CHAPTER TEN

Developmental cascades and educational attainment

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Abstract

Developmental cascades describe how systems of development interact and influence one another to shape human development across the lifespan. Despite its popularity, developmental cascades are commonly used to understand the developmental course of psychopathology, typically in the context of risk and resilience. Whether this framework can be useful for studying children's educational outcomes remains underexplored. Therefore, in this chapter, we provide an overview of how developmental cascades can be used to study children's academic development, with a particular focus on the biological, cognitive, and contextual pathways to educational attainment. We also provide a summary of contemporary statistical methods and highlight existing data sets that can be used to test developmental cascade models of educational attainment from birth through adulthood. We conclude the chapter by discussing the challenges of this research and explore important future directions of using developmental cascades to understand educational attainment.

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The developmental cascades framework seeks to understand whether aspects of human development influence distal outcomes via their cumulative and transactional effects on more proximal processes (e.g., Cicchetti & Tucker, 1994; Dodge et al., 2009; Fry & Hale, 1996; Rutter, 1999; Sameroff, 2000). A central tenet of developmental cascades is that processes within one system of development influence other developmental systems to shape human development across the lifespan. Theoretically, these transactional processes begin early in life, span multiple levels of development, and accumulate over time to place children on different developmental pathways to adulthood (Masten & Cicchetti, 2010). Developmental cascades are born out of, and build on, various foundational theories of human development, including the transactional model (Sameroff, 2009; Sameroff & Chandler, 1975); the bioecological model (Bronfenbrenner, 1992; Bronfenbrenner & Morris, 2006), and the dynamic systems theory of human development (Smith & Thelen, 1993; Thelen, 2005).

Despite its broad applicability to several areas of human development research, developmental cascades are most commonly applied to understanding developmental psychopathology, typically in the context of risk and resilience (see Masten & Cicchetti, 2010, for review). However, the extent to which developmental cascades can be a useful framework for studying children's educational attainment is less understood. Educational outcomes are influenced by interactive and transactional processes within and across biological, cognitive, and contextual systems that dynamically shift throughout development– and as such, can be understood through a developmental cascades lens. Therefore, in the current chapter, we explore the utility of developmental cascades for understanding academic achievement, with a specific focus on the biological, cognitive, and contextual pathways to educational attainment from birth to adulthood. We also provide a resource table of existing data sets and showcase contemporary methods for testing developmental cascades models across multiple levels of influence. We then conclude the chapter by discussing the challenges and future directions of using developmental cascades to understand educational attainment.

1. Developmental cascade model for understanding educational attainment

In the next sections, we outline and discuss the factors associated with educational attainment and propose a developmental cascades model for studying educational attainment that (1) takes into account the several biological, cognitive, and contextual factors associated with academic outcomes, (2) considers how these systems of influence interact and accumulate across development, and (3) aims to identify the various positive pathways to educational attainment. Although developmental cascades are typically used to describe mechanisms underlying maladaptive outcomes, they can also be applied to understanding the positive pathways to adaptation (Masten & Cicchetti, 2010). Specifically, this framework can be used to understand how aspects of early human development (e.g., events, experiences, abilities) interact with environmental conditions (e.g., schools, neighborhoods, cultural norms) to lay the foundation for the development of later skills and influence children's educational attainment. Similar to developmental theories of competence and positive chain reactions, as well as economic theories of early skill formation, a major principle of developmental cascades is that early influences and abilities accumulate over time to shape future outcomes, creating a snowball effect that leads to positive adaptation (Heckman, 2006; Masten et al., 2005; Rutter, 1999). In the context of educational attainment, biological influences (i.e., genetics, hormonal changes, neural maturation), cognitive development (executive processes underlying achievement), and contextual factors (e.g., home, peers, schools, neighborhood, and culture) all interact over time to influence academic development. Importantly, the salience and consequences of these influences differ across development and build upon one another over time. Fig. 1 depicts this complex system in a general developmental cascade model of educational attainment, which starts in infancy and extends through adulthood.

An illustrative developmental cascade model of educational attainment could begin with biological, cognitive, and contextual factors measured at birth or in early childhood. These could include polygenic scores of educational attainment, measures of early brain development (particularly in regions related to language and memory) as well as contextual factors (e.g., parenting practices, peer groups, home environments, and neighborhood effects) that are associated with children's academic development. These early conditions could stimulate (or limit) the development of executive functioning and social competencies during the early school years, causing spillover effects in early academic domains (e.g., better letter and symbol recognition). Academic, social, and self-regulatory competencies could then propagate over early and middle childhood, culminating in better academic performance, more school engagement, and more academic motivation. This process could be accelerated by normative biological (e.g., pubertal onset, changes in neural reactivity), social (e.g., transition to middle

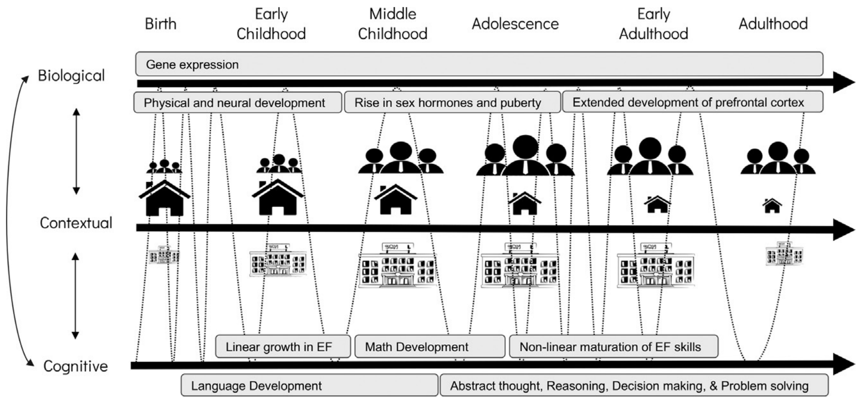

Fig. 1 Developmental cascade models of educational attainment. *Note*. Conceptual depiction of developmental cascades of educational attainment from birth to adulthood. The thick black arrowed lines depict time. The blocked texts represent the general timing of major developmental processes occurring in biological and cognitive domains. The importance of the home environment, schools, and peers are illustrated by their relative size in each domain (e.g., the home environment decreases in size as youth begin to spend more time in their neighborhoods and schools and with their peers instead of their parents). The thin dotted lines connecting the biological, contextual, and cognitive domains depict the cascading influences across systems of development. Cascades occur more frequently early in development (e.g., birth and early childhood) and during sensitive windows of development (e.g., adolescence) when dramatic biopsychosocial changes occur. These processes are also embedded within a larger sociocultural context and intersect with various micro-and macro-level cultural norms and expectations over time to influence educational attainment.

and high school), and psychological (e.g., race/ethnic identity formation) events that occur later in development and may act as critical developmental switches.

Throughout development, environmental contexts interact with child characteristics (e.g., race, ethnicity, gender, disability status) to shape and constrain the scope of academic development via proximal (e.g., socioeconomic factors, racism, immigration status) and distal (e.g., neighborhoods, cultural norms, country or state-wide laws and regulation) processes, but also change over development. Stable contexts such as the home environment may exert less influence over time while new, time-varying contexts (e.g., increased time in neighborhoods or with peers) may trigger different academic goals and motivations. Accumulating advantages (or disadvantages) then explain continuous and discontinuous trajectories experienced by youth across time. We expand on each of these areas in the next sections to provide the research foundation for their inclusion in the model and how they reciprocally affect one another in complex and dynamic ways to influence educational attainment.

2. Biological cascades and educational attainment

Biology plays a significant role in shaping children's development. Among others, genetic influences, physical maturation, and neurological development interact with environmental influences (e.g., home environment, schooling, cultural norms) to influence a range of developmental outcomes throughout the life course. Biological cascades can have considerable impacts on future growth and development—some of which (e.g., neural development, epigenetic effects, etc.) can occur early, while others (e.g., physical development, hormonal changes) are observable across different stages of development, affecting children's academic development through cognitive and behavioral mechanisms. Here, we review some of the major biological systems that can be examined via the developmental cascades framework to understand educational attainment, focusing specifically on genetic, maturational, and neurological changes across childhood and adolescence.

Genetic Influences. Recent advances in behavioral genetics have revealed substantial genetic architecture underlying educational attainment. Polygenic scores of educational attainment, which combine the effects of genetic variants across the entire genome, explain approximately 10–13% of the variance in education attainment (Lee et al., 2018; Okbay et al., 2016; Rietveld et al., 2013). Children and adolescents with higher polygenic scores of educational attainment tend to get better scores on academic tests (Krapohl & Plomin, 2015; Rea-Sandin et al., 2021) and are more likely to attend post-secondary institutions compared to their peers (Harden et al., 2020; Rabinowitz et al., 2019). These genetic effects operate through both direct and indirect pathways. For instance, the polygenic score of educational attainment has been linked to individual differences in brain size and development (particularly in regions related to language, memory, and cognitive processing; Judd et al., 2020; Merz et al., 2022; Mitchell et al., 2020) as well as to differences in cognitive ability, self-control, and interpersonal skills which have unique and direct contributions to academic achievement at each life stage (Elliott et al., 2019; Lee et al., 2018).

However, genetic influences on educational attainment are also filtered and shaped by proximal and distal environmental contexts. Proximally, parental genotypes can contribute to child educational attainment *through contextual pathways*: Mothers with higher education polygenic scores tend to be healthier during pregnancy (Armstrong-Carter et al., 2020) and are more likely to be warm, sensitive caregivers, which contribute to their children's later academic achievement over and above direct genetic effects (Wertz et al., 2019). Distally, genetic influences on educational attainment may differ by socioeconomic status (see Krapohl & Plomin, 2015), with research suggesting that the education polygenic score is more predictive for those who face less socioeconomic adversity (e.g., environment bottleneck theory; Herd et al., 2019; Wickrama, Lee, O'Neal, & Lorenz, 2021). Thus, epigenetic modifications (i.e., the regulation of gene expression by environmental conditions) can also contribute to educational attainment.

Genetic and epigenetic influences are considered the first of many developmental cascades (see Armstrong-Carter et al., 2020), but their influences likely vary and compound across childhood and adolescence in ways that depend on youth characteristics, their life stage, and their environment. For instance, polygenic scores of educational attainment may be particularly relevant for the development of brain regions associated with learning and memory (Merz et al., 2022), but in adolescence and early adulthood, polygenic scores may be more salient for specific cognitive skills or academic persistence (Harden et al., 2020; Wickrama, Lee, et al., 2021). Furthermore, in older cohorts, the relation between genetics and educational attainment is weaker for women than for men, but as opportunities for women's education have increased, this gender difference has diminished (see Herd et al., 2019). This suggests that structural impediments (e.g., sexism, racism, xenophobia) but also programs targeting these disparities (e.g., universal preschool, free or reduced college tuition) are key contributors to educational attainment and can moderate links between genetics and educational attainment. These effects and how they manifest across the lifespan can be investigated within developmental cascades research but must also be understood within the context of youth's environment and relation to societal structures.

Physical Influences. In addition to genetic influences, general maturational processes (e.g., birth weight, nutrition, puberty) play a significant role in educational attainment (see Black, Devereux, & Salvanes, 2007; Conley & Bennett, 2000; Glewwe, Jacoby, & King, 2001). Children experience rapid changes in body size from birth to toddlerhood which correspond to early neural development and growth in cognitive processes related to educational attainment (Gao, Alcauter, Smith, Gilmore, & Lin, 2015; Johnson, Riis, &

Noble, 2016). Children continue to grow steadily during the preschool and early school years, until adolescence when youth experience another major growth spurt related to pubertal onset (Wolf & Long, 2016). Pubertal development is the biological hallmark of adolescence, leading to reproductive maturation and initiating a cascade of hormonal, neural, and behavioral changes (Berenbaum, Beltz, & Corley, 2015; Blakemore, 2012; Sisk, 2017). Pubertal onset—which itself is a multidetermined, biopsychosocial process influenced by genetics, nutrition, body weight, and SES—begins with a rise in sex hormones (primarily testosterone in boys, estradiol in girls, and DHEA in both) in middle childhood (DelGiudice, 2018). These hormonal changes precede the physical signs of puberty but are ultimately responsible for the development of secondary sex characteristics (e.g., breast development; pubic hair growth; Auchus & Rainey, 2004); changes in neural reactivity to socioemotional and motivational stimuli (Crone & Dahl, 2012); and the recalibration of other biological processes (e.g., stress; Holder & Blaustein, 2014).

Girls tend to begin puberty one to two years before boys (Farello, Altieri, Cutini, Pozzobon, & Verrotti, 2019), but even within sex, there are large interindividual differences in pubertal onset (Graber, Nichols, & Brooks-Gunn, 2010; Mendle, Harden, Brooks-Gunn, & Graber, 2010) that have long-term implications for cognition and educational attainment. For example, early maturing girls and boys had faster growth in attention during adolescence (Chaku & Hoyt, 2019) and converging evidence indicates that earlier pubertal maturation has persisting effects on educational attainment as well: For boys, earlier pubertal timing is associated with higher educational attainment (Koerselman & Pekkarinen, 2018; Koivusilta & Rimpela, 2004), but for girls, pubertal timing effects are less clear: Some studies find few effects for girls generally (e.g., Koerselman & Pekkarinen, 2018), but others find that pubertal effects may operate through intermediary pathways. For example, one study found that early pubertal timing predicted girls' probability of course failure at the start of high school and contributed to the likelihood they would drop out of high school, potentially because of increased psychosocial risks associated with early pubertal timing (e.g., depression, associating with deviant peers; substance use; Cavanagh, Riegle-Crumb, & Crosnoe, 2007).

Thus, pubertal development may have indirect or cascading effects on educational attainment through ongoing changes in other neurobehavioral processes. For example, substantial changes in motivation, academic drive, and academic self-concept have been associated with hormonal changes occurring during puberty (Blakemore, 2010). Indeed, in one study, early pubertal timing did not directly predict academic achievement but did predict lower academic motivation, which was, in turn, related to lower academic achievement (Martin & Steinbeck, 2017). Puberty also reshapes the adolescent stress response, and evidence suggests that adolescents respond to stressors (in particular, social stressors) differently than children or adults (Foilb, Lui, & Romeo, 2011; Holder & Blaustein, 2014). Given research linking stress with worse academic achievement (see Schraml, Perski, Grossi, & Makower, 2012), pubertal effects on educational attainment may operate through differential and perhaps heightened stress responses as well. These effects may be exacerbated for early maturing individuals who often face multiple stressors before the rest of their peers (Ge, Conger, & Elder Jr, 2001). Thus, puberty may represent a cascading process where developmental differences across individuals widen and become more salient for educational decisions and outcomes.

Neurological Influences. The normative physical changes that occur over childhood and adolescence are associated with brain development. There are two key periods of brain development relevant to children's educational outcomes. Beginning prenatally and continuing over early childhood, the brain undergoes a period of synaptogenesis (i.e., growth in neural connections), synaptic pruning (i.e., experience-sensitive removal of neural connections), and myelination (i.e., production of neural sheaths; see Bethlehem et al., 2022 for brain growth charts). Although a detailed review of these processes is outside the scope of this chapter (see Gilmore, Santelli, & Gao, 2018), they are essential for the development of a vast repertoire of behaviors (e.g., language, early numeracy) that characterize early cognitions and eventually educational attainment (Haist, Wazny, Toomarian, & Adamo, 2015; Phan et al., 2021).

Although the basic structure and functions of the brain are laid down during the prenatal period and in early childhood, neural networks continue to form and are refined throughout development (Foulkes & Blakemore, 2018). During adolescence, for example, increases in pubertal hormones are associated with structural and functional brain growth and reorganization, especially in regions associated with memory, motivation, decision making, and sensation seeking (Fuhrmann, Knoll, & Blakemore, 2015; Sisk & Zehr, 2005). Specifically, neural reactivity to socioemotional and motivational stimuli is enhanced during early adolescence (Goddings et al., 2014), but long-term reductions in cortical gray matter, along with increases in cortical white matter in the frontal and temporal lobes, contribute to better cognitive performance over time (Perrin et al., 2008; Vijayakumar et al., 2016; Vijayakumar, Op de Macks, Shirtcliff, & Pfeifer, 2018).

Brain development in both childhood and adolescence occurs in tandem with adaptive responses to environmental exposures. In infancy and early childhood, exposure to positive environmental stimuli (e.g., sensitive caregiving) is associated with adaptive functioning and lays the foundation for future learning (Fox, Levitt, & Nelson, 2010). However, adverse experiences associated with lower SES (lower funded schools, impoverished neighborhoods, family stress, etc.) and other adverse childhood experiences are associated with structural differences in areas of the brain associated with language and reading development (Noble, Wolmetz, Ochs, Farah, & McCandliss, 2006), executive functioning (Hackman, Farah, & Meaney, 2010; Kishiyama, Boyce, Jimenez, Perry, & Knight, 2009), and school readiness (Blair & Raver, 2016; Noble, Tottenham, & Casey, 2005), which can have long-term implications for educational attainment (see Tooley, Bassett, & Mackey, 2021). Adolescence represents a second period of brain reorganization (Blakemore & Choudhury, 2006; Crone & Dahl, 2012) and potentially a second opportunity for growth and development (especially as related to higher-order cognitive skills; Fuhrmann et al., 2015; Knoll et al., 2016; Mark, 2013). These positive trajectories, however, can also be disrupted not only by earlier stressors but also by new ones that become more relevant in adolescence (e.g., peer victimization, social rejection, or exclusion; Masten et al., 2009; Silk et al., 2014; Stroud et al., 2009).

3. Cognitive cascades and educational attainment

The important periods of brain development also coincide with the rapid development of children's cognitive abilities. Among the many cognitive factors related to educational outcomes, interest has mounted steadily on a constellation of cognitive processes commonly referred to as executive function (EF). This broad set of cognitive skills is responsible for the regulation of important frontal lobe functions (e.g., attention, memory, inhibition, and cognitive flexibility) and facilitates complex thoughts and behaviors such as planning, problem-solving, and purposeful goal pursuits (Diamond, 2013; Miyake, Friedman, Emerson, Witzki, & Howerter, 2000; Posner & Rothbart, 2000). Although EF skills emerge during early infancy and continue to develop into adulthood, research has highlighted the importance of the early childhood and adolescent periods for the growth of these skills (Ahmed, Ellis, Ward, Chaku, & Davis-Kean, 2022; Best, Miller, & Naglieri, 2011; Blakemore & Choudhury, 2006; Crone, Peters, & Steinbeis, 2017; Willoughby, Wirth, & Blair, 2012). These patterns of EF development parallel models of neural and cortical development and undergo significant reorganization across development (Hughes & Ensor, 2011; Miyake et al., 2000; Wiebe et al., 2011; Willoughby, Blair, Wirth, & Greenberg, 2010; Zelazo, Blair, & Willoughby, 2016).

The childhood and adolescent periods of EF growth have also been linked to children's academic outcomes across development. Notably, EF development during early childhood has been shown to robustly predict academic development during early and middle childhood (Ellis et al., 2021; Morgan et al., 2019; Nguyen & Duncan, 2019; Woods, Ahmed, Katz, & Morrison, 2020), into adolescence (Ahmed, Tang, Waters, & Davis-Kean, 2019; Duncan et al., 2007; Watts, Duncan, Siegler, & Davis-Kean, 2014), and is also associated with college attainment (Ahmed, Kuhfeld, Watts, Davis-Kean, & Vandell, 2021; McClelland, Acock, Piccinin, Rhea, & Stallings, 2013). A smaller body of research has also documented the role of adolescent EF and academic achievement in math, reading, and science domains, as well as overall grade point average during high school (Latzman, Elkovitch, Young, & Clark, 2010; Samuels, Tournaki, Blackman, & Zilinski, 2016). Adolescent EF has also been shown to explain early-life socioeconomic disparities in high school academic achievement and is associated with persistence in higher education (Andersson & Bergman, 2011; Deer, Hastings, & Hostinar, 2020).

Research has also begun to examine whether and to what extent early cognitive development lays the foundation for the development of other cognitive, behavioral, and academic abilities across childhood and adolescence that influence educational attainment (Ahmed et al., 2021; Bornstein, Hahn, & Wolke, 2013; McClelland et al., 2013). For example, using a developmental cascades framework, one study found that EF skills during preschool predicted children's college attainment through positive and cascading effects on EF during middle childhood in a prospective longitudinal sample (Ahmed et al., 2021). Researchers have also examined how early EF development might predict educational attainment via its effect on academic achievement. For instance, high school academic achievement has been shown to mediate associations between preschool attention span and adult educational attainment (McClelland et al., 2013). Finally, a handful of studies have applied a developmental cascade framework to study early EF and academic outcomes across narrower stages of development. For example, EF has been shown to mediate associations between processing speed and academic achievement in a sample of 8–16-year children (Cassidy, White, DeMaso, Newburger, & Bellinger, 2016), and birth status (preterm vs. full-term) predicted math and reading achievement at age 11 through cascading effects on EF across childhood (Rose, Feldman, & Jankowski, 2011). It's important to note that although EF has emerged as an important predictor of children's educational success across the lifespan, it too exists in a complex system and interacts with other cognitive skills, biological systems, and contextual influences to shape children's academic development across the lifespan.

4. Contextual cascades and educational attainment

In addition to the biological and cognitive influences on educational attainment, several contextual factors are associated with children's academic development and educational attainment. These contextual influences are time-varying and thus, wax and wane across development and interact with biological and cognitive influences in cascading ways. In the next sections, we review the most common contextual influences relevant to educational attainment (parenting, early home environment, schooling, and peers).

Early Home Environment. The home is a child's primary developmental context before school entry; thus, considerable attention has been paid to the roles of parenting and the home environment in shaping children's early academic development. Among the many theoretical models that outline important family processes that can impact children's development, (for review, see Davis-Kean, Tighe, & Waters, 2021) the family stress and family investment models have received considerable attention as it relates to children's educational attainment. First, the family stress model posits that economic hardship has a deleterious effect on children's academic development indirectly via its influence on parents' psychological well-being and disrupted parenting (Masarik & Conger, 2017). Numerous studies have provided empirical evidence for this model, demonstrating the impact of parents' stress on children's academic development through various parenting behaviors (e.g., Guo & Harris, 2000; Linver, Brooks-Gunn, & Kohen, 2002; Mistry, Biesanz, Taylor, Burchinal, & Cox, 2004; Yeung, Linver, & Brooks-Gunn, 2002).

Conversely, the family investment model proposes that higher-resourced families have greater access to the knowledge and resources that can promote children's academic development (Conger & Donnellan, 2007). The family investment model has also garnered considerable empirical support, with researchers identifying factors like warmth and responsiveness (e.g., Davis-Kean, 2005; Davis-Kean & Sexton, 2009; Yeung et al., 2002) and the provision of cognitively stimulating resources and experiences (e.g., Davis-Kean, 2005; Davis-Kean & Sexton, 2009; Raver, Gershoff, & Aber, 2007) as key contributors to children's academic development. Taken together, these findings highlight the importance of parenting and the home environment for shaping children's academic development and underscores the need to consider how contextual processes might impact children's academic and other developmental outcomes.

Recently, researchers have begun to expand these models as they attempt to identify the mechanistic pathways that underlie associations between parenting and the home environment and children's academic development. Given that executive function skills are thought to serve as foundational cognitive tools for academic learning (Blair, 2002; Morrison, Cameron Ponitz, & McClelland, 2010), and that associations between parenting and children's executive function skills are well-established (Fay-Stammbach, Hawes, & Meredith, 2014; Valcan, Davis, & Pino-Pasternak, 2018), some have begun to examine whether parenting and the home environment might shape children's academic development indirectly via their cascading influences on children's cognitive development (e.g., Bernier, Beauchamp, & Cimon-Paquet, 2020; Bindman, Pomerantz, & Roisman, 2015; Devine, Bignardi, & Hughes, 2016; Korucu, Litkowski, & Schmitt, 2020). For example, one study tested a developmental cascade model linking family socioeconomic status to children's academic achievement indirectly through contextual and cognitive mechanisms, finding multiple parenting and executive function pathways to children's math and reading development across early childhood (Waters, Ahmed, Tang, & Davis-Kean, 2022).

Schooling Influences. The influence of the home environment begins to decrease as children spend more time in schools. The transition into formal schooling, thus, represents a key developmental milestone and is a critical period for children's social, cognitive, and academic development. Decades of developmental and educational research has demonstrated the role of schooling for children's development, particularly during the early years of school. Using quasi-experimental techniques, research has identified the unique contribution of schooling on children's cognitive and academic development (for review, see Morrison, Kim, Connor, & Grammer, 2019). For example, the school-cutoff method offers a "natural experiment" that takes advantage of arbitrary birthdate cutoffs that determine when children of virtually the same age are eligible to begin formal schooling (Ferreira & Morrison, 1994; Varnhagen, Morrison, & Everall, 1994). If a state's cutoff date for kindergarten entry is September 1st, all children who turn five before September 1st are eligible to begin kindergarten that year, while those born after that date must wait until the following year to enroll. Using the school-cutoff method, researchers can constrain their sample to include just those children with birth dates that cluster around the cutoff (e.g., 2 or 3 months on either side of the cutoff). For both groups of children, skills are assessed at the beginning and the end of the school year, allowing for an examination of the effect of one year of schooling to be separated from that which is related to maturational growth. Similar to the school-cutoff method, the regression discontinuity design also takes advantage of school cutoff dates. Unlike the school-cutoff method, however, there is no need to constrain the sample, allowing researchers to more flexibly to model the relation between the outcome of interest and the age-related continuous scale (for review, see Jacob, Zhu, Somers, & Bloom, 2012).

The majority of studies that have employed these techniques have focused on isolating the effect of schooling on children's academic development. Although predominantly studied in U.S. samples, results from these studies indicate an added benefit of schooling for growth in emerging literacy and reading skills across the school transition period (e.g., Burrage et al., 2008; Christian, Morrison, Frazier, & Massetti, 2000; Kim, Ahmed, & Morrison, 2021; Kim & Morrison, 2018; Morrison, Smith, & Dow-Ehrensberger, 1995; Skibbe, Connor, Morrison, & Jewkes, 2011; Varnhagen et al., 1994). Evidence for schooling effects on children's math development, however, is more equivocal, with some studies (e.g., Bisanz, Morrison, & Dunn, 1995; Gormley, Gayer, Phillips, & Dawson, 2005; Weiland & Yoshikawa, 2013; Wong, Cook, Barnett, & Jung, 2008) but not all (e.g., Finders, Geldhof, Dahlgren, Olsen, & McClelland, 2022; Kim et al., 2021), observing an effect of schooling on children's mathematical development. Although not studied widely, there is some evidence that schooling also impacts children's EF development (Brod, Bunge, & Shing, 2017; Burrage et al., 2008; Kim et al., 2021; Weiland & Yoshikawa, 2013; see also Finders et al., 2022). Additionally, Weiland and Yoshikawa (2013) found that schooling effects were largest for preschool children from disadvantaged backgrounds, suggesting that school can serve as a positive pathway to academic success. From a developmental cascades perspective, these types of quasi-experimental designs can be used to understand how schooling might interact with contextual variables to impact children's academic development directly, and through their cascading effects on different child-level and contextual variables. Importantly, they can offer researchers with tools to test causal relationships that might exist within developmental cascade models.

Peers Groups and Social Context. As children enter school, they encounter a new social landscape consisting of interactions with peers and teachers. Navigating this new social context not only lays the foundation for the development of children's social skills but also plays a significant role in other areas of children's development. Starting as early as preschool, children's classmates have been shown to exert an influence on their language development, emergent math and reading achievement, as well as EF and social-emotional competence (e.g., Choi et al., 2018; Mashburn, Justice, Downer, & Pianta, 2009; Montroy, Bowles, & Skibbe, 2016; Neidell & Waldfogel, 2010; Skibbe, Phillips, Day, Brophy-Herb, & Connor, 2012). As children progress through schooling, the salience and influence of their peers also increase (Kerr, Stattin, Biesecker, & Ferrer-Wreder, 2003). For example, adolescents in the same peer groups tend to have similar academic goals (Gallardo, Barrasa, & Guevara-Viejo, 2016), school engagement (Li, Doyle Lynch, Kalvin, Liu, & Lerner, 2011), and educational attainment outcomes (Wang, Kiuru, Degol, & Salmela-Aro, 2018). Across development, this generally occurs via selection effects—youth tend to seek out friends with similar goals and tend to reinforce each other's behaviors (Dijkstra & Gest, 2015; Gremmen, Dijkstra, Steglich, & Veenstra, 2017), but may also occur via social influence—youth also respond to (and are influenced by) their friends' disruptive behaviors, school attendance, and academic motivation (Kindermann, 2016; Molloy, Gest, & Rulison, 2011; Shin & Ryan, 2014a; Shin & Ryan, 2014b).

In the U.S., social acceptance (i.e., general likability or positive regard from peers) and popularity (i.e., the shared consensus that a particular adolescent has a higher social status than others) also play important roles in educational attainment. Social acceptance is associated with higher academic achievement and more competence, whereas social rejection (e.g., peer victimization, rejection, or exclusion) is associated with consistently worse academic performance (Greenman, Schneider, & Tomada, 2009; Rambaran et al., 2017). In contrast, popularity has mixed effects on educational attainment (for review, see Cillessen & Marks, 2011; Veenstra & Laninga-Wijnen, 2022). For example, popular but aggressive adolescents tend to report more difficulties with school adjustment compared to less popular youth (Schwartz, Gorman, Nakamoto, & McKay, 2006; Troop-Gordon, Visconti, & Kuntz, 2011). Notably, popular youth also tend to be influential; their endorsements of positive or negative educational goals are more likely to be endorsed by others (Veenstra & Laninga-Wijnen, 2022). Thus, peer effects can influence educational attainment via proximal (e.g., friend selection), distal (e.g., social acceptance), or even bidirectional processes (e.g., when popular youth set norms around academic motivation).

5. Existing datasets and statistical methods for testing cascades across development

The dynamic and transactional nature of testing developmental cascade models across multiple levels of influence requires rich longitudinal data and advanced statistical methods. However, gathering data that span decades and include biological, cognitive, and contextual variables can be extremely challenging and expensive. In the following section, we provide information on several datasets that can be used to test complex cascade models, highlighting the features of longitudinal datasets that make them well-suited for testing developmental cascades. We also provide a short review of statistical analyses for testing developmental cascades across childhood and adolescence, focusing on promising, but underutilized models.

Existing Datasets for Testing Cascade Models. The number of openly available longitudinal data sets that can be used to test developmental cascades—due to the rich longitudinal and cross-domain scope of the data they contain—is growing. These datasets include multiple observations of the same individuals over time and across biological, cognitive, and contextual domains. For example, the Fragile Families and Child Well-Being Study (FFCWS; Reichman, Teitler, Garfinkel, & McLanahan, 2001), a longitudinal birth cohort study, is publicly available to researchers and includes biological, cognitive, and contextual variables across development. The FFCWS sampled a birth cohort of 4,898 children in 20 major U.S. cities between 1998 and 2000 and followed them into adulthood to understand the conditions and capabilities of new parents and the well-being of their children (Reichman et al., 2001). Home interviews, surveys, and direct child assessments were conducted when the children were 1, 3, 5, 9, 15, and 22 years old and included cognitive and academic assessments; biomarkers, such as genetics, epigenetics, and neuroimaging; and extensive information about children's family, home, neighborhood, and school contexts. Additionally, new waves of data collection are ongoing that will include comprehensive data on adult functioning in the domains of health, employment, education, and social functioning, making it an ideal data set to test complex cascade models across development.

Another exemplary data set that can be leveraged to test developmental cascade models is the NICHD Study of Early Child Care and Youth

Development (SECCYD; NICHD Early Child Care Research & Network., 2005). This longitudinal study was originally conducted at 10 research sites across the United States. Beginning in 1991, 1364 children and their families were recruited through hospital visits and enrolled at birth. The study's initial purpose was to examine the effects of children's early childcare experiences on various aspects of development throughout infancy, early childhood, middle childhood, and adolescence. Later, the study investigators received a multiyear extension to investigate the effect of schooling experiences (e.g., quality and quantity of instruction) on children's development. Like the FFCWS, the SECCYD also collected rich information about children's family experiences, the home environment, and neighborhood contexts. Using diverse methods, including observational coding, interviews and questionnaires, and direct child assessments, the SECCYD offers a comprehensive evaluation of the many factors that serve to promote or undermine children's cognitive, social, emotional, and physical development. After the conclusion of NICHD sponsorship, study investigators obtained additional funding to evaluate the period from the end of high school through age 26, allowing for an examination of the complex pathways that link early life experience to long-term outcomes in various domains of adult functioning, including educational attainment.

Several other longitudinal studies are appropriate for examining developmental cascades. Some of these are presented in Table 1. Although not exhaustive, the studies listed in this table are generally openly available (albeit subject to data use agreements), feature multiple time points that span childhood to adulthood, have data from biological, cognitive, and contextual domains, and include large sample sizes (which are necessary to conduct well-powered analyses). We note that not all studies have annual data or data available during both childhood and adulthood. For example, the Adolescent Brain Cognitive Development (ABCD) study began data collection at 9–10 years old and will continue to collect yearly data from participants until early adulthood, and the Midlife in the United States (MIDUS) study did not begin data collection until participants were middle-aged. However, the developmental cascades framework can be used within a shorter developmental time period, depending on the research question and theoretical framework. For example, peer effects on educational attainment accelerate in adolescence, and the ABCD study could be used to investigate a smaller developmental cascade focused on popularity. Some of these longitudinal datasets also have retrospective reports of adverse childhood experiences or pubertal development, which can be used to create longer developmental cascades if appropriately measured (Krinsley, Gallagher,

Table 1 Existing datasets for testing cascade models.

Secondary data sets	Data availability	Biology	Cognition	Context	Website
Avon Longitudinal Study of Parents and Children (ALSPAC)	Public access[a]	X	X	X	http://www.bristol.ac.uk/alspac/
British Cohort Study (BCS)	Public access[a]	X	X	X	www.cls.ioe.ac.uk/
Dunedin Multidisciplinary Health & Development Study (Dunedin)	Public access[a]	X		X	https://dunedinstudy.otago.ac.nz/
Early Childhood Longitudinal Study-Kindergarten Class of 1998–1999 (ECLS-K)	Public access		X	X	www.nces.ed.gov/ecls/kindergarten.asp
Early Childhood Longitudinal Study-Kindergarten Class of 2010–2011 (ECLS-K:2011)	Public access		X	X	www.nces.ed.gov/ecls/kindergarten2011.asp
Early Childhood Longitudinal Study-Birth Cohort (ECLS-B)	Public access		X	X	www.nces.ed.gov/ecls/birth.asp
Midlife in the United States (MIDUS)	Public access[a]	X		X	http://midus.wisc.edu/
Millennium Cohort Study (MCS)	Public access[a]	X	X	X	www.cls.ioe.ac.uk/
Monitoring the Future (MTF)	Public access[a]			X	www.monitoringthefuture.org/
National Child Development Study (NCDS)	Public access[a]	X	X	X	www.cls.ioe.ac.uk/
NICHD Study of Early Child Care and Youth Development (SECCYD)	Public access[a]		X	X	https://www.nichd.nih.gov/research/supported/seccyd

Continued

Table 1 Existing datasets for testing cascade models.—cont'd

Secondary data sets	Data availability	Biology	Cognition	Context	Website
Progress in International Reading Literacy Study (PIRLS)	Public access[a]		X	X	https://timssandpirls.bc.edu/databases-landing.html
The Adolescent Brain Cognitive Development (ABCD) Study	Public access	X	X	X	https://abcdstudy.org/
The Fragile Families and Child Wellbeing Study (FFCWS)	Public access[a]	X	X	X	https://fragilefamilies.princeton.edu/
The National Longitudinal Study of Adolescent Health (Add Health)	Public access[a]	X	X	X	www.cpc.unc.edu/projects/addhealth
The Panel Study of Income Dynamics (PSID)	Public access[a]	X	X	X	https://psidonline.isr.umich.edu/
Trends in International Mathematics and Science Study (TIMSS)	Public access		X	X	https://timssandpirls.bc.edu/databases-landing.html

[a]Includes both public and restricted access data.

Weathers, Kutter, & Kaloupek, 2003; Van den Bergh & Walentynowicz, 2016). It is important to note that the existing datasets summarized in this section, although suitable for testing developmental cascade models, are predominantly from western countries—which can limit the generalizability of conclusions from a global perspective. Longitudinal birth cohort studies from non-western countries are critically needed to understand whether developmental cascade models of educational attainment generalize across different societies around the world.

Statistical Methods for Testing Cascade Models. Models used to test developmental cascades are presented in Table 2 along with citations and tutorials. To date, most research using developmental cascades has been conducted using path analyses or cross-lagged panel models. Both are special types of structural equation models. In path analysis, a series of regressions are applied sequentially to longitudinal data, allowing researchers to assess direct relations between variables but also indirect effects via a mediating variable (e.g., higher SES is directly associated with higher achievement but also indirectly associated with achievement via higher teacher quality; see Stage, Carter, & Nora, 2004 for review). In cross-lagged panel models, directed relations are used to describe associations between two or more variables over time (see Selig & Little, 2012 for review). This model is considered 'crossed' because it considers relations between variables (e.g., teaching quality at time 1 is associated with higher achievement at time 2) and 'lagged' because it accounts for the autoregressive stability of one variable over time (e.g., higher achievement at time 1 is associated with higher achievement at time 2 as well).

These types of models are useful for mapping or specifying key factors and pathways in the developmental cascades. Furthermore, path analyses and cross-lagged panel models are flexible—they can accommodate both latent and observed variables (Stephenson & Holbert, 2003), model non-linear relationships (with extensions; see Asparouhov & Muthén, 2016), and handle various study designs and missing data assumptions (Nachtigall, Kroehne, Funke, Steyer, & Schiller, 2003). However, concerns persist, particularly regarding cross-lagged models (see Hamaker, Kuiper, & Grasman, 2015; Mulder & Hamaker, 2021; Mund & Nestler, 2019). Critically, these models fail to adequately disaggregate within- and between-person effects (e.g., time nested within individuals) and so fail to align with the developmental cascade models they intend to test and yield parameter estimates that are difficult to interpret in meaningful ways.

Table 2 Statistical models for testing developmental cascade models.

Modeling framework	Model	Citation	Tutorial/code
Structural equation modeling	Mediation models	Yuan, Y., & MacKinnon, D. P. (2009). Bayesian mediation analysis. *Psychological Methods, 14*(4), 301.	https://cran.r-project.org/web/packages/bama/vignettes/bama.html
	Path analyses	Stage, F. K., Carter, H. C., & Nora, A. (2004). Path analysis: An introduction and analysis of a decade of research. *The Journal of Educational Research, 98*(1), 5–13.	https://rpubs.com/tbihansk/302732
	Random-intercept cross-lagged panel	Mulder, J. D., & Hamaker, E. L. (2021). Three extensions of the random intercept cross-lagged panel model. Structural Equation Modeling: A *Multidisciplinary Journal, 28*(4), 638–648.	https://jeroendmulder.github.io/RI-CLPM/
	Parallel process latent growth curve	Ram, N., & Grimm, K. (2007). Using simple and complex growth models to articulate developmental change: Matching theory to method. *International Journal of Behavioral Development, 31*(4), 303–316.	https://www.christopherloan.com/blog/growth-ppm/
	Growth mixture models	Jung, T., & Wickrama, K. A. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass, 2*(1), 302–317.	Wickrama, K. A., Lee, T. K., O'Neal, C. W., & Lorenz, F. O. (2021). *Higher-order growth curves and mixture modeling with Mplus: A practical guide*. Routledge.

	Autoregressive latent trajectory model	Curran, P. J., Howard, A. L., Bainter, S. A., Lane, S. T., & McGinley, J. S. (2014). The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals. *Journal of Consulting and Clinical Psychology*, 82(5), 879.	https://github.com/cddesja/lavaan-reproducible/blob/master/bollen2004-autoregressive.R
Mixed effects models	Multilevel models	Leeuw, J. D., & Meijer, E. (2008). Introduction to multilevel analysis. In *Handbook of multilevel analysis* (pp. 1–75). New York, NY: Springer.	https://rpubs.com/rslbliss/r_mlm_ws
	Generalized additive mixed model	Wood, S. N. (2006). *Generalized additive models: An introduction with R*. Chapman and Hall/CRC.	https://rdrr.io/cran/gamm4/man/gamm4.html
Network models	Graphical vector autoregression	Wild, B., Eichler, M., Friederich, H. C., Hartmann, M., Zipfel, S., & Herzog, W. (2010). A graphical vector autoregressive modeling approach to the analysis of electronic diary data. *BMC Medical Research Methodology, 10*(1), 1–13.	https://kevinkotze.github.io/ts-7-var/
	Group Iterative Multiple Model Estimation	Beltz, A. M., & Gates, K. M. (2017). Network mapping with GIMME. *Multivariate Behavioral Research, 52*(6), 789–804.	https://rdrr.io/cran/gimme/

Fortunately, new methods have been developed to better disaggregate within- and between-person effects. We highlight several promising but underutilized approaches for describing developmental cascades here. First, the random intercepts cross-lagged panel model (RI-CLPM; an extension of the cross-lagged panel model) is gaining popularity in developmental cascades research (Mulder & Hamaker, 2021). In the RI-CLPM, a random intercept is specified that accounts for trait-like stability of a construct over time (e.g., individual differences in teacher quality and educational attainment). The lagged paths then represent within-person dynamics (e.g., how changes in teacher quality are associated with changes in educational attainment). Thus, the RI-CLPM is a better technique for determining whether there are unique and cumulative cascading effects from one domain to another.

Second, some latent growth curve modeling techniques can be applied to developmental cascades research. Parallel process growth curve models (Ram & Grimm, 2007), autoregressive latent trajectory models with structured residuals (ALT-SR; Curran, Howard, Bainter, Lane, & McGinley, 2014), and mixture models (McLachlan, Lee, & Rathnayake, 2019) are all extensions of the latent growth curve model that allow for the specification of within- and between-person effects over time. For example, in parallel process growth curve models, relations between two or more variables can be assessed over time. Between-person differences are represented by a random intercept and within-person changes over time are represented by a random slope; then, directed relations can be specified to assess how intercepts and slopes interrelate over time (see Chaku & Hoyt, 2019). Extensions of this model, such as the ALT-SR, can be used to further capture *time-varying* cross-lagged effects (e.g., peer effects may become more important in adolescence) and mixture models (e.g., latent class/profile analysis, growth mixture model) can be used to assess heterogeneity across samples (e.g., uncovering constellations of biological, cognitive, and contextual risk factors related to educational attainment; see Jung & Wickrama, 2008 for review).

Finally, network models might show promise for the study of developmental cascades. Network models—such as vector autoregressive (VAR) models and group iterative multiple model estimation (GIMME)—are well-suited to revealing the reciprocal, dynamic processes that unfold between and within individuals across multiple domains, emphasizing heterogeneity and temporal relations (Beltz & Gates, 2017; Sporns, 2014; Van Der Maas, Kan, Marsman, & Stevenson, 2017). In VAR models, each variable is modeled as a function of its past values and of past values of other variables in the model, which together quantify how variables affect each other over time (see Costantini et al., 2015; Epskamp, Waldorp, Mõttus, & Borsboom, 2018, for review). GIMME integrates VAR models and unified structural equation models to create sparse *person-specific* networks of directed relations among a set of variables (see Beltz & Gates, 2017; Chaku & Beltz, 2022; Gates & Molenaar, 2012; Gates, Molenaar, Hillary, Ram, & Rovine, 2010 for review). However, these relations are estimated separately for each individual in a sample and contain both contemporaneous and lagged relations. Thus, networks are person-specific, and group-level data are derived without aggregating across the sample. Although these network models assume stationarity and require intensively collected data, they may be useful for understanding spillover or reciprocal effects, for identifying clusters of individuals with similar cascading patterns, or for understanding temporal covariation. Other networks models that account for non-stationarity (e.g., continuous time series models; Ariens, Ceulemans, & Adolf, 2020) have not yet been used in developmental cascades research but would be an area ripe for future exploration. We also note that mixed effects models (e.g., multilevel models, generalized additive mixed models) can be used to conduct developmental cascades research; the differences between mixed effects models and structural equation models are primarily conceptual, and conventions regarding the use of mixed effects models and structural equation models are primarily (but not always; see Curran, 2003; Kashy & Donnellan, 2008) due to their use in different fields (e.g., psychology versus education). Although an extensive review of mixed effects modeling is outside the scope of this chapter, we encourage researchers interested in these models to explore their applications in the following texts (McCormick, Byrne, Flournoy, Mills, & Pfeifer, 2021; Mehta & West, 2000; Wu & Zhang, 2002).

6. Challenges, opportunities, and future directions for developmental cascades research

A major challenge of conducting developmental cascades research is acquiring the data needed to test complex longitudinal models. Developmental cascades typically involve modeling repeated assessments over time within and across multiple levels of influence, the data for which can be difficult and expensive to collect. However, as highlighted previously, several secondary data sets appropriate for testing developmental cascades models of educational attainment already exist (e.g., FFCWS, SECCYD, PSID). Moreover, as data sharing, open-source repositories, and data archives become more commonplace in developmental science (e.g., Davis-Kean, Jager, & Maslowsky, 2015), the number of secondary data sets appropriate for testing cascade models is increasing. The American Psychological Association (https://www.apa.org/research/responsible/data-links), for example, provides links to publicly available data sets and repositories, and the Inter-university Consortium for Political and Social Research (ICPSR) at the University of Michigan (https://www.icpsr.umich.edu/web/pages/ICPSR/index.html) houses over 70,000 social and behavioral science datasets, many of which are well-suited for testing developmental cascade models. In some cases, these data can be harmonized to create larger datasets as well.

There are also other sources of data underutilized in developmental science that can be used to test complex longitudinal models. For example, federal and state-wide administrative data, such as public-school records, census data, and other national surveys, can be accessed and linked to primary data collection efforts to test developmental cascade models. Additionally, there is a growing number of federal (e.g., National Institutes of Health, American Educational Research Foundation, U.S. Department of Health and Human Services) and foundation (William T. Grant Foundation, Spencer Foundation, etc.) funding mechanisms available for analyzing existing data sets, and for conducting follow-up studies on existing birth cohort studies. Designing new population birth cohorts that adopt a developmental cascades framework would be a promising future direction of this research as well. Doing so would create opportunities to develop multisite collaborations across disciplines to gather data that span multiple levels of influence from birth through adulthood.

Another important challenge of developmental cascades research is ensuring measurement continuity across time. Given that cascades models typically span multiple developmental stages and often involve repeated assessments, it is important to ensure that measures are developmentally appropriate. This is especially important for researchers studying psychological constructs that differ across development (e.g., frontal lobe processes such as EF) or become more salient during different developmental periods (e.g., identity development during adolescence). Without greater standardization of psychological assessments across development, it is difficult to interpret cascades models that use repeated measures, as the effect (or lack thereof) could represent psychological reorganization or the onset of new psychological functions (Masten & Cicchetti, 2010). The measurement challenges associated with modeling psychological constructs across development, however, are not unique to developmental cascades and are present across the developmental science literature. Furthermore, these challenges can create opportunities to design more developmentally appropriate measures and can contribute to the refinement of developmental theories.

Another challenge of this research is the high level of conceptual complexity inherent in cascade models. Developmental cascade models involve testing how processes within one system of development (e.g., neural development) interact with other systems of development (e.g., early schooling) to shape aspects of human development across the lifespan. Although this complexity is a notable strength of developmental cascade models, it also requires extensive knowledge and expertise in multiple areas and stages of human development. However, this complexity also presents opportunities for collaborative science, which can bring together researchers from different disciplines to answer questions that can move the field of developmental science forward in important ways.

It is also important to note, however, that cascade models can vary in complexity and do not require modeling every relevant developmental system, nor do they need to span all stages of human development. Developmental cascades can operate entirely within one system and stage of development as long as they involve modeling mechanistic pathways to distal outcomes via proximal processes (Masten & Cicchetti, 2010). For example, in this chapter, we reviewed research linking EF to educational attainment, however, motivation, academic self-concept, and identity develop during late childhood and adolescence as well and are also important for educational attainment. Similarly, we focused specifically on home, schooling, and peer contexts, yet there are other important contextual factors (e.g., health, immigration status, structural racism), as well as major structural changes (e.g., change in laws and technological advancements), and broader societal factors (e.g., large political shifts and major pandemics) that can enhance or disrupt positive developmental cascades. Ultimately, cascades models do not necessarily need to offer a comprehensive explanation of human development, but one of its strengths is that it provides an organizing framework that incorporates multiple levels of influence across multiple stages of development which can shed light on novel developmental processes and advance developmental science.

Additionally, cascade models of educational attainment can be used to understand the development of underrepresented populations using a strengths-based approach. For instance, race/ethnicity is primarily conceptualized as a single, youth-level variable that is associated with increased or decreased risk (see Williams & Deutsch, 2016). However, developmental cascades can be used to consider how child characteristics (e.g., gender, race, and ethnicity) and experiences (racial discrimination, harassment, etc.) intersect with micro- (e.g., racial socialization, familial ties) and macro-level (e.g., laws and regulations targeting minoritized populations) norms and expectations over time to influence educational attainment (Coll, Crnic, Lamberty, Wasik, & Jenkins, 1996). Doing so can broaden the diversity of developmental science research and help illuminate important child-level and contextual assets that can promote academic success across the lifespan.

Finally, a particularly promising future direction of this research would be to understand whether educational interventions can influence educational attainment via their cascading influences on more proximal processes across development. Typically, evidence of intervention effectiveness is evaluated via baseline testing before intervention implementation and after exposure to the intervention (e.g., Morris et al., 2014). Indeed, this approach is considered the gold standard for evaluating randomized controlled trials of educational interventions (e.g., Deaton & Cartwright, 2018). However, the vast majority of educational interventions do not conduct follow-up examinations beyond the end of the intervention, nor do they examine intervention effectiveness via mediating mechanisms through other domains of development (Yoshikawa et al., 2013). The developmental cascades framework, however, could be used to test the effectiveness of interventions on educational attainment via cascading processes within and across developmental domains, which can shed light on the pathways to adaptation. Under the developmental cascades framework, interventions could be designed to promote positive educational outcomes directly, as well as through their cascading effects on other developmental domains (Hinshaw, 2002; Masten & Cicchetti, 2010).

7. Conclusion

The goal of this chapter was to demonstrate the promise of developmental cascade models for research related to educational attainment. To that end, this chapter reviews the major tenets of the developmental cascades model, focusing on how they could be applied to understanding positive educational trajectories, and highlighting relevant biological, cognitive, and contextual domains associated with educational attainment. We also provided resources on statistical methods and existing data sets that can be used to test developmental cascade models of educational attainment from birth through adulthood. We hope this chapter encourages researchers to consider the dynamic and transactional processes underlying educational attainment using a developmental cascades framework.

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