Computational Approaches to Characterizing Cognition in Socioeconomic Contexts: Deprivation, Opportunity, and Neural Embedding in Development

by

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Dedication

仅以此论文献给我的祖父母，张格和魏肖莹。是他们在我年少时播下了求知与探索的种子，并始终以他们非凡的人生激励着我前行。

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Abstract

Executive functioning (EF), a set of top-down processes supporting goal-directed behavior, is a critical domain of development associated with a broad range of psychological and life outcomes. The prolonged development of EF from childhood through young adulthood renders it particularly susceptible to environmental influences, such as the socioeconomic context. Yet, the mechanisms through which socioeconomic experiences shape EF development remain incompletely understood, in part due to challenges in precisely characterizing EF using behavioral tasks. This dissertation integrates computational modeling of cognition and neuroimaging approaches to investigate how socioeconomic contexts, spanning both family disadvantage and neighborhood opportunity, may shape the development of cognitive efficiency and its functional neural correlates. Drawing on data from a 22-year longitudinal population-based birth-cohort sample, the present dissertation examined cognitive efficiency as the drift rate parameter from the Drift-Diffusion Model (also known as Diffusion-Decision Model), which is hypothesized to be driven by a task-general EF-related efficiency of evidence accumulation factor. Chapter 2 examined longitudinal associations between childhood material hardship, namely insecurity in housing, utilities, food, and medical care, adolescent drift rate, and attention difficulties. Results indicated that adolescents exposed to greater material hardship showed lower drift rate, suggesting less effective information processing. Growth curve modeling revealed that initial exposure to material hardship, but not changes across childhood, was associated with drift rate in adolescence. Lower drift rate was also associated with concurrent attentional problems

and served as a significant indirect pathway linking material hardship to adolescent attention Chapter 3 extended this work beyond the family context by examining neighborhood opportunity during adolescence, characterized using census-tract indicators of educational, socioeconomic, and health and environmental resources. Findings revealed that that greater neighborhood opportunity during adolescence was associated with higher drift rate, measured multiple years later in young adulthood. At the same time, families experiencing greater economic disadvantage were also more likely to reside in neighborhoods with fewer resources and opportunities, highlighting the challenges of disentangling family- and neighborhood-level influences on EF development. Chapter 4 investigated the functional neural correlates of adolescent drift rate using the connectome-based predictive modeling method with resting-state functional connectomes. Although a functional network that was overall significantly predictive of drift rate was not identified, preliminary findings revealed that higher household income-to-needs ratio was linked with greater average connectivity in the network consisting of edges significantly associated with drift rate, suggesting that the expression of these neural networks may be sensitive to the socioeconomic context. Together, these studies demonstrate that the multidimensional socioeconomic contexts are associated with meaningful individual differences in cognitive efficiency across development, showcasing the utility of computational modeling of cognition in developmental cognitive neuroscience research. Studies also highlight the importance and challenges of disentangling interconnected socioeconomic conditions that operate across multiple levels of the environment. By integrating computational modeling, longitudinal developmental data, and neuroimaging methods, this dissertation advances understanding of how socioeconomic contextual factors may shape EF and informs future work

for identifying mechanisms through which socioeconomic conditions contribute to developmental outcomes.

Chapter 1 General Introduction

Executive functioning (EF), particularly attention, inhibition, and behavioral regulation, is a critical domain of development that is associated with a broad range of outcomes in life such as academic achievement and mental health (Diamond, 2013; Feinstein & Bynner, 2004; Nigg, 2017). Notably, EF assessed in early childhood has been shown to predict outcomes well into adulthood, highlighting its lasting developmental significance (Moffitt et al., 2011). At the same time, EF is not a fixed trait – it is shaped by a dynamic interplay between environmental contexts and individuals' experiences throughout development (Munakata & Michaelson, 2021). Amongst these influences, socioeconomic disadvantage has been identified as a major risk factor for worse cognitive performance, with evidence that growing up in poverty is associated with lower EF development in children, adolescents, and adults, potentially contributing to a range of downstream outcomes (Evans et al., 2021; Farah et al., 2006; Hackman et al., 2015; Lawson et al., 2018; Müller & Kerns, 2015). Conversely, growing up in high opportunity environments, characterized by better educational resources, physical environment and more economic and social support, may promote EF (Gornik et al., 2024; Munakata & Michaelson, 2021). Thus, understanding how socioeconomic context shape EF is essential for promoting healthy developmental trajectories.

Despite strong empirical foundation, critical gaps remain in the literature. First, the multidimensional nature of socioeconomic resources is often overlooked. While studies most commonly examine socioeconomic disadvantage characterized by low household income and

poverty status, these measures do not fully capture the diverse environments that may inhibit or promote EF. Recent work has emphasized the importance of examining distinct aspects of the socioeconomic contexts, such as material hardship, which reflects unmet basic needs (Gershoff et al., 2007), as well as the availability of neighborhood-level resources, which captures broader contextual opportunities (Acevedo-Garcia et al., 2020; Leventhal & Brooks-Gunn, 2000). These dimensions may exert unique influences on EF development that are obscured when examining only income-based indicator of poverty. Second, methodological issues are present in how EF is measured using behavioral performance tasks across studies, with conventional performance metrics such as response time and accuracy providing limited insight into the underlying cognitive processes. Finally, there is a limited understanding of the neural mechanisms that link socioeconomic factors to EF. While some studies have identified associations between poverty and alterations in brain structure or activation patterns, findings are heterogeneous, and the pathways through which economic adversity impacts neurocognitive development remain obscured.

The present dissertation sought to address these limitations through a series of three studies that integrate computational modeling of cognition and neuroimaging in a longitudinal data set. Specifically, the studies in this dissertation employed the diffusion decision model (DDM) to estimate drift rate, which is the efficiency of information processing and is hypothesized to be driven by a latent cognitive factor, the efficiency of evidence accumulation (EEA). The three studies combined computational modeling with longitudinal contextual data and functional neuroimaging to disentangle the effects of distinct dimensions of socioeconomic factors on drift rate and identify candidate functional neural underpinnings of EEA across adolescence and young adulthood.

1.1 Theoretical Background

1.1.1 Multidimensional Nature of Socioeconomic Context

Socioeconomic contextual factors are powerful social determinants that shape outcomes across development. Among these factors, socioeconomic disadvantage has been the most extensively studied, with research consistently linking childhood economic disadvantage to mental health problems (e.g., depression), neurocognitive dysfunction (e.g., ADHD), and poorer general life outcomes (e.g., academic achievement, life satisfaction) (Brooks-Gunn & Duncan, 1997; Haushofer & Fehr, 2014; Peverill et al., 2021; Russell et al., 2016). In most research, socioeconomic disadvantage is operationalized using family income or poverty ratio (household income relative to the federal poverty threshold). However, income-based indicators capture only one dimension of socioeconomic disadvantage, which is often multifaceted and intertwined with other contextual factors. As a result, definitions of socioeconomic disadvantage vary substantially across studies, contributing to inconsistencies in the literature (Antonoplis, 2023). In addition, while research on disadvantage factors is abundant, a more complete understanding of developmental processes requires consideration of the opportunities and resources that may support cognitive growth, particularly within broader contexts such as neighborhoods. The present dissertation focuses on two complementary socioeconomic contextual factors at two different levels of influence and their associations with EF: material hardship, a household-level indicator of deprivation, and neighborhood opportunity, a census-tract level indicator of environmental enrichment.

1.1.1.1 Material Hardship

In studies that examine income-based measures of socioeconomic disadvantage, one often overlooked aspect is the reality that a family's income does not always reflect their day-to-day

access to essential resources. Income measures assume a uniform cost of living across households, which fails to account for regional variability in living expenses such as housing, healthcare, and transportation. A complementary measure of understanding socioeconomic disadvantage is material hardship, which is the difficulty to affording everyday living essentials such as housing, food, utilities, and medical care, and is a more direct indicator of economic strain on everyday life (Gershoff et al., 2007). Importantly, material hardship experiences are not limited to families living below the poverty line. For example, recent estimates show that among children in families earning two to four times the poverty threshold, 33.1% experienced food insufficiency, 4.2% faced housing instability, and 12.6% encountered difficulties affording medical care (U.S. Census Bureau, 2023). Therefore, by capturing the tangible hardship experienced by families, material hardship provides a complementary and often more nuanced perspective on socioeconomic disadvantage that accounts for income and cost of living, compared with income-based indicators.

A growing body of research highlights material hardship as a salient factor contributing to developmental outcomes. Exposure to material hardship during childhood and adolescence has been associated with elevated risk for anxiety, depression, and externalizing behaviors (Bellair et al., 2021; Heflin & Iceland, 2009; Huang et al., 2021; Schenck-Fontaine & Ryan, 2022). However, much of the existing literature tends to focus on isolated aspects of material hardship, such as food insecurity or housing instability, rather than examining cumulative or multidimensional hardship. Moreover, findings on the strength and consistency of these associations remain mixed, in part due to variability in how hardship is measured. As such, more research is needed to clarify the developmental consequences of material hardship, particularly on EF.

1.1.1.2 Neighborhood Opportunity

A prominent theoretical framework guiding research on socioeconomic contextual influences on child development is the bioecological model of human development (Bronfenbrenner, 1994), which posits that individuals develop within multiple, nested environmental systems, ranging from proximal (e.g., family) to distal (e.g., neighborhood, culture). In addition, the transactional model emphasizes the dynamic and reciprocal interactions between individuals and their surrounding environments over time (Sameroff, 2010). These ecological perspectives underscore the importance of looking beyond family-level socioeconomic context to consider the broader environmental conditions in which children grow up (Hyde et al., 2020). In particular, neighborhood contexts can play a critical role in shaping development, especially given the increasing importance of contexts outside of the home (e.g., peers, neighbors, schools) as children mature.

Studies have linked neighborhood-level poverty with a range of adverse developmental outcomes, including lower academic achievements, greater internalizing and externalizing behavior (Leventhal & Brooks-Gunn, 2000; Mair et al., 2008; McBride Murry et al., 2011; Minh et al., 2017). At the same time, a growing body of research suggests that neighborhood-level opportunities, such as access to enriching educational, health, social, economic, and environmental resources, can foster positive developmental outcomes across domains including mental and physical health, cognitive functioning, and social adjustment (Acevedo-Garcia et al., 2020; Donnelly et al., 2016; Putnick et al., 2025). Importantly, neighborhood opportunities may also serve a protective role by buffering individuals from the negative effects of more proximal disadvantages, such as low family socioeconomic status or exposure to household violence (Cubides-Mateus et al., 2023; Minh et al., 2017; Roubinov et al., 2018). Nonetheless, findings

across studies remain mixed, highlighting the need for further research to clarify the impact of neighborhood-level effects on development.

Multiple mechanisms have been proposed to explain how the neighborhood contexts may impact youth development. From a deprivation perspective, reduced access to institutional resources (e.g., high-quality schools, healthcare, job opportunities), weakened social cohesion and collective efficacy, and higher exposure to violence or environmental hazards could lead to negative consequences in children's outcomes (Leventhal & Brooks-Gunn, 2000). On the other hand, access to those resources may promote healthy development (Chetty et al., 2016). In addition, neighborhood conditions may indirectly affect children through more proximal processes such as parenting and family resources (e.g., Finegood & Blair, 2017). However, recent studies have found that neighborhood poverty and opportunities have distinct effects beyond family-level factors, such as household income and parental education (Vargas et al., 2020; Zhou et al., 2025). This may suggest that where children live has an additive effect on development beyond family-level factors and challenges the assumption that neighborhood effects are merely proxies for household-level disadvantage, highlighting the need for more research that simultaneously considers both levels of influence.

1.1.1.3 Other Considerations: Developmental Timing

Much of the research on socioeconomic disadvantage adopts a cumulative risk framework, which posits that the accumulation of exposure to poverty and related adversities over time leads to increasingly negative developmental outcomes (Evans et al., 2013). While this perspective captures the overall magnitude of exposure, it often overlooks the potential importance of *when* adversity occurs. A complementary line of research focuses on developmental timing, which posits that the effects of socioeconomic disadvantage may vary

depending on the specific period of exposure (Levesque et al., 2021; McLeod & Shanahan, 1996). Neurobiological evidence has suggested that early childhood represents a particularly sensitive window for development due to heightened neural plasticity (Fox et al., 2010; Knudsen, 2004). At the same time, developmental timing effects may not be uniform across domains. Different areas of the brain may develop at varying pace (e.g., prefrontal cortex continues to mature into adolescence and young adulthood, whereas the amygdala develops earlier in life), as such, the saliency of timing may differ depending on the type of outcome (Andersen, 2003; Casey et al., 2005; Johnson, 2011). The relative importance of different socioeconomic contextual factors may also shift over time. During early childhood, family-level factors such as material hardship may play a more central role, whereas in adolescence, distal environmental contexts such as neighborhood quality may become increasingly influential as youth gain independence and spend more time outside the home (Bronfenbrenner, 1994; Leventhal & Brooks-Gunn, 2000). These theoretical perspectives collectively underscore the need to examine when disadvantage or opportunities occurs, beyond whether it occurs, when evaluating its impact on developmental outcomes.

1.1.2 Defining and measuring executive functioning

Although EF is widely studied and is integral to development, it remains a difficult concept to define and measure, with some researchers describing the field as filled with "conceptual clutter" and "measurement mayhem" (Barkley, 2012; Karr et al., 2018; Morrison & Grammer, 2016; Nigg, 2017). Generally, EF, sometimes used interchangeably with "cognitive control" or "self-regulation", refers to a set of top-down mental processes that support regulation of goal-directed behavior (Diamond, 2013; Miyake et al., 2000). Although EFs are often conceptualized as a collection of separable processes, accumulating evidence suggests that much

of the variance shared across EF tasks reflects a common underlying cognitive factor (Löffler et al., 2024; Miyake et al., 2000). In the Unity-yet-Diversity framework, this shared variance is captured by the common EF factor, which is thought to reflect broad goal maintenance and top-down control processes that contribute to performance across diverse EF domains (Miyake et al., 2000; Miyake & Friedman, 2012).

From a measurement perspective, EF is often evaluated using performance-based behavioral tasks that also typically contrasts between different conditions (e.g., hard vs. easy stimuli), where faster and more accurate responses, particularly under difficult stimuli conditions, are interpreted as suggesting better EF (Farah et al., 2006; Johnson et al., 2021; Wei et al., 2025). Although many tasks are intended to assess similar EF processes, performance and measures on different EF tasks often show only modest correlations, a phenomenon frequently attributed to the task impurity problem (Eisenberg et al., 2019; Hedge et al., 2018; Price et al., 2015). Further, response time (RT) and accuracy reflect only coarse aggregates of underlying cognitive processes that include the targeted EF (e.g., inhibition in a Flanker task) as well as other irrelevant processes (e.g., response caution, motor response speed) (Hedge et al., 2018; Lerche & Voss, 2019). As a result, findings from prior research may not reflect, as intended, differences in cognitive ability but are instead confounded by other processes that are not directly related to the construct of interest. Together, these factors might contribute to inaccurate interpretations of performance results.

One promising approach to resolving the conceptual and measurement challenges surrounding EF is the use of model-based computational methods that move beyond surface-level behavioral metrics. The Diffusion-Decision Model (DDM, also known as the Drift-Diffusion Model), a well-validated model in cognitive psychology, offers a powerful means of

quantifying latent neurocognitive processes underlying performance in two-choice decision tasks (Ratcliff, 1978; Ratcliff & McKoon, 2008; Voss et al., 2004). By modeling decision-making as a process of evidence accumulation toward one of two response thresholds, the DDM captures not only decision speed and accuracy but also dissociates distinct cognitive mechanisms, such as non-decision time, response caution, and the efficiency of evidence accumulation.

Of particular relevance in the literature is the drift rate, which indexes how efficiently an individual gathers task-relevant information to make a decision. Drift rates across diverse tasks appear to be largely explained by a task-general trait-like factor, termed efficiency of evidence accumulation (EEA), that drives individual differences in task performance across many domains of EF (Weigard et al., 2021; Weigard & Sripada, 2021). Consistent with the idea of a common EF factor, EEA may represent a computationally specified mechanism underlying the task-general variance shared across many EF tasks. Notably, EEA has demonstrated good test-retest reliability (Eisenberg et al., 2019; Lerche et al., 2020; Schubert et al., 2016), making it a stable measure of how efficiently individuals accumulate goal-relevant information. EEA has also been implicated as a transdiagnostic marker linked to externalizing behaviors, substance use, depression, and ADHD (Duyser et al., 2025; Letkiewicz et al., 2023; Paige et al., 2024). Despite the promise of EEA in adults, studies have just begun to examine EEA in younger populations and its application in studying the effects of socioeconomic contexts has been especially limited, highlighting an important gap that this dissertation aims to address.

1.1.3 Socioeconomic factors and EF

The relationship between socioeconomic factors and EF is complex, with substantial evidence linking socioeconomic disadvantage to poorer cognitive performance, as well as evidence emerging on environmental opportunities promoting EF (Farah et al., 2006; Munakata

& Michaelson, 2021). In addition, emerging research also highlights contexts in which certain cognitive skills may be preserved or even enhanced in response to adversity (Mittal et al., 2015; Young et al., 2022). Early studies focused on poverty-related disparities in IQ and verbal skills, both of which are correlated concepts with EF, during early childhood (McLoyd, 1998), and more recent studies have found socioeconomic status disparities on EF in children as young as two years old (Blair et al., 2011; Hackman et al., 2015; Noble et al., 2005; Wiebe et al., 2011). These results have also been replicated in examining income or poverty ratio, finding worse performance on behavioral tasks involving EF, such as working memory, inhibition, and attention tasks (Assari et al., 2020; Evans et al., 2021; Lawson et al., 2018; Noble et al., 2007). In addition, disparities in EF have been shown to persist longitudinally across early and middle childhood (Hackman et al., 2015). Together, these findings point to early and enduring effects of socioeconomic disadvantage on EF skills.

Beyond income-based indicators, research on material hardship has also begun to link specific types of deprivation, such as food insecurity or housing instability, to EF-related outcomes, such as reduced academic performance and lower problem-solving abilities in children, though the number of studies specifically on EF measures remain limited (Alaimo et al., 2001; Schenck-Fontaine & Ryan, 2022; Solari & Mare, 2012). At the neighborhood level, several studies have found that greater exposure to socioeconomic disadvantage (e.g., higher area deprivation index) is associated with poorer performance on EF-related tasks (Röhr et al., 2024; Sutin et al., 2022; Taylor et al., 2020). Conversely, youth growing up in neighborhoods with better opportunities demonstrated stronger EF performance (Gornik et al., 2024; Zhou et al., 2025). Importantly, these associations often remain significant after controlling for family-level socioeconomic conditions, suggesting that neighborhood conditions contribute unique variance

to cognitive outcomes (Tomlinson et al., 2020). Together, this work highlights the importance of considering multiple dimensions and levels of socioeconomic factors in relation to EF development.

Emerging research challenges the view that adversity uniformly impairs cognition, instead suggesting that certain cognitive abilities may adapt, under specific conditions, in response to harsh or unpredictable environments (Fields et al., 2021; Mittal et al., 2015; Young et al., 2022). Aligning with the life history theory (Belsky et al., 1991; Promislow & Harvey, 1990), youths growing up in harsh conditions, can develop stress-adapted cognitive skills, such as in attention, perception, and learning, such that the resulting behavior is advantageous in particular stressor conditions, but incurs costs in other domains (Ellis et al., 2022; Frankenhuis & de Weerth, 2013). For example, young adults who grew up in unpredictable home environments displayed enhanced task-switching abilities, but only under stressful conditions (Mittal et al., 2015). Similarly, another study found that caregiver instability predicted enhanced cognitive flexibility in a group of school-aged children (Fields et al., 2021). These findings suggest that EF is not simply at risk in the face of socioeconomic disadvantage, but rather might be a form of adaptation to environmental demands.

To date, few studies have applied computational methods to examine associations between socioeconomic advantage and disadvantage and EEA, as an index of EF ability, despite the potential affordances. Within the context of broader adversity research, one study found that greater exposure to violence, but not material deprivation, was associated with lower EEA generalized from several cognitive tasks whereas task-specific EEA was not influenced by adverse experiences (Vermeent, Young, DeJoseph, et al., 2024). Additionally, two other studies have explored the relationship between adversity and computational parameters derived from

DDM or similar modeling approaches (He et al., 2024; Vermeent, Young, van Gelder, et al., 2024). Critically, no longitudinal studies have been conducted to examine the link between different aspects of socioeconomic contextual factors, such as material hardship or neighborhood resources, and EEA, leaving a gap in understanding the effects of these factors on EF. Given EEA's potential as a robust marker of EF, additional research using longitudinal designs is needed to clarify how different types and timings of socioeconomic factors influence EEA across development.

1.1.4 Neural Embeddings of Socioeconomic Contextual Factors

One pathway through which socioeconomic advantage and disadvantage factors may shape EF is through its underlying neurobiological basis. Evidence from animal models has long established that the brain is highly plastic, with environmental experiences shaping behavior through structural and functional neural changes (Luby et al., 2020; McEwen et al., 2016). Two primary mechanisms have been proposed to explain how socioeconomic context becomes biologically embedded (Hyde et al., 2020). The first involves a stress pathway, where individuals living in poverty may experience stress from the environment that dysregulates the stress physiological responses in the body (e.g., disruption of the Hypothalamic-Pituitary-Adrenocortical axis that leads to neuroinflammatory responses and altered cortisol release) (Gunnar & Quevedo, 2007; Miller et al., 2021; Raymond et al., 2018). While these changes may be adaptive in the short term, persistent stress can also alter brain development in ways that are maladaptive over time (Blair & Raver, 2012; Gunnar & Quevedo, 2007; Lupien et al., 2009). A second proposed pathway is through lack of stimulation, or deprivation. Work in animal models have shown that deprivation, in the form of lack of reliable maternal sensory signals and care in

rats, have resulted in loss in hippocampal dendrites and synapses that is associated with impairment in learning (Davis et al., 2017; Ivy et al., 2008).

Aligning with these animal models, research in human neuroscience has found evidence of socioeconomic contexts shaping brain function and structure pertaining to EF. Lower socioeconomic status has been linked with smaller volume of the prefrontal cortex (PFC) and altered functional activity within the middle and inferior frontal gyri and the anterior cingulate cortex, which are key components of the frontoparietal network (FPN) that supports EF (Farah, 2017; Johnson et al., 2016). In particular, material hardship, aligning with the deprivation pathway, has been suggested as a specific dimension of socioeconomic disadvantage that may be especially influential in shaping the structure and function of the PFC (see Johnson et al. (2016) for a detailed review). From a broader ecological perspective, emerging work also implicates neighborhood-level factors in shaping brain function and structure. For example, Tomlinson et al. (2020) found that neighborhood poverty, but not family-level SES, predicted activation in the inferior frontal gyrus, which in turn mediated performance on a response inhibition task, suggesting distinct neural signatures of distal versus proximal socioeconomic disadvantage. On the other hand, neighborhood opportunity (e.g., quality education, housing resources, social support) has also been found to promote cognitive functioning through cortical structure of the brain (Zhou et al., 2025).

Studies have also investigated the neural correlates of EEA using electroencephalogram (EEG) or functional magnetic resonance imaging (fMRI) in human neuroscience research, generally finding that brain regions in the FPN plays a key role (Heekeren et al., 2008; Liu & Pleskac, 2011; Mulder et al., 2014). A recent study evaluating whole-brain functional networks has found that flexible adaptation of the FPN and dorsal attention network to cognitive demands

may contribute to better EEA (Weigard et al., 2024), which aligns with the broader literature implicating both networks in cognitive efficiency and decision-making (Cole & Schneider, 2007; Dosenbach et al., 2008). However, to date, no studies have directly examined whether and how socioeconomic contextual factors impact the neurobiological underpinnings of EEA. Addressing this gap is crucial for understanding how contextual factors may shape neurocognitive processes.

1.2 Specific Aims

The overarching goal of this dissertation is to advance our understanding of how socioeconomic disadvantage and opportunity shape EF by integrating computational modeling and neuroimaging approaches in a longitudinal scope. Specifically, this dissertation applies the Drift-Diffusion Model (DDM) to examine how different levels and timing of socioeconomic advantage and disadvantage, across material hardship and neighborhood opportunities, are associated with drift rate, a computationally derived marker of cognitive efficiency hypothesized to be driven by the trait-like efficiency of evidence accumulation (EEA) factor. This dissertation addresses key gaps in the literature by: 1) Using computational modeling of cognition to examine how childhood material hardship predicts adolescent drift rate and attentional problems; 2) Testing how neighborhood opportunity during adolescence is linked to young adult drift rate and its associations with family-level disadvantage; and 3) Identifying the functional neural architecture of drift rate and its associations with socioeconomic disadvantage in adolescents using a connectome-based predictive modeling approach.

All three studies in the dissertation use a longitudinal sample drawn from the Future of Families and Child Wellbeing Study (FFCWS) (Reichman et al., 2001). The FFCWS is a population-based longitudinal cohort of 4,898 families who were recruited from 20 large cities in the U.S. (population greater than 200,000). The study oversampled for children of non-marital

births (3:1) and included a large representation of minority and low-income families (33% Black, 17% Hispanic, 12% White, 5% other/multiracial; median household income at child's birth $22,500). Data were collected at child's birth, ages 1, 3, 5, 9, 15, and 22 through a series of home visitations, phone interviews, and survey administration. At age 15 and 22, subsamples of individuals from the FFCWS were invited to participate in the Study of Adolescent to Adult Neural Development at the University of Michigan, Ann Arbor. At age 15, data were collected from 237 youth and families (76% Black, 13% White, 6% Hispanic, 5% other/multiracial). At age 22, data were collected from 530 young adults (57% Black, 27% White, 8% Hispanic, 8% other/multiracial).

1.2.1 Study 1: Childhood Material Hardship Linked to Adolescent Neurocognition: A Computational Modeling Approach

Aim 1: Examine the associations between childhood material hardship and adolescent drift rate

Aim 2: Examine the associations of developmental trajectory of material hardship and drift rate

Aim 3: Test indirect effects of material hardship via drift rate on adolescent attentional problems

Aim 4: Compare results between drift rate and conventional behavioral performance metrics

1.2.2 Study 2: Neighborhood Matters: Longitudinal Associations Between Child Opportunity Index in Adolescence and Young Adult Evidence Accumulation Efficiency

Aim 1: Examine the associations between adolescent neighborhood opportunity and young adult drift rate

Aim 2: Examine links between specific dimensions of neighborhood opportunities (i.e., education, health and environment, and social and economic) and drift rate

Aim 3: Examine buffering effects of neighborhood opportunity against family-level disadvantage on young adult drift rate

Aim 4 (Exploratory): Compare effects of resource-based contemporary measure vs. outcome-based historical measure of neighborhood opportunities

1.2.3 Study 3: Characterizing the Functional Connectome of Cognitive Efficiency and Its Links with Socioeconomic Disadvantage in Adolescents

Aim 1: Identify the functional neural correlates of drift rate (i.e., "EEA network") using connectome-based predictive modeling

Aim 2: Examine the associations of childhood socioeconomic disadvantage and changes in the EEA network

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Chapter 2 Childhood Material Hardship Linked to Adolescent Neurocognition: A Computational Modeling Approach

2.1 Introduction

Growing up in poverty poses significant challenges for the development of cognitive functioning and mental health (Lawson et al., 2018; Müller & Kerns, 2015). Poverty-related hardships can shape the development of higher-order processes that facilitate attention, inhibition, and behavioral regulation, which has long-lasting implications for academic achievement, mental and physical health (Diamond, 2013; Feinstein & Bynner, 2004; Moffitt et al., 2011). However, measures of socioeconomic disadvantage frequently fail to capture the daily challenges, such as insecure housing and lack of nutritious food, that are experienced by many families. Furthermore, methodological issues exist in how cognitive functioning is measured across studies. To address these gaps, the current study investigated how material hardship, a measure of the lived challenges of poverty, is associated with drift rate, a cognitive process measured using a well-validated computational model of cognition that has been shown to be a key underpinning of goal-directed behavior. Drawing on 15 years of longitudinal data from the Future of Families and Child Wellbeing Study (FFCWS), results from this study shed light on the unique impact of material hardship on adolescent cognitive development, highlighting the importance of using computational approaches to better understand the associations between socioeconomic disadvantage, cognitive functioning with implications for attentional problems in adolescents.

2.1.1 Material Hardship, Developmental Risks, and Cognitive Functioning

Nearly one in five children in the United States live in poverty, with over 40% having experienced challenges meeting basic needs (U.S. Census Bureau, 2023). The widespread prevalence of poverty has prompted extensive research into its psychological consequences, revealing that growing up in poverty is linked to adverse developmental outcomes (Haushofer & Fehr, 2014; Peverill et al., 2021; Schenck-Fontaine & Ryan, 2022). However, common indicators of poverty, such as socioeconomic status or income level, offer limited insight into the daily realities of those affected because the impact of family income can vary significantly depending on factors such as cost of living and social support. To better capture the lived experience of poverty, researchers have advocated for alternative measures to income or socioeconomic status. One such measure is material hardship, which provides a more direct assessment of tangible challenges, such as food insecurity, housing instability, and difficulties meeting basic needs (Gershoff et al., 2007). Notably, experiences of hardship can occur in families that have income levels above the poverty line, which remains a relatively low benchmark (e.g., $30,000 for a family of four in 2023).

Material hardship during childhood has been increasingly recognized as a critical factor influencing developmental outcomes. Exposure to such hardship in childhood and adolescence can undermine psychological well-being, increasing the risk of anxiety, depression, and externalizing behaviors (Huang et al., 2021; Pechtel & Pizzagalli, 2011; Peverill et al., 2021). A less investigated developmental outcome is attention-related functioning. Prior studies have linked poverty and related risk factors to elevated attention difficulties in children and adolescents, though findings remain mixed and intertwined with genetic influences (de Zeeuw et al., 2020; Russell et al., 2016). Less work has specifically examined the specific role of material

hardship on attentional difficulties, often combining it with factors like environmental pollution (Dellefratte et al., 2019; Perera et al., 2018). Some studies have found significant associations of food insecurity and housing tenure with attentional problems from childhood to adolescence, but findings on the strength and consistency of these effects remain mixed (Hanson, 2025; Lu et al., 2019; Paquin et al., 2021; Russell et al., 2015).

While research that specifically examined the effects of material hardship on cognitive functioning remains limited, broader evidence suggests that early exposure to aspects of material hardship, such as food insecurity and housing crowding, is associated with lower cognitive skills across various domains, including math, reading, and problem-solving (Alaimo et al., 2001; Jyoti et al., 2005; Schenck-Fontaine & Ryan, 2022; Solari & Mare, 2012). Beyond material hardship, socioeconomic disadvantage has long been linked to deficits in cognitive functions such as inhibition, task-switching, and working memory in childhood and adolescence (Hackman et al., 2015; Lawson et al., 2018). These findings align with theories suggesting that chronic stress from adverse experiences—including economic hardship—can alter neural development in regions responsible for higher-order cognitive processes, resulting in decreases in functioning (Farah et al., 2006; Sheridan et al., 2020). Recent theoretical framework suggests that these changes are not just deficits, as adversity-exposed youth may also develop context-sensitive adaptations in cognition that reflect trade-offs rather than impairments (Ellis et al., 2022). Empirical work has indeed found support that certain cognitive abilities may adapt in response to harsh environments to match the challenges of that environment (Fields et al., 2021; Mittal et al., 2015; Young et al., 2022). This complexity highlights the need for more nuanced approaches to studying cognition under adversity.

2.1.2 Measurement of Cognitive Functioning: Drift Rate and EEA

Cognitive functioning has frequently been assessed with performance on behavioral tasks, typically measured by mean response times (RTs) and accuracy/error rates (Johnson et al., 2021; Wei et al., 2025). These tasks often rely on fast and accurate responses to assess individuals' ability in particular cognitive domains (Farah et al., 2006; Fields et al., 2021). However, this approach has several limitations. First, cognitive assessments encompass a diverse range of tasks that measures different domains of higher-order functioning, including simple decision-making, inhibition, and attention shifting (Diamond, 2013; Nigg, 2017). The variability in tasks used across studies makes direct comparisons challenging and introduces psychometric issues, such as poor test-retest reliability of many commonly used measures (Eisenberg et al., 2019; Hedge et al., 2018; Price et al., 2015). A second issue is that traditional task performance measures are often "black box" aggregates that obscure the many cognitive processes involved in completing a task. For example, fast and accurate performance on an inhibition task is typically assumed to reflect stronger inhibitory control. However, task performance is also influenced by unrelated factors such as response caution and motor response speed (Hedge et al., 2018; Lerche & Voss, 2019), which are typically not accounted for. As a result, findings from prior research may not reflect, as intended, differences in cognitive ability, but instead be confounded by other processes that are not directly related to the construct of interest.

A promising solution to these issues is the application of formal mathematical models that describe neurocognitive processes underlying task performance. The Diffusion Decision Model (DDM, also known as Drift Diffusion Model; Figure 2.1) is a well-validated model that explains individual behavior on simple two-choice decision tasks and has been widely used in cognitive psychology (Ratcliff & McKoon, 2008; Voss et al., 2004, 2013). The model posits that within each trial, people gather evidence for possible responses continuously until a critical

threshold has been reached for either one of the two options. Once the threshold is reached, the participant will make the decision. The model also accounts for preparation and execution processes that occur outside of decision-making as well as an individual's level of caution in responding (i.e., prioritizing accuracy versus speed). By integrating RT and accuracy information on a trial-by-trial basis, the model provides a more nuanced and reliable measure of cognitive function than traditional behavioral indices (Voss et al., 2004).

The DDM decomposes task performance into several underlying cognitive processes, each represented by distinct parameters that influence behavior (Voss et al., 2004). Four parameters from the DDM are commonly examined. The drift rate (v) reflects how efficiently an individual gathers goal-relevant information to make a decision that is consistent with the goals of the task. Boundary separation (a) represents response caution, with larger values indicating a more conservative decision strategy that requires more information before committing to a choice. Starting point (z) reflects response bias, or the tendency to favor one option over another, such as when one response is more probable. Finally, non-decision time (t_0) accounts for the time it takes for processes unrelated to the decision stage, such as stimulus encoding and motor execution of response.

Among these parameters, the drift rate has received particular attention in the literature because drift rates across diverse tasks appear to be largely explained by a general trait-like factor, termed efficiency of evidence accumulation (EEA), that drives individual differences in task performance across many domains of cognitive functioning (Weigard et al., 2021; Weigard & Sripada, 2021). This task-general process has been supported by studies using latent factor approaches, which show that drift rates from diverse tasks load moderately to strongly (typically .50–.80) onto a single EEA factor (Löffler et al., 2024; Schubert et al., 2016; Vermeent, Young,

DeJoseph, et al., 2024). EEA has also demonstrated strong test-retest reliability, internal consistency, and cross-task validity compared to conventional behavioral measures (Eisenberg et al., 2019; Lerche et al., 2020; Schubert et al., 2016; Tomlinson et al., 2025). Although the most robust estimates of task-general EEA are derived from performance across multiple tasks, prior research suggests that drift rate estimates from even single tasks can serve as reasonable approximations of the broader EEA construct, including based on tasks that do not have a focus on higher-order cognitive functioning, such as simple perceptual decision-making tasks (Löffler et al., 2024; Weigard et al., 2021). Given its conceptual links to general cognitive functioning, EEA has been increasingly used to study cognitive processes in a variety of contexts and has been implicated as a transdiagnostic trait in understanding externalizing behaviors, substance use, and depression, among other outcomes (Duyser et al., 2025; Letkiewicz et al., 2023; Paige et al., 2024; Weigard & Sripada, 2021). The most extensive use of DDM in examining psychopathology has been in research on ADHD and related attentional challenges, where individuals with ADHD consistently exhibit reduced EEA across various tasks, including simple perceptual decision-making and inhibition tasks, further supporting the idea that EEA is a task-general cognitive trait (see Weigard & Sripada, 2021 and Ziegler et al., 2016 for detailed reviews).

2.1.3 Drift rate, Material Hardship, and Attentional Problems

Despite the implication of drift rate and EEA in understanding attention-related symptoms and the methodological advantages of DDM, the cognitive parameter has yet to be examined as a mechanism through which material hardship can increase risk for attentional difficulties. In addition, only a few studies to date have used DDM to examine the associations between material hardship and drift rate as an index of cognitive ability. One study found that

while material hardship was not significantly associated with changes in drift rate across cognitive domains (e.g., processing speed, inhibition, and attentional control), greater exposure to threat was linked with lower EEA (Vermeent, Young, DeJoseph, et al., 2024). Additionally, two other cross-sectional studies have explored the relationship between material hardship, among other types of adversity, and other computational parameters derived from DDM or similar modeling approaches, finding mixed results with how hardship exposure are impacting aspects of cognition (He et al., 2024; Vermeent, Young, van Gelder, et al., 2024). In addition to the limited research on the topic, no longitudinal studies have been conducted to examine the link between material hardship exposure, or poverty broadly, and adolescent drift rate, leaving a gap in understanding the cumulative effects of childhood material hardship on cognitive development. Longitudinal studies allow for examination of the accumulation of hardship exposure, which has been shown to have critical importance for adolescent development (Evans et al., 2013; Hardi et al., 2024). Beyond cumulative exposure, evidence also suggests that changes in poverty and hardship experience across time may be important to consider, such that decrease in household economic status is associated with decrease in cognitive outcomes (Levesque et al., 2021; McLeod & Shanahan, 1996). These changes in hardship experiences over time can be captured using longitudinal assessments. Therefore, further research is needed to clarify these links in a longitudinal framework.

As discussed, most research examining task-based cognitive performance in relation to adverse experiences and poverty has relied on RT and accuracy as primary measures with the oversimplistic assumption that slower RTs and higher error rates necessarily indicate lower cognitive functioning. The DDM framework suggests that multiple cognitive processes contribute to task performance on a single trial, meaning that observed variations in RT and

accuracy may reflect differences in multiple underlying processes rather than ability alone. If conventional interpretations were accurate, drift rate would consistently align with observed RT and accuracy, such that adverse experiences would have a similar impact on drift rate as conventional performance measures. However, if this relationship does not hold, it suggests that other cognitive processes, such as response caution or decision strategies, may be influenced more by adversity than general cognitive functioning. Further, given the prior findings of a general relationship between adversity and performance across diverse cognitive domains detailed above, drift rate's task-general influence makes it a compelling mechanistic explanation for why adversity's impacts are so broadly reflected across cognitive tasks.

2.1.4 Current Study

The present study sought to address the gaps in literature by employing the DDM to characterize adolescent cognitive functioning in a perceptual emotional-faces gender-identification decision-making task in a 15-year longitudinal sample. This is the first longitudinal study to examine associations among childhood material hardship exposure, adolescent drift rate, and attentional problems. Aim 1 examined whether cumulative exposure to material hardship across childhood (ages 1, 3, 5, and 9) was associated with drift rate in adolescence (age 15). Aim two, building upon the first aim, tested whether the developmental trajectory of material hardship exposure across waves impacted drift rate. Third, we tested whether drift rate served as an underlying mechanism linking material hardship to attentional problems in adolescence. Finally, Aim 3 assessed whether drift rate provided additional insights into cognitive processes beyond traditional behavioral measures, such as average RT and accuracy.

To distinguish the specific effects of household material hardship, our analyses adjusted for co-occurring types of adversity – violence exposure and social deprivation – across

childhood, in addition to demographic covariates. Additional sensitivity analyses examining the link between hardship and violence exposure are reported in the Supplement. We hypothesized that greater material hardship experience would be uniquely associated with lower adolescent drift rate (i.e., less efficient information processing). Growth curve modeling was used to address the aim of investigating material hardship changes across childhood, characterizing latent trajectory of changes in hardship exposure across childhood and evaluated its link with drift rate. We hypothesized that an increase in material hardship over time would be associated with lower drift rate. With regards to links with attentional problems in adolescents, we hypothesized that lower drift rate would be associated with greater attentional problems in adolescents, and that drift rate would partially explain the association between material hardship exposure and attentional problems. Furthermore, we hypothesized that the associations observed with drift rate would be distinct to the computational parameter and not observed when examining average RT and accuracy.

2.2 Methods

2.2.1 Sample and procedure

Participants were recruited from the Future of Families and Child Wellbeing Study (FFCWS), a population-based longitudinal birth cohort study (Reichman et al., 2001). The original sample included 4,898 children born in 20 large U.S. cities (population over 200,000), with an oversampling (3:1) for non-marital births. This led to a sample of predominately unmarried and low-income families. During adolescence (ages 15-17), a cohort of 237 families from midwestern cities (Detroit, MI; Toledo, OH; Chicago, IL) was invited to the University of Michigan, Ann Arbor to participate in the Study of Adolescent Neural Development (SAND) (Hein et al., 2018). Given the demographics of these cities, most youth in SAND identified as

Black non-Hispanic (76%), with 54% female. Adolescents and their primary caregivers completed a series of surveys and interviews, some of which are included in this study. Adolescents additionally completed behavioral tasks and magnetic resonance imaging (MRI) scans. Analyses were restricted to those with usable performance data from the behavioral task, resulting in a final sample of 187 adolescents (see section on EEA below for exclusion details). Demographic characteristics are included in Supplemental Table 2.5. The study was approved by the University of Michigan Institutional Review Board (IRB: HUM00167754; HUM00074392).

2.2.2 Measures

2.2.2.1 Material Hardship

Longitudinal measures of household material hardship exposure during childhood were collected across four waves at ages 1, 3, 5, and 9. At each wave, caregivers indicated whether or not they had experienced hardship related to housing, utilities, food, healthcare, or finances within the last twelve months. Eight items that were repeatedly asked across waves were included in the analysis following a previous study (Hardi et al., 2022). These items were derived from the 1996 Survey of Income and Program Participation; the 1997 and 1999 New York City Social Indicators Survey; and the 1999 Study of Work, Welfare, and Family Wellbeing of Iowa families on Iowa's assistance program (Bauman, 1999; Mayer & Jencks, 1989).

At each wave, the primary caregiver responded yes (1) or no (0) on each of the following items: (1) received free food or meals, (2) evicted from home or apartment for not paying full rent/mortgage, (3) moved in with other people because of financial problems, (4) stay in a place not meant for long-term housing (e.g., shelter, abandoned building, automobile), (5) did not receive medical care because of cost, (6) did not pay full gas/oil/electric bill, (7) did not pay full rent/mortgage, and (8) borrowed money from family/friends to pay bills. A sum score of material

hardship experience was computed at each wave, with higher scores indicating greater material hardship. Cumulative household material hardship was computed as the sum of endorsed items across all waves. Correlations of hardship scores are reported in Supplemental Table 2.6.

2.2.2.2 Adolescent Drift Rate (v)

Behavioral performance data for DDM parameter estimation was collected using a simple perceptual decision-making task on emotional-faces gender-identification that was completed in an MRI scanner (Hardi et al., 2023; Hein et al., 2018, 2020). Participants were asked to identify the gender of the actor by pressing their thumb (male) or index finger (female) on a button box. Faces were selected from the NimStim set (Tottenham et al., 2009) and were counterbalanced for gender and race (White and Black). Each participants underwent 100 pseudo-randomized trials with 5 types of emotional faces (20 faces per emotion): fearful, happy, angry, sad, and neutral. Each trial consisted of a 500ms fixation cross, a 250ms face stimuli, then a black screen of 1500ms during which participants were instructed to respond to the face. Response times (RTs) and accuracy were recorded. Although the stimuli are emotionally-salient, our analyses (see Supplement section on Emotion-specific drift rate for supporting analyses) indicate that the specific parameters extracted here do not appear to be sensitive to the emotions being shown, and therefore we can still retain a theoretically valid estimate of drift rate from the performance data. Initial exploratory functional MRI analysis with contrast activation did not identify any reliable associations with drift rate (see Supplement for details).

A total of 201 youths completed the task. On average, participants completed almost all trials (98.8 trials), with an average accuracy of 93.8% and average RT of 644ms. 13 participants were excluded due to poor performance: completed less than 75 trials (i.e., omission rate > 25%) and/or accuracy was below 55%, which might indicate that participants did not understand the

task or were not engaged, resulting in 188 participants included in DDM modeling process. We additionally removed trials with RTs less than 200ms as fast guesses, following standard procedures for fitting the DDM (Ratcliff & Tuerlinckx, 2002). Because we were interested in the general cognitive abilities, we combined all trials for each participant without distinguishing between specific emotions. Doing so also preserved statistical power and stability of modeling given that the total trial numbers (max 100 trials per person) were below ideal number of trials for reliable estimations (200-400 trials) (Lerche et al., 2017; Voss et al., 2013).

DDM parameters were estimated using the Dynamic Models of Choice package in R (version 4.3.2, Heathcote et al., 2019; R Core Team, 2023). Four main DDM parameters were estimated for each individual: drift rate (v), response caution (a), non-decision time (t_0), and response bias (z). One participant was further excluded based on poor model fit, resulting in a final sample of 187 participants. A simulation recovery study was conducted to show good recovery of DDM parameters (Figure 2.2). Point estimates of parameter values were summarized using the medians of posterior distributions (descriptives are shown in Table 2.1). Modeling details are reported in the Supplement.

2.2.2.3 Adolescent Attentional Problems

We created multi-informant, multi-method measures of adolescent attentional problems using confirmatory factor analysis (CFA), which provides a more robust and less biased representations of the symptoms (De Los Reyes et al., 2015). Indicators in the CFA included 26 item-level responses of parent-reported from the Child Behavioral Checklist (CBCL) attention problems subscale (Achenbach & Rescorla, 2001) and the clinician-rated inattention and hyperactivity subscales from a DSM-V semi-structured clinical interview using the Kiddie Schedule for Affective Disorders and Schizophrenia (K-SADS-PL) (Kaufman et al., 1997).

Details of the CFA are reported in the supplemental materials. The resulting latent factor in a community sample reflects dimensional variation in attention-related difficulties, rather than a clinical diagnosis, with higher scores indicating greater symptoms, which in this sample reflects a dimension of typical individual differences in attention and impulsivity to more serious attention problems.

2.2.2.4 Covariates

Violence Exposure and Social Deprivation. Composite scores of violence exposure and social deprivation were created based on procedures in previous studies (Goetschius et al., 2020; Hein et al., 2020). Briefly, violence exposure was assessed based on primary caregiver or mother report of direct child physical and emotional abuse, and indirect violence exposure (i.e., intimate partner and community violence) at child ages 3, 5, and 9. Social deprivation at child ages 3, 5, and 9 was created based on primary caregiver or mother report of physical and emotional neglect of the child, mother's intimate partner and community support. To compute the composite score, the zero-centered scores of each item were summed and then divided by the number of items for each participant. The scores were then mean centered to create the final composite score, where greater score indicated more violence exposure and social deprivation.

Demographic Covariates. To account for potential confounding effects of material hardship on drift rate and drift rate on adolescent attentional problems, the following sociodemographic characteristics were controlled for in the analyses: sex, adolescent pubertal stage, race/ethnicity, and family structure. Sex was measured using parental report at child age 1 (0 = female, 1 = male). Adolescent pubertal stage was included as a covariate to account for potential differences in adolescent drift rate due to broad impacts of pubertal development in shaping neurocognitive features (Icenogle & Cauffman, 2021). Pubertal stage was measured by

youth report on the Pubertal Development Scale (Petersen et al., 1988), which asked about changes in child height, body hair, skin, facial hair, voice (male only), and breast development and menarche (female only). Responses were coded on a 4-point scale (1 = no development, 4 = completed development) and the score was an average of all items endorsed. When adolescent report was not available, parent report was used. Ethnoracial identity was included as a covariate to adjust for potential effects of structural and interpersonal racism in shaping developmental experiences. Ethnoracial identity was self-reported by adolescents (Black, non-Hispanic; White, non-Hispanic; Hispanic, and Other). The majority of participants in the sample identified as Black/African American (77.0%). Therefore, three dummy-coded variables were created to represent ethnoracial identity with Black as the reference group. Finally, family structure was included as a covariate to adjust for potential differences in family functioning due to household composition. A household was identified as two-parent (1) when the biological mother and father were cohabitating at baseline (child's birth), or were otherwise identified as single-parent household (0).

2.2.3 Statistical Analyses

All statistical analyses were conducted in R Statistical Software v4.3.2 (R Core Team, 2023) and MPlus v8.8 (Muthén & Muthén, 2017). We accounted for missing data by using maximum likelihood estimations in regression analyses. For the first aim, we examined the bivariate correlation between cumulative material hardship and drift rate followed by a linear regression model adjusting for covariates. To investigate whether changes in the experiences of material hardship over time was associated with drift rate, we conducted a latent growth curve analysis in MPlus(details reported in Supplement). Estimated intercepts (initial time point) and

slopes (change over time) for the subsample were then extracted to predict drift rate in a regression analysis in R (Figure 2.3).

For aim 3, we examined the bivariate correlation between drift rate and the latent factor of attentional problems, and regression with covariates was conducted. Further, we tested for the indirect effects of drift rate (i.e., drift rate as a mechanism linking material hardship exposure to attentional problems) using SPSS PROCESS macro package in R to calculate 95% confidence intervals with 10,000 bootstraps (Hayes, 2021). Results were replicated in R Lavaan and MPlus. To examine the final aim, we investigated the same questions with behavioral performance metrics (i.e., average RT and accuracy) of the task instead of drift rate to compare the effects we observe from drift rate and conventional performance measures. Bivariate correlations between other parameters from DDM (i.e., a, t0, and z) with adversity items (i.e., material hardship, violence exposure, and social deprivation) and attentional problems are reported in the Supplement.

2.3 Results

2.3.1 Childhood Material Hardship Negatively Predicts Adolescent Drift Rate

Bivariate correlation between adolescent drift rate and cumulative material hardship showed a significant negative association (r = -.17, p = .020). Regression analysis including covariates showed that the effect of cumulative material deprivation on drift rate survives after including other childhood adversity and demographic covariates in the model (β = -.17, p = .038, Table 2.2, Figure 2.4). The results suggest that greater exposure to cumulative material hardship across childhood predicted less effective information processing during adolescent decision-making (i.e., lower drift rate), above and beyond childhood experiences of violence exposure and social deprivation.

To further understand the effects of developmental trajectory of childhood material hardship on adolescent drift rate, we conducted a regression analysis using the intercept and slope extracted from growth curve analysis of material hardship to predict drift rate. Bivariate correlations show that the intercept of the growth curve (r = -.17, p = .023) but not slope (r = -.06, p = .534) was significantly associated with drift rate. Regression results when including intercept and slope in the same model show similar results (intercept: β = -.18, p = .013; slope β = -.08, p = .277). This suggests that the initial exposure to material hardship, rather than changes in exposure across time, had a stronger negative association with adolescent drift rate. Results remained significant in sensitivity analysis including other adversity and demographic covariates (intercept: β = -.20, p = .017; slope: β = -.07, p = .376) (Table 2.3, Figure 2.4).

2.3.2 Adolescent Drift Rate Negatively Associated with Attentional Problems

As hypothesized, adolescent drift rate was negatively correlated with the latent factor of attentional problems (r = -.18, p = .013), suggesting that less efficient information processing in decision-making is associated with greater attentional problems in our sample of adolescents. Regression analysis (Table 2.4) revealed that the significant association between drift rate and attentional problems survived after controlling for demographic covariates (β = -.15, p = .040).

The model of indirect effects of drift rate linking material hardship exposure to attentional problems is shown in Figure 2.5. The direct effects model was not significant (F(1,184) = 3.03, p = .084). However, we did observe a small indirect effect of hardship exposure on adolescent attentional problems via drift rate (β = .03, b = .005, 95% CI [.0001, .013]). Individuals who experienced greater childhood material hardship showed lower drift rate in adolescence, which in turn, was associated with greater attentional problems.

2.3.3 Comparisons with Conventional Performance Metrics

To better understand the results we observed from analyses with drift rate, we also conducted the analyses with raw performance metrics: average response times (RTs) and average accuracy. First, we found that the correlations between drift rate and behavioral measures were in the expected directions (Table 2.1): greater drift rate (i.e., more efficient decision-making) was associated with greater accuracy (r = .49, p < .001) and faster RT (though the correlation was not significant: r = -.13, p = .080). At the same time, we did not find the same significant associations between material hardship with average RT (r = .04, p = .551) or average accuracy (r = -.12, p = .095). We also did not replicate the association between raw performance metrics and attentional problems (average RT: r = -.04, p = .540; average accuracy: r = -.03, p = .792). The null results with conventionally used behavioral metrics suggest that drift rate can help reveal specific cognitive processes and the relations with adversity and behavioral problems that would otherwise not be detected.

2.4 Discussion

This study examined the association between childhood material hardship and adolescent evidence accumulation efficiency (i.e., drift rate, v), a computational underpinning of higher-order cognitive functioning that is hypothesized to be explained by a task-general factor of cognitive efficiency EEA. Our results showed that greater cumulative material hardship across childhood was associated with lower adolescent drift rate, above and beyond exposure to violence, social deprivation, and other demographic covariates. We also found that lower adolescent drift rate was associated more attentional problems. In addition, we observed a small significant indirect effect between hardship and attention problems via drift rate. To our knowledge, this is the first study to leverage longitudinal data to investigate cognitive consequences of material hardship, a measure of the lived experiences of poverty that may be a

more accurate assessment of socioeconomic disadvantage. Additionally, the application of DDM to examine adversity-related differences in cognitive processing contributes to the growing body of research utilizing computational methods to address developmental questions. By moving beyond conventional task performance metrics, the DDM decomposes trial-wise behavior into distinct and meaningful cognitive processes, offering a more nuanced understanding of how childhood material hardship is associated with cognitive functioning in adolescents.

2.4.1 Childhood Material Hardship and Adolescent Cognitive Efficiency

Our results showed that exposure to material hardship, but not violence exposure or social deprivation, was associated with drift rate. This finding largely aligns with past research showing that economic deprivation specifically is associated with lower cognitive performance (Schenck-Fontaine & Ryan, 2022; Young et al., 2022). However, our findings contrasted with prior research specifically examining drift rate or EEA as a cognitive outcome, which reported that greater violence exposure, rather than material hardship, was associated with lower general EEA across several cognitive tasks (Vermeent, Young, Gelder, et al., 2024). The inconsistencies in results could be due to a variety of reasons, such as the use of cross-sectional designs rather than longitudinal approach used in our study, differences in samples, including demographic or socioeconomic characteristics, variations in the severity or timing of exposure to adversities, or differences in the selection of tasks used to estimate EEA. In addition, the material hardship measure used in Vermeent, Young, Gelder, et al. (2024) was a factor score that adjusted for demographic variables, which contrasts with our use of sum scores of hardship endorsements and could have contributed to the difference in results. Given that this question is only beginning to be researched, more well-sampled studies with computational models of cognition and

longitudinal designs are needed to replicate these results and clarify the nuanced effects of distinct types of adversity on cognitive processes like EEA.

Using growth curve analysis, we also investigated how initial exposure to material hardship (i.e., intercept) and changes in trajectory of experience across childhood (i.e., slope) linked with drift rate. We found that greater initial exposure to hardship at age 1, but not trajectory of change in hardship levels, was associated with lower drift rate. This finding suggests that baseline level of material hardship experience resulted in long-lasting impact on cognitive performance, whereas the increase in hardship over time may be less influential compared with initial conditions. This finding is somewhat inconsistent with past research showing that decrease in parental income over time is associated with poorer cognitive outcomes, as summarized by a recent review (Levesque et al., 2021). However, there is evidence supporting the idea that early economic disadvantage can have enduring negative effects on mental health outcomes in children, potentially due to persistent proximal experiences and social interactions that remain unchanged regardless of later economic changes (Caspi et al., 1989; McLeod & Shanahan, 1996). A similar explanation may apply to our findings: early household material hardship could have contributed to long lasting stressful conditions in the surrounding environment, such as tension in family relationships. Such chronic stress exposure has been linked with impairments in executive functioning regions in the brain (e.g., Liston et al., 2009), which could contribute to poorer cognitive performance in adolescence (Hackman et al., 2010). In addition, material hardship experiences may also involve a lack of nutrition and quality health care, which could impact the neural mechanisms underlying cognition (e.g., Gómez-Pinilla, 2008). While our study does not directly test what these mechanisms might be, future research

should aim to clarify these pathways by examining the interplay between early adversity, stress levels, and cognitive development over time.

Our finding may be explained by theories emphasizing the role of cognitive stimulation in the environment as a critical factor in promoting cognitive development (Hackman et al., 2015; Rakesh et al., 2024; Rosen et al., 2020). Cognitively stimulating environments—those that offer a variety of stimuli (e.g., books and toys) that encourage knowledge-building—support exploration and learning, which are essential for cognitive development across domains (Vygotsky, 1978). In households experiencing material hardship and struggling to meet basic needs, providing such environments may be particularly challenging. Evidence from both human intervention studies and animal models suggests that enriched environments not only enhance cognitive outcomes but also support underlying neural functioning (Jankowsky et al., 2005; Mandolesi et al., 2017; McLoyd, 1998). In households experiencing material hardship and struggling to meet basic needs, providing such cognitive-stimulating environments may be particularly challenging, potentially limiting opportunities for cognitive development.

Alternatively, our results can also be interpreted through an adaptive lens, such that lower drift rate may reflect developmentally adjusted cognitive styles that are potentially advantageous in unpredictable or resource-scarce environments. Consistent with the hidden talents framework, adversity-exposed individuals may exhibit cognitive adaptations that are context- and content-dependent, thereby showing strengths in domains that are ecologically relevant despite differences on conventional cognitive tasks (Ellis et al., 2022; Mittal et al., 2015; Young et al., 2022). Recent theoretical accounts also proposed that individuals exposed to adversity may engage in evidence accumulation less selectively across competing information sources (Niebaum et al., 2025). While we did not find any evidence for adversity exposure impacting

other facets of decision-making (i.e., response caution, non-decision time, and bias), previous work has found that adversity may impact response caution as well (Vermeent et al., 2024). Future work should examine whether these cognitive profiles confer functional advantages in real-world settings and explore how different environmental demands shape the developmental trajectory of decision-making processes.

2.4.2 Drift Rate and Adolescent Attentional Problems

We found evidence that lower drift rate is linked with greater attentional problems in adolescents. This finding aligns with past clinical research showing individuals with ADHD consistently displayed lower EEA (Huang-Pollock et al., 2017; Weigard & Huang-Pollock, 2017; Ziegler et al., 2016). Our finding also aligns with the growing body of research highlighting reductions in EEA across various domains, including perceptual decision-making (as measured by our task), attention, and inhibition, among others. We also observed a statistically significant indirect effect of childhood material hardship on adolescent attentional problems via drift rate. Although the total and direct effects of material hardship on attentional problems was not statistically significant, this finding suggests that early life material hardship may influence reduced cognitive efficiency, which in turn may influence attentional functioning in adolescence. However, the effect size of the indirect effect is small, suggesting that though significant, drift rate only explains a small proportion of the effect. At the same time, given the partially cross-sectional nature of our data and the lack of direct and total effects (i.e., drift rate and attention were measured concurrently), we interpret this indirect pathway cautiously and do not make claims about temporal or causal mediation. Future longitudinal studies with repeated assessments of both cognition and behavior will be critical for clarifying the directionality and developmental timing of these associations.

2.4.3 Drift Rate Reflects Specific Cognitive Process

We conducted the same analyses as above with conventional behavior performance metrics: average response times (RT) and accuracy. Although drift rate was significantly correlated with both measures in the expected directions, we did not see the same findings with either material hardship or attentional problems with conventional performance measures. This is consistent with simulation studies (Stafford et al., 2020) and past research showing that drift rate differentiates behavioral responses in individuals with high vs. low anxiety, whereas accuracy and RT did not capture the same effects (White et al., 2010). Similar findings have also been observed in neural patterns, where Ho and colleagues (2014) found significant activation in face-processing neural regions associated with processing efficiency (estimated similarly to EEA) in depressed individuals, but did not observe this effect with mean RT or accuracy. We also did not observe any significant associations with hardship exposure, or other types of adversity experiences, with other parameters from the DDM model, highlighting the specificity of drift rate in understanding the impact of socioeconomic disadvantage. In addition, we found that greater attentional difficulties in adolescents were linked with lower non-decision time, which aligns with past research and may suggest that individuals with attentional problems may exhibit faster encoding and/or motor responses that are not associated with the decision-process, although the specific processes are not separable in the context of DDM (Karalunas et al., 2014). Taken together, these results underscore the value of computational models in assessing cognitive performance. These findings also suggest that although task performance is related to cognitive ability (as measured by drift rate or EEA), important differences exist that could lead to problematic inferences when using these conventional measures as proxies for cognition.

Therefore, future studies should consider incorporating computational models to provide a more accurate and reliable assessment of cognitive performance.

2.4.4 Strengths, Limitations, and Future Directions

The current study has multiple strengths. First, the data is drawn from a 15-year longitudinal dataset in which adversity measures were collected prospectively at each assessment point. Second, the use of a computational model of cognition allows for a more nuanced understanding of cognitive processes, offering a novel and theoretically meaningful approach compared to conventional behavioral measures in addressing developmental questions. Third, our dataset allowed for creation of a multi-informant measure of attentional problems, which provides a more comprehensive and accurate account of symptoms based on reports from both parents and clinicians.

The present study also has several limitations. First, our sample size was modest for examining longitudinal associations between material hardship, drift rate, and attentional problems in adolescents (N = 187). While we did not conduct an a-priori power analysis, future research should aim to replicate these findings with larger samples given the small effects observed. Second, our study only included a single two-choice perceptual decision-making task that allowed for application of computational modeling. Although this limits our ability to construct a latent task-general EEA factor, prior research has shown that drift rate estimates derived from individual tasks are reasonable approximations of the general underlying cognitive process due to their strong psychometric properties (Löffler et al., 2024; Schubert et al., 2016; Tomlinson et al., 2025; Weigard et al., 2021). Thus, although we can interpret our single-task drift rate estimate as representing EEA, we acknowledge that it likely contains some task-specific variance. Notably, past studies have also shown that task-specific and task-general EEA

may differ in their susceptibility to adversity-related influences (Vermeent, Young, van Gelder, et al., 2024), highlighting the value of examining both in future work. In addition, the current task involves emotionally-salient stimuli that may engage affective processing systems differently in individuals and interact with the decision processes in various ways. Despite our efforts to account for valence by modeling emotion-specific drift rate, these subtle patterns may not be fully captured by the current modeling approaches. The task was also conducted in a lab-based, MRI scanner environment, which could have an impact on the participants' cognitive performance. Given these task-level limitations, our study results should be interpreted with caution. To provide a more comprehensive understanding, future studies should include a range of tasks that measure different cognitive processes (e.g., perceptual processing, attention, inhibition), as well as across different contexts (e.g., valence) to construct more robust latent measures of task-general and task-specific EEA. Third, our primary measure of material hardship was reported by the primary caregiver for the entire household. As a result, we were unable to distinguish between the parent's exposure to hardship and its direct impact on the child. For example, it is possible that while parents may not have enough food for themselves, they still manage to provide meals for their children, meaning the child may not directly experience food insecurity. Although research suggests that both direct and indirect experiences of material hardship can lead to negative developmental outcomes (Conger et al., 2010; McCarthy et al., 2018), future studies should explore whether differences between these forms of hardship exist and how they differentially affect child development.

Results from the present study open several avenues for further exploration. Our study provides initial support that cumulative material hardship is associated with drift rate, but the mechanism of this association remains unclear. Studies could explore this from several

directions, including investigating the level of cognitive stimulation in the environment. In addition, studies could also explore the biological underpinnings of this associations. One promising link could be alterations in white matter, which has been linked to both material hardship (Hardi et al., 2022) and cognitive functioning (Ferrer et al., 2013). More personalized methods in capturing functional connectivity patterns of EEA could also better elucidate the underlying neural mechanisms compared with activation-based analyses that generalizes across neural activity. Such analyses, ideally with larger, well-powered samples, could help elucidate how adversity impacts cognitive efficiency through structural and functional brain functioning. Furthermore, while our study replicated previous findings that drift rate is associated with attention difficulties, EEA has also been proposed as a transdiagnostic neurocognitive risk factor for various forms of psychopathology (Weigard & Sripada, 2021). Future research should test this hypothesis by examining differences in EEA between clinical and non-clinical populations to better understand its potential as a broad marker of risk across mental health conditions.

2.5 Conclusion

Taken together, our study applied diffusion-decision modeling to investigate longitudinal associations between material hardship and cognition in a sample of adolescents traditionally underrepresented in research. We found that material hardship, beyond other forms of adversity such as exposure to threat and social deprivation, significantly influences adolescent drift rate, which is further associated with attentional problems. These findings support drift rate (and EEA) as a mechanistic explanation for the broad effects of material hardship across cognitive domains and underscore the unique advantages of using computational models of cognition, compared to conventional performance measures, in uncovering associations with environmental risk factors. By identifying the specific ways in which adversity influences cognitive

development, such research could guide interventions and policies aimed at mitigating these effects, such as policies that bolster family resources or enhance access to cognitively enriching opportunities.

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2.7 Tables

Table 2.1. Distributions and Zero-order Correlations of DDM Parameters and Raw Performance Data

	1	*2*	*3*	*4*	*5*	*6*
1. Drift rate (v)	-	-	-	-	-	-
2. Response Caution (a)	-.04	-	-	-	-	-
3. Non-decision Time (t0)	**.35*****	**.43*****	-	-	-	-
4. Response Bias (z)	-.01	.06	.01	-	-	-
5. Reaction Time (second)	-.13	**.81*****	**.66*****	.01	-	-
6. Accuracy	**.49*****	.04	**.31*****	.01	.12	-
Mean	2.89	1.38	0.36	0.49	0.67	0.90
Standard deviation	0.91	0.33	0.08	0.05	0.13	0.19

***: $p < .001$

Table 2.2. Regression Analysis of Material Hardship Predicting Drift Rate (v)

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Model: v ~ Material Hardship + Control Variables					
Material Hardship	-0.04	-.17	0.02	-2.08	.038*
Violence Exposure	-0.03	-.02	0.15	-0.19	.850
Social Deprivation	0.09	.05	0.16	0.61	.543
Sex	-0.16	-.09	0.17	-0.97	.331
Pubertal Stage	0.12	.08	0.15	0.86	.389
Race: White	-0.07	-.02	0.21	-0.33	.742
Race: Hispanic	-0.10	-.03	0.29	-0.35	.730
Race: Other	0.28	.07	0.30	0.98	.325
Family Structure	-0.17	-.09	0.14	-1.26	.209

*: $p < .05$

Table 2.3. Regression Analyses of Material Hardship Growth Curve Slope and Intercept Predicting Drift Rate (v)

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Model 1: v ~ i + s					
i (intercept)	-0.21	-.18	0.09	-2.48	.013*
s (slope)	-1.43	-.08	1.31	-1.09	.277
Model 2: v ~ i + s + Control Variables					
i (intercept)	-0.23	-.18	0.09	-2.36	.017*
s (slope)	-1.19	-.06	1.40	-0.77	.376
Violence Exposure	-0.01	-0.01	0.15	-0.06	.950
Social Deprivation	0.11	0.06	0.15	0.73	.466
Sex	-0.15	-.08	0.17	-0.87	.382
Pubertal Stage	0.12	.08	0.14	0.85	.397
Race: White	-0.07	-.02	0.21	-0.33	.744
Race: Hispanic	-0.13	-.03	0.28	-0.46	.644
Race: Other	0.30	.07	0.29	1.04	.300
Family Structure	-0.16	-.09	0.13	-1.20	.229

*: $p < .05$

Table 2.4. Regression Analyses of Drift Rate (v) and Attentional Problems Latent Factor

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Model: Attentional Problems ~ v + Demographic Control Variables					
v	-0.13	-.15	0.06	-2.04	.041*
Sex	0.25	.16	0.14	1.76	.079
Pubertal Stage	-0.14	-.11	0.12	-1.18	.238
Race: White	0.03	.01	0.17	0.15	.883
Race: Hispanic	0.15	.04	0.25	0.58	.560
Race: Other	0.27	.08	0.24	1.09	.275
Family Structure	-0.08	-.05	0.12	-0.73	.468

*: $p < .05$

2.8 Figures

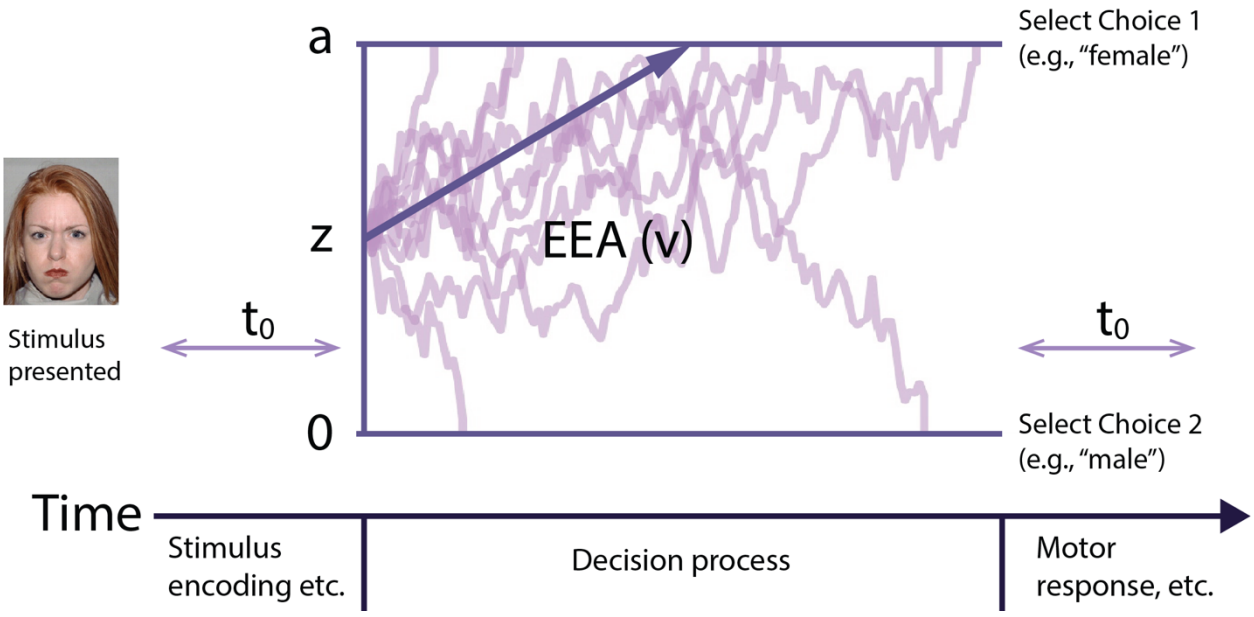

Figure 2.1. Schematic of the diffusion decision model (DDM) in a single trial

The model describes a forced two-choice decision task. This example shows the emotional-faces gender identification task used in the current study. After the stimulus has been presented, the trial is decomposed into a decision component and a non-decision component. Within the decision component, the DDM assumes a single decision variable that represents the amount of relative evidence for one of the two possible choices (i.e., male or female in this example). The decision variable starts from a starting point (z) and drifts over time in a single trial between the two boundaries representing the two choices. Once the decision variable reaches a boundary, the corresponding choice is made. The width of separation between two choice boundaries is boundary separation (a), which represents how much evidence is needed before being able to make a choice. The rate at which evidence accumulation drifts towards the boundary is drift rate (v), or EEA. Finally, the non-decision time (t_0) represented the combined time spent for any task preparation (e.g., stimulus encoding) and response execution (e.g., button pressing).

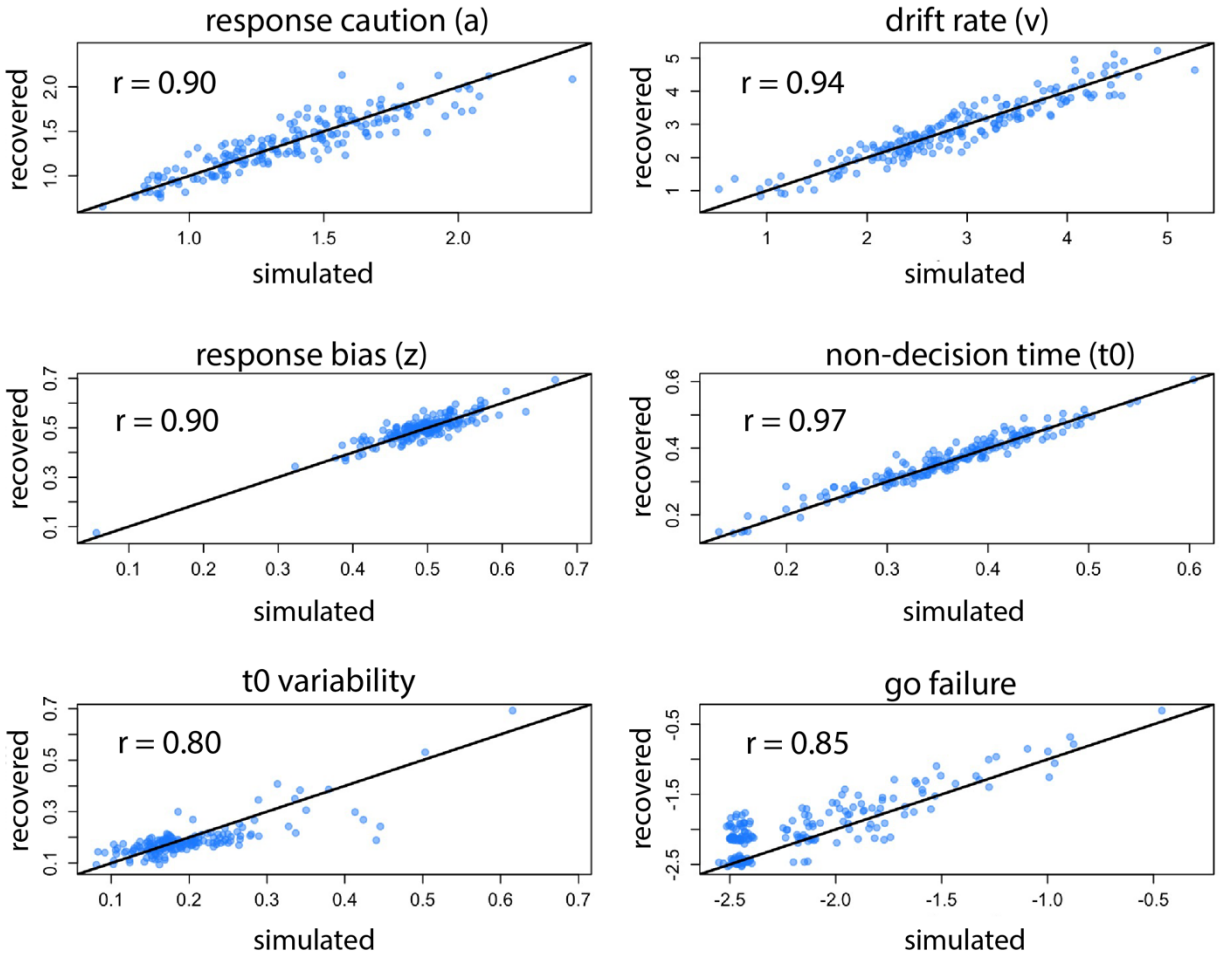

Figure 2.2. Simulation-recovery study correlation plots of DDM parameters.

Parameter values from the DDM (x-axis) was used to simulate another data set, from which another set of parameter values were recovered (y-axis). Correlation values (r) between the simulated and recovered parameter values are displayed on each plot. Diagonal lines indicate where the points would fall if the parameter recovery was perfect (r = 1). Parameter recovery for the four main parameters (top four panels: a, v, z, and t_0) are excellent (rs >= .90), and the recovery for other estimated parameters are good (rs > .75).

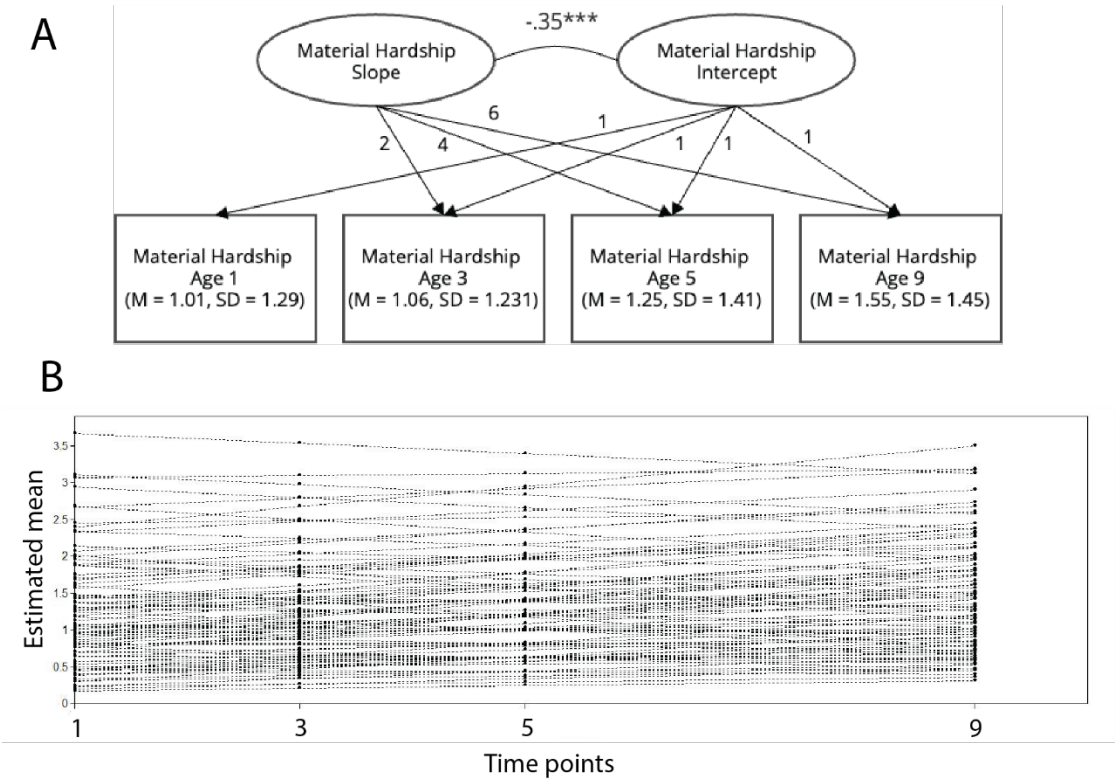

Figure 2.3. Growth Curve Analysis with Material Hardship.

(A) Material hardship data at ages 1, 3, 5, and 9 from the Future of Families and Child Wellbeing study were used to improve estimations of growth curve model (N = 3714). Loadings of hardship estimating growth curve slope were fixed at 0, 2, 4, and 6. Estimated latent slopes and intercepts were significantly correlated and extracted for further analysis. (B) Individual estimated growth curve trajectories. Illustrating that material hardship increases with age. ***: $p < .001$.

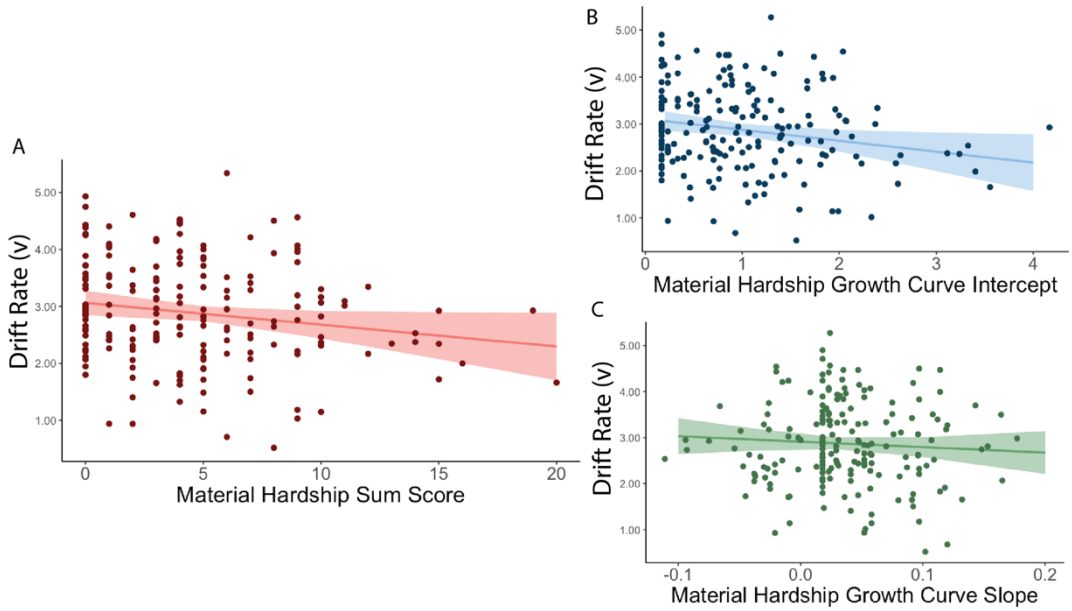

Figure 2.4. Drift Rate Predicted by Childhood Material Hardship.

(A) Cumulative material hardship negatively predicted adolescent drift rate. (B) Growth curve analysis with material hardship from ages 1, 3, 5, and 9 show that the intercept but not (C) the slope, was negatively associated with drift rate, suggesting that the initial exposure to material hardship at age 1, rather than changes in exposure across childhood, was more linked with adolescent drift rate.

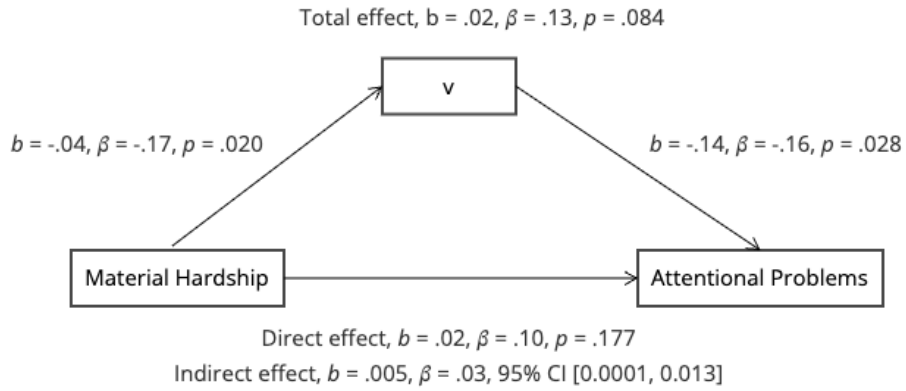

Figure 2.5. Indirect effects model of material hardship on attentional problems via drift rate (v).

The total effect of material hardship and drift rate on attentional problems was not significant (b = 0.02, t = 1.74, p = 0.084). We found a small but significant indirect effect of hardship exposure on adolescent attentional problems via drift rate (β = .03, b = .005, 95% CI [.0001, .013]).

2.9 Chapter 2 Supplemental Materials

2.9.1 Modeling and Simulation recovery study for DDM

DDM estimations were conducted with the Dynamic Models of Choice package in R (version 4.3.2, Heathcote et al., 2019; R Core Team, 2023). Beyond the four main DDM parameters (i.e., EEA, response caution, non-decision time, and response bias). Between trial variability of t_0 was also estimated. Other between trial variability parameters were fixed given the known difficulty of recovering these parameters at low trial numbers (Lerche et al., 2017). Our model also accounted for trial omissions (e.g., due to inattention to task) using a parameter that represents the probability that a response will be omitted (Damaso et al., 2022). This parameter was estimated on the probit scale. Individual level Bayesian estimation was implemented using the differential evolution Markov Chain Monte Carlo (DE-MCMC; Turner et al., 2013) approach with informed Bayesian priors based on a systematic review (Tran et al., 2021). Individual model convergence was assessed by visual examination of the posterior chains and the Gelman-Rubin's convergence diagnostic (<= 1.1 indicates good convergence; Gelman & Rubin, 1992).

A simulation-recovery study was conducted to assess DDM parameter reliability following procedure from previous studies (Weigard et al., 2023; Weigard et al., 2021). First, parameters estimated from the DDM were used to simulate a new dataset (100 trials per person). The DDM was then fit to the simulated data set using the same procedures outlined above, and parameter estimates were recovered from the simulated data set and compared with the original parameters from the actual performance data. Main text Figure 2.2 displays scatterplots and correlation *r* between the simulated and recovered parameters, which signals excellent recovery for the key parameters of interest, including drift rate (v), a, t_0, and z (*r*s > .90). Median values of

posterior distributions of DDM parameters were used in the analyses in this study. Main text Table 2.1 shows the distributions and bivariate correlations between DDM parameters.

2.9.2 CFA for adolescent attentional problems

A confirmatory factor analysis was performed to create latent factors of adolescent attentional problems, using item-level responses from the CBCL and K-SADS-PL. The CBCL attention problems subscale included 10 items on child's behavioral problems related to inattention and hyperactivity in the past 6 months. All items were rated by the caregiver on a scale of 0-2: 0 if the item was not true, 1 if the item was somewhat or sometimes true, and 2 if the item was very true or often true. Adolescent inattention and hyperactivity were also assessed by trained clinical assessors and licensed clinicians with the K-SADS-PL. Assessors administered the semi-structured interview to the adolescent and caregiver individually, arriving at initial DSM-V diagnoses, which were then reviewed in an weekly assessment meeting with the team and licensed clinicians with a final symptoms counts were derived by consensus of the clinical team using best-estimate procedures (Maziade et al., 1992). We used the final clinician rating (on a scale of 0-2, 0 if item behavior not present, 1 if subthreshold, and 2 if met clinical threshold) for each question on inattention and hyperactivity.

We started with a 2-factor model of attentional problems, separating inattention and hyperactivity, based on the theoretical basis that these two were similar but separate constructs (Toplak et al., 2009). The WLSMV estimator was used to account for categorical variables. Each question from the CBCL and K-SADS-PL was loaded onto the two latent factors equally reflect the ADHD symptoms. 1 item from the CBCL was excluded due to low loading based on an a-priori threshold of .40 ("confused or seems to be in a fog"; $\lambda = 0.388$). 1 item from the K-SADS-PL was removed ("run/climb excessively") because of complete overlap with responses of

another variable ("easily distracted"). The model showed good fit (CFI = .950, TLI = .946, RMSEA = .044 95% CI [.033, .055], SRMR = .114). However, the latent factors of inattention and hyperactivity were highly correlated (r = .86, p < .001), and therefore we decided to proceed with a one-factor CFA model of attentional problems with items loading onto one factor. The final model showed good fit (CFI = .922, TLI = .915, RMSEA = .056 95% CI [.046, .065], SRMR = .133). Items and loadings from the final one-factor model is shown in Supplemental Table 2.7. Results from the CFA were then extracted into an attentional problems latent factor for analysis in R

2.9.3 Growth Curve of Material Hardship

Following the approaches taken in previous studies (Gard et al., 2021; Hardi et al., 2022), linear trajectories were fit on material hardship data over four waves (ages 1, 3, 5, and 9). Material hardship at age 1 was set as a value of 0 as the starting point, and coefficients for ages 3, 5, and 9 are set to 2, 4, and 8, respectively. The model failed to converge with the small subsample included in the analysis. To improve fit and convergence, we utilized the full FFCWS sample data (N = 3714) and extracted the estimated intercepts (initial time point) and slopes (change over time) for the subsample to predict drift rate in a regression analysis in R. The final growth curve model showed excellent fit (CFI = .981, TLI = .977, RMSEA = .042 90% CI [.030, .055], SRMR = .028; (Hu & Bentler, 1999). Material hardship at age 1 was set as point 0, where standardized estimated mean for starting point (i.e., intercept) = 0.98 (p < .001, SE = .84) and estimated mean change over time (i.e., slope) = .26 (p < .001, SE = .01).

2.9.4 Sensitivity Analysis with Violence Exposure

Analyses reported in the main text adjusted for co-occurring types of adversity, including violence exposure and social deprivation, to estimate the unique association between material

hardship and drift rate. At the same time, it is also possible that material hardship may contribute to increased risk of violence exposure (Bywaters et al., 2016; Lacey et al., 2022; Ning et al., 2024) and controlling for it could attenuate the total effect of hardship on drift rate. Therefore, we also tested whether the link between material hardship and drift rate without violence exposure as a covariate. We found that the associations remained significant (cumulative material hardship: β = -.18, p = .029; growth curve intercept: β = -.20, p = .014; growth curve slope: β = -.07, p = .372). We also tested whether violence exposure mediated the effect between material hardship and drift rate. While violence exposure and material hardship are correlated (r = .43, p < .001), we did not find a significant indirect effect of violence exposure (β = -.01, b = -.001, 95% CI [-.02, .01]).

2.9.5 Emotion-specific Drift Rate

As an exploratory analysis, we estimated the DDM separating trials by emotions on faces. Given the limited number of trials per emotion (n = 20 max), the DDM was set to only vary drift rate by emotions. The model showed good fit and simulation recovery (Supplemental Figure 2.6). To find support that drift rate is a task-general trait-like factor, we then extracted a latent factor "emotion-general" drift rate using CFA (conducted in MPlus) from the separate emotions to replicate our previous analyses.

Overall, emotion-specific drift rate estimates were highly correlated with each other, as well as with the "general" drift rate based on all trials in the task, suggesting that drift rate is largely unaffected by the valence of the stimuli in our study (Supplemental Table 2.8). We extracted a latent drift rate factor from the emotion-specific drift rate estimates (model fit was excellent: CFI = .993, TLI = .987, RMSEA = .071 90% CI [.000, .137], SRMR = .014). As expected, the latent factor drift rate was highly correlated with the "general" drift rate estimate

from the original model (r = .99, p < .001). We replicated the finding that cumulative childhood material hardship (β = -.19, p = .026), above and beyond violence exposure (β = .01, p = .952), social deprivation (β = .06, p = .518), and demographic covariates, was significantly negatively associated with the latent factor EEA.

We also replicated our findings with attentional problems in adolescents: latent drift rate factor was significantly associated with both inattention (r = -.18, p = .015) and hyperactivity (r = -.18, p = .013), and remained significant after adjusting for demographic covariates (inattention: β = -.14, p = .050; β = -.15, p = .043).

2.9.6 Associations of Other DDM Parameters with Adversity and Attentional Problems

We examined in exploratory analyses whether other parameters from the DDM (i.e., boundary separation (a), non-decision time (t_0), and response bias (z)) were associated with adversity dimensions or attentional problems. Bivariate correlations are reported in Supplemental Table 2.9. We found no significant associations between boundary separation or response bias with adversity experiences or attentional problems. However, non-decision time (t_0) was significantly correlated with concurrent attentional problems, such that individuals with greater attentional problems showed lower (i.e., faster) non-decision time (r = -.27, p < .001). These exploratory findings should be interpreted with caution but highlight the potential value of examining parameters beyond drift rate in future studies.

2.9.7 Functional Activation and Drift Rate

We conducted initial exploratory analysis to examine whether the functional activation patterns while participants were performing the emotional-faces gender-identification task were significantly associated with drift rate derived from the behavioral performance data. Past research suggesting that EEA is associated with frontoparietal network activation in response to

cognitive load in an N-back task as well as salience network activation in response to errors (Weigard et al., 2024). While we are unable to test for cognitive load and error response directly due to the set-up of the task and our high accuracy rate (93.8%), we conducted an exploratory analysis of whether drift rate is linked with task-engagement by conducting a multiple regression group-level analysis with the contrast condition of faces vs. baseline. fMRI data was collected with a GE Discovery MR750 3T MRI scanner with an 8-channel head coil. Data acquisition, preprocessing, and first-level analysis details are reported in Hein et al. (2018). To example whether drift rate is linked with functional activation, we added drift rate as a covariate in multiple regression for the group-level analysis for the general condition of emotional faces (combined) vs. baseline. Whole-brain analysis was conducted in SPM12 (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/). Results showed no significant clusters at the voxelwise family-wise error rate of $p < .050$. Similarly, we also conducted group-level analysis for emotion-specific drift rate and emotion-specific contrasts (e.g., fearful drift rate as a covariate, with the fearful vs. baseline contrast). We also did not find any significant clusters. This is likely a reflection of the low cognitive load in our task.

2.9.8 References

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Supplemental Table 2.5. Sample Demographics (n = 187)

Variables	Group	Mean (SD)	Count (Percentage)
Age	-	15.83 (*0.51*)	-
Pubertal Stage	-	3.26 (*0.58*)	-
Sex	Female (0)	-	99 (52.94%)
	Male (1)	-	88 (47.06%)
Race	Black	-	144 (77.01%)
	White	-	22 (11.76%)
	Hispanic/Latino	-	11 (5.88%)
	Other/Multiracial	-	10 (5.35%)
Family Structure	Single-parent (0)	-	121 (64.71%)
	Two-parent (1)	-	66 (35.29%)
Material Hardship	Cumulative Sum	4.58 (*4.05*)	-
	Age 1	1.01 (*1.29*)	-
	Age 3	1.06 (*1.31*)	-
	Age 5	1.25 (*1.41*)	-
	Age 9	1.55 (*1.45*)	-
Violence Exposure	-	0 (*0.53*)	
Social Deprivation	-	0 (*0.50*)	-

Supplemental Table 2.6. Zero-order Correlations of Material Hardship Scores

	1.	*2.*	*3.*	*4.*	*5.*
1. Age 1 Hardship	-				
2. Age 3 Hardship	.54***	-			
3. Age 5 Hardship	.44***	.54***	-		
4. Age 9 Hardship	.31***	.46***	.45***	-	
5. Sum Score	.72***	.80***	.79***	.72***	-

***: $p < .001$

Supplemental Table 2.7. Attentional problems one-factor CFA items and loadings

Item	*Loading*
1. CBCL – acts too young for his/her age	.60
2. CBCL – fails to finish things he/she started	.67
3. CBCL – can't concentrate, can't pay attention for long	.82
4. CBCL – can't sit still, restless or hyperactive	.78
5. CBCL – daydreams or gets lost in his/her thoughts	.59
6. CBCL – impulsive or acts without thinking	.76
7. CBCL – poor school work	.60
8. CBCL – inattentive or easily distracted	.90
9. CBCL – stares blankly	.46
10. KSADS – careless mistakes	.72
11. KSADS – can't pay attention	.88
12. KSADS – doesn't listen	.79
13. KSADS – can't follow instructions	.75
14. KSADS – can't organize	.66
15. KSADS – avoids attentive tasks	.78
16. KSADS – loses things	.68
17. KSADS – easily distracted	.71
18. KSADS – forgetful	.73
19. KSADS – often fidgets	.81
20. KSADS – can't stay in seat	.85
21. KSADS – difficulty playing quietly	.87
22. KSADS – on the go	.67
23. KSADS – talks excessively	.74
24. KSADS – blurts out answers	.61
25. KSADS – difficulty awaiting turn	.86
26. KSADS – interrupts or intrudes	.78

Note: All items loaded onto the attention problems factors significantly, *p*s < .001

Supplemental Table 2.8. Bivariate Correlations of Emotion-specific and "General" Drift Rate (v)

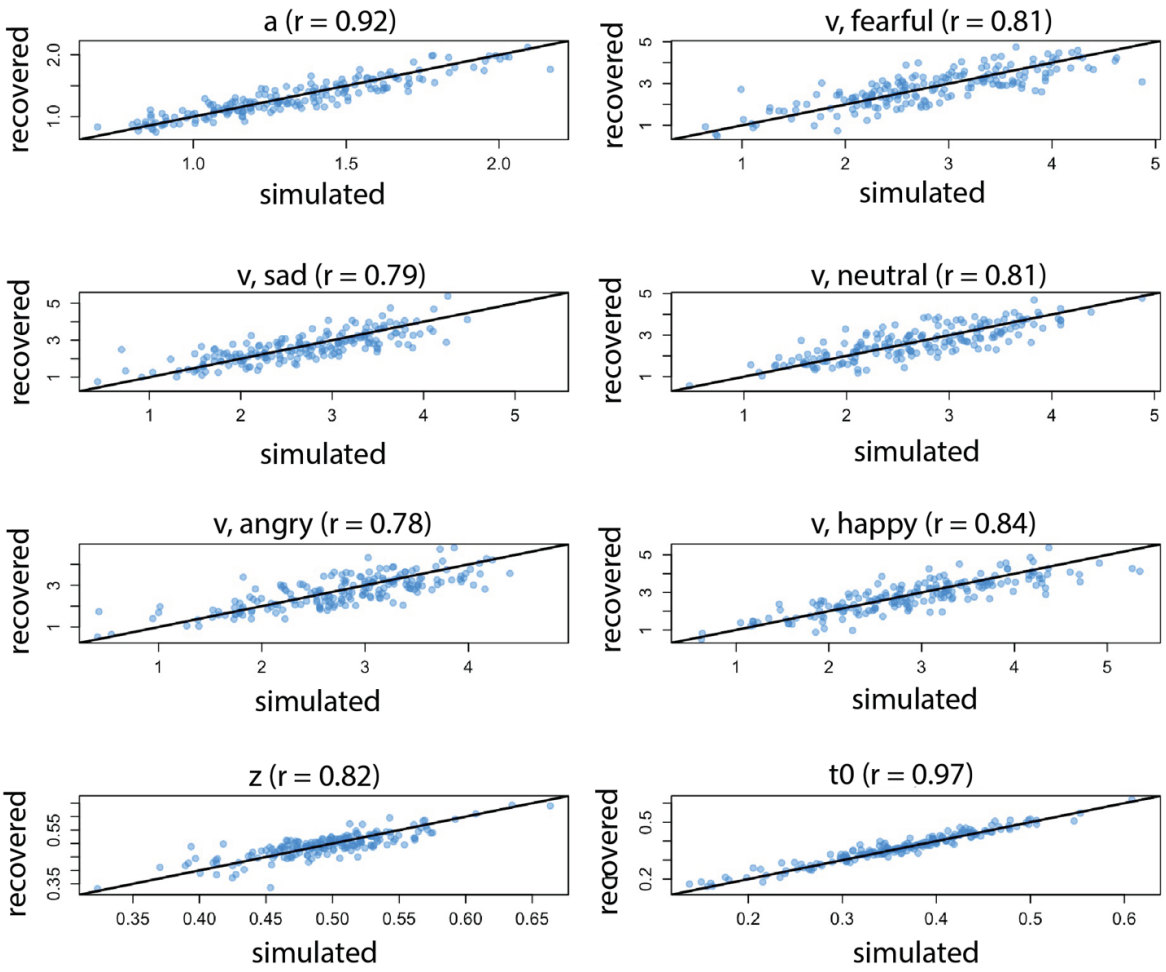
	1	*2*	*3*	*4*	*5*
1. Fearful v	-	-	-	-	-
2. Angry v	.67***	-	-	-	-
3. Sad v	.76***	.71***	-	-	-
4. Neutral v	.71***	.65***	.76***	-	-
5. Happy v	.73***	.73***	.72***	.73***	-
6. "General" v	.87***	.85***	.88***	.87***	.87***

***: $p < .001$

Supplemental Table 2.9. Bivariate Correlations of Other DDM Parameters and Childhood Adversity and Attentional Problems Variables

	Material Hardship	*Violence Exposure*	*Social Deprivation*	*Attentional Problems*
Response Caution (a)	.11	.06	.04	.004
Non-decision Time (t0)	-.09	-.06	-.07	-.27***
Response Bias (z)	-.02	.07	.03	.08

****: $p < .001$*



Supplemental Figure 2.6. Simulation-recovery study correlation plots of emotion-specific DDM parameters.

Similar to the previous simulation-recovery study with DDM, parameter values from the DDM (x-axis) was used to simulate another data set, from which another set of parameter values were recovered (y-axis). Correlation values (*r*) between the simulated and recovered parameter values are displayed on each plot. Parameter recovery for emotion-specific drift rate parameters is good (*r*s > .75).

Chapter 3 Neighborhood Matters: Longitudinal Associations Between Child Opportunity Index in Adolescence and Young Adult Evidence Accumulation Efficiency

3.1 Introduction

The environment plays a critical role in shaping the development of executive functions (EF), a critical domain of development involving inhibition control, attention, and regulation (Diamond, 2013; Miyake & Friedman, 2012). Extensive research has documented the impact of family-level poverty, particularly income and socioeconomic status, on EF (Farah et al., 2006; Lawson et al., 2018; Müller & Kerns, 2015). However, less is known about how broader structural and societal influences at the neighborhood level contribute to individual differences in cognition. At the same time, developmental outcomes are not determined solely by the presence of risk, but also by the availability of resources that foster growth (Arredondo et al., 2022; Ungar & Theron, 2020). Despite this, existing studies on neighborhood environments have largely focused on disadvantage, emphasizing a deficit-based perspective that highlights environmental risk and provides only partial understanding of how neighborhood contexts contribute to EF development. Investigating neighborhood opportunity, namely access to enriching, developmentally supportive resources and is complementary to disadvantage, may therefore offer a more complete picture of how resources in the environments may promote EF and also serve as a protective factor in the face of family-level adversity.

Theoretical models such as Bronfenbrenner's bioecological model (Bronfenbrenner, 1994) and Sameroff's transactional model (Sameroff, 2010) highlight the importance of

examining environmental influences across multiple, nested levels: from immediate contexts, such as family, to broader distal systems, such as neighborhoods. These models emphasize the dynamic and reciprocal relationships between individuals and their environments over time and suggest that neighborhood contexts should be considered alongside family-level socioeconomic disadvantage. Neighborhood contexts can play a critical role in shaping development, especially given the increasing importance of contexts outside of the home (e.g., peers, neighbors, schools) as children mature (Leventhal & Brooks-Gunn, 2000; Minh et al., 2017). Additionally, measuring neighborhood context can capture distinct aspects of contextual factors related to, but beyond socioeconomic disadvantage that may impact development as compared to family-level factors, such as neighborhood housing quality, safety level, environmental toxins, and access to green space.

Neighborhood-level factors have been found to impact individual's health, mental health, and academic outcomes across the life span (Jawad et al., 2025; Minh et al., 2017). Children living in disadvantaged neighborhoods have been found to experience higher levels of internalizing and externalizing problems (Abouzeid & Johnson, 2024; Sutin et al., 2022), while those living in more advantaged, socially cohesive neighborhoods tend to perform better academically (Jagannathan et al., 2023; Jargowsky & Komi, 2009). In older adults, higher levels of neighborhood disadvantage have also been associated with lower cognitive functioning and greater cognitive decline (Ailshire et al., 2017; Röhr et al., 2024; Vassilaki et al., 2023).

The role of neighborhood context may be especially prominent during adolescence and young adulthood in shaping EF. In particular, adolescence is a key developmental period that may be more susceptible to influences from the neighborhood given the increased autonomy, growing engagement with environments outside the home, and heightened neuroplasticity in

cognition-related brain regions (Galván, 2021; Leventhal & Brooks-Gunn, 2000). Emerging research suggests that neighborhood disadvantage during adolescence is associated with lower performance on cognitive tasks involving attention, memory, and general EF (Hackman et al., 2021; Sutin et al., 2022; Vargas et al., 2020). In addition, longitudinal studies have similarly shown that neighborhood disadvantage during adolescence predicts lower memory performance in young adulthood (Noppert et al., 2022).

Much of this work, however, has focused specifically on understanding the impact of disadvantage, with a heavy focus on economic deprivation, with limited consideration for how enriching environments may support EF. It is equally critical to examine neighborhood opportunities, which is the presence of developmentally enriching and health-promoting conditions. Opportunities are not simply the inverse of disadvantage, although the two concepts are often related. For example, high-poverty neighborhoods may still have good social capital, and relatively well-off neighborhoods may have worse environments (e.g., more pollution or less green-space). These opportunities may not only support positive outcomes, but also provide critical insight into promotive factors that can inform strengths-based research. In addition, past research has often relied on single indicators of disadvantage (e.g., poverty rate) that fail to capture the full complexity of neighborhood environments. To address this limitation, researchers have developed multi-dimensional composite indices to better characterize the broader neighborhood context (e.g., Area Deprivation Index; Singh, 2003). While these composite scores cannot capture all facets of the broader neighborhood environment in which a child lives, they offer a more well-rounded representation of contextual factors and enhance reproducibility through their public availability.

One increasingly used composite score to characterize neighborhood opportunities is the Child Opportunity Index (COI), a set of census tract–level measures that captures neighborhood-level resources across three domains: education, health/environment, and social/economic factors (Acevedo-Garcia et al., 2020, 2024). The COI provides several advantages to other available composite scores, including more comprehensive assessments of neighborhood quality (e.g., inclusion of indicators of the physical environment), standardization of indicators before aggregating to allow for comparison across time, and availability of domain-specific scores. Higher COI scores have been associated with better physical and mental health outcomes (Putnick et al., 2025), as well as enhanced cognitive skills including language, visual processing, attention, and memory in adolescents (Gornik et al., 2024; Yildiz-Ozhan et al., 2026; Zhou et al., 2025). Longitudinal evidence also supports this finding, such that youth from high-opportunity neighborhoods exhibited stronger cognitive performance two years later (Zhou et al., 2025). Notably, most of this work has relied on a single large dataset, the Adolescent Brain Cognitive Development (ABCD) study. While the ABCD study affords detection of smaller effects, the sample under-represents those in the most disadvantaged contexts and with marginalized identities, hence additional research is needed to generalize these findings across diverse samples.

Many of the studies mentioned previously had controlled for family-level socioeconomic disadvantage (e.g., income or socioeconomic status), providing evidence that neighborhoods exert influences on development above and beyond family-level disadvantage. However, less is known about how interactions between family- and neighborhood-level factors may shape developmental outcomes. Results are mixed and appears to be dependent on the specific type of contextual factors and outcomes examined (see Minh et al. (2017) for a detailed review). For

example, some studies have found that positive neighborhood characteristics (e.g., social cohesion, broad opportunity) buffer the negative effects of family-level risk factors, such as low SES or exposure to violence, on socioemotional and physical health (Riina et al., 2014; Roubinov et al., 2018). Other studies, however, have found no significant moderation effects of neighborhood context on the associations between family adversity and psychopathology (Delany-Brumsey et al., 2014; Flouri et al., 2010). When it comes to cognitive outcomes specifically, the literature is similarly limited and inconsistent. For instance, neighborhood chaos moderated the relationship between family SES and children's cognitive task performance (St. John & Tarullo, 2020). Yet, more recent work found no evidence that neighborhood opportunity buffered the association between family risk and cognitive growth (Cubides-Mateus et al., 2023). The inconsistencies may stem in part from differences in how neighborhood factors are measured, which are often isolated indicators rather than multidimensional composites. Further, whether neighborhood opportunities can buffer household poverty may be especially important to investigate in disadvantaged and marginalized populations, who often face additional adversities beyond challenges related to low income. Therefore, further research is needed to examine whether and how multidimensional neighborhood opportunity moderates the impact of family-level poverty on cognitive development.

The current study aims to address these gaps by examining how multi-dimensional indicators of neighborhood opportunity during adolescence shape young adult EF, with a focus on a computationally derived construct: the drift-rate, which are estimated using the Drift Diffusion Model (DDM), a formal cognitive modeling framework that disentangles latent decision-making parameters from observed task performance (Ratcliff, 1978; Ratcliff & McKoon, 2008), and refers to how efficiently an individual can gather information to make a

decision. Drift rates are hypothesized to be largely explained by a trait-like cognitive factor, the efficiency of evidence accumulation (EEA) and may be a more mechanistically precise indicator of EF than conventional performance metrics, such as accuracy or response time (Weigard & Sripada, 2021). EEA is hypothesized to explain behavior across a wide variety of cognitive tasks and implicated as a transdiagnostic marker of psychopathology (Weigard & Sripada, 2021). While EEA has gained traction as a risk-factor for psychopathology, only a few studies to date have examined how socioeconomic disadvantage and adverse experiences, particularly at the family level, impact EEA. Results have found that exposure to household material hardship and violence is linked with lower EEA in adolescents (Vermeent, Young, DeJoseph, et al., 2024; Vermeent, Young, van Gelder, et al., 2024; Zhang et al., 2026). However, no study to date has examined how neighborhood level factors, especially opportunities for enrichment, can promote the development of this key cognitive process.

The current study aimed to investigate 1) how broad neighborhood opportunity during adolescence is associated with young adult drift rate; 2) whether specific dimensions of neighborhood opportunity matter more for promoting drift rate; 3) whether neighborhood opportunity can serve as a protective factor against family-level poverty. It was hypothesized that better adolescent neighborhood opportunity will predict better young adult EF as measured by higher drift rate. In addition, it was hypothesized that neighborhood opportunity can serve as a buffer for family poverty such that the negative effects of family poverty will be diminished for individuals growing up in high-opportunity neighborhoods.

Exploratory analyses compared between different conceptualizations of neighborhood opportunity: a contemporary resource-based measure (Child Opportunity Index, COI) and a retrospective outcome-based measure (Intergenerational Economic Mobility, IEM, from the

Opportunity Atlas; Chetty et al., 2018). While the COI captures current neighborhood-level access to resources and conditions that promote healthy development, such as quality education, safe environments, and economic resources, the IEM reflects the long-term economic outcomes of children who grew up in a given neighborhood, effectively summarizing the neighborhood's historical capacity to promote upward mobility. Comparing these two indicators allows us to distinguish between present-day environmental affordances and the cumulative, structural potential of neighborhoods to support long-term success.

Aims were investigated using data from a subsample of a longitudinal, population-based cohort drawn from the Future of Families and Child Wellbeing Study (Hein et al., 2018; Reichman et al., 2001), following participants from birth into young adulthood. This cohort, which includes primarily individuals from low-income families and historically marginalized backgrounds, offers a valuable context for examining how neighborhood environments may shape cognitive development among youth disproportionately exposed to socioeconomic disadvantage.

3.2 Methods

3.2.1 Sample

The current study examined a subsample of the Future of Families and Child Wellbeing Study (FFCWS), a population-based longitudinal sample of 4,898 children born in 20 large cities in the U.S. (Reichman et al., 2001). Participants were oversampled for non-marital births 3:1, which led to a sample of predominately unmarried and low-income families. Focal children and their families were followed throughout infancy to young adulthood, with data collected at baseline and ages 1, 3, 5, 9, 15, and 22. At age 21, a subsample of 530 young adults participated in the Study of Adolescent to Adult Neural Development (SAND) at the University of Michigan,

where they completed behavioral tasks while undergoing magnetic resonance imaging (MRI) scans. Within this subsample, a total of 441 young adults participated in behavioral tasks, with 417 completed at least one run of the emotional-faces gender-identification task that was used to model DDM. Following procedure from Chapter 2, sample was limited to those with usable performance data from the behavioral task and good parameter recovery from the modeling of drift rate, resulting in an analytic sample size of 358 participants (see Table 3.1 for exclusion criteria). Demographics are reported in Table 3.2. All participants provided informed consent and study protocols were approved by the University of Michigan ethics committee (IRB: HUM00167754).

3.2.2 Neighborhood Opportunity

3.2.2.1 Childhood Opportunity Index.

The primary measure of neighborhood opportunity during adolescent (age 15 wave) was the Child Opportunity Index 3.0 (COI 3.0, diversitydatakids.org, 2025). The COI is a multi-dimensional composite score of 44 indicators that measures neighborhood-based opportunities from three broad domains: education, health and environment, and social and economic. The COI education domain includes measures of early childhood, elementary, high school and post-secondary education, as well as general educational resources. The health and environment domain measures pollution, healthy environment (e.g., natural environment, food quality), community safety, and health resources (e.g., insurance coverage). Finally, the social and economic domain includes neighborhood-level indicators that measure employment, economic resources, concentrated economic inequity, housing, wealth, and social resources. With its multidomain approach, the COI offers a comprehensive assessment of resource-based neighborhood opportunities.

Past versions of COI have been used in many studies to study how neighborhood opportunities are associated with child outcomes, including health and mental health wellbeing (Acevedo-Garcia et al., 2020). The COI 3.0 is the most recent and comprehensive version of neighborhood opportunities. A total composite score as well as scores for each domain are available at the census-tract level and yearly from 2012 to 2023. The scores were z-transformed and standardized at the national level. The corresponding COI 3.0 measures (i.e., overall COI and subdomain scores) were mapped to each participant based on their census tract (2010 Census tract definitions) and year of when they were interviewed (2014-2017). Therefore, each participant had one overall COI score as well as three subdomain opportunity scores. Out of our modeling sample of 358 participants, 17 (4.7%) did not provide census tract information at age 15 and missingness was addressed in analysis models using full information maximum likelihood (FIML). Missingness was not associated with drift rate (t = 0.49, p = .632), sex (χ^2 = 2.59, p = .108), or ethnoracial identity (χ^2 = 1.30, p = .254), but was correlated with young adult age (t = -2.79, p = .012), which is included in path models as demographic covariate. The missing pattern is consistent with the missing at random (MAR) assumption underlying FIML (Little et al., 2014; Rubin, 1976). Descriptives of COI, along with other main variables, are reported in Table 3.3.

3.2.2.2 Neighborhood Opportunity from Opportunity Atlas.

Exploratory analysis examined whether the same results can be found using the intergenerational economic mobility (IEM) measure from the Opportunity Atlas (Chetty et al., 2018). IEM measures the average annual household income in 2014-2015 of children who were born between 1978-1983 from low-income parents (defined as mean pre-tax income at the 25th percentile of the national income distribution across five years, 1994, 1995, 1998-2000). Because

the IEM is a measure of income for adults who were born in low-income families, it has been interpreted as a retrospective, outcome-based indicator of a neighborhood's long-term ability to support economic mobility for children in low-income families. The IEM is available at the census-tract level and was mapped to each participants' census tract.

3.2.3 Drift rate (v)

Drift rate was estimated using the drift diffusion model (DDM), which models forced two-choice decision-making tasks. Behavioral performance data for DDM estimations were collected using an emotional-faces gender-identification task that was completed in the MRI scanner. Participants were asked to identify the gender of the actor by pressing their thumb (male) or index finger (female) on a button box. Faces were selected from the NimStim set (Tottenham et al., 2009) and were counterbalanced for gender and race (White and Black). Each participant completed two runs of the task, each run with 98 trials split across seven emotional faces (fearful, sadness, angry, happy, neutral, scrambled, and morphed), resulting in a total of 196 trials. Specifically, morphed faces were created with 30% happy and 70% neutral to be "positive neutral" faces given some research suggesting that neutral faces can be perceived as negative (Tottenham et al., 2013). Each trial lasted 2,250 ms, including a fixation cross presented for 500ms, followed by the face presented for 250ms, and then a black screen of up to 1500ms for response to account for individual differences in reaction time. Response times (RTs) and accuracy were recorded.

Participants were excluded for poor performance in a similar manner as Chapter 2 (Zhang et al., 2026): if completed less than 147 trials (i.e., omission rate > 25%) and/or accuracy was below 55%, which might indicate that participants did not understand the task or were not engaged. all scrambled faces trials were removed from DDM estimations given that there is no

clear correct answer for these pixelated faces. Additionally, trials with RTs less than 200ms were removed as fast guesses following standard procedures for fitting the DDM (Ratcliff & Tuerlinckx, 2002).

DDM estimations were conducted using the same procedure as Chapter 2 using the Dynamic Models of Choice package in R (Heathcote et al., 2019; Zhang et al., 2026). Four DDM parameters were estimated for each individual: drift rate (v), response caution (a), non-decision time (t0), and response bias (z). Individual model convergence were assessed by visual examination of the posterior chains and the Gelman-Rubin's convergence diagnostic (<= 1.1 indicates good convergence; Gelman & Rubin, 1992). All models fit well according to these criteria. A simulation recovery study was conducted following procedures from Chapter 2 to show good recovery of DDM parameters. Specifically, parameters estimated from the DDM were used to simulate a new dataset, with trial numbers adjusted to match the real dataset. The DDM was then fit to the simulated data set using the same procedures outlined above. parameter estimates recovered from the simulated data set were compared with those from the original parameters using correlations (Figure 3.1). Correlation *r* values for drift rate (v), a, t_0, and z showed excellent recovery (*r*s > .88). Point estimates of DDM parameter values were summarized using the medians of posterior distributions and used in subsequent analyses. Descriptives of DDM parameters and conventional performance metrics are reported in Table 3.4.

3.2.4 Family-level poverty

Family-level poverty was measured using household-level poverty ratio, which is the ratio of total household income to the official poverty thresholds established by the U.S. Census Bureau. The poverty threshold accounts for household composition (i.e., number of adult and

children in the household). The FFCWS poverty ratio measure at the age 15 wave is computed using the thresholds from the year prior to when the interview was conducted. Higher poverty ratio indicates higher household income relative to poverty threshold (i.e., lower poverty). 12 participants (3.4%) were missing poverty ratio at age 15. Missingness was not associated with drift rate (t = -0.33, p = .750), sex (χ^2 = 0.16, p = .695), but was correlated with young adult age (t = -3.67, p = .003) and ethnoracial identity (χ^2 = 8.87, p = .254), and is consistent with the missing at random (MAR) assumption underlying FIML.

3.2.5 Covariates

To account for potential confounding effects of neighborhood opportunity on young adult EEA, analyses adjusted for the following demographic covariates: sex, young adult age, and ethnoracial identity. Sex was measured using parental report at child age 1 (0 = female, 1 = male). Age (years) was self-reported by young adults at time of data collection. Ethnoracial identity (Black, non-Hispanic; White, non-Hispanic; Hispanic; and Other) was self-reported by young adults and were included in the analyses as three dummy-coded variables with Black (48.8% of the sample) as the reference group. Ethnoracial identity was included as a covariate in the primary analyses to adjust for potential effects of structural and interpersonal racism in shaping developmental experiences. However, because the neighborhood opportunity experienced by families may also be shaped by structural factors related to ethnoracial identity (Acevedo-Garcia et al., 2020), additional sensitivity analyses was conducted without race as a covariate.

Additionally, the distribution of primary rural-urban commuting area (RUCA) codes was examined to better understand the implication of broader rural-urban geographic context on neighborhood opportunity. Descriptives of RUCA codes indicates that 90.78% of our sample

lived in metropolitan areas, and therefore RUCA codes were not included as a covariate in analyses.

3.2.6 Statistical Analyses

All statistical analyses were conducted using R Statistical Software v4.5.1 (R Core Team, 2025). Linear path models were conducted with R lavaan package (v0.6-20; Rosseel, 2012) with full information maximum likelihood estimator to account for missing variables. To address aim 1, bivariate correlation between total composite score of COI and drift rate were conducted, followed by a linear path model adjusting for demographic covariates and sensitivity analysis without ethnoracial identity as a covariate. In aim 2, separate correlations and path models for each domain of COI and drift rate were conducted to examine whether each of the three domains of COI is separately associated with drift rate in young adulthood. False discovery rate (FDR) correction of p-values for multiple comparisons were also reported. In addition, path analysis that includes all three domain scores in the same model was conducted to examine whether one domain contributes more than others. Aim 3 first examined the main effects of neighborhood opportunity and family household poverty ratio when put in the same path model, followed by the interaction between the two variables on young adult cognitive efficiency. To address the exploratory aim of comparing between COI as a contemporary resource-based measure and Opportunity Atlas as a historical outcome-based measure, a similar set of correlation and linear path analyses with the Opportunity Atlas IEM measure was conducted and results were compared. Finally, exploratory analyses also examined the associations of neighborhood opportunity with conventional behavioral measures (average RT and average accuracy), and with other DDM parameters.

3.3 Results

3.3.1 Adolescent Neighborhood Opportunity and Young Adult Drift Rate

Bivariate correlation between adolescent COI and young adult drift rate showed a significant positive association (r = .13, p = .014). The association remained significant in the linear path model with demographic covariates (β = .14, p = .025, Table 3.5, Figure 3.2), such that greater neighborhood opportunity in adolescence predicted more efficient information processing (i.e., higher drift rate) during decision-making in young adulthood. In the sensitivity analysis without ethnoracial identity as a covariate, similar associations were observed (β = .13, p = .017).

When examining domain-specific COIs, bivariate correlations showed that COI scores were moderately to highly correlated (rs = .64 - .89). As expected, similar results were found across domain-specific COI and young adult drift rate, such that higher adolescent COI across domains were significantly associated with higher cognitive efficiency in young adults (Education: r = .12, p = .025; Health & Environment: r = .13, p = .013; Social & Economic: r = .13, p = .018). The association remained significant with demographic covariates for the Health & Environment domain (β = .12, p = .027, p_{FDR} = .044) and the Social & Economic domain (β = .13, p = .029, p_{FDR} = .044), but became trending for the Education domain (β = .12, p = .054, p_{FDR} = .054) (Table 3.5; Figure 3.2). In sensitivity analysis without ethnoracial identity as a covariate, similar associations were found except that all domain scores were significantly linked with young adult drift rate (Education: β = .12, p = .030; Health & Environment: β = .13, p = .016; Social & Economic: β = .13, p = .020).

In the path model where all domain-specific COI scores were included to predict drift rate, no significant associations were found (Education: β = .03, p = .797; Health &

Environment: β = .09, p = .216; Social & Economic: β = .04, p = .738). This suggests that no COI domain was uniquely stronger in predicting young adult drift rate, which is not surprising given the strong correlations between domain scores.

3.3.2 Family-level Socioeconomic Disadvantage and Neighborhood Effects

Family-level socioeconomic disadvantage, as measured by household poverty ratio in adolescence, was significantly associated with young adult drift rate (r = .15, p = .004), such that higher family income (i.e., higher poverty ratio) is associated with higher drift rate. In path models where both COI and household poverty ratio predicted drift rate, no significant associations were found with either neighborhood or family-level measures (COI: β = .08, p = .371; poverty ratio: β = .10, p = .312; Table 3.6). Notably, COI is moderately correlated with household poverty ratio (r = .55, p < .001), which could explain the null results when both variables were included in the same model. Similar results were found with domain-specific COI scores, results are reported in Supplemental Table 3.8. No significant interaction effect was observed between COI and household poverty ratio (β = -.06, p = .476; Figure 3.3), suggesting no evidence for neighborhood opportunity in buffering against negative effects of family poverty on young adult cognitive efficiency.

3.3.3 Exploratory Analyses

3.3.3.1 Opportunity Atlas IEM.

Opportunity Atlas IEM measure was strongly correlated with COI in the sample (r = .85, p < .001), suggesting that the outcome-based measure of neighborhood opportunity is similar to the contemporary resource-based measure for our participants. similar associations of IEM with young adult drift rate were found, adjusting for demographic covariates (β = .13, p = .034).

Similar to COI, the significant positive association did not survive after adjusting for family-level poverty (β = .08, p = .261).

3.3.3.2 Conventional behavioral measures and other DDM parameters.

Correlations between conventional performance measures (i.e., average response time and accuracy) and DDM parameters are reported in Table 3.4. Consistent with theoretical expectations of the DDM (Voss et al., 2004), faster response time (i.e., lower RT) on the task was explained by higher drift rate (r = -.36, p < .001), lower response caution (r = .84, p < .001), and faster non-decision time (r = .62, p < .001), suggesting that response speed reflects contributions from evidence accumulation efficiency, response caution, and processing speed. Higher task accuracy was primarily explained by higher drift rate (r = .68, p < .001), with more modest associations with higher response caution (r = .25, p < .001), slower non-decision time (r = .41, p < .001) and higher response bias (r = .17, p = .002). Together, these expected patterns provide an important check on model validity, demonstrating that the DDM parameters map onto conventional performance metrics in theoretically coherent ways.

Adolescent COI was significantly associated with task performance accuracy (r = .16, p = .004; adjusting for covariates: β = .13, p = .029), but not with response time (r = -.05, p = .399; adjusting for covariates: β = -.04, p = .512) (Table 3.7). The association between COI and accuracy did not survive after including household poverty ratio in the model (β = .14, p = .054).

When examining the associations with DDM parameters besides drift rate, higher adolescent COI was associated with lower response caution (r = -.11, p = .040), though the effect did not survive after adjusting for covariates (β = -.07, p = .266). Additionally, higher COI was associated with higher non-decision time, such that higher neighborhood opportunity was

associated with slower encoding and motor processing time (r = .15, p = .005; adjusting for covariates: β = .12, p = .040), and the association diminished after adjusting for family-level poverty (β = .12, p = .053). Detailed results are in Supplemental Table 3.9.

3.4 Discussion

Socioeconomic context is multi-faceted, encompassing factors that extend beyond immediate household-level economic conditions to broader neighborhood environments. While poverty has long been recognized as a major risk factor for the development of executive functions, fewer studies have focused on how socioeconomic factors at the neighborhood (e.g., census-tract) level may shape cognition, particularly opportunities and resources embedded in the surrounding environment as a complementary dimension to poverty. The current study investigated whether neighborhood opportunities during adolescence is prospectively associated with young adult cognitive efficiency in a predominantly low-income birth cohort. Greater adolescent neighborhood opportunity, particularly in health and environment as well as social and economic domains, was associated with higher cognitive efficiency eight years later in young adults. Results suggest that resources across multiple ecological levels during adolescence may have meaningful long-term implications for executive functioning development.

The prospective nature of our finding between greater neighborhood opportunity and higher drift rate suggest adolescent socioeconomic environments may contribute meaningfully to shaping later neurocognitive functioning, aligning with past work positing adolescence as a sensitive period for contextual influences on cognition (Fuhrmann et al., 2015; Galván, 2021; Steinberg, 2005). These findings are consistent with prior work finding that youths residing in better-resourced neighborhoods performed better across multiple executive function tasks (Gornik et al., 2024; Yildiz-Ozhan et al., 2026; Zhou et al., 2025). More advantaged

neighborhoods may provide increased cognitive stimulation, environmental enrichment, and reduced exposure to chronic stressors, all of which may promote neurocognitive functioning through enhancing opportunities for learning and exploration, as well as reduced allostatic load (Juster et al., 2010; McEwen & Gianaros, 2010; Rakesh et al., 2024). Although the present study does not allow for direct causal inference, these findings are consistent with the idea that neighborhood opportunity may serve as one component of broader developmental context that shape cognitive outcomes over time.

Associations were observed across dimensions of neighborhood opportunity, particularly for the health and environment domain and the social and economic domain. These two domains capture neighborhood features including healthy living conditions, physical environment quality, and broad social and economic capital. These findings align with recent work showing that better physical environment, including access to greenspace and reduced pollution, may positively influence cognitive functioning and mental health outcomes (Clifford et al., 2016; Vella-Brodrick & Gilowska, 2022). Additionally, our study may reflect a complementary pattern to prior studies linking neighborhood poverty with altered executive functioning (Tomlinson et al., 2020; Vargas et al., 2020), such that greater social and economic resources in the neighborhood may promote neurocognition. Although the association was not significant for the education domain, which captures education resources and quality from early childhood to post-secondary schooling, effect sizes were largely similar across domains. At the same time, because domain-specific scores were moderately to highly correlated in our sample, disentangling unique domain-specific effects were statistically challenging. Thus, null domain-specific findings should not necessarily be interpreted as evidence that educational opportunity is unimportant. Future

work should continue to explore whether particular dimensions of neighborhood opportunity may be especially relevant for cognitive development.

Importantly, associations between neighborhood opportunity and cognitive efficiency did not remain significant after controlling for family-level poverty. Family-level poverty during adolescence was also significantly associated with young adult cognitive efficiency, suggesting that household level socioeconomic disadvantage can shape executive functions as well, aligning with prior work linking household level material hardship with lower drift rate (Zhang et al., 2026). At the same time, because neighborhood opportunity and household poverty ratio were moderately correlated, our findings may reflect a broader association between adolescent socioeconomic context and later neurocognitive functioning, rather than clearly separable family versus neighborhood level effects. From an ecological systems perspective, this pattern is unsurprising, as socioeconomic disadvantage often clusters across levels of context, with lower-income families disproportionately constrained to lower-opportunity neighborhoods due to structural inequalities (Acevedo-Garcia et al., 2020; Riley, 2018). This may be especially relevant given that our sample is primarily low-income families, and therefore, caution is warranted in interpreting neighborhood opportunity as uniquely independent of family-level disadvantage. Rather, the current findings may more so reflect the cumulative and interconnected nature of socioeconomic contexts. Both neighborhood and household factors may shape access to cognitively enriching conditions, resulting in overlapping pathways through which socioeconomic context affects executive functioning development. We also found no evidence that neighborhood opportunity buffered against the negative association between family poverty and cognitive efficiency. This absence of interaction may indicate that, within contexts of substantial household disadvantage, neighborhood-level resources alone may be insufficient to

offset more proximal economic hardship. However, limited statistical power and restricted socioeconomic variability may also have reduced sensitivity to detect such buffering effects.

As an exploratory aim, a complementary census-tract measure of neighborhood opportunity was also examined, that represents the neighborhood's historical capacity to support upwards economic mobility of children from low-income families: the intergenerational economic mobility measure from the Opportunity Atlas (Chetty et al., 2018). IEM was highly correlated with COI, suggesting that neighborhoods with greater contemporary resources also tended to demonstrate stronger historical mobility potential. This convergence supports the broader interpretation that neighborhood opportunity may represent relatively stable structural advantages or disadvantages across time, consistent with literature documenting persistent geographic inequalities in access to opportunity (Acevedo-Garcia et al., 2024; Chetty et al., 2014; Heard-Garris et al., 2021). Such findings further underscore the importance of considering structural and historical dimensions of neighborhood context when examining developmental outcomes.

Consistent with our main finding that greater neighborhood opportunity was associated with higher drift rate, in exploratory analyses, young adults who lived in higher opportunity neighborhoods in adolescence performed with higher accuracy on the task. Applying the drift diffusion model allowed for identifying the drift rate, which is hypothesized to be driven by the efficiency of evidence accumulation, as a more specific cognitive mechanism underlying behavioral differences associated with socioeconomic context. Additionally, neighborhood opportunity was not significantly associated with response caution after adjusting for demographic covariates, suggesting that neighborhood effects may be more strongly associated with information processing efficiency rather than changes in response strategies. A significant

association between higher neighborhood opportunity and slower perceptual processing and motor response time (i.e., non-decision time) was also observed, aligning with past research finding links with slower non-decision time and adaptive outcomes (e.g., less attentional difficulties; Karalunas et al., 2014). However, interpretations of this finding should remain cautious, as non-decision time reflets multiple aggregated subprocesses and are not separable in the model.

The study results should be considered with the following limitations in mind. First, while the predominantly low-income sample offers a valuable opportunity of investigating the role of neighborhood resources in shaping cognition longitudinally, the moderate overlap between family- and neighborhood-level disadvantage limited our ability to fully disentangle their unique contributions. Ideally, questions surrounding interactions effects would be examined in a larger sample, with a more diverse distribution of neighborhood and family socioeconomic context combinations. Second, cognitive efficiency was assessed using a single perceptual decision-making task, limiting broader conclusions regarding executive functioning more generally. Replication across multiple tasks would strengthen generalizability and permit latent modeling of the EEA factor. Third, neighborhood opportunity measures were only available at one developmental time point, which limited our ability to examine questions around developmental timing, chronicity, or change in neighborhood influences across time. Longitudinal neighborhood data would allow for stronger tests of developmental timing related hypotheses. Finally, although the current study identified prospective associations, it does not directly test mechanisms that may underly the associations between neighborhood factors and cognition. A previous study has found that changes in brain structure may explain associations between neighborhood opportunity and performance on cognitive tasks (Zhou et al., 2025).

Future work should examine potential mediating pathways, including stress physiology and neurobiological mechanisms such as structural or functional brain development.

In conclusion, the current study extends prior research on socioeconomic disadvantage and cognition by shifting focus beyond household poverty to neighborhood opportunity and by leveraging computational modeling to more precisely characterize cognitive efficiency. Greater adolescent neighborhood opportunity was associated with higher young adult cognitive efficiency, although these effects were not distinguishable from family poverty in this sample. Together, these findings suggest that adolescent socioeconomic environments across multiple ecological levels may contribute to long-term neurocognitive development while also highlighting the challenge of disentangling interconnected structural inequalities across family and neighborhood contexts. Enhancing community resources and opportunity structures may be an important avenue for supporting long-term cognitive development across the life course.

3.5 Reference

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3.6 Tables

Table 3.1. Participant Exclusion

Reason for Exclusion	Number of Participants	Number of Participants Excluded
	530 (SAND-21 sample)	
Ineligible or refused participation in MRI session	441	89
Did not complete any run of emotional-faces gender-identification task	417	24
Missing behavioral task file output	416	1
Poor behavioral performance (task runs with accuracy < .55 and/or omission > .25)	358 (analytic sample)	58

Table 3.2. Sample Demographics

Variables	Group	Mean (SD)	Count (Percentage)
Age	-	22.85 (*1.12*)	-
Sex	Female (0)	-	184 (51.40%)
	Male (1)	-	174 (48.60%)
Race	Black	-	175 (48.88%)
	White	-	113 (31.56%)
	Hispanic/Latino	-	34 (9.50%)
	Other/Multiracial	-	36 (10.05%)
Primary RUCA Codes	Metropolitan (codes 1-3)	-	314 (90.78%)
	Non-Metropolitan (codes 4-10)	-	66 (35.29%)
Household poverty ratio in adolescence (% of income to poverty threshold)	0-99%	-	77 (21.5%)
	100-199%	-	89 (24.9%)
	200-299%	-	54 (15.1%)
	>300%	-	126 (35.2%)
	Missing	-	12 (3.3%)

Table 3.3. Descriptives and Zero-order Correlations of Main Variables

	1	*2*	*3*	*4*	*5*	*6*
1. Drift rate (v)	-	-	-	-	-	-
2. COI	**.13***	-	-	-	-	-
3. COI - Education	**.12***	**.95*****	-	-	-	-
4. COI – Health & Environment	**.13***	**.75*****	**.64*****	-	-	-
5. COI – Social & Economic	**.13***	**.99*****	**.89*****	**.70*****	-	-
6. Household poverty ratio	**.15****	**.55*****	**.53*****	**.40*****	**.54*****	-
Mean	2.67	-0.32	-0.30	-0.10	-0.41	2.96
Standard deviation	0.71	0.87	0.98	0.62	1.00	2.87

***: $p < .001$; **: $p < .01$; *: $p < .05$

Table 3.4. Distributions and Zero-order Correlations of DDM Parameters and Raw Performance Data

	1	*2*	*3*	*4*	*5*	*6*
1. Drift rate (v)	-	-	-	-	-	-
2. Response Caution (a)	**-.13***	-	-	-	-	-
3. Non-decision Time (t0)	**.19*****	**.35*****	-	-	-	-
4. Response Bias (z)	**.20*****	.003	.02	-	-	-
5. Reaction Time (second)	**-.36*****	**.84*****	**.62*****	-.05	-	-
6. Accuracy	**.68*****	**.25*****	**.41*****	**.17****	**.11***	-
Mean	2.67	1.34	0.49	0.32	0.63	0.91
Standard deviation	0.71	0.31	0.05	0.06	0.12	0.08
***: $p < .001$; * : $p < .05$						

Table 3.5. Path Analysis of COI Predicting Drift Rate (v)

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Overall COI					
Neighborhood opportunity	0.11	0.14	0.05	2.24	.025*
Age (years)	-0.04	-0.06	0.04	-1.02	.310
Sex	-0.05	-0.04	0.07	-0.67	.502
Race: White	0.05	0.03	0.10	0.51	.613
Race: Hispanic	-0.07	-0.03	0.13	-0.52	.601
Race: Other	-0.14	-0.06	0.10	-1.36	.175
COI: Education Domain					
Neighborhood opportunity	0.08	0.11	0.04	1.93	.054 (FDR: .054)
Age (years)	-0.04	-0.06	0.04	-1.03	.301
Sex	-0.04	-0.03	0.07	-0.59	.557
Race: White	0.06	0.04	0.10	0.66	.508
Race: Hispanic	-0.06	-0.03	0.13	-0.48	.628
Race: Other	-0.12	-0.05	0.10	-1.17	.243
COI: Health and Environment Domain					
Neighborhood opportunity	0.14	0.12	0.06	2.21	.027* (FDR: .044)
Age (years)	-0.04	-0.06	0.04	-0.98	.328
Sex	-0.04	-0.03	0.07	-0.57	.566
Race: White	0.10	0.07	0.09	1.11	.267
Race: Hispanic	-0.04	-0.02	0.13	-0.30	.766
Race: Other	-0.11	-0.05	0.10	-1.10	.272
COI: Social and Economic Domain					
Neighborhood opportunity	0.09	0.13	0.04	2.18	.029* (FDR: .044)
Age (years)	-0.04	-0.06	0.04	-1.02	.306
Sex	-0.05	-0.04	0.07	-0.68	.497
Race: White	0.05	0.04	0.10	0.57	.568
Race: Hispanic	-0.07	-0.03	0.13	-0.54	.589
Race: Other	-0.14	-0.06	0.10	-1.37	.171
*: $p < .05$					

Table 3.6. Path Analysis of Household Poverty Ratio and COI Predicting Drift Rate (v)

Predictors	*b*	*β*	*SE*	*z*	*p-value*
COI	0.06	0.08	0.07	0.89	.371
Household poverty ratio	0.03	0.10	0.03	1.01	.312
Age (years)	-0.03	-0.05	0.04	-0.88	.380
Sex	-0.05	-0.04	0.07	-0.71	.480
Race: White	0.06	0.04	0.10	0.61	.544
Race: Hispanic	-0.06	-0.02	0.13	-0.45	.650
Race: Other	-0.14	-0.06	0.10	-1.31	.192

*: $p < .05$

Table 3.7. Path Analysis of COI Predicting Conventional Performance Measures

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Average Accuracy					
Neighborhood opportunity	0.01	0.13	0.01	2.19	.029*
Age (years)	-0.00	-0.01	0.00	-0.25	.804
Sex	-0.00	-0.03	0.01	-0.48	.629
Race: White	0.01	0.06	0.01	0.99	.324
Race: Hispanic	0.00	0.02	0.02	0.31	.757
Race: Other	0.00	0.01	0.01	0.12	.906
Average Response Time					
Neighborhood opportunity	-0.01	-0.04	0.01	-0.65	.512
Age (years)	0.01	0.10	0.01	1.90	.058
Sex	0.02	0.09	0.01	1.60	.110
Race: White	-0.01	-0.02	0.02	-0.36	.715
Race: Hispanic	0.02	0.05	0.02	0.75	.453
Race: Other	-0.01	-0.04	0.02	-0.84	.403

*: $p < .05$

3.7 Figures

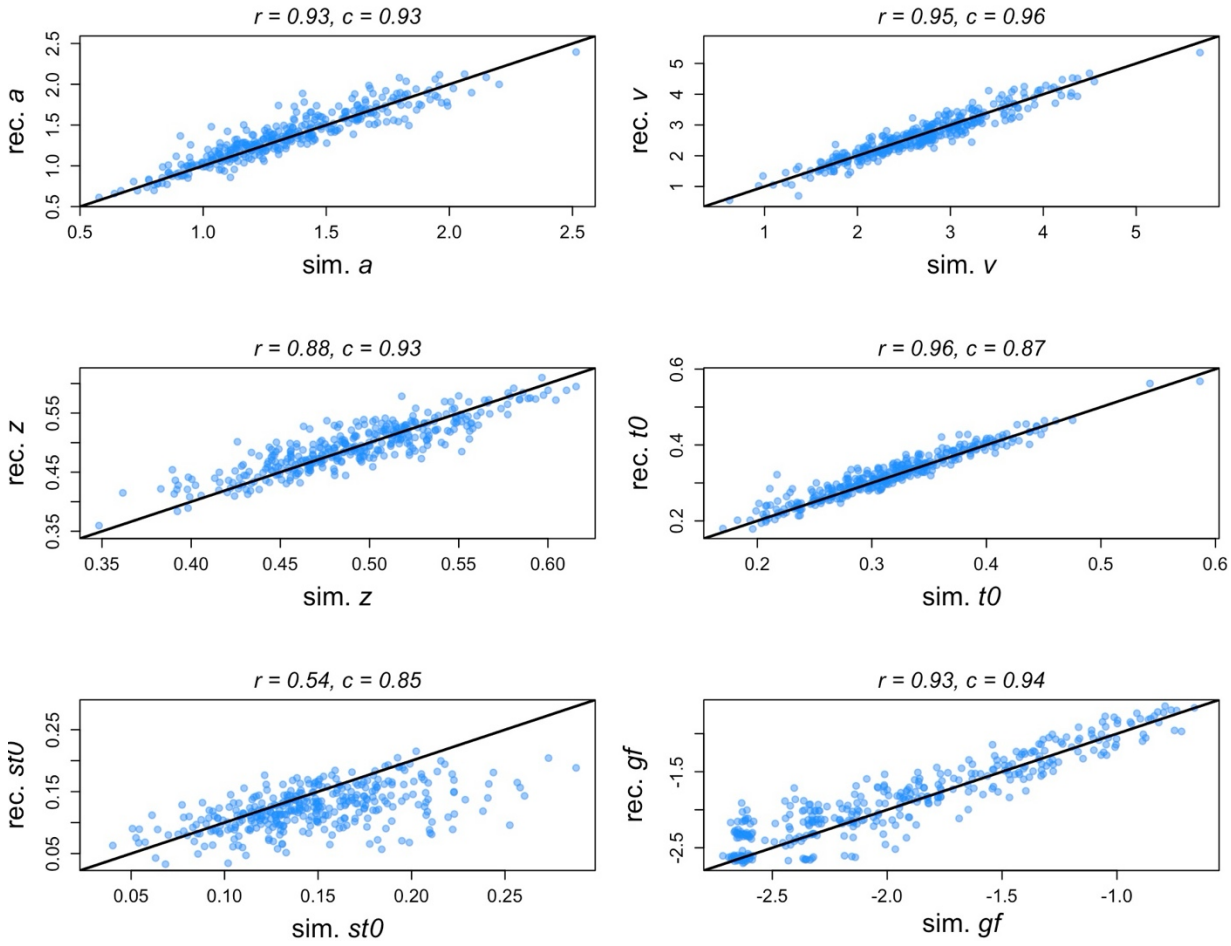

Figure 3.1. Simulation-recovery study correlation plots of DDM parameters.

Parameter values from the DDM (x-axis) were used to simulate a new data set, from which another set of parameter values were estimated (y-axis). Correlation values (r) between the simulated and recovered parameter values are displayed on each plot. Diagonal lines indicate where the points would fall if the parameter recovery was perfect (r = 1). Parameter recovery for the four main parameters (top four panels: a, v, z, and t_0), as well as go-failure (i.e., omissions), are excellent (rs >= .88). Between trial-variability (st_0) had average recovery.

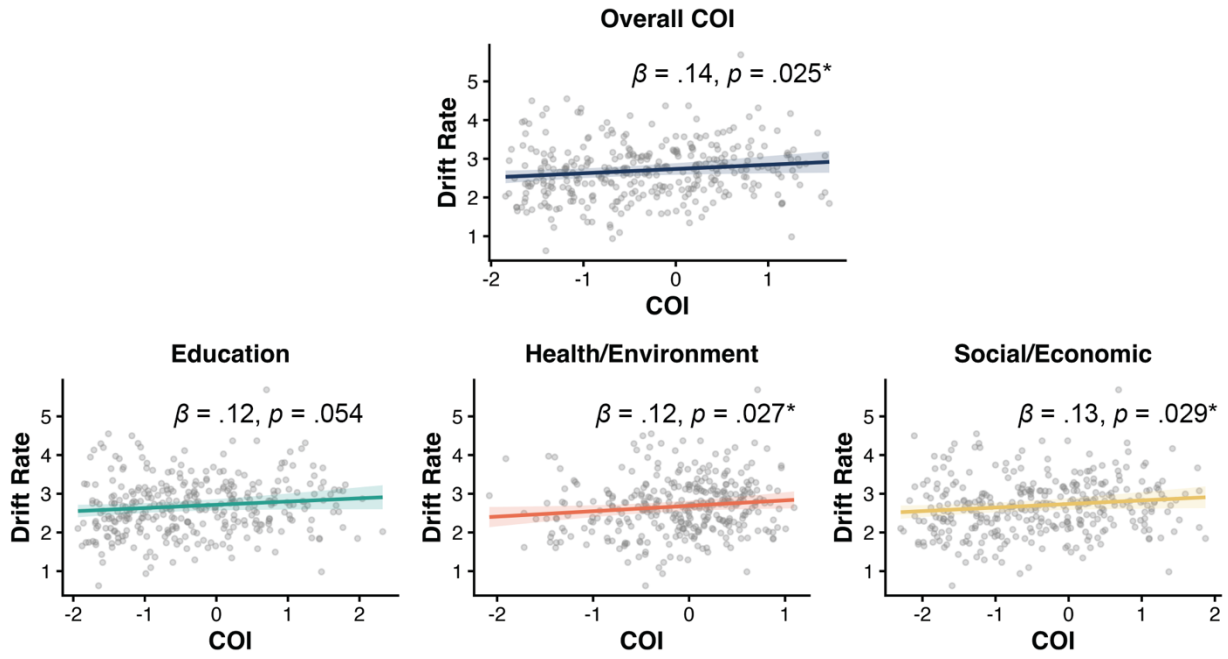

Figure 3.2. Adjusted associations between adolescent COI and young adult drift rate.

Panels display model-predicted associations between overall COI (panel A) and domain-specific COI scores (panel B: education, panel C: health/environment, and panel D: social/economic) with drift rate, adjusting for age, sex, and ethnoracial identity. Solid lines represent adjusted linear regression estimates, shaded bands indicate 95% confidence intervals, and gray points represent observed data. *: $p < .05$.

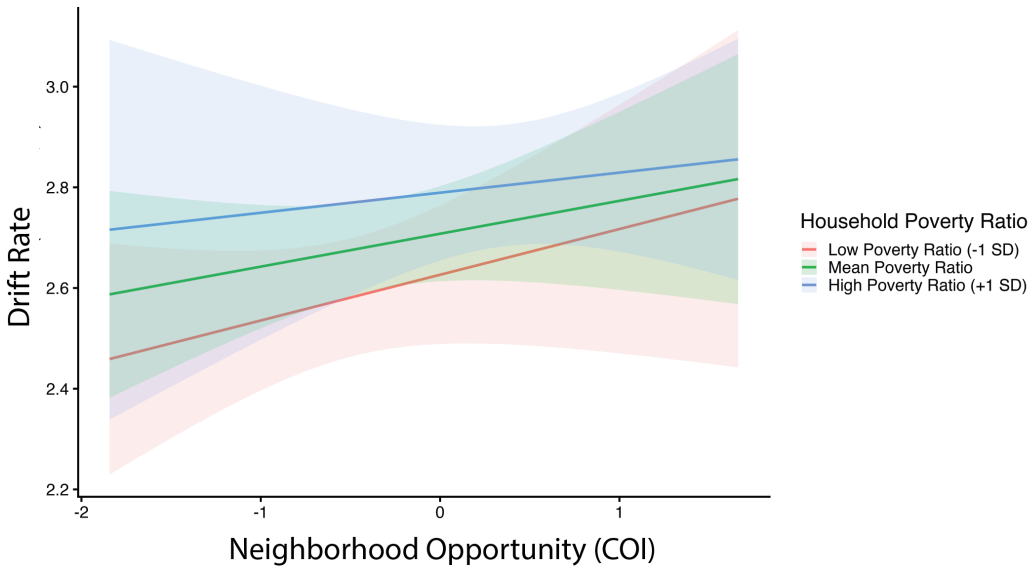

Figure 3.3. Interactions between adolescent neighborhood opportunity and household poverty ratio predicting drift rate.

We did not observe a significant interaction effect between COI and household poverty ratio in predicting young adult drift rate. (β = -.06, p = .476). Predicted values are plotted across the observed range of COI at low (−1 SD), mean, and high (+1 SD) levels of household poverty ratio. Solid lines represent linear regression estimates, shaded bands indicate 95% confidence intervals.

3.8 Chapter 3 Supplemental Tables

Supplemental Table 3.8.Path Analysis of Domain-specific COI Predicting Drift Rate (v)

Predictors	*b*	*β*	*SE*	*z*	*p-value*
COI: Education Domain					
COI	0.05	0.06	0.06	0.76	.449
Household poverty ratio	0.03	0.11	0.02	1.10	.271
Age (years)	-0.03	-0.05	0.04	-0.86	.391
Sex	-0.02	-0.01	0.08	-0.22	.825
Race: White	0.04	0.02	0.10	0.37	.715
Race: Hispanic	-0.08	-0.03	0.13	-0.60	.550
Race: Other	-0.15	-0.07	0.11	-1.42	.155
COI: Health and Environment Domain					
COI	0.10	0.09	0.07	1.48	.138
Household poverty ratio	0.03	0.11	0.02	1.28	.200
Age (years)	-0.03	-0.05	0.04	-0.82	.413
Sex	-0.02	-0.01	0.07	-0.24	.811
Race: White	0.05	0.03	0.09	0.52	.607
Race: Hispanic	-0.06	-0.03	0.12	-0.50	.620
Race: Other	-0.15	-0.07	0.11	-1.44	.151
COI: Social and Economic Domain					
COI	0.05	0.08	0.06	0.92	.357
Household poverty ratio	0.03	0.11	0.02	1.04	.299
Age (years)	-0.03	-0.05	0.04	-0.86	.390
Sex	-0.02	-0.01	0.08	-0.27	.788
Race: White	0.03	0.02	0.10	0.30	.766
Race: Hispanic	-0.08	-0.03	0.13	-0.64	.524
Race: Other	-0.16	-0.07	0.11	-1.54	.124
*: $p < .05$					

Supplemental Table 3.9. Path Analysis of COI Predicting Other DDM Parameters

Predictors	*b*	*β*	*SE*	*z*	*p-value*
Response Caution (a)					
Neighborhood opportunity	-0.02	-0.07	0.02	-1.15	0.252
Age (years)	0.02	0.06	0.02	1.06	0.291
Sex	0.01	0.02	0.03	0.40	0.690
Race: White	-0.06	-0.09	0.04	-1.46	0.145
Race: Hispanic	-0.01	-0.01	0.06	-0.11	0.914
Race: Other	-0.06	-0.05	0.05	-1.12	0.264
Non-decision Time (t_0)					
Neighborhood opportunity	0.01	0.14	0.00	2.47	.014*
Age (years)	0.00	0.08	0.00	1.54	.125
Sex	0.02	0.17	0.01	3.09	.002**
Race: White	0.00	0.02	0.01	0.36	.720
Race: Hispanic	0.01	0.07	0.01	1.14	.253
Race: Other	-0.01	-0.06	0.01	-1.09	.277
Bias (z)					
Neighborhood opportunity	0.00	0.01	0.00	0.23	.821
Age (years)	0.00	0.03	0.00	0.60	.552
Sex	-0.01	-0.15	0.01	-2.76	.006**
Race: White	-0.01	-0.06	0.01	-0.93	.352
Race: Hispanic	-0.01	-0.06	0.01	-1.09	.274
Race: Other	0.00	0.02	0.01	0.31	.754
**: $p < .01$; *: $p < .05$					

Chapter 4 Characterizing the Functional Connectome of Cognitive Efficiency and Its Links with Socioeconomic Disadvantage in Adolescents

4.1 Introduction

Executive functioning (EF) serves as the foundation for a wide range of outcomes including academic achievement, social adaptation, and mental health (Diamond, 2013; Feinstein & Bynner, 2004; Nigg, 2017). Core EF abilities, such as attention regulation, inhibitory control, and decision-making, undergo significant changes as brain systems mature into young adulthood (Blakemore & Choudhury, 2006; Casey et al., 2008; Luna et al., 2015). The prolonged period of development, which includes adolescence, renders EF especially malleable to environmental influences during these formative years (Fuhrmann et al., 2015). In addition, while growing evidence suggests that EF is sensitive to environmental contexts, the mechanisms linking socioeconomic disadvantage to changes in the neural mechanisms of EF remain incompletely understood (Farah, 2017). This highlights the need to better understand the neural underpinnings of EF and how they are shaped by environmental exposures.

EF is often assessed through performance on behavioral cognitive tasks that target processes such as perceptual decision-making, attention, working memory tasks (Diamond, 2013; Nigg, 2017). Surface-level metrics from these tasks, most commonly response times and error rates, is then used as a proxy for cognitive ability, where better performance is interpreted as better EF ability (Farah et al., 2006; Johnson et al., 2021; Wei et al., 2025). The Diffusion-Decision Model (DDM), which belongs to a class of mathematical models that describes

cognitive processes underlying observed behavior named Evidence Accumulation Models (EAMs), offers a more precise approach than these conventional metrics (Lee & Cummins, 2004; Ratcliff & McKoon, 2008). The DDM posits that individuals complete many cognitive tasks by gradually accumulating evidence for each possible choice until a critical threshold is reached. These models are well-established and have been highly successful in capturing performance across a wide variety of behavioral tasks spanning cognitive domains (Heathcote & Matzke, 2022; Ratcliff et al., 2016).

A growing literature has begun to reveal how the latent processes described by DDM play a foundational role in complex cognitive functions. Of these processes, the drift rate (v), which is hypothesized to be driven by the efficiency of evidence accumulation (EEA) is increasingly recognized as a key cognitive construct that captures how quickly and accurately individuals gather goal-relevant information to make decisions under uncertainty (Weigard & Sripada, 2021). The drift rate parameter estimates how quickly and accurately an individual gathers information to make a decision, reflecting how effectively an individual extracts useful information from noisy perceptual input in order to reach a decision threshold (Ratcliff & McKoon, 2008). The underlying EEA factor is increasingly recognized as a task-general trait, reflecting individual differences in cognitive functioning across domains such as working memory capacity, processing speed, and general intelligence (Lerche et al., 2020; Weigard & Sripada, 2021). In parallel, reduced EEA has been identified using these models across multiple psychological disorders, including attention-deficit/hyperactivity disorders (ADHD), substance use, and depression, suggesting that lower EEA is a transdiagnostic risk factor for psychopathology (Huang-Pollock et al., 2017; Lawlor et al., 2020; Paige et al., 2024).

4.1.1 Neural Underpinnings of EEA

Given the psychological and clinical importance of EEA, research has emerged to identify the neural underpinnings for this cognitive efficiency factor. Early research on the neural basis of evidence accumulation focused on trial-level dynamics using single-unit recording studies in monkeys, showing that firing patterns of neural activity in sensorimotor regions while performing oculomotor perceptual decision-making tasks mirror the decision process posited by evidence accumulation models (see Heekeren et al., 2008 for review). Similar accumulation-related signals have been observed across midbrain, premotor, motor, and frontoparietal areas in rodents and non-human primates (Cisek & Kalaska, 2005; Ding & Gold, 2010; Huk & Shadlen, 2005; Pape & Siegel, 2016).

In humans, neural signatures of evidence accumulation have also been examined using several methods including electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI). Across diverse perceptual decision-making tasks, EEG studies have identified neural decision signals in humans that reflect supramodal accumulation of sensory evidence and are parallel to those found in monkeys (Nunez et al., 2017; O'Connell et al., 2012; Pisauro et al., 2017). fMRI-based experimental studies have also investigated how evidence accumulation unfolds during decision-making tasks, finding activation in regions broadly involved in decision-making, performance monitoring, and attentional control, such as the dorsolateral prefrontal cortex and insula (Heekeren et al., 2008; Ho et al., 2009). While such studies have elucidated general neural mechanisms of evidence accumulation across individuals, the neural basis of individual differences in EEA remains understudied.

Recent work investigating individual variability in EEA has linked higher EEA with activation in the inferior parietal lobe and salience network, as well as stronger functional and white matter connectivity in the dorsal frontoparietal network (Brosnan et al., 2020; Kühn et al.,

2011; Weigard et al., 2020). Despite these advances, past studies have generally focused on specific brain regions or subnetworks of the brain, which are limited in their ability to capture distributed, network-level properties of the brain that may better characterize EEA. Emerging work in neuroimaging research have demonstrated that many psychological variables are more robustly predicted by features of largescale brain networks across the connectome compared with activations in specific regions (Marek et al., 2022; Yoo et al., 2019). Indeed, a recent study leveraging multivariate predictive methods to examine the functional connectome demonstrated a strong association between EEA and flexible adaptation to cognitive demand in frontoparietal and dorsal attention networks in adolescents and adults (Weigard et al., 2024). These findings underscore the importance of examining connectivity in whole-brain connectomes to better understand individual differences in cognitive efficiency.

4.1.2 Socioeconomic Disadvantage and Neurocognitive Development

Cognition does not develop in a vacuum; the environmental context in which an individual grows up plays a key role in shaping the development of EF (Bronfenbrenner, 1994; Farah et al., 2006). A particularly salient context is socioeconomic disadvantage, encompassing limited access to economic, educational, and social resources. Socioeconomic disadvantage has been associated with lower performance on cognitive tasks supported by EEA, including working memory, attention, and general executive function (Lawson et al., 2018). Given the promise of EEA, recent work has begun to investigate how early adversity, including aspects of socioeconomic disadvantage, may impact EEA, finding that exposure to material hardship and threat is linked with lower EEA in adolescents (Vermeent, Young, DeJoseph, et al., 2024; Vermeent, Young, van Gelder, et al., 2024; Zhang et al., 2026).

Socioeconomic disadvantage may influence EF through its neurobiological underpinnings. Animal studies have long demonstrated that the brain is highly plastic and sensitive to environmental conditions (Luby et al., 2020; McEwen et al., 2016). Chronic exposure to environmental stressors, such as socioeconomic disadvantage, activates physiological responses (e.g., HPA axis and cortisol release) that, if persistent, can alter brain development (Gunnar & Quevedo, 2007; Raymond et al., 2018). On the other hand, insufficient sensory, cognitive, and social stimulation as a consequence of socioeconomic disadvantage has been shown in rodents to impair hippocampal structure and learning (Davis et al., 2017; Ivy et al., 2008). While no study has been done to specifically examine how socioeconomic disadvantage may impact functional neural correlates of EEA, studies on broader EF has revealed that lower socioeconomic status is associated with smaller prefrontal cortex volume and altered functional activity in frontal and cingulate regions, particularly within the FPN, which is critical for executive function and cognitive control (Farah, 2017; Johnson et al., 2016). Investigating the links between socioeconomic context and functional neural correlates of EEA is especially important in adolescence given the continued maturation of EF-related neural systems and the individual differences that may emerge during this sensitive developmental period (Casey et al., 2008; Luna et al., 2015).

4.1.3 The Current Study

The present study aimed to address the current gaps in literature by (1) identifying the functional neural correlates of drift rate across the whole brain (i.e., "EEA network") and (2) investigating whether individual differences in the "EEA network" are associated with concurrent exposure to socioeconomic disadvantage in a sample of adolescents traditionally underrepresented in neuroimaging research. Given the exploratory nature of the analysis, the

current study employed connectome-based predictive modeling (CPM) method, a well-established data-driven protocol for predicting behavior from whole-brain connectivity data (Shen et al., 2017). CPM has been widely applied in predicting various cognitive traits, including fluid intelligence, sustained attention, cognitive control, and working memory, in different age groups using resting-state and task-based functional connectomes (Finn et al., 2015; Kardan et al., 2022; Lv et al., 2024; Rosenberg et al., 2018). By using machine learning models with built-in within-dataset cross-validation procedures, CPM provides insights into individual-level brain-behavior associations and reduces overfitting, making it a suitable method to address the current aim. It was hypothesized that CPM would reveal an "EEA network" that involves brain regions in the frontoparietal control, dorsal attention, visual, and somatomotor networks. In addition, it was hypothesized that individual differences in the "EEA network" will be associated with experiences of socioeconomic disadvantage.

4.2 Methods

4.2.1 Sample

The current study examined a subsample of the Future of Families and Child Wellbeing Study (FFCWS), a population-based longitudinal sample of 4,898 children born in 20 large cities in the U.S. (population greater than 200,000) (Reichman et al., 2001). Participants were oversampled for non-marital births 3:1, which led to a sample of predominately unmarried and low-income families. Children and their families were followed throughout childhood, adolescence, and into young adulthood at ages 1, 3, 5, 9, 15, and 22. At age 15, a subsample of 237 adolescents participated in the Study of Adolescent to Adult Neural Development (SAND) at the University of Michigan. Our analytic sample was restricted to those with usable behavioral task performance data and EEA measure (as modeled in Chapter 2, N = 187), as well as those

who completed resting state magnetic resonance imaging (MRI) scanning with good quality functional connectivity data (N = 183), resulting in a final sample size of 154. Details of exclusion are described in sections below. Sample demographics are shown in Table 4.1. All participants provided informed consent and study protocols were approved by the University of Michigan ethics committee (IRB: HUM00167754; HUM00074392).

4.2.2 Drift Rate (i.e., Efficiency of Evidence Accumulation, EEA)

Drift rate was estimated in Chapter 2 using the drift diffusion model (DDM; Ratcliff, 1978), a type of EAM that models forced two-choice decision-making tasks. Briefly, behavioral performance data for DDM estimations were collected using an emotional-faces gender-identification task that was completed in the MRI scanner, where participants were asked to identify the gender of the actor by pressing their thumb (male) or index finger (female) on a button box. Each participant completed 100 trials split across five emotional faces (fearful, sadness, angry, happy, and neutral). Response times (RTs) and accuracy were recorded for 201 adolescents. Participants were excluded for poor performance (N = 13) and poor model fit (N = 1). DDM was estimated using the Dynamic Models of Choice package in R (Heathcote et al., 2019). Point estimates of the drift rate parameter were summarized using the medians of posterior distributions.

4.2.3 fMRI data acquisition and analysis

4.2.3.1 Image acquisition and preprocessing.

MRIs were acquired using 3T GE Discovery MR750 scanner with an 8-channel head coil. T1-weighted gradient echo images were captured prior to functional scans (TR=12ms, TE=5ms, TI=500ms, flip angle=15°, FOV=26cm, slice thickness=1.44mm, 256x192 matrix, 110

slices). Functional T2*-weighted blood oxygenation level dependent (BOLD) images were then acquired using reverse spiral sequence with 40 contiguous axial 3mm slices (TR=2000ms, TE=30ms, flip angle=90°, FOV=22cm, voxel size=3.44x3.44x3mm, ascending acquisition, parallel to AC-PC line). During resting state fMRI scan, participants were instructed to remain still and focus on a fixation cross on the screen while undergoing an 8-minute scan (235 functional volumes).

Resting state fMRI data was preprocessed using SPM12 (Wellcome Centre for Human Neuroimaging), following similar procedures reported by previous work (Michael et al., 2024). Spike detection was conducted using the Artifact Detection Tools (https://www.nitrc.org/projects/artifact_detect/). The following preprocessing steps were conducted in SPM12: segmentation into gray matter, white matter, and cerebrospinal fluid; realignment and reslicing to correct for head motion; slice timing correction; coregistration of functional and structural data; spatial normalization into standard space using a template from the Montreal Neurological Institute; and smoothing of data with a Gaussian kernel of FWHM 6.0mm. ICA-AROMA was used to remove motion-related artifacts in the data (Pruim et al., 2015). Data was then denoised in Conn Toolbox (Whitfield-Gabrieli & Nieto-Castanon, 2012), including spike regression of movement spikes identified in ART. Of the 167 participants with EEA estimations, 165 participated in resting-state fMRI scans. Additional exclusion of eleven participants with average framewise displacement > .50mm was conducted, resulting in a sample size of 154.

4.2.3.2 Functional connectivity estimations.

After preprocessing, functional connectivity (FC) matrix for the whole brain was estimated using Conn Toolbox with 400 regions of interests (ROIs) using parcellations from the

Schaefer functional atlas (Schaefer et al., 2018). FC between each pair of ROI was calculated with a Pearson's correlation coefficient, which were then Fisher-transformed into z scores. Each participant's complete connectivity matrix comprised a dimensional z-score 400 x 400 matrix, with every non-repeating edge (N = 79,600) incorporated as predictive features in the model.

4.2.4 Connectome-based predictive modeling (CPM)

To address the first aim of identifying the functional neural correlations of EEA, CPM with k-fold cross-validation method was applied (Kardan et al., 2022; Rosenberg et al., 2018; Shen et al., 2017) and analyses were performed using MATLAB version 2024a (The MathWorks Inc, 2024). Individual's FC matrices and EEA were put into CPM to develop a model predicting EEA from connectivity matrices. For each fold (e.g., 5-fold), participants were randomly divided into training (e.g., 80%) and testing (e.g., 20%) sets. During training, connectivity matrices from the training set were first used to identify functional connections that are significantly related to EEA with partial correlations adjusting for average framewise displacement following procedure from previous studies (e.g., Rosenberg et al., 2017). This resulted in both positive (i.e., "fast EEA network") and negative (i.e., "slow EEA network") predictive networks, where connectivity edges are positively or negatively correlated with EEA at a pre-specified significant p-value threshold (e.g., $p < .05$, .01, or .001). For each individual, a summary feature was then calculated by summing the significant edge weights in both positive and negative networks (i.e., positive edge mean – negative edge mean). Next, coefficients were extracted from a robust linear model using the summary feature to predict EEA in the training set, which was then applied in the testing phase.

With the hold-out participants for testing, summary features were first created using the same positive/negative edge masks from training. Predicted EEA values were then generated

using the same linear coefficients from testing. The overall CPM model was considered as significant if the observed EEA was significantly correlated with the predicted EEA, with higher correlation indicating better fit. Importantly, overall CPM model performance should be distinguished from the significance of the edges, which are, by definition, significantly associated with EEA. However, these associations may not generalize to out-of-sample predictions, resulting in poor predictive performance.

To identify the best performing CPM model, several combinations of k-fold method (5-fold and 10-fold) and p-value thresholds (.05, .01, and .001) were tested. Once the model was identified, the final positive and negative networks were defined as edges that were included in the positive or negative network across at least 50% of the folds. Additional sensitivity analysis was conducted without framewise displacement values included in the training of the CPM model, but were instead covaried out in the model evaluation correlation between predicted and observed EEA.

4.2.5 Associations with socioeconomic disadvantage

To address aim 2, the association between socioeconomic disadvantage and CPM network strength was examined using bivariate correlations and linear regression models with demographic covariates. Socioeconomic disadvantage was measured as household poverty ratio, which is the ratio of total household income to the official poverty thresholds established by the U.S. Census Bureau. The FFCWS poverty ratio measure at the age 15 wave is computed using the thresholds from the year prior to when the interview was conducted. Higher poverty ratio indicates higher household income relative to poverty threshold (i.e., lower poverty). CPM network strength was computed as the sum of average connectivity values from the positive and negative networks (positive FC – negative FC). Correlations for the overall network, as well as

separately for the positive and negative networks, were examined. Following the bivariate correlations, linear regression models were conducted with the same covariates as Chapter 2: puberty stage, sex (0 = female, 1 = male), ethnoracial identity, and family structure (biological parents cohabitating at baseline = 1 or not = 0).

Additionally, Aim 2 re-estimated the best performing CPM model from Aim 1 with household poverty ratio added as a covariate in edge selection to evaluate whether the brain-behavior association was partially explained by SES. A hypergeometric test was conducted to compare whether the overlap between SES-included versus not-included networks were statistically significant following previous work (Kardan et al., 2022). Specifically, the probability of the overlap in edges selected across two networks being due to chance was computed using the hypergeometric cumulative distribution function in MATLAB. The p-value for significant overlap was calculated as 1-probability, where a significant p-value indicates significant overlap.

4.3 Results

4.3.1 Aim 1: EEA CPM network models

Aim 1 tested multiple combinations of k-folds and p-value thresholds for edge selection, results are reported in Table 4.2. The best performing overall CPM model used 10-fold with p-value threshold of .001, though the model predicted drift rate was not significantly associated with the observed drift rate (r = .14, p = .091). The CPM model resulted in 59 significant edges that were included in at least 50% of folds, including 24 positive network (i.e., "fast EEA" network, where edges are positively associated with drift rate) edges and 35 negative network (i.e., "slow EEA" network, where edges are negatively associated with drift rate) edges. Sensitivity analysis without framewise displacement in the edge selection step yielded a

significant CPM model with the same 10-fold and $p = .001$ parameters ($r = .17$, $p = .037$), though the model predicted drift rate was no longer significantly associated with observed drift rate after adjusting for head motion ($r = .14$, $p = .095$), consistent with our main CPM model. Notably, drift rate and head motion were not significantly correlated in the sample ($r = -.13$, $p = .119$). Although the best performing CPM model was overall not significant, the anatomy of the selected network is described below for the purpose of the dissertation, given that the model selected edges were, by design, significantly associated with EEA.

The functional anatomy of the CPM network is illustrated in Figure 4.1. In the positive ("fast EEA") network, where higher functional connectivity values were associated with higher drift rate, selected edges primarily emerged in between-network connections of the visual network (total N = 15, 62.5%), specifically with frontoparietal control network (N = 5, 21%), somatomotor network (N = 4, 16.7%), and the default mode network (N = 4, 16.7%). A small cluster of connections were also present in between-network connections of the control network and other networks (total N = 8, 33%) and the dorsal attention network with other networks (total N = 7, 29.2%). In the negative ("slow EEA") network, where lower functional connectivity values were associated with higher drift rate, edges were concentrated within default mode network (N = 8, 22.9% of the negative network). Significant contributions of between-network connections for the salience/ventral attention network (N = 12, 34.3%) and the limbic network (N = 10, 28.57%) were observed. A small cluster of edges also emerged between somatomotor, dorsal attention, and salience/ventral attention networks (Somatomotor-Dorsal Attention N = 3, Somatomotor-Salience N = 4, Dorsal Attention-Salience N = 4). When looking at the difference between positive and negative networks, similar patterns were observed as reported above (Figure 4.1). Positive ("fast EEA") network involves more edges between visual network with

control, dorsal attention, default mode, and somatomotor networks, whereas negative ("slow EEA") network showed more edges within default mode network, and between salience/ventral attention, somatomotor, and dorsal attention networks.

4.3.2 Aim 2: Associations with Socioeconomic Status (SES)

Aim 2 first examined the associations between CPM network strengths and household poverty ratio as a measure of family SES, measured at the same time point. Bivariate correlations showed no significant associations between CPM network strengths and family SES (combined network: $r = .14$, $p = .094$; positive network: $r = .11$, $p = .184$; negative network: $r = -.14$, $p = .096$). In linear regression models adjusting for demographic covariates (Table 4.3), there was a significant association between poverty ratio and combined network strength ($\beta = .14$, $p = .028$), such that higher poverty ratio (i.e., higher household income, adjusting for poverty threshold) is associated with higher CPM network strength. This was driven by a significant link with negative ("slow EEA") network strength ($\beta = -.16$, $p = .032$), such that higher poverty ratio was associated with lower negative network strength, but not with positive network strength ($\beta = .09$, $p = .137$).

CPM analysis was then repeated with household poverty ratio as a covariate in the edge selection process ("SES-CPM model"), using the parameters from the best performing model from Aim 1 (i.e., 10-fold, p = .001 threshold). The SES-CPM model performed worse ($r = .06$, $p = .479$) than the original CPM model, though neither were significant. The SES-CPM model yielded 53 significant edges, with 24 positive edges and 29 negative edges. There was significant overlap in the edges selected in both networks (N = 45, 76.27% of the original CPM network, hypergeometric $p < .001$).

4.4 Discussion

The current study sought to identify functional connectivity patterns associated with individual differences in drift rate, which is hypothesized to be driven by the EEA factor. We also aimed to examine whether these connectivity patterns were associated with family socioeconomic disadvantage. Although the best-performing CPM model did not significantly predict drift rate after accounting for head motion, preliminary evidence suggest that family socioeconomic disadvantage, indexed by household poverty ratio, was associated with the average strength of connectivity edges selected by the model. Together, this study provided an initial characterization of functional connectivity correlates of EEA in adolescence while also highlighting the methodological challenges of identifying robust brain-based predictors of cognitive efficiency in modestly sized developmental samples.

While a CPM network with significant prediction accuracy of drift rate (i.e., where the predicted drift rate was significantly associated with the observed drift rate) was not identified after adjusting for in-scanner head motion, the null finding was not surprising. First, CPM is a high-dimensional predictive method that benefits from substantially larger samples than the current study (e.g., with 300 or more participants in Xiao et al. (2024) or with the Adolescent Brain and Cognitive Development (ABCD) study; Garavan et al., 2018). Although some studies have used smaller samples similar to our study (e.g., Lv et al., 2024), their parcellation sizes were also smaller (e.g., with Shen 268 atlas). With the current 400 parcellation atlas, which yielded 79,600 edges input into the CPM model, our sample size of 154 participants likely resulted in limited statistical power to detect the brain-behavior relationship.

Consistent with this limitation, the best-performing CPM model emerged under the most stringent feature-selection p-value threshold ($p < .001$), suggesting that only a relatively small

subset of edges showed associations with drift rate that were large enough to be detected. While it is also possible that drift rate, which represents EEA as a higher-order executive functioning factor, is a specialized cognitive process and thus relies on a small set of brain functions, conclusions cannot be drawn from the current study. Similarly, in a sensitivity analysis without head motion as a covariate in the edge selection process, the same CPM model performed with significant prediction accuracy, though the association was also attenuated after adjusting for head motion during model evaluation. Given that head motion was not significantly associated with drift rate, the loss of significance was unlikely to be due to a simple confounding relationship between motion and drift rate. These findings collectively support the interpretation that our power to detect significant effects was likely limited by the sample size.

In Aim 2, exploratory analyses examined whether the connectivity of selected edges were associated with socioeconomic disadvantage in adolescent households, under the pretense that the network did not significantly predict drift rate. Although bivariate correlations were not significant, regression models adjusting for demographic characteristics indicated that higher household poverty ratio, which reflects greater economic resources relative to the federal poverty threshold, was associated with stronger overall CPM network strength. This association was primarily driven by lower connectivity strength of the negative edges. These findings are broadly consistent with literature suggesting that socioeconomic disadvantage is associated with alterations in large-scale functional connectivity networks implicated in cognitive functioning (Farah et al., 2006; Rosen et al., 2018; Shen et al., 2018). However, because the overarching CPM model did not significantly predict drift rate and therefore was did not provide a robust representation of the neural architecture underlying EEA, these results should only be interpreted

as preliminary evidence regarding associations between socioeconomic context and connectivity patterns rather than conclusions.

In addition, CPM analysis incorporating household poverty ratio as a covariate in edge selection process found substantial overlap with the original network despite worse model performance. This finding could suggest that the connectivity features associated with drift rate were not entirely attributable to shared variance with family socioeconomic disadvantage. While the worse model performance could reflect socioeconomic disadvantage explaining part of the brain-behavior association, neither CPM models were predictive of drift rate, limiting our ability to interpret the changes. The model performance could also reflect a greater lack of statistical power in detecting brain-EEA relationship after adding in another covariate. Nevertheless, the observed overlap provides a useful foundation for future work investigating how environmental experiences shape the neural systems supporting evidence accumulation and decision making.

Several limitations should be considered when interpreting the present findings. As mentioned previously, the sample size was modest relative to the dimensionality of the connectivity data and the CPM method. Future studies would benefit from larger samples, including the broader SAND-21 cohort, as described in Chapter 3 with roughly 350 participants, or large-scale developmental datasets such as the ABCD Study, to improve statistical power and model stability. Second, connectivity was estimated using a granular 400-parcel atlas, which substantially increased the number of potential features that could be associated with EEA. Future analyses using smaller parcellation schemes may improve signal detection while maintaining interpretability, though researchers should be mindful of balancing reduced spatial specificity. Third, drift rate was derived from a single behavioral task. Because EEA reflects a domain-general cognitive process, the drift rate from the current study only serves as an indicator

of the EEA factor. Future work may benefit from constructing latent EEA measures across multiple tasks to strengthen behavioral reliability. Enhancing power from the measurement perspectives may improve the ability to have a better prediction model. Finally, because the primary CPM model did not demonstrate significant predictive performance, the identified connectivity architecture should be considered descriptive and hypothesis-generating rather than a validated neural biomarker of EEA. Accordingly, interpretations regarding associations between socioeconomic context and EEA-related connectivity should remain tentative until replicated in larger independent samples. No out-of-sample validations was conducted following typical CPM procedure given the null model. An alternative future direction could consider identifying the primary "EEA network" in a larger adolescent-based sample (e.g., the ABCD study) and use the current adolescent sample as external validation instead, while keeping in mind the sample demographic and task differences. The SAND sample still serves as a meaningful tool for investigating the EEA network, and particularly the associations with socioeconomic status, given the predominantly low-income demographic.

In summary, the present study represents an initial effort to characterize the functional connectivity architecture associated with drift rate in adolescence using a predictive whole-brain connectome framework. Although we were unable to identify a connectivity model that robustly predicted drift rate, the observed connectivity patterns suggest that EEA may depend on coordinated interactions among executive control systems with visual and default mode networks. Preliminary evidence suggest that family socioeconomic circumstances are associated with the strength of these connectivity patterns, highlighting the potential relevance of environmental context for the neural systems supporting cognitive efficiency. More broadly, these findings contribute to a growing literature suggesting that evidence accumulation emerges

from distributed large-scale network interactions rather than isolated neural regions. Future studies with larger samples, more reliable behavioral measures, and independent validation datasets will be essential for determining whether these connectivity patterns constitute a robust neural signature of EEA and whether they represent one pathway through which socioeconomic context shape neurocognitive development.

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4.6 Tables

Table 4.1. Sample Demographics & Distribution of Main Variables

Variables	Group	Mean (SD)	Count (Percentage)
Pubertal Stage	-	3.29 (0.59)	-
Sex	Female (0)	-	88 (57.14%)
	Male (1)	-	66 (42.86%)
Race	Black	-	117 (75.97%)
	White	-	20 (12.99%)
	Hispanic/Latino	-	8 (5.19%)
	Other/Multiracial	-	9 (5.84%)
Household poverty ratio	-	2.08 (2.21)	-
Family structure	Single parent (0)	-	97 (62.99%)
	Not single parent (1)	-	57 (37.01%)
Drift rate (EEA)	-	2.93 (0.90)	-
Average Framewise Displacement	-	0.21 (0.11)	-

Table 4.2. CPM Model Performance with Different k-folds and p-thresholds

k-fold	p-value threshold	Correlation* r	Correlation* p-value
5	.05	.00	.991
5	.01	-.05	.549
5	.001	-.01	.945
10	.05	.02	.797
10	.01	-.04	.584
10	.001	.14	.091

*: Correlation between predicted drift rate and observed drift rate

Table 4.3. Linear Regression Models of SES Predicting Drift Rate Network Strength

Predictors	*b*	*β*	*SE*	*p-value*
Combined Network Strength				
Household poverty ratio	0.01	0.14	0.00	0.028
Puberty Stage	0.01	0.05	0.02	0.541
Sex	-0.01	-0.03	0.02	0.751
Race: White	-0.00	-0.01	0.02	0.862
Race: Hispanic	-0.06	-0.12	0.05	0.175
Race: Other	0.04	0.08	0.05	0.412
Family structure	-0.02	-0.08	0.02	0.349
Positive Network Strength ("Fast EEA" Network)				
Household poverty ratio	0.00	0.09	0.00	0.137
Puberty Stage	-0.00	-0.05	0.01	0.641
Sex	-0.00	-0.00	0.01	0.969
Race: White	0.01	0.05	0.01	0.463
Race: Hispanic	-0.02	-0.05	0.03	0.580
Race: Other	0.02	0.08	0.03	0.409
Family structure	-0.00	-0.03	0.01	0.751
Negative Network Strength ("Slow EEA" Network)				
Household poverty ratio	-0.00	-0.16	0.00	0.032
Puberty Stage	-0.02	-0.14	0.01	0.094
Sex	0.01	0.05	0.01	0.583
Race: White	0.01	0.07	0.01	0.287
Race: Hispanic	0.05	0.16	0.03	0.060
Race: Other	-0.02	-0.06	0.02	0.476
Family structure	0.02	0.11	0.01	0.158

4.7 Figures

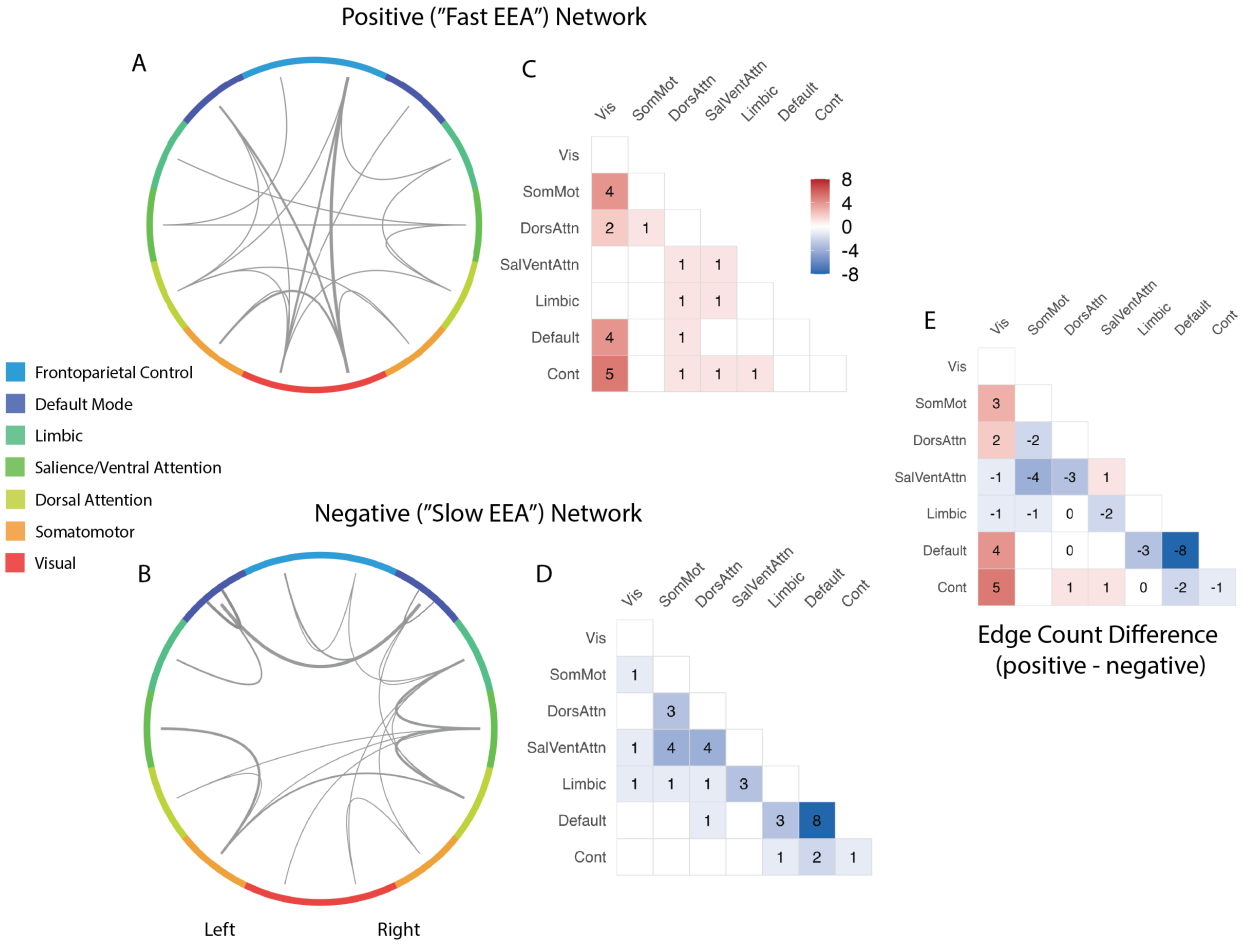

Figure 4.1. Functional Network Anatomy of the Best Fitting EEA CPM Model.

Panel A shows the positive CPM network ("fast EEA" network), in which greater functional connectivity was associated with higher drift rate. Panel B shows the negative CPM network ("slow EEA" network), in which greater functional connectivity was associated with lower drift rate. Corresponding heatmaps (collapsed across hemispheres) display the edge counts for positive network (Panel C) and negative network (Panel D), spread across seven functional networks: visual (Vis), somatomotor (SomMot), dorsal attention (DorsAttn), salience/ventral attention (SalVentAttn), limbic, default mode (Default), and frontoparietal control (Cont). Panel E shows the difference in edge counts between the positive and negative networks (positive minus negative), such that red values indicate relatively greater representation in the positive network and blue values indicate relatively greater representation in the negative network. Overall, positive-network edges were concentrated primarily in connections involving the visual network, whereas negative-network edges were more prominent within the default mode network

and between default, limbic, salience/ventral attention, dorsal attention, and somatomotor networks.

Chapter 5 General Discussion

The multifaceted socioeconomic context in which an individual grows up plays an important role in shaping the development of executive functioning (EF). Despite extensive research demonstrating poverty as a major risk factor for healthy EF development, gaps remain in current literature regarding quality EF measurement, socioeconomic context characterization, and the mechanisms through which contextual experiences become biologically embedded. The current dissertation sought to address these limitations through a series of three empirical studies that integrated computational modeling of cognition with longitudinal developmental data from a 22-year birth-cohort sample. These studies represent some of the first investigations of how socioeconomic contexts shape cognitive efficiency, as indexed by drift rate, a computational measure of higher-order cognitive efficiency from the drift diffusion model (DDM), and its functional neural correlates across development. By applying computational models of cognition to questions traditionally examined using conventional EF measures, this dissertation provides a novel perspective on the neurocognitive pathways through which socioeconomic experiences may influence development. Collectively, the results from this dissertation advance our understanding of how complex socioeconomic contexts shape neurocognitive development while demonstrating the utility of computational approaches for developmental cognitive neuroscience research.

5.1 Chapter summary

5.1.1 Chapter 2: childhood material hardship, drift rate, and attentional difficulties in adolescence

Chapter 2 examined longitudinal associations between childhood material hardship exposure and adolescent drift rate utilizing prospective data spanning 15-17 years. Findings revealed that greater cumulative household material hardship exposure in childhood, above and beyond experiences of violence exposure and social deprivation, was associated with lower drift rate (i.e., less efficient information processing) in adolescence, which in turn, is associated with greater concurrent self-reported attentional difficulties. Growth curve analysis with material hardship across four waves of data revealed that initial levels of hardship, rather than changes of hardship over time, was associated with adolescent drift rate. Together, these findings suggest that lived experiences of socioeconomic disadvantage during childhood may have long-lasting implications for EF development in adolescence. Notably, these associations were only apparent when examining drift rate and were not observed using conventional behavioral measures such as average response time and accuracy, highlighting the value of computational modeling in identifying specific cognitive processes that may be influenced by socioeconomic disadvantage.

5.1.2 Chapter 3: adolescent neighborhood opportunity, family poverty, and young adult drift rate

Chapter 3 shifted the focus from household-level disadvantage to neighborhood-level opportunity and from adolescent to young adult cognitive efficiency. Neighborhood opportunity was characterized using census-tract level indicators reflecting educational, socioeconomic, and health and environmental resources. Findings indicated that greater neighborhood opportunity during adolescence was associated with higher drift rate (i.e., more efficient processing) years

later in young adulthood. Interestingly, analyses revealed substantial overlap between family poverty and neighborhood opportunity, such that families experiencing greater economic disadvantage were also more likely to reside in neighborhoods with fewer resources and opportunities. While this finding was not surprising and likely reflects broader structural inequalities, it limited the ability to distinguish unique family- and neighborhood-level effects. When family poverty and neighborhood opportunity were included simultaneously, neither independently predicted young adult drift rate. Exploratory analysis further demonstrated that the neighborhood's contemporary resources were highly correlated with its historical ability to support upwards economic mobility, suggesting substantial continuity in neighborhood-level opportunities across time. Taken together, these findings extend on the results of Chapter 2 by demonstrating that broader contextual resources during adolescence are associated with cognitive efficiency in young adulthood. However, the effects are not distinguishable from family poverty in the sample, highlighting the challenge of disentangling interconnected socioeconomic conditions that operate across multiple levels of the environment.

5.1.3 Chapter 4: functional neural correlates of EEA and links with socioeconomic disadvantage

Chapter 4 investigated the functional neural correlates of drift rate through connectome-based predictive modeling (CPM) method using adolescent resting-state functional connectomes. A network that was overall significantly predictive of drift rate was not identified, likely due to limited sample size. However, closer examination of the specific connectivity edges in this preliminary network revealed a functional architecture associated with drift rate that primarily involved the visual, somatomotor, default mode, and frontoparietal control networks. The average strength of connectivity, particularly from edges that were negatively associated with

drift rate, was associated with household poverty ratio, such that higher family income was linked with greater connectivity in the network. Although preliminary, these findings suggest that cognitive efficiency may be supported by large-scale neural systems involved in visual processing, motor responding, executive control, and internally directed cognition, and that the expression of these systems may be sensitive to socioeconomic experiences. More broadly, the results highlight both the promise and challenges of identifying neural mechanisms underlying cognitive efficiency. While larger samples will be necessary to establish robust brain-behavior associations, this study represents an important first step toward understanding the neural architecture through which socioeconomic contexts may influence EF.

5.2 Integrative themes

5.2.1 Socioeconomic context shapes cognitive efficiency

A central finding emerging across the studies in this dissertation, particularly from Chapters 2 and 3, is that cognitive efficiency appears to be shaped by diverse aspects of the socioeconomic environment, across both disadvantage and opportunity, as well as both proximal household experiences and broader neighborhood-level contexts. These findings are broadly consistent with ecological systems theory (Bronfenbrenner, 1994), which proposes that development is shaped by multiple nested environmental systems ranging from immediate family environments to broader community and societal contexts. From this perspective, EF development is not determined by a single environmental exposure but rather emerges through the cumulative influence of resources, opportunities, and constraints operating across developmental contexts. The dissertation findings suggest that both proximal experiences of hardship within the household (Chapter 2) and broader neighborhood opportunities (Chapter 3) may contribute to the development of cognitive efficiency over time.

Chapter 2 further demonstrated that material hardship was more strongly associated with drift rate than experiences of violence exposure or social deprivation. Although adverse experiences often co-occur, these findings suggest that experiences of extreme poverty may be a particularly salient factor that influences EF development. This interpretation is consistent with emerging evidence suggesting that the direct consequences of resource deprivation, including food insecurity, housing instability, and unmet basic needs, may have implications for cognitive and neurobiological development (Hardi et al., 2022; Schenck-Fontaine & Ryan, 2022).

Chapter 4 provided an initial investigation into functional neural mechanisms underlying these associations. Although the CPM model was not significant overall and the findings should be interpreted cautiously, they offer preliminary evidence that socioeconomic context may shape cognitive efficiency through alterations in supporting functional brain architecture. Overall, the results of this dissertation suggest that improving socioeconomic conditions, whether through reducing hardship or increasing access to opportunities and resources, may promote EF development. These findings align with growing evidence from, and provides additional support for, intervention studies demonstrating that economic supports and resource-enhancing programs can improve developmental outcomes across domains, though degree of effectiveness remain a subject of research (Fernald et al., 2026; Noble et al., 2025; Troller-Renfree et al., 2022).

5.2.2 Longitudinal associations, developmental timing, and large-scale developmental datasets

Importantly, the associations observed in this dissertation emerged across substantial developmental intervals. In Chapter 2, material hardship measured during childhood (ages one through nine) predicted cognitive efficiency in adolescents aged 15-17. In Chapter 3, neighborhood opportunity during adolescence predicted cognitive efficiency seven to eight years later in young adulthood. Although the observed effect sizes were modest in the studies (βs

around .12 - .17), they are noteworthy given the long developmental periods involved. These findings underscore the importance of adopting longitudinal perspectives when investigating environmental influences on EF and suggest that socioeconomic experiences may exert lasting effects across development.

The findings are also broadly consistent with theories proposing that contextual influences may exert particularly strong effects during periods of rapid neurodevelopment, such as childhood and adolescence, both of which are characterized by substantial maturation of neural systems supporting EF (Fuhrmann et al., 2015; Luna et al., 2015; Nelson & Gabard-Durnam, 2020). Therefore, experiences of poverty and supportive environments during these developmental periods may have long lasting consequences for later EF. At the same time, Chapters 2 and 3 suggest that impact from socioeconomic contexts may not be restricted to a single developmental window, though specific sensitive periods were not tested. Future studies incorporating repeated assessments of EF and socioeconomic conditions across childhood, adolescence, and adulthood will be well-suited for providing answers to these questions.

The longitudinal findings from Chapters 2 and 3 also underscore the value of longitudinal developmental datasets for understanding how socioeconomic experiences shape neurocognitive functioning across time. The ability to investigate these questions is largely attributable to the richness of longitudinal studies like the FFCWS and SAND. By prospectively assessing family and neighborhood conditions across multiple time points, these studies provide a unique opportunity to examine how environmental experiences unfold over development. Compared to retrospective reports, prospective longitudinal data allow for more precise characterization of the timing, duration, and accumulation of environmental exposures. Importantly, the present findings should not be interpreted as causal, even with careful covariate adjustments and longitudinal

study designs. Nevertheless, longitudinal approaches provide stronger evidence regarding developmental timing than cross-sectional designs and allow researchers to generate more informed interpretations regarding how environmental experiences may shape neurocognitive development over time.

5.2.3 The utility of computational models of cognition in developmental cognitive neuroscience research

Across all three studies, this dissertation showcased the value of computational models of cognition for developmental cognitive neuroscience research investigating how early life experiences may shape neurocognition. Although DDM has been used in cognitive psychology for the past four decades, much work has focused on using drift rate to evaluate task or stimuli effects, with much less work on individual differences of drift rate, and the underlying EEA factor, and how the socioeconomic environments shape individual differences in EEA across development. To our knowledge, Chapters 2 and 3 are among the first studies to investigate longitudinal associations between socioeconomic context and cognitive efficiency indexed through drift rate. These findings therefore extend the EEA literature beyond its focus on decision-making and psychopathology (Weigard & Sripada, 2021) and demonstrate its relevance for understanding environmental influences on neurocognitive development.

Computational approaches such as the DDM provide a means of decomposing observed behavior into latent and specific cognitive processes, thus offering more precise insight into the mechanisms underlying performance. Chapter 2 provided a compelling example where the associations with material hardship and attentional problems were only observed for drift rate, but not present with average response time and accuracy measures. In Chapter 3, while neighborhood opportunity was associated with average accuracy, DDM clarified that the effect

was driven by drift rate rather than alternative processes such as response bias or caution. These findings illustrate how computational modeling can provide mechanistic specificity and reliability in identifying associations with the socioeconomic context that is often unavailable when relying solely on response times and accuracy measures. This distinction is particularly important for developmental research, where understanding how environmental experiences shape specific cognitive processes may be more informative than examining overall task performance alone. More broadly, computational modeling represents a conceptual shift from viewing EF as simple task performance towards understanding the cognitive processes that give rise to behavior.

The present dissertation also highlights the utility of applying computational models to existing longitudinal datasets such as the FFCWS/SAND dataset. By leveraging a task originally designed to assess implicit emotion processing, it was possible for studies in this dissertation to derive meaningful measures of cognitive efficiency that otherwise would not have been available. Such approaches open new opportunities for studying EF in large-scale developmental cohorts where traditional EF tasks may not have been administered. Of course, there are considerable limitations with this approach as well (described in Limitations sections below), but nonetheless, computational models may still be a useful avenue to explore.

Furthermore, computational approaches facilitate comparisons across studies and datasets by providing common latent constructs (e.g., EEA). For example, results in Chapter 2 were compared with that of another study looking at individual differences in EEA with exposure to violence, neglect, and material deprivation (Vermeent et al., 2024). As more developmental studies incorporate computational modeling, it may become increasingly possible to examine developmental changes in cognitive efficiency longitudinally and to compare findings across

diverse samples and contexts. Future work may also extend beyond drift diffusion models to examine how socioeconomic experiences influence other higher-order processes, such as reinforcement learning and value-based decision-making.

5.2.4 Methods & challenges to characterizing the socioeconomic context

The studies in this dissertation also highlight the importance and challenges of characterizing the socioeconomic environment. Traditional measures of the socioeconomic contexts often focus on household income (or income-based measures like income-to-needs ratio) or self-report measures of the environment (e.g., "Is your neighborhood safe?"). While these measures provide important information, they may not fully capture the complexity of the lived experiences of children. Chapter 2 highlighted material hardship as a complementary measure to income-based measures of poverty, capturing the direct experience of unmet needs, including difficulties obtaining food, housing, utilities, and other necessities. Beyond self-report measures of the environment, Chapter 3 demonstrated the utility of objective neighborhood-level indicators in characterizing broader developmental contexts. Measures such as the Child Opportunity Index capture multiple dimensions of neighborhood resources and highlight the importance of considering opportunities and resources in addition to deprivation. Taken together, the findings suggest that socioeconomic context should be conceptualized as a multidimensional construct encompassing both risks and resources operating across multiple ecological levels.

At the same time, the dissertation highlights several challenges inherent in studying socioeconomic context. One major challenge involves disentangling the unique effects of different contextual factors. This was especially salient in Chapter 3, where the neighborhood opportunity measures were moderately correlated with family income, therefore limiting our ability to fully differentiate between unique effects contributing to cognitive efficiency. This

challenge reflects the reality that socioeconomic experiences rarely occur in isolation. Families with greater financial resources often reside in neighborhoods with more opportunities, while families experiencing economic hardship frequently encounter multiple contextual disadvantages simultaneously (Acevedo-Garcia et al., 2020; Chetty et al., 2018; Riley, 2018). Relatedly, structural inequalities must also be considered when interpreting socioeconomic effects. Particularly relevant for the demographic composition of the FFCWS/SAND sample, structural inequalities have likely contributed to imbalanced distributions of neighborhood resources, educational opportunities, and economic mobility (Acevedo-Garcia et al., 2020; Riley, 2018; Wig et al., 2025). While attempts can be made to control for these overlapping effects by conducting regression analyses with covariates, understanding how these structural forces shape developmental outcomes remains an important direction for future research.

Finally, the availability and consistency of measures across developmental periods also limits the type of research questions one can ask. Although longitudinal datasets provide substantial advantages, measures often change across waves or become available only during specific time periods. For example, material hardship indicators in Chapter 2 were restricted to items that were consistently assessed across multiple waves. Similarly, in Chapter 3, neighborhood opportunity indices were only available during 2012-2023, limiting the ability to examine developmental trajectories of neighborhood conditions. Continued efforts to develop harmonized longitudinal measures of socioeconomic context will be critical for advancing developmental research in this area.

5.3 Limitations and future directions

5.3.1 Drift rate, interpretations of EEA, and longitudinal changes

An important consideration across all three studies concerns the distinction between task-specific drift rate and the broader construct of efficiency of evidence accumulation (EEA). Although drift rate is theorized to be driven by EEA, the parameter estimates used throughout this dissertation were derived from a single behavioral task. This distinction is important because EEA is conceptualized as a domain-general neurocognitive construct that contributes to performance across a wide range of EF tasks (Weigard et al., 2026; Weigard & Sripada, 2021). A single-task drift rate estimate inevitably contains task-specific variance and therefore cannot fully be equivalent to the broader construct. Throughout the dissertation, interpretations were therefore framed in terms of drift rate and cognitive efficiency rather than EEA itself. At the same time, past work has demonstrated strong psychometric properties for EEA and substantial associations between single-task drift rate and latent EEA factors (Löffler et al., 2024; Schubert et al., 2016). These findings suggest that the present measures capture meaningful variance related to broader cognitive efficiency, allowing us to make inferences about EEA. Nevertheless, future studies should seek to construct latent EEA factors using multiple tasks to provide stronger tests of developmental hypotheses.

At the same time, the interpretation of drift rate and EEA factor warrants considerations, particularly in the context of broader debates regarding the nature and measurement of EF. As described in the Introduction, although EF has been extensively studied in developmental and cognitive psychology, the construct remains challenging to define and measure precisely. Seminal work has proposed EF as separable but interrelated components of unity-yet-diversity model (Miyake et al., 2000), as well as a common top-down process that reflect the ability to actively maintain goal-directed behavior (Diamond, 2013; Friedman & Miyake, 2017). These frameworks have advanced our understanding of EF as a meaningful construct with trait-like

individual differences, while also highlighting longstanding challenges, including task impurity, as well as low convergence and specificity among conventional EF measures (Morrison & Grammer, 2016; Nigg, 2017). With this in mind, computational approaches such as the DDM, as well as the broader Evidence Accumulation Models (Lee & Cummins, 2004), offer a useful complement to traditional frameworks by identifying a common latent component that give rise to observed behavior implicated in EF-related tasks.

Throughout this dissertation, drift rate was used as an index of cognitive efficiency and interpreted within the broader EEA framework as related to EF. However, the precise nature of EEA and its relation to EF remain active research debates. The current dissertation adopts the view that EEA may reflect the efficiency with which individuals selectively amplify and accumulate goal-relevant information while minimizing the influence of goal-irrelevant information during decision-making (Weigard et al., 2026; Weigard & Sripada, 2021). This perspective aligns closely with theories of EF emphasizing a unified, overarching factor that supports the active maintenance of goals and top-down prioritization of goal-relevant representations (Botvinick et al., 2001; Cohen, 2017; Friedman & Miyake, 2017). From this viewpoint, EEA may represent a domain-general mechanism supporting performance across diverse cognitive demands rather than any single EF domain. At the same time, alternative perspective in the literature interprets drift rate as pure processing speed, finding evidence that a common speed of information uptake factor accounts for substantial variance in drift rates across cognitive tasks (Frischkorn & Schubert, 2018; Hedge et al., 2018; Löffler et al., 2024). While emerging evidence argues against this view by showing evidence of drift rate being associated more with the quality of information processing rather than quantity or speed (Molloy et al.,

2026; Weigard et al., 2026), more research needs to be done to fully disentangle the mechanistic basis of EEA and its relationship to EF.

The present dissertation is not positioned to clarify these competing theoretical interpretations, but nonetheless, contributes to a growing literature demonstrating that drift rate, and potentially broader constructs such as EEA, is meaningfully associated with developmental experiences, behavioral outcomes, and functional brain organization. Across all three studies, EEA functioned as a common computational framework through which environmental experiences could be linked to both behavioral and neural phenotypes. In this sense, cognitive efficiency may represent an important intermediate mechanism through which environmental experiences become embedded in neurodevelopment. Future studies aiming to refine and validate computational measures of cognitive efficiency may therefore provide a valuable bridge connecting socioeconomic context, brain development, and psychological functioning across adolescence and early adulthood.

In addition, although the SAND study includes the same faces-genders decision-making task during both adolescent and young adult waves, the overlap of participants with drift rate estimates at both time points was relatively small. Therefore, neither controling for cognitive efficiency in adolescence when investigating Chapter 3, nor compare changes from adolescence to young adulthood was possible. Future studies with larger longitudinal samples will be better positioned to investigate developmental trajectories of cognitive efficiency and examine whether socioeconomic contexts influence rates of EF growth or decline across development.

5.3.2 Mechanisms underlying associations between socioeconomic contexts and cognitive efficiency

A major contribution of this dissertation to the literature is the identification of longitudinal associations between socioeconomic contexts and cognitive efficiency. However, the mechanisms underlying these associations remain incompletely understood. Several plausible pathways warrant future investigation.

5.3.2.1 Functional and structural neural mechanisms.

One possible pathway through which contextual factors may shape cognitive efficiency, and executive functions broadly, is through changes in the functional and structural neural architecture. Experiences associated with socioeconomic disadvantage may repeatedly activate biological stress systems such as the hypothalamic-pituitary-adrenal (HPA) axis (Blair & Raver, 2012; Evans et al., 2007; Lupien et al., 2009). Over time, chronic activation of these systems may contribute to allostatic load and influence the development of neural systems supporting executive functioning (Evans et al., 2007; Juster et al., 2010; McEwen & Gianaros, 2010). Research has suggested that chronic stress may affect brain regions involved in cognitive control and information processing, including the prefrontal cortex, anterior cingulate cortex, hippocampus, and associated large-scale functional networks, which may impact cognitive efficiency (Hackman et al., 2010; Lupien et al., 2009). Although the present dissertation did not directly test biological stress pathways, this framework provides one plausible explanation for how socioeconomic experiences become embedded within neurocognitive systems.

Chapter 4 represented an initial attempt to identify the functional neural architecture underlying cognitive efficiency. While findings were preliminary, several identified neural systems overlapped with prior work examining EEA-related functional connectivity. Future studies should seek to replicate and extend these findings in larger neuroimaging samples (e.g., with the larger young adult SAND wave). In addition, investigations of multimodal measures of

brain organization such as structural brain development, white matter connectivity, or task-related activation patterns may provide further insight into the neural mechanisms linking socioeconomic context to cognitive efficiency.

5.3.2.2 Cognitive stimulation in the environment.

As discussed in Chapter 2, another potential pathway involves variation in cognitive stimulation across environments. Socioeconomic contexts may differ in opportunities for learning, exploration, and cognitive engagement. Children growing up in more enriched environments may encounter greater exposure to educational materials, cognitively stimulating activities, and supportive learning experiences that facilitate EF development (Rakesh et al., 2024; Vygotsky, 1978). Future studies with direct measures of environmental stimulation, such as quality of the home environments and classrooms, parental engagement, and availability of stimulating toys, may be able to assess this pathway directly. Relatedly, the availability of opportunities may not be sufficient on its own. Children and adolescents must also engage with available resources for those opportunities to influence development. For example, high-quality schools may provide substantial educational opportunities, but the benefits may depend on students' engagement, attendance, and participation. Future work incorporating indicators such as academic engagement or school connectedness may help clarify how opportunities are translated into developmental outcomes.

5.3.2.3 Parenting and Family Processes.

Broader contextual factors, such as neighborhood resources, may also influence cognitive efficiency through more proximal family processes. Neighborhood opportunities may affect parenting behaviors by shaping parental stress (Ceballo & McLoyd, 2002; Cuellar et al., 2015; Hyde et al., 2020). Families residing in higher-opportunity neighborhoods may experience fewer

chronic stressors and greater access to supports that facilitate responsive caregiving and cognitive enrichment. Conversely, lower-opportunity environments may place additional demands on caregivers, increasing stress and reducing opportunities for engagement in cognitively enriching activities. Through these pathways, broader contextual influences may indirectly affect children's EF development. Future studies utilizing mediation models may be particularly valuable for examining how parenting behaviors and family relationships translate neighborhood-level opportunities and disadvantages into EF outcomes, providing a more comprehensive understanding of how environmental influences become embedded in developmental processes.

5.3.2.4 Other forms of adverse experiences.

Socioeconomic disadvantage frequently co-occurs with other forms of adversity, including maltreatment, neglect, family conflict, and community violence (Bradley & Corwyn, 2002). These experiences may have direct implications for cognitive and neurobiological development and may partially explain associations between socioeconomic conditions and EF. Although no significant indirect effect of material hardship on drift rate through violence exposure was found in Chapter 2, the current findings do not rule out possibilities of other adverse experience contributing to the associations. Future research should continue investigating how multiple forms of adversity interact across development and whether specific combinations of experiences confer greater risk for cognitive difficulties than any single exposure alone.

5.3.3 Implications for mental health outcomes

Extensive research has documented associations between socioeconomic disadvantage and a wide range of internalizing and externalizing outcomes (Reiss, 2013; Santiago et al., 2011).

Aligning with research initiatives such as the Research Domain Criteria (RDoC) framework (Insel et al., 2010), which aims to understanding psychopathology in the context of neurobehavioral functioning, characterizing changes in EF may benefit our understanding of mental health outcomes. Previous studies have shown changes to executive functioning associated with internalizing and externalizing psychopathology, as well as mediating the associations between socioeconomic disadvantage and mental health outcomes (McNeilly et al., 2021; Pennington & Ozonoff, 1996; Snyder et al., 2015). Relatedly, EEA has emerged as a potentially important transdiagnostic construct, where previous studies have linked lower EEA to a variety of psychopathology-related outcomes, suggesting that inefficient evidence accumulation may reflect a general cognitive vulnerability associated with difficulties in self-regulation, decision-making, and adaptive behavior (Weigard & Sripada, 2021). Rather than being specific to any one disorder, EEA may represent a common neurocognitive process that contributes to risk across multiple forms of psychopathology.

Findings from Chapter 2 provide preliminary support for this perspective, where lower drift rate was associated with greater attentional difficulties and statistically linked childhood material hardship to adolescent attentional problems. Although additional replication is needed, these findings suggest that cognitive efficiency may represent one pathway through which socioeconomic disadvantage influences mental health outcomes. Future research should continue investigating whether cognitive efficiency serves as a developmental mechanism linking environmental experiences to psychopathology. Such work may contribute to a more mechanistic understanding of mental health risk and help identify intervention targets that cut across traditional diagnostic categories.

5.3.4 The role of covariates in analyses

Analyses throughout this dissertation adjusted for various demographic covariates (e.g., age, biological sex, ethnoracial identity, pubertal stage) to help account for potential confounds to the associations of the main socioeconomic contextual variables of interest on drift rate. By doing so, the main associations are then interpreted as links between socioeconomic context and drift rate above and beyond potential effects of demographic variables and therefore, become more robust. However, the inclusion of demographic covariates should not be interpreted as suggesting that they are simple nuisance variables. Demographic characteristics themselves may be associated with developmental trajectories of executive functioning outcomes as well as socioeconomic factors. Chapter 3 explored this possibility briefly with sensitivity analyses using ethnoracial identity, given the potential implications of race-related structural inequalities on the neighborhoods where participants may reside. At the same time, ethnoracial identity as a covariate cannot fully account for structural racism or related social processes that may shape neurocognitive development, warranting future work that continues to clarify broader structural mechanisms through which these characteristics become associated with developmental outcomes.

Additional considerations should also be given to sex and pubertal stage, which may be especially important sources of heterogeneity in executive functioning development for adolescents. Adolescence is characterized by substantial variation in the timing and pace of pubertal maturation, which is closely linked with biological sex and may interact with environmental experiences to shape neurocognitive development (Deater-Deckard et al., 2019; Dorn & Beltz, 2023; Schulte et al., 2020). Likewise, growing recognition of sex as a biological variable highlights the possibility that socioeconomic experiences may differentially influence cognitive development in males and females (Assari et al., 2020; Nooner et al., 2018; Schulte et

al., 2020). Although the present studies were not designed to comprehensively examine such interactions, future work should explicitly investigate whether associations between socioeconomic context and evidence accumulation efficiency differ across sex or pubertal development.

5.3.5 Beyond correlational studies and steps towards causality

Although the longitudinal design of studies in this dissertation strengthens temporal ordering by investigating associations between childhood exposure to adolescent outcomes, and adolescent exposure to young adult outcome, the findings are nonetheless correlational rather than causal. The complexity of co-occurring socioeconomic and biological factors, amongst others, makes it possible that the observed associations may reflect other factors not measured or included in current analyses. Future research should consider integrating study designs that provide stronger leverage for causal inference. For example, quasi-experimental and natural experimental designs, including policy changes (Woods-Jaeger et al., 2021) and housing mobility programs (Chetty et al., 2016), offer valuable opportunities to evaluate whether changes in socioeconomic environments lead to corresponding changes in development. Genetically informed approaches, such as twin comparisons (Hyde et al., 2011), or adoption studies (Nelson et al., 2007), can help distinguish environmental influences from shared familial and genetic factors. Ultimately, converging evidence across studies with different designs will provide a stronger foundation for identifying causal mechanisms and informing policies aimed at reducing socioeconomic disparities in neurocognitive development.

5.4 Conclusion

The socioeconomic context in which children develop are complex and multifaceted. Understanding how these contexts shape EF development remains a challenge for developmental

science. The present dissertation sought to address this challenge by integrating a well-established computational cognitive modeling approach with a developmental lens to examine how diverse socioeconomic experiences can shape neurocognitive functioning across development. Across three studies, findings demonstrated that both household-level disadvantage and neighborhood-level opportunity were longitudinally associated with cognitive efficiency, highlighting the importance of examining multiple dimensions of socioeconomic context. The dissertation further demonstrated the utility of computational approaches for identifying specific cognitive processes that may be sensitive to environmental influences and provided preliminary evidence regarding neural systems that may support these associations. Ultimately, promoting healthy developmental outcomes requires understanding not only whether socioeconomic contexts matter, but also how and why they matter. Continued efforts to identify the cognitive and neural mechanisms linking environmental experiences to developmental outcomes may help inform interventions and policies aimed at promoting equitable opportunities for healthy development. Through this lens, the present dissertation contributes to a growing body of research seeking to understand how environments shape neurocognitive development, with the hope that one day, as developmental scientists, we can generate actionable interventions and policy suggestions to improve the lives of children from marginalized and disadvantage communities.

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