Risk and resilience factors for primary school dropout in Côte d'Ivoire

Brooke Wortsman[1], Angela Capani[1], Henry Brice[1], Mary-Claire Ball[1], Benjamin Zinszer[2], Fabrice Tanoh[3], Hermann Akpé[4], Amy Ogan[5], Sharon Wolf[6], Kaja Jasińska[1,7*]

Affiliations

1. University of Toronto, Toronto, Canada
2. Swarthmore College, Swarthmore, PA, USA
3. University Péléforo Gon Coulibaly de Korhogo
4. Félix Houphouët Boigny University
5. Carnegie Mellon University, Pittsburgh, PA, USA
6. University of Pennsylvania, Philadelphia, PA, USA
7. Haskins Laboratories, New Haven, CT, USA

*Senior/Corresponding Author:

Kaja Jasińska

Applied Psychology and Human Development
University of Toronto
252 Bloor Street West
Toronto, ON, M5S 1V6
kaja.jasinska@utoronto.ca

Co-author contact information:
Brooke Wortsman: brooke.wortsman@mail.utoronto.ca
Angela Capani: angela.capani@mail.utoronto.ca
Henry Brice: henry.brice@utoronto.ca
Mary-Claire Ball: maryclaire.ball@mail.utoronto.ca
Benjamin Zinszer: bzinszer@gmail.com
Fabrice Tanoh: fabio85tanoh@gmail.com
Hermann Akpé: akpermann@gmail.com
Amy Ogan: aeo@cs.cmu.edu
Sharon Wolf: wolfs@upenn.edu
Kaja Jasińska: kaja.jasinska@utoronto.ca

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Abstract

We examined child-, family-, and school-level risk and resilience factors associated with dropout using longitudinal data of fifth-grade students in rural Côte d'Ivoire (N=1195, M_{age}=10.75, SD_{age}=1.42). Children who dropped out were older, involved in more child labour, had poorer literacy, owned fewer books, and attended schools with poorer learning environments. Cumulative risk (CR) indices revealed that child-level CR most strongly predicted dropout (b=-0.86, OR=0.42); further, children with low child-level CR were more likely to drop out when family-level CR was high (b=0.23, OR=1.25). Better school infrastructure and teachers were protective for children who were at high risk of dropout yet remained enrolled. Although child- and family-level factors contribute to risk of dropout, school-level factors may mitigate risks and promote academic resilience amongst students in West Africa.

Keywords: Primary school dropout; educational risk and resilience; ecological systems; Côte d'Ivoire; West Africa

Introduction

Education is central for children to flourish; there are global commitments to this (e.g., the United Nations' Sustainable Development Goal 4.1; 2015). Yet children face adversity across many ecological levels that impede their education and rarely are these risk factors examined in tandem, nor are protective factors examined. Limited progress has been made in reducing the global number of out-of-school children over the past few decades; in sub-Saharan Africa (SSA), despite an increase in school completion rate since 2008, the current pace is insufficient to reach universal primary completion by 2030 (UNESCO, 2019).

Of the global 59 million out-of-school primary school-aged children, more than half live in SSA (UNESCO, 2019). In SSA, nearly 20% of primary school-aged children are out of school. A staggering 34% of these children drop out before completing primary school (UNESCO, 2019). In the West African country of Côte d'Ivoire, where nearly 11 million children are of primary school age (UNESCO, 2019), the primary school completion rate is just 74% (UNESCO Institute for Statistics, 2022). The remaining 26% of Ivorian children have either dropped out or never entered school at all. Despite the overwhelming number of children who do not complete primary school in Côte d'Ivoire, there has been no research into the protective factors that lead to academic resilience (i.e., remaining in school despite facing risk factors associated with dropout) and little empirical research on the risk factors that predict primary school dropout.

In this study, we examined child-, family-, and school-level risk factors associated with school dropout in rural Côte d'Ivoire. We also compared the characteristics of academically resilient children (i.e., those who remained enrolled despite high risk of dropout) with those who had dropped out to identify factors that are promotive to academic resilience. We apply an

ecological framework (Bronfenbrenner, 1979) to examine risk and resilience processes linked to school dropout. Communities in low- and middle-income countries, especially within SSA, experience a multitude of risks such as disease, malnutrition, poverty, and low availability of high-quality educational and healthcare resources that influence developmental outcomes (McCoy et al., 2016). Historically, empirical research on school dropout has primarily centred on understanding risk, adversity, and the factors that predict school dropout; much of this research has been situated in high income, western countries (e.g., Gubbels et al, 2019). Some factors that pull children away from school in western countries (e.g., being older, having a job, low family socioeconomic status [SES], and low quality schools; Gubbels et al, 2019) have also been identified as risk factors for dropout in SSA (e.g., Kuepie et al., 2015; Oruko et al., 2015). However, in understudied countries such as Côte d'Ivoire, these risk factors are often experienced or measured differently; we expand further below.

We posit that, along with understanding risk, it is equally important to shed light on how children overcome adversity and display resilience in high-risk environments. Resilience is the process that supports adaptation in order to avoid negative effects associated with risk and experience positive outcomes (Masten, 2011). This research examines protective factors at multiple ecological levels to help individuals or groups achieve these positive outcomes (i.e., mitigate risk of dropout; Masten, 2011; Ungar, 2008).

Child development is a dynamic, interactive process between an individual and their environment ranging from the child's immediate settings of family and school to broader, sociocultural influences such as regional policies and societal norms (Bronfenbrenner, 1979). Risk of dropout is influenced by a child's individual characteristics in conjunction with risk factors experienced at home and at school (Bronfenbrenner, 1979; Evans et al., 2013). Further,

risk status can be compounded by the presence of severe and multiple stressors — a theoretical framework known as 'cumulative risk' (CR); children who experience multiple risk factors across child-, family-, and school-levels are at higher risk of dropout (Evans et al., 2013; Hunt, 2008; Oruko et al., 2015).

In order to investigate risk and resilience for school dropout, we first examined child-, family-, and school-level factors and their interactions to understand liabilities that increase a child's likelihood of dropping out of school. We then consider academic resilience; what child-, family-, and school-level factors are protective (i.e., associated with remaining enrolled in primary school despite experiencing several risk factors associated with dropout)? Rather than examining factors in isolation, it is imperative to consider the context in which individuals are situated when examining risk and resilience factors associated with dropout (Ungar, 2008). We posit that dropout results from interactions between child-, family-, and school-level factors (Hunt, 2008).

Risk and Resilience in an Ecological Systems Framework

Previous research has identified risk factors for dropout that apply to communities in SSA, such as involvement in child labour, while others have been found to apply more broadly, such as low SES and poor school quality (Ampiah & Adu-Yeboah, 2009; Colclough et al., 2000; Kuepie et al., 2015; Oruko et al., 2015). Of the children who experience high CR, some remain enrolled in primary education. A few existing studies have identified protective factors, including academic achievement and higher SES (Zuilkowski et al., 2016). However, protective factors that have been identified in the literature are often simply the inverse of the risk factors, and thus cannot be protective against those very same risks. Therefore, to understand resilience, we must examine protective factors that exist above and beyond risk factors. Additionally, much

of the limited research on protective factors and academic resilience has been conducted in North America, where dropout rates are lower and children face different adversities (i.e., rates of child labour and poverty are much higher in SSA; UNESCO, 2019); it is unclear what protective factors are relevant in rural West African communities that face an accumulation of risks.

Risk and Resilience Factors for Dropout

Child-Level Risk Factors

Child-level factors contributing to dropout in SSA include variables such as age and gender. Due to a combination of delayed entry into school and high grade repetition levels, many children are older than the prescribed age for their grade (i.e., the prescribed age for grade 5 in Côte d'Ivoire is 10 years old, but the mean age of fifth graders in our sample was 10.81 with 54% of children being 11 years old or older). In Côte d'Ivoire, the age at which a child enters primary school ranges from four to 12 years old (Gulemetova et al., 2016). Existing research on dropout in SSA has determined that children over-age for their grade are less likely to remain in school compared to their younger classmates (Kuepie et al., 2015). Gender and biological relatedness also play a role in SSA as female children who are not biologically related to the head of the household (i.e., those who have been fostered into the family) are less likely to attend and stay in school (Kuepie et al., 2015). In Côte d'Ivoire, girls are significantly less likely to enrol in primary school or continue their education beyond primary school than boys (UNESCO, 2019). This gender disparity may be linked to different expectations in educating boys versus girls (e.g., education for boys is often favoured in SSA as it is thought to lead to paid work opportunities; UNESCO 2021; Jasińska & Guei, 2022; Academy for Educational Development, 2002).

Child labour and low academic achievement increase a child's risk of dropping out of school in SSA (Kuepie et al., 2015; Woldehanna et al., 2021). Côte d'Ivoire is the largest producer of cocoa in the world; thus, the Ivorian economy is highly dependent on the production of cocoa (African Development Fund, 2018). Children in Côte d'Ivoire often support their families by working; in agricultural communities, 38% of children are engaged in cocoa production (Sadhu et al., 2020). Child labour pulls children away from their education, reducing their academic participation and achievement, and ultimately, increasing risk of dropout (Colclough et al., 2000; Tang et al., 2018). Child labour also has an impact on health; children in Côte d'Ivoire who work have greater rates of illness and injury and are less likely to receive medical care (Grootaert, 1999).

Child-Level Resilience Factors

Academic self-efficacy and growth-mindset, which refer to an individual's belief in their abilities to successfully perform academic tasks, acquire knowledge, and master material, has been found to contribute to academic resilience and performance (McMillan & Reed, 1994). High academic self-efficacy has also been linked to greater student engagement, attendance, and school completion rates (Niehaus et al., 2012). This research has mostly been done in Global North contexts, however, emerging research has also linked self-efficacy and academic performance in the context of SSA (Ansong et al., 2019). Though research has repeatedly demonstrated the link between having a growth-mindset and better academic performance, we acknowledge that it can perpetuate inequality (Allen et al., 2022). That is, by focusing research and intervention on individual, child-level characteristics such as growth mindset, structural barriers (e.g., teachers being well equipped and trained) that bar a child's access to education become overlooked (Gorski, 2019).

Family-Level Risk Factors

Family-level factors interact with child-level factors highlighted above to influence the likelihood of dropout (Oruko et al., 2015). Factors including low SES (typically measured with a household assets index in low-income communities in SSA, rather than income and education levels; see Methods for discussion) and low parental education have been repeatedly associated with school dropout in SSA (Colclough et al., 2000; Kuepie et al., 2015; Sabates et al., 2013). In Côte d'Ivoire, 46.1% of the population experiences multidimensional poverty (i.e., deprivations at the household level in health, education and standard of living; UNDP, 2020). The poverty rate (i.e., percentage of the population living below the national poverty line) in the country is 46.3%, but is over 60% in some rural communities (Fonds Monetaire International, 2009; World Bank, 2021).

Family-Level Resilience Factors

Protective factors in the home are the level of parental education and, relatedly, academic support. The rate of adult literacy in Côte d'Ivoire is low, sitting at 36.8% for females and 50.7% for males (UNESCO, 2019). Children of parents who are more educated are less likely to drop out of school as they may receive academic support and their parents may value education (Zuilkowski et al., 2016).

School-Level Risk Factors

In SSA, poor school quality (which consists of elements such as large class sizes, poor infrastructure, and inadequate teacher training) has been linked with low levels of academic achievement, high rates of grade repetition, and dropout (Taddese & Tadele, 2019). This is especially relevant in low-income and rural regions in SSA, which generally have fewer and lower quality schools (Colclough et al., 2000). In Côte d'Ivoire, school infrastructure and

teacher education have been linked to academic outcomes; children in schools with higher quality infrastructure and more qualified teachers score better on measures of literacy (Ball et al., 2022).

School-level factors also interact with child- and family-level factors to influence dropout. This interaction is exemplified in a study by Colclough and colleagues (2000), which found that poor school quality was more detrimental to girls. In particular, the absences of private latrines and female teachers contributed to poor attendance, achievement, and subsequent dropout in girls. Further, teachers (who were predominantly male) were found to reinforce gender roles causing girls to spend more time performing non-school activities during school hours (e.g., cleaning classrooms, latrines, offices), which reduced their self-confidence and manifested into poor academic performance (Colclough et al., 2000).

School-Level Resilience Factors

School-level factors can contribute to academic resilience. For example, Runhare and colleagues' (2021) interviews with teachers, children (including those who dropped out and remained enrolled), and education board members highlighted that school-level interventions are powerful for student retention. Intervention features included no-fee schooling, nutrition programs, provision of educational resources, employing diverse teaching methods to reduce grade repetition, and early identification of children who are at risk of grade repetition or dropout. Schools (and teachers) are optimal contexts to intervene against dropout (Runhare et al., 2021; Zuilkowski et al., 2016), yet we were unable to find interventions specifically targeting primary school dropout in Côte d'Ivoire or surrounding countries.

The Interaction of Child-, Family-, and School-Level Risk and Resilience

What is clear from this literature is that child-, family- and school-level factors interact in important ways that contribute to a child's risk of dropout. A wealth paradox, in which higher SES is achieved through means of child labour, sets a complex stage for understanding how SES and dropout may be related in understudied rural West Africa (Bhalotra & Heady, 2003; Mols & Jetten, 2017). Families with low SES are more likely to require their child to be involved in labour activities, drawing the child away from school (Colclough et al., 2000; Hunt, 2008; Tang et al., 2018). Further, parents who received inadequate schooling are less likely to value education for their children; thus creating an intergenerational cycle of education disengagement (Pryor et al., 2003; Sabates et al., 2013). This interaction of child-, family- and school-level factors, rather than as discrete factors, highlights the need to apply a theoretical framework that centres on situating a child with their familial and educational ecosystems to understand risk and resilience of school dropout.

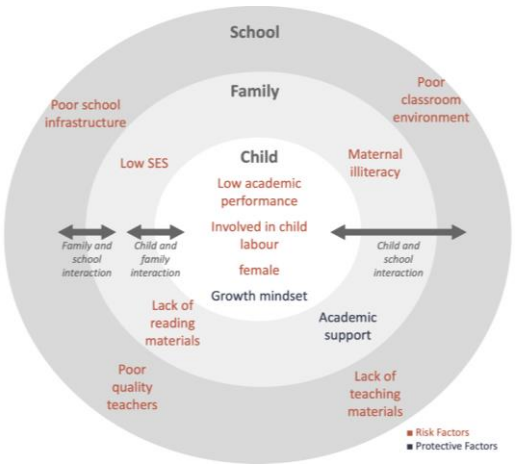

Figure 1. *Factors examined in the current study. To examine dropout risk, we consider a system within which a child's individual characteristics interact with aspects of the child's family and school environments to influence the likelihood of dropout. Children who remain in school may exhibit protective factors to mitigate their risk of dropout.*

The Current Study

Our study had two major objectives. First, we aimed to identify risk factors that predicted primary school dropout in rural Côte d'Ivoire and understand the interactions of risk across child-, family-, and school-levels. We examined child-, family-, and school-level risk factors and CR indices for each level of risk in a cohort of 5th grade children. We tested the hypothesis that interactions between high levels of child-, family-, and school-level risk factors predict a higher probability of drop-out two years later. Second, we aimed to identify protective factors for academic resilience. We examined children who were academically resilient (i.e., high dropout risk, yet remained enrolled in school) and compared their characteristics to those who dropped out. We tested the hypothesis that protective factors highlighted above (e.g., high growth-mindset and homework help) predicted a higher probability of remaining enrolled, despite experiencing a high level of risk. Protective factors examined stem literature identifying protective factors as having a growth-mindset (Niehaus et al., 2012) and receiving educational support from parents (Woldehanna et al., 2021; Zuilkowski et al., 2016).

By applying a developmental risk and resilience framework to a critical educational outcome (school dropout), our study sheds new light on risk and resilience in understudied Côte d'Ivoire, where learning levels are extremely low (UNESCO, 2019) and dropout rates are high. An understanding of both risk and protective factors can inform more evidence-based policies to produce better outcomes and make progress on Target 4.1 of SDG-4.

Methods

Data from this study come from a two-year longitudinal intervention study on literacy in rural Côte d'Ivoire which examined the relationships between social, cognitive, and linguistic factors and literacy development (Jasińska & Ogan, 2020; pre-registered on OSF [Madaio et al.,

2020]; Madaio et al., 2019) in 32 schools. Schools were randomly assigned to receive either a phone-based literacy intervention (*N*=740) or no intervention (*N*=407). There was no significant impact of the literacy intervention on the likelihood of school dropout (see Table 2). All children in the control group and half of the children in the literacy intervention group completed the full battery of measures and the remaining half of the children in the literacy intervention group completed a subset of the measures. For this latter subset of participants, certain measures were omitted from data collection; the measures omitted that pertain to our analysis include growth mindset, maternal literacy, and owning a book. The risk data used in this study were collected at baseline (from October to December 2019) and educational outcome data was collected nearly two years later from April to May 2021.

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Participants

Children

Participants were 1195 children (Female: *N*=582, Male: *N*=613) aged eight to sixteen years (*M*=10.75, *SD*=1.42) from eight villages in the rural Adzope region of Côte d'Ivoire. At the beginning of the study, all children were enrolled in CM1 (equivalent to fifth grade in North America). See Table 1 for the endline schooling status of participants. 68 children had missing data and were excluded from analyses. Our analyses included only children with data collected at baseline and endline who stayed enrolled (*N*=913; Female: *N*=443) and those who dropped out (*N*=76; Female: *N*=34). The percentage of students who dropped out was nearly 7%. As we were unable to determine whether children marked as "absent", "moved", "died", or "unknown" (11% of the sample) had dropped out, they were excluded from our analyses. Children with developmental disorders or auditory or visual impairments were not eligible to participate.

Table 1

Children's Schooling Outcomes at Endline Data Collection

Outcome		Number of Children	% of Sample
Enrolled		975	81.60%
	Enrolled CM2	859	71.90%
	Repeat CM1	108	9.04%
	Enrolled in new school	8	.67%
Dropout		79	6.61%
Absent		79	6.61%
Moved		35	2.93%
Died		3	.25%
Unknown		21	1.76%
Total		1195	100%

Teachers

Teachers (*N*=32; 10 Female) taught CM1 at one of 32 schools in the Adzope region of Côte d'Ivoire. Teachers were between the ages of 30 and 58 (*M*=44.1 ; *SD*=8.4) and had between 3 and 38 years of teaching experience (Males: *M*=19, *SD*=8.29; Females: *M*=7.44, *SD*=5.22). Teachers' education background is reported in Supplementary materials.

Measures

Child-Level Factors

Child questionnaire. Children completed a direct assessment interview using questions adapted from three questionnaires: the Early Grade Reading Assessment Child Questionnaire (EGRA; Cronbach's alpha reliability was α=0.87; RTI International, 2015), the Bilingual Language Background and Use Questionnaire (Berens et al., 2013; Jasińska & Petitto, 2013, 2014, 2018; Kovelman et al., 2008), and Tulane University's Survey Research on Child Labor in West African Cocoa Growing Areas (2015). These questionnaires were previously used with

primary school children in Côte d'Ivoire (e.g. Ball et al., 2022) and more broadly in West Africa (e.g. EGRA in Senegal and Mali; Gove & Wetterberg, 2011; RTI International, 2015; Sprenger-Charolles, 2008; Tulane survey in Ghana). Responses were used to measure child-level dropout risk factors and calculate child-level CR scores.

Children self-reported their age, grade, and gender. An "age-for-grade" score was created for each child using their current age in years minus ten (i.e., the policy age at which they should have entered 5th grade). The questionnaire asked children about their beliefs regarding their own intelligence, that is, whether they believe they can improve their innate intelligence. This question was scored on a 4-point likert scale and was used to measure children's growth mindset.

Children were asked questions about their involvement in domestic, economic, and agricultural cocoa labour (i.e., working on cocoa production farms). Previous research has found large discrepancies in parent versus child reports of child labour; however, a recent study explored the accuracy of child versus parent reports found that child reports are more accurate (Lichand & Wolf, 2022). For domestic labour, items included preparing meals, cleaning, and washing clothes. For economic labour, items included fishing and hunting, looking for water, and working for a salary. For agricultural cocoa labour, items included spreading fertiliser, burning trees, and moving pods (Tulane University, 2015). Due to significant correlations between the types of labour (domestic and economic: r=0.35, t(978)=12, p<.001; domestic and agricultural: r=0.26, t(975)=8, p<.001; economic and agricultural: r=0.38, t(976)=13, p<.001), we created a summary score representing participation in all labour activities.

Literacy Measures. Children completed letter, word, and pseudoword reading tasks from the French version of the Early Grade Reading Assessment (EGRA), which was previously

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used in Senegal and Mali (Gove & Wetterberg, 2011; RTI International, 2015). The French version was determined to be appropriate by a group of educational researchers and linguists who were native Ivorian French speakers. Prior to each task, children completed a practice round, receiving scaffolding and feedback. Children had 60 seconds to complete each reading task. Scores from the letter, word, and pseudoword reading tasks were composited to obtain a measure of literacy and to calculate child-level CR scores.

Letter Reading. Children were instructed to read 100 unique letters and letter combinations (e.g., "on") as quickly and accurately as possible. All letters included in the task were frequently found in Ivorian French. Incorrect items were marked and the task was discontinued after 60 seconds had elapsed or after the participant incorrectly read the first ten items (Gove & Wetterberg, 2011; RTI International, 2015).

Word Reading. Children were instructed to read a list of 50 words (e.g., *carte*, *papa*) as quickly and accurately as possible. All words included in the task were familiar to the children and were commonly used by Ivorian French speakers. Incorrect items were marked and the task was discontinued after 60 seconds had elapsed or after the participant incorrectly read the first ten items (Gove & Wetterberg, 2011; RTI International, 2015).

Nonword Reading. Children were instructed to read a list of 50 pronounceable nonwords as quickly and accurately as possible, assessing children's ability to decode unfamiliar words. All nonwords included in the task contained one or two syllables and conformed to French phonotactic structure (e.g., *donré*, *toche*). Additionally, the nonwords were matched in difficulty with the familiar words from the word reading task. Incorrect items were marked and the task was discontinued after 60 seconds had elapsed or after the participant incorrectly read the first ten items (Gove & Wetterberg, 2011; RTI International, 2015).

Family-Level Factors

Child Questionnaire. Children were asked about their home background, including whether they have literate family members (e.g., mother) and whether they receive homework help. Children also reported a household inventory (ownership of certain items such as books, a television, and a refrigerator); the total number of reported household inventory items (ranging from zero to 15) was used to create an SES score for each child. This is a common measure of SES for low- and middle-income countries as maternal education or household income do not accurately reflect household SES in this context (this is the measure used in the EGRA [Gove & Wetterberg, 2011; RTI International, 2015; Sprenger-Charolles, 2008]). Similar household asset-based measures such as the Poverty Probability Index (Innovations for Poverty Action, 2022) and Multidimensional Poverty Index (UNDP, 2022) are widely used in SSA. Whether or not the household owned a book was also included separately in the analyses as a family-level risk factor. A family index variable was created using the homework help, maternal literacy, and book ownership factors as noted below.

School-Level Factors

Teacher Questionnaire. The teacher questionnaire (RTI International, 2015; Tulane University, 2015) was used to measure school-level dropout risk factors and to calculate school-level CR scores. Teachers were asked their age, teaching qualifications, job satisfaction, education level, the languages they speak, and their capacity for using these languages for classroom instruction. They were also asked questions about their classrooms and school environment; teachers provided information on the class size, availability of teachers/teacher absences, availability of appropriate pedagogical materials, school security, public health, and the infrastructure/facilities available at the school (e.g., canteen, toilets, classroom furniture,

running water, electricity, student supplies). School-level variables examined in our study were four indices: teacher quality (years teaching, education rating, satisfaction), school infrastructure (electricity, water, toilets, tables/benches, classroom condition, student supplies), teaching materials (French pedagogical materials, child appropriate materials, problems with language of instruction), and learning environment (class size, canteen, problems with public health, problems with security, lack of teachers).

Cumulative Risk (CR) Scores

We created child-, family-, and school-level cumulative risk (CR) scores for each participant. CR is operationalized by taking the sum of multiple, dichotomous risk factors and assigns risk based on statistical criterion. For continuous variables, one standard deviation above the mean for each factor equals 1 risk point while all others equal 0. For binary variables, one risk point is attributed to individuals in the category with higher risk (e.g., for maternal literacy, illiterate mothers equal 1 risk point, literate mothers equal 0 risk points). See Figure 2 for all CR indices. Within understudied contexts, there is no clear-cut way to define risks; though research has been done in SSA to examine school dropout, students in different countries and communities experience risk factors in unique ways. The previous literature cited in the child-, family-, and school-level factor review above provides the rationale behind the inclusion of each risk and resilience variable.

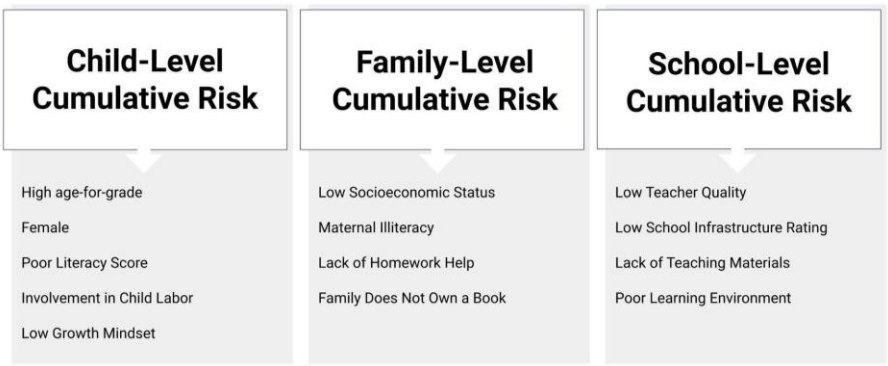

Figure 2. *Cumulative risk score variables for child-, family-, and school-levels. Each factor listed equals one risk point.*

Procedure

This study was authorised by the Ivorian Ministry of Education and received approval from the University of Toronto, University of Delaware, and Yale University research ethics boards. The research team presented the study to community leaders (village chiefs, school directors, parent-teacher groups [Comité de Gestion d'Écoles - COGES]) to obtain community consent congruent with the oral traditions in Côte d'Ivoire (see Jasińska & Guei, 2018). Trained experimenters, who were native speakers of Ivorian French, administered individual structured interviews and literacy assessments in French with children during school hours at the baseline and endline visits. Each experimenter, at a minimum, had an undergraduate degree in Psychology, Sociology, Economics, or Linguistics, and many were enrolled in graduate studies. Children received a small gift (book and small packet of cookies) after completing the assessments. Each teacher completed a structured interview in Ivorian French with a trained experimenter at the baseline school visit. All data were collected and managed using REDCap hosted at the University of Delaware and University of Toronto (Harris et al., 2009, 2019).

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Data Analysis

Please see Supplementary Materials for a detailed description of the coding of child-, family-, and school-level variables. All data were analysed using R software (RStudio Team, 2019), individual R packages used are described in Supplementary Materials.

Dropout Risk Analysis. We first conducted multilevel model logistic regressions for each distinct child-, family-, and school- level independent variable on the categorical dependent variable of outcome (dropout versus enrolled), with a random intercept for school. The independent variables were either continuous (e.g., academic performance and school environment) or categorical and binary (e.g., maternal literacy).

Cumulative Risk Analysis. Multilevel logistic regression tested the main effects of each level of CR and their interactions on the categorical dependent variable of outcome (dropout versus enrolled), with a random intercept for school. To interpret the significant interaction term, we performed a simple slope analysis. We tested the strength of the association between family-level CR and school dropout for children with high (1 *SD* above the mean) and low (1 *SD* below the mean) child-level CR.

Resilience Analysis. To understand academic resilience, we used the results from our first analysis (see "Dropout risk analysis" above) to determine which risk factors to include to identify a "high-risk enrolled" subset of children. We then compared the high-risk enrolled children to the children who dropped out by running single-predictor multilevel logistic regressions on the variables not included in the dropout risk factors with school as the random intercept. We then conducted a logistic regression model with dropout versus high risk enrolled as the dependent variable and all variables in the risk analysis excluding those that were associated with dropout. We replaced the categorical family-level variables with a family index.

We tested main effects of all independent variables as well as interactions between family- and school-level variables. This study was not preregistered. All data are publicly available at Open Science Framework at https://osf.io/5yubf/.

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Results

Descriptive Results

We first examined associations between child-, family-, and school-level factors. See Table 4 in the Supplementary Materials for correlations between all variables. Children who were old for their grade were more likely to report more child labour and to have lower literacy scores. Furthermore, children who were older for their grade were more likely to be male, have illiterate mothers, receive less homework help, and were less likely to have literacy materials in the home. High participation in child labour was significantly correlated with being male and having a school with poorer infrastructure. Low reading scores were correlated with lower growth mindset, lower SES, and a lack of literary materials at home. Illiterate mothers were associated with having lower SES, giving less homework help, and a lack of literary materials at home. Poorer learning environments were associated with having fewer teaching materials yet having a higher teacher rating. Schools with fewer teaching materials also had poorer infrastructure yet higher teacher ratings. Poor school infrastructure was associated with lower teacher ratings, higher age for grade, and more child labour.

Child-, Family-, and School-Level Factors and Dropout

Children who dropped out were significantly older for their grade, reported more child labour, had lower literacy scores, were less likely to own a book, and attended schools with poorer learning environments relative to their enrolled peers, see Table 2.

Table 2

Multilevel Logistic Regressions for Child-, Family-, and School-Level Variables of Students who Remained Enrolled versus Dropped Out with School as Grouping Variable

		Outcome					
Level	Predictor	Enrolled *M (SD)*	Dropout *M (SD)*	Estimate	Statistical Test	Significance	Odds Ratio
Child	Age for Grade	.65 (1.36)	1.95 (1.62)	b=-.625	z(986)=-7.170	p<.001***	.535
	Gender	48.6% female	44.7% female	b=-.153	z(986)=-.640	p=.520	.858
	Child Labour	-.01 (.73)	.28 (.80)	b=-.477	z(974)=-2.980	p=.003**	.621
	Reading Score	-.34 (.89)	-.81 (.84)	b=.655	z(935)=4.09	p<.001***	1.930
	Growth Mindset	2.29 (.76)	2.17 (.78)	b=.234	z(673)=.990	p=.322	1.260
Family	SES	6.7 (2.58)	6.62 (2.56)	b=.016	z(986)=.350	p=.730	1.020
	Maternal Literacy	55.5% literate	50% literate	b=.230	z(679)=.760	p=.450	1.260
	Homework Help	72.3% receive help	68.4% receive help	b=.191	z(986)=.730	p=.460	1.210
	Family Owns a Book	63.5% own book	50% own book	b=.548	z(673)=1.80	p=.072^{+}	1.730
School	Teacher Quality	.01 (.43)	.11 (.04)	b=-.538	z(986)=-1.590	p=.110	.584
	School Infrastructure	-.07 (0.5)	-.3(.53)	b=-.187	z(986)=-.620	p=.530	.829
	Teaching Materials	0 (.59)	.01 (.55)	b=.025	z(986)=.100	p=.920	1.030
	Learning Environment	.01 (.42)	-.14 (.43)	b=.848	z(986)=2.640	p=.008**	2.330
	Intervention	65.7% intervention	71.1% intervention	b=-.208	z(986)=-.660	p=.510	.812

We conducted post-hoc analyses on child labour as this variable was comprised of three domains of work activities: domestic, economic, and agricultural cocoa labour. For post-hoc

tests, *p*-values of .008 were considered significant. Children who participated in more economic activities were more likely to drop out (b=-.196, z=-2.96, p=.003, OR=.82; $M_{dropout}$=4.74, $SD_{dropout}$=1.94; $M_{enrolled}$=4.05, $SD_{enrolled}$=1.79) and children who participated in more agricultural cocoa labour activities were marginally more likely to drop out (b=-.040, z=-2.38, p=.017, OR=.96; $M_{dropout}$=7.76, $SD_{dropout}$ 7.63; $M_{enrolled}$=5.67, $SD_{enrolled}$=6.72). As the school learning environment variable was a composite of several variables, post-hoc analyses revealed that a larger class size marginally predicted dropout (b=-.018, z=-2.44, p=.015, OR=.982; M_{dropout}=51.5, SD_{dropout}=17.6, M_{enrolled}=45.7, SD_{enrolled}=17.8). Children in schools with poorer public health were also marginally more likely to drop out (b=.269, z=1.79, p=.074, OR=1.31; M_{dropout}=-.18, SD_{dropout}=.99, M_{enrolled}=.06, SD_{enrolled}=1.00). As insufficient water, sanitation and hygiene (WASH) facilities have been linked to dropout for girls (Chirgwin et al., 2021), we tested whether public health predicted dropout based on gender but did not find a significant result. These results warrant further investigation into the relationships between dropout and participation in child labour, large class sizes and public health issues.

Cumulative Risk (CR) Results

We found a significant main effect of child-level CR on dropout (b=-.858, z(981)=-3.700, p<.001, OR=.424). Children with high child-level risk scores experienced significantly higher rates of dropout (M_{dropout} =1.37, SD_{dropout} =.95; M_{enrolled} =.94, SD_{enrolled} =.75). We found a marginally significant main effect of family-level CR on dropout (b=-.401, z(981)=-1.730, p=.084, OR=.670). Children with higher family-level risk scores experienced marginally higher rates of dropout (M_{dropout}=1.11, SD_{dropout}=.95; M_{enrolled}=1.03, SD_{enrolled}=1.00). We found a marginally significant interaction between child risk and family risk (b=.227, z(981)=1.670, p=.095, OR=1.250). The main effect of school-level risk as well as interactions between child-

and school-level CR as well as family- and school-level CR were not significant. Results are shown in Table 3. See Table 5 in Supplementary Materials for comparison of null model, main effects only model, and two interaction models.

A post-hoc simple slope analysis of the marginal interaction revealed that for children with low child-level CR scores (one standard deviation below the mean), high versus low family-level CR scores increased the probability of a child dropping out (b=.397, t(985)=1.982, p=.047; see Figure 3). For children with high child-level CR scores (one standard deviation above the mean), the probability of dropout did not differ between high and low family-level CR scores (b=-.033, t(985)=-.237, p=.813).

Table 3

Cumulative Risk Model

Cumulative Risk Level(s)	Estimate	Statistical Test	Significance	Odds Ratio
Child-Level	b=-.858	z(981)=-3.700	p<.001***	.424
Family-Level	b=-.401	z(981)=-1.730	p=.08^{+}	.670
School-Level	b=.179	z(981)=.410	p=.68	1.200
Child-Family Interaction	b=.227	z(981)=1.670	p=.095^{+}	1.250
Child-School Interaction	b=-.032	z(981)=-.150	p=.88	.969
Family-School Interaction	b=.019	z(981)=.100	p=.92	1.020
Conditional R^2		.142		
Marginal R^2		.087		
Adjusted ICC		.060		
Conditional ICC		.055		

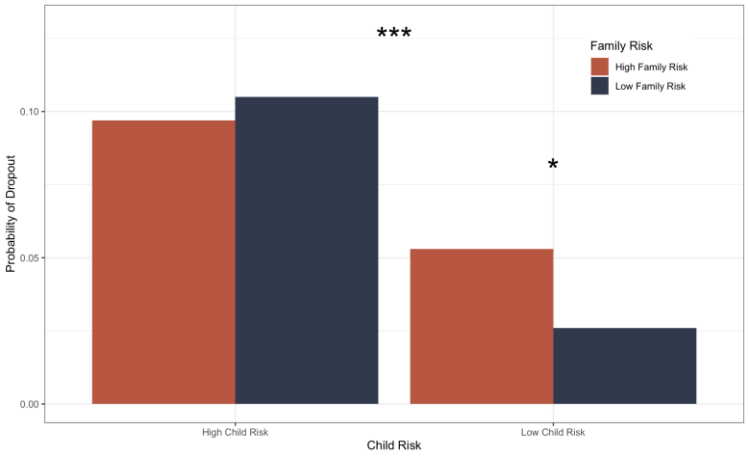

Figure 3. *For children with low child-level cumulative risk scores (1SD or lower than the mean) , high family-level cumulative risk scores (1SD or above the mean) increased the probability of a child dropping out.*

Resilience Results

Upon finding the most significant predictors of dropout were high age-for-grade, high child labour participation, low reading scores, and poor school environment, we created a "high dropout CR" score using these four variables. We identified a subset of "high risk enrolled" children whose "high dropout CR" score was one standard deviation above the mean. We compared high-risk enrolled children to those who had dropped out. There were 85 children in the high-risk enrolled group (Female: *N*=29, Male: *N*=56). The 85 high-risk enrolled children made up 9% of the 913 children who remained enrolled. The children in the high-risk enrolled group were as or more at risk than the children who dropped out based on the factors of age,

reading score, labour, and learning environment ($M_{\text{high risk enrolled}}$=2.13, $SD_{\text{high risk enrolled}}$=.34; M_{dropout}=1.09, SD_{dropout}=1.05).

P-values in each single predictor model were greater than .22 except gender which was marginally significant (*b*=.66, *z*(158)=1.75, *p*=.08, *OR*=1.94); boys were marginally more likely to be resilient.

We built a logistic regression model that included main effects of child-level variables (gender and growth mindset; we did not include age-for-grade, child labour, or reading score as they were used in create the "high dropout CR" group) and main effects and interactions between family- and school-level (teacher quality, infrastructure, and teaching materials; we did not include learning environment as it was used in creating the "high dropout CR" group) variables. We compared this model to a model that included child-level variable interactions; it did not significantly improve the model fit. We found a significant interaction between teachers and school infrastructure (*b*=-7.810, *z*(78)=-3.210, *p*=.001, *OR*=.0004). In a poorer infrastructure school, a better teacher is protective. Similarly, a higher infrastructure school can be protective against poorer teachers. To further probe this interaction, we conducted post-hoc tests with the three variables that comprise the teacher index variable: years teaching, education rating, and teacher satisfaction. We found significant interactions between education rating and infrastructure (*b*=-6.978, *z*(66)=-2.110, *p*=.035, *OR*=.0009) and teacher satisfaction and infrastructure (*b*=-2.85, *z*(41)=-2.19, *p*=.029, *OR*=.058). We also found a marginally significant interaction between family index and teachers (*b*=-2.16, *z*(78)=-1.71, *p*=.09, *OR*=.115). In a family environment with less homework help, low maternal literacy, and absence of literary materials, teachers can be protective and vice versa.

Discussion

This study examined risk and resilience factors associated with primary school dropout in rural Côte d'Ivoire. In line with the United Nations' SDG-4.1, our research aims to inform the goal of dismantling the inequities and systemic barriers that prevent children from completing high quality primary and secondary education (UN, 2015). We hypothesised that interactions between child-, family-, and school-level risk factors would predict a higher probability of dropout and that promotive factors would predict academic resilience.

Child-, family-, and school-level factors all contributed to increased risk for dropout, supporting our hypothesis. Children who were older for their grade (i.e., those who started school late and/or repeated grades), had lower academic performance, and performed more child labour were more likely to drop out of primary school. Children from homes with a lack of literary materials and who were enrolled in schools with poorer learning environments were also more likely to drop out of school. Our findings on resilience showed that, for children who are at high risk of dropout yet remained enrolled, teachers were protective when school infrastructure was poor and vice versa. Interactions between different levels of risk (e.g., low child risk and high family risk) highlights how context influences dropout.

Examining risk and protective factors across multiple ecological levels recognizes the complexity of individuals and their environments and allows for a more holistic understanding of the factors that contribute to primary school dropout. This research can inform education policy in rural Côte d'Ivoire and West Africa more broadly by helping to identify at-risk children and introduce targeted interventions that are linked to academic resilience.

Child-, Family-, and School-Level Risk

Our findings revealed that many child-level factors significantly influence children's likelihood of dropping out of school. Children who were closer to the recommended age for their grade, (i.e., closer to age ten, which is the age at which children should enter CM1 [fifth grade]) were more likely to remain enrolled in school. These findings corroborate existing research on risk of dropout in SSA (Colcolough et al., 2000; Sabates et al., 2013). Children in Côte d'Ivoire may be older than the recommended age for grade for several reasons. It is not uncommon for children to start schooling late. Furthermore, the rate of grade repetition among children in Côte d'Ivoire is high (UNESCO Institute for Statistics, 2019). Older children had significantly poorer reading scores. As both reading scores and age for grade significantly predicted dropout, it is important to highlight the connection between academic performance and an older age-for-grade. Children who were older for their grade were also engaged in significantly higher levels of child labour. Older children are more physically developed and their parents may rely on them more for domestic, economic, and agricultural work. Child labour is detrimental to participation in education; labour impacts school attendance and the time children have to complete homework (Bhattacharya et al., under review; Huebler, 2008). In turn, participation in child labour may increase the likelihood of grade repetition, making children older for their grade. These findings indicate that being old for your grade is not solely detrimental to staying in school, but that the factors that lead children to being old for their grade (i.e. poor academic performance and child labour) likely play a major part in increasing a child's risk of dropout. Our results corroborate existing research (e.g., Woldehanna et al., 2021) connecting poor reading scores to school dropout. The negative correlation between academic performance and age-for-grade indicates that children who start school late and who have

repeated grades continue to score poorly on reading tests. Importantly, children who were engaged in higher rates of child labour were significantly more likely to drop out of school. Further, when we examined which domains of child labour were associated with dropout, we found that increased participation in cocoa labour and economic work were associated with risk of dropout whereas domestic activities (i.e., chores) were not. Our findings underscore the detrimental effect of child labour on academic and developmental outcomes.

While we did not find a significant connection between growth mindset and dropout, we did find a positive correlation between growth mindset and literacy scores. Children who believed that they had control over their academic success scored higher on reading tests; however, they were just as likely to drop out as their peers who did not share this belief. Zuilkowski, Jukes, and Dubeck (2016) found that, even when they were determined to succeed, children can become disengaged from school and drop out when they experience low levels of achievement. Indeed, a meta analysis by Sisk and colleagues (2018) demonstrated the limited effects that growth-mindset interventions have on students with low SES or experience academic risk. Our study highlights the importance of working with Ivorian educators and schools to increase students' academic performance as a means of decreasing risk of dropout.

Considering family-level factors, we were surprised that SES was not significantly related to dropout. Though there is variation in the SES of the children in this study, many families in rural Côte d'Ivoire live below the poverty line (UNESCO Institute for Statistics, 2019; Fonds Monetaire International, 2009; World Bank, 2021). Given that it is common for children to engage in child labour to support their families (DeBuhr & Gordon, 2018), child labour also contributes to household SES when children generate income. This wealth paradox in rural cocoa farming communities (Bhalotra & Heady, 2003; Mols & Jetten, 2017) clouds

straight-forward relationships between SES and dropout and highlights the need to examine multiple interacting factors in a child's environment. Despite relatively average or high SES, children may be more likely to drop out of school due to child labour. Furthermore, SES was highly correlated with literacy scores, access to literacy resources in the home, maternal literacy, and receiving homework help. Neither maternal literacy nor receiving homework help were related to dropout, however, children who remained dropped out were marginally less likely to own a book. It follows that having reading materials at home may increase the likelihood of a child remaining enrolled in school.

Children in classes with poorer learning environments, specifically large class sizes, were more likely to drop out. Furthermore, children in schools where teachers reported more problems with public health were marginally more likely to drop out. Although it was beyond the scope of this study to examine this in depth, the connection between girls' educational attainment and WASH facilities has been well established (Chirgwin et al., 2021).

Cumulative Risk (CR)

Studies have shown that the number and severity of risk (i.e. CR) exposures influence the likelihood of resilience (Evans et al, 2013). We hypothesised that a combination of child-, family-, and school-level risk factors contributed to a higher probability of drop-out, that these risk factors may interact, and that protective factors will contribute to a greater probability of children staying in school, despite experiencing a high level of risk.

Child-level CR was the most significant predictor of dropout and family-level CR was marginally related to dropout. Our findings corroborate existing studies that link factors such as low SES, parental illiteracy, and academic support (Sabates et al, 2013; Colclough et al., 2000) to risk of dropout. Though we did not find a significant relationship between school-level CR

and risk of dropout, our resilience results link higher quality schooling to academic resilience, which we discuss in detail below.

Interestingly, we found a significant interaction between child- and family-level CR. For children with low child-level CR, the probability of dropout was significantly higher when family-level risk was high. When we consider the risk-factors attributed to the child alone, we do not gain a full understanding of risk; nor can we identify mechanisms for resilience. As illustrated by ecological systems theory and CR frameworks, when considering risk and resilience it is imperative to examine factors unique to the child in tandem with their family and school environments.

Academic Resilience

We identified a group of children who experienced high amounts of child-level CR, yet remained enrolled in school (9% of the enrolled sample). High-risk enrolled children were marginally significantly more likely to be male. This result may be due to the complex decisions that parents face when sending their children to school. Costs associated with sending a child to school are high ranging from 70 to 135 USD. Côte d'Ivoire's average annual income is 2,549 USD (World Bank, 2021) and the average fertility rate is 4.5 births per woman (UNESCO, 2019); families are therefore expected to allocate a substantial proportion of their income on schooling fees. It follows that families often prioritise the education of males over females (Abras et al., 2012). Family-level poverty is associated with dropout as impoverished families require girls to stay home and contribute to domestic work (Ohba et al., 2020). At the school-level, lack of school safety and access to sanitary facilities and menstruation products are barriers towards girls' education in rural West Africa (Hunt, 2008). These interactions between gender, poverty, school quality, and dropout highlight that a child's gender may not be the driving force

of academic resilience. Rather, resilience (or barriers towards it) may be tied to societal expectations placed on the roles of both boys and girls. This, compounded by infrastructure that is unsupportive of girls' needs, may be underlying the gender difference in academic resilience.

One of our initial predictions was that having a growth mindset would be associated with academic resilience. The link between growth mindset and academic performance has been documented (OECD, 2019) and we therefore aimed to explore whether growth mindset may indicate similar outcomes in Côte d'Ivoire. Despite some children believing that they are able to control their academic outcomes, our study demonstrated that there is no significant relationship between growth mindset and school dropout. We find this to be an important consideration given the problematic connection between growth mindset and resilience. Had we found a connection between the two, pressure may be taken off of policy makers to implement necessary changes in reducing child labour and increasing the quality of education, citing the idea that children can "pull themselves up by their bootstraps". As we previously highlighted, risk of dropout is the result of interactions between children's individual characteristics and factors of their environment. It is imperative that the systems surrounding children support their ability to remain enrolled in school. Allen and colleagues (2022) discuss the problem of suggesting that growth mindset and 'grit' can lead to social mobility; this argument often perpetuates inequality. Children, women, people of colour, and other marginalised populations are expected to "pull themselves up by their bootstraps." These meritocratic ideologies deny the influence of structural forces that provide privileged groups with unearned systemic privileges, while placing other groups at a disadvantage (Caouette & Taylor, 2007). Children need systems in place to support academic resilience; simply believing in themselves is not enough.

We found that better teachers were protective against a poor infrastructure school. Similarly, better infrastructure was protective against poor teachers. Further, teacher and infrastructure interaction was particularly driven by teachers' education rating and job satisfaction. These interactions between school-level variables demonstrate the complexity of environmental factors that lead to a student's academic resilience.

Taken together, our results indicate that the relationship between child-level CR and dropout may be moderated by school-quality variables such as teacher quality and school infrastructure. Importantly, recent work suggests that children enrolled in higher quality schools are less likely to be engaged in child labour (Bhattacharya et al., under review; ICI, 2019; Abou, 2021). Due to the strong link we found between participation in child labour and dropout, increasing school infrastructure and equipping teachers with more training and ensuring job satisfaction may be powerful ways to increase academic resilience.

We created CR indices using both risk and protective factors. Similarly, when examining resilience, we considered risk variables that were not included in the high-risk enrolled score. Though we posit that protective factors should not simply be the inverse of risk, we found it important to consider "both sides of the same coin" in order to extend our exploration beyond our theoretical predictions. In other words, we aimed to better understand as many factors as possible that may promote resilience. Indeed, Luthar and colleagues (2006) discuss the usefulness of investigating multiple processes that may contribute to resilience.

Limitations and Future Directions

The enrolment status of 11% of students during endline was unknown due to absence, moving away, or other factors. Half of the intervention group did not complete several measures studied including growth mindset, book ownership, and maternal literacy (see Note in

Supplementary Materials). Additionally, our study was conducted in rural villages in Côte d'Ivoire; child-, family-, and school-level risk and protective factors in urban areas may be very different. Another limitation of the current study is that Côte d'Ivoire does not have national norms for the measures used. While this does not allow for standardisation and subsequent validation of our risk or resilience variables, it represents a broader limitation of internationally representative research in developmental and educational psychology. These limitations emphasise the need for further research to understand the diversity of contexts and factors that contribute to educational risk and resilience in Côte d'Ivoire and West African contexts more broadly.

Due to the interactions we found between ecological levels, we stress the importance of investigating risk and resilience through an ecological systems framework. For example, as reading scores and access to literacy resources in the home were related to dropout, further research on moderating variables at the family- and school-levels that keep high-risk children in school may shed light on our understanding of academic resilience.

Conclusion

Our study demonstrates that the presence of multiple risk factors increases risk of dropout. Furthermore, different levels of risk can interact to either increase the likelihood of or to protect against dropout. Risk factors for dropout overwhelmingly apply at the child-level; cumulative child-level risk significantly increases the likelihood of dropout. Importantly, our findings highlight that increased education quality can be a protective factor for high-risk students. Our research shows that policy makers must focus on mitigating factors that prevent children from entering school at the correct age (i.e., high involvement in child labour), ensuring enough academic support to progress to the next grade each year, and reducing absenteeism.

It is imperative to consider the context in which a child develops to understand risk of dropout; children in low- and middle-income countries face a higher proportion and more severe risks that contribute to poor developmental outcomes (McCoy et al, 2016). For example, our findings highlight how detrimental child labour is to educational progress. Governments and policymakers hold power to aid families in poverty reduction thereby alleviating the pressure that families feel to have their children working instead of learning. Our research suggests that high-quality schools can support the learning needs of their students and ameliorate academic outcomes, supporting previous findings of fellow researchers in the field (e.g., Zuilkowski et al., 2016; Taddese and Tadele, 2019; Hunt, 2008) who indicate that poor school quality increases rates of school dropout. School quality interventions are desperately needed to increase academic resilience and bring us closer to achieving SDG-4. Although child- and family-level factors contribute significantly to dropout, certain school factors may mitigate these risks and promote academic resilience. Studies focused on child-, family-, and school-factors and how they interact to predict educational outcomes in West Africa, and Côte d'Ivoire specifically, are crucial to understanding and improving academic resilience in populations at greatest risk of dropout.

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Supplementary Materials

Teacher Education

Teacher education levels were coded based on their credentials received. The qualifications include a range of teacher training starting with the Elementary Certificate of Pedagogical Aptitude (CEAP): government training to lower secondary school graduates who later become assistant teachers with a reduced salary. Teachers who held CEAP received a rating of 1 (*N*=5). The next most qualified teachers receive the CAP: holders of the Bacalauréat who receive primary school teacher training. Teachers who held CAP received a rating of 2 (*N*=19). The most qualified teachers in this study received a professional diploma in which primary school training courses are provided in vocational and technical training establishments to students with a Bacalauréat degree. Teachers who held this baccalaureate or higher received a rating of 3 (*N*=2). Five teachers did not provide their education rating and were excluded from the analysis.

Child-, Family-, and School-Level Factors

Age for grade was calculated by subtracting 10 (i.e., the age at which a student should enter CM1 [fifth grade]) from the child's age. To measure reading scores, we created one composite score using the mean of z-scores for letter reading (α=.85), word reading (α=.82), and pseudoword (α=.86) reading tasks. To account for some scores being negative and the distribution being positively skewed, we normalised the distribution of reading scores by adding one to each total score and calculating the log scores. The variable for child labour was a composite score based on three measures of child labour: domestic, economic, and agricultural. The variable for SES was a sum totalling between zero and 15 calculated based on children's reports of whether or not they owned household items.

Each school-level factor was a composite of several items on the teacher questionnaires. Based on the International Cocoa Initiative's (2019) quality of education indices, we created four variables to measure the school quality. Variables related to school infrastructure consisted of access to electricity, water, latrines, classroom furniture, classroom condition, and student supplies. Variables related to teaching materials consisted of the availability of French pedagogical materials, teacher-reported problems with child-appropriate materials, pedagogical materials, and instructional materials in the Ivorian language. Variables related to the teacher consisted of teacher education, years of teaching experience, and teacher satisfaction. Variables related to the school environment consisted of class size, lack of teachers, school security, public health, and whether there is a functioning canteen. For each variable, a positive value indicated higher quality school. Indicators in which a positive value indicated poorer quality (e.g., large class sizes) were reversed.

Note

In the design of our study, 20 children per classroom were randomly selected to complete the full task battery which included every test measure. Due to timing constraints, the remaining children in each class completed a reduced test battery. The measures included in our study that were not included in the reduced test battery (and therefore not collected from approximately half of the intervention group) were growth mindset, book ownership, and maternal literacy. Please refer to the design of the study on OSF (Madaio et al., 2020).

Commented [8]: blind

Data Analysis

Data analysis was conducted using RStudio (RStudio Team, 2019). For the linear regression models, the stats (R Core Team, 2020), nlme (Pinheiro et al., 2022), and lme4 (Bates et al., 2015) packages in R were used. The stats package was also used to conduct ANOVA for

comparing fit across models and chi-squared tests to examine relationships between categorical variables. To investigate interaction terms, we used reghelper (Hughes and Beiner, 2021) and emmeans (Lenth, 2021) packages in R. Figures were created using ggplot2 (Wickham, 2016), apaTables (Stanley, 2021), and corrplot (Wei and Simko, 2021). Statistics for our models was Tjur's R^2 (Tjur, T., 2009) in the Performance package and sjstats (Lüdecke et al., 2021). Please note that nonlinear effects were examined but did not improve the models. Effect sizes were calculated with the effectsize R package (Ben-Shachar et al., 2020).

Table 4

Associations between child-, family-, and school-level variables

Variable	Descriptive Statistics	1	2	3	4	5	6	7	8	9	10	11	12
Child-Level													
1. Age For Grade	*M*=.75 *SD*=1.42												
2. Gender	48.2% female	*z*=4.38 **											
3. Child Labour	*M*=.01 *SD*=.74	*r*=.25 **	*z*=5.26 **										
4. Reading Score	*M*=-.37 *SD*=.90	*r*=-.22 **	*z*=-.89	*r*=-.05									
5. Growth Mindset	*M*=2.34 *SD*=.68	*r*=-.02	*z*=.90	*r*=.06	*r*=.10 *								
Family-Level													
6. SES	*M*=6.70 *SD*=2.58	*r*=-.05	*z*=-2.11 *	*r*=.05	*r*=.08 *	-.03							
7. Maternal Literacy	55.1% literate	*z*=-3.33 **	*z*=-.93	*z*=-1.52	*z*=1.39	*z*=-.07	*z*=3.83 **						
8. Homework Help	72% get help	*z*=-2.61 **	*z*=-.79	*z*=-.95	*z*=.18	*z*=-1.05	*z*=4.18 **	*z*=3.4 **					
9. Owns a Book	62.6% own book	*z*=-2.73**	*z*=.30	*z*=-.59	*z*=3.43 **	*z*=-.81	*z*=3.74 **	*z*=1.96 *	*z*=.85				

School-Level													
10. Teacher Quality	*M*=.01 *SD*=.43	*r*=.01	*z*=.85	*r*=.03	*r*=.05	*r*=.01	*r*=.02	*z*=-.24	*z*=-.99	*z*=-.20			
11. Infrastructure	*M*=-.06 *SD*=.50	*r*=-.08 *	*z*=-.82	*r*=-.07 *	*r*=.00	*r*=.01	*r*=.03	*z*=1.49	*z*=.87	*z*=.09	*r*=.27 **		
12. Learning Materials	*M*=0 *SD*=.59	*r*=-.01	*z*=.17	*r*=.02	*r*=-.00	*r*=.07	*r*=-.02	*z*=1.41	*z*=-.14	*z*=-.93	*r*=-.08 *	*r*=.22 **	
13. Environment	*M*=0 *SD*=.42	*r*=.02	*z*=.83	*r*=-.03	*r*=.01	*r*=.03	*r*=-.03	*z*=.36	*z*=-.30	*z*=.77	*r*=-.39 **	*r*=-.05	*r*=.23 **

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Relationships between continuous variables were tested using correlations. Relationships of categorical variables were tested using multi-level logistic regressions.

* indicates $p < .05$. ** indicates $p < .01$.

We compared the fit of each model and found that the best fit model was a model that included all main effects and an interaction between child and family risk. Including additional interactions in our model decreased the model fit.

Table 5

Cumulative Risk Model Comparisons

Cumulative Risk Level (s)	'Null' Model	'Main Effects Only' Model	'Child-Family Interaction' Model	'Multiple Interactions' Model
Child-Level		*b*=-.650, *z*(984)=-4.50, *p*<.001***	*b*=-.876, *z*(983)=-4.40, *p*<.001***	*b*=-.859, *z*(981)=-3.70, *p*<.001***
Family-Level		*b*=-.109, *z*(984)=-.90, *p*=.370	*b*=-.388, *z*(983)=-1.93, *p*=.054^{+}	*b*=-0.401, *z*(981)=-1.73, *p*=.084^{+}
School-Level		*b*=.167, *z*(984)=.74, *p*=.46	*b*=.161, *z*(983)=.720, *p*=.472	*b*=.180, *z*(981)=.41, *p*=.682
Child-Family Interaction			*b*=.226, *z*(983)=1.66, *p*=.097^{+}	*b*=.227, *z*(981)=1.67, *p*=.095^{+}
Child-School Interaction				*b*=-.032, *z*(981)=-.15, *p*=.883

Family-School Interaction				*b*=.019, *z*(981)=.10, *p*=.920
Conditional R^2	.067	.135	.141	.142
Marginal R^2	.000	.074	.086	.087
Adjusted ICC	.067	.065	.060	.060
Conditional ICC	.067	.061	.055	.055
Comparison of Model Fit		$\chi^{2(3,989)}$=20.62, *p*<.001***	$\chi^{2(1,989)}$=2.72, *p*=.099^{+}	$\chi^{2(2,989)}$=0.04, *p*=.982

Supplementary Material References

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Highlights

- In Côte d'Ivoire, about 1 in 4 children who enrol in primary school do not complete primary school
- Children who start school late, child cocoa labourers, and children with low literacy skills were more likely to dropout
- Poverty and limited home literacy resources increased dropout risk, even when other child-level risk factors were low
- Quality education was a protective factor against dropout for high risk children
- Risk and resilience factors highlight that child-, family-, and school-levels interact and contribute to dropout