
3. Functional difficulties experienced by caregivers in the past month, including challenges with work, home management, and interpersonal relationships (Rachamose & Harvey, 2025; Tseng et al., 2021).

To control for potential confounding and explore moderating effects of variables, key sociodemographic and relational variables, such as caregiver age, education, employment status, household assets, and presence of biological parents in the household were included in the analysis.

Data Analysis

Data analysis was conducted using Stata (Lumivero - Software Solutions for Data Analysis & Management, n.d.) comprising of the following steps: First, descriptive analysis of the sample's demographic characteristics, child early learning scores (i.e., ELOM 4&5 domains scores and composite score), caregiver mental health risk factors, socioeconomic status, relational factors, and ELP participation was conducted. This was followed by the second step, bivariate correlation analyses examining the relationship between all variables and the ELOM outcomes. We employed Pearson correlations for continuous variables (24 relationships), Spearman correlations for ordinal variables (90 relationships), and independent t-tests for binary predictors (18 relationships). Third, to examine associations between risk factors to caregiver mental health; namely caregiver- and household data; and child early learning outcomes, we estimated theory-driven multivariable linear regression models. Multivariable linear regression models were specified a priori based on the study's conceptual framework. Stepwise model selection procedures were not used, in line with methodological guidance discouraging data-driven variable selection due to risks of overfitting, instability, and inflated Type I error rates. Instead, all theoretically relevant predictors were retained in a single multivariable model. Socioeconomic status was modelled as a continuous household asset score rather than being categorised, in order to preserve information and statistical power. Child sex was included as a covariate in all models rather than using stratified analyses. Where multiple indicators reflected the same underlying construct, a single theoretically representative variable was retained to reduce redundancy and improve model stability. This approach allows for formal assessment of sex differences while avoiding loss of precision associated with subgroup-specific models. Given the clustered sampling structure of the data, standard errors were adjusted for clustering at the Early Learning Programme (ELP) level using the ECD centre identifier, thereby accounting for shared contextual influences among children attending the same programme.

Missing data were present for some caregiver-reported variables, primarily due to conditional survey routing and non-response. Analyses were conducted using complete-case analysis for each model. Given the large final analytic sample and the descriptive aim of the study, multiple imputation was not undertaken. However, we acknowledge that estimates may be biased if missingness is not completely at random.

Results

Descriptive Statistics

Tables 1 and 2 presents the descriptive statistics of the continuous and categorical variables, respectively. The sample of children was approximately evenly distributed in terms of sex (51.11% female and 48.89% male), with the average age being 54.84 months (i.e. 4 years, 6 months) at the time of data collection.

Table 1 Descriptive statistics for all continuous variables.

Variable	Mean	SD	Range
Child Demographics			
Child age in months (N = 3841)	54.84	2.50	49.73 - 59.50
ELOM Cognitive Outcomes (N=3841)			
ELOM Total Score	44.95	13.60	8.41 - 91.69
ELOM Domain 1*	7.84	3.88	0.0 - 20.0
ELOM Domain 2*	10.97	3.62	0.93 - 20.0
ELOM Domain 3*	8.256	4.04	0.0 - 20.0
ELOM Domain 4*	7.16	4.20	0.0 - 20.0
ELOM Domain 5*	10.73	4.34	0.0 - 20.0
Socioeconomic Status			
Household asset score (N = 3829)	6.39	1.96	1.0 - 10.0

*ELOM Domain 1 = Gross Motor Development. *ELOM Domain 2 = Fine Motor Coordination & Visual Motor Integration. *ELOM Domain 3 = Emergent Numeracy & Mathematics. *ELOM Domain 4 = Cognition & Executive Function. *ELOM Domain 5 = Emergent Literacy & Language

Table 2 Descriptive statistics for all categorical variables.

Variable	Response Category	Count	Percentage
Child Demographics			
Child Sex (N=3841)	Girl	1963	51.11
	Boy	1878	48.89
Caregiver Mental Health Risk Factors			
Receive Child Support Grant (N=3810)	Yes	2729	71.05
	No	1081	28.14
	Don't know	31	0.81
Support from family (N=3841)	Agree	3293	85.74
Support from friends (N=3841)	Agree	1972	51.34
Home difficulties in last 4 weeks (N=3841)	Somewhat difficult	930	24.21
	Very difficult	355	9.24
	Extremely difficult	142	3.70
Work difficulties in last 4 weeks (N=1986)	Somewhat difficult	400	20.14
	Very difficult	174	8.76
	Extremely difficult	78	3.93
Difficulty getting along with people in last 4 weeks (N = 3841)	Somewhat difficult	509	13.25
	Very difficult	152	3.96
	Extremely difficult	26	0.68
Family member meal skipping due to food shortage in the last 3 months (N = 3841)	Yes	270	7.03
Child meal skipping due to food shortage in the last 3 months (N = 270)	Yes	114	42.22

Table 2 Descriptive statistics for all categorical variables.

Variable	Response Category	Count	Percentage
Father Living in Residence (N = 3553)	Yes	1639	46.13
Mother Living in Residence (N = 1037)	Yes	666	64.22
Socioeconomic Status (N=3841)			
Caregiver Education (N = 3841)	No schooling	2729	71.05
	Grade R/0	1081	28.14
	Some primary school	31	0.81
	Completed primary school	3293	85.74
	Some high school	1972	51.34
	Completed high school	930	24.21
Caregiver Highest Tertiary Education (N = 1553)	Certificate	355	9.24
	Diploma	142	3.70
	Bachelor's degree	400	20.14
	Post-graduate	174	8.76
Caregiver Employment Status (N = 3841)	Learner at school	78	3.93
	Studying at College/University	509	13.25
	Paid employee	152	3.96
	Self-employed	26	0.68
	Employer/business owner	270	7.03
	Retired	114	42.22
	Unemployed		
	Other/Unknown		

Correlation Analyses

Bivariate correlations between early learning outcomes and caregiver- and household-level risk factors relevant to caregiver mental health are presented in Table 3. Variables included in this table were selected a priori based on their conceptual relevance and subsequent inclusion in the multivariable regression analyses.

Table 3. Bivariate correlations between early learning outcomes and household- and caregiver- risk factors to mental health.

Variable	Correlation with ELOM total score	Correlation type
Household asset score	$\rho = 0.16$	Spearman
Child age (months)	$\rho = 0.26$	Spearman
Perceived family support	$\rho = 0.02$	Spearman
Household food insecurity (meal skipping)	$r = -0.05$	Point-biserial
Caregiver employment (employed)	$r = -0.11$	Point-biserial
Child sex (male)	$r = -0.13$	Point-biserial

Note. N = 3,841. Spearman rank-order correlations (ρ) were used for continuous or ordinal variables, and point-biserial correlations (r) were used for binary variables. Correlations are presented descriptively and were not selected based on statistical significance.

Higher household asset scores ($\rho = 0.16$) and older child age ($\rho = 0.26$) were positively associated with ELOM total scores. Male child sex ($r = -0.13$), caregiver employment ($r = -0.11$), and household food insecurity ($r = -0.05$) showed small negative associations with early learning outcomes, while perceived family support demonstrated a negligible association ($\rho = 0.02$). For transparency, a full descriptive correlation matrix of all study variables is provided in Appendix Table A1.

Multivariate Regression Models

A multiple linear regression was conducted to identify predictors of children's learning outcomes, as measured by the ELOM Total Score. All regression models included the full set of theoretically specified predictors without stepwise selection, with standard errors adjusted for clustering at the ELP level.

Table 4 presents the results from the multivariable linear regression model examining associations between household- and caregiver-related risk factors to caregiver mental health and early learning outcomes (ELOM total scores), with standard errors adjusted for clustering at the Early Learning Programme (ELP) level. The model explained approximately 12% of the variance in ELOM total scores ($R^2 = 0.12$). Multicollinearity diagnostics indicated no evidence of collinearity among predictors (all variance inflation factors < 1.1).

Table 4. Multivariable Linear Regression Predicting ELOM Total Score.

Predictor	β	SE	95% CI	*P*
Household asset score	1.00	0.12	[0.76, 1.25]	< 0.001
Household food insecurity (meal skipping)	−0.45	0.82	[−2.05, 1.15]	0.582
Perceived family support	0.25	0.16	[−0.06, 0.57]	0.111
Caregiver employment (employed)	−0.46	0.11	[−0.68, −0.25]	< 0.001
Child age (months)	1.43	0.09	[1.25, 1.61]	< 0.001
Child sex (male)	−3.54	0.40	[−4.33, −2.75]	< 0.001
Constant	−31.33	5.65	[−42.42, −20.24]	< 0.001

Note. N = 3,841. Unstandardised regression coefficients (b) are reported with cluster-robust standard errors and 95% confidence intervals. Standard errors were adjusted for clustering at the Early Learning Programme (ELP) level (1,318 clusters). Model fit: $R^2 = .12$; $F(6, 1317) = 68.85$, $p < .001$. Higher ELOM scores indicate better early learning outcomes.

Higher household asset scores were strongly associated with higher ELOM total scores (β = 1.00, p < .001). Child age showed robust positive association with ELOM scores (β = 1.43 per month, p < .001). Boys scored significantly lower on their ELOM total scores than girls (β = −3.54, p < .001). Caregiver employment status was negatively associated with children's ELOM total scores (β = −0.46, p < .001). After adjustment for socioeconomic status and child characteristics, household food insecurity, caregiver work difficulties, and perceived family support were not independently associated with ELOM scores.

Discussion and Conclusion

Summary of Key Findings

This study examined associations between caregiver- and household-level risk factors relevant to caregiver mental health and early childhood learning outcomes in South Africa using 2024 Thrive by Five Index data. Older children, girls, and those from households with higher asset scores performed better on the ELOM. Caregiver employment was associated with lower ELOM scores. While perceived social support and food insecurity were not significant predictors once socioeconomic factors were controlled.

Contextualization of Findings

These findings align with prior literature demonstrating that household resources are strong predictors of early learning outcomes across diverse contexts (Bluett-Duncan et al., 2021; Smith et al., 2023; Zhang et al., 2020). These studies associate better resources with enriched home environments and greater access to material and cognitive stimulation, all of which support early learning (de Souza Morais et al., 2021; Shin et al., 2019). Similarly, our finding of the positive role of household asset score reflects the advantages of economic stability and access to resources that enable engagement with early learning opportunities. Household assets likely reflect cumulative advantages, including access to learning materials, stable housing, and reduced exposure to chronic stressors that can undermine caregiver well-being and caregiving capacity.

Child age was the strongest predictor of ELOM performance, reflecting expected developmental gains across the narrow age range assessed. The lower ELOM scores observed among boys are consistent with evidence that male children may be more vulnerable to early developmental risks, particularly in contexts characterised by socioeconomic adversity and household stress. This is consistent with results found by Tredoux et al. (2024) on children across South Africa in the 2021 Thrive by Five Index. These findings emphasise the need for interventions primarily focused on building resilience in boy children facing early life adversity and susceptibility to home and caregiver risk factors such as parental stress due to unemployment, housing instability, lack of resources and potentially maltreatment (Coe et al., 2020).

The negative association between caregiver employment and ELOM scores warrants cautious interpretation. In low-resource settings, caregiver employment may be associated with precarious or time-intensive work that limits caregiver availability for responsive interactions, rather than reflecting economic security. This finding underscores the importance of considering employment quality and caregiving context, rather than employment status alone.

Some variables demonstrated weak bivariate associations with early learning outcomes but became more salient in the multivariable models, suggesting the presence of confounding or suppression effects once shared variance with socioeconomic position and child characteristics was accounted for. This pattern highlights the importance of multivariable modelling when examining complex caregiving environments, as reliance on bivariate associations alone may obscure relationships that only emerge after adjustment for broader structural context.

Implications

At the research level, the attenuation of several bivariate relationships in the multivariate models highlights the need for rigorous modelling that accounts for overlapping socioeconomic and relational influences. Future research should explore mediating mechanisms (such as caregiver stress regulation) to better understand how caregiver education and resources translate into developmental gains.

At the practice and policy levels, the findings reinforce the importance of addressing structural socioeconomic inequalities as a pathway to improving early learning outcomes. Interventions that strengthen household economic stability and reduce caregiving strain may indirectly support caregiver well-being and children's developmental outcomes. Given the observed sex differences, early interventions may need to be particularly attentive to the developmental needs of boys in resource-constrained settings.

Strengths, Limitations and Future Directions

This study had several strengths, including the use of a large, nationally representative dataset, a validated and locally normed measure of early learning (ELOM 4&5), and the inclusion of a diverse range of socioeconomic and relational predictors relevant to caregiver well-being. However, several limitations should be acknowledged. First, the cross-sectional design precludes causal inference, highlighting the need for longitudinal studies to explore developmental trajectories over time.

Second, the lack of variability with all children being enrolled in ELPs, potentially impacting early learning outcomes made it impossible for comparison with those who have had no exposure to ELPs. Third, the absence of validated caregiver mental health measures limits our ability to directly link caregiver psychosocial symptoms or diagnoses with child outcomes. In this analysis we relied on proxy indicators (i.e., household food insecurity, perceived social support, and caregiver functional difficulties) that are theoretically and empirically associated with caregiver mental health risk, but do not constitute mental health assessments per se.

Our findings should therefore be interpreted as reflecting how structural and relational conditions that are related to caregiver well-being are associated with early learning outcomes, rather than as direct estimates of the effects of caregiver mental disorders. Future studies should incorporate standardized caregiver mental health assessments alongside these contextual indicators to clarify the mechanisms linking caregiver well-being and child development. Second, the cross-sectional design prevents causal inference and limits examination of developmental trajectories.

Third, missing data in some caregiver variables may have introduced bias, particularly where/if non-response was associated with household vulnerability. Although the final analytic sample remained large, and clustered standard errors were applied, future work should explore sensitivity analyses or multiple imputation approaches to assess the robustness of findings under different missing data assumptions. Fourth, clustering at the ELP and household levels may influence standard errors, thus future analyses should apply multilevel modelling to explicitly model this structure. Finally, stratified analyses were used to explore subgroup differences, but interaction-term approaches in future studies may provide a more statistically robust test of moderation effects. These limitations should be considered when interpreting the findings.

Conclusions

This study provides evidence that child learning outcomes in South Africa are shaped by structural socioeconomic conditions and child characteristics. Higher household asset scores and older child age were associated with better early learning outcomes, while boys and children of employed caregivers demonstrated lower ELOM scores. These findings highlight the importance of addressing household-level conditions that influence caregiving environments to support early childhood development. By leveraging proxy indicators relevant to caregiver mental health risk, this study offers some pragmatic understanding of how structural and relational conditions may be intertwined with child development in low-resource settings.

References

Aboud, F. E., & Yousafzai, A. K. (2015). Global health and development in early childhood. *Annual review of psychology, 66(1)*, 433-457.

Aranbarri, A., Aizpitarte, A., Arranz-Freijo, E., Fano, E., de Miguel, M. S., Stahmer, A. C., & Ibarluzea, J. M. (2023). What influences early cognitive development? Family context as a key mediator. *Journal of Applied Developmental Psychology, 84,* 101480.

Beharie, N., Lennon ,Mary Clare, & and McKay, M. (2015). Assessing the Relationship Between the Perceived Shelter Environment and Mental Health Among Homeless Caregivers. *Behavioral Medicine, 41(3),* 107–114. **https://doi.org/10.1080/08964289.2015.1046415**

Bluett-Duncan, M., Kishore, M. T., Patil, D. M., Satyanarayana, V. A., & Sharp, H. (2021). A systematic review of the association between perinatal depression and cognitive development in infancy in low and middle-income countries. *PLoS One, 16(6),* e0253790.

Burger, K. (2010). How does early childhood care and education affect cognitive development? An international review of the effects of early interventions for children from different social backgrounds. *Early childhood research quarterly, 25(2),* 140-165.

Chauhan, A., & Potdar, J. (2022). Maternal mental health during pregnancy: a critical review. *Cureus, 14*(10).

Coe, J. L., Micalizzi, L., Josefson, B., Parade, S. H., Seifer, R., & Tyrka, A. R. (2020). Sex differences in associations between early adversity, child temperament, and behavior problems. *International Journal of Behavioral Development, 44(6),* 490-504.

Dattani, S., Rodés-Guirao, L., Ritchie, H., & Roser, M. (2023). Mental Health.
de Souza Morais, R. L., de Castro Magalhães, L., Nobre, J. N. P., Pinto, P. F. A., da Rocha Neves, K., & Carvalho, A. M. (2021). Quality of the home, daycare and neighbourhood environment and the cognitive development of economically disadvantaged children in early childhood: A mediation analysis. *Infant behavior and development, 64,* 101619.

Dawes, A., Biersteker, L., Girdwood, E., Snelling, M.J.T.L., Tredoux, C.G. & Kafaar, Z. (2025). Early Learning Outcomes Measure 4&5 Years Assessment Tool Technical Manual. DataDrive2030 Westlake, Cape Town. **https://DataDrive2030.co.za**

Duncan, G., & Magnuson, K. (2012). Socioeconomic status and cognitive functioning: Moving from correlation to causation. *WIREs Cognitive Science, 3 (3),* 377–386. In.

Fibriana, A. I., Budiono, I., Pribadi, F. S., & Handayani, O. W. K. (2025). Factors Influencing Cognitive Development In Early Childhood: A Systematic Literature Review. Proceedings of International Conference on Health Science, Practice, and Education.

Fletcher AC, Buehler C, Buchanan CM, Weymouth BB. Parenting stressors and young adolescents' depressive symptoms: Does high vagal suppression offer protection? Physiology & Behavior [Internet]. 2017 Mar [cited 2025 Oct 28];170:78–87. Available from: **https://linkinghub.elsevier.com/retrieve/pii/S0031938416302463**

Ford, N. D., & Stein, A. D. (2016). Risk factors affecting child cognitive development: A summary of nutrition, environment, and maternal–child interaction indicators for sub-Saharan Africa. *Journal of developmental origins of health and disease, 7(2)*, 197-217.

Goldfeld, S., Bryson, H., Mensah, F., Price, A., Gold, L., Orsini, F., Kenny, B., Perlen, S., Mudiyanselage, S. B., & Dakin, P. (2022). Nurse home visiting to improve child and maternal outcomes: 5-year follow-up of an Australian randomised controlled trial. *PLoS One, 17*(11), e0277773.

Handa, A., Gaidhane, A., & Choudhari, S. (2024). Shedding light on maternal mental health in LMICs: a cornerstone of maternal and child health care. *Discover Mental Health, 4*(1), 55.

Harewood T, Vallotton CD, Brophy-Herb H. More than Just the Breadwinner: The Effects of Fathers' Parenting Stress on Children's Language and Cognitive Development. Infant and Child Development [Internet]. 2017 [cited 2025 Oct 28];26(2):e1984. Available from: **https://onlinelibrary.wiley.com/doi/abs/10.1002/icd.1984**

Heany, S., Phillips, N., Myer, L., Zar, H., Stein, D., & Hoare, J. (2021). Physical development and mental health in South African perinatally HIV-positive adolescents on antiretroviral therapy and their caregivers with and without household food insecurity. *Southern African Journal of HIV Medicine, 22*(1), Article 1. **https://doi.org/10.4102/sajhivmed.v22i1.1316**

Hoyniak, C., Bates, J., Staples, A., Rudasill, K., Molfese, D., & Molfese, V. (2018). Child sleep and socioeconomic context in the development of cognitive abilities in early childhood. *Child Development, 90*(5), 1718-1737. **https://doi.org/10.1111/cdev.13042**

Kang, D.-H., Boss, L., & Clowtis, L. (2016). Social support and cognition: Early childhood versus older adulthood. *Western journal of nursing research, 38*(12), 1639-1659.

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: validity of a brief depression severity measure. *J Gen Intern Med, 16(*9), 606-613. **https://doi.org/10.1046/j.1525-1497.2001.016009606.x**

Lee JY, Lee SJ, Ward KP, Pace GT, Chang OD. Shared parental responsiveness among fathers and mothers with low income and early child outcomes. Family Relations [Internet].

Lumivero—Software Solutions for Data Analysis & Management. (n.d.). Lumivero. Retrieved February 4, 2025, from **https://lumivero.com/202**4 [cited 2025 Oct 28];73(2):683–702. Available from: **https://onlinelibrary.wiley.com/doi/abs/10.1111/fare.12913**

Marrie, R. A. (2011). Demographic, Genetic, and Environmental Factors That Modify Disease Course. *Neurologic Clinics, 29*(2), 323-341. **https://doi.org/https://doi.org/10.1016/j.ncl.2010.12.004**

Mtati, C. N., & Munnik, E. (2023). Instruments measuring emotional-social competence in preschoolers in South Africa: A review study. *African Journal of Psychological Assessment, 5*(0), Article 0. **https://doi.org/10.4102/ajopa.v5i0.111**

Munnik, E., Wagener, E., & Smith, M. (2021). Validation of the emotional social screening tool for school readiness. *African Journal of Psychological Assessment, 3*(0), Article 0. **https://doi.org/10.4102/ajopa.v3i0.42**

Moore SE. Sex differences in growth and neurocognitive development in infancy and early childhood. Proceedings of the Nutrition Society [Internet]. 2024 Dec [cited 2025 Oct 28];83(4):221–8. Available from: **https://www.cambridge.org/core/journals/proceedings-of-the-nutrition-society/article/sex-differences-in-growth-and-neurocognitive-development-in-infancy-and-early-childhood/0C5FB412FBCFADD31FAD313AF2E527D4**

Oryono A, Iraguha B, Musabende A, Habimana E, Nshimyiryo A, Beck K, et al. Father involvement in the care of children born small and sick in Rwanda: Association with children's nutrition and development. Child Care Health Dev. 2021 July;47(4):451–64.

Panter-Brick, C., Grimon, M.-P., & Eggerman, M. (2014). Caregiver—child mental health: A prospective study in conflict and refugee settings. Journal of Child Psychology and Psychiatry, 55(4), 313–327. **https://doi.org/10.1111/jcpp.12167**

Pettersson Gelander, G., Giese, S., Dawes, A., Ardington, C., Tredoux, C., Cook, C., Carnegie, T., Brophy,T., Zastrau, E. (2025). Thrive by Five Index 2024: Technical Report. DataDrive2030, Cape Town.

Prom, M. C., Denduluri, A., Philpotts, L. L., Rondon, M. B., Borba, C. P., Gelaye, B., & Byatt, N. (2022). A systematic review of interventions that integrate perinatal mental health care into routine maternal care in low-and middle-income countries. *Frontiers in Psychiatry, 13*, 859341.

Rachamose N, Harvey C. 'It shuttered down our hearts': the mental health of caregivers of children with cerebral palsy in rural Limpopo, South Africa. *South African Journal of Psychology.* 2025;55(2):217-229. doi:**10.1177/00812463251315869**

Rao, N., Cohrssen, C., Sun, J., Su, Y., & Perlman, M. (2021). Chapter Eight - Early child development in low- and middle-income countries: Is it what mothers have or what they do that makes a difference to child outcomes? In J. J. Lockman (Ed.), Advances in Child Development and Behavior (Vol. 61, pp. 255-277). JAI. **https://doi.org/https://doi.org/10.1016/bs.acdb.2021.04.002**

Roberts, M., Tolar-Peterson, T., Reynolds, A., Wall, C., Reeder, N., & Rico Mendez, G. (2022). The effects of nutritional interventions on the cognitive development of preschool-age children: a systematic review. *Nutrients, 14*(3), 532.

Sansweet, S., Roach, A., Pappalardo, A. A., Yost, J. C., Asante, J., & Warren, C. (2024). Food Insecurity and Psychosocial Burden in a National Community-Based Sample of Households Managing Food Allergy. *Health Promotion Practice, 25*(4), 634–643. **https://doi.org/10.1177/15248399231223740**

Seraj, R. (2025). The Impact of Personality Traits and Social Support on Mental Well-Being among the Caregivers of Children with Autism Spectrum Disorder. *EAS Journal of Psychology and Behavioural Sciences, 7*(02), 21–29. **https://doi.org/10.36349/easjpbs.2025.v07i02.002**

Shin, E. K., LeWinn, K., Bush, N., Tylavsky, F. A., Davis, R. L., & Shaban-Nejad, A. (2019). Association of maternal social relationships with cognitive development in early childhood. JAMA network open, 2(1), e186963-e186963.

Smith, T. A., Kievit, R. A., & Astle, D. E. (2023). Maternal mental health mediates links between socioeconomic status and child development. Current Psychology, 42(25), 21967-21978.

Snelling, M., Dawes, A., Biersteker, L., Girdwood, E., & Tredoux, C. (2019). The development of a South African Early Learning Outcomes Measure: A South African instrument for measuring early learning program outcomes. *Child: Care, Health and Development, 45*(2), 257–270. **https://doi.org/10.1111/cch.12641**

Spitzer, R. L., Kroenke, K., Williams, J. B., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: the GAD-7. Archives of internal medicine, 166(10), 1092-1097.

Surkan, P. J., Park, S., Ridgeway, K., Ribeiro, M., Fidalgo, T. M., Martins, S. S., & Caetano, S. C. (2023). Caregiver social capital and supportive relationships are associated with better child social-emotional development. Child Psychiatry & Human Development, 54(4), 1102-1111.

Tredoux, C., Dawes, A., Mattes, F., Schenk, J.-C., Giese, S., Leach, G., van der Berg, S., & Horler, J. (2024). Are South African children on track for early learning? Findings from the South African Thrive By Five Index 2021 Survey. *Child Indicators Research, 17*(2), 601-636. **https://doi.org/10.1007/s12187-023-10093-3**

Tseng, H.-W., Tsai, C.-S., Chen, Y.-M., Hsiao, R. C., Chou, F.-H., & Yen, C.-F. (2021). Poor Mental Health in Caregivers of Children with Attention-Deficit/Hyperactivity Disorder and Its Relationships with Caregivers' Difficulties in Managing the Children's Behaviors and Worsened Psychological Symptoms during the COVID-19 Pandemic. *International Journal of Environmental Research and Public Health, 18*(18), Article 18. **https://doi.org/10.3390/ijerph18189745.**

Thielman, J., Orr, S., Naraentheraraja, S., Harrington, D., & Carsley, S. (2024). Cross-sectional analysis of the association between household food insecurity and mental health conditions in children aged 5–11 years in Canada. **https://doi.org/10.1136/bmjopen-2023-081538.**

Thrive by Five Index. (2022). **https://thrivebyfive.co.za/**

Walker, S. P., Wachs, T. D., Grantham-McGregor, S., Black, M. M., Nelson, C. A., Huffman, S. L., Baker-Henningham, H., Chang, S. M., Hamadani, J. D., & Lozoff, B. (2011). Inequality in early childhood: risk and protective factors for early child development. *The Lancet, 378*(9799), 1325-1338.

Wang, L., Emmers, D., Sylvia, S., Bai, Y., & Rozelle, S. (2024). Rural–urban differences in the intergenerational transmission of cognitive capabilities in China: evidence from a northwestern province of China. China Agricultural Economic Review, 16(4), 747-762. **https://doi.org/10.1108/caer-12-2023-0374**

Whitney SD, Prewett S, Wang Z, Chen H. FATHERS' IMPORTANCE IN ADOLESCENTS' ACADEMIC ACHIEVEMENT. International Journal of Child, Youth and Family Studies [Internet]. 2017 [cited 2025 Oct 28];8(3/4):101–26. Available from: **https://journals.uvic.ca/index.php/ijcyfs/article/view/18073**

Zhang, Z., Liu, H., & Choi, S. (2020). Early-life socioeconomic status, adolescent cognitive ability, and cognition in late midlife: evidence from the Wisconsin longitudinal study. Social Science & Medicine, 244, 112575. **https://doi.org/10.1016/j.socscimed.2019.112575**

Appendix Table A1: Descriptive bivariate correlations among study variables.

Variable	1	2	3	4	5	6	7	8	9	10	11
1. ELOM total score	—										
2. Household asset score	0.16	—									
3. Child age (months)	0.26	0.02	—								
4. Family support	0.02	−0.01	0.00	—							
5. Friends' support	0.00	−0.06	0.02	0.35	—						
6. Caregiver education (years)	−0.13	−0.35	0.01	0.00	0.02	—					
7. Household food insecurity	−0.05	—	—	—	—	—	—				
8. Child food insecurity	0.04	—	—	—	—	—	—	—			
9. Caregiver employment (employed)	−0.11	0.12	0.09	—	—	—	—	—	—		
10. Child support grant receipt	−0.13	0.11	0.09	—	—	—	—	—	—	—	
11. Child sex (male)	−0.13	0.02	−0.08	—	—	—	—	—	—	—	—
12. Father resident in household	0.06	−0.09	−0.05	—	—	—	—	—	—	—	—

Note. Appendix Table A1 presents a comprehensive descriptive correlation matrix of all study variables included in the descriptive analyses. Correlations are provided to enhance transparency and to document the bivariate associations among variables examined in the study. Spearman rank-order correlations are reported for continuous or ordinal variables, and point-biserial correlations are reported for binary variables. Correlations are presented for descriptive purposes only and were not used for variable selection or hypothesis testing

DATADRIVE 2030

Learn more at **DataDrive2030.co.za** | Follow us on LinkedIn **@DataDrive2030**